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Spatial Metrics of Structure and Diversity:

Calculation from Earth Observation and map data, for use as indicators in environmental management

Submitted to Lancaster University,

Department of Geography

for the Ph.D. degree, May 2004

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0.1 ABSTRACT

The use of spatial metrics for characterisation of landscape structure was investigated, and their application as indicators for biological diversity, sustainable land use and forest management evaluated. The main objective was to define and select spatial metrics to be derived through processing of satellite images and from map data existing in Geographical Information Systems. Metrics applied as indicators should be insensitive or predictable with respect to scale changes, appropriate for description of landscape diversity and structure and mutually uncorrelated, thus ensuring that they describe different aspects and functions of landscapes.

From eight types of spatial metrics identified in the literature survey, five were applied in this study, namely Area, Edge, Shape, Patch (count) and Diversity metrics. EO based forest maps and land use/land cover data, mainly from Italy and Denmark, were analysed. Shape metrics, especially the Matheron index, proved usable for quantification of fragmentation, while Patch metrics should be used with care due to sensitivity to grain size.

The hierarchical structure of landscapes and the Modifiable Areal Unit Problem were addressed through application of the Moving Windows method. No direct solutions to the effects of these phenomena on the values of metrics of landscapes and their representation in images and maps could be devised. Rather, it was found that multi-level descriptions of landscapes using presence-absence masks from different window sizes, metrics from a number of watershed-levels and scalograms provide useful information on forests and landscapes.

A Hemeroby index was introduced for assessment of degree of disturbance at landscape spatial and thematic level. The thematic resolution of the forest classes was however found insufficient to allow calculations of Hemeroby of forests *per se*. However, the Hemeroby index appeared to be a promising tool for summarising the amount of human influence expressed in land use maps.

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1 Introduction

The forests of Europe constitute the habitats for a wealth of animals and plants - by definition not least trees. At the same time, they form parts of cultural landscapes, or when of appropriate size, they constitute landscapes in their own right. Most forests are also production systems that provide timber and other products, as well as having important recreational functions. There are thus many reasons to take interest in the way forests are managed and their ecological state. Field-based forest mapping and inventories are however expensive and time consuming, and not considered feasible for environmental monitoring tasks. Therefore methods for rapid and inexpensive mapping and analysis of forest have been requested during the last centuries. At the same time, the discipline of landscape ecology has emerged, providing a framework for spatial analysis and quantification of landscape structure. Meanwhile the availability of satellite images, starting with the successful launch of the Landsat-1 satellite in 1972, offers synoptic views of landscapes and data in digital format that, if interpreted correctly can be converted to maps of land cover and possibly land use. Today several satellite platforms provide very-high-resolution imagery of pixel size down to 60cm as well as multi-spectral data well suited for discrimination of vegetation types. Following the revolutionary development of computers and their exponentially increasing power to perform calculations, it has been possible to readily implement extraction of the many metrics of spatial structure, that has been proposed in the ecology and landscape ecology literature. The intuitive observation, that spatial structure affects biological diversity and habitat quality, supported by findings from island biogeography, has led to several attempts to statistically link measures of landscape structure and ground-survey based observations of flora and fauna, accompanied by definition of new metrics.

This specific study aimed at contributing to sustainable forest management and land use through use of spatial metrics as indicators in monitoring frameworks, using existing general land cover data, as well as satellite imagery that was processed to produce forest maps. The **objective** of this thesis was thus to **select, and if necessary develop spatial metrics that can be used to relate forest and landscape structure with the state of ecological systems at the landscape level.** It should be possible to derive the metrics through processing of satellite imagery and from existing map data stored in Geographical Information Systems (GIS).

Several theoretical and empirical studies have shown that ecological processes are hierarchically structured, as has also been found for landscape features. Values of spatial metrics appear to depend on the scale at which they are calculated, typically expressed by the pixel size of the imagery from which the underlying maps are derived. It was therefore considered important to assess the influence of scale on the selected metrics, and if possible to quantify scaling effects in order to allow comparison of metrics values derived from different data sources.

In the literature survey (chapter 2 of this thesis), the complex relationship between spatial structure and biological diversity and naturalness of landscapes is explored, with focus on forest and woodlands. The concepts of scale in Remote Sensing, biology and landscape ecology respectively were compared, and the issue of scaling addressed, especially relating to influence of scale on metrics values. The relation of metrics to dominating theories in conservation biology and landscape ecology is discussed, as well as the possible use of Earth Observation (EO) data and derived metrics in forest management. Fragmentation, seen as a state as well as a process, is introduced as field of study of special interest.

The theoretical considerations and practical approaches taken throughout the studies for this thesis can be summarised in the following **hypotheses**:

- Certain relationships can be found between biological diversity and naturalness (state) of landscapes and spatial metrics derived from EO data of the same areas.

- Different properties of landscapes are/can be revealed from data at different spatial and thematic resolutions.
- The scaling behaviour of spatial metrics can be quantified and displayed graphically.
- Combinations of spatial metrics can be optimised to yield information on forest and landscape structure in order to characterise landscapes at local and regional levels.

The last three of hypotheses above naturally lead to formulation of various research questions, posed in order to test different assumptions, these questions are stated in the empirical chapters, which are structured as follows:

Chapter 3 describes the first empirical study, where focus was on metrics describing forest structure, with the Umbria region in central Italy as the study area. Forest maps were made from detailed GIS information and from high resolution (Landsat-TM sensor) and medium resolution (IRS-WiFS scanner) satellite images. Scaling effects on metrics of fragmentation were predicted from synthesised images degraded to increasingly coarser resolutions and compared with metrics values from the EO based forest maps, and the possibility of extrapolating values found at high resolution through use of larger-area maps at lower resolution was assessed.

In the subsequent study, described in chapter 4, the objective was to describe forest structure and diversity over larger areas, with output as maps as well as tables and graphs. The spatial extent increased to cover Central and Northern and Italy and surrounding areas. Existing land use/land cover (LUC) data from the Corine Land Cover (CLC) database and a satellite based forest map were used for comparison of metrics values over large areas, now including metrics of forest area, patch numbers and diversity. A Moving-Windows (M-W) method for extraction of metrics values in areas of similar extent was implemented, allowing output of results as thematic maps of metrics values, thus visualising spatial structure. Scalogram curves were used to describe scaling effects. Results from M-W calculations were analysed at watershed and administrative region level, allowing for reporting of metrics values at different hierarchical levels. A Forest Concentration (FC) profile metric was proposed, which allowed multi-scale description of the distribution of forest within a region or study area (however any object of interest can be described).

Then, chapter 5 presents results from in a study that covered Vendsyssel, the northernmost part of Denmark. Here focus moved to application of spatial metrics for description of landscape structure and diversity, particularly for assessment of naturalness and disturbance. Spatial metrics derived from maps at different thematic levels were compared, with the objective of evaluating their sensitivity to changing spatial and thematic resolution. Input data were vector and raster based LUC maps from the Area Information System (AIS). Changing resolution was found to influence patch count metrics strongly and with an unpredictable response to grain size; metrics of fragmentation changed linearly with grain size and metrics of cover area and diversity showed little change. Correlations between metrics values from different data sources and thematic levels were found to change significantly with window size employed in the M-W method. A spatial Hemeroby index was introduced and metrics values from LUC data at 25m pixel size found to be highly correlated with values from CLC data at 250m pixel size. This provided evidence in favour of creating large-area Hemeroby-maps, based on CLC data.

The final empirical study is described in chapter 6. Here the objective was to demonstrate possible applications of spatial metrics and M-W for forest and landscape management. Different afforestation scenarios were created for Vendsyssel, a simple and fast method was used for assignment of new forest types to selected target areas, and changes in metrics values and FC profiles were calculated. Different responses to the simulated landscape changes were observed, and change-maps as well as tables and FC-curves provided promising tools for spatial planning.

In the conclusion in chapter 7, a synthesis of the findings from the empirical studies is made, and recommendations are provided for quantification of fragmentation using EO data and spatial metrics and on the use of spatial metrics for environmental monitoring at landscape, regional and national levels.

All references used are listed in chapter 8, and chapter 9 contains some more personal comments regarding the process of preparing this thesis as well as acknowledgements. The implementations of moving-windows calculation of the spatial metrics, scaling and averaging operations are documented in the IDL-scripts in Appendix 1, while Appendix 2 contains a list of the various types of software used for image processing and statistical analyses of the data.

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2 Literature review

This chapter opens with a discussion of the terms criteria and indicator, using the meanings attributed to them in the so-called Helsinki Process (Granholm *et al* 1996). Then other approaches to the indicator concept are presented, such as the CIFOR definitions (Stork *et al* 1997). Direct assessment and quantification of biodiversity is a large and complicated task, which requires intensive fieldwork, often by researchers with specialised knowledge. It was therefore considered outside the scope of this and previous projects to devise methods for quantifying on-the-ground biodiversity with values derived *only* from EO data. However, it was found important to provide an overview of how (and if) biological diversity can be measured and quantified - and how precise and reliable the results are - in order to find the extent to which the use of remote sensing can contribute to or supplement conventional (labour intensive) methods of environmental monitoring.

Spatial metrics derived from digital EO data are more valuable, and applicable for (ecosystem/conservation) management purposes, when there are solid theoretical links between the biological processes and properties of land cover maps (Haines-Young and Chopping 1997, McCormick and Folving 1998, Gustafson 1998). Thus a section of the literature review is devoted to outlining basic ecological theories with spatial aspects and discussing how they relate to and incorporate statistical measures of diversity and of landscape geometry. The nature of natural (forest) ecosystems, in that they are complex and nested systems makes it relevant to look closer at scaling issues, as done in section 2.3.3. The potential relationships between spatial metrics from land cover maps and results from numerical modelling of meta-populations in real and simplified landscapes are addressed, and the use of "neutral" models discussed, i.e. assessment of metrics values from artificially generated 'images' of ideal landscape where the properties under investigation can be controlled (Gardner and O'Neill 1991, With and King 1997). This can help select a group of spatial indices to be used in assessment of sustainable forestry at landscape or regional level.

Working with EO data poses some practical problems during the process of moving from raw sensor data to reliable land cover or habitat maps. It is not within the scope of this thesis to review the wide range of possible image processing techniques, to that end ′standard approaches' based on recommendations found in the literature will be used, and examples of their implementation are shown in subsequent chapters.

2.1 Sustainability and Biodiversity in environmental policy

In this section, a summary will be made of how the concepts of criteria and indicators, sustainability and biodiversity are defined and applied in environmental sciences, policy and management.

2.1.1 The need for definitions

For the purpose of protection and planning of Europe's forests at inter-national and continental level, a strong interest exists in getting a broad view of their state, be it in terms of vegetation health, species composition or environmental conditions in general (Granholm *et al* 1996, European Commission 1999, Duniker 2000). In particular, it has been considered worth investigating the potential of Earth Observation and Geographical Information System (GIS) techniques for characterising and monitoring forests and their stability as habitats (Scott *et al* 1993, Haines-Young and Chopping 1995, Jones 1998, Hansson 2000).

The spatial structure of forests, and knowledge of the processes that it reflects, can be used to derive some of the criteria and indicators that are needed for monitoring of forest sustainability. Thus, one of the intentions of this review is to examine and describe how the spatial structure within forests influences biological diversity. This implies identifying methods for (a quantitative) description of the shape or outline the forest elements and their position relative to other land-cover types (typically expressed in terms of connectivity and/or fragmentation) – and an assessment of whether quantitative measures of spatial structure can be used as indicators of sustainable forest management or naturalness. It must be stressed here, that these indicators are tools for the assessment of the sustainability of forest- and landscape-management, their numerical values are not goals in themselves. Thus this review will not go into detail with the precise definitions, but rather look at the link between what should be indicated (level of sustainability) and the available remote sensing based techniques to monitor forested landscapes.

However before doing so, some definitions and concepts must be clarified. Standardised, operational definitions are essential if different persons are to make similar measurements of similar entities in order to be able to analyse and compare the results (Morrison and Hall 2002). What is for example meant by this much talked about "landscape level" at which we aim to do our analyses? What do we understand by a "habitat" – perhaps the spatial expression of (the presence of) a niche – depending on the species? How are ecosystems defined and delimited? What actually are "Core Areas" and "Hot Spots" – and to what degree do these concepts depend on the context in which they are used? And finally, what do we mean by words such as "criteria" and "indicator"? (ibid.) The following section provides some material to address these questions.

2.1.2 Criteria and Indicators

The concepts of Criteria and Indicators (C&I) are widely used, and their use as parts of systems for environmental assessment is a special case of their general use – the specification and/or selection of C&I for specific uses, such as assessing the sustainability of forestry being far from simple or without conflicts (Stork *et al* 1997, Mosseler and Bowers 1998, Hansson 2000).

According to Stork *et al* (1997) a <u>criterion</u> is a standard that a thing is judged by. In the forest context it can be seen as a state or aspect of the dynamic process of the forest ecosystem, or a state of the interacting social system, which should be in place as a result of adherence to a principle of sustainable forest management (or well managed forest). The way criteria are formulated should give rise to a verdict on the degree of compliance in an actual situation (van Bueren and Blom, in Dobbertin 1998). In the framework of the 'Montreal process' (ref. Section 2.1.3) a criterion is characterized by a set of related indicators which are monitored periodically to assess change (Granholm *et al* 1996) – thus a criterion can be seen as a category of conditions or processes by which sustainable forest management may be assessed.

An indicator is a measurable attribute of a system component (Duinker 2000), that can ultimately be expressed as a number, i.e. quantified. An indicator is a quantitative or qualitative parameter, which can be assessed in relation to a criterion. It describes in an objectively verifiable and unambiguous way features of the ecosystem or the related social system, or it describes elements of prevailing policy and management conditions and human driven processes indicative of the state of the eco- and social system (van Bueren and Blom, in Dobbertin 1998).

In the Montreal Process (see section 2.1.3), an indicator is a measure (measurement) of an aspect of the criterion, a quantitative or qualitative variable which can be measured or described and which, when observed periodically, demonstrates trends (Granholm *et al* 1996).

In a CIFOR working paper, Stork *et al* (1997, Box 1, p.3), note that C&I form indispensable parts of a hierarchy of assessment tools:

Principle: A fundamental truth or law as the basis of reasoning or action.

Criterion: A standard that a thing is judged by.

Indicator: An indicator is any variable or component of the forest ecosystem or the relevant management systems used to infer attributes of the sustainability of the resource and its utilisation.

Verifier: Data or information that enhances the specificity or the ease of assessment of an indicator.

These definitions are good for theoretical considerations, but in disagreement with the definitions given above following Duinker (2000). According to the CIFOR definitions, the word 'indicator' is often used when it should rather be verifier, the border between these concepts will in practice be hard to define. A review of the different meanings of criteria and indicators can also be found in Granholm *et al* (1996, report 1). Accepting the definitions in the Helsinki process of a **criterion, as something describing the different sides of sustainability *on a conceptual level*** (Ministry of Agriculture and Forestry 1994), the goal of *developing* criteria is clearly outside the scope of this thesis – which will instead look more into how indicators can be defined or selected and calculated. This is in line with the Helsinki process definition of **indicators as typically quantitative measures of change**. Thus an important criterion for selecting an indicator based on EO data is that it is sensitive to environmental changes as manifested in spatial structure at the landscape level.

2.1.3 Sustainability – the concept applied to forestry

The definitions found indicate a close relationship with management, which is reasonable, as the concept of sustainability generally refers to processes and (land use) practices. Following the resolutions from the Ministerial Conference on the protection of forests in Europe, Helsinki, June 1993 (Finnish Ministry of Agriculture and Forestry 1993): *"sustainable management means the stewardship and use of forests and forest lands in a way, and at a rate, that maintains their biodiversity, productivity, regeneration capacity, vitality and their potential to fulfil, now and in the future, relevant ecological, economical and social functions, at local, national and global levels, that does not cause damage to other ecosystems"*. The last part indicates the awareness that no part of the landscape can be monitored in isolation. Just as we can not ignore the forested parts when examining agricultural landscapes, we can not leave out the surrounding "matrix" consisting of land used for agricultural, urban or other purposes, when we examine the structure of forests in order to monitor their environmental status, for nature protection and conservation purposes. Meanwhile, we can not leave out the processes related to the human use of forested lands, be they driven by social, economic, practical or even aesthetic motives (Haines-Young and Chopping 1996). Thus, criteria for sustainable forest management should not only focus on maintaining production capacity, nor on the actual biological diversity, but also on the structure and dynamics of forest in relation to the surrounding landscape and the people that inhabit it. This point of view is reflected in the six criteria agreed upon at European ministerial level through the decisions of the ministers at the Helsinki meeting (Finnish Ministry of Agriculture and Forestry 1993). The criteria for sustainable forest management are:

1. Maintenance and appropriate enhancement of forest resources and their contribution to global carbon cycles;

2. Maintenance of forest ecosystem health and vitality;

3. Maintenance and encouragement of productive functions of forests (wood and non-wood);

4. Maintenance, conservation and appropriate enhancement of biological diversity in forest ecosystems;

5. Maintenance and appropriate enhancement of protective functions in forest management (notably soil and water);

6. Maintenance of other socio-economic functions and conditions.

The follow up on these decisions and the reporting from the countries is are often referred to as 'the Helsinki Process'. A 'liaison unit', since 2004 situated in Warsaw (before that in Vienna), manages service to the member countries and the exchange of information, and amongst other activities information is shared at the web site: http://www.mcpfe.org/. Worldwide, several established international initiatives to develop criteria and indicators for sustainable forest management (the Montreal Process, Helsinki Process, the International Tropical Timber Organization (ITTO) Process) are now reaching an implementation stage (United Nations 1998). The Montreal process is concerned with the temperate and boreal forests outside Europe, and thus includes North America and Australia. The Tapparo protocol is concerned with protecting Amazon forests through development of C&I for sustainable management, while the ITTO has produced guidelines on sustainable management of tropical forests (Granholm *et al* 1996, United Nations 1998). According to the Subsidiary Body on Scientific, Technical and Technological Advice to the Convention on Biological diversity (UNEP 1997, annex III), C&I provide a conceptual framework for forest policy formulation and evaluation. Criteria define the essential elements of SFM while Indicators provide a basis for assessing actual forest conditions. C&I, when combined with national goals are also useful for assessing progress towards SFM and they can play an important role in defining the goals of national forest programmes and policies.

2.1.4 Biodiversity – definitions and assessment

According to the convention of biological diversity (CBD 1992): *"Biological diversity means the variability among living organisms from all sources including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems."*

2.1.4.1 The value of biodiversity

The economic value of biological diversity and possible future benefits, for instance in the medical field, is being recognised, along with the realisation that the more diverse an ecosystem is, the better equipped it is to withstand and recover from disturbance. In a strategy paper from the European Commission (European Commission 1998, p. 1), the importance of biological diversity is outlined as: *"Biological diversity (biodiversity) is essential to maintain life on earth and has important social, economic, scientific, educational, cultural, recreational and aesthetic values. In addition to its intrinsic value biodiversity determines our resilience to changing circumstances. Without adequate biodiversity, events such as climate change and pest infestations are more likely to have catastrophic effects. It is essential for maintaining the long term viability of agriculture and fisheries for food production. Biodiversity constitutes the basis for the development of many industrial processes and the* *production of new medicines. Finally, biodiversity often provides solutions to existing problems of pollution and disease."*

With the growing awareness at global and continental political decision making level (internationally and within large countries such as USA, Canada, Brazil and Australia) it is becoming clear that the relation between sustainable development and the maintenance of biological diversity is becoming increasingly important, as well as the growing awareness of the interactions between ecosystem composition, structure and functioning (EWGRB 1998, part A, chapter 1). In the proceedings from the first expert meeting of the European network for forest ecology (EFERN), Oswald (1996) states that: *"The conservation of 'biodiversity' is considered today as a major and integrated part of sustainable forest management. But, as biodiversity can concern different levels of appreciation, i.e. populations, individuals and genes, several often quite diverging definitions are used".*

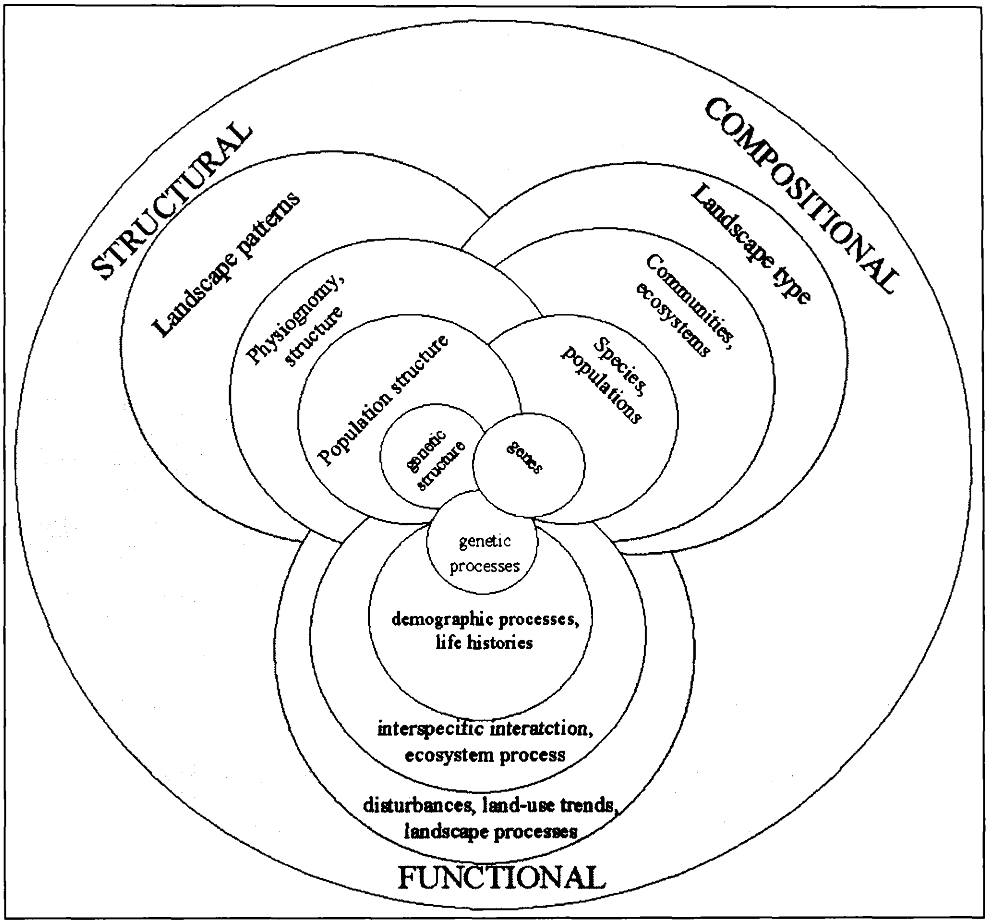

Figure 2.1. Compositional, structural and functional biodiversity, after Noss (1990).

2.1.4.2 Types of biodiversity

It has become a widespread practice to define biodiversity in terms of genes, species and ecosystems, corresponding to three fundamental and hierarchically-related levels of biological organisation (WCMC 1995). In the context of this discussion focus will be placed not so much on the species diversity, but more on the ecosystem 'domain' when it overlaps (spatially) with concepts such as habitat and landscape.

Hierarchy theory shows that higher levels of organisation incorporate and constrain the behaviour of lower levels (King 1990, Marceau 1999). Thus, knowledge of structures and processes dominant at one level – coinciding with a certain spatial scale - will allow us to infer the processes that can take place and which species that will 'fit in' at lower levels or 'smaller' or more restricted spatial scales (Mackey 1996, Mackey and Lindenmayer 2001), as utilised by McGarigal and McComb (1995) and by Rolstad *et al* (2000) in a study of woodpeckers in a mosaic of forests and cultivated land. In a report on ecological conditions of old-growth.Douglas-fir forests in the North-western United States, Franklin *et al* (1981, referred in Noss (1990)) distinguished between compositional, structural and functional biodiversity, as illustrated in Figure 2.1, see also Table 2.4, page 56. This approach has since been applied intensively in ecological research, where 'function' sometimes is replaced by 'development', indicating that this is the component of biodiversity with the strongest temporal dependence, or sensitivity to temporal scale when it comes to observation of parameters. For a recent review of concepts, terms and applications, see Puumalainen (2001).

2.1.4.3 Spatial levels of biodiversity

Whittaker (1972) defined and discussed a selection of diversity metrics. He introduced the measures of Alpha, Beta and Gamma diversity, to be used along with the concepts of niche and hyperspace (of niches). The definitions below are taken from Gale (1996), but are commonly accepted.

Alpha diversity is the variety of the organisms that occur in a particular place or habitat, this is often also called the 'local diversity'.

Beta diversity is defined as

a) The diversity between or among more than one community or along an environmental gradient, or
b) The variety of organisms within a region arising from turnover of species among habitats.

Beta diversity can thus be considered the change rate of the Gamma diversity, which is the Landscape-level or regional diversity. Clearly what should be aimed at and focused on, when investigating the applications of remote sensing techniques, is whether and how it is possible define some links between the Gamma diversity and the spatial structure of forests and wooded lands.

The terms Epsilon and Delta diversities are used to respectively denote inventory or area diversities and gradients of Alpha and Gamma diversity across regions and continents (Stoms and Estes 1993), thus making comparisons possible on a global scale. The concepts are illustrated in Figure 2.2.

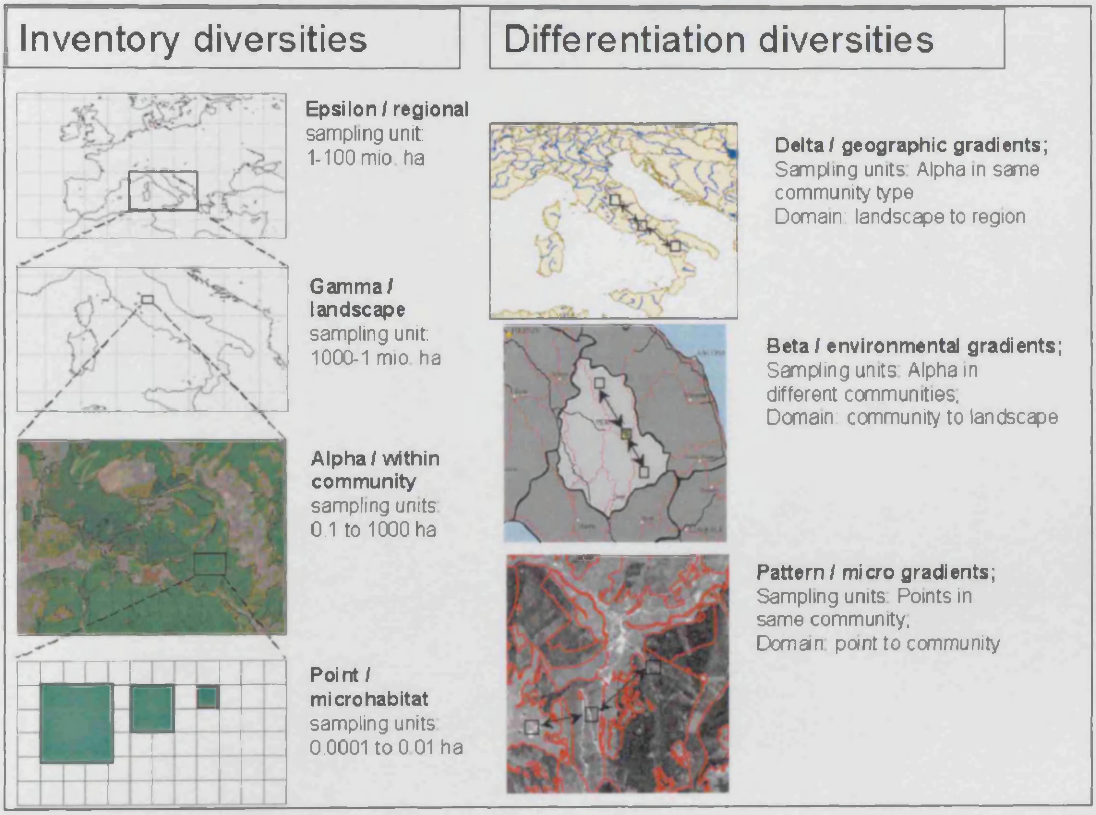

Figure 2.2 Levels of biological diversity as defined by Whittaker (1972). The maps sketches to the left represent inventory levels of richness; those on the right show differentiation levels or changes in composition across gradients. Sampling unit sizes indicate approximate spatial dimension for each ecological scale

2.1.4.4 Demands for indicators of biodiversity

At the European level a project was initiated by the European Environment Agency (EEA) to define criteria and indicators of forest diversity. The object of the BEAR project is to "*formulate an integrated system of indicators of forest biodiversity that are applicable over a wide range of European biogeographic regions, and at regional, landscape and stand levels.* (Hansson 1998, p. 2). It is further stated (ibid. p. 4) that ideally an indicator should be:

• relevant to ecologically significant phenomena,

• able to differentiate between natural cycles/trends and those induced by anthropogenic stress,

• capable of providing continuous assessments over a wide range of stress,

• sufficiently sensitive to provide an early warning of changes,

• distributed over a broad geographical area, or otherwise widely applicable,

• easy and cost-effective to measure, collect, assay and/or calculate.

The work done in this project is presented in Larsson *et al* (2000) and partly at the project web site: http://www.algonet.se/~bear/. Among the main achievements of the project was the agreement on a common scheme of key factors of biodiversity applicable to European forests. These factors are divided into structural, compositional and functional factors. There are different factors for the structural (physical characteristics) and compositional (biological component) types at different spatial scales while the functional key factors, which relate to natural disturbances and human influence are the same across the scales (Larsson *et al* 2000, chapter 3.1). The main recommendations from the project are as follows:

1) to introduce the key factor approach in monitoring of forest biodiversity, and
2) to make a further division into different 'forest types for biodiversity assessment' in the reporting of the key factors (in all 33 different forest types were identified, they mostly correspond to the national classification schemes), and finally
3) to standardise indicators, methodology and protocols.

2.2 Use of landscape ecology concepts in forest and landscape assessment and monitoring

This section is intended to provide conceptual links between the types of information needed by forest managers at different levels and the tools provided by landscape ecology in terms of understanding processes and identifying and quantifying patterns that are of relevance. Important concepts in this context are habitat and habitat quality, structure and scale, which are introduced and reviewed in separate sub-sections.

2.2.1 Forest management information use and needs

Rural landscapes, of which forest and woodland are important parts, need protection and careful management. This is reflected in the principles outlined in the declarations from the European ministerial conferences in Helsinki 1993 (Forest) and Sofia 1995 (The Pan-European Biological and Landscape Diversity Strategy, PEBLDS (Smith and Gillet 2000))[1]. Sustainable management includes preservation of the structural and biological diversity of the agricultural and forested landscapes. In order to develop such management practices, an understanding of the landscapes spatial and temporal dynamics is needed, as stated by Stoms and Estes (1993), Turner *et al* (1993), European commission (1999).

According to Köhl and Päivinen (1996), remote sensing has the potential to act as an instrument to provide harmonised European forestry statistics. Lin and Päivinen (1999) list five user groups for forest information:

- International organisations, NGO's and environmental organisations
- National ministries
- Research and academic institutes
- Forest Industry
- Forest owners

These groups obviously have different information needs, which are only to a certain degree to be fulfilled using EO techniques, as illustrated in Lin and Päivinen (1999) and discussed by Köhl and Päivinen (1996) – refer Table 2.1, see also Table 2.5, on page 58.

[1] The full text of the strategy is available at http://www.strategyguide.org/fulltext.html (accessed 22/2 2004)

Function, type and level of information	Variable / data type
Forest protection	
Stand	Forest area (actual/potential ratio) Species Composition Structure (horizontal, vertical)
Site	Soil Vegetation types Topography (elevation, aspect, slope) Climate
Stability	Forest condition, Quality, health
Management	Value of protected infrastructure Water resources Objectives
Ecosystem / environment	**Variable / data type**
Carbon Cycle	Woody and herb biomass Soil organic matter Climate
Biodiversity - Ecosystem	Vegetation type Vegetation cover Pattern of vegetation Naturalness; management history, age, exotic species Management objectives Forest condition (rate of change)
Biodiversity - Species	Species composition (including rare species) Species richness (indicator species) Pattern (corridors / networks) Threats to sp. diversity; human disturbance, pollutant deposition, exotic species
Sustainability	Management objectives / history / planning and Land use change

Table 2.1 Forest management information needs as function of forest use, issues related to ecological functions – from Lin and Päivinen (1999), based on Kennedy and Luxmoore (1994).

Forest owners and the wood/paper industry will typically have an interest in maintaining resources for production, while environmental organisations and other NGO's are concerned with the biodiversity aspects. Thus, there is a challenge to define the correct level on which to monitor forest conditions and ecosystem parameters. Often, much information can be found and (perhaps just as important) changes be made in current practices at the Forest

Management Unit (FMU) level (Duinker 2000) – even if the size of a typical FMU will vary from country to country depending on tradition and geographical conditions.

A European Forest Information and Communication System (EFICS) has been proposed, (McCormick el al 1995) in which EO data would have a central role and contribute to monitoring and management of rural environment in general (Estreguil *et al* 2001, fig. 2). This project currently continues as the European Forest Information System (EFIS)[2]. Different NGO's and parts of the forest industry have during the last decade been working on developing various certification initiatives. These obviously need and do use some criteria for sustainability (Baharuddin 1996). Such an 'ecocertification' procedure focuses on the quality of forest management and thus requires a prior definition of the criteria and indicators to be used as a basis for the guarantees that buyers are expected to demand (Berthod 1998).

In Europe, 'old growth forest' is the closest we come to 'natural' forests, and special attention is given to them, as it has become clear that they have a higher number of species, many of which can only live only under the special conditions found there, (Diamond 1988, Davis *et al* 1990, Spies 1998). The particular information needs of such special forest types, that typically serve as important habitat for specialised species were discussed as part of the BEAR project (Hansson 1998, Larsson *et al* 2000).

2.2.2 A biotope approach: Habitat quality

There is a knowledge gap – a lack of precise 'laws of nature' between the levels of individual organism behaviour (movement) and the one of spatial dynamics of ecosystems that should be protected (Karieva and Wennergren 1995, Mann and Plummer 1995). As ecosystems and their dynamics *per se* can not be directly observed, they are either represented by some 'indicator species' or substituted by features such as habitat, guild, vegetation type and disturbance and

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[2] Information on project status, data and software development at http://www.ec-gis.org/efis/ (accessed 24/2 2004)

guilds, which are then used to make possible assessments of biological diversity and naturalness. One promising approach is assessment of habitat quality, for which some approaches are presented in this section.

In terrestrial environments, plants form a structured environment that provides the habitat for the diversity of animal species (Franklin, 1995, May 1988). Forests are unique amongst ecosystems in the degree to which a certain type of vegetation, i.e., trees modify the environment, and so to say define the available niches. It follows that in forests the habitat quality or naturalness will vary according to management practices, ownership status and history, as human intervention in forests normally consists of planting and removing trees of certain species at certain times, often done in specific non-random spatial patterns (Franklin and Forman 1987, Borgesa and Hoganson 2000).

It is beyond doubt that the biological diversity of an area depends on environmental factors. The most basic of these are geological and climatic factors that follow geographic position and topography (Nichols *et al* 1998, Griffiths *et al* 1999). Since trees are able to alter the local microclimate, it follows that in forests and woodlands the diversity of the fauna depends strongly on the compositional, structural and developmental diversity of the vegetation (McCormick and Folving 1998). This in turn altered by faunal activity ranging from insects, harmful or just pollinating, to human settlement and forestry practices. Thus any quantification or description of biological diversity in forested areas will, to some degree, be a 'snapshot' of many dynamic feedback processes, and only sustained monitoring can reveal the dynamics and thus the functional diversity of the area. Another important factor determining how many species a given patch of land, landscape or island can host is its area. The use and reliability of area-species curves are described by e.g. May (1975) and later reviewed and discussed by Reid (1992) and recently by Lomolino (2001).

Diamond (1988) provides an interesting conceptual framework for assessing species diversity with the QQID concept: resource Quality and Quantity, Interaction and Dynamic processes. Quality is here to be understood as the habitat and resource factors that determine the 'number of niches' or habitat diversity. Quantity represents the availability of area and productivity. Interaction represents the complex issue of species interactions, be it predation or plant community successions, while finally D denotes the spatial dynamics including immigration, extinction and in the long-term speciation. Roughly, Quality and Quantity correspond to the structural and compositional aspects of biodiversity, while Interaction and Dynamics correspond to the functional aspect. Stoms and Estes (1993), in a review of what types of biological diversity that can be monitored, and at what scales, argue for QQID as a useful approach, although in practice the Structure-Composition-Function(Development) framework is generally used. Wilson (1992, chapter 10, pp.171-199) mentions some factors of importance for establishment and maintenance of biological diversity (species richness): climatic stability, energy availability and area extent, and Griffiths *et al* (1999, table 1) provide a list of factors thought to influence species richness, including habitat heterogeneity (diversity/complexity) and disturbance, where moderate disturbance is seen as positive for maintenance of high biodiversity - as competitive exclusion is thus prevented. These factors obviously have to be incorporated in sustainability assessment at landscape and regional levels – perhaps more than has previously been done in biodiversity assessments. Along the same lines, Angermeier and Karr (1994) recommend using the concept of 'biological integrity' in environmental and conservation policy, in order to rethink prevailing views of land stewardship.

The EU-level report to the CBD (European Commission 1998) mentions that for "Woodlands", there are several threats to biodiversity, amongst these are, listed by the sectors from which they stem:

- Agriculture: neglect of small woodlands,
- Forestry: Logging of old-growth forests, management intensification (and exotic species),
- Transport and energy: fragmentation and acidification,
- Tourism: forest fires,

i.e. largely threats that are eventually reflected in land cover changes, and thus can potentially be monitored using earth observation and GIS techniques (Firbank *et al* 1996, Gallego *et al* 2000, Mucher *et al* 2000).

EEA has established a European-wide nature information system (EUNIS)[3]. A central part of this system is habitat definition and classification, with the aim of providing a common and easily understood language for the description of all marine, freshwater and terrestrial habitats throughout Europe (Davies and Moss 2002). The EUNIS definition of habitat is "plant and animal communities as the characterising elements of the biotic environment, together with abiotic factors (soil, climate, water availability and quality, and others), operating together at a particular scale." For the purpose of categorising habitats *sampling sizes* ranging from $1m^2$ to $100m^2$ are found adequate, – at the smaller scale, still, microhabitats are found, at larger spatial scales the EUNIS habitats can be grouped to "habitat complexes" – of which estuaries are used as an example, but which also will be the case for many woodland types. The EUNIS habitat classification system has been used for designation of NATURA 2000 sites (European Commission 1999, Estreguil *et al* 2001, see also section 2.3.1.1). Thus, a prerequisite of this project is the ability to map *relevant habitats types* using RS data – at a spatial resolution that requires high-resolution input imagery, refer section 2.3.2.

[3] The portal to background information and data is at http://eunis.eea.eu.int/index.jsp (accessed 24/2 2004)

2.2.3 Approaches to spatial structure in ecology – the landscape perspective

In landscape ecology, *landscapes* can be considered as *mosaics* of natural and managed *patches* that vary in size, shape and arrangement. The pattern that this arrangement forms is not only reflecting the processes going on, but also influencing a variety of ecological phenomena (Franklin and Forman 1987, Forman 1995, chapter 9). Combined with the notion of corridors, typically strips of land with a composition and structure that differ from the surrounding (Forman 1995, p. 145) and may enhance flow of resources and movement of plants and animals between patches, the patch-corridor-matrix model emerges. In this conceptual model patches are seen is habitable 'islands', where the distance (difficulty of movement) between them can be modified by the presence and quality of corridors (for instance hedgerows or strips of riparian forest, ref. Hanson *et al* (1990), Petit and Usher (1998), Brooker *et al* (1999). A similar concept, or just corridors with a 'negative' function is the one of barriers, ref. Robson (1996).

The theoretical foundation for these assumptions is to be found in the ecological sub-discipline of island biogeography, or the island theory by MacArthur and Wilson (1967), as referred by Delbaere and Gulinck (1994). Basic assumptions of this theory are that the number of species will be found in a spatial entity (island, forest, habitat type) will depend on

- the area of the entity as well as the
- number of ecological niches available (habitat quality) and the
- distance to and number of similar entities (other islands or mainland)

The underlying theories of island biogeography have been hard to test in practice (see e.g. Simberloff and Abele, 1976, Karieva and Wennergren 1995, Petit and Burel 1998), and Griffiths *et al* (2000) observe that only few studies have used explicitly landscape ecological approaches for biodiversity monitoring. Recent advances in computing capacity have however made it possible to model individuals' movements, breeding patterns and survival/extinction across landscapes and the consequences for species under consideration (Green 1994, Verboom 1996, Firbank *et al* 1996, Petit and Burel 1998). The use of island biogeography concepts and species-area relations in design of protected areas has led to the discussion about "few large or several small" wildlife preserves – sometimes referred to as the SLOSS dilemma, see e.g. Simberloff and Abele (1976), Andren (1994), Haines-Young and Chopping (1996).

Meta-population theory is a further development and sophistication of the Island Biogeography approach (Wu and Vancat 1995), and appears to be the best model for understanding species dynamics in the context of landscapes made up of habitats that are distributed as discrete patches (Hanski 1998, Hanski and Ovaskainen 2000). This theory describes species and guilds of species as being in a dynamic equilibrium or metastability within the landscapes they inhabit (Wu and Loucks 1995); where local extinctions are compensated by immigrations from nearby patches (Hanski 1999, chapter 8).

In cases where entire landscapes of a given scale have been distinguished and mapped, the LUC map itself provides a visual estimate of ecosystem type richness and homogeneity/heterogeneity (evenness). A clear and useful introduction to the links between landscape structure and ecological processes, with the intention of applying quantitative, spatial methods for analysis are provided by McGarrigal and Marks (1994) in the manual and background document for the Fragstats software (for description, see appendix 3), but see also Noss(1990), Hansson and Angelstam(1991), Kupfer (1995), Dreschler and Wissel (1998). Table 2.2 represents an attempt to outline the various concepts of diversity and the spatial scales at which they operate or at which they can be observed, compare also Figure 2.2.

Concept for diversity mapping/monitoring	Type	Area extent (scale) for observation/ mapping	Objects
Bio diversity	Compositional (Genetic)	$1m^2$ - 1 ha	All plants, animals
Habitat diversity	Compositional	1 ha - 100 km^2	Ecosystems (internal structure) Forest internal structure
Habitat structure and (biotope) distribution	Compositional (Populations)	1 ha - 100 km^2	Ecosystems Forest internal structure
Landscape diversity	Structural	1 ha - 100 km^2	Tree species, crops, Other land cover types
Forest or landscape Structure	Structural	100 – 10000 km^2 (possibly continental scale)	Distribution of Forest stands / patches Forests (outline/shape)
Forest diversity	Compositional & Structural	100 km^2 – 1000000 km^2 (entire continent)	Broad land cover classes

Table 2.2. Summary of concepts for diversity mapping / modelling - the area extent is somewhat arbitrary and is based on currently available satellite data, partly based on table 1 and 2 in (Stoms and Estes 1993).

According to Forman and Godron (1986), structure analysis in Landscape Ecology is defined as setting the distribution of energy, materials and species in relation to sizes, shapes, numbers, kinds and configurations of landscape elements or ecosystems. **The *structural* component of forest diversity thus, in this Landscape Ecology-context, refers to the spatial pattern of the forest blocks and patches that are identified in a forested area** (McCormick and Folving 1998), see also Figure 2.1, on page 23 and section 2.2. Structure is the one component of forest diversity that can most easily be analysed using Remote Sensing and GIS applications (McGarigal and McComb 1995, Ricotta 2000). Furthermore, since it is assumed, that the structural diversity of forested landscapes is an indicator of biological diversity in general, assumptions have been made that statistical relations can be found at the landscape level between some spatial metrics and e.g. species richness – and thus the comparison of structural diversity of different areas with objective methods is made possible, see e.g. Turner (1990), Wrbka *et al* (1998), Jensen at al (1998), Häusler *et al* (2000).

2.2.4 Scale issues in landscape ecology

Scale can be defined as **the resolution at which patterns are measured, perceived or represented** (Morrison and Hall 2002), in landscape ecology scale primarily refers to grain (resolution) and extent in space and/or time (Wu and Qi 2000). In cartography, scale denotes the ratio between pairs of point on the map and distance as measured between the corresponding pair of points on the Earth's surface (Goodchild and Quattrochi 1997, p. 2). This is somehow similar to the way the term is used when dealing with data in vector format, then scale normally denotes the cartographic scale at which it will be feasible to display the data or at which to print them as a map – "scale" is actually used to describe the accuracy of the data (Goodchild and Quattrochi 1997, p. 4). The concept of scale is also related to sampling issues, as in biology/ecology (Carlile *et al* 1989, Noss 1990, Bowers and Dooley 1999) and soil science (Oliver and Webster 1986).

The variogram, sometimes mentioned as the "semivariogram", is a tool that has been proposed and commonly used for description of spatial structure and charcteristic scale, where variance between point measurements is plotted against distance (Curran 1988). According to Curran and Atkinson (1998), one may use variograms not only to estimate summary statistics such as the dispersion or sample variance, but also to design optimal sampling strategies before the actual survey takes place.

In Landscape Ecology, the concept of scale is closely related to the concepts of grain and extent. Grain here means the spatial and temporal resolution of observations; the smallest resolvable unit of study (Morrison and Hall 2002), technically often identical to the size of the basic/atomic picture elements – in Remote Sensing terms referred to as the pixel size. This is in line with the notion of grain as the resolution of an image or the minimum area perceived as distinct by an organism (Farina, 1998, in Dobbertin 1998). Grain size can also be seen as an inherent property of a landscape: it then is defined as the average, and the variability in, diameter or area of the landscape elements present (Forman and Godron, 1986, p. 216).

Extent is the area over which observations are made and the duration of those observations. (Morrison and Hall 2002), often used in the meaning of the geographical size of map or an image scene under analysis. In an ecological sense, extent is the coarsest scale of heterogeneity, or upper threshold of heterogeneity, to which an organism responds (McGarigal and Marks 1995, p. 5).

The term 'scale' is often used as synonymous with 'level', ie. 'the landscape scale', or even in the resolution domain with 'grain', ie. 'coarse-scale' pattern. Throughout this thesis, I will try to avoid confusion, using scale as describing only *spatial scale*, thus more or less synonymous with *resolution*. It follows from this, that a central problem of this thesis, the *scaling* issue is actually an investigation of the behaviour of spatial metrics (see section 2.3.1.3), for the same landscape imaged/mapped at different spatial resolutions, corresponding to different grain sizes and extents of the representations.

2.2.5 Application of landscape ecology in landscape monitoring

Before applying land cover information derived from remote sensing or land cover data in general for the assessments of sustainability and biodiversity, it is important to know the causative relations between landscape structure and biodiversity. For instance, it is widely recognised that in natural systems, the number of species are in dynamic equilibrium, local extinctions being matched by immigration (Saunders *et al* 1991, Hanski 1998) – but how should a natural system, within which these processes are taking place, be delimited, the administrative borders relevant for land managers might not fit with ecological units or regions. Furthermore, if we look only at the forested part of landscapes, is it then relevant to apply landscape ecological analysis to these areas in isolation from the surrounding agricultural and urban areas – which in Europe are never far away? Saunders *et al* (1991) claim that research in "Island biogeography" has provided only little valuable information to forest managers and decision makers. On the other hand there is no doubt that optimised forest management can contribute significantly to the overall biological diversity of landscapes, though there is also no doubt that this diversity can be further enhanced by "good", environmentally friendly or even "organic" agricultural practices (Kutzenberger and Wrbka (1992), van Mansvelt and van der Lubbe (1998)).

O'Neill *et al* (1997), in accordance with the recommendations given by Noss (1990), outlines a useful approach for analysing landscapes in relation to habitat requirements of a given species. Consider a "window" the size of an organism's home range. Within the window are found a variety of habitat requirements, such as vegetation mixture, edge, and available water. By placing the window over a corner of the landscape map, it is possible to determine whether the land covers that are within the window meet all habitat requirements. The window could then be moved systematically over the map, yielding an overall indicator of the status of the landscape for this organism. In digital image processing terms, such a moving window is similar to a filter kernel, this facilitates implementation in GIS and software for processing of Remote Sensing data. A suite of windows for individual species, guilds, or populations could be designed by adjusting the resolution of the data, the size of the home range window, and the habitat requirements. This approach provides a simple indicator of the impact on wildlife of a change in landscape pattern. Häusler *et al* (2000) demonstrated an implementation of moving-windows for assessment of structural diversity of European forests and change detection (see ibid. fig. 9-11), and concluded that it was possible to make local and regional scale comparison of forest (tree) species diversity, making possible also detection of temporal trends. A functioning system however, must be flexible regarding species and their respective "ranges" of occupation and movement.

Wrbka *et al* (1998) describe different aspects of the Austrian SINUS (Study of Structural Features of Landscape Ecology as Indicators for Sustainable Land Use) project. Landscape structure was characterised using a hierarchical theory approach, focusing on the relation between pattern and intensity of land use. Field work was done in 140 quadrates of 1*1 km, which were also mapped from aerial photos. The sampling design for the selection of the test areas was a 'stratified random' approach. A similar approach has been used for measuring the 'Hemeroby' ('cultural influence' or lack of naturalness) of Austria's forests (Grabherr *et al* 1995). These approaches seem to assume that the feature of Hemeroby or 'un-naturalness' for a landscape is the directly opposite of 'sustainable', as also seen from the nomenclature used in Table 2.3, something professional foresters would surely not agree to. Steinhardt at al (1999) proposed a Hemeroby index for landscape monitoring, and demonstrated the application using land cover data from eastern Germany from 1944 and 1989 respectively, finding significant changes. Brentrup *et al* (2002) use the Hemeroby concept for Life Cycle Impact analysis of LUC, through definition of a Naturalness Degradation Potential (NDP) applied corresponding to different degrees of Hemeroby, which again can be assigned to land use classes in map data such as CLC.

Degree of Hemeroby	Degree of Naturalness	Human Impact
Ahemerobe	Natural	None
Oligohemerobe	Close to natural	Limited removal of wood, pastoralism, limited emissions from through air and water
Mesohemerobe	Semi-natural	Clearing and occasional ploughing, clear cut, occasional slight fertilisation
β-euhemerobe	Relatively far from natural	Application of fertilisers, lime and pesticides, ditch drainage
α-euhemerobe	Far from natural	Deep ploughing, application of pesticides and intensive fertilisation
Polyeuhemerobe	Strange to natural	Covering of biotope with external material
Metahemerobe	Artificial	Total

Table 2.3 Levels of Hemeroby for description and evaluation of biotopes, from Steinhardt *et al* (1999).

However, one must be aware that the spatial arrangement of landscape elements cannot explain everything happening in forest landscapes, neither in terms of mass- and energy-flows nor absence or presence of species. Also the total forest area of a country or region and the physical conditions determine forest structure, function – and diversity. In countries where forests only occupy a few percent of the surface area, they play a proportionally larger ecological role, as they host a larger number of species than agricultural land - and often function as a refuge, corridor or feeding area for species normally dwelling somewhere else (Oswald 1996, European Commission 1998, 1999). These countries are among the most densely populated, and thus where we can expect to find the strongest pressures on the environment and biodiversity in general. In such countries, forest cover is then found to be already fragmented and is continuously being threatened by expanding transport networks, urban sprawl and intensification of agricultural practices. In countries with high forest covers, in Europe typically found in the Boreal and the Alpine zone, the structure and naturalness of the forest itself is of the greatest interest, such as variance between and shape of patches, managed as well as natural.

Research in densely forested countries tends to have focused on management applications such as forest mapping and timber volume estimates, but fortunately the methods developed for these ends can also be used for land cover mapping. What is now needed in terms of monitoring for assessment of sustainability (mostly from an ecological point of view) of forest and land management is methods and systems that for a given selection of land cover data can answer questions like:

- Does this landscape have a sound structure (promoting/inhibiting natural processes)?
- How far is the structure of this landscape from its natural state?
- Has it become better or worse during a certain period?

The answers (in terms of indicator values) should allow decision makers to evaluate whether the principles and criteria for sustainable land use are being followed and fulfilled. The biggest challenge in application of landscape ecological concepts is now to link the various levels of diversity with spatial scale for practical applications (Kareiva and Wennergren 1995, Firbank *et al* 1996, Blaschke and Petch 1999), thus finding methods to quantify the concepts shown in Figure 2.2 - or as was one of the initial objectives of this project: find surrogate parameters, derived from EO data, that correlate with (measures of) the biological diversity in the forested landscape.

2.3 Spatial approaches to analysis of structure and diversity at landscape level

This section will present some promising approaches to spatial analysis of ecological conditions and processes, especially biological diversity as expressed through species richness – and provide an assessment of their applicability for larger-area monitoring. The methods presented and discussed in the following sections are all based on the fact that land cover maps at various spatial and thematic resolutions can be derived from Earth Observation data (section 2.3.2), and the observation that the precision of these is mainly a technical problem and dependent on available data sources – and not least cost (and to a lesser extent time) considerations.

2.3.1 Use of Geographical Information in environmental management

A Geographical Information System (GIS) is a suite of computer software used for the capture, storage, manipulation, display and analysis of spatial data, describing physical properties of the geographical world (Sparks *et al* 1994, Elmasri and Navathe 2000, p. 891), developed for a particular set of purposes (Burrough 1986, p. 6). In studies on the ecology of separate landscape components, typically carried out by organisations such as research councils, government bodies, conservation groups and university departments – GIS has helped integrate the findings and making better use of the results. Meanwhile GISs are increasingly being used in forest mapping and for organisation of and data management in National Forest Inventories (Nel *et al* 1994, Pitt *et al* 1997, Blaschke 1999), as well at international level (Lund and Iremonger 1998) and have potential for use in monitoring of deforestation (Skole and Tucker 1993, Mertens and Lambin 1997) or for verification of national commitments to the Kyoto protocol (Goodenough *et al* 1998). According to Dykstra (1997), GIS represents a tremendously powerful tool that has the potential to enhance greatly the capabilities of forestry organisations in tactical planning – although he warns that "*GIS will be useful for forestry analysis only if the foresters use it*".

2.3.1.1 Gap Analysis

An approach for the analysis of the effects of land use and land cover changes for larger regions, typically loss of natural habitats, is the so called "Gap Analysis", an approach to "optimise" networks of natural and protected areas. In this context, Remote Sensing has been seen as a useful tool (Davis *et al* 1990, Scott *et al* 1993). Forman (1995, p. 312), explains how, in Gap Analysis a map of species-rich spots is superimposed onto a map of existing protected areas, and then the difference between the maps indicates the areas or 'gaps' that need protection based on species rich sites. Gap Analysis can thus be seen as a way of combating habitat fragmentation, or at least as a way of finding ways to relieve the effects of processes that lead to habitat loss such as (sub)urbanisation or intensification of agriculture and forestry. Monmonier (1994) raises the issue of weighting species against each other for their protection value, and points to the limitations of regional Gap Analysis when data availability is limited by for instance state borders. Seen from a management point of view Geographical Information Systems show great promise, perhaps most consistently demonstrated in the American 'Gap Analysis Project' (Scott *et al.* 1993, Jennings 2000)[4].

Gap Analysis is normally carried out for large areas of natural land cover, so that this approach is probably not directly transferable to the cultural landscapes of Europe, where natural and uninhabited areas are scarce and limited by pressure from human activity and population density. Still relevant, however, is the multi-layer approach to identify, if not gaps, then at least areas with over- and under-representation of species relative to what is expected from environmental and topographic (and geological etc.) parameters.

The European Commission (1999) introduced a common framework for preserving biodiversity within the "Natura 2000" network, stressing the need for urgent measures to be taken. It refers directly to the obligations following from the birds and habitat directives – and

[4] The US National GAP web site at: http://www.gap.uidaho.edu/ (accessed 21/2 2004)

from the United Nations Conference on Environment and Development (UNCED, the 1992 "Earth Summit" in Rio de Janeiro).

2.3.1.2 Modelling ecological processes in a landscape framework

There are several reasons that it is practical to use GIS for modelling ecological processes with a spatial aspect. Firstly, it allows establishment of general relations between the structure of certain landscapes or some special features within them and the potential for certain species to maintain a population there (Herr and Queen 1993, Sparks *et al* 1994, Westervelt and Hopkins 1999). Secondly, it easily allows testing of models by verification using geo-referenced field data (Davis *et al* 1990, Verboom 1996, Scott and Jennings 1998). Kareiva and Wennergren (1995) reviewed current research in the field and identified two types of ecological models for population dynamics:

1) occupied - un-occupied patches

2) dynamics within patches

They found that given the practical aspect of these investigations, it was time to ask whether any general principles were emerging from the explosion of spatially explicit theories. For instance, cellular automata models suggest a stabilizing effect only on the scale of landscapes orders of magnitude larger than the lifetime dispersal of the organisms under study. Finally, GIS naturally form an integrated part of the landscape assessment projects mentioned in section 2.3.2, and thus modelling of the historical processes that have shaped the current landscape or prediction of the effects (e.g. on biodiversity) of future developments of the landscape structure can easily be integrated in GIS analyses (Vasconcelos *et al* 1993, With 1997, Borgesa and Hoganson 2000, Petit and Lambin 2001). The role of RS data in this context is to provide the structural and compositional framework for models of environmental functions. Also the visual consequences of landscape modifications, which can be very important, can now be modelled using GIS techniques (Weidenbach and Proebstl 1998, Hunziker and Kienast 1999).

2.3.1.3 Calculating spatial metrics

A spatial or landscape metric is a numerical value describing a property of a map or an image, or an object contained therein, utilising the spatial heterogeneity that is ubiquitous in nature across all scales (Wu *et al* 2000), in line with Pickett and Cadenasso's (1995) recommendation of using spatial heterogeneity in ecology to perform valuable and predictive functions rather than excluding it as a troublesome source of error.

In this context it is assumed that maps or images represent landscapes, as when McGarigal and Holmes (2000) use the term 'landscape pattern metrics'. Fortin (1999), in Leitão and Ahern (2002), specifies the difference from spatial statistics, which are tools that estimate the spatial structure of the values of a sampled variable, while landscape metrics area tools that characterise the geometric and spatial properties of a patch or a mosaic of patches.

McCormick and Folving (1998) use the concept of 'landscape structural parameters', thereby implying that differences in these metrics across a landscape or between landscape units will reflect 'structural diversity'. Fry (1996) provides some clear definitions of the goals and methods of landscape ecology, with a relevant discussion of how and when spatial metrics can be applied. Fry (1996) further argues that landscape metrics are needed in order to investigate the role of landscape in determining ecological processes, and compares these metrics to the parameter that we lack to place on the x-axis of a graph of landscape versus biodiversity.

Spatial metrics can be added *ad infintum*, many of them being redundant and, see e.g. Riitters *et al* (1995). The capacity to generate information about spatial properties of landscapes generally exceeds our ability to apply or interpret such information ecologically (Griffiths *et al* 2000), and according to McGarrigal and Marks (1994), the task is not so much to define metrics, but rather to find out how to interpret them. That is also what Häusler *et al* (2000) conclude from a study, where spatial metrics are derived semi-automatically from EO data and applied in forest monitoring. One of the challenges to environmental scientists ranging from entomologists to physical geographers is thus to find ways of combining models based on individual or sub-population behaviour with quantitative metrics of landscape structure.

In this thesis 'spatial metrics' is used to mean quantitative description of spatial structure as it appears in land cover maps. These metrics can be simple, geometric information that can be obtained from most GIS programs, such as patch area or edge length or more complicated metrics defined from information theory and/or landscape ecology, where special software is required for their calculation.

Spatial metrics can be calculated on at least three levels (McGarigal and Marks 1994):

- Patch: a spatially and functionally coherent object (ideally a forest stand or biotope)
- Class: the set of (functionally) similar objects in the scene/on the map, typically the same as a land cover class, vegetation or habitat type.
- Landscape: the entire image/scene, possibly excluding a class defined as 'background'. Metrics of compositional diversity can only be calculated at the landscape level.

Spatial metrics can be seen as belonging to one of the types listed below and illustrated in Figure 2.3 (McGarigal and Marks 1994, Häusler *et al* 2000):

- **Area** metrics describe the extent of patches, classes or the total landscape. This can be done in absolute values, as mean values or in percentages.
- **Edge** metrics describe the amount of occurring edges between patches or classes. This is done by perimeter calculations of each patch. In that way, these indices can give information about the spatial variance of an area. A high number of edges can indicate variable ecological conditions, which is e.g. necessary for the occurrence of specific species. Low edge frequencies typically indicate monotonous conditions for the subject/species of interest. It is possible to assign different weights to certain edge-types, e.g. if forest-agriculture edges are considered more drastic than forest-natural grassland edges (McGarigal and Marks 1994, p. 30 ff.).
- **Shape** metrics are based on perimeter-area relationships of the patches, where e.g. the perimeter of a patch is compared to the perimeter of a square with the same area (such as done by Frohn (1998, p. 17)). High values may indicate the occurrence of many patches

with complex and convoluted shapes, while low values represent the dominance of simple geometric shapes, like rectangular or circular shapes. Fractal metrics are also shape metrics, since they can the calculated from information of patch area and perimeter, although in this case the value characterising the landscape is based on a regression between single patches surface area and their perimeters (Olsen *et al* 1993, see also this reference for definitions and discussions of alternative fractal metrics).

- **Core Area** metrics. Core area is defined as the area within a patch beyond certain edge distance or buffer width. Core area metrics compute statistics regarding the inner/central parts of patches in relation to the total patches. These metrics can give information about habitat quality for certain species. For instance, some species might not be able to exist within narrow forests like riparian forests, even if the total forest area was sufficient (following simple species area relations).
- **Patch** metrics describe the total number of patches and their relative proportion (if more classes are present) in a given area.
- **Nearest-Neighbour** metrics are based on the distances from patches to the nearest neighbouring patch of the same type/class. These indices are calculated by using the minimum distance measured as edge to edge distance from one patch to the nearest neighbouring patch of the same class type. They thus quantify landscape configuration. These measures can be used for describing migration possibilities of species or species interaction of separated populations. This type of indices clearly describes the spatial configuration of landscapes and of the different land cover classes.
- **Diversity** metrics measure landscape composition and are function of the richness and evenness of the patch types in the landscape. The simplest diversity metric is the one of *richness* i.e. the number of different species or land cover types found within a certain area, but as illustrated in Figure 2.3 on page 48 where the three example landscapes (in the bottom right) have the same number of classes but do become more diverse from right to left, this number can be misleading, or at least not sufficient. However, more advanced metrics do exist. Most of these diversity measures are originally developed for

information theory, such as the Shannon-Wiener index, (ref. O'Neill *et al* 1988) or for biology with no spatial dimension in mind (Simpson 1949). Dependent on the probability of the occurrence of all cover types these is a measures indicate to which degree all cover types are evenly proportioned in terms of their spatial extent. Vice versa, this index measures the extent to which one or a few class types dominate the landscape. A prerequisite to meaningful application of diversity measures although is the existence of a number of land cover types that are well defined, functionally and physically separated (also spectrally/texturally), preferably equidistant - as far as it is possible to measure distance in terms of functionality.

- **Contagion** and **Juxtaposition** metrics are calculated using the actual rate of adjacency of each occurring class type with all other class types. The resulting values express the probability of adjacency of different class types. Herewith, contagion can give an idea about the extent of aggregation or clumping of patches. High values indicate big continuous areas, while small values represent many small, dissected areas. On the other hand, juxtaposition and interspersion metrics indicate how 'well mixed' the patches in a landscape or the pixels in an image of different types are – for example, the version implemented by McGarigal and Marks (1994, p. 58) in the Fragstats software is based on "patch" adjacencies, each patch is evaluated for adjacency with all other patch types. This means that, while the values of the juxtaposition metric in the example in Figure 2.3, on page 48, will increase from left to right, while values of the contagion metric will decrease. Various modified versions of the contagion metric have been proposed for use in description and quantification of forest fragmentation (O'Neill *et al* 1988, Li and Reynolds 1993). For a discussion of the usefulness of this and similar 'advanced' metrics, see Frohn (1998).

Amongst the shape metrics are indices of 'fractality' of the patches, following the definition by Mandelbrot (1967), and thus the assumption of self-similarity, i.e. that pattern observed at one level are repeated at higher and lower levels or larger and smaller spatial scales. It is generally believed that high fractal values reflect natural conditions (de Cola 1989, Hargis and Bissonette 1998) while if the values are lower, the pattern and thus the landscape must be assumed to be artificial/un-natural. The self-similarity if "real" fractal patterns should make them insensitive to scaling effects, but Frohn (1998) found that there is an intimate relation between scaling properties and fractal properties of land cover classes and patches.

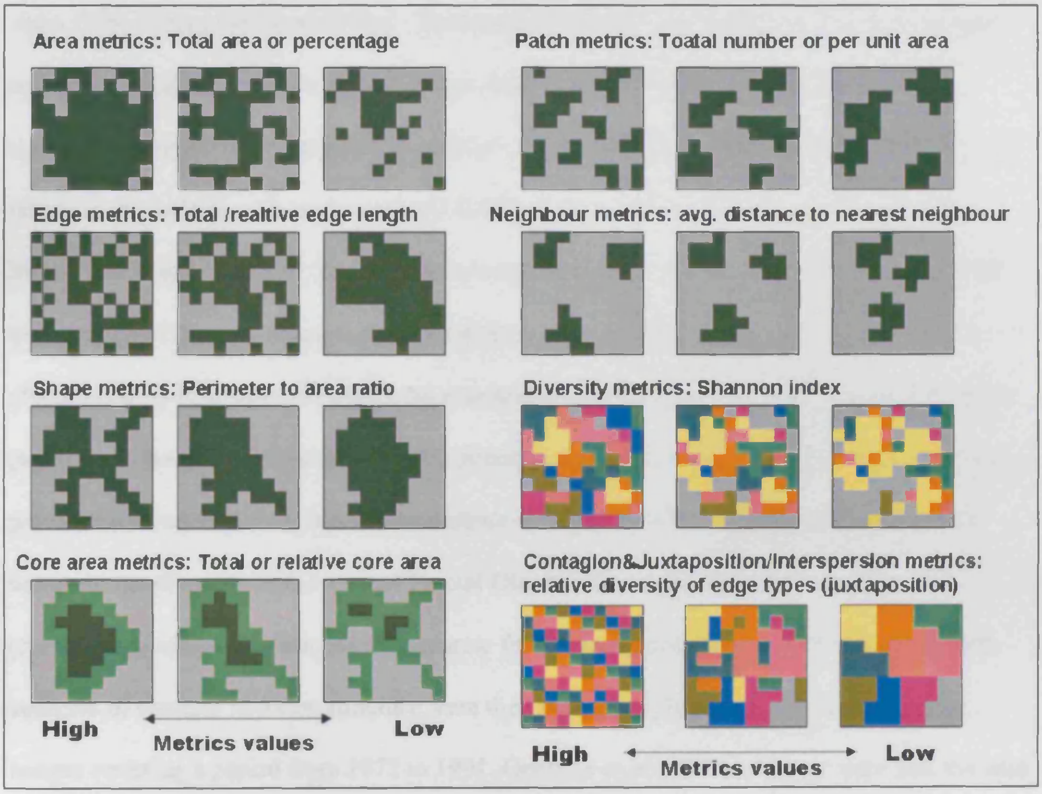

Figure 2.3 Examples of the eight main types of spatial metrics defined by McGarigal and Marks (1994), partly after Häusler *et al* (2000), fig. 8.

2.3.1.4 Perspectives for the use of spatial/geo-referenced data for environmental analysis

Spatial metrics can function as indicators that can be compared between landscapes or watersheds – preferably using "natural" instead of administrative units. It is assumed that differences in the values of these metrics reflect real differences in landscape quality/naturalness/usefulness as habitat. Additional information could possibly be gained by calculating spatial indices at different resolutions (with grain sizes equivalent to the different sensors) and displaying them together - or using them as a N-dimensional data set, as demonstrated by Riitters *et al* (1995).

When 'returned' into a GIS, in geo-referenced format, spatial metrics can serve as indicators of structural diversity and are therefore potentially a landscape management tool. Geographical Information Systems in themselves are useful tools for linking and visualising geo-referenced data, area-covering maps and statistical data computed for administrative units. O'Neill *et al* (1999) state that: *"The combination of remote imagery data, geographic information system software and landscape ecology theory provides a unique basis for monitoring and assessing large-scale ecological systems."* This claim can be justified by be results from projects such as the national GAP project in USA (Scott and Jennings 1998, Stoms 2000) and the Britsh 'countryside survey' (Bunce *et al* 1996, Brandt *et al* 2002), with assessments of the usefulness at pan-European scales in EU-DG AGRI *et al* (2000) and at global scale by Riitters *et al* (2000). An example of application of selected spatial metrics for provision of base-line information on the structure of forests within a natural reserve area is provided by Luque (2000), who chose metrics of Diversity, Dominance and Contagion to represent the diversity of forests and Fractal Dimension to represent spatial pattern (complexity) at two thematic levels: separate forest classes and forest-non-forest. Temporal analyses of changes in forest structure were then performed, based on a series of satellite images covering a period from 1972 to 1991. Griffiths *et al* (2000) however warn that the land cover map for the countryside survey, produced from Landsat TM data and including 25 target classes is *not* a map of biotopes - as it can be shown that the level of detail is much lower that in the Corine biotopes classification (see end of section 2.3.2.2).

After the listing of potential spatial metrics, it is possibly worth recalling Forman's (1995) demands for an ideal shape index, that should :

- be easy to calculate,
- work over whole domain of interest,
- unambiguously and quantitatively differentiate between different shapes, and finally
- permit the shape to be drawn based on knowledge of the index number alone.

Unfortunately he had to conclude that such an index could not exist. Which means that the actual challenge is to find a combination of spatial metrics and possibly other geographical information, that together provide a useful description of forested landscapes.

2.3.2 Uses of Earth Observation techniques in landscape analysis

The term Earth Observation (EO) is used here, because it is typically directed more towards environmental management applications, than Remote Sensing (RS), a term which can be used to describe the use of satellite imagery anywhere (for instance on other planets). At the same time the EO concept includes airborne photography and scanner data, but the use of satellite data has two main advantages over airborne data. First of all it makes possible a regional approach, where the area of investigation only depends on the extent of the areas from where data are available. Secondly it makes it possible to directly assess changes over large areas over time, such as monitoring of deforestation or afforestation, although it must be kept in mind that also repeated airborne data acquisition can be a relevant tool.

2.3.2.1 Potential uses of Earth Observation data for landscape analysis

It is generally agreed that effective mapping and monitoring can be carried out using optical satellite data of high to medium spatial resolution (around 20 to 200m ground resolution cells), such as for Landsat TM and SPOT data as described by Cohen and Spies (1992), Häme *et al* (1999 and 2000), Häusler *et al* (2000), McCormick and Folving (1998), Pitt *et al* (1997) and many others. The use of Landsat MSS data is described by Hall *et al* (1991), Ripple (1994) (in combination with NOAA AVHRR data), Mayaux and Lambin (1997), and of WiFS data by Häme *et al* (1999) and Häusler *et al* (2000). A typical approach is to 'calibrate' or train large area classifiers on low or medium resolution data using the high resolution data as a sort of 'ground truth' (Mayaux and Lambin 1995, Häme *et al* 1999).

The use of radar (microwave) sensors still have some way to go for operational classification purposes (Kasischke *et al* 1997), but the use of multi-polarised channels seems promising

(Saatchi and Moghaddam 2000, Corr *et al* 2003). It should be noted that data from the Shuttle Radar Topography Mission (SRTM) that was accomplished in February 2000 is currently becoming available in the form of high resolution (1 to 3 second resolution, corresponding to 30-100m cell size) topographic/elevation models and probably also useful land cover information[5] (Rabus *et al* 2003).

It is widely recognised that maps of habitat diversity as derived from remote sensing data can potentially provide powerful indirect indicators of species diversity (Noss 1990, Bell *et al.* 1991, ref. in Stork *et al.* 1997). The review in the previous section (2.3.1) shows that it makes some sense to assign structural and ecological meaning to selected spatial indices, as derived for landscape ecological applications in RS and GIS, and to calculate these for subsets of large land-cover maps. Furthermore, the resulting thematic layers can be applied directly as map information in management of structural and (thus) biological diversity – thereby ensuring multiple uses of the image data, which can otherwise be expensive.

An obvious potential pitfall in the application of spatial data for assessment of biological diversity is that no standardised way exists in which to map and analyse land cover. Using terms from a more "physical" approach to remote sensing, a list of factors influencing the results of spatial analysis of land cover maps include (Duggin and Robinove 1990):

- <u>Thematic</u> resolution (i.e. the number of vegetation or land cover classes) The thematic resolution is of great importance for first of all the edge-and diversity metrics, a scheme with more classes automatically will produce maps with more edges (borders between patch types) and a higher number of different classes within a (sub-) landscape.
- <u>Spatial</u> resolution (i.e. precision of vector data and grain size of raster data), closely linked with scaling issues, as discussed in section 2.3.3.3).

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[5] Information on the mission and the results at http://www.jpl.nasa.gov/srtm/ Data are located at ftp://edcsgs9.cr.usgs.gov/pub/data/srtm/ (February 2004 3-sec data were available only for the Americas and Eurasia)

- Temporal resolution (i.e. how much land cover changes from season to season and year to year). It is of importance to know whether a change in land cover as appearing on EO derived maps reflect real changes or e.g. sensor degradation or different weather conditions at the time of acquisition. Even more, large areas land cover maps like the CORINE are mosaics of classifications done on imagery from different years, the current CORINE database having differences of up to ten years between neighbouring countries.
- Sensor system and image processing (more or less refined) influence, there can be many causes such as point spread function of the radiometer, robustness of classification algorithms, pre- or post processing filtering of image data.

Other factors than spatial pattern are of great importance for real and potential bio diversity, such as available energy for photosynthesis and actual evapo-transpiration, as described in section 2.2.2 on Habitat quality. Values of these can be derived from remote sensing data, typically from low-resolution sensors such as the AVHRR instrument on the NOAA satellites (Cihlar *et al* 1997), or the MODIS instrument on the Terra satellite (Moody and Woodcock 1994, Running *et al* 1994). The applications of both instruments for description of ecosystems using remote sensing are discussed in Justice and Townshend (1994) and Waring and Running (1998, chapter 7). See (Goward 1989, Wulder 1998) for reviews of 'bioclimatological' i.e. vegetation applications, and Roughgarden *et al* (1991) for a general discussion of the (potential) role of Remote Sensing in ecology.

2.3.2.2 Use of remote sensing for forest and land cover mapping

The process of getting from "raw" satellite data to land cover "maps" is by now well established in applied Remote Sensing (Cihlar and Jansen 2001), and includes such steps as geo-referencing, calculation of spectral indices, supervised or unsupervised classification (Campbell 1996 chapters 10 and 11), clean-up operations such as low-pass filtering or merging of classes (McCormick 1996, Banko and Kusche 2000) and export to GIS data formats for further analysis (Wilkinson 1996).

For some years ecologists and foresters have recognised, that remote sensing techniques can deliver useful data for land cover mapping and forest inventories. Blackburn and Milton (1996), McCormick *et al* (1995), Ekstrand (1994), Cohen and Spies (1992) provide specific examples of how parameters relevant to forest management and ecology are derived, and Pitt *et al* (1997) and Innes and Koch (1998) review the state-of-the-art within the field of "forestry remote sensing" with special focus on ecological applications. Wulder (1998) discusses the 'trade off' that must be made between cost and detail (see table 3, p. 455) when choosing between air photography and satellite images. He also compares spectral vs. spatial techniques (such as textural metrics) and finds the former more mature and better tested. Païvinen and Köhl (1997) provide an assessment of feasibility of remote sensing in forest applications for harmonisation of forest data. A similar approach was taken by the BEAR-project (Larsson *et al* 2000, see also section 2.1.4.4), in defining key factors of forest diversity, although with less focus on satellite data. Some research has focused on whether and how natural forest can be distinguished from managed forest using remote sensing techniques (Franklin and McDermind 1993, Nel *et al* 1994). Häme *et al* (2000) present a new method for the estimation of forest variables at sub-pixel level. In this study, problems associated with using conventional image classification techniques when pixels do not belong exclusively to one distinct ground class are addressed, and an approach presented for overcoming this by applying a probability based classification method. Of special interest for forest monitoring is the completion of a 'Forest Probability Map' covering the entire European continent, based on a mosaic of NOAA AVHRR images, with original pixel size 1*1 km. This employed an approach similar to the one used by Foody *et al* (1999), although at a very different spatial scale, as in that study, airborne scanner data with a resolution around 4 m were used to identify and characterise forest gaps originating from wind throw.

An interesting approach to solving the problem of what spatial entities to use as the basal mapping units for assessing diversity is to use catchment areas, also referred to as watersheds. These have the advantage of being functional natural units, that can be delineated from digital terrain models or existing maps and analysed using a hierarchical approach, ranking the watersheds from headwaters (highest altitude, often forest covered) to the uplands of large rivers. For an approach examining landscape patterns at catchment level see Hunsaker *et al* (1996), and Tinker *et al* (1998). In the latter study, a number of different spatial metrics were calculated from Fragstats software (McGarigal and Marks 1994). They were subsequently reclassified into uncorrelated components, using principal components analysis (PCA), in an attempt to find few significant parameters describing the environmental state of the watersheds, in this case especially the process of forest fragmentation.

The European Environment Agency (EEA) is carrying out a continental level land-cover mapping project, through the Topic Centre for Land Cover (ETC/LC)[6]. This 'Co-ordination of Information on the Environment' (CORINE) land cover database has been created mainly through manual interpretation of satellite imagery, mostly from the Landsat TM and SPOT XS sensors. The CORINE land cover (CLC) dataset has a nomenclature of 44 land cover classes, organised hierarchically at three levels. The first, highest level has 5 classes and corresponds to main categories of LUC: artificial areas, agricultural land, forest and semi-natural areas, wetlands, water surfaces (EU-DG AGRI *et al* 2000, table 1, p.4); the second level has 15 classes that cover physical and physiognomic entities in more detail (urban zones, forest, lakes etc.); the third level is composed of all 44 classes, including only three forest classes: coniferous, deciduous and mixed, but other classes such as "agro-forest areas" and "woodland-shrub" might be included in analyses of forest structure at landscape level, depending on the objectives. CLC data are available in vector and raster format, the raster data as 100*100 or 250*250 meter cells (note that these data are 'created' by sampling the vector data). CLC data have the potential to become powerful tools for monitoring the sustainability of land use in Europe, especially in combination with the CORINE biotopes database, that is being assembled by EEA as part of the NATure/LANd Cover information package

[6] The status of the project can be followed at: http://terrestrial.eionet.eu.int/CLC2000 (accessed 22/2 2004)

(NATLAN). With these, it should be possible to compare landscape metric over large areas (Jongman 1994, Gallego *et al* 2000), however the accuracy still has to be evaluated – as it seems to vary form country to country (Dubs 1999).

2.3.2.3 <u>Approaches to use of remote sensing for forest monitoring</u>

Forestry applications have hardly been considered so far in the design of remote-sensing projects and sensor-configurations. This complicates the process from data acquisition or changes in the management of spatial data (typically substitution of traditional forest maps with GIS systems) to changes in land use practices (Blaschke 1999). The same situation exists for conservation management and monitoring of biological diversity – no dedicated spaceborne missions exist (Innes and Koch 1998). Thus it is up to the scientific community working with forest applications to find the best ways of applying this technology and the data streaming from it. In doing so, it should be kept in mind that the 'raw' outputs from airborne and satellite sensors are nothing but measurements of emitted and reflected radiation, and estimates of e.g. biomass, are inferred based on statistical relations. This obviously puts some limitations on the types of information, that can be expected to be derived from remote sensing. In each case the analyst or organisation monitoring a forest environment must make clear what kind of information is required and check whether remote sensing can really deliver that, or if other data sources have to be drawn upon. Table 2.4, is an attempt to link some forest ecology and –management concepts with terms used in and parameters available from remote sensing data sources. The role of Remote Sensing for Gap Analysis or similar large area monitoring and planning applications, is thus to provide information on the location, extent and shape of potential habitats for the objects in question which need protection/monitoring, be it plant or animal species or habitats or ecosystems.

Monitoring of ..	Elements of Diversity		
Using..	Composition	Structure	Development
Ecological concept	Identity Species composition	Spatial pattern Network	Change
Entities that must be measured	Stand type Stand age Stand density	Number, size and shape of patches Distance between patches of same type	Clearance Gap creation Growth
Relevant Image Processing Technique(s)	Classification	Spatial and textural analysis	Change detection

Table 2.4 Working concept for forest diversity assessment, modified from McCormick and Folving (1998).

The processes within forests that control structure and thereby forest diversity and the suitability of the forest as habitat is illustrated in Figure 2.4, on page 60, which is a modified 'Strommel diagram', together with the approximate spatio-temporal domain of different ecological processes, the domains where the different types of biological diversity are observed and the domain covered by operational remote sensing. Blackburn and Milton (1996) discuss gap creation mechanisms (the function/development component) process and regeneration dynamics, natural successional processes in deciduous woodland at landscape level (landscape-community according to Figure 2.2, and how these can be monitored using remote sensing techniques, with the New Forest in England used as test area.

It is important to recognise that Remote Sensing offers some approaches that are different from, but possibly complementary to the use of landscape level spatial metrics. With these approaches, other types of information can be extracted from remotely sensed data, and used for classification purposes and determination of surface parameters. Analysis of spectral properties of the surface, as derived from RS data have long been used for assessment of vegetation health and forest damage (Häusler and Akgöz 1997, Kenneweg *et al* 1997) and chemical composition of the foliage (Martin *et al* 1998, Blackburn 1998), and a variety of 'spectral indices' have been developed to describe vegetation properties (Leblon *et al* 1993, Blackburn 1998, McDonald *et al* 1998,). Other methods include texture analysis (Cohen and

Spies 1992, Nel *et al* 1994, Coops and Culvenor 2000), spectral un-mixing (Cross *et al* 1991, Garcia-Haro *et al* 1996, Peddle *et al* 1999, Brown *et al* 2000), use of geometrical-optical models (Albers *et al* 1990, Jasinski 1990, St-Onge and Cavayas 1995) and time series analysis (Cihlar *et al* 1997, Waring and Running 1998, chapter 5).

2.3.2.4 Applicability of EO data for assessment of forest and landscape diversity

Not only has the direct use of RS data for the assessment of biological diversity been disputed (Roughgarden *et al.* 1991, Mann and Plummer 1993 and 1995, Roe 1996), in general the practical applications of satellite RS in forestry remain unclear (Blaschke 1999). Nevertheless, remote sensing data are beginning to be used for assessment of structural diversity, especially within the field of Landscape Ecology (Eiden *et al* 2000). Furthermore there are some examples of use in Gap Analysis projects, mostly derived from USA and Australia, where the landscape units are generally of larger extent and simpler composition compared to those found in Europe (Scott *et al* 1993, Scott and Jennings 1998, Loomis and Echohawk 1999).

Hunter (1990, in Koch (2000)) describes seven 'criteria' for the classification of forest diversity: species composition, age structure, horizontal spatial heterogeneity, edges, islands, vertical structures and (the presence of) dead trees. These correspond quite well to a short list of indicators of forest naturalness (Riitters *et al* 1992, Davies and Moss 2002), from the structural and compositional domains of diversity. In Table 2.5 on page 58, these are compared to the remote sensing data sources that are available today – in the form of images at the visible and near-infrared wavelengths, thus excluding RADAR and Light Detection and Ranging (LIDAR) techniques. For a discussion of these techniques and their applicability, see Innes and Koch (1998).

	Data source	High resolution Aerial photogr.	Low res. (high alt.) Aerial photogr.	Very high resolution satellite imagery	High resolution satellite imagery	Medium resolution satellite imagery	Low res. satellite imagery
Feasibility/	Spatial Resolution	<1 m	1-5m	~1m	5-50m	50-500m	>500m
Forest feature	species composition	+	+	+	+	+	+
	age structure	+	+	+	?	-	-
	horizontal spatial heterogeneity	+	+	+	+	?	?
	Edges	+	+	+	+	+	+
	Islands	+	+	+	+	+	+
	vertical structures	?	?	?	-	-	-
	dead trees	+	?	?	-	-	-

Table 2.5 Features considered relevant to forest diversity and the potential of different sensor types to monitor them. Based on Hunter(1990) in Koch (1999), and Wulder (1998, table 3 p. 455).

+ : detection/mapping is possible, ? : dubious/not verified, - : not possible.

The possibility of assessing species composition at even low resolutions, are based on the results from large area mapping projects, applying the AVHRR instrument of the NOAA satellites (Cihlar *et al* 1997, Häme *et al* 2000, Riitters *et al* 2000). The first European forest map reported to be made was based on NOAA-AVHRR data with 1 km spatial resolution (Häusler *et al* 1993), in which it proved possible to map forest over large areas – even under very different terrain and climatic conditions.

Errors, noise and potentially bias (on reflectance values and thus land cover proportions) are added to the satellite imagery by atmospheric properties and terrain effects, and the establishment of time series for environmental monitoring is sensitive to degradation or change of sensor response to the upwelling reflected radiation. The sensor models used for corrections of reflectance/temperature values, may simply not be valid (for instance due to degradation of the instruments on board the satellite), or they may be used in inappropriate ways (Duggin and Robinove 1990, McGwire *et al* 1993). Finally strong bias can be added from the whole suite of methods/software for image processing and handling of geographic (vector) data. These processing steps include reflectance correction, geo-referencing, segmentation, classification and spatial (clean up) filtering procedures (Moody and Woodcock 1994, Duggin and Robinove 1990). Mapping of structural factors such as edges and 'islands' (typically equal to number of patches) is obviously highly scale dependent, as the edge-length and the number of patches/island will decrease with increasing grain size, in a non-linear way (Benson and MacKenzie 1995, Riitters *et al* 1997).

So why use high-resolution satellite data at all? The first reason is that the (spatial) information that we get from them is closer to or more directly related to the "processes" taking place in the landscape than cadastral maps or statistical information (Blackburn and Milton 1996, Pitt *et al* 1997, Pitkänen 1998, Lucas and Curran 1999). Figure 2.4, on page 60, is intended to illustrate how remote sensing techniques, as available at the moment, fit the spatio-temporal dynamics of forest ecosystems. The lower and the left side of the RS box represent the best obtainable resolution/grain size, the right and upper sides represent the maximal possible extent or coverage using single images (with mosaicing, Word-Wide coverage is possible, as already demonstrated in various land-cover-mapping exercises). The second reason for using satellite image data, is that they allow us to check how well connected the indices calculated from medium resolution data are to the information that can be extracted from low-altitude, aerial photographs – a data source considered too expensive for mapping and monitoring of larger areas (Wulder 1998).

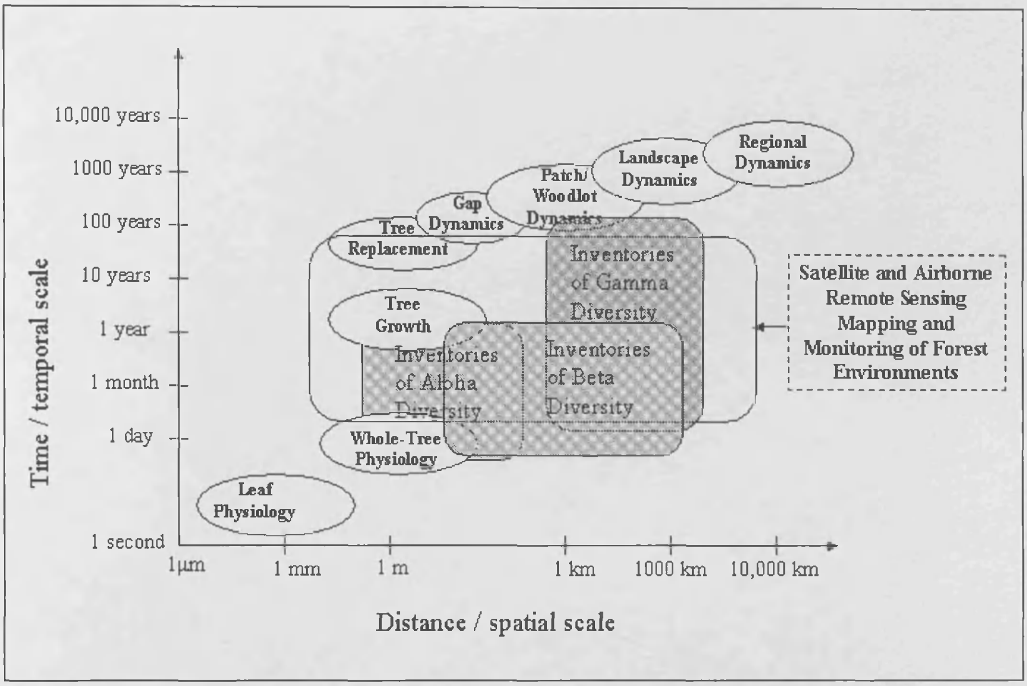

Figure 2.4 A hierarchical representation of forest dynamics and the role for Remote Sensing in monitoring of forest environment. Adapted from King (1990).

In spite of the scepticism expressed above, there has been little doubt that in Europe there is a strong potential for mapping the diversity of land cover types (in this case more or less equivalent to vegetation types), situated within wholly or partly forested landscapes, by use of Remote Sensing techniques (Blaschke 1994, McCormick *et al* 1995, Häme *et al* 1999, Häusler *et al* 2000). Furthermore, some improvements appear to be possible, based on expected developments in conceptual and mathematical models, software and sensors (higher spatial resolution as well as multi-spectral sensors). This should make possible operationalisation of RS data in the following fields:

- Detection of areas threatened or in need of special management techniques/consideration, e.g. fire or erosion risk.

- A better understanding of relations between spatial/textural measures/information from high resolution to medium scale spectral and/or spatial information

Potential advantages from the use of Remote Sensing in large-area environmental monitoring include:

- Satellite image data offer synoptic views, also over larger areas.
- Satellite image data makes it possible to repeatedly update Land Cover maps. Compared with LUC maps from other sources, such as 'normal' topographical maps. This will be an advantage when analysing habitat structure, as land cover maps/images show what type of (and/or how much) vegetation is actually present in the landscape.
- Remote Sensing techniques have been developed for monitoring vegetation health, and can be used for detecting sudden changes such as wind throw, clear-cutting and burned areas.
- Comparison will be possible across borders and administrative levels, independent of ownership of the areas of interest.
- Satellite image data can provide unbiased historical datasets, in the best case more than 30 years back (launch of first Landsat satellite in 1972), though the results must be tested for sensitivity to different kinds of changes (sensor type, resolution etc.).
- As different types of information are available from RS/EO data with inherently different spatial resolution/grain size, additional information can be gained from combinations of these, as they reflect processes taking place at different hierarchical levels of the ecosystems.

2.3.3 Scaling issues related to raster GIS and EO derived image data

Contrary to traditional disciplines as biology and geography, work with digital EO data restricts the user to certain levels of observation – and the spatial resolution of the data automatically becomes the scale on which the data will be analysed. In the Remote Sensing community the term "scale" is often used synonymously with resolution, i.e. pixel size, and thereby becomes yet another sensor dependent parameter. However, natural phenomena occur in widely varying temporal and spatial domains, and ideally data sources should be selected from (monitoring) task to task and from (research) project to project, depending on the level of occurrence of the phenomenon under investigation, ref. Section 2.2.4.

A fundamental question is then, how to define the scale at which the processes of interest are taking place, and how, with that information available, to choose the correct solution of image data that will be used to map and monitor the objects of interest (Davis *et al* 1990, Stoms and Estes 1993).

2.3.3.1 Concepts of scenes, models and scale in Remote Sensing

Almost from the beginning of Remote Sensing as a discipline, it has been characterised by two very different approaches. On one side, much theoretical and practical work related to RS has been about acquisition of data and derivation of their physical meaning, typically reflectance (directional) and temperature. Practitioners of this approach have often worked with radiation and sensors, and calibration of these. Not surprisingly, many engineers and (geo) physicists have taken this direction – but it has also found applications in forestry, through analyses of leaf reflectance properties and light interception models for canopies (Jasinski 1990, Kuusk 1991, Blackburn 1998). On the other side, users of EO data from many various subjects such as geography, botany, agronomy – and certainly forestry, have expressed strong interest in immediate use of whatever data available for studies of phenomena on the Earth surface, preferably in a handy (GIS) format. This has called for application and development of statistical methods for image classification, feature extraction and change detection (Koch 2000, Banko and Kusche 2000).

Strahler *et al* (1986) provided a review of the developments outlined above, at a time when (what was then known as) high-resolution satellite data started to become available from the Landsat satellite's TM sensor and the SPOT satellites HRV and Panchromatic sensors. They recognised the need for a common ground or starting point and clear, common concepts to be understood and used by people working with RS data. Their proposed definitions are briefly reviews below.

A scene is defined as the spatial distribution of matter and energy-fluxes, on which a given sensor is measuring (Strahler at al 1986). An image is then a set of (distance) measurements over the scene, typically arranged systematically in rows and columns, so they can be treated as a matrix. The term "resolution cell" describes the area over which the measurements of the sensor are integrated or averaged, and that normally corresponds to a "pixel" in the images that are subsequently displayed and analysed.

Two sub-types of scene models are defined

a) Discrete models, where it is assumed that the scene consists of separate elements, ideally distributed on a homogeneous background. If the elements have different reflectance properties, they can be identified in time and space.

b) Continuous models assume that changes in matter and energy fluxes are continuous in time and space. It is possible to determine these properties as precise as the instruments allow – and to broaden these properties to cover larger scenes using averaged values from RS sensors. More and better measurements will provide a better description of the field of (the values of) properties such as crown cover or Leaf Area.

The elements in a discrete model are abstractions of real objects in the scene, for which it can be assumed that they have similar properties or parameters. Simple discrete models have only one (type of) element apart from the background, while complex discrete models have more, or even several types of background. The elements can be unique, or belong to one or more classes, it is then assumed that all elements in a class are characterised by the same set of properties/parameters. Thus, forest-non-forest maps belong to the simple discrete models, while land cover maps of CLC type, also known as categorical maps, belong to the complex discrete type.

Also the concept of nested models is useful. In these, the basic elements and their properties and parameters are used to infer properties of larger elements that are aggregated by smaller ones – such as the element forest may be composed of coniferous trees, deciduous tree and (litter covered) ground. Often the shadows from any of the basic elements constitute a separate class, such as in most approaches to spectral unmixing (Garcia-Haro *et al* 1996, Peddle *et al* 1999). Clearly, the theoretical/physical approach described above relate to deterministic models, using known properties of the scene elements to extract parameters of interest. In contrast, empirical models will associate sensor observations (pixel values) with certain elements, normally using statistical methods – as in standard Minimum Distance and Maximum Likelihood classifications, where the user supervises the selection of training areas, i.e. selected groups of pixels that are known to belong to a certain element type or class.

Types of RS scenes can also be categorised based on the relation between the size of certain (selected) elements and the sensor resolution, i.e. pixel size. Strahler *et al* (1986) introduced the concept of H- and L-resolution. It should be noted that the concept of resolution here is relative, thus not similar to what is elsewhere called high- and low-resolution (imagery, as e.g. used in Table 2.5 on page 58).

H-resolution denotes a situation when the elements are notably larger than the resolution/pixel size, while on the contrary, at L-resolution they are notably smaller than the resolution. This implies, that in H-resolution imagery, the elements can be directly seen, identified, labelled, measured and counted, while at L-resolution a parameterisation of the spatial distribution is necessary if anything is to be known of their size and proportion, this leading directly to sub-pixel analysis (Woodcock *et al* 1994, Peddle *et al* 1997). Furthermore, L-resolution imagery should have two-dimensional stationarity to allow mapping of the scene properties over several pixels – meaning that the same spatial pattern and/or texture should be present all over the scene, or at least the segment being investigated or characterised. This obviously calls for a working segmentation of the images before sub-pixel properties are assessed on L-resolution imagery – such as is for instance the case when assessing forest composition and internal structure using Landsat TM and SPOT HRV imagery (Wulder 1998, McCormick and Folving 1998).

Undertaking environmental analyses with use of RS imagery forces the analyst to use data acquired at certain levels of observation, making their spatial resolution the scale at which analysis is carried out – still knowledge of the scale of the objects in the imagery will be important in order to know whether the data type and methods used are feasible, and if the characteristic scale of the imagery corresponds to the size of the 'real world' objects of interest. In an influential paper Woodcock and Stahler (1987) describe a simple method to show local variance in images as function of their spatial resolution. The variance in an image is described through gradual degradation to lower resolutions and calculation of the average variance in 3*3 pixel windows. Analyses of high-resolution aerial photographs from a forest area showed the local variance to be highest at a resolution equal to or slightly smaller that the diameter of the dominating objects of the images: the trees. Less clear results are achieved with images from urban and agricultural areas. A theoretic analysis with simulated images of dark disks placed randomly on a light background shows a curve that peaks at cell-sizes between ½ and ¾ of the objects' size. Irons *et al* (1985), studying actual and degraded Landsat TM data from a complex agricultural and urban landscape in Maryland, USA, point out two consequences of altering spatial resolution: that spectral variability often increases when spatial resolution is increased - and that statistical separability decreases as pixels become less homogeneous.

Raffy (1994), in a special issue of the International Journal of Remote Sensing on scaling, in the introduction paper titled "Change of scale: a capital challenge for space observation of earth", provides some good examples of how bad things can turn when e.g. merging data to change pixel size, and arguments that a 'spatialisation' method is needed if RS data are to be combined with computer simulation (of ecological processes).

2.3.3.2 Texture and scale in image processing

Similar to the difference between the statistical and the physical approach to analysis of multi-spectral data a difference exists between spectral and textural image analysis, or per-pixel statistics versus contextual or per-object statistics. In broad image processing terms, texture refers to the pattern of brightness variations within an image or a region of the image (Musick and Grover 1991, p. 79). When aerial photographs are used as the basis for manual/visual delineation and labelling of spatial entities (such as forest stands), the analyst is using the textural properties of the image, as well as the average colour or grey level values of the segment of interest. Obviously, this has been done as long as aerial photography has been available for mapping and landscape analysis – in the process giving birth to the discipline of landscape ecology (see e.g. Forman 1995, ch. 1). On the other hand, much of the scientific progress related to and spurred by the development of new satellites and sensors, has been directed towards achieving a better understanding of the spectral properties of land surfaces and vegetation (Woodcock and Strahler 1987). However, with increased availability of panchromatic image data from the SPOT, IRS-C and IKONOS satellites, attention has again been drawn to the possibilities of gaining extra information from images through analysis of the relation between pixel values at different positions in the matrix – since it has already for some time been known that textural features can reduce the classification error rate and improve the analysis (Haralick *et al* 1973). A distinction can be made between a structural approaches which resemble the way humans perceive visual impressions, and statistical approaches, where certain, pre-defined parameters are calculated from sub-images or windows (Sali and Wolfson 1992). The structural approach assumes that the images consist of primitive elements or objects (in this case patches of a certain shape and size), repeated in a certain pattern, and that differences in texture result from differences in the elements, the pattern of their repetition or both (Musick and Gover 1991). In the statistical approach, texture is modelled as a grey-level function, with more or less continuous values over the land surface – depending on the value of interest and of the size of the window uses in the calculation.

The link between variograms and geo-referenced image data is provided by the key concept of geostatistics: the regionalised variable, which is defined as any variable of which the geographic position is known (Vogt 1992). Within EO based mapping for forestry, semivariongrams have been used for analysis of canopy structure (Cohen and Spies 1990, Levesque and King 1996), tree growth in grasslands (Hudak and Wessman 1998) and various stand parameters (Franklin and McDermid 1993). These studies conclude that costumised texture windows (for which the semivariograms are calculated) are most useful for estimating canopy coverage.

2.3.3.3 The influence of scale changes on land cover classification and spatial metrics values

Ideally, it should be possible to predict the values of spatial metrics at one resolution from the same or other metrics at higher or lower resolution, in the latter case it would help extrapolation of structural properties over large areas using low-resolution RS data. Such an approach was attempted by Mayaux and Lambin (1997). They found that integration of spatial information into a correction model to retrieve fine resolution cover-type proportions from coarse resolution data improved the reliability of the estimates by up to 35%. The Matheron index calculated from NOAA AVHRR images was used as estimator, and correlated to cover proportions derived from Landsat TM images.

The Modifiable Areal Unit Problem (MAUP) was first identified by S. Openshaw, who defined it as a form of ecological fallacy associated with the aggregation of data into areal units for geographical analysis – where aggregated data are treated as individuals in analysis (Openshaw 1977 and 1984, Marceau and Hay 1999). The concept is also widely used in social sciences, e.g. it is recognised that census layout in form of size and shape and (demographic) composition of statistical units will strongly influence the results (Green and Flowerdew 1996). Hay *et al* (1997) propose 'object specific upscaling', a procedure in which the spectral 'influence' of image-objects are spatially modelled and integrated within a user defined upscaled representation (which could be a land cover map at lower spatial resolution). Marceau and Hay (1999) describe Remote Sensing as a particular case of the MAUP, and propose this as an explanation to many of the inconsistencies observed in studies where EO data were used to produce thematic maps or as inputs to physical models – without the scale taken explicitly into account.

Aggregation A common problem in aggregation of LUC data is the variability in results obtained through variations in the shape of areas, an example of this is the dependence of forestry statistics on how the basic spatial units, the stands or forest management units are delineated. Cao and Lam (1997) point to the similarity between trials with different aggregation levels and mechanical 'zooming' in and out to find the best 'focus' of an image of a certain area. All methods that involve modifying the units of measurement and reporting will lead to loss of details. Some methods however better retain statistical characteristics of the original data, while others are better for revealing spatial patterns at another resolution. Within a particular aggregation level, some classes are better classified at fine spatial resolutions, while others require coarser spatial resolutions (Marceau *et al* 1994b). All aggregation methods lose details, but some better retain statistical characteristics of the original data, while other methods are better for revealing spatial patterns at another resolution (Bian and Butler 1999). The same authors find that the averaging method for aggregation produces data and errors with the most predictable behaviour. Using simulated images gives better control of statistical and spatial characteristics of the data, and is suitable for *systematic evaluation of aggregation effects*. If research is focused only on the effect of aggregation on model output, it will not be possible to separate inherent flaws of the methods from operational errors. Skov-Petersen (1999) describe the aggregation of point data on buildings types and uses as well as floor space to a grid covering the entire surface of Denmark, and summarise the considerations that must be made during the aggregation process: *Fidelity,* *Reality, Objectivity, Accessibility, Data-handling, Sensitivity to lack of accuracy of single in-going points, Handling of 'noise'.*

Coarsening or degradation of images results in images with a larger pixel or grain size, where each pixel holds information representative of several pixels in the original imagery. Theoretically, application of this operation will mean that the larger or more common land cover classes will tend to become more dominant, while smaller or less common classes will have even smaller proportions or completely disappear (Gustafson and Parker 1992). The magnitude of this effect although depends on how clumped, spread or fragmented these land cover classes are (or the elements/objects belonging to them). Moody and Woodcock (1994) performed a simulation from 30 m resolution, Landsat TM based maps to test the use of MODIS based land cover maps, and found that while class proportions change in a regular way, the proportional errors differ between classes. Degradation of image data from higher to lower resolutions should ideally simulate sensor response (Townshend and Justice 1988), so that degraded images from for instance Landsat TM would resemble images form the IRS-WiFS sensor. When spatial degradation or thematic and spatial aggregation is performed, it must be considered whether to apply methods/algorithms that account for the (relative) importance of different land cover/vegetation types, typically through application of a weighting function, rather that 'brute force' methods that treat all pixel values or land cover classes equally.

Wickham and Riitters (1995) analysed the behaviour of metrics of diversity and structure (contagion) for a data set derived from aerial photographs at 4, 12, 28 and 80m, and found that metrics values were not 'dramatically' affected by this scale change. Wu *et al* (2000) demonstrated use of scale variance analysis and landscape metrics as methods for testing as well as describing multi-scale or hierarchical structures in landscapes. Response curves of metrics values as function of grain size were found to characterise different metrics types and to differentiate between landscapes better than variograms and scale variance curves. Wu *et al*

(2002) and Wu (2003) further developed the use of these response curves, now termed <u>scalograms</u>, for characterisation of metrics at class- as well as at landscape level and also investigated the response of metrics values to extent, i.e. the size of the image or window (in terms of number of pixels) for which the metrics are calculated.

In summary, finding an appropriate scale of measurement for geographical entities remains a fundamental, still unresolved problem (Marceau *et al* 1994a, Wu 1999), thus it shouldn't be expected that this project will provide a final solution, it rather aims at providing recommendations on methods to better overcome the problems of using and extracting spatial metrics from multi-resolution data.

2.3.3.4 <u>Evaluation of spatial metrics using neutral models</u>

When spatial metrics are calculated from images with different grain sizes and extents, and differences in metrics values observed, one can ask whether these are due to real differences in the two landscapes represented in the images or to scale effects. Thus methods are desirable that isolate the effects on observed landscape or habitat structure, which are induced by changed point of view. Also methods that evaluate the usefulness of fine-scale detail in examining broad-scale patterns[7] are important steps in development of useful and reliable models (Gardner and O'Neill 1991). One such approach to assess the influence of scale of observation is neutral models, which in the two-dimensional form are more or less realistic artificial maps showing the distribution of a number of 'classes'. Neutral models do NOT model landscape processes, they are rather used to produce data for comparison with maps of real landscapes, in order to identify non-random patterns, resulting from processes that can hopefully better be described/quantified (With and King 1997).

Early uses of neutral models were based on percolation theory (Gustafson and Parker 1992, O'Neill *et al* 1988), and the outputs had the form of random maps. Later spatial contagion was

[7] When for instance aerial photographs and satellite imagery are combined.

introduced into maps by adjustment of the correlation among sites (Gardner and O'Neill 1991). A new 'generation' of models applied fractal algorithms and hierarchical random landscapes (With and King 1997, fig. 1), and since then still more advanced algorithms have been applied, in order to create models that produce realistic images and thus metrics values. For a review of landscape simulation methods see Saura and Martinez-Millan (2000). The general purpose of using neutral landscape models is twofold (With and King 1997):

- Determine the extent to which structural properties of landscapes (such as patch size and shape, connectivity) deviate from theoretical spatial distributions, random or structured.
- Predict how ecological processes will be affected by known spatial structures.

The first approach uses models to find out how processes affect landscape patterns, the second uses models to investigate how ecological processes are affected by known spatial structures.

The performance of spatial metrics on neutral landscapes has been used for interpretation of the significance of these metrics when they are calculated on real landscapes, by separation of the effects of topography, natural disturbances and human activities from the expected behaviour of the metrics if such effects were absent (Gardner and O'Neill 1991).

Johnson *et al* (1999) extended the concept of neutral landscape models to provide a general Markovian model of landscape structure (based on assumptions of landscape development processes). A stochastic transition matrix was used to create patterns, which were compared with maps of real landscapes, watersheds in Pennsylvania, USA. Saura and Martinez-Millan (2000) present a new simulation method: Modified Random Clusters (MRC), that provides more general and realistic results than commonly used landscape models and describe the development of the Simmap software[8] where it is implemented. Saura and Martinez-Millan (2001) apply simulated landscapes based on MRC to asses the sensitivity of map extent (corresponding to window size) and Saura (2002) uses simulated thematic (land cover)

[8] Description, instructions for use and contact details for the programmer at: http://www.udl.es/usuaris/saura/simmap.htm (accessed 23/2 2004).

patterns to assess the influence of minimum mapping unit (MMU) on the values of a number of spatial metrics.

2.3.3.5 Perspectives for scaling of calculated spatial metrics

Textural measures can be of great value and improve classification, although it must be stated that when textural measures are used in image processing and reporting in this thesis, the approach is implicitly *statistical* (as opposed to modelling). The MAUP provides a relevant approach to the problem of how robust spatial metrics are to changes in spatial resolution and change of reporting unit (e.g. level of watershed or administration). Also the strategy described by Woodcock and Strahler (1987), see section 2.3.3.1, could potentially be applied on landscape or land cover maps, for calculation of spatial metrics in windows of increasing size. When the index values cease to change, the texture values or contrast between neighbouring cells decrease, or both, it must be assumed that the typical or characteristic size or distance for the actual landscape has been passed. Such an approach will build on and investigate the hypothesis that texture at one level (coarse) corresponds to spatial structure at another (finer). This might provide an approach to the regionalisation and the MAUP problems, that is relevant with forest maps and CLC- or National Vegetation Classification type (as used by the United States' GAP project) land cover maps in raster format. The variance approach described here could be supplemented by scalograms as described by Wu *et al* (2002).

In the context of this thesis and the challenges it poses, it is important to test whether the effects are the same when degrading land cover maps from finer to coarser resolution as they are when classifying EO imagery that has corresponding fine and coarse resolutions – as this is crucial for approaches that *extrapolate* from localised, well described plot or test areas to larger regions. This might allow extrapolation beyond the landscape level in subsequent experiments with large land cover datasets, in order to test whether spatial metrics are comparable at the continental scale.

2.3.4 An example of quantification of spatial structure using EO data: description and measurement of fragmentation

This section will provide an example of how the fragmentation concept can be assessed operationally with EO data through the application of spatial metrics. Fragmentation was chosen partly because interest in the concept has been expressed from environmental managers, and partly because the literature is rich with examples of how spatial metrics of forest structure in general and fragmentation in particular are defined and applied, in very different ways.

Forman (1995, p.39) defines <u>fragmentation</u> as the *breaking up* of a habitat, ecosystem, or land-use type into smaller parcels (considered to be one of several spatial processes in land transformation) and later on states that the concept includes perforation and shrinkage (ibid p. 408). Frohn (1998, p. 9-10) adapts this definition to an EO context and sees fragmentation as *the opposite of contagion*, which he defines as the tendency of land covers to clump into a few large patches. The term fragmentation can also be used to describe a landscape where areas of forest have been removed in such a way that the remaining forest exists as islands of trees in a cutover environment (Natural Resources Canada 1995, in Dobbertin 1998). The major concern with fragmentation is in this case the effect of the loss of contiguous forest cover on species movement and dispersal, making relevant (and possible) the application of Island Biogeography models to the 'fragmented' landscape, while Fry (1996) argues that habitat loss in general have more serious effects that changes or differences in spatial distribution with constant or equal habitat area, see Figure 2.5 on page 74. According to Kouki and Lofman (1998), the concept of fragmentation has been widely applied in recent years to denote *landscape transformation* from uniform to more patchy and heterogeneous types, although the usage of the word has not been consistent. According to Delbaere and Gulinck (1994) the term fragmentation refers to the broader term *connectivity* (and can thus be defined as lack or loss of connectivity).

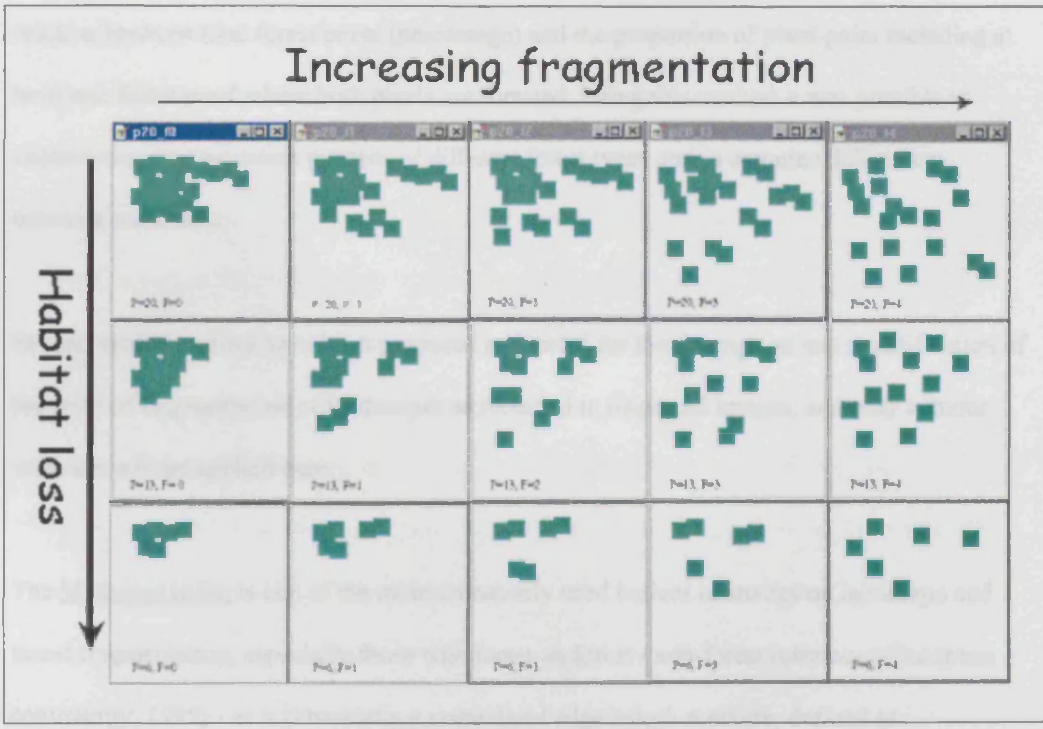

Figure 2.5 Conceptual model of how fragmentation is related to habitat loss. The size of the arrows indicates the respective importance of the processes. After Fry (1996).

In a continental-level study Skole and Tucker (1993) defined fragmented forest as isolated patches < 100 km^2 area, while Mayaux *et al* (1998) simply define an area to contain fragmented forest if within an AVHRR pixel, approx. 1 km^2, the forest cover is between 10 and 70 % of the surface. These two definitions seem to be more *ad hoc* for specific and mapping scale purposes, and defined more from knowledge about the properties of the remotely sensed data that happen to be available than from knowledge about the processes to be mapped and monitored. Riitters *et al* (2000) performed an analysis of forest fragmentation based on 1-km resolution land-cover maps for the entire globe, the Global Land Cover Characteristics database (GLCC). The measurements used a 'moving windows' approach with window sizes ranging from 81 km^2 (9*9 pixels, "small" scale) to 59,049 km^2 (243*243 pixels, "large" scale). The value calculated for the window was then used to characterize the fragmentation around the central pixel – if it was forested, otherwise it would be left blank -

with metrics of fragmentation based on the occurrence of adjacent forest pixels. The types of forest structure used was: Interior, Edge, Perforated, Transitional, and Patch – based on the relation between total forest cover (percentage) and the proportion of pixel-pairs including at least one forest pixel where both pixels are forested. Using this method it was possible to characterise fragmentation patterns of different forest types and to examine differences between continents.

Several spatial metrics have been proposed and tested for the description and quantification of the level of fragmentation of landscapes as recorded in maps and images, and only a minor selection will be applied here.

The Matheron index is one of the more commonly used indices in studies on landscape and forest fragmentation, especially those who focus on forest / non-forest interfaces (European community, 1995) - as it is basically a normalised edge length measure, defined as:

$$M = 10 * \frac{\textit{number of runs between forest and other LC type pixels}}{\sqrt{(\textit{number of forest pixels})} * \sqrt{(\textit{total number of pixels})}} \qquad [1]$$

The index has been used as a tool (Mayaux and Lambin, 1995 and 1997) to describe the fragmentation of forest cover as observed in Landsat TM images as well as in NOAA AVHRR images and to derive a correction function for use of the latter for the creation of tropical forest maps. Mertens and Lambin (1997) used the index to describe the spatial fragmentation of forest cover - as one amongst several spatial variables, some derived with GIS analysis. In European Commission (1995), the index is calculated for representative forest / non-forest interfaces on land cover data derived from NOAA AVHRR data in 34 'sites' that are found to be typical for forested, tropical regions.

Also more sophisticated measures have been used of which some are mentioned here, for a more in-depth review, see McGarigal and Marks (1994) and Riiters *et al* (1995). Amongst the indices to have drawn most attention are those which attempt to measure fractal dimension, which can be seen as a measure of as well the self-similarity as of the complexity of patch shape/borders (Mandelbrot 1967). Already Ramstein and Raffy (1989) link this measure with the structure of variograms derived from image data. De Cola (1989) found that forests have high fractal dimensions - and that for agricultural regions the fractal dimension is inversely related to land-use intensity. Hargis *et al* (1998) developed a new measure termed "mass fractal dimension", and compared it with other commonly used landscape measures, but found that no measure could differentiate between landscape patterns with dispersed vs. aggregated patches. The contagion metric has been used, revised and subjected to some criticism, as there are diverging opinions about what it actually measures (Frohn 1998, Hargis *et al* 1998). The same thing can, to some degree, be said about the different measures of fractal dimension (Olsen *et al* 1995, Frohn 1998) and some warnings are found in literature on the subject, that the use of complex quantitative descriptors for overall general concepts should be done with great care (McGarigal and Marks 1994, Brandt and Holmes 1995, Frohn 1998). In a study modelling the dynamics of butterfly populations in a real landscape, Moilanen and Hanski (1998) found that the impact of landscape structure only is influential on species persistence within a certain interval along a gradient of fragmentation. This could by to the use of fragmentation metrics for stratification of larger areas before regional analyses are performed.

Frohn (1998) proposed two mathematically simple indices for quantification of fragmentation, as alternatives to the more complicated indices of contagion and fractal dimension. They are defined as follows. The number of Patches Per Unit area (PPU):

$$\text{PPU} = \frac{m}{(n * \lambda)} \qquad [2]$$

where m is the total number of patches (in the window), n is the total number of pixels in the area of interest (window) and λ is the scaling constant equal to the area of a pixel. Dependent on the extent of the area of interest the unit of λ can be m^2, ha or km^2. The advantage of the PPU index is that it reflects the number of patches, normally thought of as something describing much of the information on the structure of a classified image.

The Squareness of Patches (SqP) index is defined as:

$$\mathrm{SqP} = 1 - \frac{4*\sqrt{A}}{P} \quad [3]$$

where A is the total area of all pixels and P is the total perimeter of all pixels belonging to the land cover class of interest in the area (window). The theoretical value for this index is between 0 and 1; 0 is for the case of the landscape mask element (the forest) consisting of one large square; if it is made up of more patches, the values will be > 0; the value will approach 1 when the cover type becomes more scattered over the landscape.

Once these spatial measures of (forest) fragmentation have been defined and selected, scaling issues must be considered with special focus on fragmentation. The central problem is whether is it the same processes that are observed when landscapes are imaged at different resolutions. Thus scaling effects should be quantified, in order to determine if efforts can be concentrated on assembling land cover datasets at one specific (standard) resolution, or if it will be possible to recommend a series of spatial metrics that allow comparison between data derived from images with different resolution or summarised over different spatial units. These issues are addressed in the following chapters of this thesis.

2.4 Conclusions on the use of spatial and Earth Observation data for monitoring of sustainable land use and biological diversity

In this section, the findings and considerations in the literature review are summarised and evaluated, with applications for environmental monitoring and management in mind.

2.4.1 Forest mapping and monitoring

At the local or Forest Management Unit (FMU) level, maps constitue an integrated management tool and foresters are normally familiar with use of aerial photography. This should be seen as an advantage and taken into consideration when EO data are introduced in management practices. GIS is increasingly being installed and used for forest management at the lowest administrative levels, aided by the developments in surveying techniques through cheap and easy-to-use GPS equipment. Thus remote sensing data have the potential to become increasingly integrated in GIS applications for improved land cover classification, better assessment of (production related) stand parameters and change detection, i.e. updating of forest inventory maps. The real challenge is to make use of the EO data for ecologically oriented purposes as well, either by the actual agents, the forest mangers themselves or public or private ecologists/environmental experts cooperating with the forest administrations. In order to make this happen, the role of the scientific community is to provide methods for utilizing EO data in combination with forest inventory data as well as with data for conservation planning and monitoring and ecological/biodiversity surveys.

At regional and national levels, where EO data currently have few forest applications – at least in Europe - EO data is expected to be used for broader overviews of landscape structure, such as in Gap Analysis and for regular updates of forest statistics. High resolution EO data could also be used for monitoring the environmental conditions around protected areas, e.g. by assessing edge effects due to land use changes. In general EO data can supplement statistical data such as results of national forest inventories that are without spatial aspects, in the sense that values are reported for administrative units.

For assessment of sustainability and potential biological diversity, large amounts of information with potential use are available, recently also through Internet-applications, at low or no cost for researchers. Such data (sets) include national and regional forest inventories and maps, forestry statistics, data on forest ownership, protection status etc., national monitoring programs for monitoring of biodiversity that the countries have committed themselves to according to the CBD, and statistics about e.g. forest products, tourism and agriculture. At European level data are available through EUROSTAT, EEA, and potentially EFIS, and forest fragmentation can be quantified through analysis of existing EO based forest maps.

2.4.2 Land cover mapping and Landscape monitoring

Landscape diversity can be quantified through analysis of existing LUC maps, as demonstrated in EU-DG AGRI (2000) and Gallego (ed. 2002). The existing CLC database and national LUC mapping initiatives provide useful input data for landscape level analyses. Within the EU, national land evaluation, survey or mapping initiatives are often modified or at least it is made sure that the outcome can form part of CLC, meanwhile providing information at higher thematic and spatial resolutions, see Brandt *et al* (2002), Weiers *et al* (2002), Büttner *et al* (2002). Landscape level metrics can be calculated from CLC data and used to establish comparisons between regions and countries. Such metrics however, should not stand alone, but rather be used along with (other) agri-environmental indicators (see European Environment Agency 2001, Gallego 2002).

LUC data can serve as contextual information for assessment of habitat quality, at correctly chosen spatial scales, and will be indispensable for applications of (calculations based on) island biogeography, meta-population theory or the patch-matrix-corridor model. Hemeroby levels or index values could be calculated from LUC data, preferably in combination with information on land use history and on point 'sources' of human activity, pollution etc. Spatially explicit models of ecological processes, including animal movements and species colonisation and extinction could help establish statistical relations between values of spatial metrics and either habitat quality or species richness of landscapes. These relations might differ with the size (extent) of the landscapes investigated. Thus neutral models could be used to assess the effects of extent before moving-windows methods are applied for calculation of metrics (map) over large areas. In addition such models (outputs) may help separate scale influence of metrics values from differences due to real-world differences in spatial structure.

Figure 2.6 is intended to provide a conceptual overview of the factors involved in a system for assessing landscape structure (of which forest structure is a special case), integrating remote sensing and 'ancillary' data, probably using a Geographic Information System for the data management.

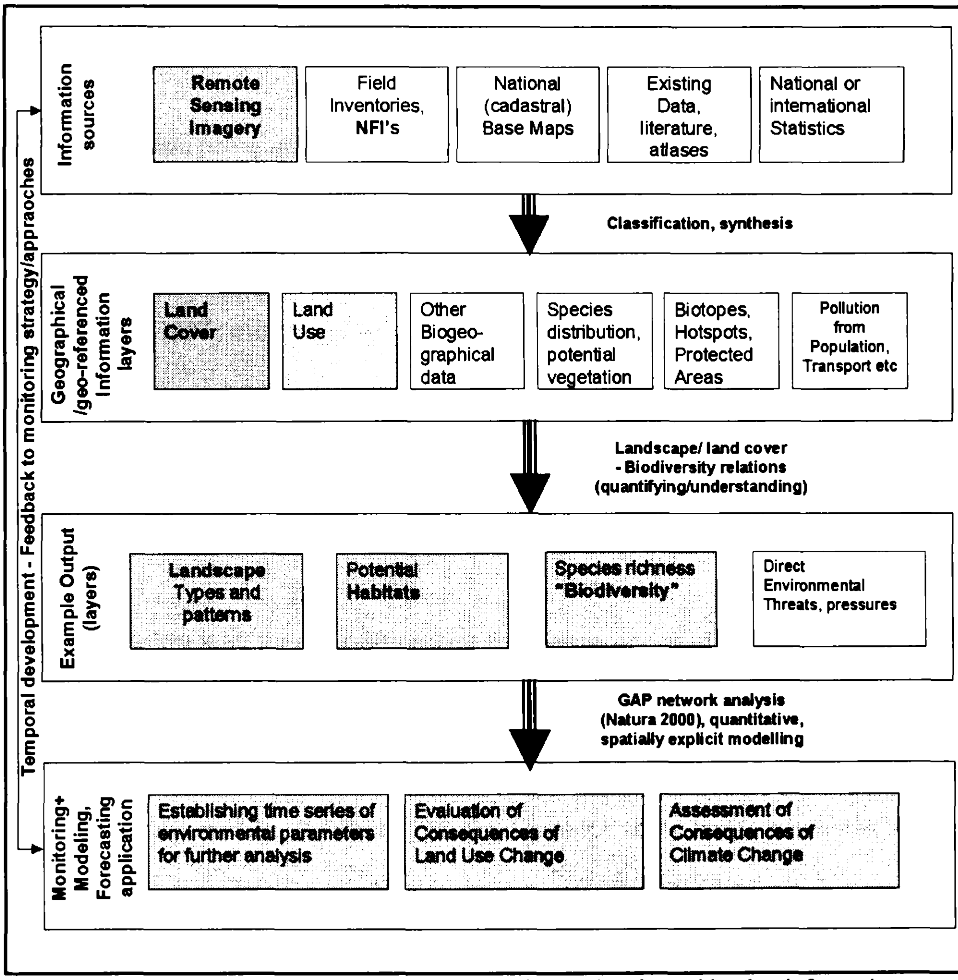

Figure 2.6 Conceptual model for integration Earth Observation data with other information sources for environmental monitoring in a habitat based monitoring approach (from Estreguil *et al* 2001).

2.4.3 Applications of spatial metrics in an EO-GIS framework

Relative to traditional land use maps, land cover/vegetation maps derived from EO data provide more relevant input data for calculation of metrics such as diversity – on the other hand there are several potential error sources in the processing chain from spectral bands of satellite data to classified images. The choice of which geographical data to use for specific management/monitoring tasks will however depend on the information need as well as availability and price of data and not least the on potential to combine data and metrics for description (and prediction) of biological properties of the landscape or forest of interest – and on the ability to detect changes when data from different times are compared. This potential can be clarified through scaling and sensitivity analyses.

There is a certain pedagogic value of calculating spatial metrics from LUC, in the sense that it makes the user think in landscape ecological terms (patches, corridors, edges etc.). Furthermore implementation of moving-windows methods, in line with those envisioned by O'Neill *et al* (1997) will be useful for illustration purposes, as demonstrated by Häusler *et al* (2000). However, when the outputs from such calculation are used as raster-GIS layers there may be particular scaling problems associated with the window size(s) used – especially if the 'maps' are made from input data with different pixel/grain size.

Through this literature survey, relationships between on one hand biological diversity and naturalness (state) of landscapes and on the other hand spatial metrics derived from EO data of the same areas have been identified, some simple and some rather complex, based on intricate numeric models. It follows from the discussion above that is relevant to focus further studies on development of methods to derive <u>indicators</u> from EO data, which meet the information needs of potential users. Such metrics must contain information about processes or 'state variables' that is of concern (ref. Table 2.5) or central in reporting according to e.g. the Helsinki process or for the EU member states in relation to designation and monitoring of Natura 2000 habitat areas. Examples are forest fragmentation, landscape diversity, connectivity and disturbance. Also temporal metrics like change rate would be relevant as indicators. It is however still important to keep in mind what purpose the spatial metrics are being calculated for, and who will in the end be using them.

A possible flow of information and decisions in the application of software for calculation of spatial metrics aimed at forest or landscape management is outlined in Figure 2.7, which is partly based on the recommendations in McCormick and Folving (1998) and Häusler *et al*

(2000). This figure will be used for discussion of the actual implementation of spatial metrics calculation and image and landscape analyses performed during the studies for this thesis.

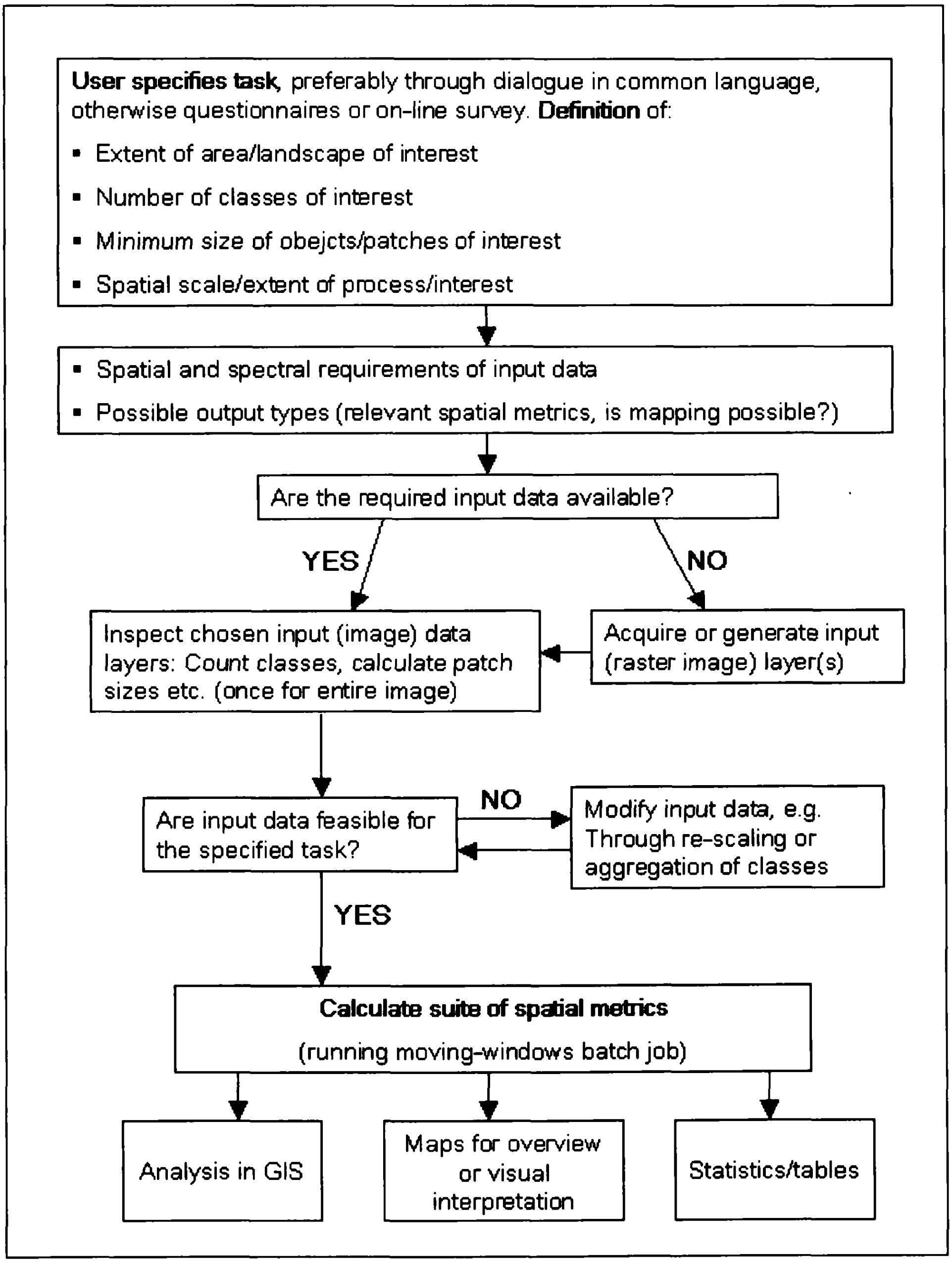

Figure 2.7 Proposed schedule for landscape ecological analysis using EO data and spatial metrics.

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3 Measures of forest fragmentation at varying spatial resolutions, a study from central Italy

The purpose of the analysis carried out in this chapter was to investigate the potential of using spatial metrics to describe the structure of a forested landscape, and to investigate further how these metrics behave when calculated at different scales and based on different input data types. The analyses carried out here formed part of studies for the Eurolandscape project, where selection of indices for forest structural assessment at the European level was one of the work packages. The early phases of that work concentrated on some relatively simple measures, which also had the advantage of being possible to control visually by comparison with the input data, in this case images classified into forest-non/forest maps.

One commonly used approach for examination of scaling (grain size) effects is to spatially degrade raster data (high resolution imagery) that is assumed to express the "real" situation, i.e. the "true" shape and distribution of forest patches (Turner *et al* 1989). Here, it was investigated whether the use of spatial indices can assist in the scaling process or deliver supplemental information about it. A particularly important task, given the data available and considerations of data costs, was to investigate the possibility of relating the values of spatial indices derived from medium resolution data (e.g. WiFS-based forest maps) to those derived from high-resolution data or detailed forest/land cover maps. If such relations were established, it could make possible the extraction of information at the scale where processes important to ecosystems take place. A part of the justification for this study was to look deeper into the usefulness of the two new metrics proposed by Frohn (1998) and to compare them with the better known and more commonly used Matheron index.

3.1 Methodology

The first step included simulation of how a forested landscape appears as raster images from EO sources at different spatial resolutions (pixel or grain sizes). The indices mentioned in section 2.3.4 were calculated for the same cells or sub-landscape, thus assessing the influence of the apparent aggregation and isolation processes which are known to take place when changing sensor or pixel size (Bian 1997, Cao and Lam 1997). The forest-non-forest maps with different resolutions were derived from a synthetic image, produced by assigning pixel values to the cells of a grid, from a vector coverage. The initial (base) image was the one with the highest spatial resolution, i.e. smallest pixel size; this cell size can be as small as the resolution of the data from which the maps or GIS coverages were originally made. Images at coarser resolution were made by majority filtering of the binary images, using gradually larger kernels (2, 4, 8 and finally 16 pixels).

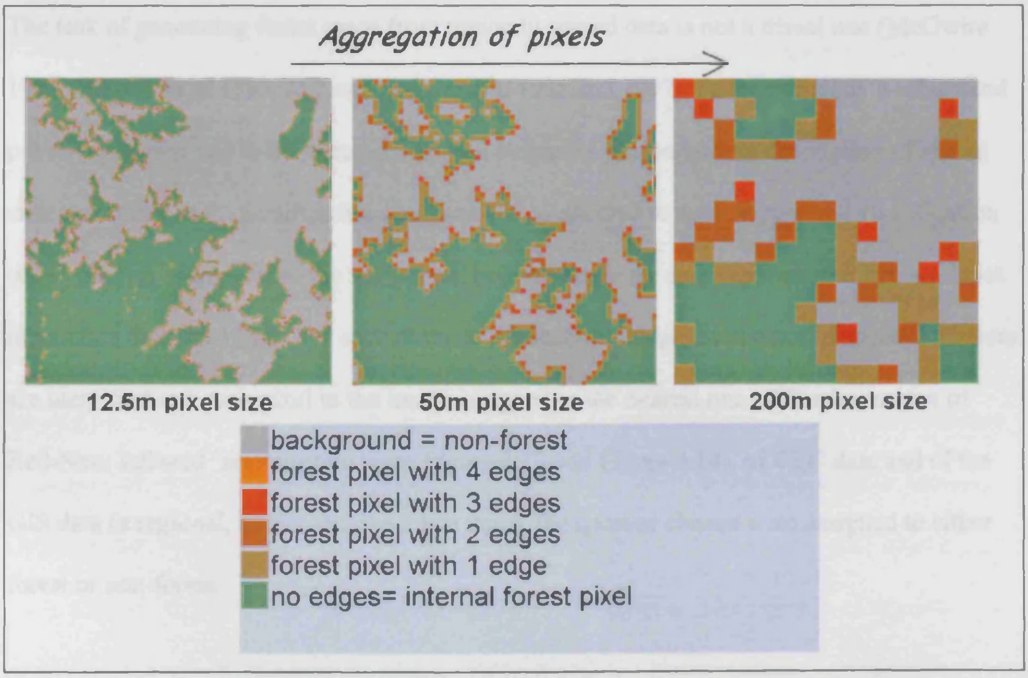

Figure 3.1 Aggregation of pixels from synthetic forest-non-forest image A 3*3 km subset is shown here, similar to one of the windows used for calculation of spatial metrics.

In the second step, real satellite images were used and the effort focused on establishing relations between the spatial measures derived from forest/non-forest images for cells or sub-landscapes of the same spatial extent but necessarily of different size measured in pixels. Even when this was not possible, the results point to some reasons why scaling or multi-sensor problems occur.

Assuming that a linear relation exists between spatial scale, expressed as grain size (in this case equal to pixel size) and the values of the metrics, a relation like this is expected:

$$\mathbf{SM = Ap+B}$$

Where SM is the actual spatial metric, p is the pixel size (diameter or edge length), A and B are coefficients characteristic to the dataset or data type in question, such as the geographic region or the type of land cover map. This follows the methods of Benson and MacKenzie (1995) and Turner *et al* (1989), although in the latter study, the regressions were performed between metric values and the log of the aggregate pixel size.

The task of generating forest maps from remotely sensed data is not a trivial one (McGwire 1992, Häusler *et al* 1993, Mayaux and Lambin 1995 and 1997), so for this study a robust and proven approach had to be selected. Because emphasis was on correct description of spatial structure rather than classification accuracy, it was decided to do unsupervised classification of the satellite images from the study area, in order apply the same approach to the two types of satellite data used here. For each of the multi-spectral images, a number of spectral clusters are identified and each pixel in the image assigned to the nearest one. After inspection of Red-Near Infrared 'scattergrams' (see Figure 3.13 and Figure 3.14), of CLC data and of the GIS data (a regional, administrative forest map), the spectral classes were assigned to either forest or non-forest.

Filter kernel:

0	1	0
1	5	1
0	1	0

Pixel value	Edges
<5	Non-forest pixel
5	4
6	3
7	2
8	1
9	No edges = internal pixel

Figure 3.2 Extraction of edge (count) data from binary (forest-non-forest) images.

The map images were then filtered at each resolution, as illustrated in Figure 3.2. This was done for two reason, first to provide input to edge-counting for calculation of the Matheron and the SqP indices and secondly for illustrations of the effects of spatial degradation, as they e.g. appear in Figure 3.1.

Assuming that the satellite images, the results of the classifications, and the land cover maps made from these describe a landscape, it follows that in order to meaningfully apply metrics that describe the structural variation within the landscape which is important for its stability (Kareiva and Wennergren 1995), smaller subsets of these maps (sub-landscapes) must be used. For that reason it was found appropriate to use a modified version of the Fragstats software package (McGarigal and Marks 1994), in order to make it possible to apply a "moving-window" approach. This approach was developed and applied in a study carried out for the FIRS project (Häusler *et al* 2000), as part of a study financed by the Directorate General VI of the European Commission, called "Pilot Study in the Field of Monitoring Forested Areas"[9]. The aim of the project was to demonstrate satellite based methods for the operational assessment of changes and structural diversity of European Forest Ecosystems and

[9] (Contract N° 9662CO001), carried out by a European Consortium lead by GAF, Munich. The name of DG VI has since been changed to DG Agriculture.

to define the requirements for the implementation of a monitoring system, and the use of spatial indices was considered a natural part of such a system. The outputs from the calculation of the various metrics are initially stored in table format in text-files (or files that can be read using any text editing software tool). These files can be imported into spreadsheets for statistical analysis, or converted to three-dimensional grids using e.g. Surfer (Keckler 1997), or even directly imported (as ASCII files, given the number of rows and columns is known) into image processing programs. Back in an image processing environment the grids can be edited, typically by adding header-information to, once again be geo-referenced, and thus used in combination with GIS data vector layers or other raster images.

The image processing software used for this study was WinChips (Hansen 2001), statistical processing and drawing of graphs was done with the Microsoft Excel spreadsheet. Calculation of the Matheron index is not implemented in Fragstats, thus this index was calculated from image statistics extracted for each grid cell of an (Arc-View format) shape-file, using the grids shown in Figure 3.5 and Figure 3.6. In this particular case the method applied was calculation of spatial metrics in moving windows *without overlap*, thus there are no smoothing effects.

3.2 Data

The test site is an intensively forested area, located in the Italian region of Umbria near the city of Foligno (south of Perugia), in the Apennine Mountains. The forests are mainly deciduous in composition, and are made up of oak, beech, and other species. The forests are managed using both coppice and high-forest silvicultural systems. The topography is mountainous, with elevation from 207 to 1425 metres above sea level. The test site is located in Landsat TM scene 191-030, with the scene centre at 43.30 latitude, 12.75 longitude.

The Landsat TM data were acquired as part of a study on the application of the Forest Light Interaction Model (FLIM) for mapping forest structural parameters, following the approach described by McCormick (1996). A sub scene of an image acquired 12th July 1996 was extracted, 50*50 kilometres in extent. This image was ortho-rectified to UTM projection using a digital terrain model. Only bands 3, 4, and 5 have been used. An area of slightly greater extent than the subscene was described in detail by a GIS coverage of forest types and properties (Grohmann 2000), made at the forest department of the Regione di Umbria. The nominal resolution of Landsat TM images is 28.5*28.5m, in this study the images were rectified to pixel size 25*25 m.

	Landsat TM		IRS WiFS	
	band nr.	wavelgt. µm	band nr.	wavelgt. µm
Red	3	0.63-0.69	1	0.62-0.68
NIR	4	0.76-0.90	2	0.77-0.86
MIR	5	1.55-1.75		

Table 3.1 Satellite data used for forest mapping.

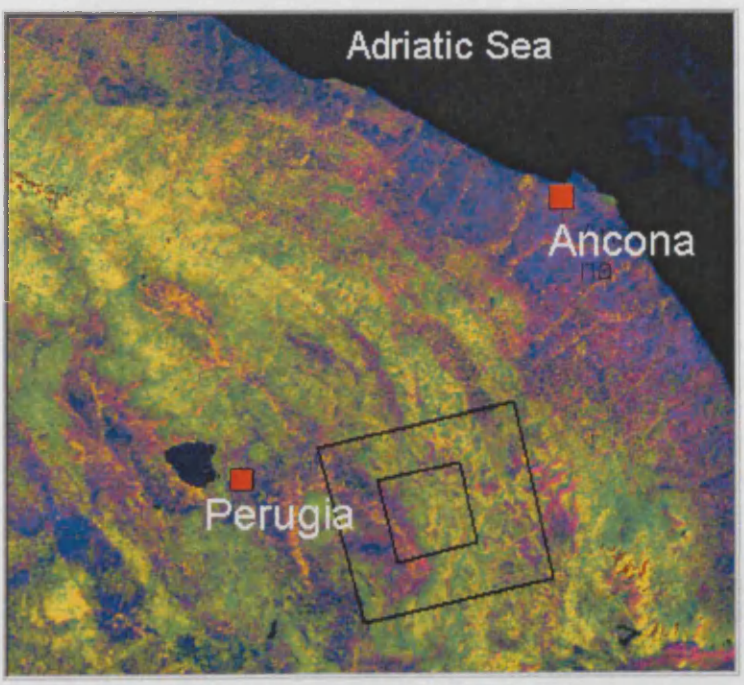

Figure 3.3 Location of the test areas, shown on false colour WiFS image, red band = WiFS channel 2 (NIR), green band = NDVI ((b2-b1)/(b2+b1)), blue band = WiFS channel 1 (red refl.). Forested areas are seen as green/yellow, agricutural areas as red/blue. The image was acquired 2. Sept. 1997, the extent is the same as a full Landsat scene, i.e. 180*180 km.

The WiFS data were acquired on Sep. 2 1997, and has been used in a pilot study about forest mapping at regional scales by medium resolution data, carried out at VTT, Finland (Häme *et al* 1999). The data have undergone atmospheric correction using the 6S code (Tanre *et al* 1992) and a BiDirectional Reflectivity Function (BDRF) correction for surface topography. The data were supplied in the projection of the CORINE land cover database (Lambert Azimutal) re-projected to Universal Transverse Mercator (UTM) zone 33 coordinates, and finally had to be shifted to fit the TM data exactly, by interactive inspection and changing offset values of the two images. The locations of the subsets used in this study, the 50*50 km TM and WiFS images and the 25*25 km synthetic image are shown in Figure 3.3. The nominal resolution of the WiFS sensor is 180 m, the data used here were rectified to a pixel size of 200 m. The spectral characteristics of the satellite data used are shown in Table 3.1.

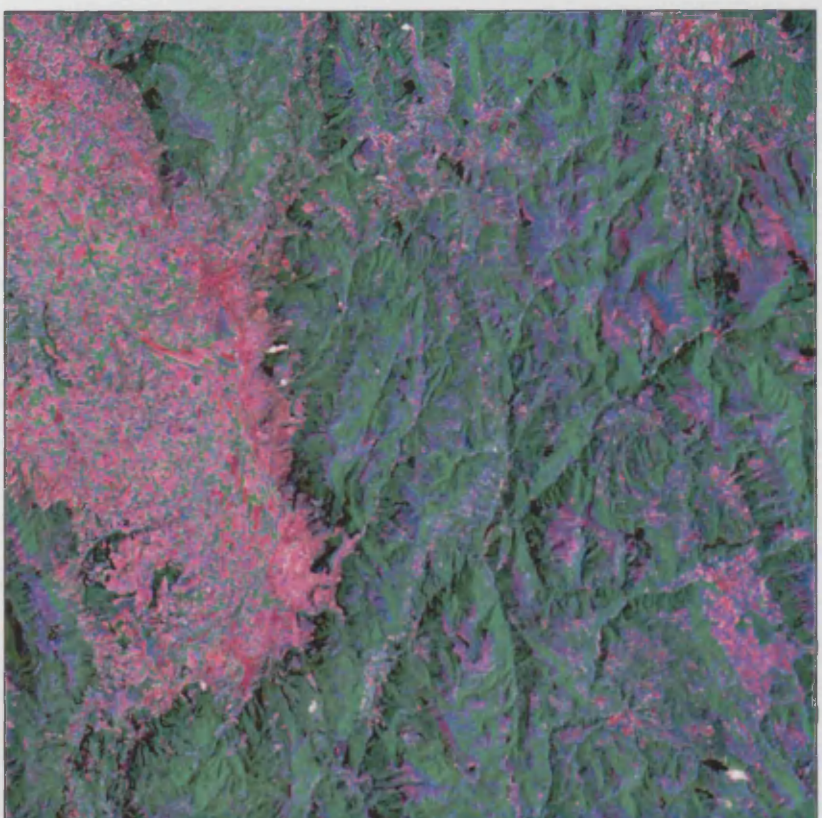

Figure 3.4 Geo-rectified subset of the Landsat TM scene recorded 12 July 1996, bands 3 (red), 4(green) and 5 (blue), extent 50 km. Agricultural fields, dominant in the Val Umbra to the left (west) appear red, grasslands bright green and forest in darker green shades.

3.3 Results

In this section, the main findings from simple statistical analysis of the results from image processing and calculation of spatial metrics are presented, with focus on scaling effects. Also the display of the calculated spatial metrics and in map-form and graphical display of their scaling behaviour are addressed.

3.3.1 Synthetic images, scaling properties

All forest class layers of the GIS coverage were combined and used for creating a raster image that could simulate high resolution satellite imagery. The pixel size was set to 12.5m, and the extent of this image was 25*25km. The image was then gradually degraded to pixel sizes of 25, 50, 100 and 200 m, as described in the previous section. For each image SqP, PPU and M were calculated for each cell, in this case the image was viewed as 64 cells of each 3*3 km, thus excluding the the southernmost and easternmost edge areas, as seen in Figure 3.5 and Figure 3.6. These figures also show the two extremes in form of the initially created image and the result of the last degradation step.

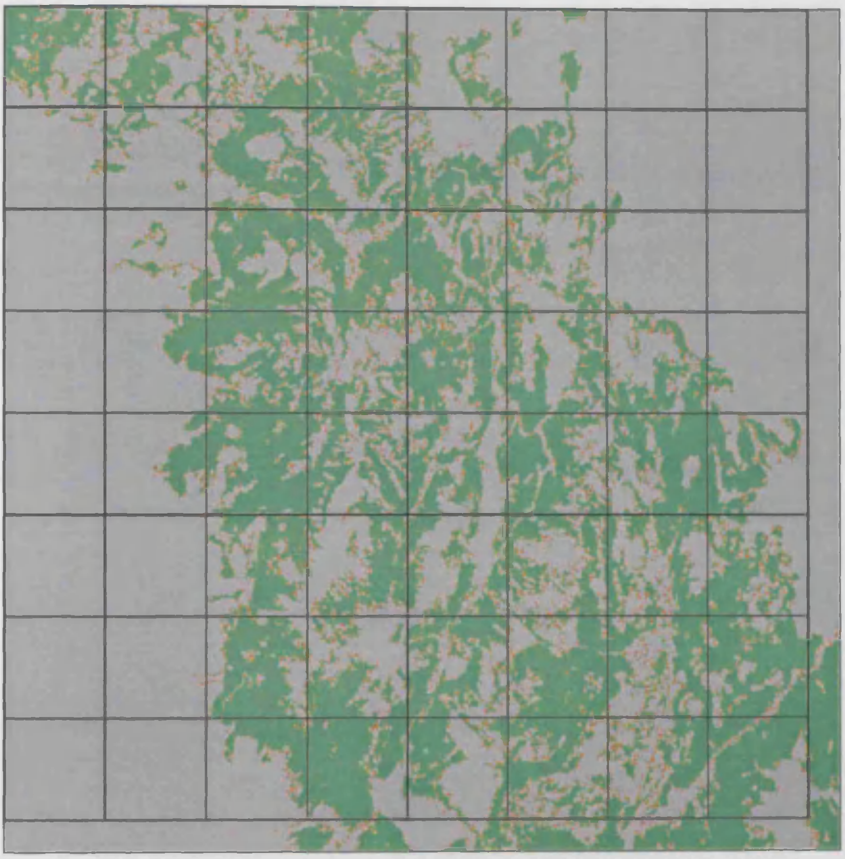

Figure 3.5 Synthesised forest mask, pixel size 12.5 m., after edge detection. Forest appear as green, background as grey, edge pixels in red and brown, same legend as in Figure 3.1. Image extent 25*25 km, grid cell size 3*3 km.

Windows with no forest cover were excluded from the calculations of M and SqP, since these indices are undefined when the number of forest pixels is zero. For all metrics and at each resolution the results were plotted against the forest area. The most striking observation here was the non-linear relation between the number of patches (per unit) and the total forest area (calculated for the start-image with 12.5m resolution) within the grid cell, as illustrated in Figure 3.7.

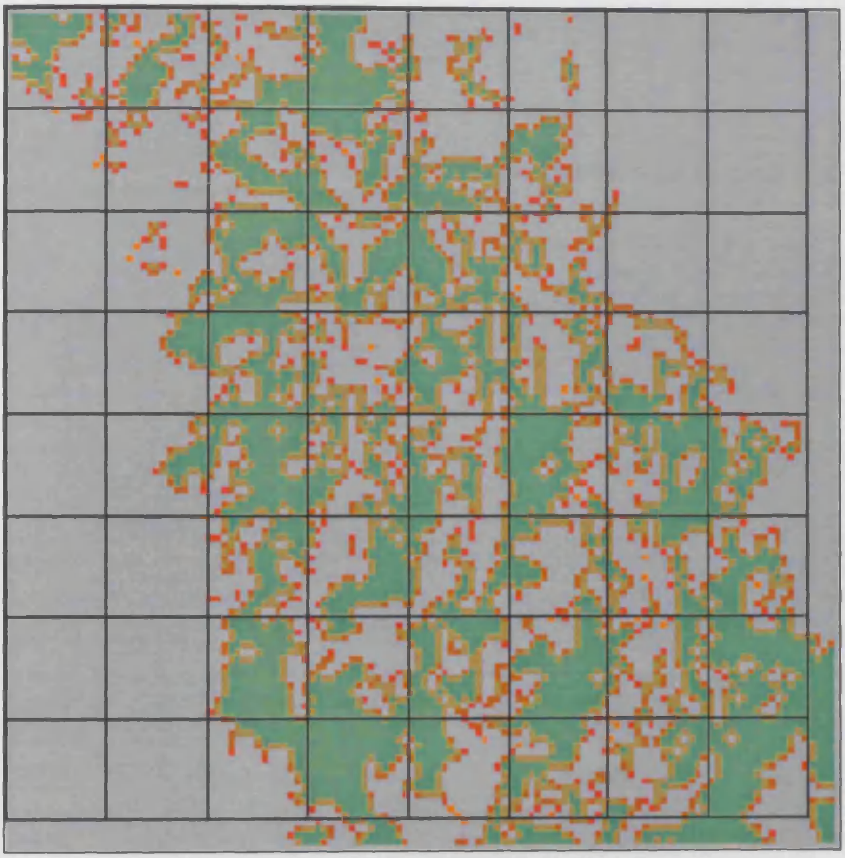

Figure 3.6 Synthesised forest mask, pixel size 200 m, after edge detection. Colouring as for Figure 3.1.

After the initial inspection of the results, it also appeared that especially the SqP values were related to the forest area. The indices are seen either to increase or decrease uniformly with the coarsening of the image, but a dependence on the type of the input cells was found with regard to forest cover percentage and to the number of patches. Regressions performed on the averaged values of the three metrics and the resolution as expressed by pixel size (p) gave the following results:

$$\mathbf{SqP = 0.8359 - 0.0013p,\ R^2 = 0.99}$$

$$\mathbf{PPU = 1.66 - 0.00083p,\ R^2 = 0.64}$$

$$\mathbf{M = 1.33 + 0.0222p,\ R^2 = 0.93}$$

These scaling relations are characteristic of this particular landscape, or landscape type, and can in principle be used for the prediction of metrics values at finer spatial resolutions from values calculated at coarser ones.

3.3.2 Synthetic images, metrics behaviour

For this part of the analysis, the values of the spatial metrics were grouped according to the percentage of the area that is forested, in order to further investigate the behaviour of the metrics with changing resolution, and to confirm or reject the assumption the they behave differently with different forest cover proportions. The groups were selected based on visual inspection of plots such as shown in Figure 3.7 and Figure 3.8, in such a way that they would contain the same number of samples.

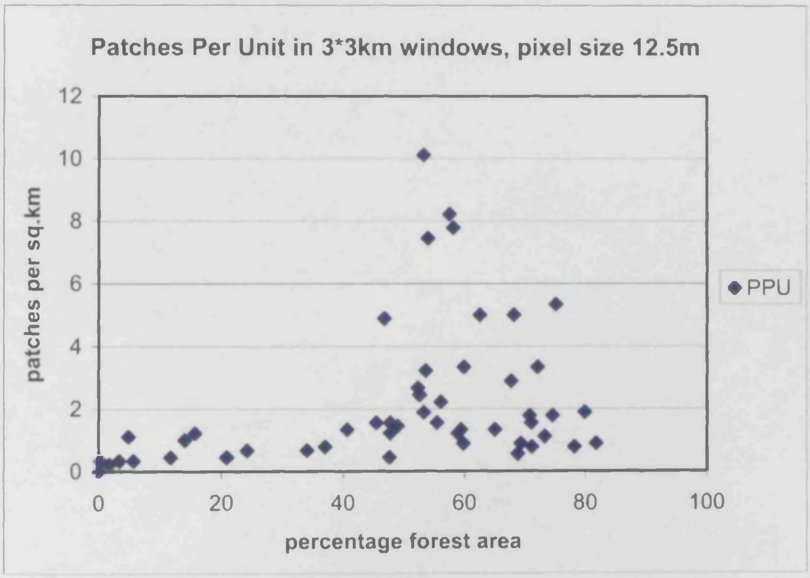

Figure 3.7 Patch density in synthetic forest map plotted against forest cover in each window. The number of patches per unit peaks when about half of the grid cell is forest covered.

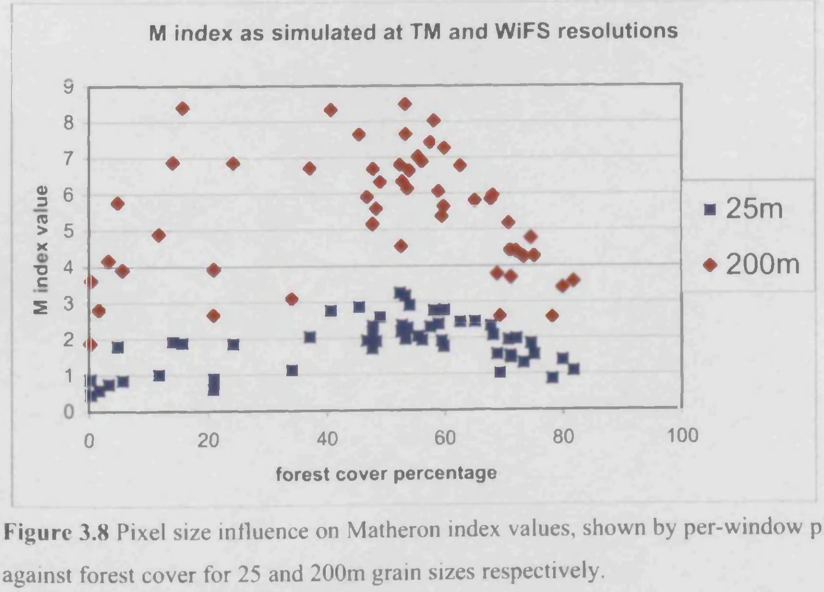

Figure 3.8 Pixel size influence on Matheron index values, shown by per-window plots of M values against forest cover for 25 and 200m grain sizes respectively.

From Figure 3.9 and Figure 3.10, it appears that both the SqP and the PPU metrics have their highest values when about half of the landscape is covered by forest. The decline in SqP with increasing pixel size is due to the relatively larger amount of interior or non-edge pixels in images at high spatial resolution, see also Figure 3.1. The fact that the values of SqP become smaller with increasing pixel size, is in accordance with the less complex shapes observed at lower resolutions, due to the "filtering out" of small patches with a high edge/area ratio, narrow linear patches and "gaps" within forest patches. The SqP values are surprisingly predictable under spatial degradation, thus the best metric for multi-scale comparisons, even between 12.5m and 200m pixel size.

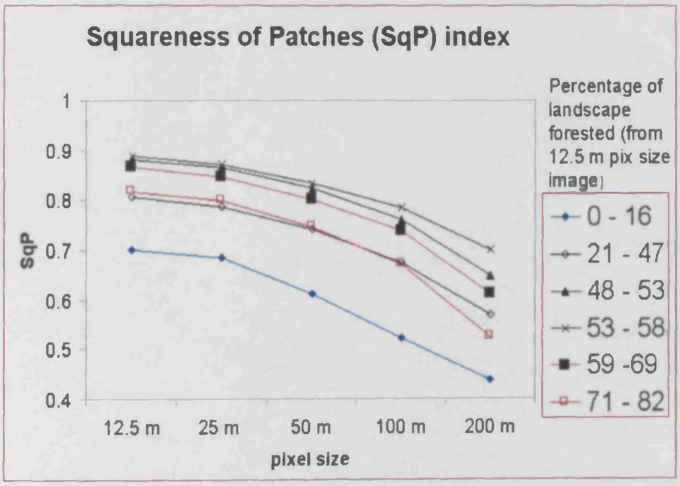

Figure 3.9 SqP as function of pixel size and forest cover for synthetic images. The values are grouped by amount of forest cover in the windows for which they were calculated.

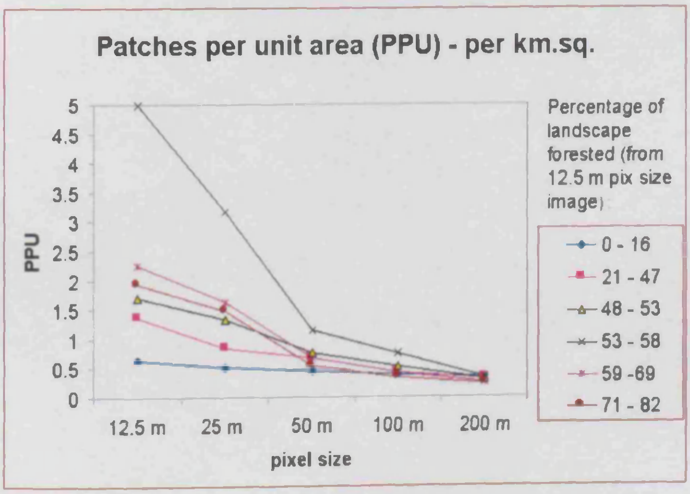

Figure 3.10 PPU as function of pixel size and forest cover (grouping as above) for synthetic images. Most patches are "lost" during the initial phase of pixel size degradation.

The decline of the PPU values is strongest in the initial phase of degradation, probably due to the effect of eliminating patches consisting of one or a few pixels. The values of the metrics within each window at each resolution were regressed, along with the amount of forest cover in the cell, and the correlation coefficients are shown in Table 3.2 and Table 3.3. The results indicate that SqP is a more robust metric for comparison across scales.

SqP	*Area12.5*	*12.5*	*25*	*50*	*100*
Area12.5	1				
12.5	0.533924	1			
25	0.526287	0.997263	1		
50	0.50381	0.990373	0.991971	1	
100	0.472774	0.970723	0.974048	0.987853	1
200	0.343242	0.918761	0.928397	0.936453	0.96009

Table 3.2 Correlation of the SqP metric derived from different pixel sizes. n=53

PPU	*Area12.5*	*12.5*	*25*	*50*	*100*
Area12.5	1				
12.5	0.480305	1			
25	0.498294	0.912379	1		
50	0.460977	0.726954	0.805893	1	
100	0.42592	0.589735	0.690656	0.877039	1
200	0.350249	0.372709	0.358311	0.668289	0.764104

Table 3.3 Correlation of the PPU metric derived from different pixel sizes. n=64

The Matheron index, M was found to increase with increasing pixel size, again a consequence of the higher perimeter to area ratio. The response curves in Figure 3.11 show that M assumes its highest values when around half of the window is covered by forest, while no relation is observed between the number of patches and the ordering of the curves in

Figure 3.12. These findings contrast with the better correlation between M and NP (equivalent to PPU) than between M and the forested area, as presented in Table 3.4. This is possibly due to the limited number of samples used in this study, where extreme values in one window can seriously affect the average value for the (patch number or coverage) interval.

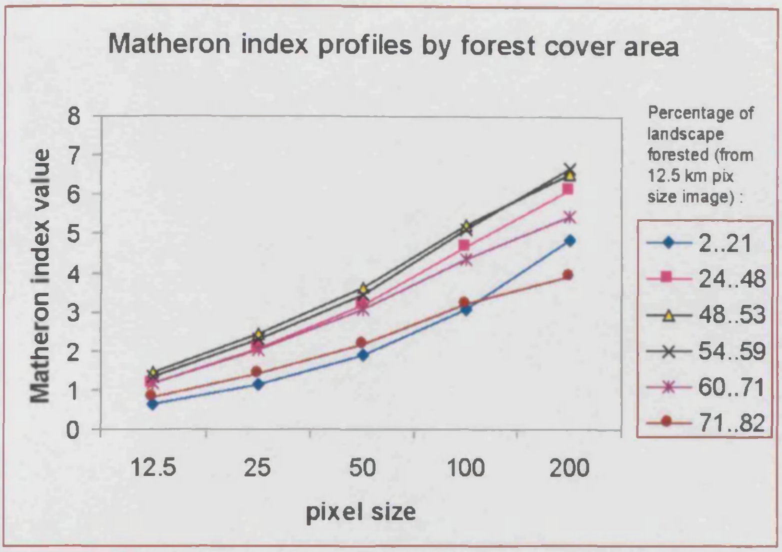

Figure 3.11. M values as function of pixel size and forest cover for synthetic images. The results were grouped according to percentage of landscape forested in the window.

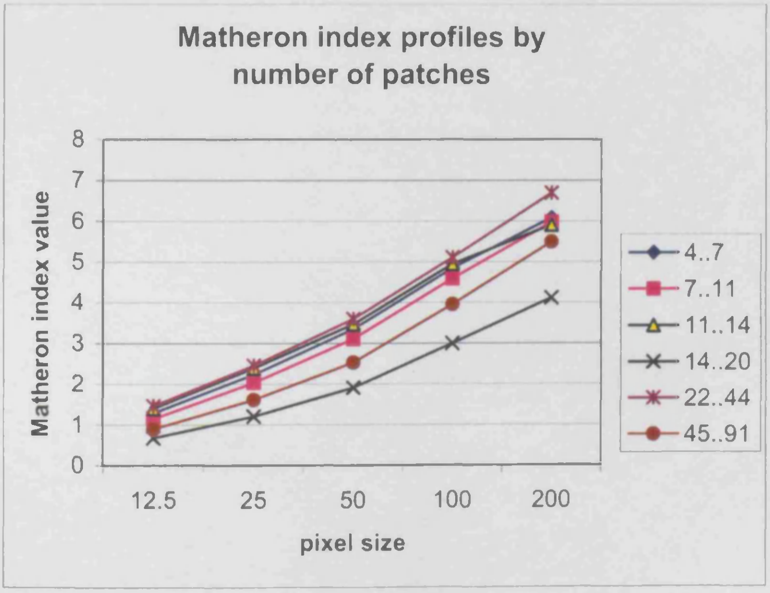

Figure 3.12. M values as function of pixel size and number of patches for synthetic image. The results were grouped according to the number of forest patches in the window (a number proportional to PPU).

Regression between the M values in each of the 53 windows with forest present (Table 3.4) shows this measure to be stable with changing resolution, though not as well as the SqP index. The findings of this part of the study indicate that it is possible to compare at least some landscape structure measures derived from images of different resolution, assuming that the behaviour of the sensors are simulated correctly by the spatial degradation.

Matheron	*Area (12.5m)*	*NP*	*12.5*	*25*	*50*	*100*
Area (12.5m)	1					
NP	0.33494	1				
M(12.5m)	0.371358	0.623638	1			
M(25m)	0.367724	0.585393	0.993583	1		
M(50m)	0.324514	0.559507	0.978305	0.990239	1	
M(100m)	0.287044	0.519934	0.930624	0.951433	0.965819	1
M(200m)	0.066402	0.491389	0.809905	0.83091	0.858397	0.923352

Table 3.4 Correlation between M derived at varying pixel sizes, forest cover as derived from the 12.5 m pixel size image and number of patches within each window. N=53.

Finally, it was found that the values of the spatial metrics correlate to each other in similar ways at 'coarse' as at 'fine' resolutions when degraded, as shown in Table 3.5, while the values get 'decoupled' from their relation to (initial) forest area. The M and the SqP metrics are more correlated with each other than with the PPU metric, which is not surprising since they both depend on edge-counts and area measures, while PPU values only depend on patch counts.

25m grain	*Area12.5*	*SqP25*	*PPU25*		*200m grain*	*Area12.5*	*SqP200*	*PPU200*
Area12.5	1				Area12.5	1		
SqP25	0.560686	1			SqP200	0.33633	1	
PPU25	0.343091	0.48181	1		PPU200	-0.1605	0.465624	1
M25	0.367724	0.888674	0.610049		M200	-0.03194	0.818425	0.555968

Table 3.5 Correlations between initial forest area and the three spatial metrics from synthetic images at resolutions corresponding to imagery from the TM and WiFS sensors.

3.3.3 Satellite images, classification and mapping

It was attempted to classify the TM and the WiFS data with methods as similar as possible, and the unsupervised classification yielding 40 classes was performed for each image. As illustrated in Figure 3.13 and Figure 3.14, 19 of the spectral classes from the WiFS image and also 19 out of 40 classes from the TM image were chosen to make up the forest masks, that ware used in the further analysis. The three 'possible forest classes' indicated in Figure 3.13 were mostly found in the western part of the scene, which is dominated by agriculture, and may be olive groves or other plantations mistaken for forest. It was chosen to keep these classes as forest in order to avoid fragmentation effects in the areas that was known to be forest according to the GIS coverage, although the classification result obviously looked more perforated than the synthesised coverage (e.g. compare Figure 3.15 with Figure 3.5). The resulting forest mask images are shown in Figure 3.15.

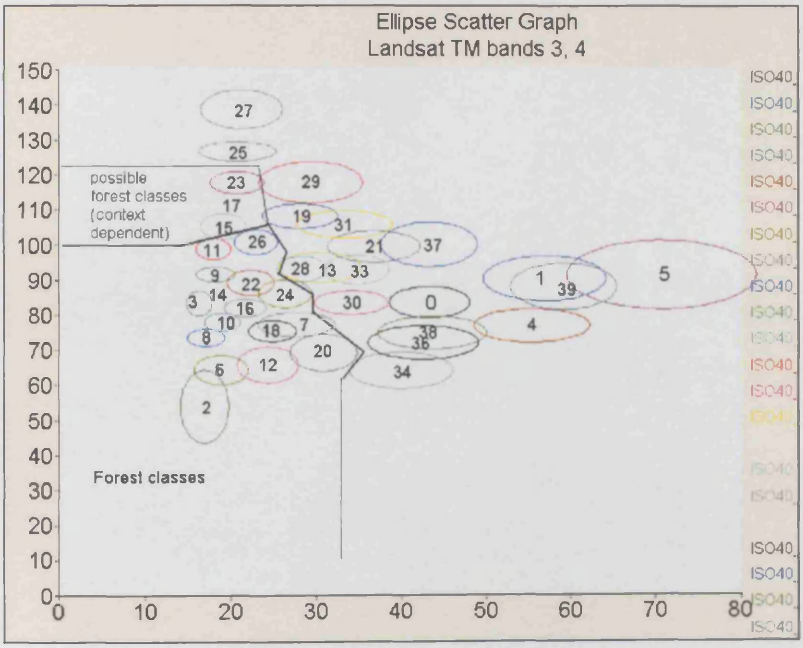

Figure 3.13 Scatter graph for Landsat TM band 3 and 4, with the resulting classes from unsupervised classification (ISOCLASS routine of WinChips).

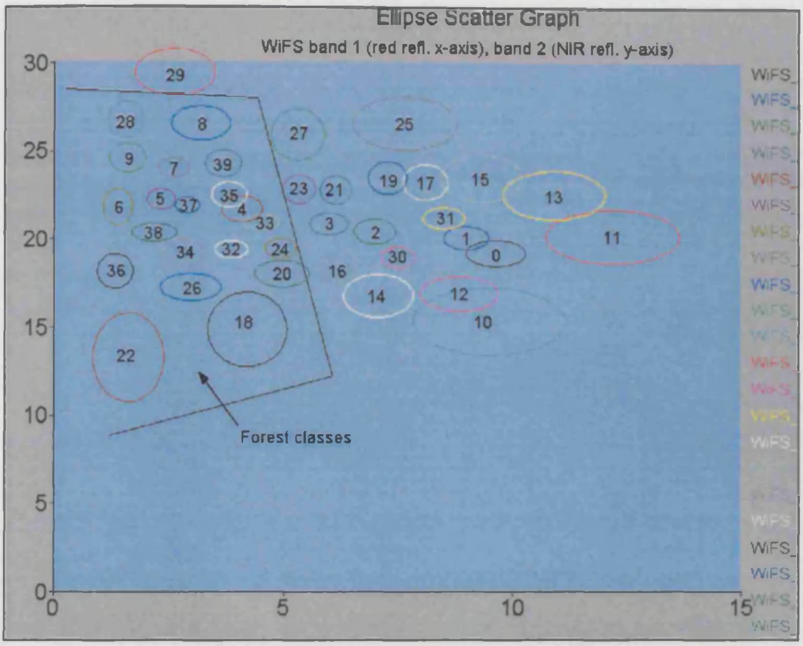

Figure 3.14 Scatter graph for WiFS band 1 and 2, spectral clusters defined by unsupervised classification.

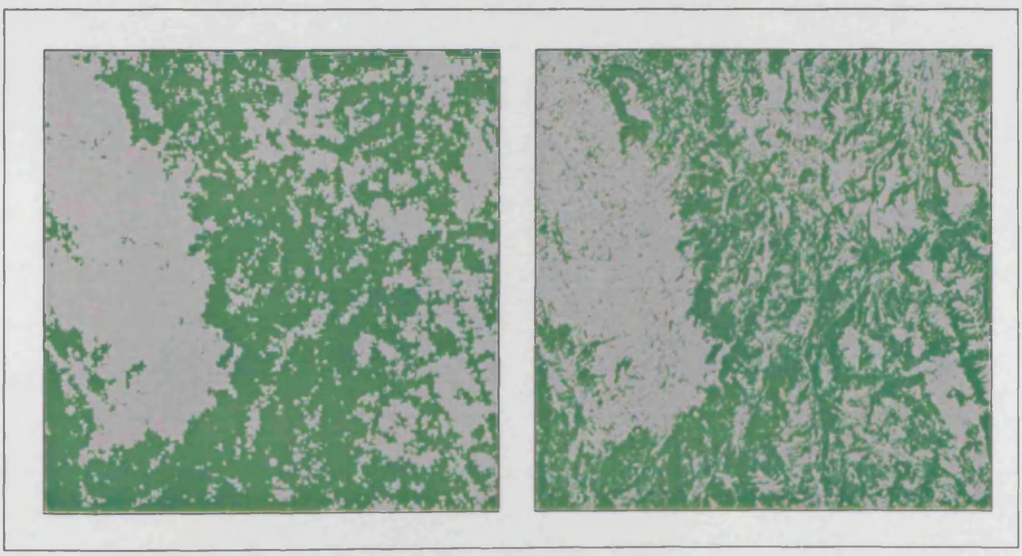

Figure 3.15 Forest -non forest masks from classified images. To the left derived from classification of WiFS image, pixel size 200m, over all forest cover 54.9 %. To the right as derived from classification of Landsat TM image, pixel size 25 m, over all forest cover 44.9%. Extent of image area 50*50 km.

3.3.4 Satellite images, metrics derivation and display

In the next step of image analysis, the two classified images were processed using the modified Fragstats program. As with the synthetic images, the window size was 3*3 km, so the maximum number of windows for which the indices could be calculated was 256. The results can be displayed in map format, as illustrated in Figure 3.16 below.

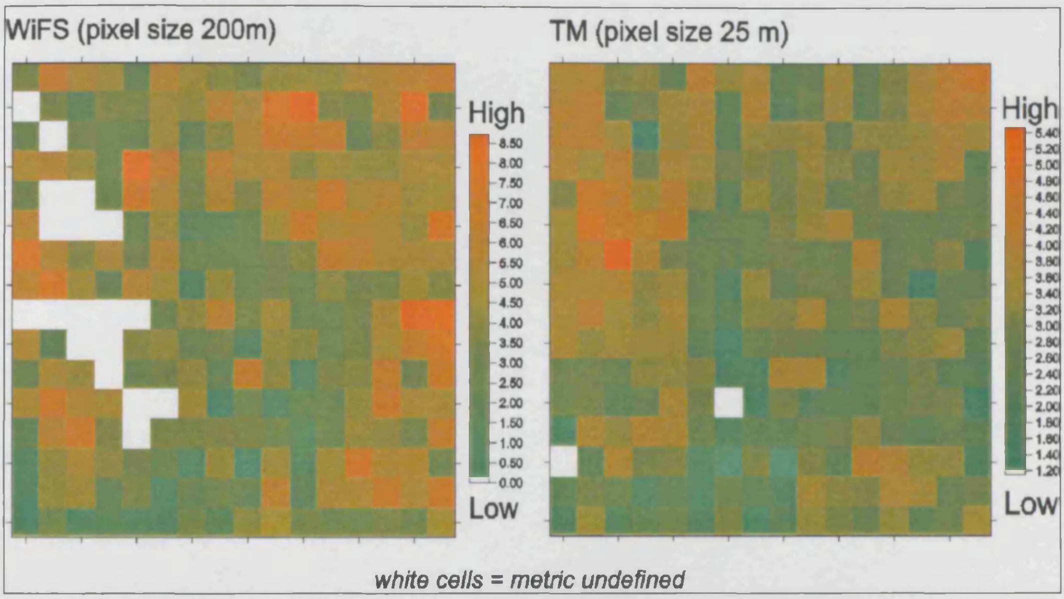

Figure 3.16 Spatial configuration of the values of the Matheron index, calculated from the forest mask images shown in Figure 3.15.

Statistical analysis of the per-window values of the metrics showed that the values from the two different sensors are not as well correlated as the synthesised images at similar resolutions. The plots in Figure 3.17 show the relation between the values derived from TM and WiFS data for the PPU and SqP metrics. Correlations were found between the Matheron Index and the Square-Patch metric; as derived from Landsat TM and IRS - WiFS data respectively (for M: $R^2 = 0.237$, for SqP: $R^2 = 0.393$) – for the PPU metric there was no correlation between the values derived for the different sensors ($R^2 = 0.04$) – which indicates that the landscape property of 'having a certain number of patches per unit area' is level (or sensor) -specific and not scalable or possible to translate between resolutions.

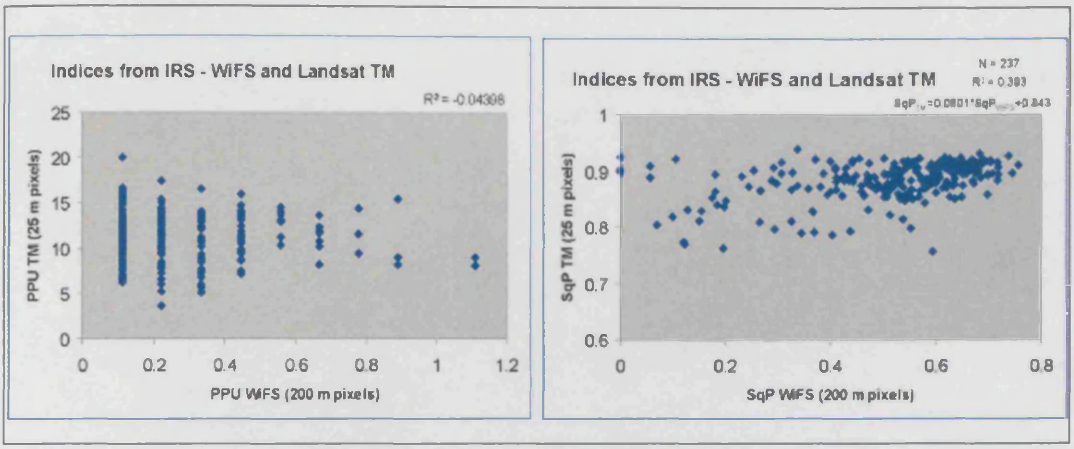

Figure 3.17 Comparison of metrics values between data sources. To the left the PPU values from TM and WiFS respectively are plotted, note that the area unit is km^2, which for WiFS data correspond to only 25 pixels, thus the very low values compared to the TM data. To the right. SqP values, vague trends are found in the relation between the values from the two sensors.

As a 'verification' of the reliability of the overall description of the forest distribution derived from the two images, the forest area in each window was compared, Figure 3.18 shows a plot of this relation. The bias towards a larger area being classified as forest is apparent, but the overall relation is satisfactory, and thus it has been confirmed, that the low correlations between the values of the spatial metrics owe to their response to scaling.

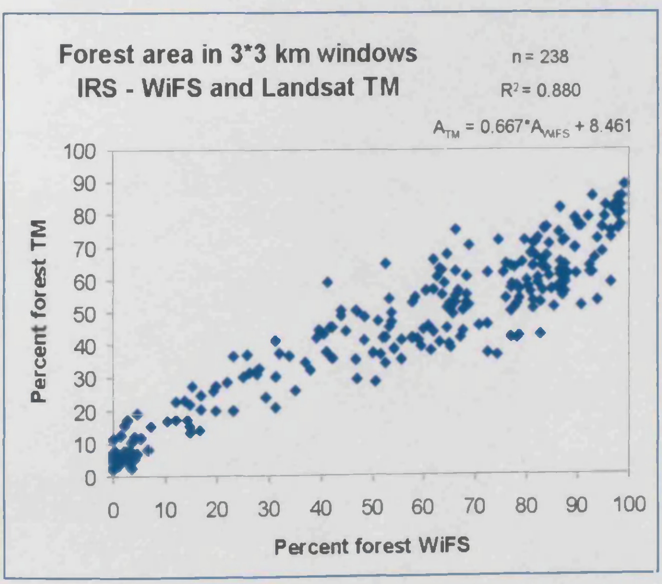

Figure 3.18. Forest cover in windows with forest cover >0. The area estimates appear to be well in accordance.

The Matheron index, as derived from the two image types, did not behave as well as expected from the simulated images, as seen in Figure 3.19, left side. This is assumed to result from a combination of differences in classification and scaling effects. It can also be attributed to the effect of windows with only a few forest pixels, where their spatial organisation has a large influence on the value of M. This assumption is confirmed by applying a forest cover mask to exclude windows with less that 10 % forest cover in the TM image, which improves the correlation coefficient to 0.467. In order to assess the amount of influence by scaling effects, a forest mask image with pixel size 200 m was generated from the forest mask derived from TM data at a pixel size of 25 m. The comparison of these two images (shown in Figure 3.19, right side) produces a better correlation, although still far from what could be expected from the synthesised images. A possible explanation to this 'under-performance' is that the degradation processes applied in the described procedure (section 3.1) are not optimal. Therefore a degradation process might be required which takes into account the influence of sensor behaviour, such as point spread function and the spectral characteristics of the bands used.

Finally, a 'multi-spectral' approach was tried in order to increase the information content of the maps of spatial metrics. A possible output from a combination of the least correlated metrics (found according to the methods described by Riitters *et al* (1995)) is shown in Figure 3.20. It is possible to distinguish different regions in terms of structural properties, although guidelines for interpretation and possibly classification or regionalisation based on these remain to be developed.

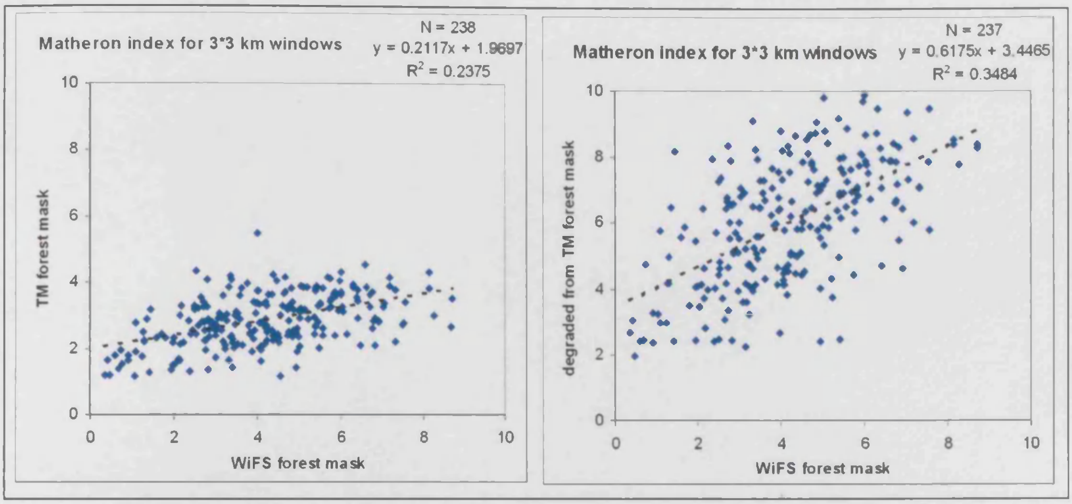

Figure 3.19 To the left M derived from WiFS data with pixel size 200 m plotted against M derived from TM data with pixel size 25 m. To the right M derived from WiFS data with pixel size 200 m plotted against M derived from TM data degraded to pixel size 200 m.

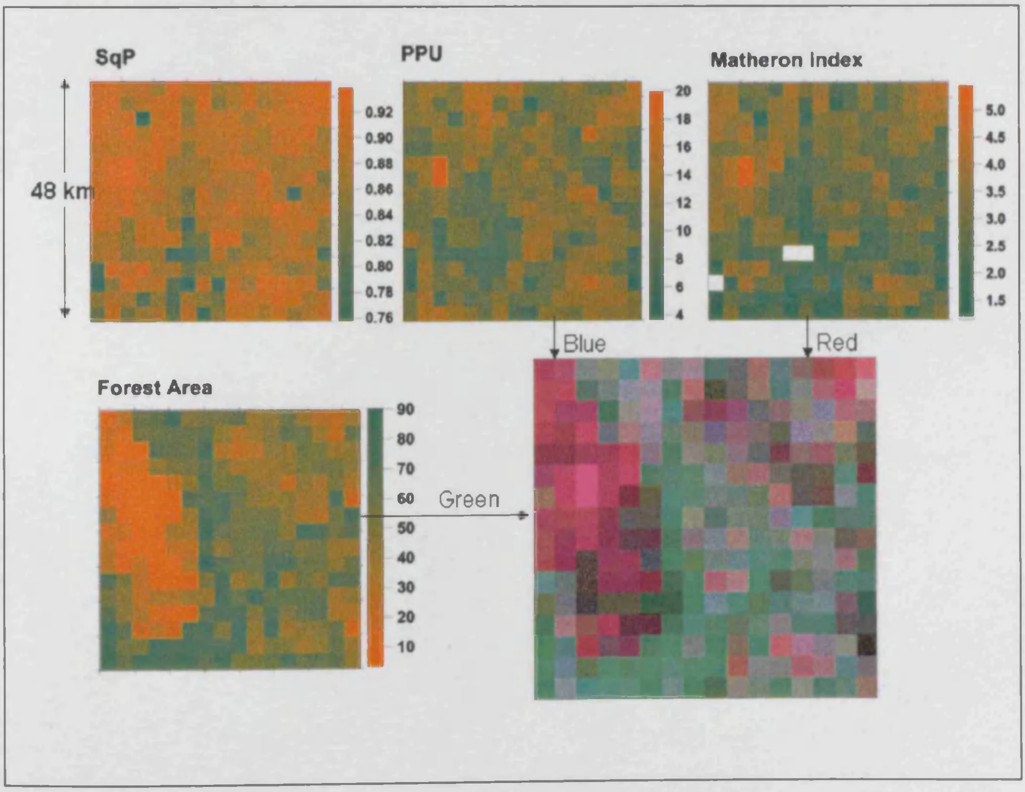

Figure 3.20 Spatial metric maps displayed together as different 'channels' in a false colour image. In this example the indices calculated from the Landsat TM based forest-non-forest map. Cell size 3 km, in a grid of 16*16 cells.

3.4 Discussion and Conclusion

In this study, the Matheron index and the SqP metric are observed to change consistently with the scale of observation, while PPU the metric changes in a more unpredictable way, so as an indicator of fragmentation across scales, this metric must be used with caution. Nevertheless trends are observed for all three metrics following grain size, and it is thus assumed that this procedure of degradation of images, calculation and graphical display of metrics can be improved for use in landscape structure assessment. The results obtained from degradation of simulated images demonstrate that this relationship exists and has a potential for describing landscape structure. The apparent increase in fragmentation as expressed by relative edge length and the apparent decrease in fragmentation as expressed in number of patches are both artefacts of the scaling process. The correlations found between the metrics as derived from TM and WiFS images respectively are lower than the correlations found between the same grain sizes in synthetic images, but the order is the same: SqP values are more consistent than M values, which are again more consistent than the PPU values.

The differences in the values of the metrics investigated here underline the difficulties in quantifying the concept of fragmentation, and confirm the assumption that landscape structure will manifest itself in different ways at different scales of observation. Furthermore, the forest distribution in the test area appears to be related to the topography of the landscape, thus separate experiments should be performed in structurally different areas, in order to assess the influence of the physical setting of the landscape.

Remote sensing provides synoptic images at different scales, potentially making it a powerful tool for applications in multi-scale landscape analysis, including use as illustrations and maps that highlight areas with a particular landscape structure, such as very fragmented or very diverse patterns. Still, the users will have to deal with data from different sensors, often recorded at different times, under different conditions, so it is not trivial to derive comparable land cover maps - something crucial to the comparison of spatial indices.

Assuming that the metrics investigated in this chapter are related to fragmentation processes or the connectivity of the landscape elements (Mertens and Lambin 1997, Hargis *et al* 1998), the analyses carried out here show that it is possible to use processed EO-data to assess structural parameters of importance to forest ecology, and to compare them at different scales and over time, supplying a structural dimension to forest monitoring and change detection.

The methods demonstrated here has potential for operational use, however before the moving windows approach is applied to larger datasets, further assessment of sensitivity to data structure and scaling effects must be carried out. Also more sophisticated though computationally demanding metrics should be tested. Such work could include development of weighted edge metrics, as well as a modified Matheron index to be used on images with more that two land cover classes (Mead *et al* 1981, McGarigal and McComb 1995, Petit and Burel 1997). The pre-processing (first of all classification) of EO data before metrics are calculated could be improved by application of edge preserving smoothing, segmentation and/or neural networks (Wilkinson 1996). For the interpretation of metrics values and their relation to ecological processes, multiple regression of metrics such as the ones studied here or other parameters describing ecological (and physical landscape) conditions should be carried out. This will aid the understanding of what the indices depend on identification of inter-relations and redundancies (Riitters *et al* 1995). The inclusion of indices derived from classifications of aerial photos of the area (preferably at or below one meter resolution) could aid in relating ground observations of forest structure to metrics derived from high- and medium resolution satellite data (Pitt el al 1997, Petit and Burel 1997, Wulder 1998).

In the studies related to this thesis, the results presented here led to focusing of further studies on the comparison of maps derived directly from satellite imagery with CORINE land cover data, which are mostly based on vectorised, high-resolution satellite imagery. In the current, limited study, 'moving windows' approach with square sub-landscapes was used for derivation of spatial metrics. Better alternatives may however be available in form of geo-referenced polygons with the borders of watersheds or administrative units (Weber and Hall 2001, Vogt et at 2003) – to which the spatial properties as expressed in the various metrics can be assigned. This seemed a promising way of addressing the MAUP, and thus a combination of these two approaches was tested in subsequent studies, described in the following chapter.

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4 Comparison of Corine Land Cover and FMERS-WiFS raster images for description of forest structure and diversity over large areas

4.1 Introduction:

In the previous chapter, focus was on forest structure, and it was demonstrated how it is possible to use spatial metrics from medium-resolution satellite images to predict the values of the same metrics when derived from high-resolution images. The study area was in Umbria in central Italy, and GIS-data from the same geographical window were used to analyse the effects of scaling i.e. changing pixel size on the value of the metrics. An important finding was that in order to quantify and compare the *distribution of* spatial properties over landscapes, subsets of the particular landscapes can be analysed, and results represented in geo-referenced map or table form. For the analyses, binary images were used – allowing calculation of only structural parameters, whereas in this chapter thematic maps with a number of forest classes are used – making it possible to calculate metrics of diversity and patch numbers.

The purpose of the analyses carried out here is to evaluate the use of land cover data in raster format for mapping of forest structure and composition over large areas[10], with intended use in monitoring of ecological conditions and forest resource management. For such larger areas, i.e. at national to continental scale, a need for methods to assess landscape structure and, as part hereof, diversity has been identified, in order to supplement traditional forest area and production statistics (Haines-Young and Chopping 1996, McCormick and Folving 1998, Häusler *et al* 2000, Riitters *et al* 2000, Weber and Hall 2001). The spatial metrics were here extracted by application of a moving-windows (M-W) method to data originating from high- to medium-resolution satellite imagery. As part of the study, some software tools were developed, that take categorical maps (in raster image form) as input and output quantitative

[10] The total extent of the area studied here being 350,000 km^2, corresponding to areas for estimation of *epsilon* and *delta* diversities, ref. Figure 2.2.

information on such landscape parameters as fragmentation and diversity. The information is contained in raster images format (through the rows and columns of a landscape metrics matrix), which can be subjected to further statistical analysis for the entire image, selected regions or strata. At the same time, 'window size profiles' or scalograms were used to describe the scaling effects on the calculation of the chosen spatial metrics.

4.1.1 Large area forest mapping and M-W analyses

M-W methods are an obvious choice for extraction of large map-like sets/tables of spatial metrics from raster-format land-cover maps, as they allow comparison of spatial metrics for various landscapes (O'Neill *et al* 1996, Schumaker 1996, Saura and Millan-Martinez 2001), However, the interpretation of the outputs is not always straightforward (as discussed in detail by McGarigal and Marks 1995, O'Neill *et al* 1996, Haines-Young and Chopping 1996, EU-DG AGRI and others 2000, Remmel and Csilag 2002). In this chapter, the challenges that accompany selection of the central parameter window size will be illustrated and discussed. The task is, expressed in landscape ecological terms (Forman and Godron 1986, McGarigal and Marks 1995), to find the relevant extent of the sub-landscapes for which the different spatial metrics should be derived and used. This is primarily done by modifying the size of the 'moving window'. The MW approach with optional overlap is illustrated in Figure 4.8, below. As stated above, the outputs from MW-analysis themselves can be used as maps illustrating e.g. forest structure.

Some research and pilot projects have already been carried out, in which land cover maps and MW techniques are used to assess forest and landscape structure, even at continental to global level. In a report produced for the EU's general directorate for Agriculture, with the title "From Land Cover to Landscape Diversity in the European Union", a group of researchers investigated the use of CORINE land cover (CLC) data for assessment of landscape diversity with the use of M-W and per-region methods (EU, DG AGRI and others 2000). The methodology has later on been used for development of "Agri-environmental indicators" at EU level (EU-DG AGRI and others 2000, Gallego 2002). As a contribution to these studies, Eiden *et al* (2000) assessed different types of reference units for appropriate retrieval of landscape metrics, including administrative regions, German "Naturräumliche Einheiten" (landscape units) and French "Region Agricole" (agricultural regions) as well as a simple M-W approach with window sizes at 20, 40, 60 and 80km and 50% overlap between each window step to extract values of Shannon's Diversity index . They concluded that it was possible to delimit "hard core" zones of diversity or homogeneity of the European territory. At 20km window size, it was possible to identify region specific properties of the structural indicators, while at 80km window size, regional differences were smoothed out and only the strongest features remained. To produce a clearer image, the M-W results were re-sampled to a 2km grid, using bilinear interpolation.

At a global level, Riitters *et al* (2000) used 1-km resolution land-cover maps for analysis of forest fragmentation world wide[11], and extracted spatial information for windows ranging from 9 x 9 pixels, termed "small" scale to 243 x 243 pixels, termed "large" scale. The information on pixel numbers and adjacency was then used to characterize the fragmentation around each forested pixel. The result of the analysis was reported as a kind of thematic map, with pixels assigned to a certain 'fragmentation class'. This approach is rather subjective, although the output maps are illustrative and provide a useful overview of the selected structural parameters. It is worth noting, that as window sizes increased, forest areas shifted from being characterised as *interior, perforated* and *undetermined* into the types *edge, transitional* and *patch*. Furthermore, more fragmentation was detected as the number of included forest types increased, especially in areas where savannah is dominant. This is one among many examples of the influence on metrics values from the definition of forest in the mapping phase.

[11] This study is also presented in section 2.3.4 about measurement of fragmentation.

The European Environment Agency (EEA) has conducted a study of how forest in Europe is fragmented by transportation networks (EEA 2000)[12]. In this study CLC data were used, aggregated to 1*1 km grids – thus the forest patches were defined at a different scale from the original data. The results were clear: fragmentation measured as 'average size of non-fragmented land parcels' was highest (i.e. smallest parcel sizes found) in highly urbanised countries like Belgium and Luxemburg and lowest (largest parcel sizes) in the sparsely populated countries Finland and Sweden, which have large areas of continuous forest. This last study adopted a more traditional GIS-method, in reporting the results a country level – which makes sense as the desired output is indicators for the included countries. O'Neill *et al* (1996) analysed landscape patterns in the South-eastern USA using classified NOAA AVHRR images and metrics calculated for hexagons of 640 km^2 each. They also used compositional (Dominance) and shape (Shape Complexity) metrics and found that in order to get meaningful results, the grain should be 2 to 5 times smaller than the features of interest (i.e. forest or landscape patches); meanwhile the sample area or window must be 2 to 5 times larger than the patches in order to get representative metric values.

Medium resolution forest maps covering all or most of Europe have been constructed independently in at least two instances. During the FMERS project, the Technical Research Centre of Finland (VTT) led a consortium, which produced forest maps at a resolution of 200m for large parts of the continent, based on data from the satellites/sensors of the types Spot, Landsat, IRS-WiFS, Resurs MSU-SK, and ERS SAR. The purpose of this study was mostly method development (Häme *et al* 1999). Later on, another project concerned with creation of a pan-European forest map, also based on WiFS data was carried out by the Munich-based company GAF, on a similar contract to SAI. This project has demonstrated the

[12] The indicator fact sheet is available at http://themes.eea.eu.int/Sectors_and_activities/transport/indicators/consequences/fragmentation/TERM_2002_06_EUAC_Fragmentation.pdf Accessed 12/8 2003.

feasibility of creating a coherent and reliable forest map, which covers all of Europe, and the resulting map is available for later analysis[13] (GAF 2001).

The existence of the above-mentioned data sets, methodologies and results together provide the potential for analysis and mapping of forest structure in Europe, based on spatial metrics and land cover data. However, a need for methods to assess the robustness and flexibility/transferability of the various proposed metrics still exists. In this chapter methods for comparison of metrics derived in multiple matching geographical windows are proposed, and their use demonstrated on a data set consisting of two forest maps in raster image format.

4.2 Objectives

The main objective of this chapter is to compare the spatial metrics that result from applying similar methods of calculation to land-cover data sets available at different thematic and spatial resolutions. The goals are

(i) Development of new spatial metrics, particularly suited for description of forest structure and diversity over large areas and/or recommendations for the use of existing ones.

(ii) To find the optimal window size for display and reporting of landscape spatial metrics.

(iii) To test the robustness of the metrics through their use with two different data sources that provide forest maps of the same area.

(iv) Furthermore, the aim is to examine and compare scaling effects as expressed by window size on the values of various spatial metrics. This will be done through comparison of the values of the different spatial metrics, as well as the variability and autocorrelation against window size for each metric, and calculating the correlation coefficients for these relations.

[13] On request to the JRC which managed the project on behalf of the EU commission.

(v) Also of interest is the 'internal' correlations between values of different metrics (from the same input image) at a fixed window size, and comparison of these 'patterns of correlation' at different window sizes

(vi) To find out how well one land cover data set can substitute the other for mapping of structural features. This will be assessed and shown through correlations between values from the two different input types at similar window sizes (representing identical geographical areas).

(vii) Finally, catchment/watershed information and regional/administrative borders as vector GIS data are used for reporting and summarising metrics values, thus addressing the MAUP, which is an issue of concern in Remote Sensing and GIS, especially in relation to (the use of) spatial metrics. Though the metrics values are known to vary with window size, their relative values in different, separate regions might co-vary with window size, to yield the same order or ranking of the regions. This property is also expected for the two different data sets at similar window sizes.

Throughout this chapter, different types of scalograms will be used as tools to describe landscape structure and to compare maps and landscapes. At the end of the chapter, the MAUP addressed through different regionalisation approaches. It can however be argued that the use of M-Ws itself is an attempt to overcome the MAUP (Marceau *et al* 1994, Marceau 1999a and b, Marceau and Hay 1999a).

4.3 Data

In this section, the test area for this study is briefly presented, then the different data types used are described as well as the approaches to convert them to compatible forest maps.

4.3.1 Study area

In order to address the objectives stated above, forest maps of the study area were extracted from CLC and FMERS data respectively. The area investigated in this study is shown in Figure 4.1.

Figure 4.1 The selected subset, as shown by the red rectangle, covering Northern Italy and small parts of France, Switzerland and Slovenia. Dominant natural features are the Alpine and Apennine mountain chains and the Po river valley. The spatial extent of the subset is 500 by 700 km. To the left location on a political map with relief, to the right forest strata from the FIRS project (Kennedy *et al* 1997)[14]. Forest strata included are Mediterranean region (orange), the warm/moderate temperate region (light brown) and the Alpine and Apennine orobioms (elevational communities and associations - dark brown).

This area contains a variety of different landscape- and forest types, and includes the area in Umbria that was covered in the previous chapter. Other criteria for the selection of this test area was the presence of different forest and landscape types, and the availability of good quality forest maps. The image files are of size up to 5000*7000 pixels (at 100m cell size), large enough to produce statistically significant results even when the number of output cells decreases following the use of larger window sizes. The types of forest diversity under investigation are thus epsilon diversity (broad region) in the inventory domain and delta (between landscapes) diversity in the differentiation domain, as defined in section 2.1.4.

4.3.2 Raster data

4.3.2.1 WiFS – FMERS data

The forest map derived 'directly' from EO data used here is based on a mosaic of WiFS images from the IRS 1-C satellite, these are the same images that were used in chapter 3 – the project is introduced in section 4.1.1. The map was produced by VVT-Finland on contract to

[14] The (sub)project web site is at http://www.vtt.fi/tte/research/tte1/tte14/proj/firs/found1.html, accessed 25/4 2004

SAI, and the steps of the image preparation and processing are described in Häme *et al* (1999), for spectral properties etc. refer section 3.2. The aim of that study was in particular to develop a fast, reliable and cost-efficient method for mapping and monitoring of forest at the continental level. The 'demonstration' forest map, that was created, has the following classes, defined in accordance with the FIRS nomenclature system (Kennedy *et al* 1997):

1. **Coniferous**
2. **Broadleaved Deciduous**
3. **Broadleaved Evergreen**
4. **Mixed forest**
5. **Other Wooded Land Coniferous**
6. **Other Wooded Land Broadleaved**
7. **Other Land.**

The resolution of the original images is 188m pixel size, the mosaic was re-sampled to a pixel size of 200m. The resulting, simplified forest map is shown in Figure 4.2.

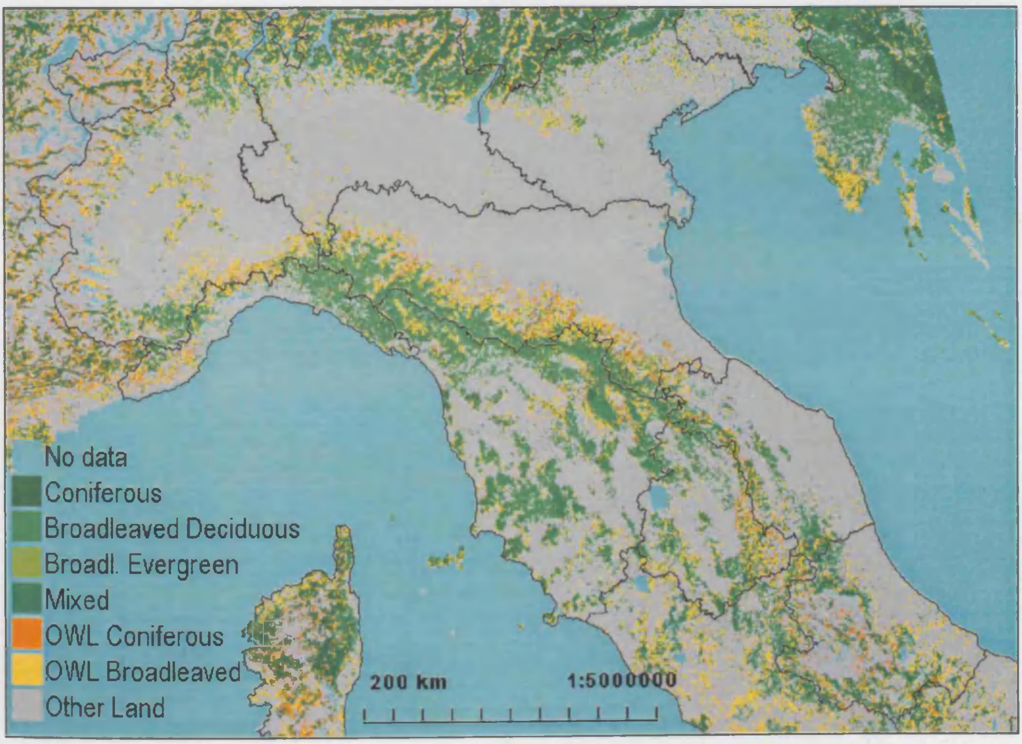

Figure 4.2 FMERS forest map for area of interest, vector layer showing NUTS-level 2 regions.

4.3.2.2 CORINE land cover data

Data from the CLC (described in section 2.3.2) are used here in the form of raster images with a pixel size of 100m. The data were extracted from the CLC database in February 2001

(Liberta 2001). The information in the database is based on Landsat TM and SPOT HRV imagery, which has been digitised manually, with a minimum patch (polygon) size of 25 ha. CLC data are interesting because they are regularly updated and standardised between the individual countries and producers (with next updated version, termed CLC2000 expected early 2004[15]). This makes CLC data useful for monitoring purposes and comparisons across Europe (EU, DG AGRI and others 2000). The three 'pure' forest classes from CLC were included in the present analysis, along with the classes Agro-forest areas, Sclerophyllous Vegetation and Transition woodland-scrub. The agro-forest class was included as forest, since it is defined as Annual crops or grazing land under the wooded cover of forestry species (Bossard *et al* 2000). This land-cover class includes areas of forest trees mixed with fruit and olive trees. The CLC image data were then re-classified to provide a forest map similar to the WiFS, though direct comparison is complicated by different nomenclatures, as seen from Table 4.1, below. Figure 4.3 shows an example of how the data are aggregated to a forest map and Figure 4.4 shows the resulting CLC-based forest map for the study area.

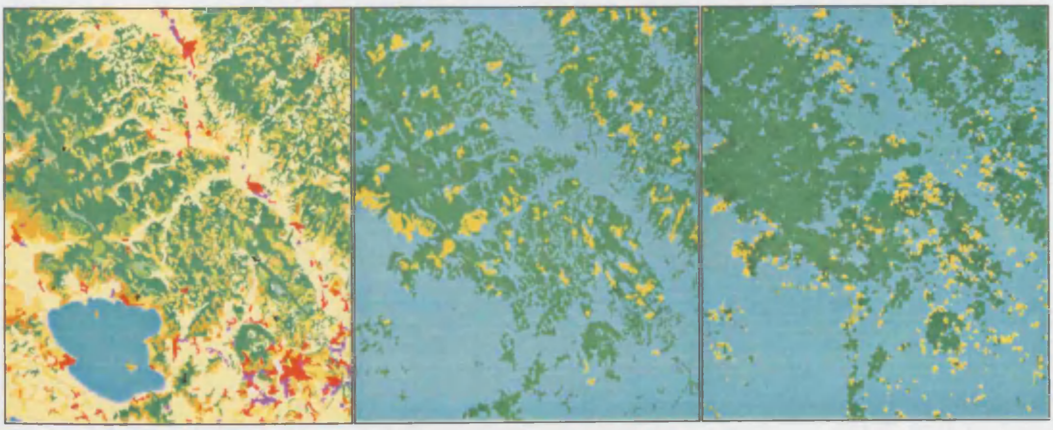

Figure 4.3 Subsets of CLC and FMERS maps located in Umbria and Toscana, Area extent 42*50 km, with the Trasimeno lake and regional capital Perugia at the bottom. From left to right: Original CLC map with all possible land cover classes, map with only the forest classes (both pixel size 100m) and FMERS map of same area (pixel size 200m).

[15] Regular updates on mapping and availability status are provided at http://terrestrial.eionet.eu.int/CLC2000

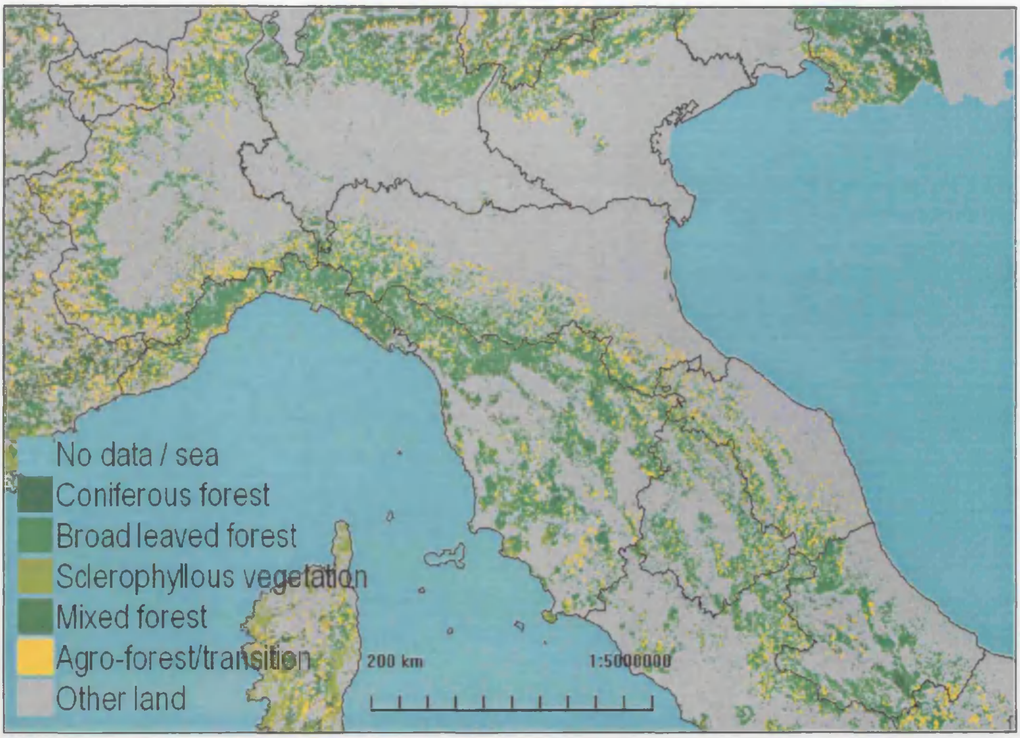

Figure 4.4 CLC image for the area of interest, after re-classification to forest map.

CORINE		FMERS	
LC class:	**Description:**	**Number**	**Description**
0	Not inventoried	0	No data
2.4.4	Agro-forest areas	6	OWL Broadleaved
3.1.1	Broad Leaved Forest	2	Broad Leaved Deciduous
3.1.2	Coniferous Forest	1	Coniferous
3.1.3	Mixed Forest	4	Mixed
3.2.3	Sclerophyllous Vegetaion	3	Broadleaved Evergreen
3.2.4	Transition woodland-scrub	6	OWL Broadleaved
	Not defined	5	OWL Coniferous

Table 4.1 Matching CORINE and FMERS forest cover classes for the current study.

4.3.2.3 <u>Comparison of derived forest maps</u>

The definition of forest can have a large influence on the types and degree of fragmentation detected in any survey (Riitters *et al* 2000). It is thus no trivial task to select and possibly re-classify the themes that define forest, for studies of forest structure like this, where it is a central task to compare forest maps derived from satellite imagery with land cover maps made for other purposes[16].

The two data sets are both satellite based and have more or less the same *thematic* resolution. It is however worth noticing that a partly manually delineated land cover databases like the CORINE have a very low *temporal* resolution, compared to maps based on spectral classification algorithms, which can now be updated more or less automatically. The land surface covered by the selection is approximately 195,150 km^2, of which 34.4% is forest according to the CLC classification and 37% according to the FMERS classification. The distribution of the separate classes is shown in Table 4.2.

CLC				FMERS			
LC type	pixels	percentage of forest areas	percentage of land area	LC type	pixels	percentage of forest areas	percentage of land area
0	28314165	N/A	N/A	0	6944905	N/A	N/A
1	848669	12.69%	4.35%	1	482593	26.74%	9.89%
2	3792008	56.72%	19.43%	2	574189	31.81%	11.77%
3	274834	4.11%	1.41%	3	7266	0.40%	0.15%
4	911814	13.64%	4.67%	4	296940	16.45%	6.09%
5	0	0.00%	0.00%	5	87400	4.84%	1.79%
6	858510	12.84%	4.40%	6	356707	19.76%	7.31%
TOTAL FOREST	**6685835**	**100.00%**	**34.26%**		**1805095**	**100.00%**	**37.00%**

Table 4.2 Distribution of land cover classes in the two data sets.

A direct comparison of the two data sets is done using a "confusion matrix" at per-pixel level for similar pixel sizes and calculating the Kappa statistics (Congalton and Green 1999, p 45 ff). In order to compare the input data from CLC and FMERS pixel-to-pixel, the CLC image was degraded to 200m pixel size, by assigning the dominant land cover type in a 2*2 pixel window to the pixel in the output window. Table 4.3 shows the resulting co-occurrence-matrix, on which the Kappa statistics is based.

[16] As in this case the CLC database that has been made for environmental assessment and management in general.

	0	1	2	3	4	6	Total
0	6420421	67101	297683	25606	53365	80729	**6944905**
1	186382	84144	104595	15653	61153	30666	**482593**
2	198056	20476	285787	2267	43671	23932	**574189**
3	4350	332	756	1230	340	258	**7266**
4	119442	13337	114982	10132	24782	14265	**296940**
5	47552	10360	14137	2435	5611	7305	**87400**
6	219627	14461	79456	7255	16000	19908	**356707**
Total	**7195830**	**210211**	**897396**	**64578**	**204922**	**177063**	**8750000**

Table 4.3 Co-occurrence of pixel values in FMERS and CORINE land cover maps. The CORINE data were re-sampled to 200m pixel size. CORINE data are in columns and FMERS data in rows.

The Kappa coefficient was calculated using IDRISI and used as accuracy measure. It assumes acceptable values for categories 1 and 2, coniferous and broadleaved evergreen, which are also the most common forest types in the images. These land cover types also have the lowest error coefficients. The overall Kappa for this comparison is as low as 0.095. It must however be noted that when comparing forest-non-forest maps from the two image types, as illustrated in Figure 4.5, below, the overall Kappa increases to 0.5218. This, along with visual inspection of the maps, clearly shows that a pixel-to-pixel comparison is not possible or meaningless, and instead we have to test whether the spatial metrics at different cell sizes are appropriate.

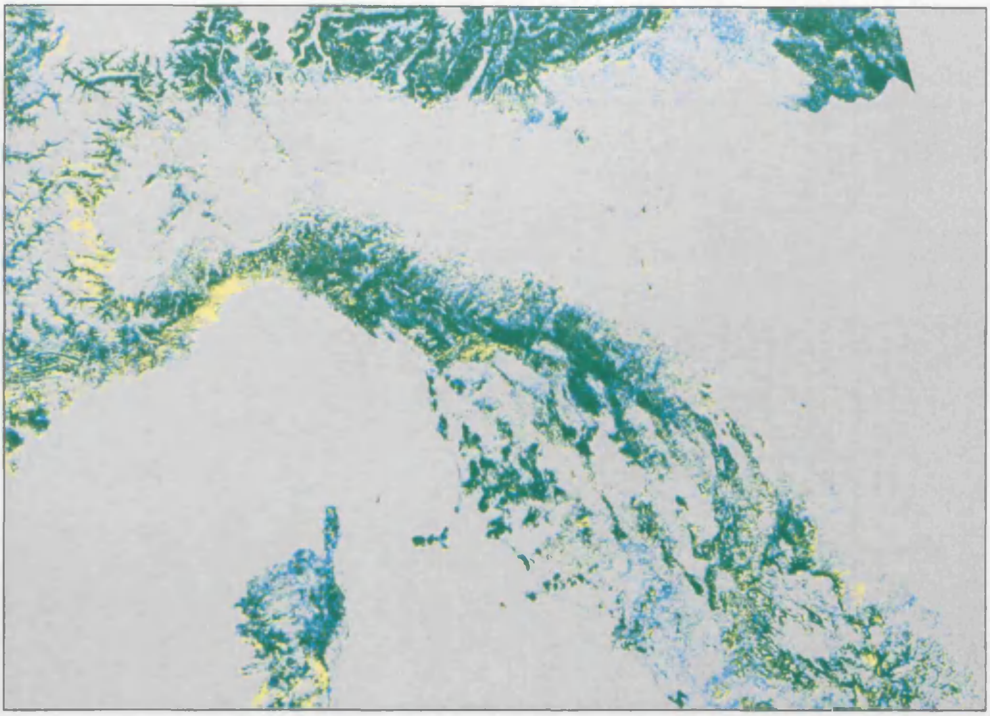

Figure 4.5 Cross-tabulated image from CORINE and FMERS forest masks: background pixels are grey, pixels only in the FMERS map are blue, pixels only in the CORINE map are yellow and pixels in both forest maps are green.

The preparation of the forest-masks for parameter extraction provided an interesting insight in the structure of the CLC and FMERS data, as illustrated in Figure 4.7, where the CLC data maps more coherent riparian forest, a feature that is typically hard to separate and eventually is 'lost' in solely spectral classifications like the one performed in the production of the FMERS map.

4.3.2.4 Digital elevation model

The digital elevation model (DEM) used here is based on the data set that was assembled and used for development of a pan-European database of rivers, lakes and catchments (Vogt *et al* 2002). The current DEM is an 8-bit version of the file that was used for deriving the river-network for Italy in the initial part of the project, this means that the altitude resolution is 20m and the grid cell size is 250m. The DEM is shown with a typical colour legend in Figure 4.6 below. For use with the different output maps of spatial metrics, the DEM was re-sampled to cell sizes to the images, using the image-rectification routine of WinChips (bi-linear interpolation), with resulting average elevation values.

4.3.3 Vector data

Ancillary vector data were used to extract information from the metrics images, using the statistical functionalities of WinChips. This was done in order to summarise and evaluate the evenly distributed (gridded) metrics values. The GIS data used include the watersheds from level 1 to 6 for Italy from the project described above, their shape and extent is shown in Figure 4.6 below. A subset of catchments were extracted for the upper Po valley and for the entire Tevere (the Tiber) catchment, supplemented with two 4th order catchments in Toscana. A set of polygon layers with the NUTS (Nomenclature of Territorial Units for Statistics) administrative regions were also used, they were made available from Eurostat[17], in the Corine projection. From this database, the Italian regions ('regioni' = NUTS-level 2) were extracted and used for derivation of average metrics values within these. The CLC dataset with 100m pixels, together with the NUTS-coverage were used to make a base-map showing land surfaces and excluding only open sea. This base-map has been re-sampled to various pixel sizes, and these derived maps have been used as background image for illustrative purposes throughout the project.

[17] Description and interactive maps at:
http://europa.eu.int/comm/eurostat/ramon/nuts/home_regions_en.html (accessed 28/12 2003)

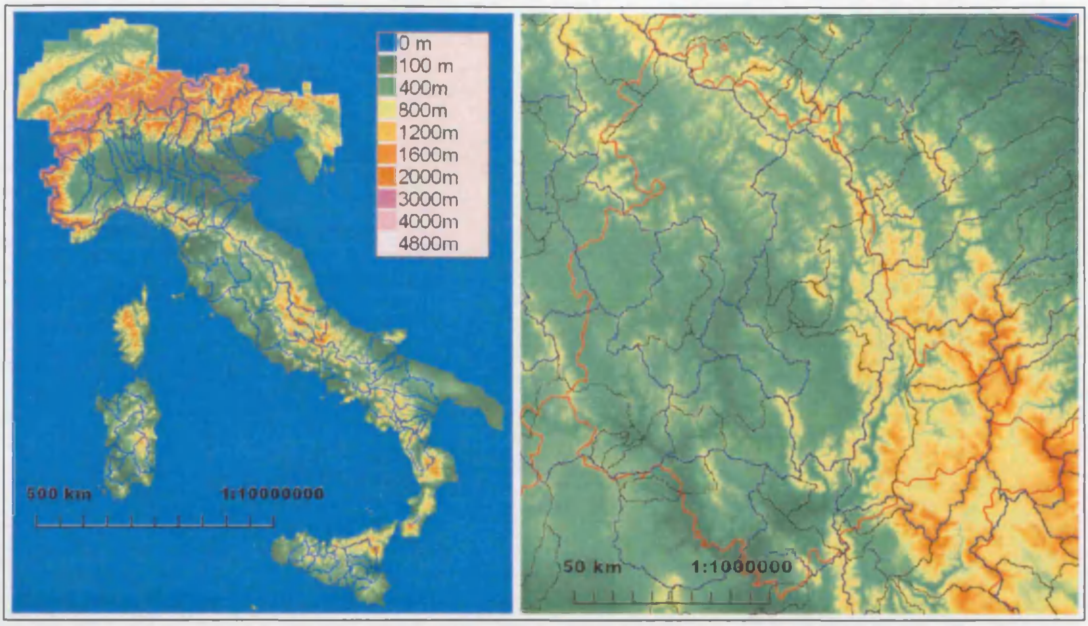

Figure 4.6 Digital Elevation Model of Italy. To the left full extent with 4st to 6rd order catchments – there is just one 6th order catchment: the Po river basin with tributaries. To the right a subset with the Umbria region (borders as red lines), overlaid by 2nd and 3rd order catchments, extent 140*150 km.

4.4 Methods

In this section, first the intended outputs in terms of spatial metrics are listed and discussed, then the practical image processing and statistical approaches for how to derived them from the input data set are presented.

4.4.1 Selection and definition of spatial metrics

The metrics selected for this study are the same as in previous chapter, supplemented by metrics of cover proportion and diversity. The types of structural metrics calculated are:

- cover (percentage), total forest and for each class
- percentage of edge pixels, of total number of pixels in window
- a simple edge index: proportion of edge pixels to number of pixels in actual class
- the Matheron (M) index, for each class and for combined forest layers
- the Square Patch index (SqP) – for forest-non forest
- Patches Per Unit area (PPU), both following Frohn's definition and a modified, 'normalised' version that accounts for changing window sizes.

These last three are described in section 2.3.4. The edge pixel percentages and proportions area used here only as intermediate steps to get to the M and SqP metrics and for development and testing purposes, though they have the potential to be used as indicators in their own right.

The diversity metrics used are:

- Number of class types (richness)
- Simpson's diversity
- Shannon's diversity (Entropy)

The richness metric is the simplest possible measure of diversity, and has the advantage of being easily understood and easily implemented. Simpson's diversity SIDI, which expresses the degree to which one or more classes *dominate,* is defined as follow (McGarigal and Marks 1995):

$$SIDI = \sum_{i=1}^{n} P_i^2$$

Where P_i expresses the proportion of the entire landscape occupied by class i, the different values of P_i should sum to 1 for each landscape/subset. In this study 1-SIDI is used for reporting the metrics values, in order to have the highest values for the smallest amount of dominance, i.e. for the landscapes with largest *evenness* between classes. Then we have <u>maximum</u> value of $SIDI_{max}$ for P1=P2=....Pn=1/n., and

$SIDI_{max}$ = 1-1/n .

Shannon's diversity index, also known as the Shannon-Weaver or Shannon-Wiener information index (Whittaker 1972), is based on information theory, expresses the 'bandwidth' needed for description of a system and thus the 'disorder' or distance from predictability of it (McGarigal and Marks 1995). The index defined as:

$$SHDI = -\sum_{i=1}^{n} (P_i * \ln P_i)$$

The maximum value of the SHDI for a landscape with n classes is simply ln(n), and the minimum values is 0 for the case when the landscape contains only one patch type (no diversity). These two diversity metrics are very commonly used in the ecological literature, and thus it is found to be of interest to look closer into their behaviour with changing pixel- and window size.

In this study, it was chosen not to include the pixels that represent background in the diversity calculations, since the phenomenon under study is the structure of the forests and the diversity of the forest types. Including background pixels would give a measure of *landscape diversity* rather than *forest diversity,* and then it could be argued that the aggregation (see section 2.3.3.3) should not have taken place, and the various natural and agricultural land cover types preserved as separate classes. This issue is addressed in the following chapter, when CLC and high-resolution land use data are used, compared and discussed in more detail. Thus, as part of the preparation of the images, they were processed so that only the forest classes of interest were preserved, and any other class set to zero (i.e. constituting the 'background class'), as seen in Figure 4.2 and Figure 4.4.

Concerning the structural metric Patches per unit area (PPU), based on the count of number of patches in the window, there is a problem of bias towards higher values for small window sizes, since if any part of a larger coherent forest is present in the window, one patch will already be counted there. In other words, the sampling method acts like a "cookie cutter" (O'Neill *et al* 1996, p. 174). For instance, if 10*10 km of continuous forest cover is analysed with 1*1 km windows it will result in 100 output cells with 1 patch per km^2, and from a 10*10 km window, the result will be one output cell with 0.01 patch per km^2. The present study investigate whether it is possible to remove – completely or partly - this effect of window size, especially for densely forested areas (where a low number of separate patches can be expected). This is done with PPU-Normalised (PPUN), defined as:

$$PPUN = \frac{NP-1}{A} + \frac{1}{A_{min}}$$

Where A_{min} is the area of the smallest window used in the current analysis. The last part of the expression is included in order to avoid having the values of PPUN approach zero for large windows, thus PPUN will be one for the case of just one patch present at all sizes, with values approaching one for larger window sizes with more patches present – as examplified in Table 4.4. After inspection of the results from the first tentative runs of the patch-counting script, it was chosen also to include the number of 'background patches' as a spatial metric, for the reason that a patch of non-forest surrounded by forest is an expression of fragmentation and perforation of the forest cover in the area/window of interest. It is similar to but much simpler than metrics of lacunarity (Plotnick *et al* 1993). The PPUN_B value, as it will hereafter be called, is easily derived, as the patch counting script anyway will deliver the number of patches in the window of analysis for each land-cover class in the input image. It is calculated in the same way as the PPUN metric.

Area	No. Of patches	PPU	PPUN	No. Of patches	PPU	PPUN
1	1	1	1	5	5	5
10	1	0.1	1	5	0.5	1.4
100	1	0.01	1	5	0.05	1.04
1000	1	0.001	1	5	0.005	1.004
1	2	2	2	10	10	10
10	2	0.2	1.1	10	1	1.9
100	2	0.02	1.01	10	0.1	1.09
1000	2	0.002	1.001	10	0.01	1.009

Table 4.4 Theoretical values of PPU and PPUN for varying window sizes and number of patches.

For the regression analysis performed in order to find the agreement between the different metrics, the 'original' patch count metrics are used, i.e. the NP values from the M-W results. This is possible due to the nature of the transformations from NP to PPUN and PPUN_B, and because the regressions only take place for one window size at a time, and as such not are affected by the transformations.

When average values of spatial metrics are reported from the different output (image) files, only those output cell which represent forest cover of one per cent or more are included, the others are masked out. When values for the two different data sources are compared, the criterion for inclusion is that one of the results should represent a window with a forest cover of one per cent or more. In practical terms, this is done through constructing of a binary forest cover map, using the arithmetic functionality of WinChips. Such non-forest cells are typically found in river basins with intense agricultural activity and to a lesser extent in mountain areas above the tree line. This means that *three types of forest mask* are applied: one for each of the map types and one for analyses where they are combined or compared – in this case the "OR" image from the right hand side of Figure 4.7 below. A consequence of this masking approach is that the average forest cover values reported for entire images and selected regions will be higher than the actual forest cover as percentage of the entire land area, since output cells with no or very little forest are excluded.

The preparation of the forest-masks for parameter extraction provided an interesting insight in the structure of the CLC and FMERS data, as illustrated in Figure 4.7, where the CLC data has more and coherent riparian forest, a feature that is typically hard to separate and eventually lost in solely spectral classifications like for the FMERS map.

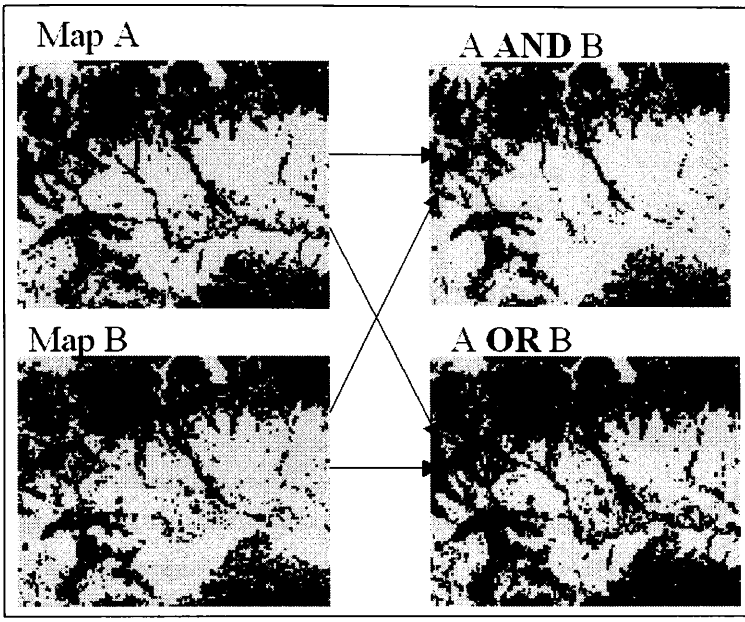

Figure 4.7 An example of how maps of forest presence are combined for masking in extraction of statistical parameters. The subset used here is the upper part of the Po river basin, for a cell size of 1200m. Map A is based on CLC and Map B on FMERS data. Note that the agreement between these two data sets improves as the cells become larger (and there are fewer cells with no forest), see for instance Table 4.19, page 154, row 'Cover'.

4.4.2 Implementation of Moving Windows and analysis of outputs

The 'moving window' calculations were carried out using IDL scripts (Research Systems Inc. 1999), that allow modification of the window and the step size, as part of which overlap between windows is possible. The principles of M-W analyses as implemented here and the basic terms referred to throughout the text are illustrated in Figure 4.8 below. The main difference between this implementation and the one used in for instance Fragstats for Windows is that here, the user can define not only the extent (size) of the window, but also the step and thus the output cell size which determines the grain size of the output image. These window sizes and steps are implemented as parameters of for-next loops that operate on image-matrices in the various IDL-scripts used here (Appendix 1).

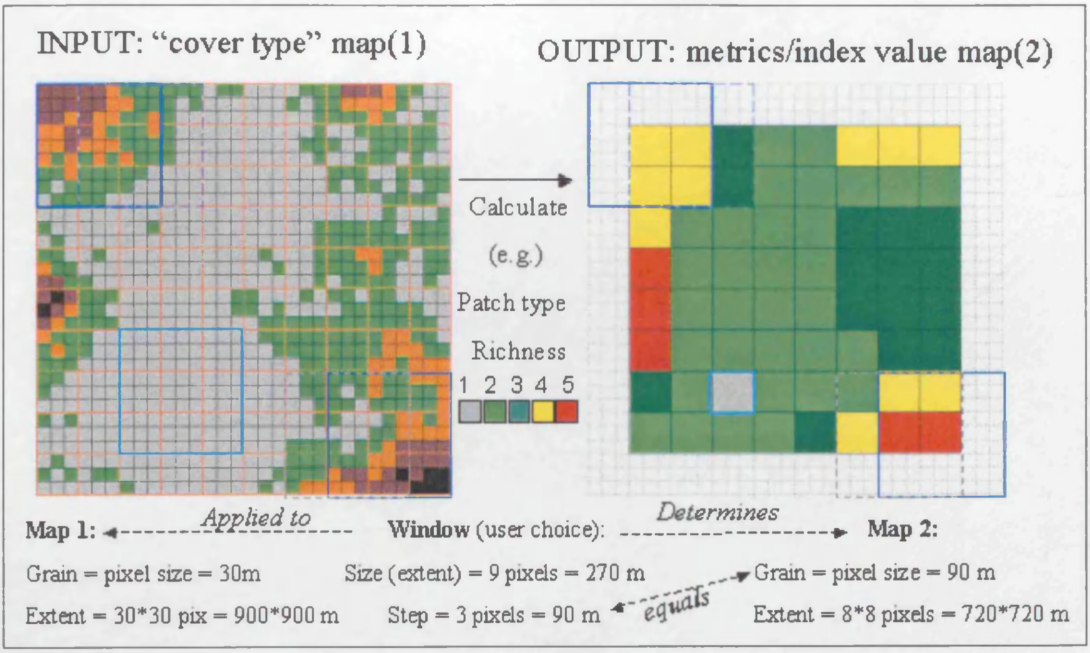

Figure 4.8 Moving windows concepts with and without overlap.

As part of the processing chain, which is only partly automated, simple spatial statistics such as cover proportion and number of land-cover classes are calculated. This information can also be used for inspection of the input data and visualisation of basic landscape properties (see for instance Figure 4.10 on page 134). The diversity metrics are based on histograms of pixel values collected for each window, the fragmentation metrics are based on per-window counts of edges, both for each land-cover class and between forest and non-forest pixels. As an aid for the further presentation of the types of calculations and files used in this study, a sketch of the way from input data to the various types of results has been made, Figure 4.9.

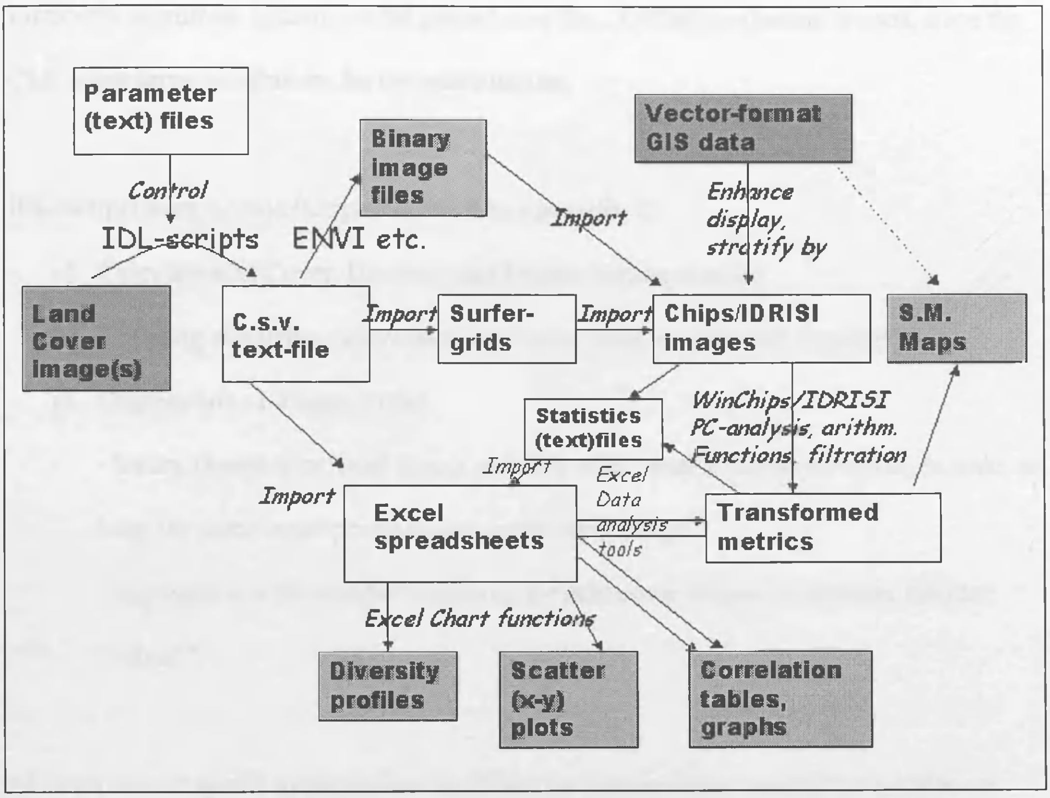

Figure 4.9 Simplified flowchart showing how the results presented below are derived. The boxes represent final or temporal data (to be) stored as files.

The output images are easily geo-referenced. The coordinates for the upper left corner of the output images depend on the parameter for the MW-calculations, in the following way:

Pixel size = step

$UL\_X_{out} = UL\_X_{in} + ((size\text{-}step)/2)$

$UL\_Y_{out} = UL\_Y_{in} - ((size\text{-}step)/2)$

The number of pixels in the output image is determined by the equations:

$$Outcolumns = INTEGER\left(\frac{incolumns - wsize + wstep}{wstep}\right)$$ for the columns (X-size) and

$$Outrows = INTEGER\left(\frac{inrows - wsize + wstep}{wstep}\right)$$ for the rows (Y-size).

These numbers are needed for correct import and geo-referencing of the resulting maps, so they for instance can be used with vector data in a GIS. In this implementation of the method, this is achieved by importing the outputs (text files) into the image processing software and assigning the correct pixel sizes and edge coordinates. All image data have ‘UTM-style’ lower-left coordinate systems, in the present case the CORINE-projection is used, since the CLC maps serve as reference for the entire dataset.

IDL Scripts used include (scripts are listed in Appendix 1):

a) Calculation of Cover, Diversity and Fragmentations metrics
b) Counting of patches, where each land cover class is processed separately.
c) Degradation of images, either

   - binary (forest-non-forest maps), possibly with variable threshold values, in order to keep the same cover percentage as in the input image

   - aggregation with possible weighting for land cover classes of different interest/ "value"[18]

For each dataset spatial metrics were calculated for window sizes ranging from 1200m to 19200m, corresponding to windows of 6*6 to 96*96 (9216) pixels for the FMERS map and of 12*12 to 192*192 (36864) pixels for the CLC based forest map. Further on, the two data types are compared at window level, i.e. between output cells representing the groups of pixels, that cover the same part of the forested landscape. This is done by finding the correlation coefficient for the two variables or M_{CLC} and M_{FMERS} (or in standard terms y_i and y_j) representing the spatial metrics from the two data sources. The number of observations n is the number of windows/output cells where forest is present – with the criterion that at least one of the land cover images should have a forest cover of one percent.

For a comparison of the M-W results for the entire maps with results from previously defined regions that form subsets of the test area, vector data were used to extract metrics values for catchments as well as administrative region (through the creation of WinChips statistics files, see Figure 4.9). The spatial metrics values are reported at regional level (highest level of

[18] Note that simple averaging of pixel values, as applied to photos or satellite images will not work on categorical maps.

Italian administrative regions) and for the catchments of highest orders, i.e. of largest spatial extent

4.4.2.1 Tests for significance of results

As test for the significance of the correlations, a simple 'rule of thumb' is used, namely that for large values of *n*, the minimum (absolute) value needed to attain significance is defined as (from Rogerson 2001, p. 94):

$$r_{crit} = 2/\sqrt{n}$$

.. when $\alpha=0.05$. For this type of analysis a "combined forest mask" is used, where the criterion for a pixel to be included is that forest cover is > 1% in either the CLC *or* the FMERS forest map – based on the cover value calculated at the given window size. These combined, all inclusive forest masks are also used for extraction of (average) metrics values for administrative regions and watersheds.

As an alternative to the pixel-to-pixel approach described above, and in order to test whether the two different data sources give the same *general picture* of regional forest structure, the areas (admin. regions and catchments) are ranked according to the average values of each metric and compared using Spearman's Rank Correlation Coefficient (Rogerson 2001, pp 94-95). The results from these tests contribute to understanding which metrics are sufficiently robust to be used with different image sources and over large areas. The ranking approach also helps illustrate in which geographical areas or zones agreement of metrics values are found, and in which areas the differences are – and whether these 'problematic' areas are similar or different for metrics assessed in this study.

4.4.3 Local variance and autocorrelation

The concepts of variability and autocorrelation are of interest because they describe not only the structure (clustered or scattered landscape elements and derived spatial metrics) but also the information content in the output 'maps'. For the current study focusing on mapping of spatial structure and diversity, it is assumed that higher local variability means that more information is present in the outputs (refer section 2.3.3). This information is potentially used for display of landscape properties and ultimately prediction of biological diversity. The spatial variances of the resulting 'spatial metric maps' are calculated in two ways: local standard deviation and autocorrelation expressed through Moran's I.

4.4.3.1 Local variance approach

The approach to find the local variance follows the methodology described by Woodcock and Strahler (1987), for assessment of characteristic scales in remotely sensed images, insofar as the extraction of spatial metrics can be seen as applying a low-pass filter, in the same way that remote sensing imagery is degraded to lower resolutions, ref. Wu *et al* (2000).

Here, the local standard deviation (stdv.) of the metrics values is found under a mask defined by (percentage of forest cover => 1), with edge pixels excluded, as these are set to zero values during calculation of variance (as during filter operations in general).

The steps in the creation of variance statistics at each extent are:

- Create mask from pixels with cover > = 1% AND not along edges
- Calculate stdv. of pixel values in 3*3 window around each pixels
- Calculate mean and max. value of stdv. from under the mask
- Calculate coefficient of variance, based on average and st.dev.values for each metric and data source, this gives a nicely normalised expression of the local variance of the metric.

The results are reported in table and graphical form.

4.4.3.2 Autocorrelation approach

The Moran's I (MI) measure of spatial autocorrelation is derived using Idrisi (Eastman 1997), where it is implemented as a statistical function. It is defined as follows:

$$MI = \frac{n\sum_{i}^{n}\sum_{j}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(n\sum_{i}^{n}\sum_{j}^{n} w_{ij})\sum_{i}^{n}(y_i - \bar{y})^2}$$

where n are the number of regions/pixels/windows, W_{ij} is a measure of proximity and y_i and y_j are the metrics from the different data sets. Similar to a correlation coefficient, MI assumes values from –1 to 1, where values near 1 indicate a strong spatial pattern (high values near each other, low values near each other), values around 0 indicate no particular pattern (random distribution) and values near –1 indicate a case where high values are located near low values (this is rarely seen and geographical data normally never have values of MI below 0). MI can also be seen as a simple measure of self-similarity or the potential of using cell values to predict the value of neighbouring cells in raster images (Costanza and Maxwell 1994).

4.4.4 Masking and Forest Concentration

The work with image masks at different output cell sizes have led to proposing a new spatial metric particularly for use with MW methods: a measure of forest concentration (FC) or landscape concentration. It stems from the observation of characteristic values in selected regions of the forest cover percentage for respectively the entire landscape and under the 'forest presence' mask. When the value under the forest mask is high relatively to the entire landscape it means that the forest is concentrated in a limited number of output cells, whereas when the two values are nearly similar the forest cover must be spread out over the image/region of interest. The metric is defined:

$$FC = \frac{Cover\_mask}{Cover\_landscape} - 1$$

The theoretical values range from 0 when the two cover metrics are similar (the forest presence mask covers the entire region) to near infinite, depending on the size of the output cells relative to the output image. For the same input image the values of FC will decrease with increasing output cell size, as the chance of finding windows with no forest will decrease, but also the shape of the resulting FC-profiles might provide additional information on the structure of forest (or other element of interest) in the region. To derive a FC-profile, MW analysis with a number of different window sizes is required.

4.5 Results

The results of image processing and subsequent statistical analysis are presented along the lines laid out in the objectives of this chapter. This section thus begins with a presentation of and some comments on the values of the metrics *per se* and in relation to window sizes, then the spatial structure of the output 'maps' are looked at, followed by examination of the regressions between pairs of metrics from the two data sources for a range of window sizes. After that values of metrics from different spatial units are compared (administrative regions vs. river catchments) and finally, the visual appearance of the metrics (maps), interpretation and applications for statistical reporting and use as indicators are discussed.

Figure 4.10, below shows an example of an immediate result of the application of M-Ws to the two data sets, where the resulting text files have been imported and visualised as grids using the Surfer software (Keckler 1997) , following the flow outlined in Figure 4.9. Already this visualisation of a relatively simple metric, the number of land cover classes gives the impression of not only where forest is found but also where environmental conditions allow several different forest types to be found within a limited geographical area, in this case within squares of 4.8*4.8 kilometres. The apparent broad agreement between the outputs for the two different map data sources is tested statistically in section 4.5.4.

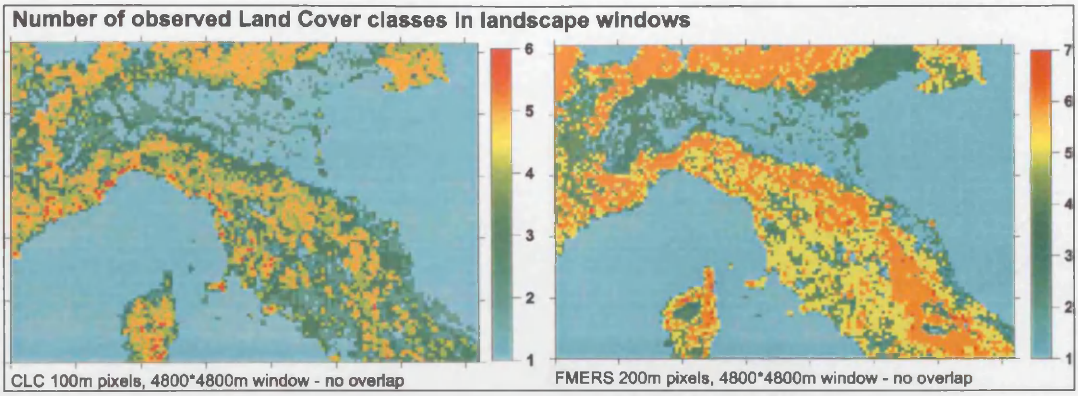

Figure 4.10 Land cover "richness", i.e. count of different land cover types present within windows of 23km^2, figure created in Surfer for windows, using text file outputs from IDL script processing of input images.

4.5.1 Response of metrics to window size

For each output map of the specific spatial metric for each of the datasets the average value was calculated – though only for cells/pixels with a forest cover fraction >= 1%. In Figure 4.11, these values are plotted against the size of the moving window. In order to make the metrics of forest cover fit in the graph, they have been divided by 100, resulting in fraction values between 0 and 1. The percentage values of forest cover in the windows are listed in Table 4.5.

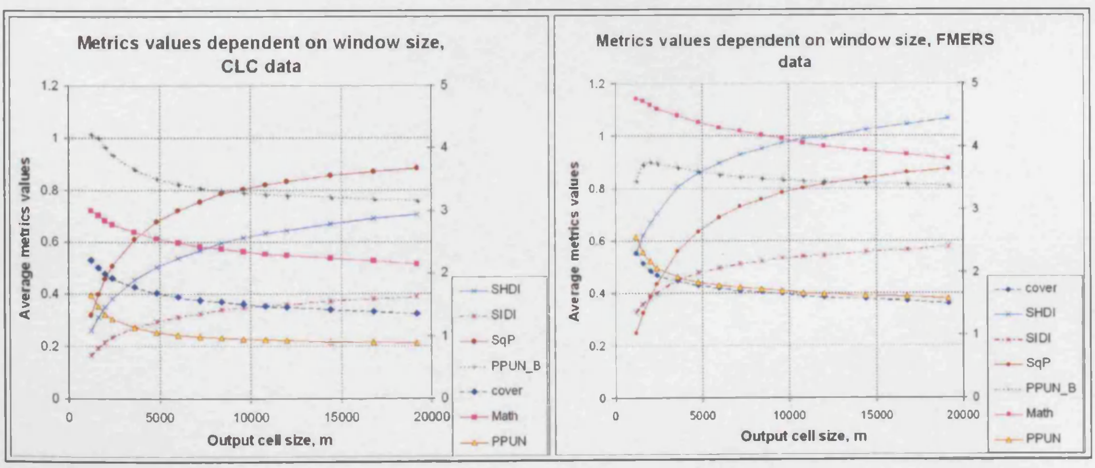

Figure 4.11 Metrics 'response curves' or scalograms with values plotted against window size or (sub-landscape) extent. CLC and FMERS data for the entire study area (under the forest masks). Note that M and PPUN metrics map to 2nd axis values.

When these graphic outputs are compared, it is obvious that the metrics behave very much in the same way for the two datasets, for the shape as well as the relative position of the curves. Thus, they show similar *scaling properties*. The almost complete overlap of the PPUN and cover curves for the FMERS data is accidental, but clearly shows the relation between these two metrics. It is noteworthy though that for the CLC data, the PPUN values are markedly lower – but not the PPUN_B values. As expected, the value of the diversity metrics increase with window size, as more land cover classes get included in each window.

The most noteworthy differences are observed for the SqP metric, that starts out at a lower level for the FMERS data and grows more rapidly than for the CLC data with increasing window size. This is probably due to the fact that the small window sizes correspond to very few pixels, where the probability of finding 'blocks' of forest is much higher, while on the other hand large windows will include a mixture of forest and non-forest. The same phenomenon is reflected in the decrease of the average forest cover with window size. Note that due to the definition of the metric, high values of SqP (approaching 1) indicate forest that is more scattered/fragmented across the landscape, i.e. distributed on a number of patches. The higher values for the SqP metric from CLC relative to the values from FMERS data is in agreement with the observation in section 3.3.1 where synthesised images were analysed, and SqP found to decrease with increasing pixel size (for a fixed size of the spatial window, thus representing the same "ground truth" = forest structure across the scalogram). Figure 4.12 shows that the numeric values of SqP is more closely related to the size of the geographical window than to the number of pixels included in the calculations. This is a reassuring result, and speaks in favour of using this metric as an indicator of forest structure, given that a correction for window size can be applied.

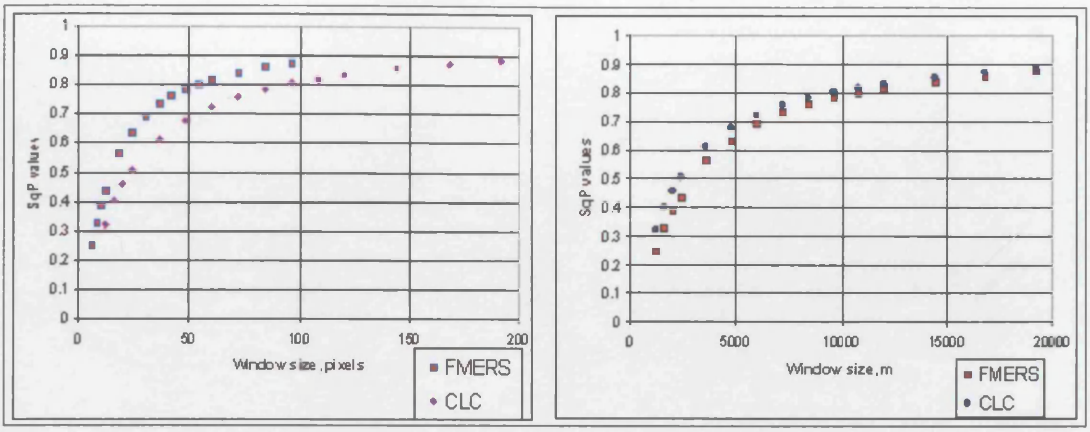

Figure 4.12 Average values of the SqP metric for the two data types plotted against window size in pixels resp. meters

4.5.1.1 Patch counting and the PPU metric

Values of patch count metric values are influenced by the size of the windows, due to the effects of "cutting off" of patches that are partly within the window, as seen from the plots of average PPU versus window size. Thus, the smaller the window, the greater the number of separate patches, which are parts of larger patches, with centre outside or on the edge of the window. This effect will also influence the values of calculated average patch sizes (a metric that only makes sense for entire landscapes or vary large windows). Another notable effect is that as the window size increases, more non-forest area is included, as seen from Table 4.5 (last column). This is due to the non-random (i.e. clumped) distribution of forest across the landscape. It is hard to separate these two effects, and caution must be taken when metrics based on the number of patches in a given area are used, especially at small (< 30-40 pixels) window sizes. In Figure 4.13 and Figure 4.14 the values of PPUN and PPUN_B are plotted against window size and forest cover fraction respectively.

cell size, m	side factor	area factor	PPUN_CLC	PPUN_FMERS	Mean_cover_percent CLC image
1200	1	1	2.57	1.66	47.33
1600	1.333	1.778	2.33	1.48	45.14
2000	1.667	2.778	2.18	1.35	43.34
2400	2	4	2.08	1.27	42.10
3600	3	9	1.94	1.13	40.23
4800	4	16	1.85	1.06	38.77
6000	5	25	1.80	1.02	37.79
7200	6	36	1.76	0.99	37.01
8400	7	49	1.73	0.97	35.90
9600	8	64	1.71	0.95	36.07
10800	9	81	1.68	0.94	35.27
12000	10	100	1.66	0.93	34.99
14400	12	144	1.63	0.91	34.10
16800	14	196	1.61	0.90	33.36
19200	16	256	1.58	0.89	32.80

Table 4.5 Patch count values from different window sizes, the unit of the PPU metric is no. of patches per square km. The shaded rows of the table indicate values calculated using WinChips, the remaining ones are calculated in Excel.

The agreement in the shape of the PPU-curves between the two data sources seen in Figure 4.13 indicates that their behaviour is an inherent effect of the way in which the metrics are calculated – as much as of the spatial distribution of forest on the Italian peninsula! Here it would be very relevant to test on data from a neutral model, as done by Saura and Martinez-Millán (2001). These authors also described the sensitivity of spatial metrics values to window size, and found that for their artificial data, measures of patch density increased with window size. Such tests were carried out early in this project, but with no conclusive results, and have since been determined to be outside the scope of this study.

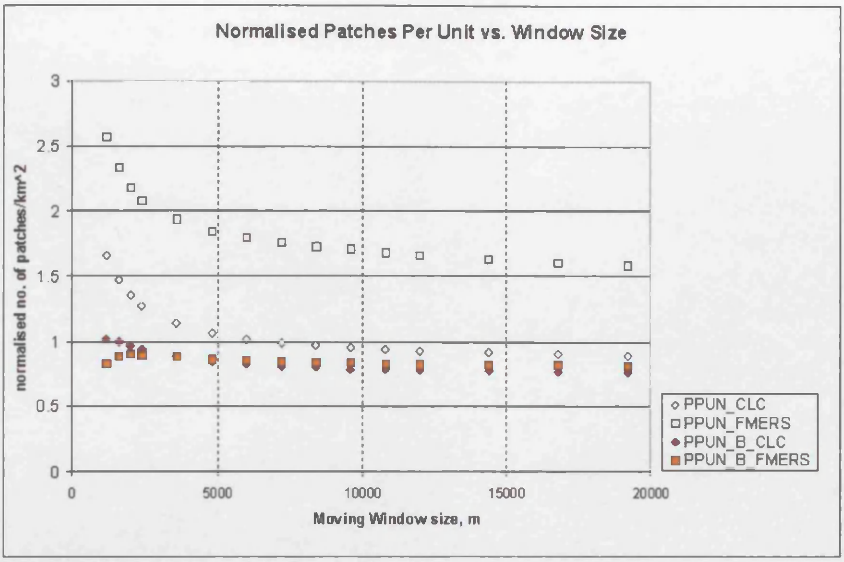

Figure 4.13 Average patch density plotted against window size, CLC and FMERS. Note the different shapes of curves for forest respectively background patch densities.

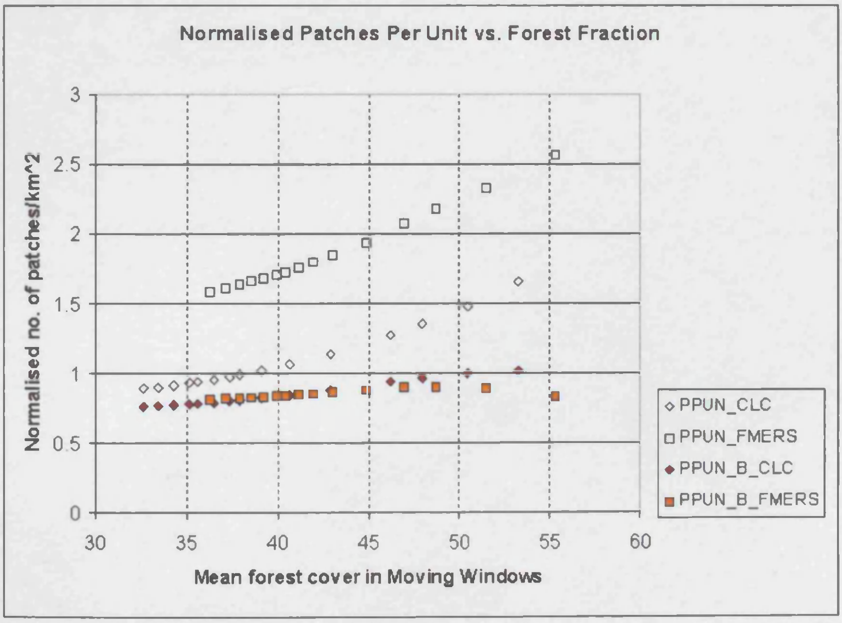

Figure 4.14 Average patch density plotted against the average forest cover, for CLC and FMERS data in the respectively included windows/output cells. Note that the right hand side of the curve, with largest forest cover values represents the smallest window sizes (compare Table 4.5).

By visual inspection of the maps produced and comparison with the input data, it appeared that the number of patches in the "background" class, i.e. all non-forest pixels was a good indicator of one aspect of forest fragmentation, namely the perforation or lacunarity of the forest landscape. Maps of the number of "background patches" at window sizes ranging from 1200 and 4800m, from the CLC and FMERS data is shown in Figure 4.15.

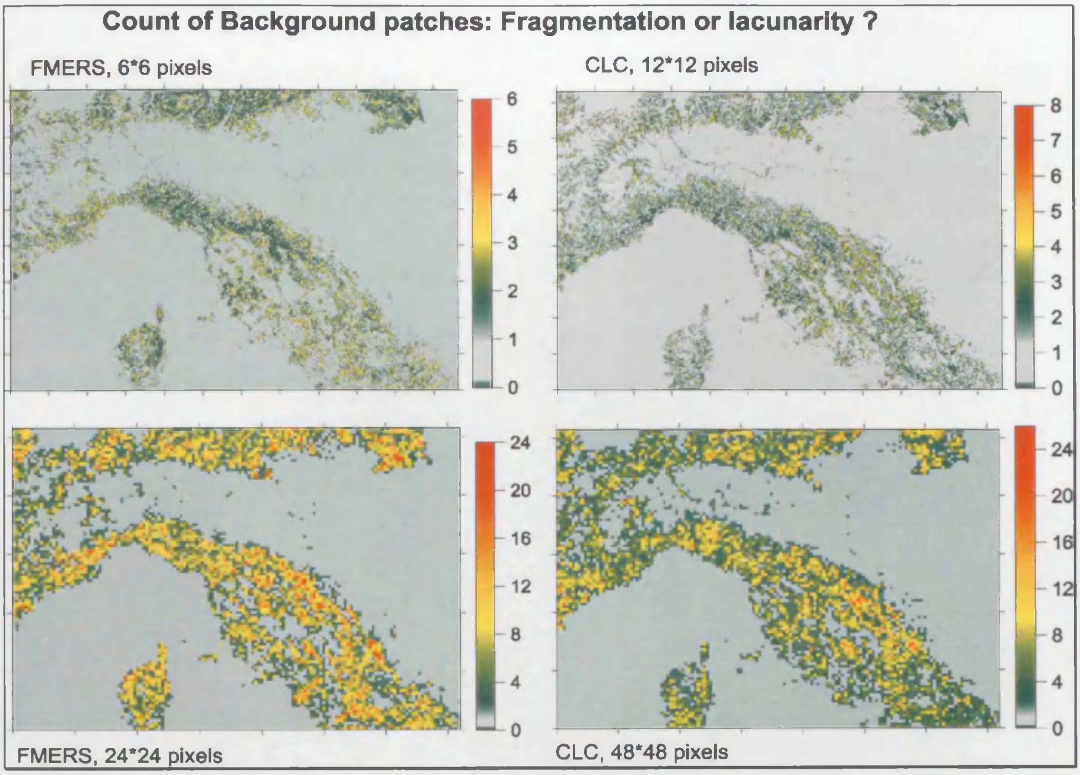

Figure 4.15 Background patch count applied as possible fragmentation metric. Derived maps show the number of separate patches belonging to the "background" class in FMERS and CLC images respectively. These maps are outputs from the Surfer software, where the text-files from the IDL calculations are converted to grids.

4.5.2 Variability and autocorrelation of the metrics

The local standard deviation was calculated for the full series of metrics images, using a WinChips filtering function (Hansen 2000) and the results extracted as a statistics file. In Figure 4.16 and Figure 4.17 the local variation of two metrics: forest proportion and Shannon's diversity are plotted against the size of the moving windows. The first observation from the figures is that the variation behaves in a similar way for the two different data types. In both cases the variability in cover fraction initially falls with increasing window size, then stabilises or increases, indicating that for CLC data there is a characteristic size of forest areas between 15 and 20 km where a slight maximum is observed, for FMERS data there is possibly a maximum above 20 km. For the CLC data there is a slight increase in the variability of the SHDI diversity metric, which is not found for the FMERS data. This is in contrast to the increase in the absolute values of this metrics seen in Figure 4.11. Similar behaviour is seen for the SqP metric, where the standard deviation decreases in spite of an increase in the absolute values of this metric with window size. For both data types, the variance of the PPUN metric decreases in the same way as the absolute values. The difference of the response curves for forest cover and diversity metrics indicate that these properties have different spatial domains/characteristic distances. This is theoretically possible, and could for instance owe to changes of composition within forested areas following altitude variations – this possibility is evaluated in the chapter 5.

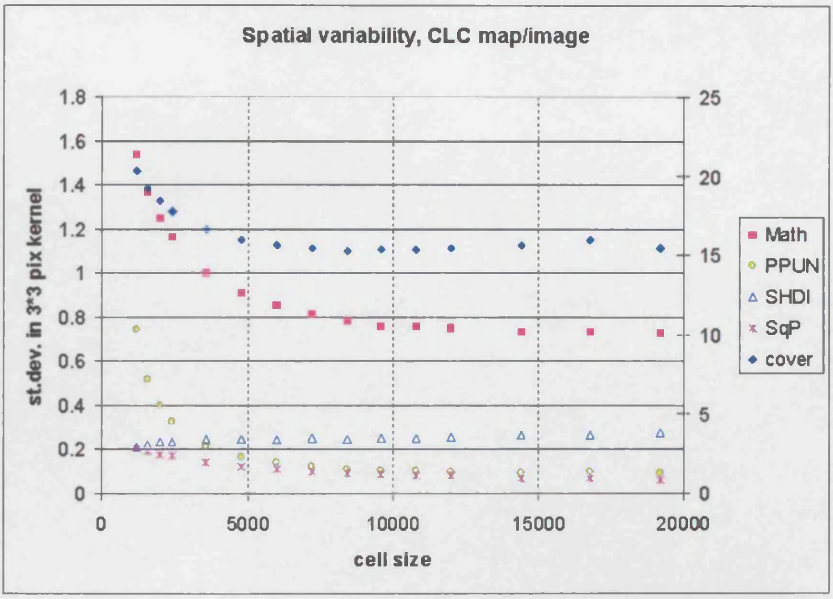

Figure 4.16 Standard deviation of the values in output cells for CLC data, calculated in 3*3 cell windows and averaged over the non-empty parts of the image. Note that the 'cover' (percentage) values map to the 2nd y-axis.

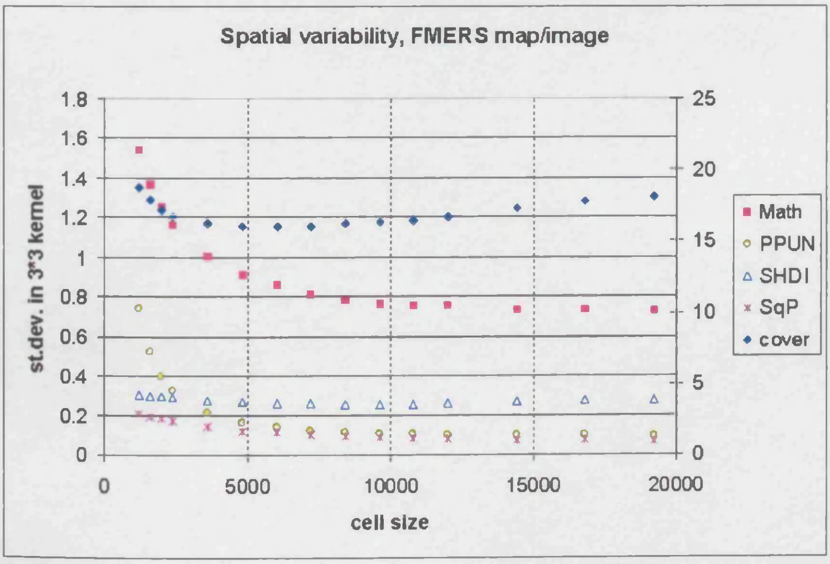

Figure 4.17 Standard deviation of the values in output cells, for FMERS data the curves of both forest cover and SHDI show a distinct minimum. Note that the cover values map to the 2nd y.axis.

When the coefficient of variance is calculated for each metric and displayed as function of the window size, it becomes clear that the different metrics show different responses to change of scale, see Figure 4.18 and Figure 4.19, below. The 'peak' in the variance of the forest cover for the CLC data is still visible, and also the Matheron metric of fragmentation increases after having its minimum average values around a window size of 10 km, most clearly for the CLC data but also visible for FMERS. All other metrics have steadily decreasing coefficient of variation.

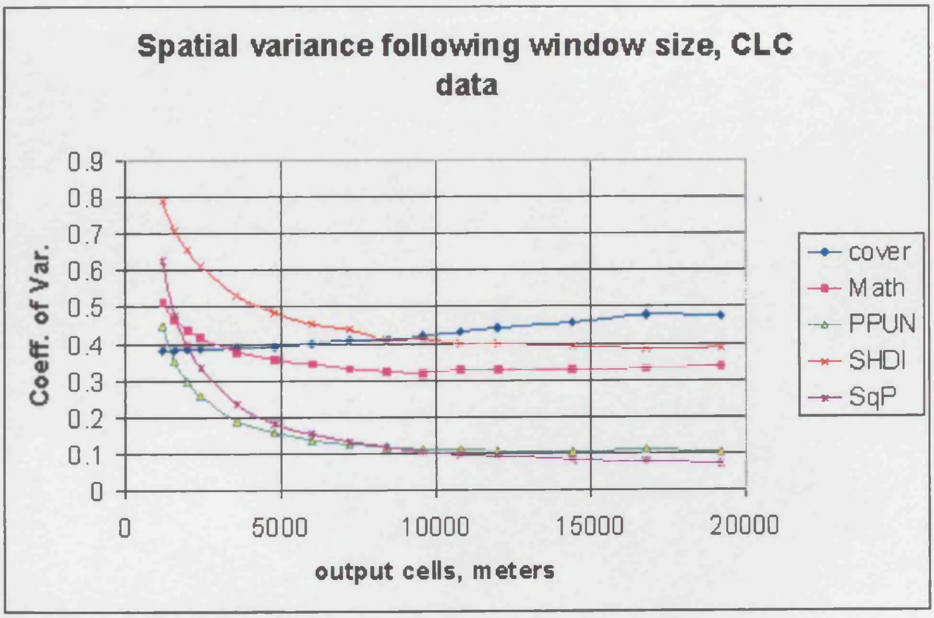

Figure 4.18 Local variability of CLC data. Coefficient of variation from the suite of spatial metrics as function of the window sizes for which they are calculated.

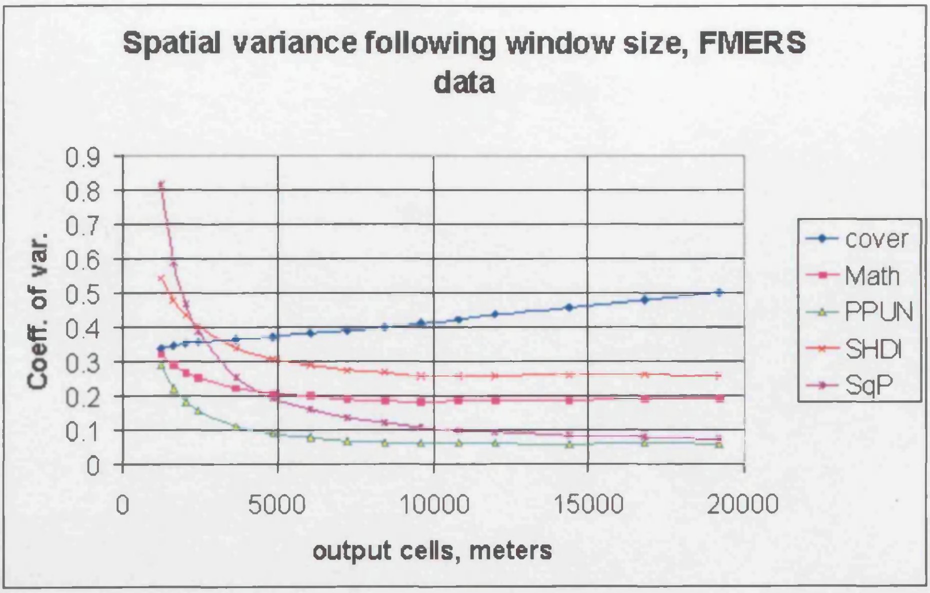

Figure 4.19 Local variability of FMERS forest map data. Calculated as described above.

An alternative way of describing spatial variability is through the Moran's I metric of autocorrelation, as shown in Figure 4.20 and Figure 4.21, below:

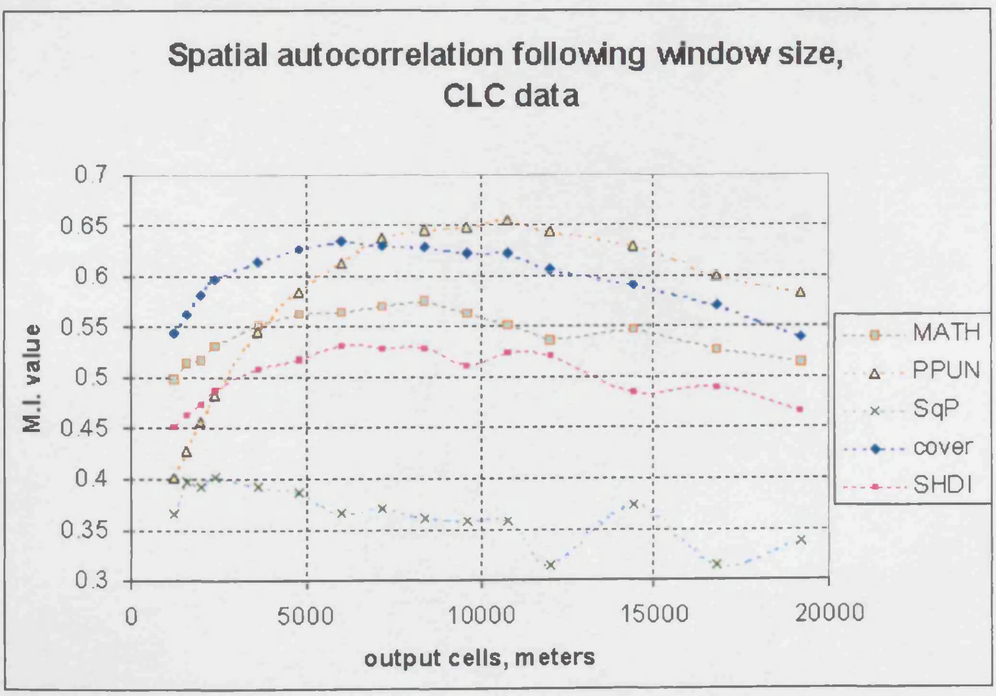

Figure 4.20 Local variability of spatial metrics from CLC data, expressed with Moran's I as function of the cells for which they are calculated.

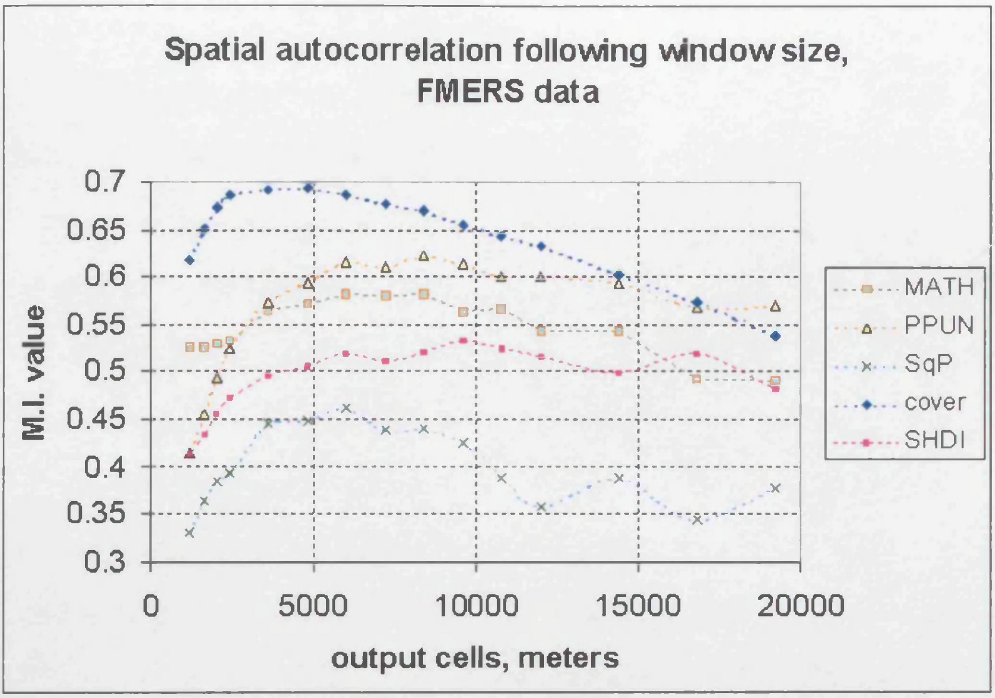

Figure 4.21 Local variability of spatial metrics from FMERS forest map expressed with Moran's I.

For this method of measuring local variance, all the metrics show distinct peaks. The shape of the curves are quite similar for the two data types, but as for variance measures, the position of the peaks differ.

In principle, low values of MI should correspond to high values of variance, but the behaviour of the values as expressed in Figure 4.20 and Figure 4.21 differ from what is observed for the standard deviation and coefficient of variance values in Figure 4.16 to Figure 4.19. The troughs on the graphs represent window sizes with relatively lower spatial autocorrelation, and thus the highest information content on landscape structure. This indicate that SqP and M should be reported and/or mapped with window size 12 km and SHDI at 14.4 km. On the other hand, the distinct peaks of MI values for the cover metric indicate that window sizes around 6 km for CLC data and 4 to 5 km for FMERS data should be avoided when maps of forest cover are made – keeping in mind that the purpose of such maps is to highlight differences between areas. The fact that the Matheron index for description of fragmentation peaks at larger window sizes than the cover fraction metric could mean that the spatial structure of the forest area is a property that characterises different regions, and is more or less independent of the actual forest cover. This assumption can be confirmed by inspection of the correlation between values of cover and M, as done in the next section.

4.5.3 Relationships between different metrics

The values of the different spatial metrics are far from independent of each other, as shown in a number of studies (for instance Riitters *et al* 1995, Hargis *et al* 1998, Gallego *et al* 2000). The way in which the correlation coefficients vary with window size is a scaling property of the metric as well as of the data. In this study with a fixed study area and increasing window sizes, the number of samples i.e. output cells or windows will decrease as the size and number of 'input-pixels' for each window increases. The number of windows with 'forest presence' has been counted, and the critical values of the correlation coefficient r to attain significance are listed in Table 4.6, below. Note that for large sample sizes, even small values of r are significant.

cell size, meters	Number of observations	r_crit	cell size, meters	Number of observations	r_crit
1200	86431	0.007	**8400**	2726	0.038
1600	60113	0.008	**9600**	2088	0.044
2000	40152	0.010	**10800**	1681	0.049
2400	28644	0.012	**12000**	1364	0.054
3600	13271	0.017	**14400**	968	0.064
4800	7773	0.023	**16800**	724	0.074
6000	5095	0.028	**19200**	574	0.083
7200	3606	0.033			

Table 4.6 Critical R values for varying number of observations with α=0.05, calculated following the formula given in section 4.4.2.1.

Table 4.7 and Table 4.8 below represent the correlations between the different spatial metrics at the smallest window size in this study, namely 1200*1200 m as defined by 6*6 pixels of the FMERS map and 12*12 pixels of the CLC map. The area of this geographical window is 1.44 km^2 or 144 hectares. The number of output pixels, representing windows included (covered by the forest mask), which is also the number of observations, is 86,431, out of a total 242,528 pixels/windows in this largest or most detailed output image.

CLC_1200m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1						
SHDI	0.437	1					
SIDI	0.421	0.993	1				
Math	-0.191	0.005	0.013	1			
SqP	-0.641	-0.264	-0.255	0.081	1		
NP	0.481	0.741	0.72	0.312	-0.339	1	
NP_back	0.044	0.027	0.032	0.476	0.153	0.106	1

Table 4.7 Correlation coefficients between metrics, CLC image with 12*12 pixels window.

FMERS_1200m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1						
SHDI	0.513	1					
SIDI	0.48	0.989	1				
Math	-0.367	0.037	0.072	1			
SqP	-0.555	-0.264	-0.256	0.096	1		
NP	0.575	0.871	0.837	0.09	-0.313	1	
NP_back	-0.046	0.114	0.114	0.388	0.219	0.118	1

Table 4.8 Correlation coefficients between metrics, FMERS image with 6*6 pixels window.

According to the coefficients given in Table 4.6, all correlations in Table 4.7 and Table 4.8 are significant, as their absolute value is greater than 0.007. For both data types, the highest correlation is found between the two metrics of diversity, which is not surprising given their definitions. Therefore, for the further analysis in this chapter only SHDI will be used – in order to avoid redundancy. SHDI expressing dominance however correlates better with the cover proportion than SIDI expressing evenness. This was expected, since densely forested areas tend to be dominated by one forest type. There is a strong positive correlation between the values of NP (patches per window, shown earlier to be proportional to PPUN), the cover fraction and SHDI. The reason for the correlation between metrics of diversity and patch density is probably that, when more than one land cover type is present in the window, more than one patch is counted – there are at least as many separate patches as land cover types within each window. The correlations are stronger for the FMERS data than for the CLC data, probably due to the fact that the land cover types are more evenly distributed in the FMERS map (see Table 4.2, page 117). In both data sets, the metrics of forest structure M and SqP show strong negative correlations with the forest cover fraction. This is probably because at this small window size there are many pixels representing 100% forest cover, which by definition give zero values of M and SqP. At this window size M and SqP values are only weakly correlated, indicating that they describe different aspects of landscape structure, at least at small window sizes. The count of background patches, NP_back are, for both data types highly correlated with the Matheron index. This confirms that NP_back (or the transformed version PPUN_B) has potential for use as an indicator of one important aspect of forest fragmentation. On the other hand it is worth noting that, while M correlates quite well with NP for the CLC data, the correlation is weak for the FMERS data. Finally, it is seen that for both data types the SqP metric is negatively correlated to the NP metric but positively correlated to the NP_back metric. This may result from the fact that SqP approaches zero as the forest cover approaches 100%, and the possibility of finding background patches is reduced.

The maximum number of forest patches at this window size is 19 for the CLC data and 37 for the FMERS data. This is a somewhat counterintuitive finding, as there are four times as many pixels in the CLC windows for similar resolutions, but it must be attributed to the way in which the data are prepared, namely the pixel-by-pixel classification of the FMERS data and the area-delineation for the CLC data, compare Figure 4.3 on page 115.

When the window side length is doubled to 2400m and the size is quadrupled to 5.76 km^2, the general pattern of correlations remain the same, as shown by the coefficient values in Table 4.9 and Table 4.10. The cover proportion becomes more positively correlated with the diversity metrics, and less negatively with the fragmentation metrics. At the same time, the diversity metrics are less correlated with the patch count metrics, a trend that continues for increasingly larger windows.

CLC_2400m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1						
SHDI	0.472	1					
SIDI	0.443	0.991	1				
Math	-0.080	0.115	0.129	1			
SqP	-0.481	-0.196	-0.185	0.211	1		
NP	0.512	0.740	0.718	0.382	-0.148	1	
NP_back	0.444	0.237	0.228	0.359	0.071	0.322	1

Table 4.9 Correlation coefficients between metrics, CLC image with 24*24 pixels window.

FMERS_2400m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1						
SHDI	0.509	1					
SIDI	0.460	0.986	1				
Math	-0.323	0.131	0.168	1			
SqP	-0.389	-0.077	-0.065	0.401	1		
NP	0.622	0.829	0.784	0.131	-0.066	1	
NP_back	0.467	0.327	0.299	0.120	0.112	0.421	1

Table 4.10 Correlation coefficients between metrics, FMERS image with 12*12 pixels window

Figure 4.22, below plots the relation between two pairs of metrics: forest cover percentage – SqP metric (cover vs. fragmentation) and PPUN – SHDI (patchiness vs. diversity) for both types of input data. The window size of 2400 m represent the smallest window size for which it was possible to use the graphic functionality of Excel (initial number of windows/output cells is 291*208=60,528, and Excel in the version used can handle a maximum of 65,536 rows). The negative correlation coefficient for SqP and cover seen in the tables above point to a general pattern of more square forest patches with higher forest cover, while the positive correlation coefficient for SHDI and PPUN (or NP = number of patches) reflects an increasing land cover diversity with more separate patches – or vice versa.

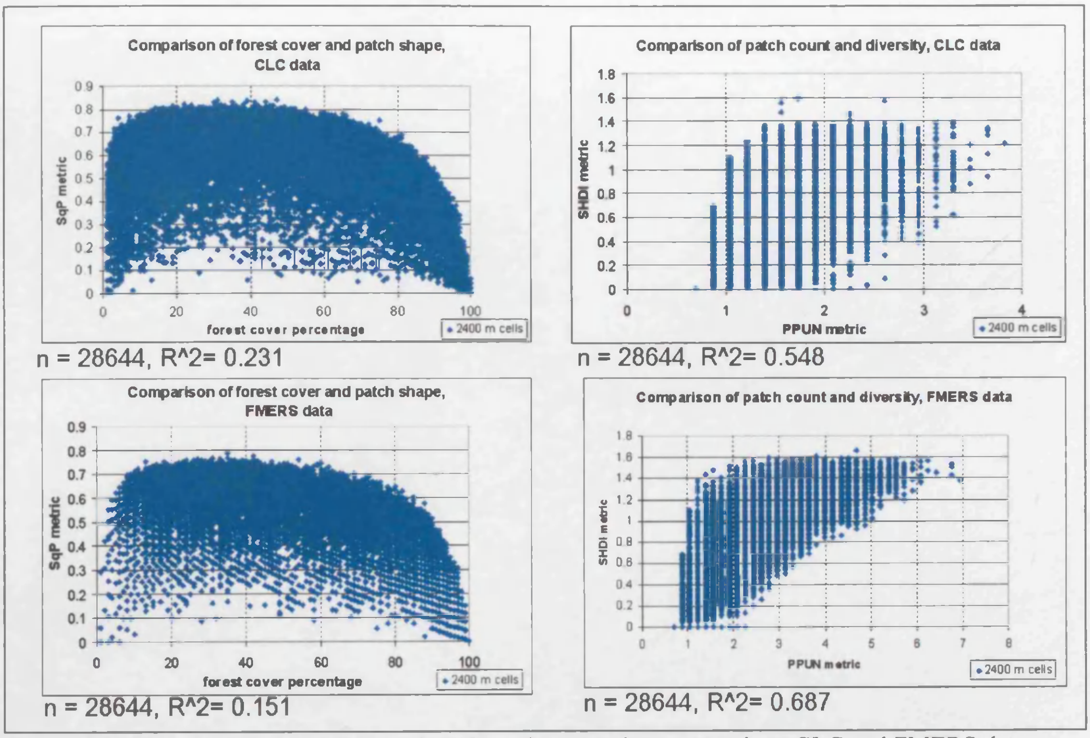

Figure 4.22 Plots of different metrics values from the same data source, here CLC and FMERS data with metrics calculated for 2400*2400 m windows. Only output cells with forest cover >= 1% are used.

The relations between metrics for the window size of 4800*4800 m corresponding to 23.02 km^2 are reported in Table 4.11 and Table 4.12. For the CLC data, the M metric is observed NOT to be significantly correlated with the cover proportion, the value of –0.003 represents a turning point, in the sense that for larger window sizes, the correlation coefficient is (significantly) positive.

CLC_4800m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1.000						
SHDI	0.468	1.000					
SIDI	0.418	0.988	1.000				
Math	-0.003	0.162	0.174	1.000			
SqP	-0.183	-0.025	-0.022	0.413	1.000		
NP	0.545	0.694	0.666	0.449	0.124	1.000	
NP_back	0.685	0.327	0.290	0.279	0.133	0.469	1.000

Table 4.11 Correlation coefficients between metrics, CLC image with 48*48 pixels window.

FMERS_4800m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1.000						
SHDI	0.482	1.000					
SIDI	0.418	0.981	1.000				
Math	-0.233	0.190	0.223	1.000			
SqP	-0.256	0.038	0.043	0.570	1.000		
NP	0.683	0.765	0.707	0.196	0.079	1.000	
NP_back	0.731	0.384	0.332	-0.009	0.048	0.585	1.000

Table 4.12 Correlation coefficients between metrics, FMERS image with 24*24 pixels window

For the window size of 9600*9600 m corresponding to 92.16 km^2, the relations are collected in Table 4.13 and Table 4.14 below. For both data types, both fragmentation metrics have now become clearly positively correlated with the diversity metrics. For the CLC data, M and SqP have positive correlations with cover proportion, while for the FMERS data, SqP is at the turning point with the value of –0.001, an r-value which is not a significant correlation to the cover proportion.

CLC_9600m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
SHDI	0.431	1.000					
SIDI	0.363	0.986	1.000				
Math	0.102	0.164	0.167	1.000			
SqP	0.165	0.175	0.163	0.621	1.000		
NP	0.590	0.604	0.575	0.522	0.374	1.000	
NP_back	0.806	0.323	0.267	0.280	0.281	0.567	1.000

Table 4.13 Correlation coefficients between metrics, CLC image with 96*96 pixels window.

FMERS_9600m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
SHDI	0.472	1.000					
SIDI	0.401	0.976	1.000				
Math	-0.119	0.230	0.253	1.000			
SqP	-0.001	0.262	0.264	0.684	1.000		
NP	0.743	0.707	0.644	0.275	0.267	1.000	
NP_back	0.850	0.402	0.337	-0.012	0.118	0.685	1.000

Table 4.14 Correlation coefficients between metrics, FMERS image with 48*48 pixels window

At the largest window size used, 19.2*19.2 km corresponding to a window area of 368.64 km^2, all correlation coefficients are positive and significant. Table 4.15 and Table 4.16 show that the correlation between cover fraction and number of background patches, which for both data types had low absolute values for small window sizes, has now grown to yield high values. This must be attributed to the fact, that for large window sizes, there are no windows which are completely covered by forest (for 19.2*19.2 km windows the maximum values are around 90% for both data types), and thus the effect that densely forested areas include a number of background patches here and there become dominant. Due to the nature of the two data sets, this effect is most apparent for the FMERS data, which have a more scattered appearance and no minimum area condition for mapping of patches – opposed to the CLC where the minimum area is 25 ha (corresponding to 6 ¼ FMERS pixels).

CLC_19200m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1.000						
SHDI	0.396	1.000					
SIDI	0.326	0.984	1.000				
Math	0.267	0.131	0.119	1.000			
SqP	0.394	0.272	0.247	0.728	1.000		
NP	0.645	0.480	0.453	0.630	0.505	1.000	
NP_back	0.872	0.318	0.256	0.373	0.397	0.657	1.000

Table 4.15 Correlation coefficients between metrics, CLC image with 192*192 pixels window.

FMERS_19200m	Cover	SHDI	SIDI	Math	SqP	NP	NP_back
Cover	1.000						
SHDI	0.441	1.000					
SIDI	0.358	0.968	1.000				
Math	0.059	0.242	0.247	1.000			
SqP	0.216	0.329	0.317	0.786	1.000		
NP	0.795	0.639	0.567	0.408	0.443	1.000	
NP_back	0.911	0.407	0.332	0.109	0.246	0.765	1.000

Table 4.16 Correlation coefficients between metrics, FMERS image with 96*96 pixels window.

The plots in Figure 4.23 below show the nature of the relations between different metrics for 19.2*19.2km windows, the largest extent examined here. These relations have been expressed here through the values of correlation coefficients – although the reality can be more complex than the linear relationships that are normally assumed. For instance, the shape of the curves for the M-SqP relations indicate a form of power-law relation between these two metrics.

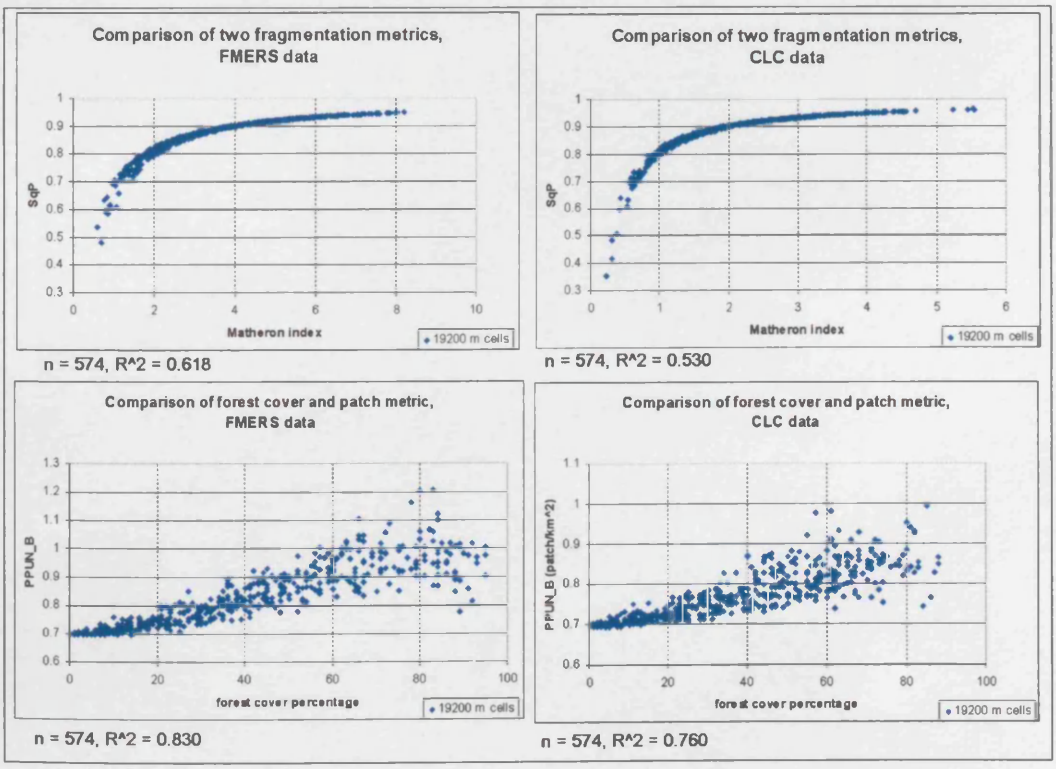

Figure 4.23 Plots of different metrics values from the same data source, here CLC (left) and FMERS (right) data with metrics calculated for 19200*19200 m windows. Only output cells with forest cover >= 1% are used.

Due to such relationships, when these metrics are used as indicators, we should not expect them to describe completely different aspects of landscape structure, but rather different interpretations of the relationship between forest area, edge length and total (landscape) area. Table 4.17 and Table 4.18 below summarise the correlations between cover fraction and the other metrics for the range of window sizes examined in this study. Correlation coefficients are observed to increase with window size for all the fragmentation and patch-count metrics and diversity metric to decrease slightly.

CLC	correllation between metric and cover%				
window size	**SHDI**	Math	SqP	NP	NP_back
1200	0.437	-0.191	-0.641	0.481	0.044
2400	0.472	-0.080	-0.481	0.512	0.444
4800	0.468	-0.003	-0.183	0.545	0.685
9600	0.431	0.102	0.165	0.590	0.806
19200	0.396	0.267	0.394	0.645	0.872

Table 4.17 Summary of correlation coefficients between cover proportion and metrics values at increasing window sizes for CORINE land cover data.

The difference between the CLC and the FMERS data is notable for the 'fragmentation metrics' M and SqP, where for the CLC data the correlations become positive for window sizes between 4800 and 9600m, while for the FMERS data they do so above 9600m. For both data types the SqP values become more highly correlated with forest cover at large window sizes.

FMERS	correllation between metric and cover%				
Window size	**SHDI**	Math	SqP	NP	NP_back
1200	0.513	-0.367	-0.555	0.575	-0.046
2400	0.509	-0.323	-0.389	0.622	0.467
4800	0.482	-0.233	-0.256	0.683	0.731
9600	0.472	-0.119	-0.001	0.743	0.850
19200	0.441	0.059	0.216	0.765	0.911

Table 4.18 Summary of correlation coefficients between cover proportion and metrics values at increasing window sizes for FMERS forest map.

4.5.4 Relationships between metrics derived from the two different data types

The degree of correlation between the values of the same spatial metric derived from two different data sets informs us about the degree to which the (metric) values from one data set can be used to predict and eventually substitute the values derived from the other (Costanza and Maxwell 1994). Examination of this degree of predictability provides information on the nature and usefulness of the (image) data sets as well as on the behaviour of the chosen metrics, however not distinguishing effects due to the 'nature' of the metrics from effects owing to the 'nature' of the data, as discussed by for instance Turner *et al* (1989) and Saura (2002).

Table 4.19 A and B summarise the agreements found between the *same metrics*, from the two *different image sources* with *different resolutions*, at varying window sizes. The R-square values are plotted against the window size in Figure 4.24.

comparing CLC-FMERS **A**		Window size, meters						
		1200	**1600**	**2000**	**2400**	**3600**	**4800**	**6000**
Cover	Multiple R	0.543	0.626	0.684	0.724	0.787	0.819	0.840
	R Square	0.295	0.392	0.468	0.524	0.619	0.670	0.705
SHDI	Multiple R	0.192	0.237	0.274	0.301	0.336	0.352	0.366
	R Square	0.037	0.056	0.075	0.090	0.113	0.124	0.134
Math	Multiple R	0.009	0.077	0.137	0.187	0.280	0.340	0.382
	R Square	0.000	0.006	0.019	0.035	0.078	0.116	0.146
PPU	Multiple R	0.237	0.305	0.360	0.394	0.459	0.499	0.527
	R Square	0.056	0.093	0.130	0.155	0.211	0.249	0.277
SqP	Multiple R	-0.019	0.014	0.027	0.045	0.144	0.204	0.227
	R Square	0.000	0.000	0.001	0.002	0.021	0.042	0.052

comparing CLC-FMERS **B**		Window size, meters							
		7200	**8400**	**9600**	**10800**	**12000**	**14400**	**16800**	**19200**
Cover	Multiple R	0.854	0.864	0.870	0.879	0.884	0.894	0.902	0.903
	R Square	0.730	0.747	0.757	0.772	0.781	0.799	0.814	0.816
SHDI	Multiple R	0.364	0.379	0.385	0.345	0.376	0.381	0.373	0.371
	R Square	0.132	0.144	0.148	0.119	0.142	0.145	0.139	0.138
Math	Multiple R	0.405	0.421	0.447	0.467	0.489	0.510	0.524	0.534
	R Square	0.164	0.177	0.200	0.218	0.239	0.260	0.274	0.285
PPU	Multiple R	0.538	0.567	0.571	0.582	0.598	0.620	0.633	0.642
	R Square	0.289	0.321	0.326	0.339	0.357	0.384	0.401	0.412
SqP	Multiple R	0.268	0.332	0.325	0.364	0.378	0.376	0.433	0.453
	R Square	0.072	0.110	0.106	0.132	0.143	0.141	0.188	0.205

Table 4.19 A and B Agreement between metric values from different image sources at varying window size. The values for output cell sizes < 2400m are calculated using the statistical functions of WinChips, for larger (and fewer) windows using the analysis module of Excel.

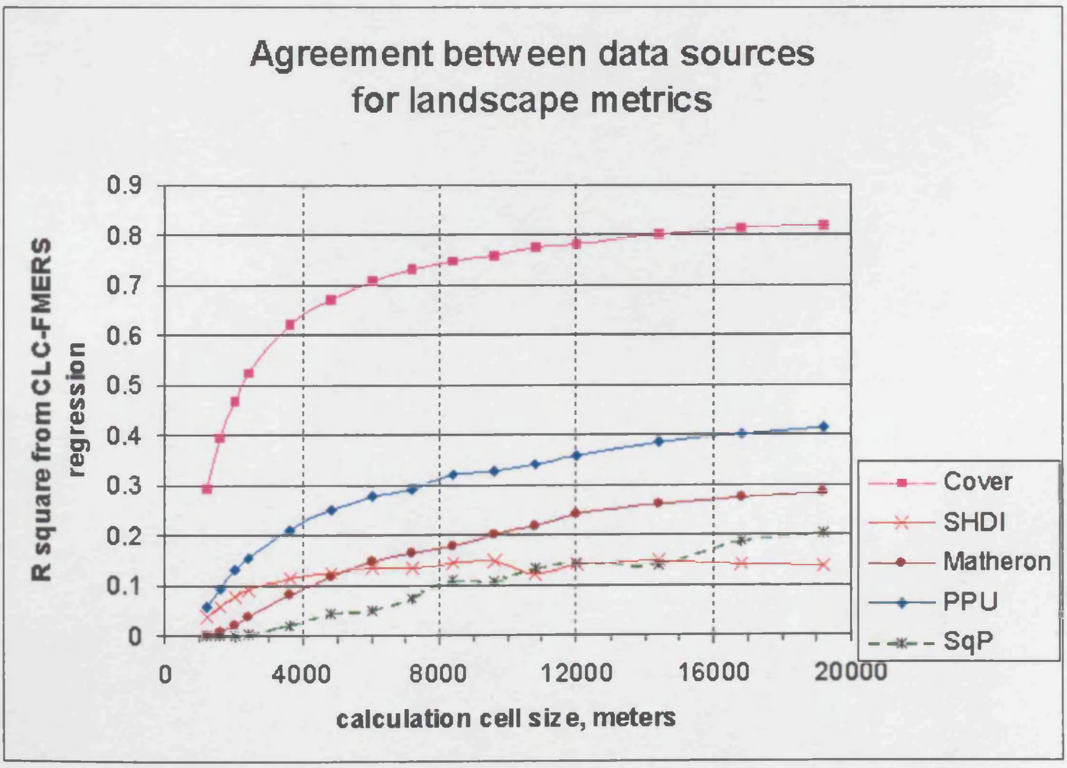

Figure 4.24 R-square, expressing agreement between metrics values from CLC and FMERS data, plotted against spatial extent/window size. Smallest windows are 6*6 pixels for FMERS and 12*12 pixels for CLC data, largest windows 96*96 pixels for FMERS and 192*192 pixels for CLC.

As shown in Chapter 3, the different metrics show quite different correlations at the same window size. More surprisingly they respond in different ways to the changes in window size, as expressed by the shape of the window size-correlation curves. In general, the increasing window size will even out differences between spatial structure as mapped in the two data sets, leading to higher correlations, most notably and understandable for the forest cover fraction, which also has the highest correlation coefficients at all window sizes. This is partly due to the elimination of possible errors in the geo-referencing of the datasets (how well the two 'maps' fit each other), a common problem for large-area data in grid format. The "dip" on the curve for the correlation of the SHDI–value at 10.8 km window size is not easily explained, as it has been computed in the same way as its neighbouring values and checked more than once. Perhaps the lower correlation of the SHDI diversity values at this window size reflects a change in spatial domain from landscape to regional level (following the size of characteristic landscape structuring elements like the width of valleys). Also the response curve for the SqP metric behaves in an irregular, step-wise fashion. The shape of the cover-curve suggest that the response of R^2 to window size follows a power-law or logarithmic relation, and that is confirmed by plotting these values against window size on a logarithmic scale as shown in Figure 4.25.

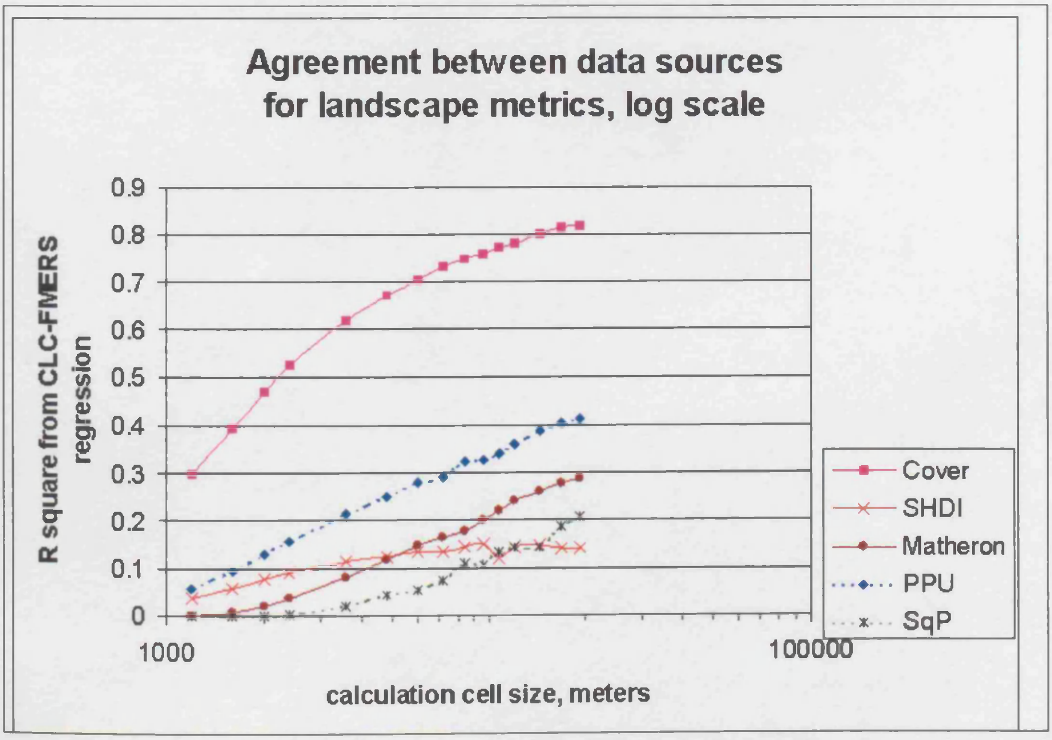

Figure 4.25 R-square-plot similar to Figure 4.24, but with window size values transformed logarithmically.

The correlation for the patch count metric PPU/PPUN (count of forest patches per unit area) improves steadily with window size, also in a log-linear fashion. This is an interesting and quite promising result, since the degree of patchiness and thus number of patches is amongst the largest differences between the CLC and the FMERS data sets (see the difference of the absolute (average) values of the metrics listed in Table 4.5). Though not shown above, correlations between the count of background patches in the two different data types were also derived for the window sizes described here in detail, and are reported in Table 4.20. The correlation of background patches-count values follows the pattern of correlation (of NP_back) with forest cover fraction seen in Table 4.17 and Table 4.18. When the metric of background patches correlate well for large windows, it is in agreement with the high correlation of forest cover-fraction values between the two data sets for large windows.

	Inter-correlation CLC-FMERS images	
window size	**NP**	**NP_back**
1200	0.237	0.093
2400	0.394	0.272
4800	0.499	0.518
9600	0.571	0.681
19200	0.642	0.791

Table 4.20 Agreement between the two data sources on the number of "background patches", as expressed through the correlation coefficient R, improves drastically with increasing size of output cells (and thus the number of input pixels).

4.5.5 Comparisons of metrics values with different regionalisation approaches

The use of watersheds or catchments (the term used here) is becoming increasingly popular for environmental assessment in general and for reporting of spatial metrics in particular. Intuitively it seems reasonable to use these naturally delineated, functional regions as the basis for reporting of environmental parameters, especially when these are related to water quality or sediment load. Recently, there has been a number of studies on the use of spatial metrics at watershed level (Tinker *et al* 1998, Patil *et al* 2000, Jones *et al* 2001, Cifaldi *et al* 2003). Vogt *et al* (2003) used satellite based forest maps in combination with catchment and elevation data[19] to describe forest-water interactions such as the fraction of rivers running through forest. Administrative regions, on the other hand, have the advantage of already forming a hierarchy of levels from nation state to parish, farm or forest plot for which GIS data are readily available.

A central question that can possibly be answered with the MW-approach is whether catchments are more homogeneous than the administrative regions within the study area. This is relevant because watersheds/catchments have been proposed as natural reporting units for landscape properties and environmental indicators (Apan *et al* 2000, Paracchini *et al* 2000, Patil *et al* 2000, Vogt *et al* 2003). In this section the question is addressed through extraction of spatial metrics values for selected NUTS-regions and for selected 4th to 6th order catchments. Thus, the MAUP is treated through data analysis on overlapping but different regions. Also the coefficient of variance is calculated for the administrative regions and the catchments for both data types, and for a number of window sizes – since it can be hypothesised that if a more homogeneous forest structure is found within the catchments, the variation of the metrics values that characterise structure will be smaller within the region (in practice/GIS-implementation the polygon used to extract statistical parameters).

Another dimension is the comparison of the two different data sources. When the same set of results is derived from both data sources, in terms of output cell size and metrics, the agreement between them can be investigated at the level of catchment or region. Thus, regression between CLC and FMERS metrics was performed separately within the geographical areas of interest. Finally the averaged values per region were compared. Given the limited number of regions and the problem with regression of such averaged values, the rank-size correlation was applied, in order to test whether the metrics were sufficiently robust to point out areas with high/low diversity, fragmentation etc. even with different input data.

[19] The catchment and elevation data used in this thesis are based on the ones used in Vogt *et al*'s study, which is carried out at the JRC. The current version of the database is available through the web site http://agrienv.jrc.it; follow the link Activities - Catchments, and data can be requested and downloaded.

The administrative regions used are illustrated in Figure 4.26, and the catchments with numbering are shown in Figure 4.27.

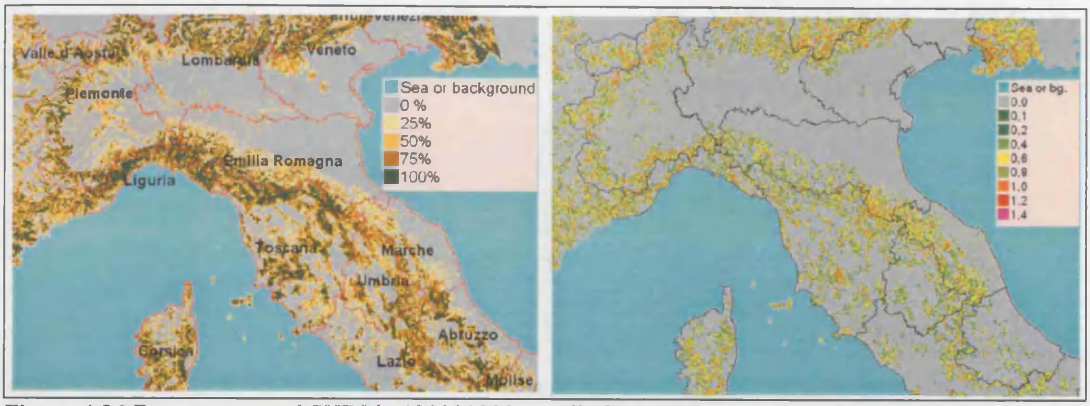

Figure 4.26 Forest cover and SHDI in 1200*1200 m cells from CLC forest map. To the left, forest cover overlaid with Italian regions (NUTS-2 level). To the right map with values of Shannon's diversity index (SHDI), created in the same IDL batch-run.

Figure 4.27 CLC data with high-order catchment polygons. To the left, the original CLC data overlaid with the 4th order catchments used in this study. To the right, forest cover fraction from the CLC-based forest maps for 4.8*4.8 km windows, overlaid with 5th and 6th order catchments.

Note that Corsica is included in the administrative theme, even though the island is a French region. In the text and tables, the catchments are named by their order, followed by an underscore and the code that functions as unique identifier, so possible names are i.e. 5_01.

Statistical properties of the MW-outputs were extracted per administrative region and catchment for a subset of spatial resolutions, namely 1200, 2400, 4800, 9600 and 19200m output cells. This is deemed sufficient to describe scale effects on the metrics values, though the entire set of metric images as used in the previous sections were available. Not all of the extracted values are shown here in table form, but scaling profiles are used to illustrate their properties for the selected geographical units. Note that the way in which the graphs are constructed result in a 'logarithmic' appearance, as the window size is doubled for each step.

Figure 4.28 below presents examples of how spatial metrics are derived with the M-W method and reported either as raster maps with pixels corresponding to the output cells or as vector maps with metrics values assigned to regions (the ones used for delineating the parts of the image from where statistical information is extracted). Note that in the figure, image 2 is derived from image 1, and that image 3,4 and 5 subsequently represent different way of describing the MW-outputs in image 2.

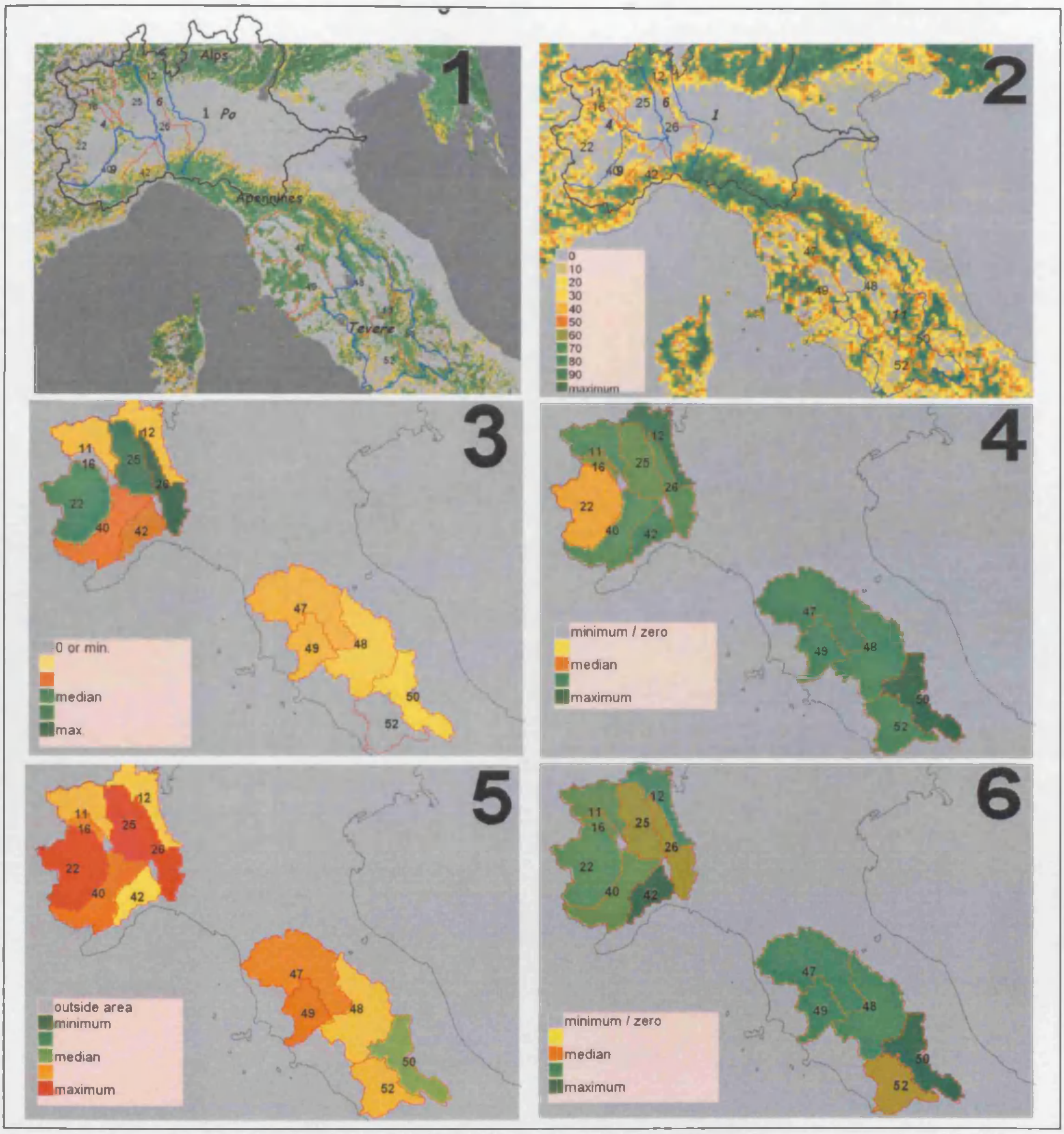

Figure 4.28 Examples of landscape metrics values reported at catchment level, in this case relatively simple forest cover information.

In Figure 4.28, Image 1 shows the catchments of 4[th] to 6[th] order that are used here on a background of the FMERS forest map that is used as input to the MW-calculations. Image 2 shows M-W output at window size 4800m, for each output cell measured forest cover percentage. These values are used in the following derived images. Image 3 shows the FC metric values, ranging from 0 in the lower Tevere to 0.425 on the upper Po plain. Image 4 shows the cover percentage (under the forest mask) per catchment, and image 5 shows the coefficient of variation within the catchment of the cover percentage values. Finally, image 6 shows the cover percentage values from the CLC data also at 4800m cell size, and is thus directly comparable with image 4. The rank correlation between these two particular outputs is found to be significant at 5% probability level (Table 4.34, below). Due to the nature of the image data (floating point) and a wish to use the full range of colours of the look-up-tables relative values are shown in the image legends.

4.5.5.1 Metrics values within catchments

The statistics for the various output cell sizes were collected in spreadsheet files – one for catchments and one for administrative regions, making it possible to report and summarise the metrics values. Examples for the catchments delineation are shown in Table 4.21 and Table 4.22 below. It appears here that according to CLC, the highest values of diversity metrics and lowest values of fragmentation metrics are found at relatively high altitudes in the Po catchments in the northern part of the area. The lowest diversity and highest fragmentation is then in the catchments that contribute to the Tevere. Catchment 4_48 (region 11 in the tables below) is the upper catchment of that river, an area that more or less coincides with the Umbria administrative region. The highest FC value is found for 4_26 (7 in the tables) that is situated across the Po plain on the upper to middle part of the rivers longitudinal extent, east of the confluence with the Ticino river at Pavia, while the lowest FC value is found for catchment 4_49 (10) in Toscana, with a mixture of agricultural plains and forested hills.

CLC	4800m	pixels	cover	PPUN	PPUNB	SHDI	SIDI	Math.	SqP	Elevation	FC
6th ord	6_01 Po (1)	2168	39.87	1.039	0.829	0.507	0.299	2.301	0.655	788.9	0.306
5th ord	5_04Po (1)	622	36.31	1.04	0.814	0.576	0.344	2.157	0.645	1122.4	0.172
	5_06 Po (2)	286	37.31	1.023	0.813	0.452	0.265	2.33	0.656	516.4	0.206
	5_09 Po (3)	331	42.25	1.103	0.835	0.516	0.308	2.691	0.69	679.4	0.085
	5_11Teve (4)	704	42.21	1.074	0.881	0.343	0.191	3.123	0.734	592.1	0.095
4th ord	4_42 Po (1)	111	54.81	1.146	0.868	0.58	0.341	2.408	0.654	468.6	0.036
	4_40 Po (2)	213	36.31	1.088	0.82	0.487	0.293	2.876	0.714	794.6	0.084
	4_22 Po (3)	286	38.28	1.032	0.817	0.565	0.335	2.047	0.63	1082.7	0.154
	4_16 Po (4)	35	36.43	1.101	0.847	0.728	0.436	2.266	0.663	1258.5	0.057
	4_11 Po (5)	148	36.88	1.051	0.804	0.665	0.398	2.082	0.648	1730.5	0.101
	4_25 Po (6)	146	32.71	1.04	0.807	0.497	0.297	2.357	0.661	608.0	0.308
	4_26 Po (7)	114	32.44	0.976	0.797	0.357	0.212	2.324	0.636	360.7	0.325
	4_12 Po (8)	145	45.11	1.089	0.842	0.568	0.331	2.305	0.67	684.0	0.069
	4_47 Tosc (9)	377	42.18	1.077	0.86	0.547	0.319	3.039	0.723	342.4	0.085
	4_49 Tosc (10)	154	42.01	1.068	0.862	0.469	0.274	3.102	0.727	341.3	0.019
	4_48 Teve (11)	335	39.86	1.104	0.901	0.331	0.182	3.665	0.771	462.6	0.042
	4_50 Teve (12)	213	53.76	1.092	0.904	0.407	0.223	2.536	0.708	934.7	0.047
	4_52 Teve (13)	156	31.49	0.984	0.805	0.284	0.166	2.759	0.688	402.4	0.276
	avg. 5th order	*413*	*38.63*	*1.055*	*0.821*	*0.515*	*0.306*	*2.393*	*0.664*	*772.7*	*0.154*
	avg. 4th order	*149.75*	*39.12*	*1.065*	*0.825*	*0.556*	*0.330*	*2.333*	*0.660*	*873.5*	*0.142*

Table 4.21 Summary at catchment level of spatial metrics from the CLC map, with medium window size 4800m. The Highest metrics values are highlighted in yellow, lowest values in blue. Average elevation from the terrain model is included as a supplementary description of the area. Note that this value is an average for the forested windows in the area only.

Figure 4.29 below shows the scaling profiles of the SHDI and Matheron indices respectively, for six 4th order catchments with pronounced differences in the shapes of the curves. The continuous increase and fall of the values are expected from previous results (section 4.5.1), so what is interesting are the edges on the curves. The sharp increase of the SHDI values for catchment 4_26 from 9600 to 19200m window size reflects that a characteristic forest (patch) size has been exceeded and additional forest classes are included in each instance of the window, this is especially clear for the southern part of the catchment, with hills to the north of the Apennines. On the other hand, the SHDI values for catchment 4_22 increase only little when the window side length is doubled from 9600 to 19200m, because only few of the larger windows include more forest classes (implying that the characteristic landscape or forest size in the area, in terms of side length, is not larger then 10 km). For both CLC and FMERS based metrics, the average values for the 13 fourth order and the 4 fifth order catchment areas are almost the same, and that the fifth order values show less variation, since they represent average values taken over larger areas. As the catchment areas become larger, the metrics values approach the averages for the entire study area that are shown in Figure 4.11.

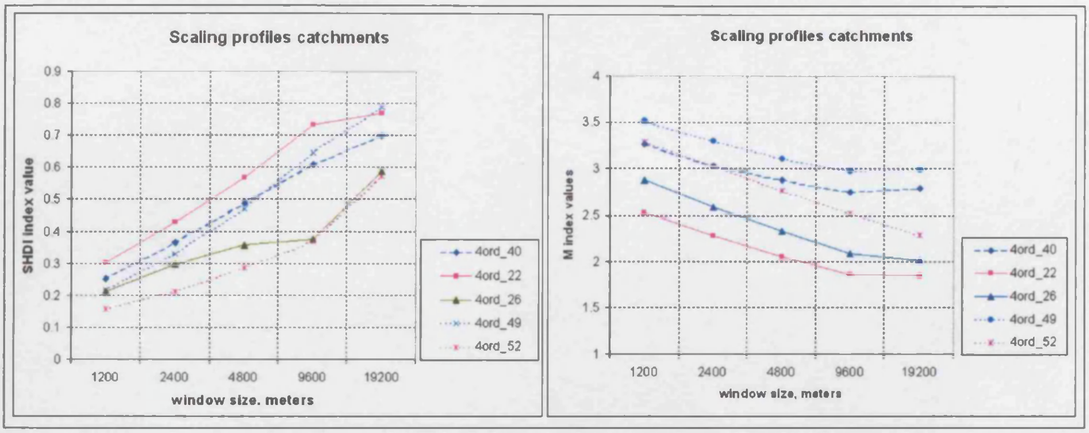

Figure 4.29 SHDI and Matheron metrics, extracted from CLC data to catchment areas, for a range of output cell sizes.

For the FMERS data, reported in Table 4.22 there is a clear difference between the catchments in the northern and southern part of the study area, as expected from the input forest maps (compare Figure 4.2 and Figure 4.27). The 4th order catchments of Tevere have high diversity and fragmentation values, including the patch count metrics. The lowest fragmentation metric values are found in the 4th order catchments of Po that include a substantial part of the plain where agriculture is dominant – and the map indicates little or no forest presence. Catchment 4_22 is shown as having surprisingly little forest cover, but this is partly due to problems with clouds in the input images, as often in mountains. This effect also contributes to observed low forest cover for the administrative region of Piemonte, and it is obviously a source of error in the calculations (where pixels marked as cloud, snow etc. should preferably not be counted in).

FMERS	4800m	pixels	cover	PPUN	PPUN B	SHDI	SIDI	Math.	SqP	Elevation	FC
6th ord	6_01 Po (1)	2027	42.99	1.684	0.851	0.799	0.446	3.913	0.608	851.7	0.397
5th ord	5_04Po (1)	598	29.32	1.507	0.803	0.745	0.431	4.273	0.636	1198.2	0.219
	5_06 Po (2)	283	40.22	1.629	0.852	0.758	0.417	3.948	0.622	531.6	0.219
	5_09 Po (3)	315	38.67	1.853	0.89	0.805	0.454	5.198	0.695	706.8	0.140
	5_11Teve (4)	757	43.66	2.129	0.915	0.966	0.527	5.404	0.716	561.0	0.018
4th ord	4_42 Po (1)	103	44.76	1.924	0.943	0.851	0.454	5.562	0.716	494.1	0.116
	4_40 Po (2)	209	35.89	1.823	0.866	0.784	0.455	5.038	0.686	807.0	0.105
	4_22 Po (3)	257	21.97	1.337	0.771	0.736	0.433	4.209	0.622	1137.2	0.284
	4_16 Po (4)	37	31.87	1.659	0.802	0.834	0.45	4.482	0.663	1347.6	0.000
	4_11 Po (5)	156	35.85	1.687	0.821	0.835	0.474	4.566	0.672	1794.0	0.045
	4_25 Po (6)	142	34.42	1.588	0.833	0.653	0.379	3.968	0.612	670.9	0.345
	4_26 Po (7)	106	35.30	1.332	0.845	0.537	0.295	3.979	0.627	382.2	0.425
	4_12 Po (8)	149	48.26	1.928	0.879	0.949	0.52	3.823	0.618	683.9	0.040
	4_47 Tosc (9)	386	44.61	1.968	0.869	0.929	0.518	4.509	0.633	334.3	0.060
	4_49 Tosc (10)	149	40.52	1.75	0.853	0.823	0.473	4.706	0.655	347.9	0.054
	4_48 Teve (11)	339	42.43	2.016	0.905	0.955	0.532	5.354	0.71	459.9	0.030
	4_50 Teve (12)	219	51.79	2.595	0.951	1.188	0.625	4.651	0.688	924.8	0.018
	4_52 Teve (13)	199	36.83	1.81	0.892	0.741	0.409	6.317	0.756	333.1	0.000
	avg. 5th order		*36.07*	*1.663*	*0.848*	*0.769*	*0.434*	*4.473*	*0.651*	*812.2*	*0.193*
	avg. 4th order		*36.04*	*1.660*	*0.845*	*0.772*	*0.433*	*4.453*	*0.652*	*914.6*	*0.170*

Table 4.22 Summary at catchment level of spatial metrics from the FMERS map, with medium window size 4800m as example. The highest metrics values are highlighted in yellow, lowest values in blue. The reason that the average elevation values are not the same as for the CLC data, is that different inclusion/forest presence masks are used.

The graphs in Figure 4.30 show the same general pattern in the selected catchments as observed for the CLC data, although for the FMERS data used here catchment 4_52, lower Tevere including the Rome metropolitan area, stands out with high values of M at all window sizes, indicating high fragmentation. For the CLC data, this area does not stand out in the same way, so the profile partly reflects the tendency of the FMERS mapping to place many small forest patches of type OWL broadleaved in areas where CLC show no forest. Catchment 4_40, reaching from the summit of the Maritine Alps to the Po valley east of Torino, has a profile of SHDI value similar to catchment 4_22 with CLC data. Also the SHDI diversity metric for this catchment reaches a maximum when the sub-landscapes get sufficiently large to include all possible forest classes. Catchment 4_26 has constantly low values for both metrics, because the two FMERS classes broadleaved and mixed forest dominate in the area, and because the forest patches are relatively coherent – in fact having the highest FC value of the catchments for this data type. Catchment 4_22 has a steeper M-value curve, with higher values at small window sizes, this must more small-scale fragmentation, i.e. more open forest or fringed edges, a structure typically found on mountain slopes.

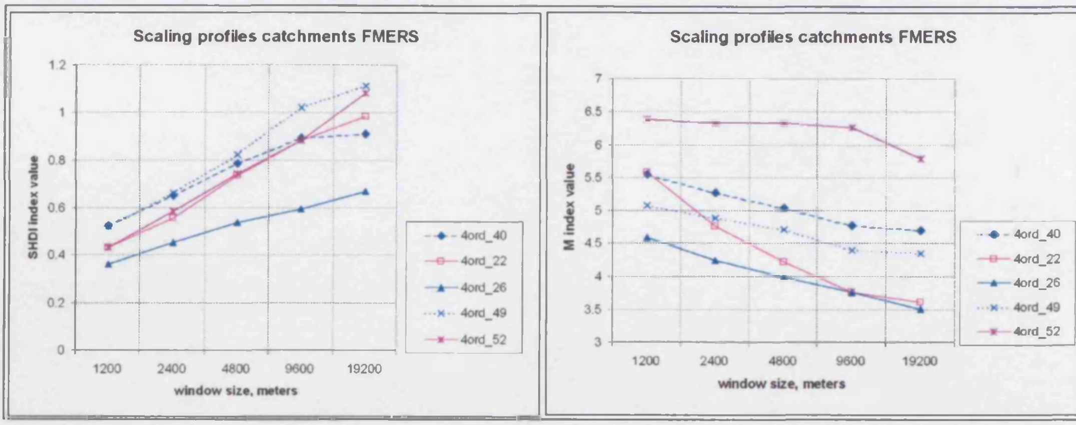

Figure 4.30 SHDI and Matheron metrics extracted from FMERS data to catchment areas, for a range of output cell sizes.

The hierarchical nature of the catchment delineations at different orders allows comparison of metrics for catchments at lower levels with those of higher levels. In general, the values at higher orders are close to the average of those at lower orders, that together constitute the catchment, as can be seen from the values in Table 4.21 and Table 4.22, and more clearly from Table 4.23, where the intention has been to make a table structure that reflects landscape structure. Matheron index values are used as examples, since fragmentation is indeed a phenomenon that manifests itself in different ways at different spatial levels. All the 5th order catchments have small areas in the lower parts that are not amongst the 4th order catchments used here, but the effect of that is assumed negligible.

CLC				Math.	FMERS			
6th	5th	4th	4th level number	4800m	6th	5th	4th	4th level number
2.301	2.691	2.408	4_42 Po (1)		3.913	5.198	5.562	4_42 Po (1)
		2.876	4_40 Po (2)				5.038	4_40 Po (2)
	2.157	2.047	4_22 Po (3)			4.273	4.209	4_22 Po (3)
		2.266	4_16 Po (4)				4.482	4_16 Po (4)
		2.082	4_11 Po (5)				4.566	4_11 Po (5)
		2.357	4_25 Po (6)				3.968	4_25 Po (6)
	2.33	2.324	4_26 Po (7)			3.948	3.979	4_26 Po (7)
		2.305	4_12 Po (8)				3.823	4_12 Po (8)

Table 4.23 The hierarchical approach illustrated. Average Matheron index values from windows with extent 4800m, extracted for selected catchments in the upper Po valley plus the entire river basin (6th order). The 5th order catchments are from the top: 5_09, 5_04 and 5_06.

As expected, and shown in a previous section, the FMERS data yield higher values of diversity as well as fragmentation type metrics relative to the CLC data in all catchments. The ordering or ranking of the areas according to M value however differ significantly, as discussed below.

4.5.5.2 Metrics values within administrative regions

Administrative regions have the advantage of being known beforehand by the people who should use spatial metrics as environmental indicators. Areas like Piemonte and Toscana and are also well known for certain landscape characteristics such as mush or dense forest or large open areas with views over rolling hills. The observed metrics values for these regions are shown in Table 4.24 and Table 4.25 below for CLC and FMERS maps respectively, and scale profiles for selected areas and metrics are shown in Figure 4.31 and Figure 4.32. Two small regions almost coincide with catchments: Valle d'Aosta with 4_11 (which include a bit of the plains around Ivera to the SE of the valley) and Umbria with 4_48[20].

The regionalisation results mark Liguria, situated between the Northern coast of the Mediterranean and the Apennines, as a partiular area with dense forest cover and low

[20] Mountains can provide natural borders, and Umbria has been a stable geographical unit for thousands of years.

fragmentation. Also Valle d'Aosta has low fragmentation and high diversity, but this might be an artefact of the re-classification since the CLC class "transitional woodland-shrub" has been aggregated into OWL broadleaved (see Table 4.1 on page 116), though in this area it constitutes the zone around the tree line, where it can be questioned if it constitute a separate type of forest rather than less dense deciduous forest. Corsica, another region with large differences in elevation within short distances, has similar high diversity values. High fragmentation is found in middle Italy, with highest values for the Marche region, where the forest structure can be interpreted as rather perforated with low cover but high PPUN_B value.

CLC 4800m	nr_pix	Cover	PPUN	PPUNB	SHDI	SIDI	Math.	SqP	Elevation	FC
Veneto	327	33.59	1.012	0.842	0.465	0.27	2.594	0.661	444.8	1.046
Lombardia	612	39.55	0.952	0.83	0.419	0.245	2.085	0.632	627.1	0.511
Piemonte	931	37.75	1.086	0.824	0.573	0.339	2.423	0.67	838.6	0.147
Valle d'Aosta	123	38.55	1.069	0.802	0.712	0.43	1.921	0.631	1976.6	0.146
Emilia Romagna	589	36.08	1.1	0.838	0.45	0.269	2.903	0.702	473.8	0.630
Liguria	236	70.96	1.059	0.884	0.608	0.342	1.731	0.598	559.2	0.004
Toscana	945	48.41	1.063	0.868	0.519	0.299	2.756	0.696	385.0	0.044
Marche	385	29.06	1.331	0.875	0.511	0.317	3.948	0.78	441.1	0.096
Umbria	348	42.18	1.114	0.921	0.312	0.169	3.595	0.769	517.5	0.052
Abruzzo	423	37.85	0.921	0.803	0.254	0.151	2.397	0.664	866.3	0.116
Lazio	494	33.74	0.996	0.812	0.33	0.19	2.654	0.694	494.6	0.144
Corsica	328	43.81	1.022	0.842	0.678	0.388	2.292	0.682	635.8	0.003
average value		*40.96*	*1.060*	*0.845*	*0.486*	*0.284*	*2.608*	*0.682*	*688.3*	*0.245*

Table 4.24 Summary at administrative region level of spatial metrics from the CLC map, window size 4800m used as example. Highest metrics values are highlighted in yellow, lowest values in blue.

FMERS 4800m	nr_pix	Cover	PPUN	4.5.5.2.1.1 PPUNB	SHDI	SIDI	Math.	SqP	Elevation	FC
Veneto	472	29.97	1.614	0.818	0.669	0.406	4.97	0.65	318.3	0.417
Lombardia	574	45.99	1.759	0.85	0.827	0.46	3.386	0.566	665.9	0.612
Piemonte	882	34.12	1.634	0.837	0.767	0.438	4.459	0.65	882.4	0.211
Valle d'Aosta	134	36.84	1.697	0.823	0.842	0.475	4.28	0.653	2058.9	0.052
Emilia Romagna	552	48.22	1.755	0.876	0.847	0.46	3.753	0.588	499.8	0.739
Liguria	231	50.99	1.836	0.92	0.87	0.465	4.77	0.67	561.2	0.026
Toscana	953	50.38	1.904	0.879	0.903	0.504	4.12	0.614	381.9	0.036
Marche	326	32.59	1.95	0.857	0.956	0.525	4.912	0.665	491.0	0.294
Umbria	350	43.17	2.18	0.908	1.053	0.577	5.139	0.703	514.5	0.046
Abruzzo	455	35.84	2.049	0.846	0.933	0.5	5.218	0.698	808.7	0.037
Lazio	561	38.31	1.982	0.888	0.871	0.474	5.979	0.742	448.9	0.007
Corsica	329	56.83	1.873	0.93	0.86	0.477	3.993	0.631	641.0	0.000
Average value		*41.94*	*1.853*	*0.869*	*0.867*	*0.480*	*4.582*	*0.653*	*689.4*	*0.206*

Table 4.25 Summary at administrative region level of spatial metrics from the FMERS map, window size 4800m used as example. Highest metrics values are highlighted in yellow, lowest values in blue.

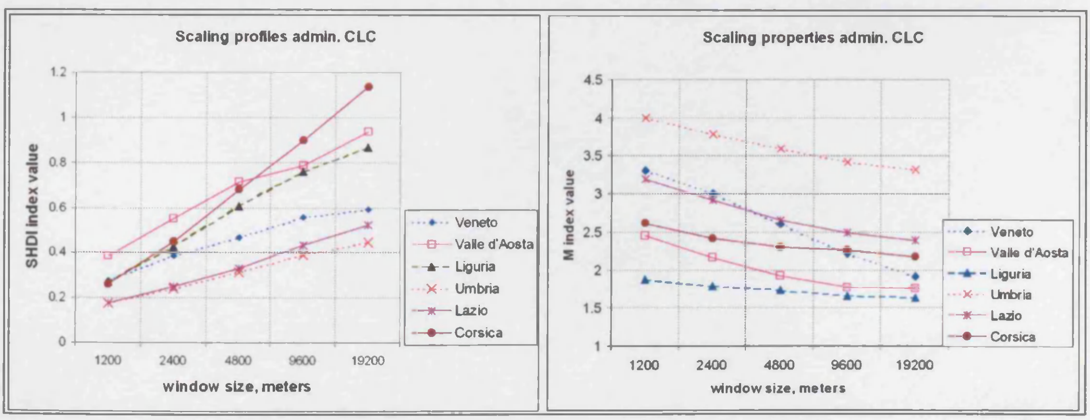

Figure 4.31 SHDI and Matheron metrics from CLC data, selected administrative regions, for a range of window sizes.

The higher contrasts in the landscapes of Corsica and Valle d'Aosta is also reflected in the shape of the scale-diversity curves, in Figure 4.31, right side. On the contrary, the Lazio and Umbria regions have low and slowly increasing diversity values. Liguria maintains low fragmentation values even at small window sizes while for Veneto they decrease rapidly with increasing window size, Figure 4.31, left side. This corresponds well with the high FC value found for this region from the CLC forest map.

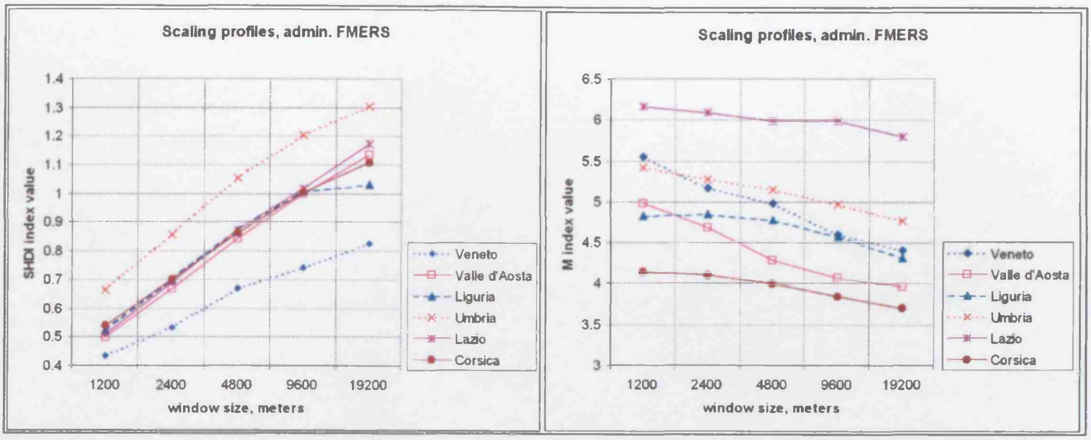

Figure 4.32 SHDI and Matheron metrics from FMERS data extracted to regions, for an interval of window sizes.

In the FMERS data, Veneto is marked by low forest cover and low diversity *within the windows of calculation*, i.e. the forest types are concentrated in specific geographical areas and not much interspersed, i.e. the (class) richness is low throughout (this is the case for both map types and all extents). High values of the fragmentation indicating metrics are found in middle Italy, most in Lazio and Abruzzo, now along with high diversity values, with Umbria having highest SHDI and SIDI values. The combination of high diversity and high fragmentation indicates a complex interspersion of forest and other land cover types.

The biggest difference between the metric values from CLC and FMERS is observed for Umbria, which has constantly high diversity values for the FMERS data, along with fragmentation values less than for neighbouring region Lazio. Inspection of statistics for the input data show that Umbria actually is a site of strong disagreement between the CLC and the FMERS classifications.

The forest cover proportions for Veneto and Umbria from CLC and FMERS are listed in Table 4.26, in order to examplify the effects of classification disagreements at region level (and to illustrate how diversity metrics are calculated). Although the forest percentage is almost the same from the two data sources in Umbria, the diversity values are at opposite ends of the scale. For Veneto there is better agreement, but again the FMERS data give a higher estimate of the forest diversity in the region.

	CLC	% of tot.	% of land	% forest	FMERS	% of tot.	% of land	% forest
Veneto	No data	0.01			No data	5.01		
	Coniferous	2.13	2.13	12.85	Coniferous	5.76	6.07	26.86
	Broadleaved Deciduous	9.72	9.72	58.62	Broadleaved Decid.	9.32	9.81	43.44
	Broadl. Evergreen	0.00	0.00	0.00	Broadl. Evergreen	0.00	0.00	0.00
	Mixed	2.24	2.24	13.49	Mixed	1.90	2.00	8.87
	OWL Coniferous	0.00	0.00	0.00	OWL Coniferous	0.19	0.20	0.88
	OWL Broadleaved	2.49	2.49	15.03	OWL Broadleaved	4.28	4.51	19.95
	Other Land	83.42	83.42		Other Land	73.54	77.42	
	total	100	100	100	Total	100	100	100
	land_map	1.00	**SHDI_forest**	**1.13**	land_map	0.95	**SHDI_forest**	**1.29**
	% forest	0.17	**SHDI_land**	**0.87**	% forest	0.23	**SHDI_land**	**0.94**
Umbria	No data	0.00			No data	2.67		
	Coniferous	0.60	0.60	1.50	Coniferous	5.55	5.70	13.45
	Broadleaved Deciduous	35.08	35.08	87.88	Broadleaved Decid.	13.79	14.17	33.42
	Broadl. Evergreen	0.02	0.02	0.05	Broadl. Evergreen	0.14	0.14	0.34
	Mixed	0.86	0.86	2.15	Mixed	11.89	12.22	28.82
	OWL Coniferous	0.00	0.00	0.00	OWL Coniferous	1.35	1.39	3.27
	OWL Broadleaved	3.36	3.36	8.43	OWL Broadleaved	8.54	8.78	20.70
	Other Land	60.09	60.09		Other Land	56.06	57.60	
	total	100	100	100	Total	100	100	100
	land_map	1.00	**SHDI_forest**	**0.47**	land_map	0.97	**SHDI_forest**	**1.45**
	% forest	0.40	**SHDI_land**	**0.41**	% forest	0.42	**SHDI_land**	**1.18**

Table 4.26 A comparison of forest proportion values and derived diversity metrics from the input data for two administrative regions.

4.5.5.3 Forest Concentration profiles

For the previously used metrics, the values at higher orders of regions and catchments are averages of the values for lower order areas – as a consequence of the way they are derived from the M-W outputs. This is not the case for FC values, where it is possible to have higher values at higher orders, due to the integrative nature of this metric (i.e. the files from the masking process are used indirectly). The inclusion of areas with little or no forest cover, typically in the lower parts of the catchments can give higher contrast between forested and non-forested cells and thus higher FC values. This effect is actually seen in Table 4.27 and Table 4.28, where values are reported for the smallest window size, 1200m and an intermediate window size, 4800m. Furthermore, there is a remarkably good agreement between the values extracted from the two image types, which initially shows the FC metric as a potentially useful description of landscape structure.

CLC				FC	FMERS			
6th	5th	4th	4th level number	1200m	6th	5th	4th	4th level number
0.760	0.343	0.192	4_42 Po (1)		0.866	0.452	0.320	4_42 Po (1)
		0.368	4_40 Po (2)				0.453	4_40 Po (2)
	0.673	0.626	4_22 Po (3)			0.851	1.257	4_22 Po (3)
		0.515	4_16 Po (4)				0.507	4_16 Po (4)
		0.530	4_11 Po (5)				0.342	4_11 Po (5)
		0.962	4_25 Po (6)				0.984	4_25 Po (6)
	0.668	0.998	4_26 Po (7)			0.686	1.079	4_26 Po (7)
		0.333	4_12 Po (8)				0.330	4_12 Po (8)

Table 4.27 FC values for catchments in Northern Italy for window size 1200m. Highest contrasts forest-non forest areas are found for the highest orders of catchments.

CLC				FC	FMERS			
6th	5th	4th	4th level number	4800m	6th	5th	4th	4th level number
0.306	0.085	0.036	4_42 Po (1)		0.397	0.140	0.116	4_42 Po (1)
		0.084	4_40 Po (2)				0.105	4_40 Po (2)
	0.172	0.154	4_22 Po (3)			0.219	0.284	4_22 Po (3)
		0.057	4_16 Po (4)				0.000	4_16 Po (4)
		0.101	4_11 Po (5)				0.045	4_11 Po (5)
		0.308	4_25 Po (6)				0.345	4_25 Po (6)
	0.206	0.325	4_26 Po (7)			0.219	0.425	4_26 Po (7)
		0.069	4_12 Po (8)				0.040	4_12 Po (8)

Table 4.28 FC values for same catchments as above, but with window size 4800m . The larger window/mask cells used, give lower metric values, again with highest values for highest orders of catchments.

The visual appearance of FC profiles for different types of catchments are shown in Figure 4.33 and Figure 4.34 below. Only values for window size up to 9600m are used, because most catchments have zero FC values at 19200m, and many have so few cells that calculations become statistically uncertain. The catchments (contributing to Po) in the northern part of the area generally have higher FC values, but they also decrease more rapidly with window size. The crossing of the curves for 4_22 and 4_26 from FMERS data indicates that catchment 4_22 has forest patches scattered across the landscape with typical distances between 1.2 and 2.4 km (the steepest part of the curve), while catchment 4_26 further down the valley has larger and more compact forest patches – or larger areas where no forest is found.

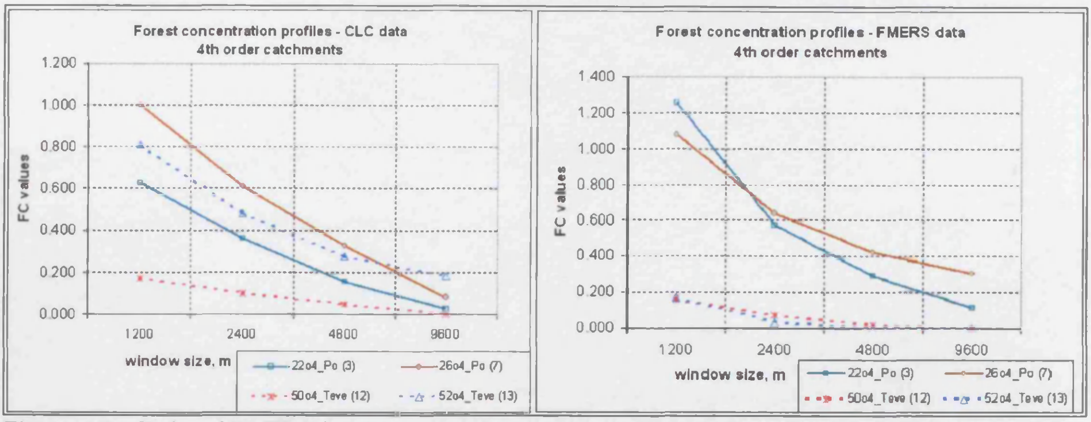

Figure 4.33 CLC and FMERS inputs compared for creation of FC-profiles of selected catchments in northern and middle Italy.

The selected administrative regions also show differences for the shape of the FC curves in Figure 4.34, but there is good agreement between the two different data sources. There are marked differences for Liguria, where the forest cover in the CLC maps is so dense that hardly any non-forest cells are found (when they *are* found in the FMERS map it can however be due to cloud cover), and for Lazio, where the CLC map has larger non-forest areas and thus higher FC values at small window sizes.

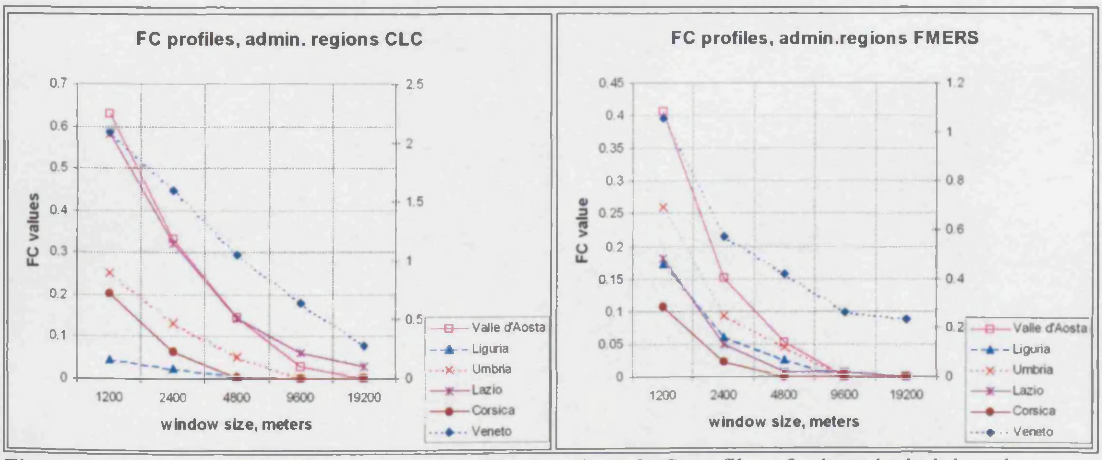

Figure 4.34 CLC and FMERS inputs compared for creation of FC-profiles of selected administrative (NUTS-level 2) regions. Note that for both data sets the curve for Veneto corresponds to the 2^{nd} y-axis.

Generally, it seems that CLC data yield FC-curves of more different shapes and placement, thus making it easier to characterise and distinguish between regions. Again it is the more scattered nature of the FMERS data that is reflected in spatial metric values.

4.5.5.4 Regressions between metrics derived from different data sources within selected areas

The calculations made here are basically repetitions of what was done in section 4.5.4 where correlations between values from the two different input types were made for a forest mask of the entire study area, with results summarised in Table 4.19, Figure 4.24 and Figure 4.25. However, here the regressions are performed for subsets of the study area. The subsets are defined in two different ways, namely delineation by terrain and by following man-made borders. The SHDI diversity metric and the Matheron index of fragmentation are used as examples, and for comparison with the profiles that illustrate how metrics values vary with window size.

Catchment – SHDI	1200 m	2400 m	4800 m	9600 m	19200 m
4_42 Po (1)	0.184	0.059	0.256	0.33	0.096
4_40 Po (2)	0.254	0.219	0.39	0.522	0.58
4_22 Po (3)	0.147	0.077	0.257	0.427	0.552
4_16 Po (4)	0.338	0.114	0.283	0.826	N/A
4_11 Po (5)	0.268	0.192	0.278	0.614	0.874
4_25 Po (6)	0.369	0.263	0.486	0.713	0.791
4_26 Po (7)	0.267	0.19	0.368	0.583	0.744
4_12 Po (8)	0.212	0.356	0.531	0.311	0.367
4_47 Tosc (9)	0.24	0.344	0.539	0.19	0.217
4_49 Tosc (10)	0.263	0.489	0.644	0.234	0.254
4_48 Teve (11)	0.206	0.411	0.643	0.069	0.103
4_50 Teve (12)	[illegible]	0.291	0.472	0.046	0.429
4_52 Teve (13)	0.326	0.104	[illegible]	0.614	0.209
Average	*0.245*	*0.239*	*0.408*	*0.421*	*0.363*
st.dev.	*0.075*	*0.135*	*0.156*	*0.247*	*0.369*
coeff.var.	*0.305*	*0.563*	*0.383*	*0.587*	*1.015*

Admin. - SHDI	1200 m	2400 m	4800 m	9600 m	19200 m
Veneto	0.291	0.449	0.563	0.622	0.675
Lombardia	0.219	0.383	0.476	0.519	0.538
Piemonte	0.255	0.418	0.505	0.622	0.682
Valle d'A.	0.245	0.446	0.464	0.343	0.442
Emilia R.	0.266	0.432	0.538	0.549	0.549
Liguria	0.094	0.143	0.283	0.485	0.709
Toscana	0.221	0.337	0.314	0.325	0.432
Marche	0.34	0.537	0.611	0.547	0.665
Umbria	0.203	0.263	0.228	0.203	0.293
Abruzzo	0.067	0.096	0.114	0.15	0.222
Lazio	0.287	0.417	0.435	0.378	0.069
Corsica	[illegible]	-0.069	-0.146	-0.219	-0.278
average	*0.206*	*0.321*	*0.365*	*0.377*	*0.417*
st.dev.	*0.106*	*0.179*	*0.219*	*0.243*	*0.298*
coeff.var.	*0.513*	*0.557*	*0.6*	*0.645*	*0.714*

Table 4.29 Correlation coefficients for agreement between CLC and FMERS based values of the SHDI diversity index at different output cell (window) sizes for selected geographic areas. Highest metrics values are highlighted in yellow, lowest values in blue.

Table 4.29 shows that the SHDI values have large differences between the different areas and correlations values somewhat fluctuating with respect to window size, especially for the catchment regions. This is contrary to what is observed for the entire study area. The average values for the administrative regions (representing a larger part of the maps than the catchments), however have values similar to the multiple R values at the same window sizes in Table 4.19. The regions with highest forest concentration (FC values) and lowest fragmentations or dense forest cover seem to have the best agreement between CLC and FMERS data. A notable exception is the Corsica region, where the negative correlation coefficients indicate strong disagreement between the data sources as to where the most diverse forest areas are found. The fluctuations can be attributed to random effects, such as the influence of where the windows happen to be placed in the landscape. The higher correlation coefficients for large windows do not necessarily mean that they are more reliable, this is because, with a small number of samples or output cells, confidence intervals are correspondingly narrower. Thus the potential for establishing relations or predictions of metrics values from one data type to another based on smaller areas remains doubtful. It also remains to be examined whether strata such as botanical or climatic zones or based on terrain/altitude give better agreements.

Catchment - Math.	1200m	2400m	4800m	9600m	19200 m
4_42 Po (1)	-0.039	0.261	0.181	0.34	0.046
4_40 Po (2)	0.006	0.451	0.509	0.486	0.542
4_22 Po (3)	-0.112	0.28	0.377	0.311	0.272
4_16 Po (4)	-0.132	0.544	0.498	0.509	N/A
4_11 Po (5)	-0.009	0.449	0.466	0.348	0.595
4_25 Po (6)	0.014	0.52	0.643	0.661	0.858
4_26 Po (7)	-0.092	0.504	0.577	0.57	0.554
4_12 Po (8)	0.144	0.345	0.407	0.726	0.91
4_47 Tosc (9)	0.117	0.376	0.285	0.68	0.8
4_49 Tosc (10)	0.199	0.316	0.305	0.816	0.948
4_48 Teve (11)	0.128	0.251	0.207	0.744	0.742
4_50 Teve (12)	0.121	0.182	0.145	0.542	0.407
4_52 Teve (13)	-0.052	0.465	0.429	0.275	0.539
Average	*0.023*	*0.380*	*0.387*	*0.539*	*0.601*
st.dev.	*0.109*	*0.117*	*0.155*	*0.180*	*0.271*
coeff.var.	*4.817*	*0.308*	*0.400*	*0.335*	*0.450*

Admin. - Math.	1200m	2400m	4800m	9600m	19200m
Veneto	0.101	0.015	0.091	0.179	0.281
Lombardia	-0.083	0.182	0.367	0.54	0.717
Piemonte	-0.083	0.227	0.441	0.579	0.629
Valle d'A.	0.183	0.129	0.207	0.324	0.461
Emilia R.	0.043	0.315	0.548	0.709	0.814
Liguria	-0.029	0.205	0.31	0.417	0.438
Toscana	0.031	0.402	0.581	0.704	0.747
Marche	-0.1	0.276	0.552	0.727	0.795
Umbria	-0.058	0.454	0.71	0.791	0.858
Abruzzo	0.019	0.324	0.51	0.611	0.502
Lazio	0.208	0.134	0.225	0.247	0.363
Corsica	-0.01	0.113	0.248	0.339	0.488
average	*0.019*	*0.231*	*0.399*	*0.514*	*0.591*
St.dev.	*0.102*	*0.128*	*0.187*	*0.207*	*0.193*
coeff.var.	*5.505*	*0.553*	*0.468*	*0.402*	*0.327*

Table 4.30 Correlation coefficients for agreement between values of the Matheron index, based on CLC and FMERS data, at different output cell (window) sizes for selected geographic areas. Highest metrics values are highlighted in yellow, lowest values in blue.

Table 4.30 shows that, on average M values have higher correlations for the regions used here than for the entire study area (compare Table 4.19). As expected and following the large differences in the structure and composition of the data sets, as described in the above sections, there are marked differences between the regions, and no clear pattern of zones with high correlations emerge. Surprisingly, the Corsica region has positive correlation values for this forest structure metric, so the problem of agreement lies more with composition than with extent and texture of forest across the landscape. See also, for comparison Table 4.26 with description of forest composition for Veneto and Umbria.

4.5.5.5 Test for variability

Table 4.31 and Table 4.32 report the average of the coefficient of variation for each of the spatial metrics *within* administrative and catchment regions respectively. The purpose of comparing the values is to examine whether one of the delineation approaches produces more homogenous regions in terms of metric values.

catchmts.	CLC_COV	CLC_PPUN	CLC_PPUNB	CLC_SHDI	CLC_M	CLC_SqP	CLC_Alt
1200	0.625	0.582	0.629	1.291	0.618	0.604	0.603
2400	0.680	0.363	0.277	0.995	0.500	0.356	0.653
4800	0.696	0.234	0.152	0.757	0.422	0.193	0.682
9600	0.670	0.157	0.095	0.572	0.353	0.085	0.728
Admin.							
1200	0.616	0.567	0.634	1.353	0.627	0.608	0.640
2400	0.663	0.345	0.284	1.016	0.504	0.357	0.696
4800	0.690	0.225	0.164	0.783	0.426	0.196	0.760
9600	0.694	0.157	0.106	0.608	0.370	0.097	0.799

Table 4.31 Mean values of coefficients of variation for selected metrics from the CLC data and elevation from DTM, average values from the 13 4th level catchments and the 12 regions.

catchmts.	FM_cover	FM_PPUN	FM_PPUNB	FM_SHDI	FM_M	FM_SqP	FM_alti
1200	0.673	0.625	0.612	0.847	0.598	0.693	0.661
2400	0.743	0.463	0.297	0.640	0.468	0.417	0.663
4800	0.725	0.372	0.200	0.478	0.375	0.194	0.690
9600	0.674	0.312	0.141	0.360	0.303	0.078	0.719
Admin.							
1200	0.648	0.624	0.650	0.797	0.653	0.730	0.682
2400	0.737	0.488	0.301	0.624	0.521	0.453	0.744
4800	0.727	0.401	0.206	0.454	0.431	0.222	0.783
9600	0.703	0.350	0.156	0.335	0.366	0.102	0.795

Table 4.32 Mean values of coefficients of variation for selected metrics from the FMERS data and elevation from DTM, average values from the 13 4th level catchments and the 12 regions.

When comparisons are made between values of metrics from the same data source and at the same window size (within each table), no clear differences or trends emerge. Thus, it can not be concluded that one or the other regionalisation approach produces more homogenous regions with smaller internal variance of the metrics values. The decreasing values of SqP variance with increasing window size can be attributed to the nature of the metric (more separate patches in larger windows give values closer to 1) and not to an actual smaller difference in forest structure between the windows. Note however the differences in variability of the patch count metrics, where FMERS maps have the highest values and of the SHDI metric, where CLC maps have the higher values. This is also seen from Figure 4.18 and Figure 4.19, though the variance values there are calculated only for each output cell and its immediate neighbours.

4.5.5.6 Test for agreement - CLC-FMERS

This final sub-section examines the results derived at regional level, comparing the relative values per region to examine whether they give the same general image of the study area (i.e. will thematic maps of a given spatial metric look the same, when derived from CLC and FMERS data?).

When the 12 administrative regions are compared, the critical value of **observed t** (Spearman's rank transformed to t-distribution values, assuming a two–sided distribution) is 2.201 for the rank correlation at 5% confidence interval and 1.796 at 10%, corresponding to coefficients of +/- 0.6354 and +/-0.5185 respectively. When the 13 catchment regions are compared, the critical value of observed t is 2.179 at 5% confidence and 1.728 at 10%. The values in Table 4.33 and Table 4.34 below are the rank correlations, with indications of possible significance. Note that some of the correlations are negative. Though not significant, these values indicate strong disagreement between the CLC and the FMERS data. It is no surprise that this is seen for the SHDI diversity metric as calculated on admin. regions, where the CLC data generally give highest values in the northern regions, and FMERS data give highest values in middle Italy. In this test the administrative regions have 12 instances of significant agreement, hereof one at 10% confidence level, the catchments have 16, hereof five of them at 10% confidence level, so it seems that with this approach, catchments are more effective for mapping of spatial metrics.

Italian admin. regions	window size *n=12*				
Metrics	**1200**	**2400**	**4800**	**9600**	**19200**
Cover	0.510	0.727**	0.797**	0.734**	0.720**
PPUN	-0.119	-0.077	-0.021	0.112	0.224
PPUN_B	0.136	0.168	0.549*	0.703**	0.797**
Math.	0.364	0.273	0.259	0.224	0.280
SHDI	-0.517	-0.517	-0.385	-0.329	-0.378
SIDI	-0.105	0.035	0.108	-0.017	-0.332
SqP	0.140	0.070	0.080	0.262	0.367
FC	0.811**	0.755**	0.804**	0.776**	0.781**

Table 4.33 Spearman's rank correlation coefficients for agreement between spatial metrics from CLC and FMERS forest maps, extracted for the 12 northernmost administrative regions in Italy. ** indicate significance at 5% probability level, * at 10% level, assuming a two-sided Student's t-distribution.

Italian catchments	window size *n=13*				
Metrics	**1200**	**2400**	**4800**	**9600**	**19200**
Cover	0.549*	0.738**	0.761**	0.846**	0.755**
PPUN	0.234	0.475	0.703**	0.569*	0.529*
PPUN_B	-0.092	0.443	0.635**	0.620**	0.643**
Math.	-0.069	0.275	0.623**	0.503*	0.595*
SHDI	-0.086	0.003	0.132	0.140	0.063
SIDI	-0.092	-0.169	-0.006	0.114	-0.066
SqP	0.253	0.220	0.349	0.463	0.169
FC	0.658**	0.435	0.413	0.615**	

Table 4.34 Spearman's rank correlation coefficients for agreement between spatial metrics from CLC and FMERS forest maps, extracted for 13 selected 4[th] level catchments in northern and middle Italy.

The difference between the two regionalisation approaches is especially pronounced for the patch count metrics, where the catchments show good agreement for the PPUN values at larger window sizes, but not so for the admin. regions. For catchments the Matheron index value show agreement at window sizes of 4800m and above, for admin. regions neither M nor SqP show significant agreement, still M seems to be the better choice for an indicator of forest fragmentation.

The results here, along with the analysis for variability indicate that for "thematic" mapping of spatial metrics, the smallest window sizes should be avoided, if the resulting pattern should be compared with metrics from other data sources. For the catchments, the fragmentation metrics of PPUN_B and the Matheron index have higher rank correlation at 4800m window size, than at 2400 or 9600m, thus a window size of around 5km seems appropriate for mapping of forest structure. In terms of pixels that is 50*50=2500 at 100m resolution or 25*25=625 at 200m resolution.

In general, the metrics are seen to behave very differently in the different regions, administrative as well as catchments. Local circumstances rather than general scaling properties dominate, and for the diversity metrics a north-south gradient of values is visible.

4.6 Discussion of results from application of Moving-Windows

In this section, the findings from the previous section are summarised, following the structure of the results section. It is here intended to interpret the results and put them into a broader context. Then the methods used are evaluated.

4.6.1 Evaluation of results

1) Responses to window size

The examination of the metrics' response to window size show a similar behaviour for the two data sets, even though the structural metrics Matheron index and PPU have markedly different numerical values, i.e. higher values for FMERS data. Also the compositional metrics SHDI and SIDI have higher values for FMERS, confirming that (according to this map) forest patches are smaller, more scattered and the classes more interspersed. With one exception (PPUN_B which initially increased for the FMERS data) the metrics values increased or decreased steadily with window size. The diversity metrics and the SqP metric constantly increase with window size, the other metrics constantly fall. Patch count metrics are known to vary with window size, but the normalisation proposed here seem to restrain that. A remarkably good agreement was found between the forest cover-background patches curves for the two data sets. Also the SqP metric vary with window size, an effect that is so far not accounted for, but quantification of the influence of extent (working with controlled/artificial landscape maps) could prove useful.

The changes in metrics value, variability and correlations with extent is in line with the observations made by Riitters *et al* (2000), of the changing fragmentation related characteristics with increasing window sizes. The relatively rapid changes in metrics values and correlations at small window sizes point to the relevance of the observation by O'Neill *et al* (1996), that the window/extent must be at least 2 to 5 times larger than the (forest) patches in order to give representative values.

2) Variability and autocorrelation

Regarding standard deviation for an output cell and its eight nearest neighbours (3*3 window), examination of variability and autocorrelation of the metrics show better agreement between the st.dev. values from CLC and FMERS data, than for the metrics values *per se*, in terms of response to changing extent (Figure 4.16 and Figure 4.17 are very similar, compared to the response curves in Figure 4.11). For the cover metric, window sizes with low standard deviation correspond roughly to sizes with high autocorrelation as expressed with Moran's I. The latter however show more distinct peaks and troughs, allowing recommendations for making maps of forest structure, and will surely provide more characteristic profiles of forest structure in separate and different study areas. The large area of study makes it hard to distinguish any characteristic forest/landscapes from the local variability values, as it was otherwise intended, for selection of appropriate window sizes for M-W based maps of forest structural metrics. Identification of such characteristic scales will probably require studies by region or stratum and using higher resolution data as well.

3) Relationships between different metrics from one data source

Calculation of the correlations between the different metrics for each data type and (geographic) window size provides interesting insight into the behaviour of the metrics, as well as of the scale of structure and processes in the landscape, and the similarities and differences between the two data sets. Given the large number of observations (output cells) even for large window sizes, almost all correlations are significant. The development of correlations between the metrics of cover and fragmentation (Table 4.17 and Table 4.18) show that the same combination of metrics cannot necessarily be used to describe an area at different resolutions or window sizes. The two diversity metrics SHDI and SIDI are so highly correlated that very little extra information is provided by reporting both. If a group of metrics to represent landscape properties should be selected, it could for instance be, for window size 4800m: cover, SIDI and the Matheron index. They represent forest fraction, composition and structure and are only weakly correlated (Table 4.11 and Table 4.12).

4) Correlations between similar metrics from different data sources

The correlations between the values from the two different image types generally increase with window size. This is to a smaller extent due to gradual elimination of possible bias from a geographic co-registration of the images that is not sufficiently precise[21]. The increase also reflects a gradual softening of the MW-output images, as small areas with special structure (in one of the image types) become integrated with their surroundings. Across scales, the cover metric shows the best agreement between the two map types, followed by the patch count metrics and the Matheron index. The diversity metrics and SqP show low correlations even at large window sizes, the former reflecting large-area differences in (classification of) forest composition that make it hard to substitute on map type with the other, the latter showing that the Matheron index is to be preferred for comparisons of forest fragmentation etc. between data sources.

5) Comparison of regionalisation approaches

Extraction of metric values for subsets of the study area in the form of catchments and administrative regions proved interesting and illustrative. At all the window sizes used,

[21] Here the image were co-registered to the Corine projection using the definitions from the image processing software (ENVI) – perhaps for large areas and different data sets as in this exercise, GCP-collection and pixel-to-pixel comparison is needed.

average metrics values clearly varied. The set of regions (13 4th order catchments and 12 administrative regions) was not large enough to identify north-south or altitude controlled trends, but it was possible to explain extreme values with properties of the maps and the geographic reality behind them. The region approach allowed calculation of the new forest concentration (FC) metrics, which turned out to be a good descriptor of the general forest structure, but it could also apply to other land cover, vegetation or habitat types or even urban classes or population concentration. The metric is well suited for graphic reporting in the form of FC-profiles. A hierarchical structure for reporting the initial metrics and the FC values in table form seems useful. Regressions between the two data sources was performed within the regions and results for the SHDI and Matheron metrics presented. As expected low correlation values were found for small windows, and higher but varying values for larger windows (with fewer pixels to supply values). The M index on the average showed a higher correlation coefficient than for similar window sizes for the entire area, especially within the catchments. Calculations of variability within the regions showed little differences, and the pronounced differences found were related to data type rather than to region type. Thus, the recommendations given by amongst others Apan *et al* (2000), Paracchini *et al* (2000), Vogt *et al* (2003) for use of catchments/watersheds or (more locally) headwaters as reference units for landscape metrics could not be confirmed in this study.

4.6.2 Evaluation of methods

Concerning the methods used in this chapter, the use of special IDL-scripts to carry out the M-W calculation proved practical, as it has been possible to modify the scripts after initial calculations, for instance to exclude background pixels from calculations of forest diversity and to output also the number of background patches. The process of getting from input images to final statistic was however quite tedious, as illustrated in Figure 4.9 on page 128. Work is ongoing to make scripts that output the M-W results as binary map files in Idrisi raster format – this will also save disk space, as the current comma separated text format can result in very large files for small window sizes[22]. The creation of thematic maps from Corine Land Cover was simple and straightforward, the considerations mostly being on which classes to include and how to label them (Table 4.1).

Implementing and using the M-W approach has provided many useful results and insights, and highlighted some general considerations and problems related to the calculation of spatial or landscape metrics. For instance whether or not to include background pixels in metrics calculations (typically for the 'total number of pixels in window' parameter) or how to handle non-forest land. In this implementation no distinction was made between background and 'other land', and that partly explains the decrease in forest cover percentage with increasing window sizes (as water/sea became included in total window area). The definition and use of the PPUN and PPUN_B metrics for characterising patch density has proved feasible and these metrics are used along with the structure and compositional metrics in description of the total landscape structure. The results, as expressed in the appearance of the output maps and the extent-variance curves confirm the observations by Eiden *et al* (2000) that results vary strongly with window size and that too large windows smooth out potentially useful information.

The creation of scaling profiles or *scalograms* for metrics following window size has proved a useful tool for the understanding of scale (or in this chapter rather *extent*) effects on spatial metrics values. Also calculation and graphical illustration of variance and autocorrelation of the M-W outputs has helped in understanding the effects associated with this approach. Woodcock and Strahler (1987) proposed that graphs of local variance in images as a function of spatial resolution may be used to measure spatial structure in images. Here the objective was to measure spatial structure of maps of spatial metrics, and the results were not as distinct

[22] Output as Idrisi images is possible in the latest version of Fragstats for Windows, where M-W has been implemented, although with step fixed at one pixel, which results in long calculation time and large output files. The software can be downloaded for free from: http://www.umass.edu/landeco/research/fragstats/fragstats.html (accessed 15/11 2003).

as in the examples used (ibid, figure 2 and 4), and for this type of data, graphs of extent versus autocorrelation seem to be more useful. Plots of the coefficient of variance, a normalised value, against window size seems to be more informative than plots of standard deviation against window size, as the former approach produces more distinct response curves (compare Figure 4.16 with Figure 4.18 and Figure 4.17 with Figure 4.19). The values of Moran's I were calculated in Idrisi, and it might save some time, files and space if it becomes integrated in the IDL-scripts that provide the metrics values.

Regression between images at the pixel level, in order to test agreement between calculation approaches (here: choice of input data) turned out to be simple and fast, with most of the work load lying in the preparation of spreadsheet files for creation of the graphic representations. The regressions were preformed using forest (presence) masks, following the "OR" approach, in order to make sure that all possible forest cells/windows were included in the calculations, even if some of them have zero values. It was assumed that use of the "AND" approach would be too restrictive, though it would be interesting to compare results derived with these two approaches.

The extraction of spatial metrics values for administrative regions and catchments was straightforward, following standard GIS and image processing techniques. This was also done for the creation of forest concentration (FC) profiles and hierarchical tables for reporting the values at different levels, in this case hydrological, but it could also have been administrative levels. The combination of metrics calculation within M-Ws and reporting of average and variance values for physical or administrative regions makes it possible to eliminate the influence of region size, which would for instance make patch count and richness metrics less useful. The agreement between the data sources within the study area at region level was examined using rank correlation, which proved useful in distinguishing metrics and window sizes suitable for comparison (in the form of thematic maps).

In this chapter, some interesting results for the structure of the forest landscape of the study area have been found, especially with regard to indicators for reporting at regional level, and most of the methods that were introduced and proposed in relation to M-W analysis of landscape structure have proven feasible.

4.7 Conclusions – implications for forest monitoring

The CLC dataset appears to be a useful base for a forest map at 100m pixel size, with distinct forest patches and a realistic distribution of forest types following terrain and climatic gradients. The FMERS dataset give a somewhat different picture for the sub-continental forest map at 200m pixel size, but the results here show good agreement with the CLC map for basic spatial properties such as forest cover and concentration and reasonably good agreements for structural properties such as Matheron fragmentation index and the PPUN metric.

Working with two different data sources, a suite of spatial metrics and a number of different window sizes has made it clear that, there are no obvious 'best' choices of metrics and window sizes for summarising and illustration forest structure and diversity. The selections must depend on the properties of the input data (particularly spatial and thematic resolution) as well as the purpose of the M-W analysis (analytical, illustrative or auxiliary to further image processing). Then inspection of the extent-variance curves and of the correlations between metrics values can help the user to choose the metrics images with the highest information content and least redundancy.

The application of M-W methods could be seen as a way of addressing the MAUP as it appears in the use of different reference units for reporting of landscape metrics. At least for production of maps of the metrics, the potentially distorting effects of region size and shape are avoided. The grainy or edgy appearance of the outputs at large window sizes could be avoided, if the results were smoothed following the approach described by Eiden *et al* (2000) or produced with a software similar to Fragstats for Windows, where the step of the window is equal to input pixel size.

In summary, the set of methods described here provide an approach for assessment of structural and compositional properties of forests over large areas from medium-resolution satellite imagery (100-200m grain size), comparison between regions and monitoring of environmental conditions, given the availability of regularly updated images or maps. In the following chapter, a thematically detailed data set on land use-land cover delivered in vector format will be compared with satellite land cover maps at a higher spatial resolution than used here, namely 25 metres. These satellite data based maps will represent the 'monitoring' approach, in contrast to the 'mapping' approach of the Danish Area Information System and the Corine Land Cover database.

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5 The influence of thematic and spatial resolution on metrics of landscape diversity, structure and naturalness – an analysis of Land Use and Land Cover data from Vendsyssel, Denmark

5.1 Introduction

In this study, the objective was to compare different land use and land cover (LUC) data from a public service provider, the Danish Ministry of the Environment, and assess their usefulness for calculation of spatial metrics at different spatial and thematic levels, for use in a specific study area. The results were also compared with metrics derived from the Corine Land Cover (CLC) database. Information on terrain and geomorphology was used to relate metric values to the physical environment and an integrated spatial index for characterisation of landscape naturalness and impact of human activity was evaluated.

A similar suite of spatial metrics as in the previous chapter was used, with values calculated for three different data sources, and three thematic levels. The extension of scope from forest to landscape called for minor changes and additions. The concept of Hemeroby, which was introduced earlier as a measure of disturbance or land use impact was implemented in the present study, under the assumption that this can be quantified and assessed through interpretations of land use data. The moving-window application was used as an integrated tool for the analyses, this time with a specific application in mind, namely characterisation of forest and landscape structure for an Internet based atlas of cultural environments, with the northernmost part of Denmark as the test area. The forests were placed in a landscape context and metrics of forest structure related to metrics of landscape structure. So the current work was also intended as an investigation of whether spatial metrics calculated from land use data can serve as indicators of valuable cultural environments. A minor range of possible sizes of the moving windows (corresponding to the ecological term extent) was tested, and the relation between the metrics values from different sources for different window sizes was evaluated, in order to see *where* agreements between different data sources could be found.

5.1.1 Background – a cultural environment project

The cultural environment is in general seen as a third dimension of the environment, along with protection of animals and plants and prevention of pollution (Schou and Handberg 2000, Møller 2001). The concept of *the* cultural environment is related to the cultural and historical aspects of the physical surroundings, while the individual cultural environments are geographically delimited areas that reflect important features of societal development (Schou and Handberg 2000). A 'cultural environment' can thus mean an area where monuments and objects form *part of an integrated whole.* In Denmark and the other Nordic countries, new proposals for protection orders give much more priority than only a few years ago to how single objects can be preserved as part of a functional landscape context, and how this context can be maintained for posterity (Møller 2001, Møller et al 2002, Fry et al 2003). Cultural environments may be in towns and urban areas, in the agricultural landscape or in forested and other uncultivated areas. Thus, cultural environments have become a theme in landscape research and planning during the last few years. Building of basic knowledge and development of methods that must lie behind the cultural environments have however only taken place to a small degree (von Haaren 2002, Fry et al 2003). In Denmark, the Forest and Nature Agency has been working on providing guidelines for selection of valuable cultural environments (Bach et al 2001, chapter 4.2: Land use in Denmark), following a decision by the Danish parliament in January 1996, to increase the protection of the cultural environment.

The current project, hosted by the University of Southern Denmark (SDU), aims at providing Internet based and cartographically illustrated access to knowledge about cultural environments, so it has also been termed 'creation of a Digital Atlas of Cultural Environments' (DACE). The project will primarily establish this for the central parts of

Vendsyssel in northern Denmark, which has been chosen as test area. Acquisition of historical map information will focus on the two shires Børglum and Dronninglund, see Figure 5.1, while more general efforts will focus on development of methods for data handling and selection and for regionalisation in the landscape. The projects will form the basis of continued research, for selection of cultural environments and for issues of general cultural and historical interest[23].

Amongst the objectives of the DACE project is to evaluate whether individual cultural environments also have special environmental and/or recreational qualities, and it has been proposed that these could be measured in terms of diversity and landscape structure. Also modelling of forest cover in historic and pre-historic time is included, to facilitate models of settlement and former land use – and to aid planning of afforestation[24]. A need has been identified for indicators of landscape structure and means of transferring these between different map types (Ejstrud 2003). This is in line with the objectives of this thesis, so it has been obvious to apply the methods and software already developed here to the data and problems of the DACE.

[23] A description (in Danish) of the project, application text, methods etc. is found at http://www.humaniora.sdu.dk/kulturmiljoe (accessed 3/3 2004).
[24] Official Danish policy is to increase the forest cover from around 11% in 1989 to about the double area within a 'tree generation' i.e. 80-100 years. Ref. http://www.sns.dk/internat/dnf-eng.pdf (accessed 12/12 2003), see also Jensen (1999).

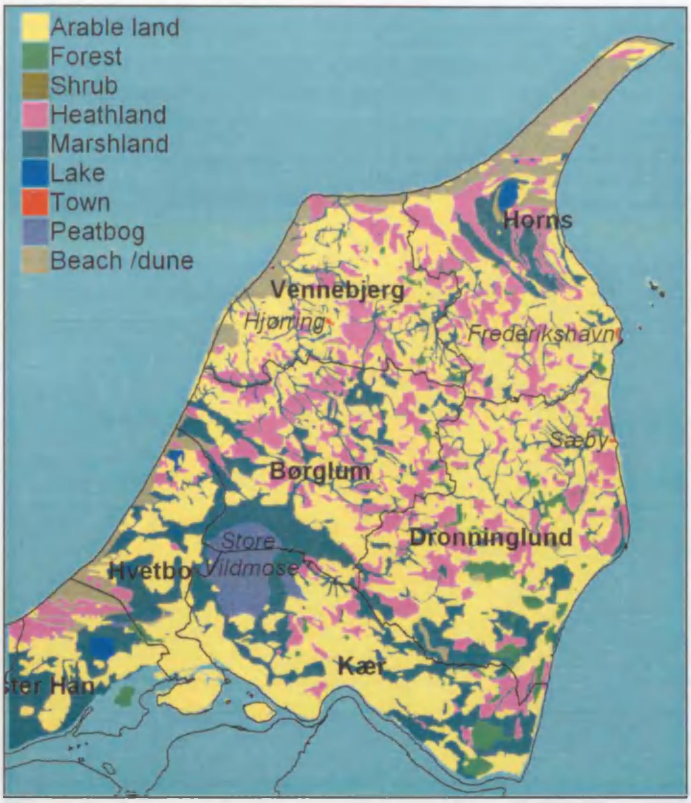

Figure 5.1 Land use in Vendsyssel around the year 1800 from Videnskabernes Selskab's (Asssociation of the Sciences) map of Denmark with shire borders. Shown are also market towns and Store Vildmose. The disagreements between the raster map and the vector with the current coastline are due to subsequent erosion, land uplift and land reclamation. The extent of this map is 78*90 km, corresponding to the box in Figure 5.2.

5.1.2 Background – the study area

Vendsyssel was chosen as test area for the DACE project because of the richness of different landscape types with very different land use history within a limited area, and thus it is also the study area of this chapter. An example of historical land use data is shown in Figure 5.1. The text in this section, which provides some background for the landscape analysis done here, is based mostly on the 'Book about Denmark' (Sehested and Wulff 2003), which is compiled by the editors of the Danish National Encyclopaedia and published by the Danish Ministry of Foreign Affairs[25].

[25] The section about Northern Jutland, which is written by the geographers K. M. Jensen and H. Kuhlman, is available in edited form at www.denmark.dk; select THE DANISH STATE > Nature & Environment > The Cultural Landscape (accessed 23/6 2004).

Vendsyssel is the northernmost landscape in Denmark, consisting of the north-eastern, main part of the Vendsyssel-Thy island, which again is normally seen as the northern part of Jutland, the rest of it being a peninsula which forms an extension of the North German Plain that is geomorphologically similar to that region. Between the two parts of Jutland runs a long, narrow strait, the Limfjord. Vendsyssel's position is shown in Figure 5.2.

Figure 5.2 Subset with Denmark from the EU-wide CLC map, following the standard CLC legend/palette. The base-map for studies of Vendsyssel is marked by the red box (size 78*90 km).

Geologically Vendsyssel consists of glacial and marine deposits, with moraines, two distinct levels of plains (*Yoldia*[26] from the 'Baltic Ice lake' ca. 14000 BP and *Littorina*[27] from the post-glacial transgression 6-7000 BP) with marine sediment and recent coastal formations as

[26] After the lead fossil, the bivalve Portlandia (formerly Yoldia) Arctica.
[27] After the lead fossil, the snail Littorina littorea.

the dominating landforms, see Figure 5.3 below. The coast mainly consists of sandy beaches with small sandy cliffs behind them. In places, however, promontories formed by ice age sediments and limestone jut out onto the coast as can be seen at Lodbjerg, Hanstholm, Rubjerg, Hirtshals and Frederikshavn. Huge dunes, some stretching up to 7 kilometres inland, have been formed by sand blown up from the coast. The dune belts are dominated by large, dark conifer plantations, intermixed here and there with white dunes, heaths and heather bogs. The dune zone is generally sparsely developed, and has some of the largest undisturbed natural areas in Denmark, but large holiday housing developments have sprung up since 1930 wherever nature conservation regulations and shifting sands have allowed. The Skagens Odde spit, with Denmarks northernmost point at the end, is one of the most remarkable dune regions in the area, not only because of its extent (it stretches 30 kilometres out into the sea), but also because of its huge migrating dunes. A prime example of this type of dune is the sparsely vegetated Råbjerg Mile which is still very active, moving eastward at a speed of app. 20 m/year. More fertile cultivated areas are however found in the strictly controlled "dune desert", particularly towards the Kattegat and in the reclaimed lake Gårdbo Sø.

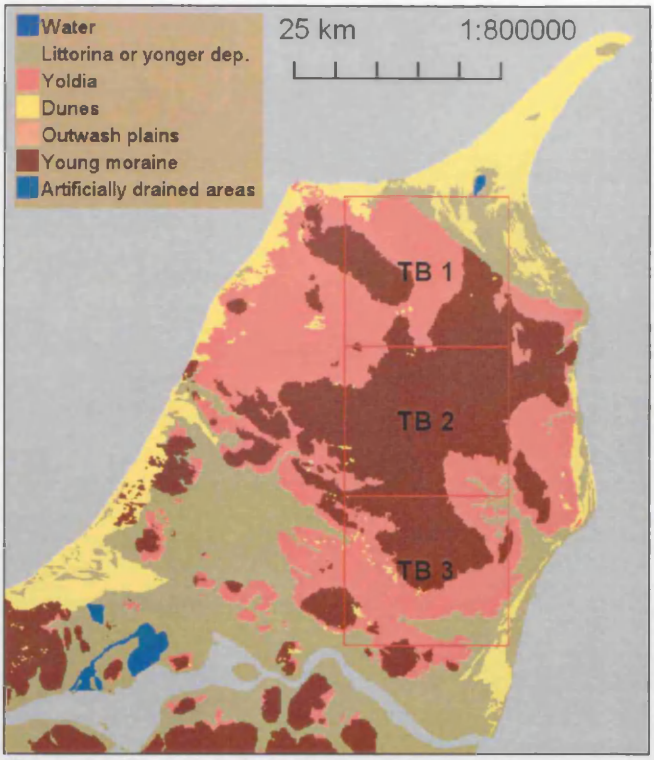

Figure 5.3 Geomorphological map of Vendsyssel, extracted from national dataset copyright Danish Institute of Agricultural Sciences. The boxes show the three test areas for test of metrics values and scaling behaviour (see below and methods section).

There are other unusual terrains and culture landscapes in Vendsyssel. The extensive, low-lying marine plains created by the Littorina Sea stretch from the dune belts of the Jammerbugten, along the Limfjord to the Kattegat coast. Since the Iron Age, several bogs have appeared on the plains north of Aalborg. The most important example is the approximately 100 square kilometres raised bogs known as Store Vildmose. The peat layer in this bog is up to 5 m thick. At the beginning of the 1900s, Store Vildmose was bought up and redeveloped by the State. It was then partly drained and marled after peat-cutting. Grass fields were sown for the rearing of disease-free cattle; the area was later divided into plots and sold off and long rows of farms were built. Other areas of the moor have been set aside as a nature reserve.

Central Vendsyssel is higher than the Littorina plains and is equally divided between high terminal moraine formations, together termed Jyske Ås (Jutland's ridge) and Yoldia flats consisting of sea deposits, mainly sandy. The highest point, 'Knøsen' at the southern end of the ridge is at 136 m above sea level. In both areas the soil is sandy and farming is hindered by drifting soil, despite the use of winter crop cover and the many windbreaks that have been constructed. Large streams such as Uggerby Å and Voers Å have worn away deep trenches in the terrain during the isostatic uplift, which has taken place since the ice age. Since the Stone Age, the sandy Littorina plains have risen between 4 and 10 m, and the area has a number of littoral cliffs formed during different geological periods by the action of the sea. These are generally found in the west and only to a lesser extent in the east. The old farm buildings are seldom grouped in villages, but are instead scattered round the area on both types of terrain. Ever since the 17th century, single farms have been much more common in Vendsyssel than elsewhere in Denmark (Hansen 1964). This is reflected in the isolated locations of the churches built during the Middle Ages. Numerous small towns, known as 'rural towns' have appeared during the 20th century to serve the scattered countryside population. These are generally found by cross-roads and near the railway stations, most of which have since been closed down.

5.2 Objectives

When spatial metrics are used for mapping and selection of cultural landscapes, it is inevitable that specific questions arise over their implementation. The overall question of special relevance to the current project is "can spatial metrics yield a significant contribution to descriptions of areas of interest?" Furthermore, following the needs of the DACE project and the availability of a comprehensive data set of land use, land cover and supplementary data, providing information on a number of forest and other land use/land cover types in the open land, it has been possible to formulate some specific research objectives and questions:

1) Examine 'thematic scaling properties' of the current data.
    a) How does level of detail (thematic resolution) affect the values of spatial metrics?
    b) How does the inclusion/exclusion of internal background (matrix class) affect the metrics values?
2) Examine spatial resolution properties of current data set.

a) How does changing grain size influence metrics values?

b) Is there an optimal spatial resolution (grain size) or interval of useful resolutions, for characterising the elements of landscape structure that are relevant to the cultural environment? If yes, can a method be described that is reproducible for similar data sets?

3) Examine comparability of data sources for landscape characterisation.

   a) What causes the differences in average metric values between the different data types?

   b) Why do some data types and some metrics agree better than others, and differently at different thematic resolutions?

   c) Can metrics values from one data source be used to predict metrics values from another (e.g. is there a link between forest diversity in vectorised land use maps and in remote sensing based land cover maps)?

4) Describe possible agreements and disagreements between metrics values from different levels of thematic resolutions and relate the values to the nature and appearance of the data of the different resolutions.

   a) Is the relation between the different thematic levels the same for different data types, or should these levels (and the metrics extracted from them) be interpreted differently?

   b) Can metrics values at one thematic level be used to predict metrics values at another, e.g. do these thematic maps provide a link between for instance landscape diversity and forest diversity?

5) Describe the influence of terrain features on spatial metrics values within moving windows.

   a) Does spatial metrics values depend on the terrain features elevation and slope?

   b) Are significant differences found in metrics values when the test area is stratified according to geomorphological types?

6) Develop methods and/or guidelines for description of landscapes using land use/land cover data.
   a) When moving-windows are used to create maps of landscape properties, what (combinations of) metrics and window size(s) are most useful for characterising cultural environments?
   b) Do the emerging patterns of spatial metrics show any agreement with the location of exicting appointed cultural environments or protected natural areas?
7) Development of an 'Integrated Hemeroby Index' and creation of comparable maps of Hemeroby based on averaging disturbance/degradation factors assigned to each grain of the maps based on land use categories.
   a) What is the agreement between Hemeroby index values from high- (the Danish AAK) and low-resolution (Corine) land use data respectively?
   b) How should the Hemeorby index images be processed in order to give the best overview of human influence on the landscapes and/or be used ?

Expected results and outputs from the spatial metrics calculations and subsequent image processing and statistical analysis included:

* Statistics on proportion of class types – for description of the input data sets.

* Values of spatial metrics for each test block at different resolutions/grain sizes; derived from those results response curves for each test area, which will allow comparison of values across scales.

* Results from MW-methods applied to maps of the entire test area, including regressions between data sources, average, minimum and maximum values for different data types, leading to choices of suitable window size(s).

5.3 Data

As already stated, data of various origins were used for the studies described in this chapter. Early in the cultural environment atlas project, it was decided to use a standard 'base map' for all raster data covering Vendsyssel. The grain size should be 25m or a multiple hereof, the projection UTM 32N and the datum WGS84. The size of the base map is 78*90 km (east-west and north-south) and the upper left corner in the UTM coordinates are 522,000E and 6,405,000N. The outline of this base-map area is shown in Figure 5.2, and it is also this geographic subset that is used in Figure 5.1 and Figure 5.3.

The Corine land cover (CLC) data are described elsewhere in this thesis (section 4.3.2.2) so here only the different AIS data are described in some detail.

5.3.1 The AIS data

The Danish Area Information System (AIS) was developed during the last half of the 1990's, on initiative from the ministry of the Environment, partly by integrating existing geo-referenced information from various public services, and partly by mapping from satellite images and aerial photography (Mielby 1999, Groom and Stjernholm 2001). The AIS represents an effort to bring together geo-referenced, environmental data that were formerly stored with different public administrative instances (state and counties, with themes such as property, agriculture, environment etc.). One of the reasons for creating the AIS was the growing interest in monitoring terrestrial environments, with management applications such as nature conservation and protection in mind (Groom and Stjernholm 2001, Weiers et al 2002). The sources of data for the AIS are thus vector maps as well as raster imagery. In particular, images from the Landsat satellite have been used, as they have recently become cheaper, and thus land-cover data can be updated with relatively low expenses (Reichhardt 1999). The intended reference year for EO data in the AIS is 1996 (Mielby 1999), although in practice images from a period around that have been used. Denmark is covered by seven Landsat scenes of 183*170 km each. A total of 20 images from the period 1992 to 1997 have been acquired, and combined to form an image archive, with all parts of the country covered by at least two images (Weiers et al 2002, table 1). During image acquisition it was ensured that the images were from two different times of the year, in order to use vegetation dynamics for the purpose of mapping natural and agricultural land cover.

A land cover map (LCM) has been derived from the satellite image archive, through an iterative 'supervised image classification', with assignment of pixel to land cover classes through the maximum likelihood algorithm (Nielsen et al 2000a, pp. 31-39, the method is also explained in Weiers et al 2002, figure 1). The LCM covers the entire Danish territory and is delivered as a raster image with pixel size 25m, in the UTM projection (zone 32N). In addition to the LCM, a product termed Land Cover Plus (LCP) is produced and made available. LCP is based on the same image data and subclasses that were used for deriving the final LCM classes. The thematic resolution of the LCM is 12 classes: "unvegetated" and different cultural and natural vegetation types. The LCP however is the result of an interpretation of as many subclasses as possible. This LCP interpretation has been done separately for seven different sections, roughly corresponding to different Danish nature/land use regions (see map in Nielsen et al 2000a p. 32). For each of seven zones, a different selection of spectral classes are assigned to land cover classes with a satisfying statistical agreement. Therefore the LCP have a varying number of classes for these regions, for Northern Jutland amounting to nineteen. The LCM and LCP classes are listed in Table 5.3. For the region including Northern Jutland, the LCP approach made it possible to distinguish five additional forest classes, including spruce plantations and thin evergreen forests, which are significant landscape elements in this region (see also Table 5.1).

At the centre of the AIS is the land use map, known as AAK[28]. It is based on topographic maps at 1:10,000 and 1:25,000 and exists in vector format, as blocks of 25*25 km; altogether Denmark is covered by 118 of these blocks[29]. The land use classes in the AAK product are

[28] From Danish: Areal Anvendelses Kortet (The Land Use Map)
[29] The blocks are available for download in MapInfo table or Arc/Info shape format at http://www.dmu.dk/1_viden/2_miljoe-tilstand/3_samfund/ais/4_Download/download.htm (accessed 7/10 2003).

partly derived using the satellite images, through (manual) use of LCM and LCP for labelling for nature and forest classes. The forest areas in the AAK are outlined from topographical maps, with the forest type defined from the satellite based LCM. Actually, the older, printed maps have two categories of forest: broad-leaf or coniferous, while newer vector-based maps have just a single forest category, a fact that underlined the need for satellite based land cover mapping (Groom and Stjernholm 2001). Thus, the satellite data has been used to determine nature LC classes in the AAK, not the other way around. The AAK data are well suited for display as maps at the scale 1:10,000, and are as such useful in detailed planning applications. For raster data this corresponds to pixel sizes of 5 to 10 meters. A direct comparison of the two data sources above reveal that the AIS vector based maps show classes that cannot be distinguished by satellite RS – compare Table 5.3 and Table 5.4 - while the LCM and LCP maps show (nature) classes that are very hard and time consuming to map in the field (thus using RS as a monitoring tool). More detailed information of the data sets of the AIS can be found in the meta-data catalogue (Nielsen et al 2000b).

The CLC spatial database is described elsewhere in this thesis, the data used here is from the 250m image data, for a further description of the data see EU – DG AGRI and others (2000, chapter 1.2), Büttner et al (2002). Neither the CLC nor AAK are land use maps in the strict sense that they show only the human use of the land surface along land register borders, they are to a large extent based on interpretation of satellite images, partly through classification of surface and vegetation types, thus the analyses here are not directly confronting land use with land cover maps, rather comparing two different approaches to creation of LUC maps for environmental management. The four available map types are compared in Figure 5.5, along with the appearance of the different thematic resolutions to which they have been re-classified (see section 5.4.2).

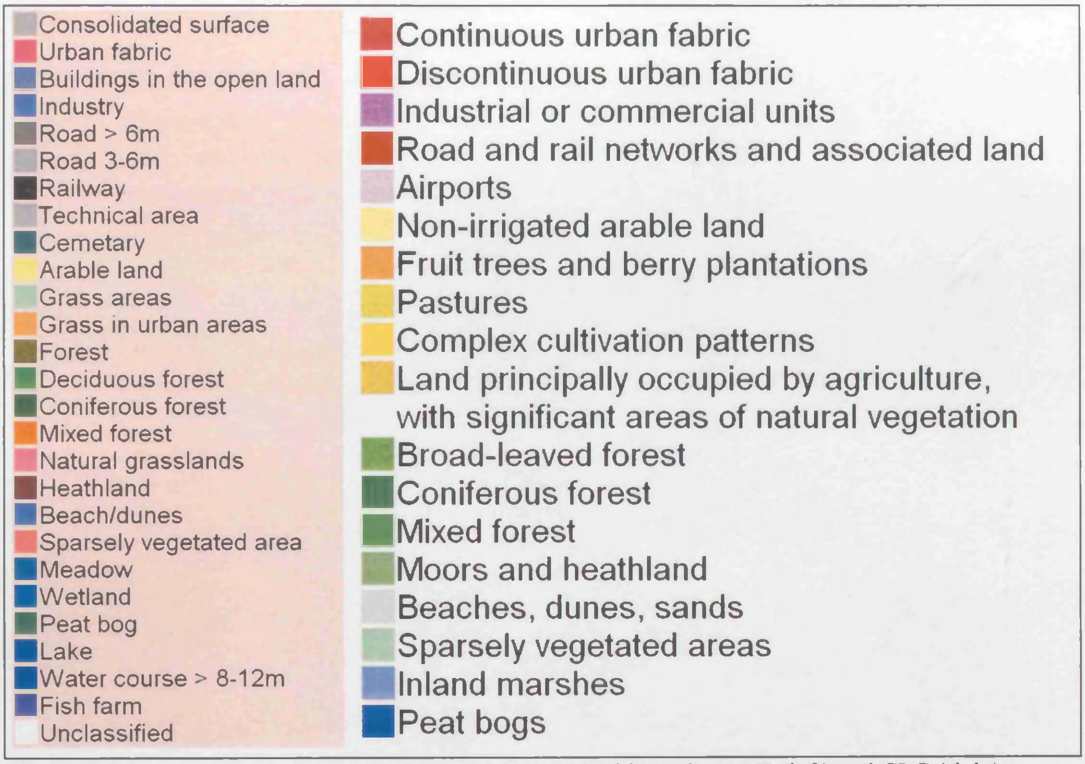

Figure 5.4 Legends for land use – land cover data used in this study, AAK (left) and CLC (right). Only the relevant classes are included, i.e. those observed within the study area.

These data sets of land use/land cover data will be used as background and context data for the DACE described in section 5.1.1. For delineation of protected areas and areas of special cultural and historical interest, data from the regional administration, Nordjyllands Amt (county[30]), has been used. Interactive maps from the region are made available to the public at the web site: http://www.nja.dk/Serviceomraader/Regionplan/KortOgLuftfoto/Kort.htm (accessed 13/10 2003, in Danish). The maps can be viewed and printed, but not (yet) downloaded as data layers in GIS-formats. Some of the county's data have however been supplied to the AIS and form part of nation-wide coverages.

[30] Denmark currently has three administrative levels: national (state), regional (counties) and local (municipalities).

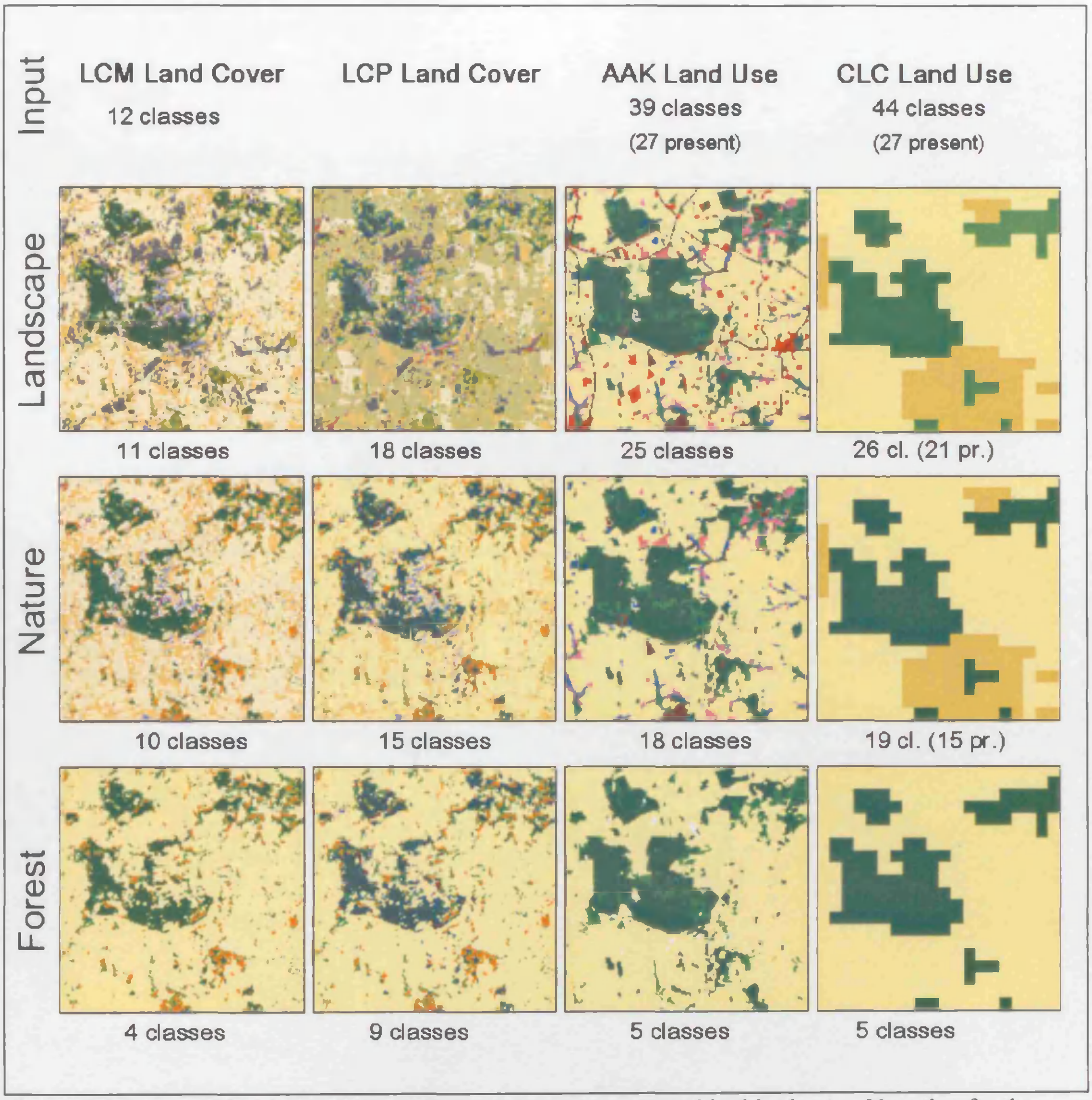

Figure 5.5 Subset of 5*5 km from the different image data sets used in this chapter. Note that for the land use data sets, not all classes are present in the study area; for the CLC-Corine data due to the location of the area, for the AAK data because some classes are very rarely used. The number of classes stated above the images is actual land use/land cover classes, excluding the "background/sea class". Upper left corner in UTM32N: E 570,000m, N 6,353,000m. The large object is Pajhede skov (forest) with strongly sloping terrain and a highest point of 112m, to the right is the small village Brønden.

5.3.2 Elevation model and supplementary data

A digital elevation model (DEM) has been acquired from Kort og Matrikel Styrelsen (KMS), the national Danish provider of geodetic services, maps and cadastral information, where it is named the DHM (Digtal Højde Model). The DHM was derived from contour lines from 1:50,000 maps, at 5m intervals. The information was delivered as point data in vector format, with points placed at the intersections of a 50m grid. For this study, the data was transformed (interpolated) to a raster grid with 25m grain size. The precision as stated by the supplier is better than 2m, however for strongly sloping terrain up to 10-20m. Other supplementary data layers include:

- Land use approx. 1800, digitised from Videnskabernes Selskab's map of Denmark (1:120,000), see Figure 5.1.
- Geomorphology, from Danish Institute of Agricultural Sciences (1:200,000), see Figure 5.3.
- Subsoil (underground/base) map from GEUS, Geological Survey of Denmark and Greenland (1:200,000).
- Danmarks Digitale Kortværk (digital map collection of Denmark). Digital versions of topographic maps, from KMS, used for illustration (see for instance Figure 5.7).

The above data have been transferred to raster format and transformed or re-sampled to UTM-32N projection with the WGS-84 datum.

5.4 Methods

The methods described and applied in this chapter include data extraction and aggregation, calculation of spatial metrics on image subsets and using moving windows, as well as analysis of the sensitivity of this particular data set to scaling of the map data in raster image form. In contrast to chapter 3 where a binary forest-non forest map was used, and chapter 4 where two forest maps with 5 and 6 forest classes were compared, LUC data with between 5 and 27 classes were used here. Concerning the image processing, the IDL-scripts used for the moving-windows application in chapter 4 could be used with only slight modifications, along with some routines in the GIS software packages Idrisi and MapInfo. The output tables and images are used for display and comparison of their relation to other landscape, terrain and cultural features. Fragstats for Windows was used for extraction of patch count metrics for the test blocks. The spatial metrics are calculated for each test block, and used for creation of grain-scalograms for the different areas, and for comparison of 'base values' for the different data sources. Finally, Idrisi MapWalker (Hovey 1998) was used for fast creation of 'average maps'.

The set of images for metrics calculations, that was compiled from the input data, was of a quite manageable size: 24 images ranging from 4000*3600 to 180*200 pixels for the scaling analysis (3 'test blocks' * grain sizes), 9 images of 3120*3600 pixels (3 thematic levels*3 data types) and 3 images of 312*360 pixels (3 thematic levels for the CLC data), in sum 36 images for the M-W analyses and two images of 3120*3600 pixels for the Hemeroby assessment. The different processing steps however spawned a large amount of text files and images that could be combined in numerous ways, and all sorts of relations investigated, resulting in more text-files and spreadsheets. A central task in this study has thus been to select among possible analyses, judging which combination of input data would yield the most relevant and interesting results.

5.4.1 Creating base-maps and geo-referencing the data

The first task for compiling a coherent data set like this is making the layers fit, i.e. match spatially. All vector and raster data have been re-projected to UTM zone 32 N with the WGS84 datum, because this datum is implicit for the UTM projection in Idrisi (Eastman 1997, Appendix 2), and thus the conversion was necessary in order to make the raster data compatible with different (additional, ancillary) vector data. The AAK vector data were thus re-projected and then converted to raster format, through gridding by use of the Vertical Mapper module of MapInfo. The CLC, LCM and LCP maps were rectified using the rectification functions of WinChips (Hansen 2000). This step was necessary because these maps could not be re-projected in MapInfo, as this system does not allow nearest-neighbour re-sampling of raster images, but insists on using a built-in interpolation algorithm (which does not make sense with categorical data). The result of these processing steps was subsets of the above mentioned maps corresponding to the previously defined base map.

5.4.2 Thematic levels and re-classifications

As stated in the objectives (in particular points 1 and 4), a set of images at different thematic resolutions, covering the study area, were to serve as input to the spatial analyses. Three possible thematic levels were identified, which could be derived from all types of original data: these are "landscape", "nature" and "forest". For the AAK and CLC images, the thematic level "landscape" is the closest to simulating a land cover map from the land use data. The reason that more classes are assigned to 'background' for the forest maps is that the land class here should represent areas that can potentially be forested[31]. This is in line with GAP analysis approaches, where the amount existing vegetation types are compared with their potential distribution, as was done for the entire European area by Smith and Gillet (2000), using CLC data and maps of potential vegetation in Europe.

The extraction of 'nature type' relevant information (layers) means that it is possible to calculate contextual metrics describing the 'nature context' of potential cultural environments in agricultural areas. Before re-classification, and in order to get a first impression of the comparability of the data types, the amounts of forest types were calculated from each data type, the results are shown in Table 5.1. From there it appears that the CLC map generally underestimates the forest area and overestimates the extent of agricultural activities, which illustrates that this kind of LUC data should be interpreted with care. This over-representation is due to the effect of aggregation that makes small forest patches disappear in open land as do background patches in forest areas, an effect shown already by Turner et al (1989), and discussed in more detail in the following section. The effect is actually *not* observed in the subset used for Figure 5.5, because a subset with an above-average proportion of forest was deliberately chosen – in order to make a clearer illustration. Note that with higher resolution of the input (image) data becomes, the lower the proportion of the 'mixed forest' class, as the need for mixed classes decreases with increasing resolution (Goffredo 1998, chapter 2, Brown

[31] Which is basically all land surfaces in Denmark, except bogs, dunes, cliffs and other special landforms.

and Duh 2003). Visual inspection of the satellite derived images reveal a problem of confusion of the urban/infrastructure and unvegetated classes in the LCM and LCP, due to their similar spectral behaviour.

Class no.	Class description	LCM	LCP	AAK	CLC
0	water/unknown				
1	non-forest land	89.12	88.39	90.55	92.26
2	bush/forest	2.84	2.84	0.01	0.97
3	Deciduous forest	2.73	2.73	2.03	0.46
4	Coniferous forest	5.31	0.32	7.39	4.46
5	mixed forest		0.47	0.02	1.85
6	Spruce plantation		1.51		
7	thin needle-leaved forest		3.02		
8	Overgrown heath		0.64		
9	Recently cut forest		0.09		
	Total forest and similar	**10.88**	**11.61**	**9.45**	**7.74**

Table 5.1 Proportion of forest land cover types from different mapping sources. The classes correspond to the ones shown for the row of forest images in Figure 5.5. Data from entire base map area, background excluded, pixel size 25m.

It was not obvious whether the 'heterogeneous' agricultural classes of CLC, type 2.4 at level 2, should count as nature (as such area can contain some natural elements) or as clean agricultural blocks which would closer resemble the AAK. In this study however, it was decided to assign the class 'complex cultivation patterns' to the landscape matrix in the nature thematic image while 'land principally occupied by agriculture, with significant areas of natural vegetation' was assigned to a class of its own at 'nature' and 'landscape' thematic levels. Table 5.2 summarises the proportions of the land area of the base maps that contain the respective thematic layers, and Figure 5.6 illustrates the visual appearance of some results of the tentative re-classifications.

Percentage of total area	LCM	LCP	AAK	CLC
Forest	10.88	11.61	9.45	7.77
Nature	36.73	28.40	24.55	25.30
Landscape level 1	36.73	40.26	34.94	48.50
Landscape level 2	81.13	85.70	89.61	93.59

Table 5.2 Proportion of non-matrix and non-background (including all objects/classes of interest) for the different thematic resolutions and different data sources used here. Landscape level 1 denotes areas that are not strict agricultural classes (for CLC including the category of complex cultivation patterns (2.4.2), while Landscape level 2 denotes areas that are not urban, infrastructure or unvegetated classes, representing all permanently or seasonally vegetated surfaces. The reason that L2 fractions are relatively low for LCM and LCP is the relatively (unrealistically) large areas classified as unvegetated, for instance seen as the grey patches in Figure 5.5. Level 1 and 2 is only used here for landscape description, not as reclassified layers.

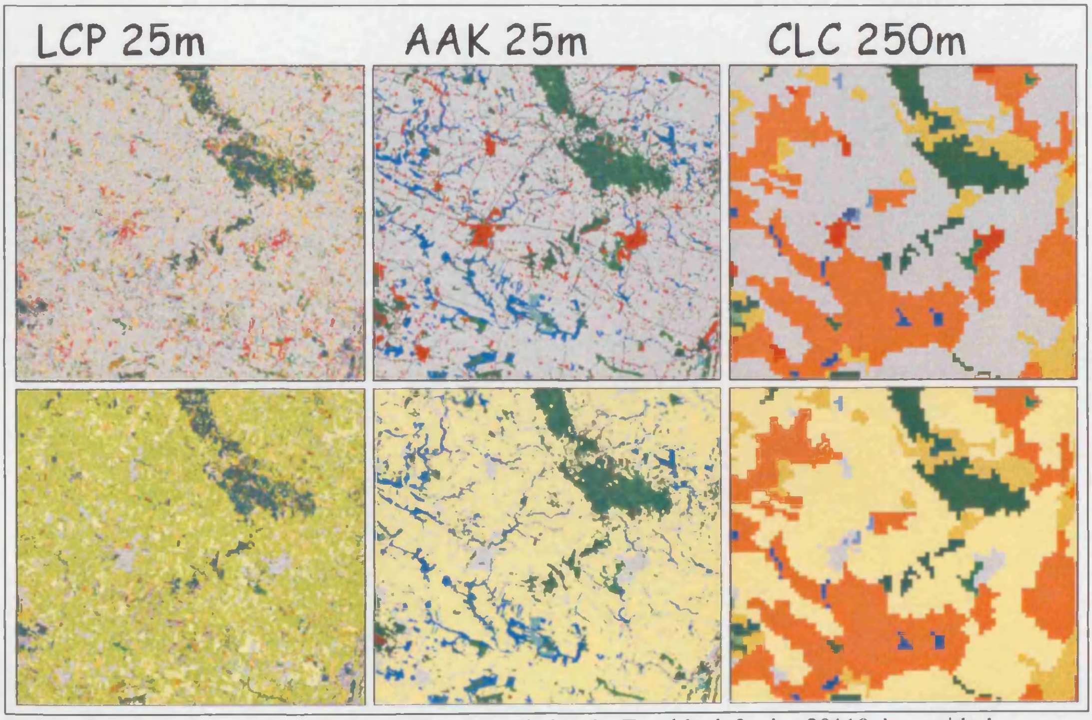

Figure 5.6 Tentative re-classifications into thematic levels, Test block 3, size 20*18 km, with the towns Hjallerup (left) and Dronninglund (right) and Dronninglund Storskov as prominent features (compare Figure 5.7). Although these images are based on the same data sets, extracted from AAK, the structure of the landscape is reflected in different ways when the selections "landscape" with agriculture as matrix – shown in light grey, top row and "nature" with arable and urban/artificial excluded – pale yellow, bottom row, are used.

It was chosen not to use the thematic level "Landscape 1" for further image processing and analysis in this study, as it would not be clear how this level differs functionally from the nature level. The names of the classes used in Table 5.2 constitute a very simple legend, but this is necessary in order to allow direct comparison of different image data sources. Still, this approach was found to allow display and evaluation of basic landscape structure.

The details of the nomenclature and re-classifications strategy chosen are listed in Table 5.3 to Table 5.5, and the visual appearance of the resulting images is seen in Figure 5.5 on page 201.

class/pixel no.	LCP/LCM classes	LCP_landscape	LCP_nature	LCP_forest	LCM_landscape	LCM_nature	LCM_forest
0	Unknown	**Background**	**Background**	**Background**	**Background**	**Background**	**Background**
1	Water	**Background**	**Background**	**Background**	**Background**	**Background**	**Background**
3	Unvegetated	Unvegetated	**Land**	**Land**	Unvegetated	**Land**	**Land**
5	Grass heath	Grass heath	Grass heath	**Land**	Grass heath	Grass heath	**Land**
7	Cropped/grazed	Cropped/grazed	Cropped/grazed	**Land**	Cropped/grazed	Cropped/grazed	**Land**
8	Meadow	Meadow	Meadow	**Land**	Meadow	Meadow	**Land**
10	Bush/grass heath	Bush/grass heath	Bush/grass heath	**Land**	Bush/grass heath	Bush/grass heath	**Land**
11	Bush/heather heath	Bush/heather heath	Bush/heather heath	**Land**	Bush/heather heath	Bush/heather heath	**Land**
14	Shrub/forest	Shrub/forest	Shrub/forest	Shrub/forest	Shrub/forest	Shrub/forest	Shrub/forest
15	Deciduous forest	Deciduous forest	Deciduous forest	Deciduous forest	Deciduous forest	Deciduous forest	Deciduous forest
16	Coniferous forest	Coniferous forest	Coniferous forest	Coniferous forest	Coniferous forest	Coniferous forest	Coniferous forest
18	Arable/rotational	Arable/rotational	**Land**	**Land**	Arable/rotational	**Land**	**Land**
21	Densely built	Densely built	**Land**	**Land**	-	-	-
28	Spruce plantation	Spruce plantation	Spruce plantation	Spruce plantation	-	-	-
29	Mixed forest	Mixed forest	Mixed forest	Mixed forest	-	-	-
33	Recently cut forest	Recently cut forest	Recently cut forest	Recently cut forest	-	-	-
34	Thin needle-leaved Forest	Thin needle-leaved Forest	Thin needle-leaved Forest	Thin needle-leaved Forest	-	-	-
35	Overgrown heath	Overgrown heath	Overgrown heath	Overgrown heath	-	-	-
37	Exposed	Exposed	**Land**	**Land**	-	-	-
40	Undifferentiated Grass or arable	Undifferentiated Grass or arable	**Land**	**Land**	-	-	-
Number of classes	20	19	15	10	11	10	5

Table 5.3 Aggregation of Land Cover Map (LCM) and Land Cover Plus (LCP) image data for landscape analysis at varying thematic resolutions.

Class no.	AAK_ID	AIS_landuse (AAK)	AIS_landscape	AIS_nature	AIS_forest
0		Unclassified	**background**	**background**	**background**
1	1100	Consolidated surface	*Unvegetated/ exposed*	**Land**	**Land**
2	1110	Continuous urban fabric	*Built*	**Land**	**Land**
3	1120	Discontinuous urban fabric	*Built*	**Land**	**Land**
4	1121	Multistoreyed houses	*Built*	**Land**	**Land**
6	1123	Buildings in the open land	*Built*	**Land**	**Land**
7	1210	Industry	*Built*	**Land**	**Land**
8	1221	Motorway	*Traffic infrastructure*	**Land**	**Land**
9	1222	Expressway	*Traffic infrastructure*	**Land**	**Land**
10	1223	Road>6m	*Traffic infrastructure*	**Land**	**Land**
11	1224	Road 3-6m	*Traffic infrastructure*	**Land**	**Land**
12	1226	Railway	*Traffic infrastructure*	**Land**	**Land**
13	1228	Bridge	*Traffic infrastructure*	**Land**	**Land**
14	1229	Embankment	*Vegetated infrastructure*	**Land**	**Land**
15	1240	Airport	*Vegetated infrastructure*	**Land**	**Land**
16	1242	Runway	*Traffic infrastructure*	**Land**	**Land**
17	1310	Mineral extraction area	*Unvegetated/ exposed*	**Land**	**Land**
18	1340	Technical area	*Other surface sparse veg.*	**Land**	**Land**
19	1341	Cemetery	*Parks and similar*	**Land**	**Land**
23	2112	Arable land	Arable land	**Land**	**Land**
25	2300	Pastures	Pastures	**Land**	**Land**
26	2310	Grass in urban areas	*Parks and similar*	**Land**	**Land**
28	3100	Forest	Forest	Forest	Forest
29	3110	Deciduous forest	Deciduous forest	Deciduous forest	Deciduous forest
30	3120	Coniferous forest	Coniferous forest	Coniferous forest	Coniferous forest
31	3130	Mixed forest	Mixed forest	Mixed forest	Mixed forest
32	3210	Natural grasslands	Natural grasslands	Natural grasslands	**Land**
33	3220	Heathland	Heathland	Heathland	**Land**
34	3250	Mixed nature	Mixed nature	Mixed nature	**Land**
35	3310	Beach/dune	Beach/dune	Beach/dune	**Land**
36	3330	Sparsely vegetated area	*Other surface sparse veg.*	Sparsely vegetated area	**Land**
37	4110	Inland marsh	Inland marsh	Inland marsh	**Land**
38	4112	Wetland	Wetland	Wetland	**Land**
39	4120	Peatbog	Peatbog	Peatbog	**Land**
40	4130	Salt marsh	Salt marsh	Salt marsh	**Land**
41	5120	Lake	Lake	Lake	**Background**
42	5121	Water course >8-12m	Water course >8-12m	Water course >8-12m	**Background**
43	5123	Lake - reed forest	Lake – reed forest	Lake - reed forest	**Background**
44	5126	Fish farm	fish farm	**Background**	**Background**
45	5230	Open sea	**Background**	**Background**	**Background**
46	6000	Unclassified	**Background**	**Background**	**Background**
Number of classes (incl. Background)		41	25	18	6

Table 5.4 Step-wise re-classification of land use data from the AAK. Classes at the Landscape level roughly correspond to Corine level 2 for the urban/agricultural parts, though the nomenclature is not the same.

Hierarchical class number	Image class number	CLC_LEVEL3	CLC_Landscape	CLC_Nature	CLC_Forest
1.1.1	1	Continuous urban fabric	*urban fabric*	**Land**	**Land**
1.1.2	2	Discontinuous urban fabric	*urban fabric*	**Land**	**Land**
1.2.1	3	Industrial or commercial units	*Industrial, commercial and transport units*	**Land**	**Land**
1.2.2	4	Road and rail networks and associated land	*Industrial, commercial and transport units*	**Land**	**Land**
1.2.3	5	Port areas	*Industrial, commercial and transport units*	**Land**	**Land**
1.2.4	6	Airports	*Industrial, commercial and transport units*	**Land**	**Land**
1.3.1	7	Mineral extraction sites	*Mine, dump and construction sites*	**Land**	**Land**
1.3.2	8	Dump sites	*Mine, dump and construction sites*	**Land**	**Land**
1.3.3	9	Construction sites	*Mine, dump and construction sites*	**Land**	**Land**
1.4.1	10	Green urban areas	*Artificial, non-agricultural vegetated areas*	**Land**	**Land**
1.4.2	11	Sport and leisure facilities	*Artificial, non-agricultural vegetated areas*	**Land**	**Land**
2.1.1	12	Non-irrigated arable land	*Arable land*	**Land**	**Land**
2.1.2	13	Permanently irrigated land	*Arable land*	**Land**	**Land**
2.1.3	14	Rice fields	*Arable land*	**Land**	**Land**
2.2.1	15	Vineyards	*Permanent crops*	**Land**	**Land**
2.2.2	16	Fruit trees and berry plantations	*Permanent crops*	**Land**	**Land**
2.2.3	17	Olive groves	*Permanent crops*	**Land**	**Land**
2.3.1	18	Pastures	*Pastures*	**Land**	**Land**
2.4.1	19	Annual crops associated with permanent crops	*Heterogeneous agricultural areas*	**Land**	**Land**
2.4.2	20	Complex cultivation patterns	*Heterogeneous agricultural areas*	**Land**	**Land**
2.4.3	21	Land principally occupied by agriculture, with significant areas of natural vegetation	Principally agriculture, significant nature	Land principally occupied by agriculture, with significant areas of natural vegetation	**Land**
2.4.4	22	Agro-forestry areas	Agro-forestry areas	Agro-forestry areas	**Land**
3.1.1	23	Broad-leaved forest	Broad-leaved forest	Broad-leaved forest	Broad-leaved forest
3.1.2	24	Coniferous forest	Coniferous forest	Coniferous forest	Coniferous forest
3.1.3	25	Mixed forest	Mixed forest	Mixed forest	Mixed forest
3.2.1	26	Natural grasslands	Natural grasslands	Natural grasslands	**Land**
3.2.2.	27	Moors and heathland	Moors and heathland	Moors and heathland	**Land**

3.2.3	28	Sclerophyllous vegetation	*other forest*	other forest	other forest
3.2.4	29	Transitional woodland-shrub	*other forest*	other forest	other forest
3.3.1	30	Beaches, dunes, sands	Beaches, dunes, sands	Beaches, dunes, sands	**Land**
3.3.2	31	Bare rocks	Bare rocks	Bare rocks	**Land**
3.3.3	32	Sparsely vegetated areas	Sparsely vegetated areas	Sparsely vegetated areas	**Land**
3.3.4	33	Burnt areas	**Background**	**Land**	**Land**
3.3.5	34	Glaciers and perpetual snow	Glaciers and perpetual snow	Glaciers and perpetual snow	**Land**
4.1.1	35	Inland marshes	Inland marshes	Inland marshes	**Land**
4.1.2	36	Peat bogs	Peat bogs	Peat bogs	**Land**
4.2.1	37	Salt marshes	Salt marshes	Salt marshes	**Background**
4.2.2	38	Salines	Salines	Salines	**Background**
4.2.3	39	Intertidal flats	Intertidal flats	Intertidal flats	**Background**
5.1.1	40	Water courses	Water courses	Water courses	**Background**
5.1.2	41	Water bodies	Water bodies	Water bodies	**Background**
5.2.1	42	Coastal lagoons	**Background**	**Background**	**Background**
5.2.2	43	Estuaries	**Background**	**Background**	**Background**
5.2.3	44	Sea and ocean	**Background**	**Background**	**Background**
	49	NODATA	**Background**	**Background**	**Background**
	50	Sea and ocean	**Background**	**Background**	**Background**
Number of classes		44+2	27	19	6

Table 5.5 Step-wise re-classification of land use classes from the CLC.

Note that the CLC landscape categories *almost* correspond to the Corine Level 2 nomenclature for the non-nature parts of the land surface. The difference lies in the splitting of group 2.4 where the class "Principally agriculture, significant nature" is kept apart from other agricultural land use, due to the assumption that it has a different functionality in terms of providing habitats and "landscape quality". The Agro-forestry class is not found in Denmark. This approach is similar to the one used by Gallego et al (2000, table 4.1), where a 23 class and 9 class legend are made for the CLC data, in a comparison of diversity metrics between sites at the European level.

The agreement between similar thematic layers from different data sources were assessed with the Kappa index of agreement (KIA), where pixel-to-pixel cross tabulation is performed. In the absence of common legends, only binary images were used. As Table 5.6 below shows, the coefficient of agreement between the AAK data of vector origin and the satellite derived LCM and LCP forest maps are similar to the value for the agreement between the CLC and FMERS forest maps in the previous chapter, where KIA was 0.522.

Forest	LCM	LCP
AAK	0.5851	0.5783
LCM		0.9656
LCP		

Nature	LCM	LCP
AAK	0.3805	0.4321
LCM		0.8441
LCP		

Table 5.6 Kappa index of agreement for forest-non forest and nature-non nature images derived from the datasets at 25m grain size.

It appears from Table 5.6 that the agreement between the nature theme maps is rather poor, and visual inspection of the AAK and LCM maps show that this is mostly due to the status of the cropped/grazed class, which is included as one of the 'nature' classes when aggregating from the landscape thematic level. In the LCP map with more classes, the cropped/grazed class has been split between cropped/grazed and 'Undifferentiated Grass or arable', which it was chosen not to consider nature.

5.4.2.1 Definitions of landscape and background classes

When dealing with spatial metrics and landscapes through the optics of landscape ecology, a central question is how to handle the parts of the images that are classified as "background". In practice, as in the current data set, that means whether one should distinguish water/unknown from non-forest (or non-nature) land. It is important to decide carefully what should be considered background and what is 'outside' the landscape, because the choices made will strongly affect the resulting metrics values (McGarigal and Marks 1995, Coulson et al 1999, Willems et al 2000). In the user guidelines for the latest version of Fragstats for Windows (McGarigal and Holmes 2000), a distinction is made between *interior* background, which is included in area calculation and *exterior* background, which is assumed to be outside the landscape of interest and completely ignored in the metrics calculations[32]. Ideally, the re-classification strategy should follow implicitly from an understanding of the model that lies behind the metric(s) used. For instance, since metrics of *forest fragmentation* describe the forest-non-forest interface, it makes sense to include a non-forest class in their calculation. On the other hand, for metrics of forest- or nature-diversity at the landscape level, the inclusion of non-forest and non-nature (i.e. mostly agricultural) areas will provide information on the over-

[32] The guidelines are available at the Fragstats project web site: http://www.umass.edu/landeco/research/fragstats/documents/User%20guidelines/User%20guidelines%20content.htm (accessed 8/12 2003)

all structure and state of the landscape (window) rather than on the objects(s) in question (such as the forest patches/classes). This effect was illustrated in the previous chapter, in comparisons of diversity metrics values for administrative regions **[insert reference to table 4.26, when combining chapters]**.

The choice of definitions for the analysis also determines the re-classification strategy, through which the images are prepared for calculation of spatial metrics. The definition of a landscape or 'matrix' class is a rather rough approach, as it defines and uses the classes non-forest and non-nature, which are not necessarily functionally homogeneous, but it is a practical approach for raster image processing. The 'matrix' class type corresponds to the 'interior background' in the Fragstats guidelines. In practice, two kinds of background are used in the implementation of metrics calculation: Cover (proportion) calculations are based on all pixels that are non-water and non-unknown. Diversity calculations on the other hand should only be performed on the pixels belonging to 'natural' or 'forest' land cover classes, and thus the landscape/matrix class is excluded or ignored. As a standard approach, the re-classified images for these analyses have been assigned a value of 0 (zero) for non-landscape pixels, i.e. sea/ocean and unclassified and a value of 1 for landscape pixels which are not in any of the classes of interest (as here "nature" and forest). Examples of the visual appearance of these re-classifications are seen in Figure 5.5 on page 201. In contrast to the 'matrix', the classes of interest (forest etc.) are here called 'patch' or 'the patch level', in order to be in line with standard terminology of Landscape Ecology.

Once the distribution of classes at different thematic resolutions has been decided, the strategy for re-classification is quite straightforward, using the RECLASS function of the Idrisi raster-GIS (Eastman 1997). Input is the land cover or land use product along with a text file that defines the reclassification, in this case an Idrisi reclass- (.rcl) file, which contains a 'look-up' table with (the numbers of the) input and output classes. Reclass-files have been made for each type of transformation from the existing maps (highest thematic resolution) to maps with the selected and merged classes (thematic subsets).

5.4.3 Selection and extraction of test areas for assessment of AAK data

The test blocks, shown in Figure 5.7 below, are situated in the central parts of Vendsyssel. Together they include almost completely the moraine ridge Jyske Ås. The blocks were chosen in order to include a certain amount of forest, and preferably contain older forests rather than the conifer plantations found in the dune areas to the north and the west, as visual inspection showed these 'original' forests to have a more diverse composition. Also the complex landscape patterns in hilly terrain were preferred to the more homogeneous agricultural areas on the Yoldia plains, as this was observed to create more complex and diverse land use patterns. Still, agriculture is the dominating type of land use in all three blocks. Test blocks 2 and 3 represent typical rural Danish landscapes with agriculture dominating the land use, while test block 1 represent a rural landscape with a significant amount of nature.

Block 1, the northernmost area, includes some marine and aeolian deposits in the north-western corner, adding a landscape that is complex in terms of nature types, particularly heaths and moors. The rest of the block is dominated by the scenic hills Tolne Bakker and Yoldia plains with the stream Uggerby Å which flows through a gap in the ridge east of the rural town Sindal. This block largely coincides with Sindal commune, which in Danish context is a large and thinly populated municipality with just 39 inhabitants per km^2.

Block 2 contains the central part of the moraine landscapes of central Vendsyssel, with the Yoldia plain in the northwest. Uggerby Å has its source near Søhedens bakke (hill, 112m) in Pajhede skov on the ridge. To the east flows Sæby Å and to the southwest Voers Å, which forms a significant valley in the Yoldia plain, filled with younger marine deposits. This block holds the interior parts of Hjørring, Sæby and Brønderslev municipalities. Hjørring is the largest town in Vendsyssel, with 35,500 inhabitants, of which 24,700 in the centre town, but there are no suburban part in the area of this block, so like for the other municipalities the parts included here are of rural character.

Block 3 includes the highest are steepest parts of central Vendsyssel, the southern end of Jyske Ås with large continuous forest areas, especially Dronninglund Storskov with an area of approx. 850 ha. In the south is Yoldia plain and the valley of the Gerå stream. The block coincides well with Dronniglund commune, which also is a large and thinly populated municipality with 48 inhabitants per km^2. Two relatively large towns are Dronninglund (2900 inhabitants) and Hjallerup (3200 inhabitants). Recently a motorway has been constructed through the area, it was inaugurated in October 2000. It runs from the village Flauenskjold in the northeast to near Hammer Bakker (hills) in the southwest, and has only a few crossings, thus forming a significant barrier to movement and flows across the landscape.

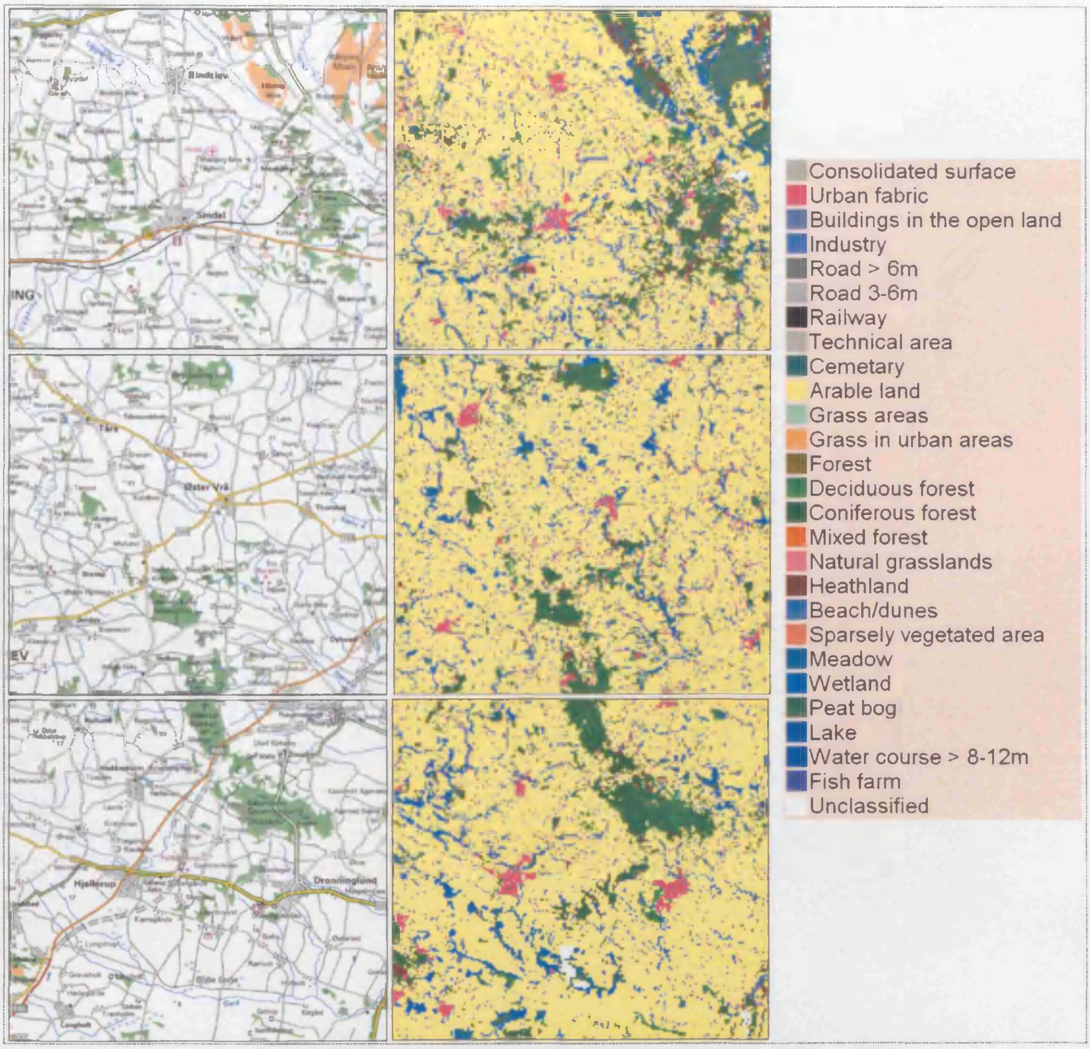

Figure 5.7 Test block 1 to 3 as KMS traffic maps. Left column from top to bottom shows the blocks as KMS traffic map 1:200.000, middle column shows AAK LULC maps of the same blocks sampled to 100m grain size, right column AAK legend with selected classes, present in the area. The extent of the test blocks is 20*18 km, an area of 360 km^2.

For these three subsets, the AAK map was converted to grids with grain sizes ranging from 5 to 100 meters, and exported as ASCII-grids for subsequent import to WinChips and/or Idrisi formats. The resulting image files have sizes from 3600*4000 pixels to 180*200 pixels. This covers a range of resolutions where linear elements such as roads, railways and streams are visible at the small grain sizes but tend to dissolve and then disappear at larger grain sizes (>20-30m). Thus, at high resolution these elements will appear as barriers or corridors in the landscape, while at lower resolutions, the landscape will seem to have lost these functions – a phenomenon that should be reflected in the spatial metrics values.

Table 5.7 shows the distribution of the AAK classes at the "landscape" thematic level in the three test blocks. Here the 5m resolution rasterised images are taken to represent the ground truth. The proportions found confirm that agriculture is the dominant land use class and constitute the landscape matrix.

Land	Use. AAK aggregated	TB1	TB2	TB3
2	Bush-forest	0.03	0.02	0.01
3	Deciduous forest	2.37	2.02	2.59
4	Coniferous forest	9.12	5.91	7.41
5	Mixed forest	0.03	0.02	0.01
6	Commons	2.42	2.29	0.76
7	Heath	1.91	0.47	0.53
10	Other sparsely vegetated	0.07	0.10	0.08
11	Meadow	1.76	1.93	1.56
12	Wetland	3.49	3.63	4.17
13	Bogs	4.78	1.65	1.75
14	Tidal meadow	0.003	0.000	0.004
15	Lake	0.40	0.42	0.34
16	Water course	0.08	0.00	0.05
19	Built	4.79	4.97	5.15
20	Traffic	1.89	1.91	1.63
22	Parks and similar	0.010	0.003	0.008
23	Agriculture	66.44	74.46	73.42
24	Grass areas	0.11	0.08	0.09
	Patches (non-external)	**99.71**	**99.88**	**99.55**
	Forest theme	11.51	7.97	10.01
	Nature theme	26.48	18.46	19.24
	Landscape theme excl.	33.27	25.42	26.13

Table 5.7 Percentage of land use types in the three test blocks, collected from 5m grain images with the "landscape" thematic resolution as described above. The bottom three lines summarise the area proportions of the thematic levels. The difference between the area of the nature themes and landscape excl. agriculture correspond to a possible urban or poly- to metahemerobic theme.

The test block images have been created independently at each resolution (grain size). Since they are based on data in vector format, thus there has been no need to consider which strategy to use for aggregating the raster land cover maps, otherwise a common problem in scaling analyses, as discussed by Goffredo (1998, chapter 3) and Wu (2003). Still the metrics values will be affected by the use of this method, which is similar to sampling the land use/land cover type at a specific geographical position (the centre of the grid cell), as shown in section 5.5.1. Different approaches for aggregation would result in different metrics values (Bian and Butler 1999, Bian 1997), but an investigation of that phenomenon was considered outside the scope of this study.

5.4.4 Selection and mathematical implementation of metrics

The NP_Backgrond metric introduced in previous chapter is here called NP_matrix, since 'matrix' is now considered to have properties different from the external background, i.e. outside the patches or landscape of interest. The *total edge length* (EL) metric is included here for the MW-analysis. This is in order to have a structural metric for the landscape thematic level, as the Matheron and SqP metrics, which use edge as well as area information, will yield spurious results when most windows have 'landscape' cover fractions that approach unity. *Edge Density* (ED) is calculated by dividing EL with the 'landscape' i.e. patch + matrix area, the unit of this metric becomes metres per hectare, corresponding to m^{-1}.

It is possible to calculate values of structural metrics such as NP and EL and of fragmentation metrics as M and SqP for separate classes (which are then 'seen' by the script as a binary landscape theme). This was used for the detailed analysis of scaling effects, reported in section 5.5.1. Table 5.8 below is intended to summarise the discussion above and the choices made for the implementation of the metrics.

Terrain slope was calculated using the SURFACE module of Idrisi (Eastman 1997). Averages of these slope values as well as of elevation within the output cells were derived using an IDL-script that allow background pixels to be ignored (Appendix 1.5).

Spatial Metric	Measures	Landscape/matrix class (internal background)	(external) Background
Cover Percentage	Coverage, proportion	Included (defines total area)	Excluded
Number of Patches (NP)	Complexity and coherence/fragmentation	Included	Excluded
NP_matrix	Perforation of patches	Included, is the object of interest	Excluded – not counted as patches even when present
Class Richness	Diversity	Included	Excluded
Shannon's Diversity Index (SHDI)	Diversity, richness	Excluded	Excluded
Shannon's Diversity Index (SIDI)	Diversity, evenness	Excluded	Excluded
Edge length (EL)	Complexity and fragmentation	Included, edges patches-matrix are counted	Excluded – edges to background are not counted
Edge Density (ED)	Complexity and fragmentation	Included, edges patches-matrix are counted. Used for normalisation.	Excluded
Matheron index (M)	Fragmentation	Included for total area	Excluded
Square Patch Index (SqP)	Fragmentation, complexity of patch shapes	Included for total area	Excluded

Table 5.8 Metrics used in this chapter, categorised according to type, with description of the handling of landscape/matrix and background pixels.

5.4.4.1 Influence on metrics potential range and maximum values

The decision to exclude external background and/or exclude matrix or internal background will influence the ranges of possible values for some of the metrics, and as a consequence the actual derived values. A summary of the consequences is given here, with each metric as a separate point.

- Cover proportions will increase when total area is based on patch area divided by (patch+matrix area), and external background excluded. The maximum value is still

100%, and the largest differences will be seen for output cells with large proportions of external background, such as coastal areas or islands.

- Patch count metrics will decrease, when background patches are not counted in.
- Changes in diversity metrics will depend on the relative proportions of the areas that are included or excluded, thus if the matrix is included and constitutes a large part of the land area, especially the Simpson's 'evenness' index will be smaller than if only the patches were used for calculations.
- Edge Length values will remain the same, but Edge Density values will increase.
- For the Matheron index, the maximum value will rise from $20\sqrt{2} = 28.284$ to 40.

For both the ED and M metrics, maximum values will occur for landscapes having a checkerboard pattern, where all pixel edges are forest-non forest borders, as illustrated in Figure 5.8 below. Excluding the external background corresponds to seeing it as having no landscape functionality at all, making the patches more isolated (as if they were separated by sea rather than land), as indicated by the higher values of the fragmentation metrics.

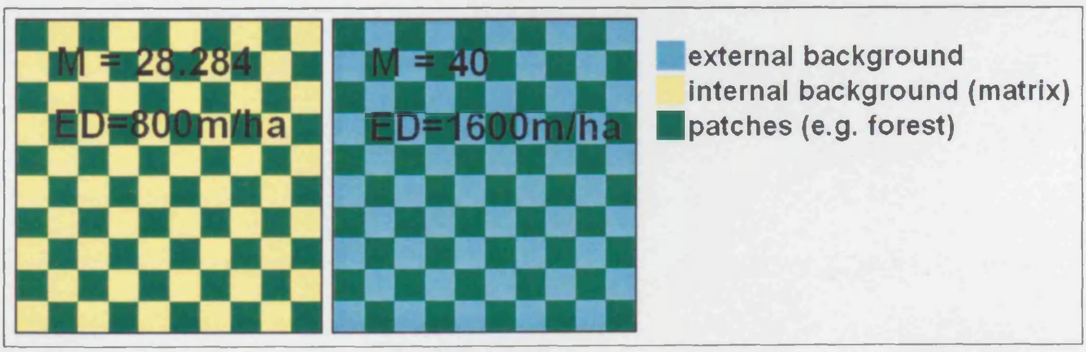

Figure 5.8 Matheron index and Edge Density maximum values with alternative status of pixels around patches.

- SqP, by definition, only depends on the patch(es) area and perimeter, and is thus not affected by the amount of internal background or matrix area.

5.4.5 Metrics calculation and statistical analysis

For the scaling exercise performed on the test block subsets, a combination of modified IDL-scripts (Appendix 1.1) and Fragstats for Windows software was used. For these calculations, the Moving-Windows loops in the scripts were deactivated so the test blocks could be treated as one large window, and the script was then run once for each thematic resolution (3 or 4 possible), each block (3 different) and each grain size (8 different). Fragstats was used for the patch count operations, as the IDL scripts turned out to be very slow for the large images (with grain sizes of 5 and 10m, of 4000*3600 and 2000*1800 pixels, and for some classes patches of very large extent). The output text files were then imported to Excel-spreadsheets for further calculations and illustration.

For the Moving-Windows calculations, a set of spatial metric-images were produced, on which comparisons could be made, and the relations evaluated here are only some of those possible, since the multiple dimensions of spatial structure gives numerous possible combinations of metrics-images. More grids and images could be produced from the output files by simple arithmetic operations, such as EL or NP *per class*, diversity metrics for landscape including matrix class etc. Window sizes used here range from 1 to 5 km corresponding to 40 to 200 pixels. In terms of geographic size, this is the interval where the largest variation of metrics values is found (compare Figure 4.11). The outputs include a large number of tables and graphs/plots, of which only representative examples and summary tables and images can be displayed here. The issue of masking or rather of, what part of the images to include in calculations was also found to be highly relevant here. For comparisons of <u>diversity</u> values, only output cells with richness of more than two classes present were used, this is because besides the matrix class, at least one forest class should be present. Windows with just one forest class will yield a zero value for the diversity of that theme, but this must be considered a valid result, showing that forest is present, but forest diversity is absent. Thus, when different themes from the same data source were to be compared, the criterion for inclusion has been the presence of at least one of the classes of interest (the background class does not suffice).

WinChips was used for extracting

a) Correlations between data sources (section 5.5.2.1),

b) Correlations between different thematic levels (section 5.5.2.2),

c) Correlations between metrics and terrain parameters (section 5.5.2.3);

since these calculations involved up to 24 different metrics 'maps', which would amount to very large spreadsheet files if the calculations were to be done in Excel. The selected metrics maps were then at the same time available for quality check by visual inspection, further image processing and use as illustrations.

The preparation of the data sets for these analyses has led to the observation that such large amount of images that can be combined in an almost endless number of ways, and all sorts of relations investigated – so a central task here has actually been to select among possible analyses, judging which combination of input data would yield the most relevant and interesting results.

5.4.5.1 Scaling and scalograms

When applicable, the metrics values response to changing pixels size are displayed using scalograms for the area of interest. The type of scalogram used in the previous chapter can be termed 'window-' or 'extent-scalogram', here they are supplemented by 'grain (size) scalograms'. It is important to distinguish between these two methods of scaling analysis, also from a third type: the MMU-scalogram (Saura 2002), which describes the influence of the minimum mapping unit on metrics values – an issue of strong relevance for the application to land use data as some metrics have been found to be extremely sensitive to MMU[33]. A fourth type of scalogram is the metric value-proportion/abundance plot, as shown by Gardner and O'Neill (1990) and Gustafson and Parker (1992), in both cases on data from neutral models). Using this type of graph can also be seen as an investigation of the relation between the metric 'cover proportion' and other (more complex) metrics, as was done in the previous chapter, see for instance and Figures 4.14 and 4.23.

[33] Especially since both the Corine classification and the AAK methodology has specific minimum polygon areas.

At the moment, only limited research has been carried out in the field of scaling behaviour of spatial metrics relating to window size in moving window applications for landscape analysis – but see O'Neill et al (1996) and Häusler et al (2000) for practical approaches and Saura and Martínez-Millán (2001) for a theoretical assessment of metrics sensitivity. The findings of Riitters et al (2000) also point out some effects of changing window sizes, but only for their methods for assessment of fragmentation. Only recently, and following theoretical advances and availability of computational power, simulations of metrics behaviour are being carried out, see Wu et al (2002), Wu (2003). The form used here is the one set out by Wu (2003), in which the metric values are plotted against either grain size or window/landscape extent.

5.4.5.2 Terrain features

Geomorphological features have been found to strongly influence plant species diversity (Burnett et al 1998, Nichols et al 1998) and a similar relation with animal diversity has been supposed (Hunter et al 1988, Forman 1995). In this study geomorphology was characterised by elevation and slope from the DEM and by geomorphological landscape types. Slope was calculated from the terrain model, using Idrisi, and measured as percentage. Average values of elevation and slope was calculated for cells corresponding to the output cells from the M-W application. The geomorphology map was aggregated to 250m, 1km and 2km grain sizes in order to allow comparisons with the CLC data and the smallest window sizes from the M-W application (using IDL-script, see Appendix 1.4).

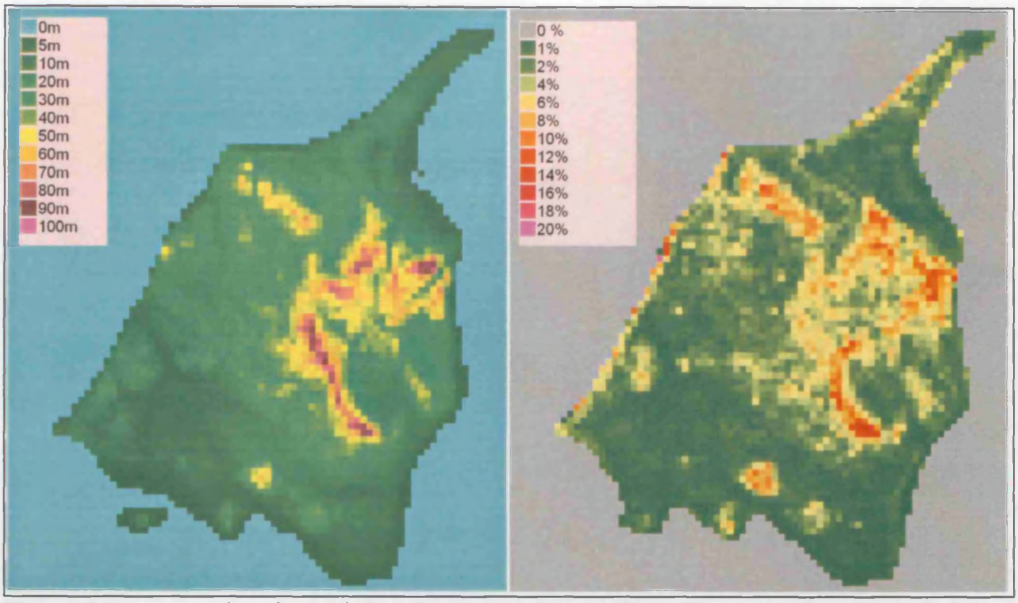

Figure 5.9 Average elevation and slope based on values in 25m cells, averaged to 1km cells for comparison and correlation with spatial metrics values in identical geographic windows.

5.4.6 Hemeroby – definition and calculation

In this chapter the previously defined and used metrics of land cover class *amount* (relative area), *diversity* and *fragmentation* will be supplemented by a quantitative measure of *Hemeroby* which expresses the human impact on and disturbance of landscapes. The concept and some previous applications is described in section 2.2.5. The implementation here follows the methods outlined by Steinhardt et al (1999) and Brentrup et al (2002). Calculation of metrics of human impact on landscapes was made possible by the availability of complete land cover maps with sufficient thematic resolution. After a critical review and interpretation of LUC map legends, an *impact factor* could be assigned to each land cover class, based on its deviance from the natural, undisturbed state. In this project these factors assumed the values of the Nature Degradation Potential (NDP), which are defined and assigned to CLC classes by Brentrup et al (2002, table 2 and Annex), with values ranging from 0: no human influence, completely natural, to 1: completely disturbed, unnatural. What is new here, relative to the above-mentioned approach, is the application of moving-windows methodology for the creation of a 'Hemeroby-map' of the area of interest and for providing context information about sites of cultural historical interest. The Hemeroby values are intended to be used for characterising areas of variable geographical extent, and they ought to be comparable, since they are 'simple' average values. Hemeroby maps have been made in other contexts, such as the project mentioned by Grabherr et al (1995), which resulted in a map of Hemeroby of Austrian forest ecosystems[34]. Such maps are however the result of a bottom-up process, i.e. based on (costly) field surveys, possibly supplemented with aerial photo interpretation.

The Hemeroby index values were calculated using images with NDP values, assigned on pixel/grain-basis to the land use maps, with values derived from re-classifications of the original CLC and AAK images. This is admittedly a crude way of assessing naturalness and disturbance of landscapes. On the other hand it is a fast, transparent and well suited methods for categorical maps in raster format. The Hemeroby types and their properties are described in section 2.2.5, Table 2.3. For practical reasons (Idrisi re-classification working only on integer values) NDP is set to values between 0 and 100. The completely undisturbed, ahemerobic class with values between 0 and 10 is not found in Denmark, owing to the relatively large population density and a long history of settlement and use of the available natural resources. A potential source of bias in the Hemeroby maps is the NDP values assigned to open sea, coastal lagoons and other water bodies, which provide the context for terrestrial landscapes. Experimentally, different values were assigned to this background class, but in all cases the result was a blurring of the coastal zones. Therefore, it was decided to completely exclude sea areas from the calculation, even if it means assigning Hemeroby values to output cells holding some coastline, that are based only on parts of the cells. Table 5.9 and Table 5.10 together show that the CLC and AAK typologies are so similar, that it is possible to make Hemeroby maps that are comparable between the two data sets. Also visual comparisons of the re-classified maps and Hemeroby-maps for the test areas showed good agreement.

[34] Available at http://www.pph.univie.ac.at/forest/hem_forest.htm (accessed 20/12 2003).

hemeroby type	NDP value	AAK surface types
oligohemerobic	15	Sparsely vegetated surfaces, wetlands, bogs, tidal meadows
	25	sand/dunes
mesohemerobic	30	broad-leaved forest, heath, reed forest,
	35	Mixed forest, meadows
	40	coniferous forest
	50	lakes, water courses, sea
euhemerobic	55	Commons
	60	Grass areas
	70	graveyards, grass in urban areas
	80	agriculture, fish farms, buildings in open land
polyhemerobic	85	low buildings
	90	high buildings, roads and railways, dams, airports, technical areas
metahemerobic	95	town centres, consolidated surfaces, industry

Table 5.9 Hemeroby types with estimated NDP values and corresponding AAK classes for re-classification to disturbance maps which are used for derivation of landscape naturalness/disturbance maps.

hemeroby type	NDP value	CLC surface types
	10	Bare rocks, glaciers and perpetual snow
oligohemerobic	15	Sparsely vegetated areas, marshes, peat bogs, intertidal flats
	25	Sclerophyllous vegetation, beaches, dunes, sand, lagoons, estuaries
mesohemerobic	30	Broad-leaved forest, moors and heathland, woodland-shrub
	35	Mixed forest
	40	Agro-forestry areas, coniferous forest
	50	Agriculture with natural vegetation, burnt areas, water
euhemerobic	55	Pastures
	60	Annual crops associated with permanent crops, complex vegetation patterns
	70	Green urban areas, sport and leisure, vineyards, fruit and berry plantations, olive groves, salines
	80	Arable land
polyhemerobic	85	Discontinuous urban fabric
	90	Roads, rail, airports, mineral extraction and dump sites
metahemerobic	95	Continuous urban fabric, industrial and commercial units, port areas, construction sites

Table 5.10 Hemeroby types with estimated NDP values and corresponding CLC level 3 classes for re-classification to disturbance.

Since the calculation of the integrated Hemeroby values is done by simple averaging of the values within the moving windows, this is (also) a spatial degradation process, similar to the derivation of the other spatial metrics implemented here – and different from the normal filtering routines implemented in GIS/image processing software (see script, Appendix 1.5). The visual impression of the outputs can be rather grainy, but it was chosen to continue with this method, in order to have comparable results and to avoid over- sampling for the statistical analyses. During calculation of the averages, an image layer with information on the proportion of non-background is created, which is used as inclusion mask during subsequent extraction of statistical properties. For the comparison of AAK and CLC results, the criterion for a cell to be included was that at least 10% of both maps should be non-background. In practice this image layer functions as a land-mask. For comparison with the traditional filtering approach, regarding the appearance of the resulting maps, a simple and fast program was used for calculations of average values (Hovey 1998), as seen in the top line of Figure 5.10 below. A simple legend was defined, for the possible creation of thematic maps to be used for planning and illustration purposes; intervals and descriptions are listed in Table 5.11. This legend also serves as guideline for re-classification of the real-value average images into byte-value 'maps' with these four themes plus background as the classes – an approach illustrated in Figure 5.10.

Hemeroby index value	**Hemeroby type**	**Description**
< 40	Mesohemerobic	Moderate human influence
40 - (just below) 60	β-euhemerobic	Strong human influence
60 - (just below) 80	α-euhemerobic	Very strong human influence
>= 80	Polyhemerobic	Mainly artificial surfaces

Table 5.11 Proposed assignment of rough Hemeroby classes to output cells from averaging operations.

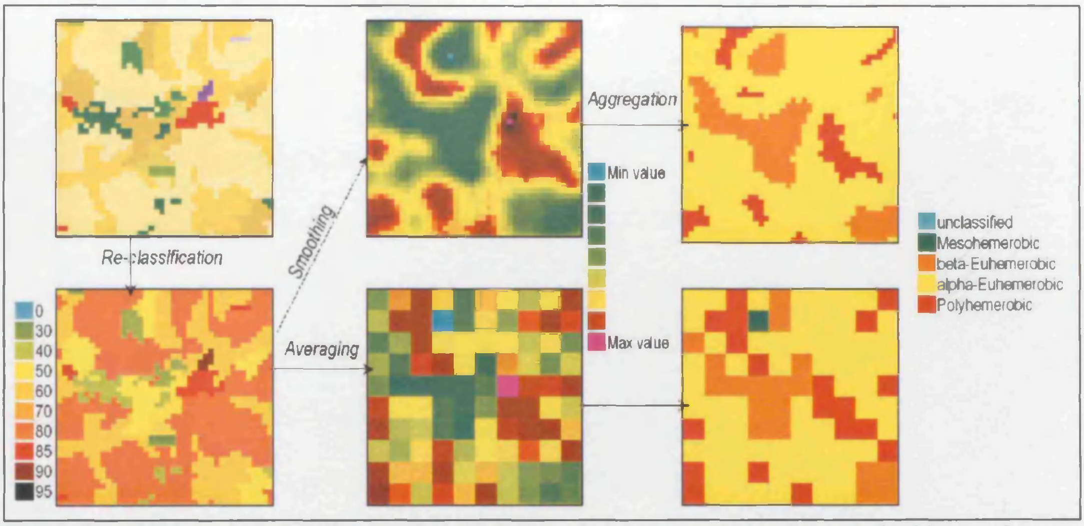

Figure 5.10 An example of the 'processing chain' from Land Use to Hemeroby map, in this case from the CLC data for a subset of 10*10 km in the northern part of the area (compare test block 1 in Figure 5.7 on page 216), around the rural town Sindal. Note that the linear feature in the upper right corner of the image is Sindal airfield which is in use, though not for regular services.

Two different approaches are presented in Figure 5.10 (as different branches of the 'flow chart'): smoothing with overlapping windows and averaging where windows do not overlap. For this illustration of method, the averaging was done for 1*1km (4*4 pixel) windows, while the smoothing was done for a circle around the central pixel with a radius of 3 pixels, using the Idrisi MapWalker (Hovey 1998). The minimum Hemeroby index value of app. 36 (accentuated with cyan colour) is found in Baggesvogn skov (forest, deciduous) and the highest value (magenta colour) of app. 84 in the centre of Sindal. For the resulting general Hemeroby classes it is worth noting that the polyhemerobic class represents the built environment as well as the 'core areas' of agricultural activity – whether this is a realistic representation of the environmental state is subject to discussion. The visual attractiveness of the maps will be improved if they are subjected to clean-up filtering, such as mode- or majority filtering or application of a low-pass (averaging) filter to the per-window averaged Hemeroby index-values. Such resulting images may be useful for illustrative purposes but of limited analytical use.

5.5 Results

In this section findings from the calculations on the LUC maps in the data set are presented, along the lines described in the Objectives section. Following these, a three-part structure has appeared: first the findings from the re-scaling of AAK data for selected test blocks are presented; then the various results from application of the M-W method to the different input types for the entire base-map area are presented; finally findings from calculation of Hemeroby values for the same area are displayed, compared with the 'traditional' spatial metrics and their relative position in a possible indicator framework are discussed.

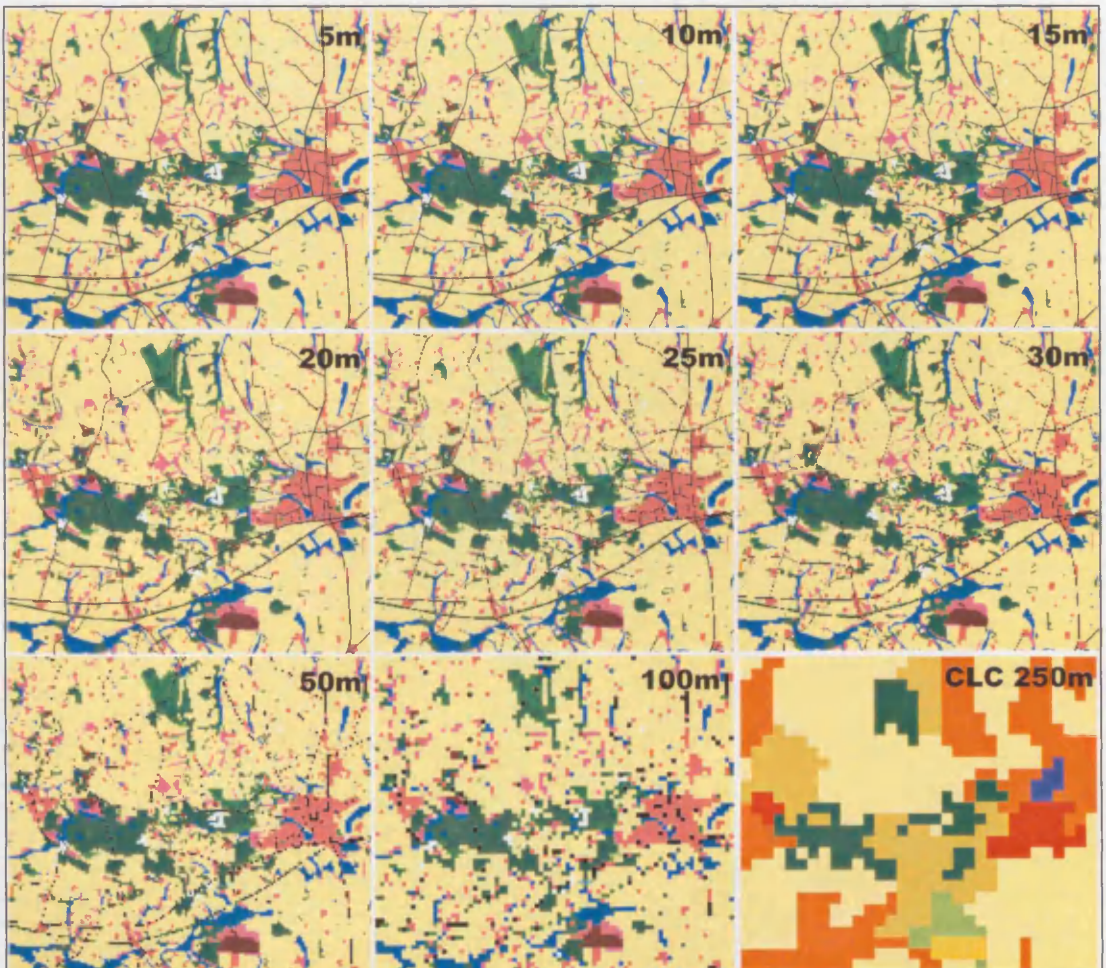

Figure 5.11 An 8*7 km subset of TB1 at the landscape thematic level, AAK images with the grain sizes used in this study – plus the corresponding subset from the CLC. The 5m grain size image is 1600*1400 pixels, the 100m grain size pixel only 80*70, and the CLC image only 32*28. To the left in the images the village Astrup, to the right the rural town Sindal, in between Bøgsted Plantage (plantation) and Slotved Skov (forest), to the north Baggesvogn Skov, supposedly the northernmost deciduous forest in Denmark.

5.5.1 Scaling properties of AAK data

In contrast to the exercise in Chapter 3 where a binary forest-non-forest map was degraded, the starting point here has been a multi-class land use map. As is well known, scaling effects can take place at three aggregation levels: patch, class and landscape (McGarigal and Marks 1995, Wu et al 2002). In this study, single patch properties are not considered, since the objects of study are forested landscapes rather than single forest patches. Separate classes are however investigated, when they are known or observed to have different (scaling) behaviour. Here the forest theme is used in the first place, but comparisons are also made to the nature- and landscape themes. The description of the scaling effects follows the order of metrics set up in Table 5.8.

Figure 5.11 shows the effects of spatial degradation applied to land use data, on a representative subset. It is clearly seen that linear features, such as roads and railway lines become fragmented, by being cut into pieces from resolutions around 20-25m, and at the largest grain size only appear as scattered points. On the other hand, the agricultural class which acts as landscape matrix here becomes more coherent as the barriers/corridors are dissolved, and at 100m grain size consists of a few patches. The forest and wetland patches assume more edgy or square shapes (implying that SqP should decrease – following the definition in section 2.3.4, equation 3. The same effect is seen for the towns, while the small rural settlements gradually 'thin out' with increasing grain size. Area proportions for total forest and nature classes change only little, while the very rare classes show the greatest changes. For the majority of classes, the change from 5 to 100m is well below one percent, relative to the area at 5m resolution, and there are no clear trends for decrease or increase of proportion. Other studies have shown that the changes in cover proportions with changes in grain size depend on the method applied in the transformation from fine to coarse images (Turner et al 1989, Wu et al 2000, Saura and Martinez-Milan 2000). The approach used here for spatial degradation, described in section 5.4.3, is similar to sampling at random points and actually ensures that the almost same cover proportions (and thus diversities) are found over the current range of grain sizes.

5.5.1.1 Patch count metrics

Table 5.12 shows patch counts for selected classes from the landscape thematic level from all three blocks, along with their area proportion and average patch size in hectares, at the highest resolution, 5m. Table 5.13 shows the proportion of the landscape occupied by the same series of classes for all resolutions, with metrics from test block 1 as examples.

Class	**broad-leaved forest**			**coniferous forest**			**wetlands**			**lake**		
block	**TB1**	**TB2**	**TB3**	**TB1**	**TB2**	**TB3**	**TB1**	**TB2**	**TB3**	**TB1**	**TB2**	**TB3**
P_{land}5m	2.375	2.019	2.587	9.119	5.913	7.412	3.489	3.634	4.174	0.404	0.419	0.336
Avg.patch size	0.958	1.055	1.527	2.177	2.622	3.386	2.292	2.361	3.006	0.125	0.136	0.169
5m	892	689	610	1508	812	788	548	554	500	1165	1110	717
10m	924	683	618	1482	787	764	545	560	469	1147	1111	700
15m	905	680	601	1385	755	722	555	572	470	1125	1073	674
20m	880	650	572	1325	742	695	555	591	475	1017	989	605
25m	861	656	582	1268	717	683	573	599	462	860	833	531
30m	827	668	571	1242	708	674	573	624	473	733	711	448
50m	740	661	541	1153	622	633	709	702	540	414	367	250
100m	343	305	282	576	311	349	384	389	346	137	105	77
Class	**built**			**traffic**			**agriculture**			**meadow**		
block	**TB1**	**TB2**	**TB3**	**TB1**	**TB2**	**TB3**	**TB1**	**TB2**	**TB3**	**TB1**	**TB2**	**TB3**
P_{land}5m	4.789	4.971	5.148	1.887	1.910	1.631	66.441	74.455	73.424	1.760	1.927	1.558
Avg.patch size	0.681	0.651	0.813	33.968	28.646	25.524	23.871	37.383	38.757	1.354	1.577	1.664
5m	2531	2749	2279	20	24	23	1002	717	682	468	440	337
10m	2623	2785	2310	17	18	27	952	652	635	497	453	320
15m	2368	2559	2043	353	347	330	627	350	371	504	478	326
20m	2143	2438	1886	2016	2143	2026	474	241	308	496	489	319
25m	2019	2316	1763	2641	2751	2524	409	198	241	492	503	327
30m	1910	2219	1688	2596	2758	2441	338	166	211	491	508	329
50m	1651	1914	1495	1596	1692	1477	246	96	123	485	543	382
100m	866	978	754	507	505	445	79	23	55	260	290	226

Table 5.12 Total count of separate patches of selected classes with different responses to image grain size (scaling behaviour).

Class	Deciduous		Confierous		Wetlands		Lakes		Built		Traffic		Agriculture		Meadows	
metric / grain	P_land	size	P_land	size	P_land	size	P_land	size	P_land	size	P_land	size	P_land	size	P_land	size
5	2.375	0.959	9.119	**2.178**	3.489	2.293	0.404	**0.125**	4.789	0.682	1.887	33.986	66.44	**23.88**	1.760	1.355
10	2.376	**0.926**	9.106	2.212	3.488	2.304	0.405	0.127	4.791	**0.657**	1.886	39.941	66.46	25.13	1.761	1.276
15	2.372	0.945	9.141	2.381	3.487	2.267	0.401	0.129	4.786	0.729	1.887	1.929	66.43	38.22	1.760	**1.260**
20	2.373	0.973	9.125	2.485	3.495	2.272	0.405	0.144	4.792	0.807	1.880	0.336	66.44	50.57	1.755	1.277
25	2.369	0.991	9.102	2.584	3.491	2.193	0.403	0.169	4.795	0.855	1.885	**0.257**	66.48	58.52	1.753	1.283
30	2.382	1.039	9.136	2.654	3.497	2.202	0.404	0.199	4.765	0.900	1.911	0.266	66.43	70.91	1.763	1.295
50	2.375	1.159	9.089	2.846	3.488	**1.776**	0.407	0.355	4.809	1.051	1.876	0.424	66.43	97.49	1.752	1.304
100	2.383	2.528	9.137	5.771	3.466	3.284	0.423	1.124	4.843	2.035	1.861	1.335	66.28	305.25	1.765	2.469

Table 5.13 Cover proportions and average patch size in hectares for Test Block 1 of the classes used in Table 5.12. For each class the lowest apparent average patch size is marked as **bold**.

Clear differences between the various classes are observed in Table 5.12, both in terms of patch size and scaling behaviour. In all three blocks lakes are so small (being mostly ponds) that they gradually disappear up to 50m grain size, and rapidly to 100m. Still, the 'sampling' like nature of the map degradation assures that this cover type's proportion of the landscape area remains the same. The stability of cover proportions is apparent in Table 5.13, as well as how the increased number of separate patches for the linear elements of the Traffic class leads to an apparent decrease in patch size. An unexpected result is seen in Table 5.12, namely that the class "meadows" show a relatively little decrease in the number of patches, indicating that the shape of the individual patches is very compact rounded or even square – which again would indicate that they are under agricultural management, and either used for grazing or set aside (lying fallow).

The forest theme was used for illustrating scale effects on patch numbers. Since the forest map is used as input, coherent forest areas, which contain different classes (forest types) will be counted as more than one patch. The gradual decrease in the number of forest patches is illustrated in Figure 5.12. The values are calculated by dividing the patch count number at the actual grain size by the number at the smallest grain size (where the largest number of patches is normally found, at least for forest classes).

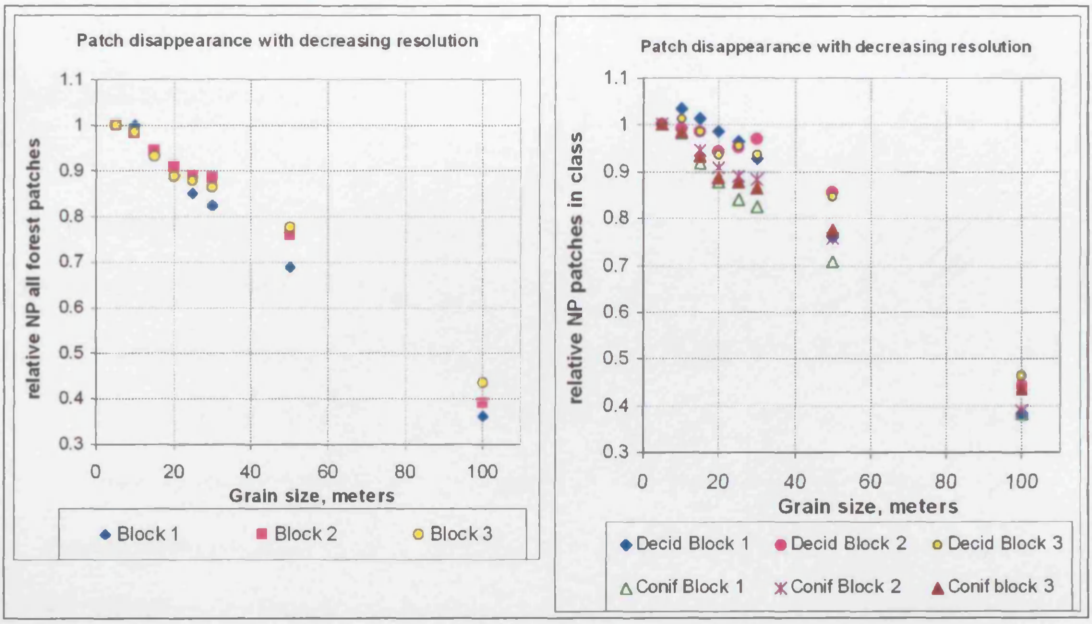

Figure 5.12 Scaling behaviour of the rasterised AAK data set in the three test blocks for number of forest patches, normalised to the amount at 5 m resolution. To the left counts of all patches, to the right counts of the two dominant classes: deciduous and coniferous.

The linear decreases shown in Figure 5.12 are in line with the findings of Wu (2003) who places the Patch Density metric among the metrics with a regular scaling behaviour – in the sense that they are predictable for changes in grain size, following a power law for metrics at landscape as well as at class level. The forest patches in Block 1 show the most rapid decrease with increasing grain size, especially the conifer class. This is in line with the observations in Table 5.12, that this block has the smallest patches – as a result of it having the most fragmented forests. However, even if the average size of deciduous patches is less than half of the coniferous patches, the *number of patches* decreases less rapidly – an indication that the patches of this class have more compact shapes.

5.5.1.2 Diversity metrics

Below SHDI is used as example of scaling behaviour for a diversity metric. For this area and these data sets SHDI has been found to be strongly correlated with the SIDI metric (R=0.990-0.998). Since the cover proportions for the themes and separate classes change so little, the metrics values are also stable across scales. This is apparent from Table 5.14 and Table 5.15, where the values of SHDI from the three test blocks, the three thematic resolutions and the eight grain sizes are compared.

The diversity metrics for the landscape subsets however depend on another 'parameter' for the calculation, namely whether the landscape matrix is included. This is particularly of interest for the themes that constitute well below half of the entire land area, such as forest and nature. When Table 5.14 and Table 5.15 are compared, it becomes apparent that the exclusion of the matrix not only results in higher metrics values, it also changes the ranking of the diversity of the blocks relative to each other. In this way it becomes apparent that the higher values of forest and nature diversity for block 1 are caused by the proportionally higher area of patches belonging to these themes there, as seen from the area percentages in Table 5.7. The "Grid" thematic level in Table 5.14 represents calculations made on the original AAK maps (having a larger number of different land-use classes, see Table 5.4), and shows that calculations at the Landscape thematic level give metrics values very close to these.

Matrix (internal background) included												
SHDI	Forest			Nature			Land			Grid		
Grain	TB1	TB2	TB3	TB1	TB2	TB3	TB1	TB2	TB3	TB1	TB2	TB3
5m	0.423	0.327	0.386	1.074	0.822	0.826	1.347	1.106	1.105	1.388	1.144	1.148
10m	0.423	0.327	0.386	1.073	0.822	0.826	1.346	1.106	1.105	1.388	1.144	1.148
15m	0.424	0.327	0.386	1.074	0.822	0.826	1.347	1.106	1.105	1.388	1.144	1.148
20m	0.423	0.327	0.386	1.074	0.823	0.825	1.346	1.107	1.104	1.388	1.145	1.147
25m	0.423	0.327	0.386	1.072	0.823	0.826	1.345	1.106	1.104	1.387	1.144	1.148
30m	0.424	0.327	0.387	1.073	0.822	0.826	1.347	1.106	1.105	1.388	1.144	1.148
50m	0.423	0.327	0.386	1.074	0.822	0.827	1.347	1.107	1.106	1.388	1.145	1.149
100m	0.424	0.325	0.387	1.078	0.818	0.824	1.352	1.099	1.103	1.394	1.136	1.146

Table 5.14 Diversity metrics values expressed as SHDI for the entire test block, i.e. including the landscape/metrics class.

Matrix (internal background) excluded						
SHDI	Forest			Nature		
Grain	TB1	TB2	TB3	TB1	TB2	TB3
5m	0.545	0.599	0.583	1.863	1.859	1.731
10m	0.546	0.599	0.583	1.864	1.859	1.731
15m	0.545	0.599	0.583	1.862	1.860	1.731
20m	0.544	0.600	0.584	1.862	1.859	1.731
25m	0.543	0.599	0.583	1.863	1.858	1.732
30m	0.545	0.597	0.584	1.861	1.858	1.731
50m	0.546	0.602	0.584	1.864	1.857	1.733
100m	0.542	0.601	0.578	1.868	1.855	1.724

Table 5.15 Diversity metrics values expressed as SHDI for the entire test block, but only for the patches/objects of interest.

The values of SIDI have a similar low variation with grain size, so only the values from 5m grains are used in Table 5.16, where the same themes and parameters are used. It is not surprising that higher values of SIDI representing greater evenness between class proportions are found for the calculations where the matrix class is excluded. The reason that the values for the forest class are relatively low, even with matrix excluded, is the dominance of coniferous forest.

	Matrix included											
SIDI	Forest			Nature			Land			Grid		
	TB1	TB2	TB3	TB1	TB2	TB3	TB1	TB2	TB3	TB1	TB2	TB3
5m	0.210	0.150	0.186	0.447	0.329	0.341	0.540	0.435	0.444	0.541	0.436	0.446

	Matrix excluded					
SIDI	Forest			Nature		
Grain	TB1	TB2	TB3	TB1	TB2	TB3
5m	0.335	0.386	0.385	0.805	0.811	0.769

Table 5.16 Diversity values expressed through the SIDI metric.

5.5.1.3 <u>Fragmentation metrics</u>

The number of landscape or "matrix" patches is included here as a measure of landscape fragmentation, following the considerations about "background patches" and forest structure in chapter 4. It was assumed here that the scaling behaviour of the number of (separate) patches could be used to describe the coherence and perforation of landscapes at the different thematic levels. The results for each of the thematic levels are shown in Figure 5.13. Block 2 clearly has the least perforated forest, while Block 1 has the most perforated or scattered nature. The increase in the number of patches at 20m grain size is due the inclusion of roads and railway lines in the matrix class. Where they pass through forest or other types of nature, these seem to be split into several separate patches. The opposite effect is seen for the agriculture class that constitute the matrix at landscape thematic level, here the patches become connected between 10 and 20m grain size, as the linear elements appear to dissolve (see Table 5.12).

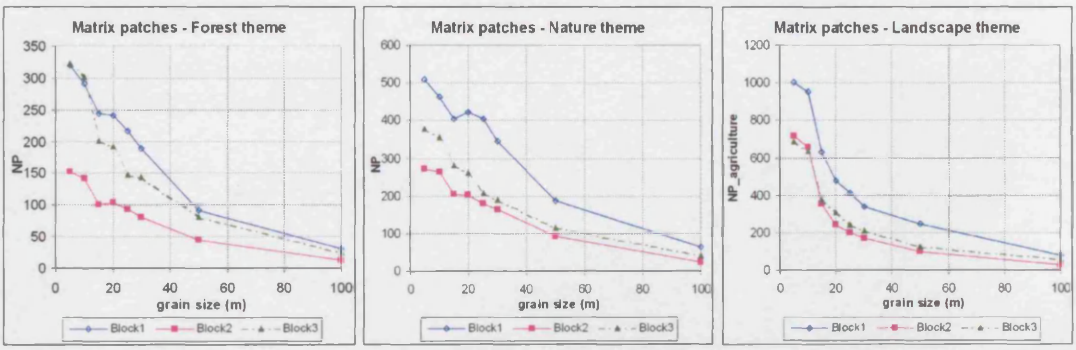

Figure 5.13 Scalograms for the number of matrix/background patches in the three test blocks, each with an area of $360km^2$.

Figure 5.14 illustrates the fragmentation effect that occurs for the matrix class when images are degraded from 5m to up to 25m pixel sizes. Here it is small roads with nature type land uses on both sides that become split into smaller fragments (while the forest patches seem to become connected).

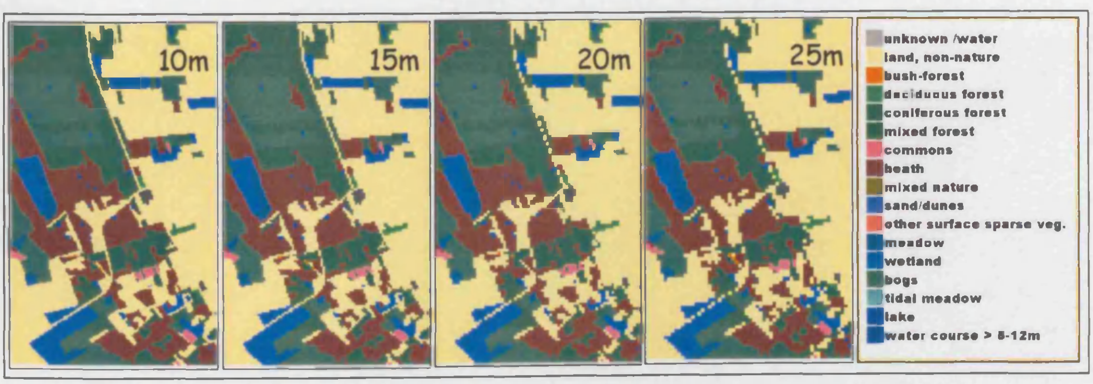

Figure 5.14 1.5*2.5 km subset from the northern part of Test Block 1 around the heath area 'Rimmerne', at the 'nature' thematic level with corresponding legend for the re-classified AAK map.

Both the Matheron index and the SqP metric are described here, as they have been found to behave quite differently in response to changes in grain and window size. Figure 5.15 shows the response of M to changing scale, a notable linear increase with grain size. For all three blocks the M value based on total forest area and forest-non forest edges (within each window) has slightly higher values than the M values for the individual classes, showing that forest as a combined/lower level land cover feature has a more complex shape than the separate forest classes. Block 1 stands out, having the most fragmented forest cover, which owes to the structure of the deciduous forest class in that area, while the other blocks and classes have very similar metrics values and scaling behaviour.

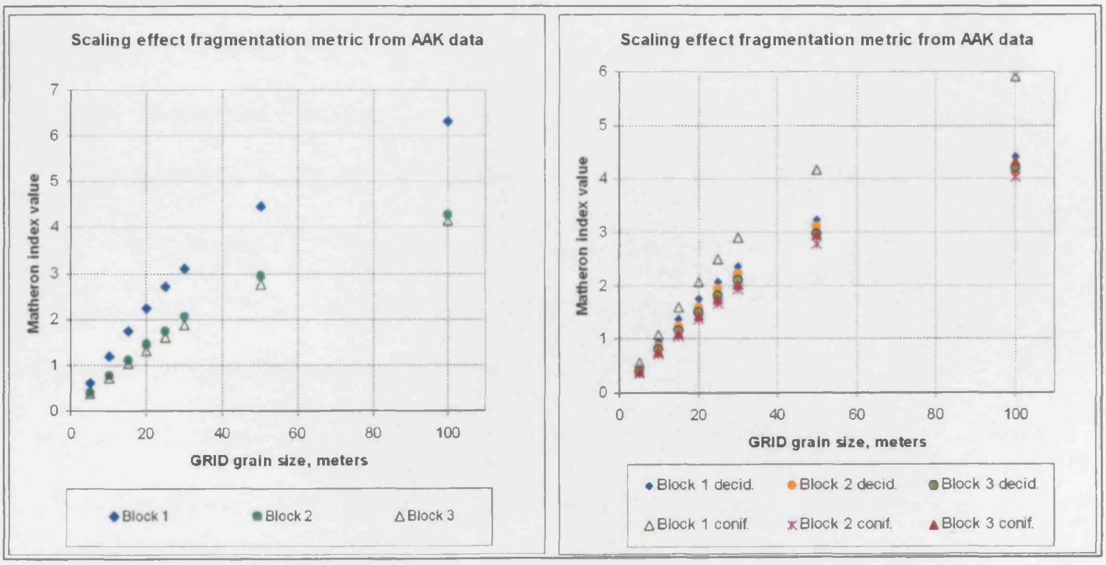

Figure 5.15 Scaling effects of changing grain size for the Matheron index., AAK data, forest thematic level.

The response of the SqP value to changing scale is illustrated in two slightly different ways in Figure 5.16 below, where the values are first plotted against grain size similar to the approach used in chapter 3 (see figure 3.13) and then against window size similar to the approach used in chapter 4. In both cases the response from this data set seems similar to that observed previously. It must be noted however, that the window sizes measured in meters represent a different number of pixels here compared with chapter 4, where medium resolution satellite data were used.

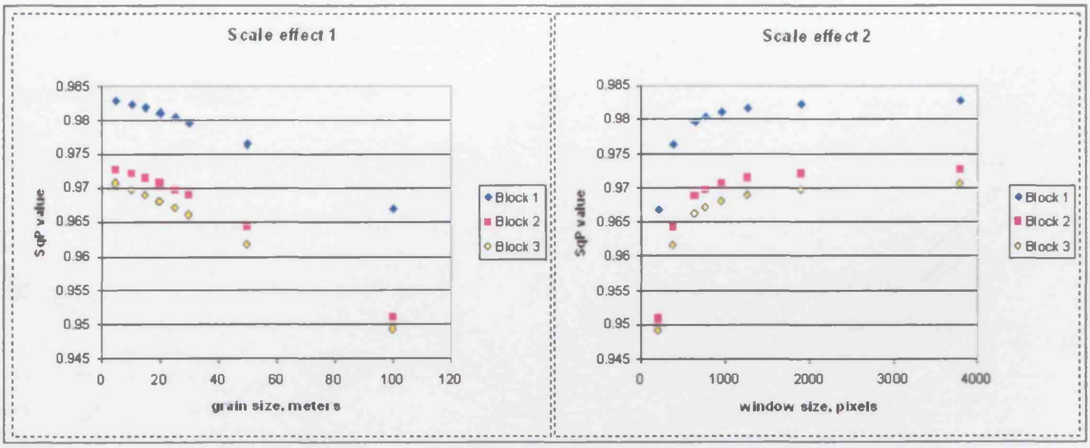

Figure 5.16 Two different approaches to depicting the scale dependence of the SqP metric: grain size and window size (extent). The occurrence of these two effects in combination is a consequence of having a fixed geographic window for data of changing resolution.

The behaviour of M and SqP is not surprising given the behaviour observed from Figure 5.11, where the coarsening of images correspond to higher apparent levels of fragmentation. As shown in Table 5.12, block 1 has the smallest patches, and that is clearly reflected in the values of both M and SqP, which more or less mirror the graphs for the patch counts. The relation between small patches and high fragmentation is confirmed by the significant correlations between NP (-total) and SqP and between NP and M for the AAK data at the thematic level 'forest' from the M-W analyses, where R values around 0.6 are found, as was also seen for the CLC data in chapter 4 (Table 4.19), though only at large window sizes. The results here show that scaling behaviour is heavily dependent on initial shape of the landscape elements.

5.5.2 M-W analysis of land cover data of different origins with different thematic resolutions

In this section of the study, the M-W methods were not used for creation of scalograms to examine the development of metrics values with grain size *per se*. M-W calculations were rather performed on different thematic resolutions for all images, and the results compared for the purpose of finding out which metrics are useful with these types of data, and for which window sizes. The calculations were carried out for five different window sizes, since initial tests showed large differences between values – and different correlations between themes and data sources at different window sizes. Therefore it was hypothesised that small windows would be useful for some purposes and larger windows for others. The average values of a number of metrics are shown in Table 5.17.

FOREST	AAK					CLC (250m grain)				
	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
PPU_N	8.063	6.139	5.365	5.010	4.814	2.245	1.427	1.226	1.151	1.117
PPU_NM	1.966	1.613	1.518	1.465	1.439	1.071	1.051	1.031	1.015	1.014
Richness	2.738	3.216	3.476	3.773	3.993	2.050	2.230	2.327	2.423	2.610
SHDI	0.293	0.429	0.459	0.474	0.484	0.056	0.126	0.159	0.211	0.299
ED(block)	71.56	60.56	54.58	51.88	50.42	25.49	16.73	12.38	10.19	9.23
M	2.857	2.386	2.220	2.113	2.084	12.045	7.458	5.753	4.734	4.372
SqP	0.587	0.757	0.817	0.852	0.879	0.187	0.263	0.332	0.383	0.440
	LCM					LCP				
	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
PPU_N	32.720	30.381	29.323	28.476	27.738	45.138	42.300	40.910	39.807	38.826
PPU_NM	2.907	2.555	2.429	2.353	2.306	3.093	2.726	2.582	2.508	2.451
Richness	3.733	3.733	3.986	3.981	3.993	6.016	7.479	8.147	8.545	8.766
SHDI	0.779	0.864	0.899	0.909	0.912	1.130	1.290	1.364	1.402	1.419
ED(block)	129.26	125.23	122.39	119.91	117.27	153.53	149.50	146.12	143.31	140.23
M	4.834	4.587	4.457	4.377	4.344	4.871	4.638	4.505	4.422	4.389
SqP	0.773	0.878	0.913	0.933	0.945	0.774	0.88	0.914	0.934	0.945

Table 5.17 Average values of spatial metrics for the forest theme from the available data types – for windows where forest was present. PPU_N (objects) and PPU_NM (matrix) represent patch densities as patch/km^2, normalised to the smallest window size of 1 km^2. ED(block) is the edge length of the window divided by the entire landscape area (not just the forest patches).

The metrics are observed to behave in a very similar way to what was seen in the previous chapter, in particular the M metric, where values from AAK data assume values similar to those from CLC 100m data for similar window sizes (geographical extent), and values from LCM and LCP assume values similar to those from FMERS data used in chapter 4, see figure 4.11. The SHDI diversity metric shows a similar behaviour to that seen for the medium-resolution data used in the study for chapter 4, with the LCM map giving values close to those from FMERS and AAK giving values close to those from CLC 100m (compare Table 5.17, Figure 4.11and Figure 4.12). The higher values of SHDI for the LCP data are due to the larger number of forest classes, as is also reflected in the values of the Richness metric. This metric however become quite useless for comparison between output cells representing sub-landscapes, when the windows are larger than 1 to 2 km, because the then most cells assume maximum values. This is especially the case for the satellite-based maps LCM and LCP. It is however interesting that for CLC data, Richness values increase steadily with window size (on the other hand 5 km only corresponds to a 20*20 pixels window).

The comparison of metrics values from different image sources in Table 5.17 shows that in spite of the fragmentation introduced to the AAK images through the sampling to 25m grain size, the patches are larger and more coherent than in the LCM and LCP images. For comparison, the average metrics values which are relevant at the landscape thematic level, are listed in Table 5.18. Similar to the observations from the test blocks, *all* of the metrics have higher values for the landscape theme. This is due to the larger number of classes, edges and patches that influence diversity/richness, fragmentation and patch count metrics respectively.

LANDSCAPE	**AAK**					**CLC**				
	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
PPU_N	30.781	27.445	26.059	25.201	24.337	2.086	1.697	1.529	1.441	1.373
PPU_NM	2.751	2.280	2.079	1.976	1.912	0.779	1.023	1.043	1.043	1.036
RICHNESS	7.926	11.366	13.064	14.086	14.883	1.964	3.035	4.044	5.005	5.818
SHDI_OBJ	0.878	1.021	1.103	1.156	1.204	0.232	0.515	0.748	0.951	1.102
ED_block	186.31	183.46	180.16	177.14	172.56	20.73	23.45	24.13	24.21	23.89
	LCM					**LCP**				
	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
PPU_N	114.744	106.613	102.641	99.992	97.009	150.071	140.931	136.293	133.117	129.265
PPU_NM	16.918	16.120	15.625	15.203	14.785	16.010	15.909	15.589	15.367	14.889
RICHNESS	8.722	9.687	9.909	9.962	9.985	12.961	15.790	16.870	17.474	17.730
SHDI_OBJ	1.271	1.148	1.189	1.217	1.236	1.414	1.508	1.556	1.588	1.617
ED_block	460.41	453.49	445.82	438.17	428.44	516.04	508.52	499.54	491.80	480.00

Table 5.18 Average values of spatial metrics for the landscape theme from the available data types under respective presence masks. The metrics are processed in the same way as for Table 5.17.

Statistics from processing of the metrics images showed high correlation between edge length- and (total) patch numbers, for instance: R= 0.898 at 1 km and R= 0.964 at 5 km window size for AAK data; R= 0.925 at 1km and R= 0.967 at 5 km window size for LCP data. Since the former metric is much faster to calculate, it could make an efficient substitute for the latter for describing one aspect of landscape fragmentation.

5.5.2.1 Agreement between data sources

The results presented here do not only show some clear differences between the behaviour of different metrics and types of metrics, they also illustrate the differences between the different thematic levels. In all of the three following tables, the AAK land use map provide one of the data sets, and correlation coefficients for agreement with one of the other data types are given for each thematic resolution and window size. The coefficients are typed in **bold** if the relations are significant at the 5% level (two sided). Table 5.19 shows the correlations for AAK and the basic land cover map LCM, both from the AIS.

These pairings of thematic levels clearly differ in their relations between metrics values and their responses to window size. For the forest theme, which is readily distinguished in satellite imagery (thus agreeing with the 'ground truth' of the AAK map), very good agreement is seen for the cover proportion metric. For the SHDI and SIDI, the best agreements are generally found for the landscape theme and the 'worst' for the nature theme, probably due to the difficulties with defining this theme from the LCM. However, the richness metric shows good agreement at this thematic level, where it seems to be de-coupled from the more complex diversity metrics. The M and SqP fragmentation metrics show rather poor agreements for the forest theme at small window sizes, the agreement however increases rapidly with window size.

correlations	**Themes**														
AAK-LCM	**Forest**					**Nature**					**Landscape**				
window size	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
n. obs.	*3597*	*963*	*449*	*255*	*172*	*3809*	*999*	*464*	*260*	*177*	*3808*	*999*	*464*	*260*	*177*
COVER	**0.901**	**0.924**	**0.930**	**0.928**	**0.900**	**0.572**	**0.581**	**0.546**	**0.637**	**0.669**	N/A	N/A	N/A	N/A	N/A
RICHNESS	**0.480**	**0.379**	**0.382**	**0.404**	**0.327**	**0.479**	**0.605**	**0.697**	**0.659**	**0.718**	**0.516**	**0.637**	**0.723**	**0.670**	**0.753**
SHDI_OBJ	**0.383**	**0.438**	**0.503**	**0.585**	**0.604**	**0.176**	0.048	0.010	-0.042	0.005	**0.578**	**0.678**	**0.717**	**0.727**	**0.757**
SIDI_OBJ	**0.331**	**0.411**	**0.496**	**0.575**	**0.598**	**0.124**	0.012	-0.031	-0.071	-0.039	**0.576**	**0.668**	**0.713**	**0.747**	**0.748**
EDGELENGTH	**0.738**	**0.788**	**0.812**	**0.815**	**0.836**	**0.609**	**0.699**	**0.761**	**0.791**	**0.812**	**0.613**	**0.748**	**0.827**	**0.860**	**0.887**
MATHERON	**0.211**	**0.214**	**0.244**	**0.311**	**0.440**	**0.144**	**0.071**	**0.387**	**0.259**	0.066	N/A	N/A	N/A	N/A	N/A
SQP	-0.002	0.002	**0.151**	**0.334**	**0.582**	**0.280**	**0.490**	**0.469**	**0.610**	**0.643**	N/A	N/A	N/A	N/A	N/A
NP_Matrix	**0.611**	**0.714**	**0.783**	**0.766**	**0.821**	**0.440**	**0.641**	**0.732**	**0.755**	**0.769**	**0.189**	**0.313**	**0.386**	**0.398**	**0.399**
NP_TOTAL	**0.669**	**0.737**	**0.774**	**0.786**	**0.810**	**0.583**	**0.661**	**0.724**	**0.732**	**0.768**	**0.545**	**0.643**	**0.721**	**0.745**	**0.788**

Table 5.19 Correlations between output cell values of spatial metrics from the AAK and LCM maps with grain size 25m.

Table 5.20 shows that there is generally better agreement between the AAK and LCP data, especially for the nature theme, probably because the LCP data could be re-classified to more realistic natural classes than the LCM data. However, the diversity metrics are not well correlated, and the fragmentation metrics M and SqP are at the same level as for the LCM data. For AAK data seen in relation to both LCM and LCP data, edge length and patch count metrics correlate well, especially the total number of patches agree well for all the thematic levels.

Table 5.21 shows relationships between the AAK and CLC data sets, which are considerably different in origin and spatial scale. The agreement on cover percentage for the nature theme is better than with the LCM and LCP data. Negative relations are observed for SqP values, even significant at small window sizes for the forest theme. The M index seems to be of little use for comparisons between these data sets, however good agreement is found for the diversity metrics. In general, the agreement for the cover metrics remains stable or increases slightly with increasing window size, and the Edge Length metric has a similar behaviour, providing significant correlations for all themes and extents; thus it is one of the most robust metrics. The diversity indices, which have poor agreements for the forest and nature themes show higher correlations for the landscape theme, even at the small window sizes, where the CLC metrics are based on few pixels.

correlations	Themes														
AAK-LCP	**Forest**					**Nature**					**Landscape**				
window size	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
n. obs.	*3625*	*966*	*450*	*256*	*172*	*3809*	*999*	*464*	*260*	*177*	*3808*	*999*	*464*	*260*	*177*
COVER	**0.886**	**0.909**	**0.915**	**0.914**	**0.891**	**0.657**	**0.668**	**0.636**	**0.722**	**0.752**	N/A	N/A	N/A	N/A	N/A
RICHNESS	**0.583**	**0.503**	**0.508**	**0.592**	**0.456**	**0.535**	**0.676**	**0.75**	**0.757**	**0.81**	**0.54**	**0.684**	**0.761**	**0.737**	**0.821**
SHDI_OBJ	**0.345**	**0.25**	**0.211**	**0.265**	**0.275**	**0.208**	**0.137**	**0.143**	**0.138**	**0.2**	**0.573**	**0.681**	**0.732**	**0.746**	**0.803**
SIDI_OBJ	**0.282**	**0.236**	**0.244**	**0.307**	**0.325**	**0.144**	**0.096**	0.091	0.094	0.141	**0.496**	**0.635**	**0.694**	**0.735**	**0.773**
EDGELENGTH	**0.747**	**0.8**	**0.827**	**0.825**	**0.846**	**0.654**	**0.753**	**0.808**	**0.833**	**0.856**	**0.638**	**0.766**	**0.838**	**0.866**	**0.893**
MATHERON	**0.208**	**0.221**	**0.236**	**0.322**	**0.487**	**0.159**	**0.101**	**0.43**	**0.316**	0.138	N/A	N/A	N/A	N/A	N/A
SQP	-0.024	-0.02	**0.114**	**0.248**	**0.575**	**0.257**	**0.472**	**0.423**	**0.592**	**0.683**	N/A	N/A	N/A	N/A	N/A
NP_Matrix	**0.613**	**0.714**	**0.784**	**0.763**	**0.819**	**0.469**	**0.659**	**0.742**	**0.767**	**0.803**	**0.242**	**0.406**	**0.491**	**0.507**	**0.557**
NP_TOTAL	**0.71**	**0.778**	**0.813**	**0.813**	**0.84**	**0.597**	**0.682**	**0.744**	**0.758**	**0.794**	**0.548**	**0.643**	**0.717**	**0.743**	**0.784**

Table 5.20 Correlations between output cell values of spatial metrics from the AAK and LCP maps with grain size 25m.

correlations	Themes														
AAK-CLC	Forest					Nature					Landscape				
window size	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
n. obs.	*2593*	*824*	*408*	*239*	*168*	*3642*	*998*	*461*	*260*	*177*	*3808*	*999*	*464*	*260*	*177*
COVER	**0.872**	**0.92**	**0.906**	**0.911**	**0.873**	**0.738**	**0.8**	**0.795**	**0.831**	**0.866**	N/A	N/A	N/A	N/A	N/A
RICHNESS	**0.2**	**0.195**	**0.315**	**0.278**	**0.407**	**0.356**	**0.34**	**0.378**	**0.354**	**0.375**	**0.36**	**0.429**	**0.542**	**0.544**	**0.546**
SHDI_OBJ	0.015	0	0.038	0.07	**0.183**	0.024	-0.079	-0.086	-0.076	-0.102	**0.512**	**0.647**	**0.649**	**0.631**	**0.549**
SIDI_OBJ	0.003	-0.013	0.027	0.074	**0.182**	0.021	-0.072	-0.056	-0.039	-0.117	**0.541**	**0.627**	**0.596**	**0.551**	**0.459**
EDGELENGTH	**0.531**	**0.639**	**0.65**	**0.672**	**0.719**	**0.522**	**0.66**	**0.705**	**0.733**	**0.751**	**0.39**	**0.525**	**0.614**	**0.67**	**0.72**
MATHERON	-0.012	0.018	0.088	**0.205**	**0.157**	-0.01	**0.126**	0.092	-0.007	**0.297**	N/A	N/A	N/A	N/A	N/A
SQP	**-0.172**	**-0.081**	-0.058	0.005	-0.144	-0.035	0.052	0.106	0.101	**0.175**	N/A	N/A	N/A	N/A	N/A
NP_Matrix	**0.092**	**0.39**	**0.555**	**0.356**	**0.418**	**-0.076**	**0.194**	**0.387**	**0.424**	**0.584**	0.001	**0.134**	**0.26**	**0.36**	**0.439**
NP_TOTAL	**0.42**	**0.477**	**0.501**	**0.484**	**0.547**	**0.425**	**0.497**	**0.488**	**0.491**	**0.44**	**0.303**	**0.352**	**0.38**	**0.418**	**0.392**

Table 5.21 Correlations between output cell values of spatial metrics from the AAK and CLC maps with 25m and 250m grain size. For small windows there are notably fewer observations, i.e. output cells with forest and to some degree nature presence in this pair of maps. Note that while the sides of the CLC grains are 10 times larger than the AAK grains, the *area* of them are 100 times larger than AAK grains, and the windows used thus have only 1/100 of the number of pixels.

Figure 5.17 represents a possible way of illustrating the outputs of the M-W calculations, comparing two data sources and stating the correlation coefficients. In this example the amount of "nature" areas is almost the same in the two maps used as inputs, but the AAK map has a more concentrated distribution compared to the blurred appearance of the LCP map. Average richness and edge length are higher for the LCP data, but the AAK data has a larger dynamic range (higher coefficients of variation for the Richness and Edge Length metrics). However, both data sets distinguish regions with different spatial arrangements of land use/land cover.

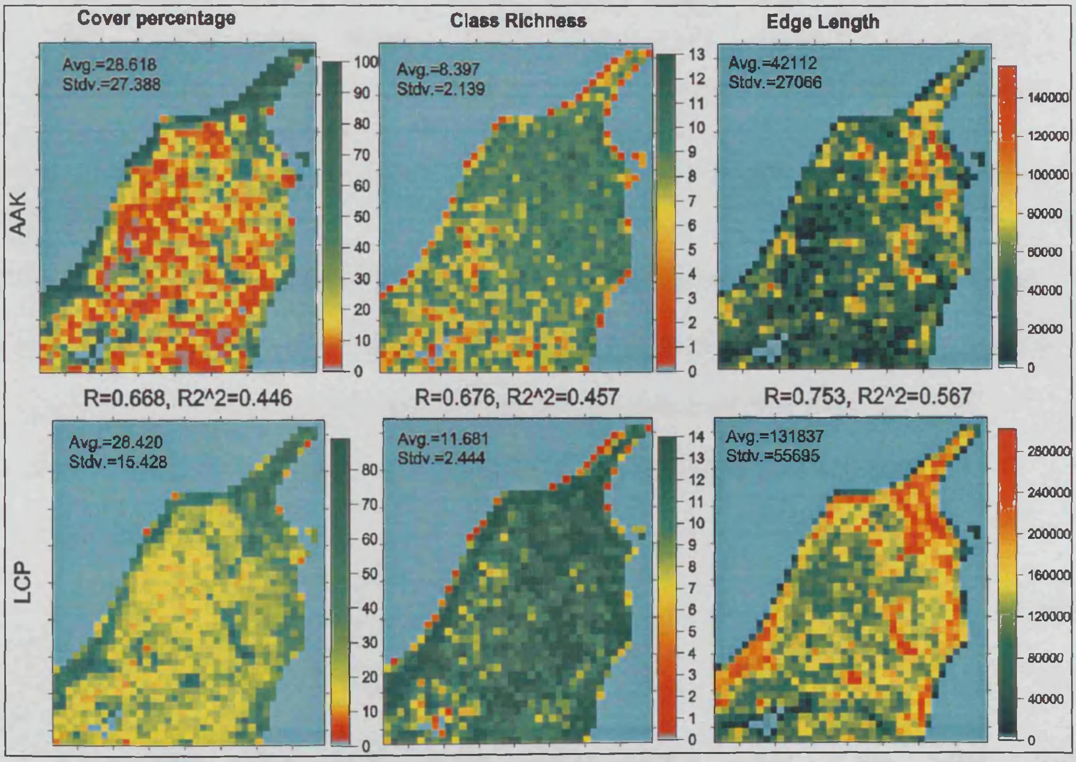

Figure 5.17 An example of pair-wise comparison of metrics maps from the different sources, here AAK and LCP for the nature theme, at window = output cell size 2km. The R-values correspond to those listed in Table 5.20.

5.5.2.2 Agreements between thematic levels

This section of the study examined whether (some or all) spatial metrics derived from maps of one thematic resolution e.g. landscape can be used to predict the metrics values at another e.g. forest. This would be useful, as redundant calculations and reporting could be avoided, given that it was justified to use just one set of metrics to describe landscape and nature in the study area. As examples of the results, the respective correlations for four of the metrics from the

AAK and the LCP data respectively are shown in Table 5.22 and Table 5.23, with significant correlations in **bold** type. The Matheron index has not been extracted for the landscape thematic level, and thus only forest and nature levels can be compared.

AAK	SHDI			NP			Edge Density			Matheron
relation: window size:	F-N	F-L	N-L	F-N	F-L	N-L	F-N	F-L	N-L	F-N
1km	**0.379**	**0.210**	**0.372**	**0.729**	**0.590**	**0.778**	**0.835**	**0.743**	**0.871**	**0.603**
2km	**0.434**	-0.033	**0.111**	**0.800**	**0.657**	**0.816**	**0.863**	**0.786**	**0.884**	**0.606**
3km	**0.494**	**-0.201**	0.009	**0.844**	**0.710**	**0.850**	**0.876**	**0.819**	**0.901**	**0.611**
4km	**0.481**	**-0.266**	-0.011	**0.872**	**0.738**	**0.870**	**0.917**	**0.881**	**0.926**	**0.621**
5km	**0.489**	**-0.440**	**-0.185**	**0.894**	**0.760**	**0.880**	**0.865**	**0.818**	**0.881**	**0.628**

Table 5.22 Correlations between metrics values for different thematic levels, AAK data. The data sets are based on the same data source = AAK, with same grain size= 25m. F-N denotes correlations between forest and nature thematic levels, F-L between forest and landscape, and N-L between nature and landscape levels.

For the AAK data, the most remarkable result is the negative correlation between forest and landscape levels. These results indicate high forest diversity low landscape diversity, and vice versa, especially when comparisons are made for larger windows. The other, structural metrics show good agreements with slightly lower correlations for the forest-landscape relationships.

LCP	SHDI			NP			Edge Density			Matheron
relation: window size:	F-N	F-L	N-L	F-N	F-L	N-L	F-N	F-L	N-L	F-N
1km	**0.569**	**0.383**	**0.786**	**0.940**	**0.882**	**0.983**	**0.823**	**0.686**	**0.891**	**0.477**
2km	**0.481**	**0.242**	**0.799**	**0.933**	**0.860**	**0.976**	**0.824**	**0.699**	**0.889**	**0.477**
3km	**0.446**	**0.163**	**0.814**	**0.946**	**0.889**	**0.982**	**0.823**	**0.732**	**0.907**	**0.575**
4km	**0.390**	0.068	**0.816**	**0.949**	**0.896**	**0.985**	**0.838**	**0.740**	**0.914**	**0.590**
5km	**0.275**	-0.009	**0.810**	**0.961**	**0.917**	**0.987**	**0.770**	**0.690**	**0.891**	**0.457**

Table 5.23 Correlations between metrics values for different thematic levels, LCP data. The data sets are based on the same data source = LCP, with same grain size= 25m.

The LCP data yield very similar results, though the SHDI values are positively and significantly correlated for the forest-landscape relation for windows of size up to 3 km. Window size strongly influences the agreement between the SHDI diversity metric for the forest theme on one side and the nature or landscape theme on the other, but not the agreement between the nature and the landscape theme. For the NP and ED structure metrics and the Matheron index describing fragmentation, there is no or little such influence from window size. For patch count metrics, the values are higher than for AAK data. This is illustrated in Figure 5.18, where the landscape-forest and landscape-nature relations are plotted for the two data sets, and trend lines with regression equations are used to illustrate the agreements.

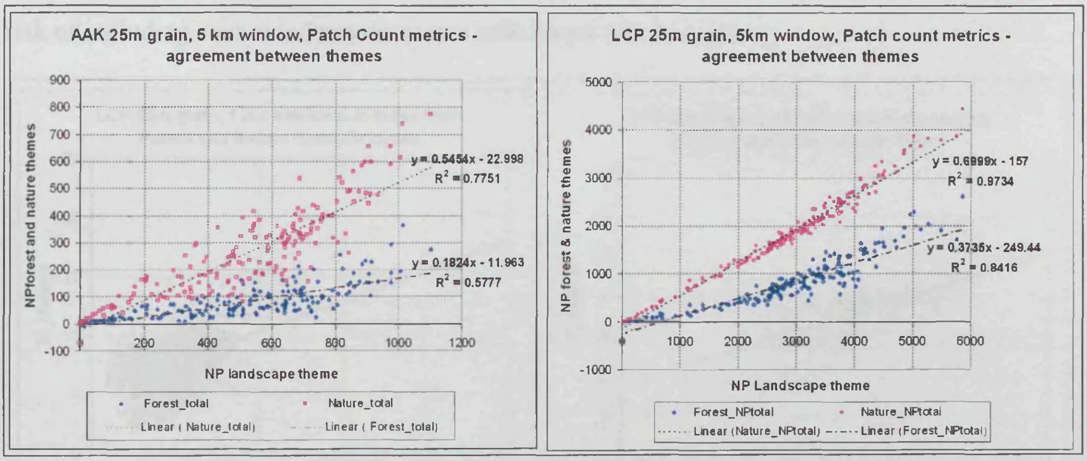

Figure 5.18 Output (5km) cell-by-cell plots of patch count metrics values between the landscape thematic level and the forest and nature levels for AAK data (left) and LCP data (right).

Figure 5.19 shows similar relations for the SHDI diversity metric, this time comparing the relations nature-forest and landscape-forest for AAK data where the shift from positive to negative regression is most pronounced.

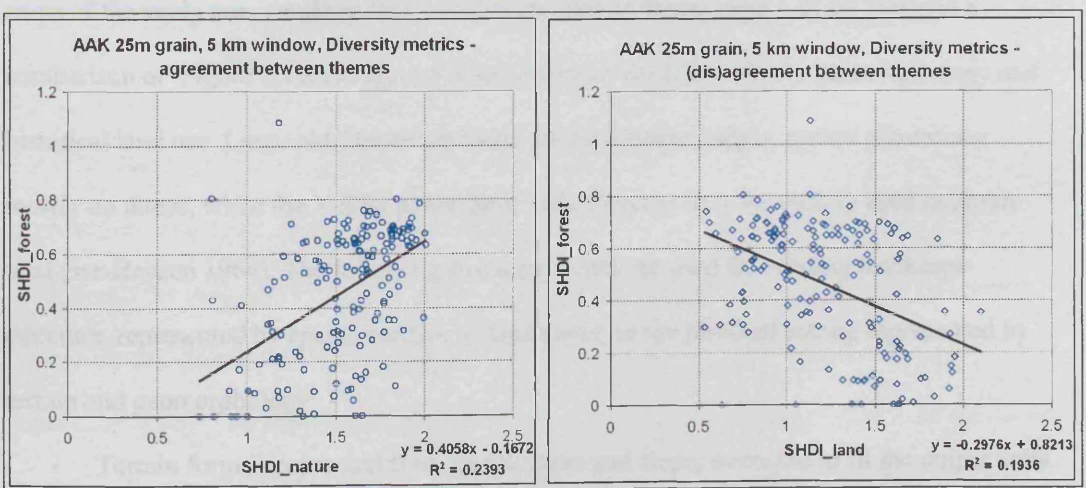

Figure 5.19 Output (5km) cell-by-cell plots of patch count metrics values between the nature and the forest thematic levels (left) and between the landscape and the forest thematic levels (right) for AAK data.

Finally, the inter-thematic relations for the Matheron index are visualised in Figure 5.20, with trend lines describing the relations. As seen in Table 5.17, the average values of M decrease with increasing window size. The graphs in Figure 5.20 also indicate that the higher metric values for small window sizes could be due to 'outliers' like the cell with a value of 25 in both images, and that larger windows minimise the chances of having extreme values. Such values are typically found for windows with only one or a few forest or nature pixels present, and the risk of including such windows decreases with larger window sizes.

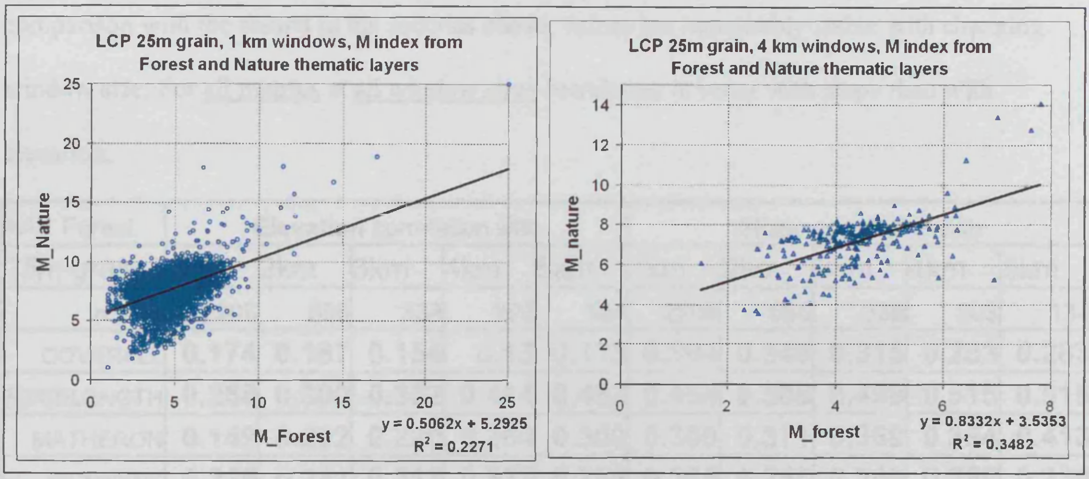

Figure 5.20 Changing relation between the Matheron index for forest and for nature thematic layers with increased window size.

5.5.2.3 Assessing the influence of terrain features on spatial metrics

It is no surprise that land cover is related to land forms, and examination of the topographical maps of the study area confirms that it is also the case in Vendsyssel – as for instance a comparison of Figure 5.1 and Figure 5.3 demonstrates the link between geomorphology and historical land use. Large old forests are found on the moraine ridges, spruce plantations mostly on dunes, while the Yoldia plains have little forest as they are mostly used as arable land (see Hansen 1964). The following two approaches are used for relating landscape structure, represented by spatial metrics of land cover, to the physical setting represented by terrain and geomorphology:

- Terrain form is expressed through elevation and slope, averaged to fit the output cells of the M-W analysis;

- Geomorphology is expressed through an aggregated thematic map of major land forms.

AAK and LCP maps are compared, in order to examine whether they also have different behaviour for these derived features.

In Table 5.24, the correlation coefficients are shown for the standard set of metrics for the forest theme from the AAK map, and average elevation and slope from the DEM. In comparison with the results in the sections above, values are remarkably stable with changing window size. For <u>all metrics</u> at <u>all window sizes</u> correlation is better with slope than with elevation.

AAK Forest	**Elevation** correlation with					**Slope** correlation with				
25m grain	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
n. obs.	2206	656	338	203	134	2206	656	338	203	134
COVERALL	**0.174**	**0.187**	**0.154**	**0.13**	0.113	**0.304**	**0.346**	**0.315**	**0.283**	**0.263**
EDGELENGTH	**0.268**	**0.300**	**0.362**	**0.414**	**0.433**	**0.454**	**0.508**	**0.498**	**0.515**	**0.515**
MATHERON	**0.149**	**0.202**	**0.220**	**0.284**	**0.309**	**0.300**	**0.371**	**0.369**	**0.394**	**0.413**
RICHNESS	**0.235**	**0.241**	**0.313**	**0.337**	**0.328**	**0.265**	**0.255**	**0.269**	**0.259**	**0.239**
SHDI_OBJ	**0.197**	**0.174**	**0.199**	**0.245**	**0.180**	**0.227**	**0.147**	**0.096**	**0.094**	**0.018**
SIDI_OBJ	**0.183**	**0.163**	**0.184**	**0.238**	**0.165**	**0.216**	**0.143**	**0.098**	**0.102**	**0.015**
SQP	**0.182**	**0.222**	**0.33**	**0.355**	**0.366**	**0.263**	**0.320**	**0.271**	**0.241**	**0.242**
NP_C1M	**0.097**	**0.127**	**0.107**	**0.075**	0.083	**0.216**	**0.288**	**0.258**	**0.213**	**0.201**
NP_TOTAL	**0.327**	**0.390**	**0.460**	**0.531**	**0.550**	**0.483**	**0.568**	**0.561**	**0.597**	**0.587**

Table 5.24 Correlations between metrics values and average elevation and slope, AAK forest theme. Significant correlations are marked in **bold** types.

For LCP data the picture is not so clear, as shown by Table 5.25. The diversity metrics have better agreements with elevation than with slope, the structure metrics have lower correlation coefficients for both map types and for the Matheron index they assume negative values for both elevation and slope. These negative relations could be due to the presence of more concentrated forest on areas with high slopes, given that forest in the LCP data from the outset (at small coverage fractions) will appear much more as small separate patches than in AAK data at the same spatial resolution. At higher forest concentration, larger and more coherent patches will be observed, resulting in a relative decrease in forest fragmentation.

LCP Forest	**Elevation** correlation with					**Slope** correlation with				
25m grain	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
n. obs	3015	789	360	209	137	3015	789	360	209	137
COVERALL	**0.092**	**0.075**	0.042	-0.006	-0.047	**0.218**	**0.211**	**0.162**	**0.115**	0.07
EDGELENGTH	**0.133**	**0.174**	**0.179**	**0.184**	**0.185**	**0.261**	**0.254**	**0.205**	**0.181**	**0.177**
MATHERON	**-0.097**	**-0.097**	**-0.098**	-0.073	-0.132	**-0.049**	**-0.109**	**-0.162**	**-0.127**	**-0.189**
RICHNESS	**0.212**	**0.208**	**0.182**	**0.178**	**0.152**	**0.299**	**0.246**	**0.158**	**0.125**	0.04
SHDI_OBJ	**0.25**	**0.32**	**0.362**	**0.364**	**0.442**	**0.29**	**0.307**	**0.279**	**0.258**	**0.31**
SIDI_OBJ	**0.236**	**0.3**	**0.335**	**0.338**	**0.409**	**0.239**	**0.24**	**0.222**	**0.204**	**0.253**
SQP	**0.038**	**0.112**	**0.111**	**0.14**	0.122	-0.03	**-0.072**	**-0.142**	-0.085	-0.096
NP_C1M	**0.13**	**0.157**	**0.134**	**0.119**	0.1	**0.239**	**0.264**	**0.236**	**0.189**	**0.175**
NP_TOTAL	**0.234**	**0.299**	**0.324**	**0.339**	**0.345**	**0.342**	**0.348**	**0.312**	**0.304**	**0.294**

Table 5.25 Correlations between metrics values and average elevation and slope, LCP forest theme. Significant correlations are marked as **bold**.

The landscape thematic level is markedly different from the forest level, as shown by Table 5.26. For the AAK data, correlation coefficients are higher except for the total number of patches, which also is a remarkable metric here, in the sense that the correlations with elevation are higher than with slope. The edge length metric, in combination with slope, gives values very similar to those seen for the forest theme, but higher values for the combination with elevation.

AAK Landscape	**Elevation** correlation with metrics					**Slope** correlation with metrics				
25m grain	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
EDGELENGTH	**0.285**	**0.419**	**0.489**	**0.545**	**0.592**	**0.399**	**0.441**	**0.436**	**0.494**	**0.489**
RICHNESS	**0.337**	**0.346**	**0.204**	0.112	-0.005	**0.358**	**0.271**	0.095	0.054	0.034
SHDI_OBJ	**0.088**	0.06	0.004	-0.015	-0.039	**0.318**	**0.28**	**0.219**	**0.169**	**0.205**
SIDI_OBJ	0.037	0.006	-0.042	-0.06	-0.075	**0.286**	**0.248**	**0.196**	**0.139**	**0.176**
NP_C23M	**0.137**	**0.17**	**0.186**	**0.175**	**0.233**	**0.274**	**0.312**	**0.314**	**0.331**	**0.39**
NP_TOTAL	**0.326**	**0.472**	**0.541**	**0.598**	**0.643**	**0.369**	**0.422**	**0.425**	**0.498**	**0.498**

Table 5.26 Correlations between metrics values and average elevation and slope, AAK landscape theme.

While the landscape level diversity metrics seem not to be related to elevation, the structure/fragmentation metrics are more closely related to this terrain feature than to slope. Class richness correlates significantly with both elevation and slope for small, but not for larger windows. This is likely to be due to this metric almost reaching its maximum value (equal to the total richness of patch types in the test area) at a window size of 3 to 4 km, as seen in Table 5.18.

At the landscape thematic level the metrics derived from the LCP data exhibit little correlation with elevation and hardly any with slope, not even for the edge length metric. No obvious explanations can be given for the negative correlations between the diversity metrics and elevation, since elevation and richness are positively correlated. The reason for the negative correlation cannot be a larger number of classes at low elevations, as seen in Table 5.27, it is thus likely to result from a more even distribution of the classes found there (or a more uneven distribution of class sizes at higher elevations).

In general, values of landscape metrics from the AAK land use/land cover data correlate better with measures of terrain features than metrics from the LCP satellite based land cover data. Thus, AAK data were chosen for illustration in Figure 5.21 of some of the relations between average 'terrain metrics' and the landscape metrics forest cover and number of patches. Note the 'peak' in forest cover percentage at low elevations, caused by the plantations on sandy soil along the west coast.

LCP Landscape	**Elevation correlation with metrics**					**Slope correlation with metrics**				
25m grain	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
EDGELENGTH	**0.117**	**0.195**	**0.238**	**0.246**	**0.275**	**0.156**	**0.147**	**0.105**	**0.136**	0.134
RICHNESS	**0.118**	**0.13**	**0.122**	**0.16**	**0.148**	**0.154**	**0.093**	0.032	0.084	0.036
SHDI_OBJ	**-0.059**	**-0.12**	**-0.164**	**-0.208**	**-0.235**	**0.107**	**0.074**	0.026	-0.037	-0.041
SIDI_OBJ	**-0.074**	**-0.139**	**-0.188**	**-0.238**	**-0.27**	**0.114**	**0.087**	0.04	-0.019	-0.027
NP_C23M	**-0.137**	**-0.147**	**-0.133**	**-0.156**	-0.08	**-0.116**	**-0.145**	**-0.185**	**-0.18**	**-0.158**
NP_TOTAL	**0.111**	**0.17**	**0.195**	**0.206**	**0.24**	**0.192**	**0.191**	**0.145**	**0.166**	**0.164**

Table 5.27 Correlations between metrics values and average elevation and slope, LCP landscape theme.

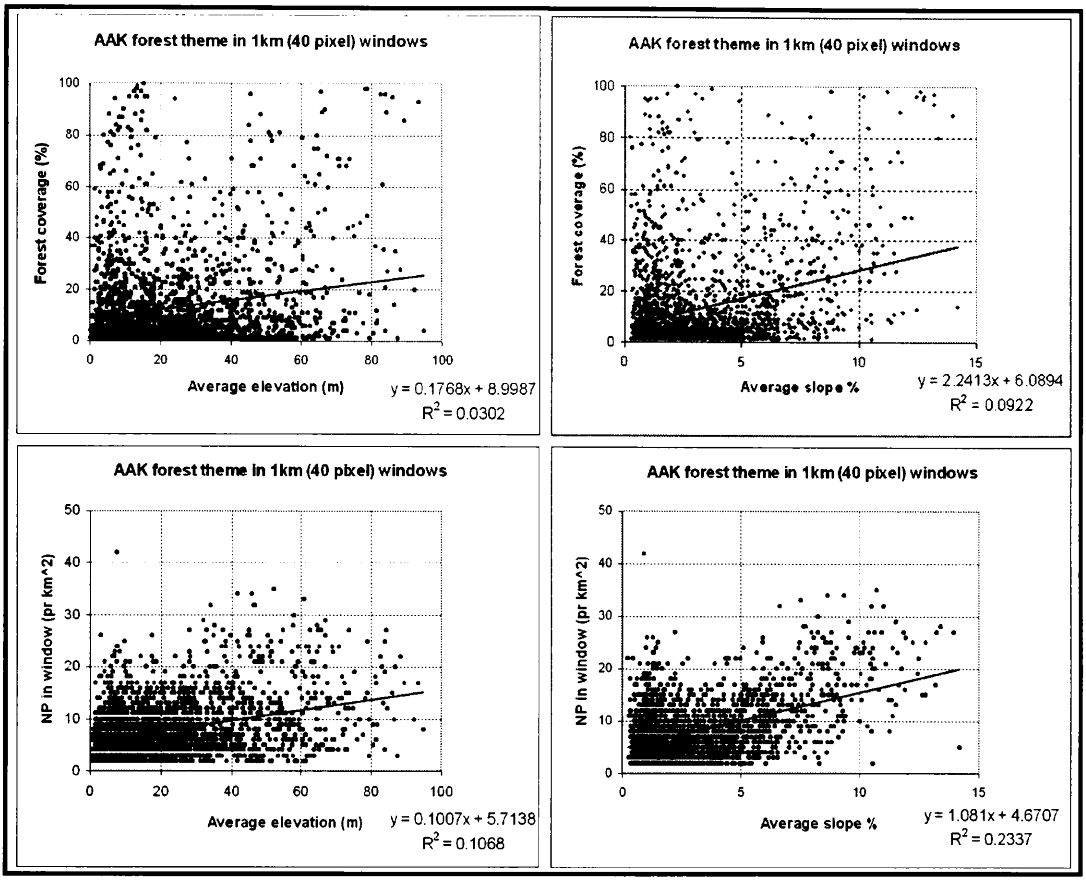

Figure 5.21 Scatter-plots of selected relations between terrain features and structural metrics for the forest theme from the AAK map in 1km windows.

The results from stratification by geomorphological type show clear differences in metrics values. Table 5.28 below summarises the metrics values and their standard deviations for the nature theme from the AAK data, while Table 5.29 summarises similar values for the LCP data, where also the nature theme has been selected as example. In Table 5.28, Proportion refers to the number of pixels where the Nature theme is present, relative to the total number of pixels in the stratum.

Mean	COVER pct.	EDGE LGT	MATH	RICHN.	SHDI	SIDI	SQP	NP_M	NP TOTAL	Pro-portion	Pixels incl.
Littorina or yonger	21.21	9094	2.81	5.179	0.789	0.42	0.588	2.098	12.161	0.913	938
Yoldia	14.53	10960	3.282	6.332	1.148	0.585	0.67	2.16	17.196	0.962	960
Dunes	67.20	16324	2.584	6.048	0.873	0.458	0.549	4.129	19.777	1.000	417
Young moraine	23.20	13664	3.297	6.579	1.084	0.549	0.662	2.759	20.32	0.964	1042
Artificially drained	28.08	11329	3.045	4.692	0.755	0.415	0.623	2.5	14.808	0.929	26
St.dev.	**COVER pct.**	**EDGE LGT**	**MATH**	**RICHN.**	**SHDI**	**SIDI**	**SQP**	**NP_M**	**NP TOTAL**	**Pro-portion**	**pixels incl.**
Littorina or yonger	22.51	7245	1.084	2.17	0.482	0.248	0.197	1.899	9.747	N/A	938
Yoldia	13.22	7292	0.914	1.982	0.447	0.207	0.132	1.853	11.04	N/A	960
Dunes	29.30	8055	1.23	1.865	0.396	0.199	0.24	3.325	11.754	N/A	417
Young moraine	22.08	8953	1.045	2.174	0.46	0.215	0.146	2.304	13.103	N/A	1042
Artificially drained	27.70	6332	1.125	2.243	0.509	0.262	0.161	2.209	9.831	N/A	26

Table 5.28 Spatial metrics from AAK, Nature theme values by (dominant) geomorphologic type in 1 km windows

Mean	COVER pct.	EDGE LENGTH	MATH	RICHN.	SHDI	SIDI	SQP	NP_C1M	NP TOTAL	pixels included
Littorina or yonger	26.08	34119	7.7	9.156	1.253	0.581	0.861	5.781	90.201	1027
Yoldia	21.07	31872	8.027	9.245	1.13	0.514	0.873	3.777	83.57	998
Dunes	54.91	50585	6.634	11.144	1.481	0.669	0.828	18.376	133.17	417
Young moraine	27.64	36252	7.483	9.994	1.197	0.532	0.86	6.144	100.848	1081
Artificially drained	23.29	26054	7.571	5.929	0.614	0.286	0.858	4.036	48.5	28
St.dev.	**COVER pct.**	**EDGE LENGTH**	**MATH**	**RICHN.**	**SHDI**	**SIDI**	**SQP**	**NP_C1M**	**NP TOTAL**	**pixels included**
Littorina or yonger	14.63	12251	1.402	2.495	0.435	0.189	0.05	6.053	39.53	1027
Yoldia	8.93	9176	0.923	2.375	0.425	0.188	0.017	3.646	31.493	998
Dunes	18.05	12607	1.802	2.442	0.424	0.156	0.066	9.201	50.46	417
Young moraine	17.04	13980	1.308	2.679	0.502	0.212	0.038	6.57	53.978	1081
Artificially drained	10.44	8199	1.419	3.184	0.545	0.254	0.02	3.343	21.251	28

Table 5.29 Spatial metrics from LCP, Nature theme values by (dominant) geomorphologic type in 1 km windows. Presence proportion is not stated for this image, as 'nature' pixels are found in all output cells, and all values thus will be unity (1).

From theses tables, clear differences between the strata are visible, most obvious for the cover percentage, where both data types indicate that most nature is found in the Dunes stratum, and least on Yoldia, in line with the description of the landscape given above. For the AAK data, the highest average richness of classes is found in the Young Moraine stratum, and the highest diversity metrics values in Yoldia, while for the LCP data, the highest values of both are found in the Dune stratum. The relatively low values for the cover percentage of LCP nature in the Dunes is partly due to the presence of the land cover class 'unvegetated', which has been re-classified to the matrix class (internal background). The small Artificially Drained stratum has lowest diversity metrics values for both data sets, which is not surprising since they have been reclaimed for agricultural purposes and are still today used for either grazing or crops. Figure 5.22 shows the separability between individual strata for a pair of metrics for the AAK and LCP data respectively, and is intended to indicate, how well spatial metrics discriminate between geomorphological regions. The LCP data have smaller standard deviations of the average metrics values within the strata and thus a visually better separation between the strata, where Artificially drained areas, Yoldia and Dunes are almost completely separated from each other.

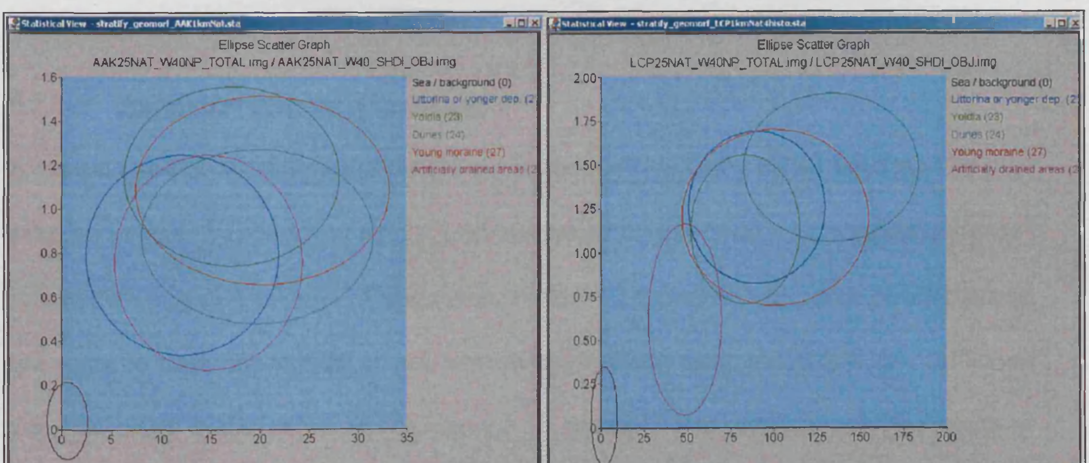

Figure 5.22 Scatter graphs of combination of the NP (x-axes) and SHDI (y-axes) metrics values in the geomorphological strata for AAK and LCP data, nature thematic level. These ellipse plots are based on average values (position), standard deviations (size) and the correlation between the bands (direction).

5.5.3 Hemeroby calculation and mapping

The Hemeroby index defined above is so simple and fast to calculate, that it tempts the user to directly apply it to large areas and all sorts of land use data sets, like the CLC at European level. However, caution is needed, and some investigations of the behaviour of this metrics in relation to scale, window size and other metrics should be carried out. Neither is it clear just how the calculation of this metric should be implemented and how maps of the resulting values should be presented. Thus, the AAK and CLC data sets were used for some test runs of index calculation, reporting of statistical properties and display in combination with environmental vector data from various sources. For the re-classification of CLC data to NDP-value images, it was decided to include the classes Lagoons and Estuaries as part of the landscape, even though Water (mostly open sea) is excluded. This is done with a nature management application in mind, since the 'land cover types' constitute important habitats for birds, and these areas in Denmark provide important rest and feeding grounds for migratory birds, also at the continental and global level (European commission, DG XI 1999, Bach et al 2001) and Denmark has a special obligation to preserve and protect the habitats found there (Bertelsen 2003, p. 5).

5.5.3.1 Agreement between data sources

A central question for this part of the project is whether Hemeroby values from the CLC can substitute values from AAK or similar high-resolution land use data – even though they are calculated using data an order of magnitude coarser. To answer this the values from the land use maps, re-classified to NDP values, were averaged to the same output cell size, following the 'flow chart' in the bottom line of Figure 5.10, page 228, and correlations of the resulting Hemeroby values carried out. The results are listed in Table 5.30.

window size	n.obs.	AAK pixels	IHI AAK	AAK st.dev.	CLC pixels	IHI CLC mean	CLC st.dev.	corr. (R)
1km	3710	40*40	67.946	14.333	4*4	65.681	15.994	**0.814**
2km	955	80*80	67.703	12.775	8*8	64.917	14.773	**0.851**
3km	435	120*120	67.812	11.505	12*12	64.714	13.405	**0.823**
4km	241	160*160	67.362	11.085	16*16	64.327	12.718	**0.878**
5km	164	200*200	67.558	10.082	20*20	63.800	12.351	**0.84**

Table 5.30 Values of integrated Hemeroby index (IHI) from AAK and CLC data respectively, with standard deviations and correlation coefficients from regression of Hemeroby values from AAK and CLC data with varying moving-window sizes.

The R-values are slightly higher than for the relation between cover fraction values for the AAK-CLC comparison at the nature thematic level (Table 5.21) and slightly lower than at the forest thematic level, in both cases over the entire range of window sizes. This similarity between agreement for cover proportion and Hemeroby index values is not surprising, since the cover proportion is the metric that come closest to being an average of pixel values (in principle of presence=1, absence=0). A visual impression of the relation for the smallest and largest windows used is given in Figure 5.23.

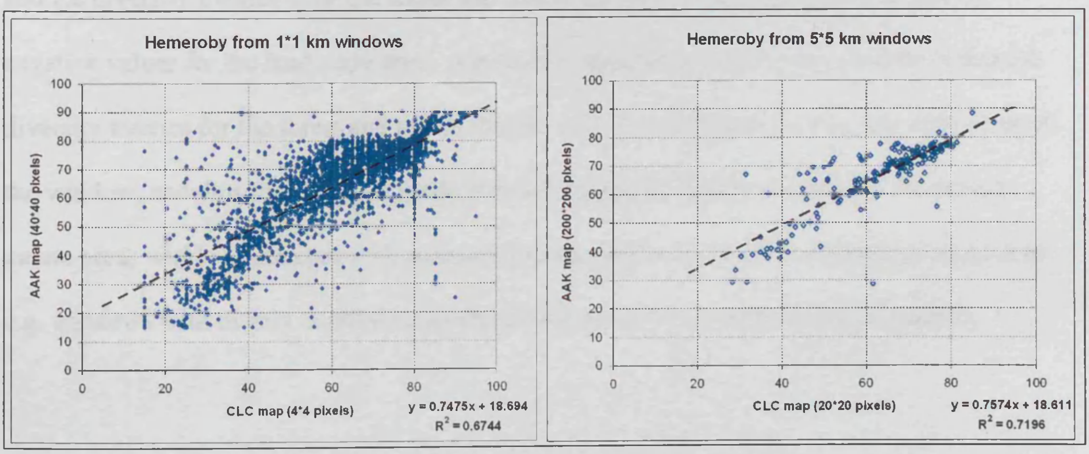

Figure 5.23 The relationship between Hemeroby values derived from AAK and CLC displayed as scatter plots.

The good agreement between values from AAK and CLC is assured through the existence of classes such as "Agriculture with natural vegetation" and "Complex vegetation patterns" in the CLC legend, with lower NDP values than the 'pure' Arable Land class. This compensates for the scaling effect of excluding small patches of natural vegetation which takes place when land use map with grain size 250m is made. In other words, the multi-functionality of mixed land use classes is incorporated in the weighting of human impact/pressure through the NDP values of these classes (Table 5.10), which is again reflected in the integrated Hemeroby index values.

5.5.3.2 Agreement with spatial metrics

As well as being an alternative to spatial metrics, the Hemeroby index can also be seen as a supplement to the suite of metrics. In that capacity it was compared with the other metrics, including the terrain features for the AAK data (Table 5.31) and the CLC data (Table 5.32). As for the correlations between spatial metrics from different data sources, it was assumed that metrics values for cover fraction and fragmentation metrics would be meaningless at the landscape thematic level (refer discussion in section 5.4.4).

For the AAK data, at the forest thematic level, the Hemeroby index is negatively correlated with cover fraction, i.e. the higher Hemeroby in the window, the less forest, not a surprising finding. More counter-intuitive is the observation of positive correlation between Hemeroby and the diversity metrics – for the forest and nature thematic levels, in contrast to clearly negative values for the landscape level. A possible explanation to this phenomenon is that the diversity metrics for the forest and nature themes only are calculated for (the relevant) parts of the window, and thus the positive correlations are caused by higher diversity of forest and nature areas *within* landscapes with human influence /higher land use pressures (in contrast to e.g. windows with mainly coniferous forest and (thereby) low Hemeroby index values).

AAK-Hemeroby	Forest					Nature					Landscape				
metric type	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km	1km	2km	3km	4km	5km
n. obs.	2206	656	338	203	134	2960	794	362	209	137	3086	796	362	209	137
COVER	**-0.564**	**-0.577**	**-0.562**	**-0.524**	**-0.59**	**-0.97**	**-0.974**	**-0.975**	**-0.977**	**-0.98**	N/A	N/A	N/A	N/A	N/A
RICHNESS	**-0.042**	0.013	0.025	**0.186**	**0.18**	**-0.106**	**0.094**	**0.156**	**0.234**	**0.095**	-0.03	**0.148**	**0.176**	**0.322**	0.098
SHDI_OBJ	**0.095**	**0.332**	**0.461**	**0.578**	**0.607**	**0.116**	**0.386**	**0.494**	**0.55**	**0.559**	**-0.466**	**-0.534**	**-0.56**	**-0.52**	**-0.713**
SIDI_OBJ	**0.108**	**0.321**	**0.442**	**0.542**	**0.585**	**0.128**	**0.358**	**0.441**	**0.496**	**0.504**	**-0.533**	**-0.607**	**-0.626**	**-0.599**	**-0.74**
EDGELENGTH	**-0.441**	**-0.492**	**-0.382**	**-0.216**	**-0.232**	**-0.449**	**-0.379**	**-0.322**	**-0.19**	**-0.179**	**-0.094**	0.041	**0.104**	**0.257**	**0.27**
MATHERON	**-0.182**	**-0.223**	**-0.226**	-0.07	-0.157	**0.191**	**0.353**	**0.421**	**0.524**	**0.443**	N/A	N/A	N/A	N/A	N/A
SQP	**-0.1**	**-0.129**	**0.029**	**0.336**	**0.265**	**0.343**	**0.611**	**0.68**	**0.739**	**0.741**	N/A	N/A	N/A	N/A	N/A
NP_Matrix	**-0.418**	**-0.481**	**-0.438**	**-0.37**	**-0.424**	**-0.426**	**-0.524**	**-0.571**	**-0.497**	**-0.629**	**-0.198**	**-0.257**	**-0.274**	**-0.23**	**-0.239**
NP_TOTAL	**-0.331**	**-0.367**	**-0.236**	-0.072	-0.062	**-0.284**	**-0.194**	**-0.111**	0.007	0.029	**0.073**	**0.231**	**0.316**	**0.426**	**0.439**
Elevation	**0.105**	**0.094**	**0.14**	**0.187**	**0.203**	**0.136**	**0.141**	**0.155**	**0.196**	**0.205**	**0.114**	**0.139**	**0.155**	**0.196**	**0.205**
Slope	**-0.133**	**-0.125**	**-0.103**	-0.052	-0.036	**-0.151**	**-0.132**	**-0.124**	-0.036	-0.028	**-0.173**	**-0.133**	**-0.124**	-0.036	-0.028

Table 5.31 Correlations between output cell values of Hemeroby and the suite of spatial metrics for AAK land use data. Significant relations are marked by **bold** types.

For the AAK data, at the nature thematic level the Hemeroby index is positively correlated with fragmentation metrics and strongly negatively correlated with the cover fraction metric. Hemeroby is positively correlated with SqP values, probably showing that this could be a good structural indicator of naturalness – noting that the M and SqP metrics are binary functions, comparing forest-non forest and nature-non nature areas – and as above, the Hemeroby values integrate characterisation of land use *outside* the forest and nature patches. The fact that there are negative correlations between Hemeroby and NP_total for the forest and nature levels but positive correlations for the landscape level, is likely to be caused by the observed fragmentation /splitting of artificial/urban land use classes like roads and railway lines shown for the 25m grain image in Figure 5.11.

CLC-Hemeroby	Forest					Nature					Landscape				
metric type	**1km**	**2km**	**3km**	**4km**	**5km**	**1km**	**2km**	**3km**	**4km**	**5km**	**1km**	**2km**	**3km**	**4km**	**5km**
n. obs.	661	305	199	142	105	1480	558	307	193	134	3086	796	362	209	137
COVER	**-0.62**	**-0.56**	**-0.53**	**-0.61**	**-0.61**	**-0.84**	**-0.87**	**-0.87**	**-0.88**	**-0.9**	N/A	N/A	N/A	N/A	N/A
RICHNESS	-0.01	**-0.19**	**-0.22**	**-0.17**	-0.09	**-0.13**	**-0.47**	**-0.58**	**-0.57**	**-0.65**	**-0.4**	**-0.43**	**-0.49**	**-0.38**	**-0.42**
SHDI_OBJ	**-0.21**	**-0.2**	**-0.18**	**-0.14**	-0.03	**-0.49**	**-0.58**	**-0.6**	**-0.6**	**-0.62**	**-0.54**	**-0.52**	**-0.49**	**-0.46**	**-0.45**
SIDI_OBJ	**-0.2**	**-0.2**	**-0.18**	**-0.14**	-0.01	**-0.48**	**-0.56**	**-0.55**	**-0.57**	**-0.56**	**-0.53**	**-0.48**	**-0.45**	**-0.41**	**-0.38**
EDGELGT.	**-0.16**	**-0.35**	**-0.43**	**-0.43**	**-0.47**	**-0.13**	**-0.48**	**-0.57**	**-0.52**	**-0.55**	**-0.42**	**-0.46**	**-0.46**	**-0.33**	**-0.29**
MATHERON	**-0.16**	**-0.3**	**-0.38**	**-0.37**	**-0.43**	**-0.12**	**-0.21**	**-0.24**	**-0.19**	**-0.29**	N/A	N/A	N/A	N/A	N/A
SQP	**-0.35**	**-0.18**	**-0.21**	**-0.19**	**-0.11**	**-0.48**	**-0.19**	0.017	0.097	0.061	*N/A*	N/A	N/A	N/A	*N/A*
NP_Matrix	0.013	**-0.2**	**-0.36**	**-0.29**	**-0.55**	**0.498**	**0.189**	**-0.11**	-0.06	**-0.38**	**0.54**	**0.305**	**0.212**	**0.208**	**0.145**
NP_TOTAL	**-0.11**	**-0.25**	**-0.38**	**-0.31**	**-0.31**	**-0.11**	**-0.44**	**-0.6**	**-0.51**	**-0.63**	**-0.39**	**-0.42**	**-0.48**	**-0.32**	**-0.42**
Elevation	**0.106**	**0.201**	**0.246**	**0.268**	**0.291**	**0.244**	**0.24**	**0.28**	**0.267**	**0.268**	**0.121**	**0.162**	**0.207**	**0.244**	**0.266**
Slope	**-0.07**	-0.02	-0.01	0.056	0.04	0.005	-0.03	-0.03	0.022	0.003	**-0.18**	**-0.13**	-0.09	-0	0.005

Table 5.32 Correlations between output cell values of Hemeroby and the suite of spatial metrics for CLC land use data. Significant relations are marked as **bold**.

For the AAK Data, at all three thematic levels, the Hemeroby index is positively correlated with terrain elevation and negatively with slope, though in the case of the latter this is only significant up to window size 3km. An interpretation of this could be, that the more natural land use classes are typically found on sloping terrain, but on the other hand they are mostly found along the coast, especially on Skagens Odde and in other dune formations, with relatively low elevations. The fact that there is a larger concentration of nature type land cover near the coast than on the Yoldia plains also contribute to the positive correlation between Hemeroby and elevation. For the CLC data the same very significant relationship between Hemeroby and cover fraction are found, with the highest correlations expressed for the nature thematic level. Here the correlations Hemeroby-diversity metrics are constantly negative, with relatively high values for the forest and landscape themes. This could be due to the low number of pixels within the windows, which gives a low probability of finding several different land use classes within the same window - as indicated by the low average values of Richness in Table 5.17 and Table 5.18. The negative correlations between Hemeroby values and NP_total appear because the dominant land cover class (agriculture) here is assigned high NDP values, so that windows with only little forest or nature (few patches) will have high Hemeroby index values. For the CLC data, the correlation coefficients for the Hemeroby - NP_matrix regressions all decrease rapidly with increasing window size. For the small windows, NP_Matrix values above zero will simply indicate the presence of matrix/agriculture with high NDP values while for larger windows, high NP_Matrix values will indicate the presence of perforated forest or nature. This confirms predictions from percolation theory and neutral model studies that, before many gaps/openings appear, a certain amount of patch area has to be present (Gardner et al 1987, With 1997). Correlations with elevation are similar to those from the AAK data, but no relation is identified for slope.

The results above indicate that, for CLC data (or other medium-resolution images/maps) Hemeroby indices and spatial metrics values should be calculated for relatively large geographical windows, in order to have clear interpretations of the metrics and their mutual relations.

5.5.3.3 Display and mapping of Hemeroby indices

Before the Hemeroby index values were transformed back to categorical values corresponding to the Hemeroby classes of Table 5.11, histograms of the distribution of the index values were constructed at window sizes of 1, 2, 3 and 5km, see Figure 5.24. The structure of the different types of input data are clearly reflected in the shape of the curves. Especially at 1 and 2 km, the presence of windows with purely agriculture (CLC category 2.1.1: non-irrigated arable land) is distinct. Since this class has been assigned an NDP factor of 0.8 (80 in the integer maps), this is the value of the Hemeroby index for a large number of output cells. This effect is not so accentuated for the AAK data, due to the larger number of pixels in each window, with increased probability of finding other classes than 'arable land' there. It is not surprising that for both data types, the over-all image variability decreases with increasing window size, as seen in Table 5.30, and that it is reflected in the histogram curves being more concentrated around the mean values.

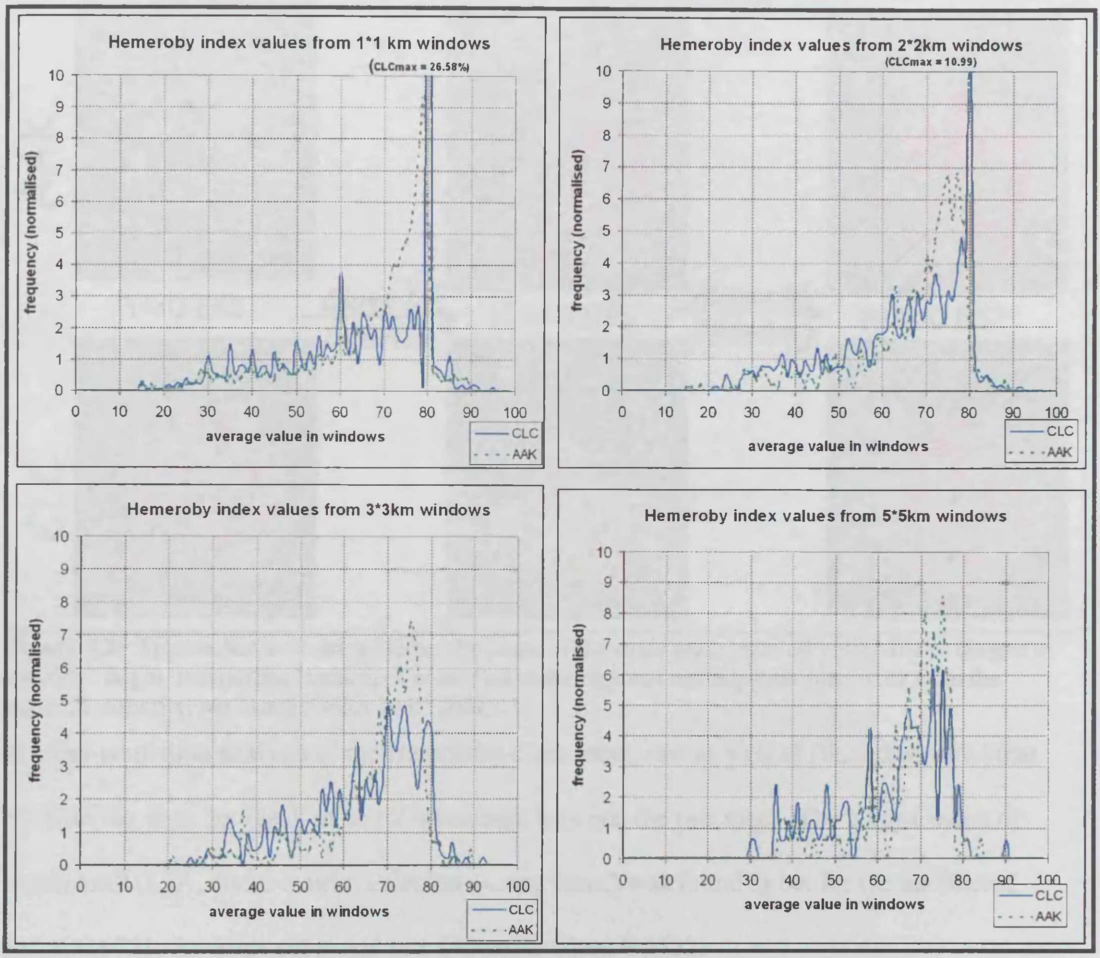

Figure 5.24 Combined histograms of Hemeroby values distribution for AAK and CLC data for window sizes from 1 to 5 km. Note that the number of observations (output cells) decrease from 3710 at 1km extent to 164 at 5km extent.

From Figure 5.22 it was obvious that if Hemeroby maps were to be made from the 1km averages that would allow comparison of AAK and CLC data, an alternative classification was necessary. Thus, the intervals of Table 5.11 were modified so that the label Polyhemrobic was assigned to values >= 78 (instead of above 80) for both datasets, in order to include the peaks of both histograms and to have a certain amount of pixels in the highest Hemeroby class. Furthermore, it was preferred that the same re-classification strategy was applied to both data sets[35]. The results, including majority filtering in a 3*3 kernel as the 'clean-up' operation, are shown in Figure 5.25 below.

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[35] Alternatively, the re-classification could be based on equally sized intervals (percentiles) of Hemeroby index values from the two data sets.

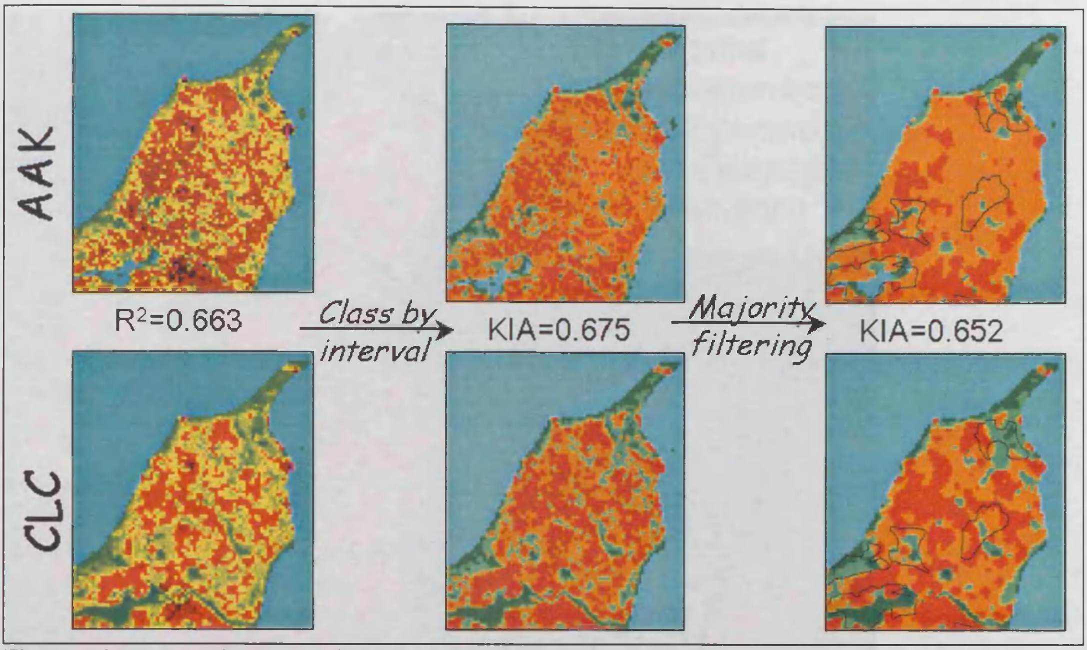

Figure 5.25 Approaches to creating Hemeroby maps of the study area. Inserted vector-file in images to the right: larger undisturbed landscapes according to the regional development plan (data from the regional authority, see Nordjyllands Amt (2001).

A cross-tabulation analysis of the Hemeroby-class maps, raw as well as filtered, showed that the filtering does not result in better agreement between the two maps. The Kappa Index of Agreement (KIA, entire matrix, calculated using Idrisi) was found to be: for the un-filtered maps: 0.6751; for maps subjected to a 3*3 mode filter: 0.6522.

An alternative to this 'clean-up' operation, which was performed in order to improve map appearance, could be smoothing of the "Hemeroby surface", either through filtering of the averaged image as shown above or through creation of a surface with overlapping windows, such as can be created with the Idrisi MapWalker (Hovey 1998), which is used in the concluding example here. Actually, a similar approach can be used with other spatial metrics, such as for maps of diversity classes or fragmentation classes, perhaps based more on histogram analyses than on ecological interpretation of metrics values, as the interval limits would change between different data sets. Potential uses of Hemeroby maps include input to models of environmental impact, use as basal layers for regionalisation efforts - or simply as base maps for illustration of certain themes like in the example in Figure 5.26 below.

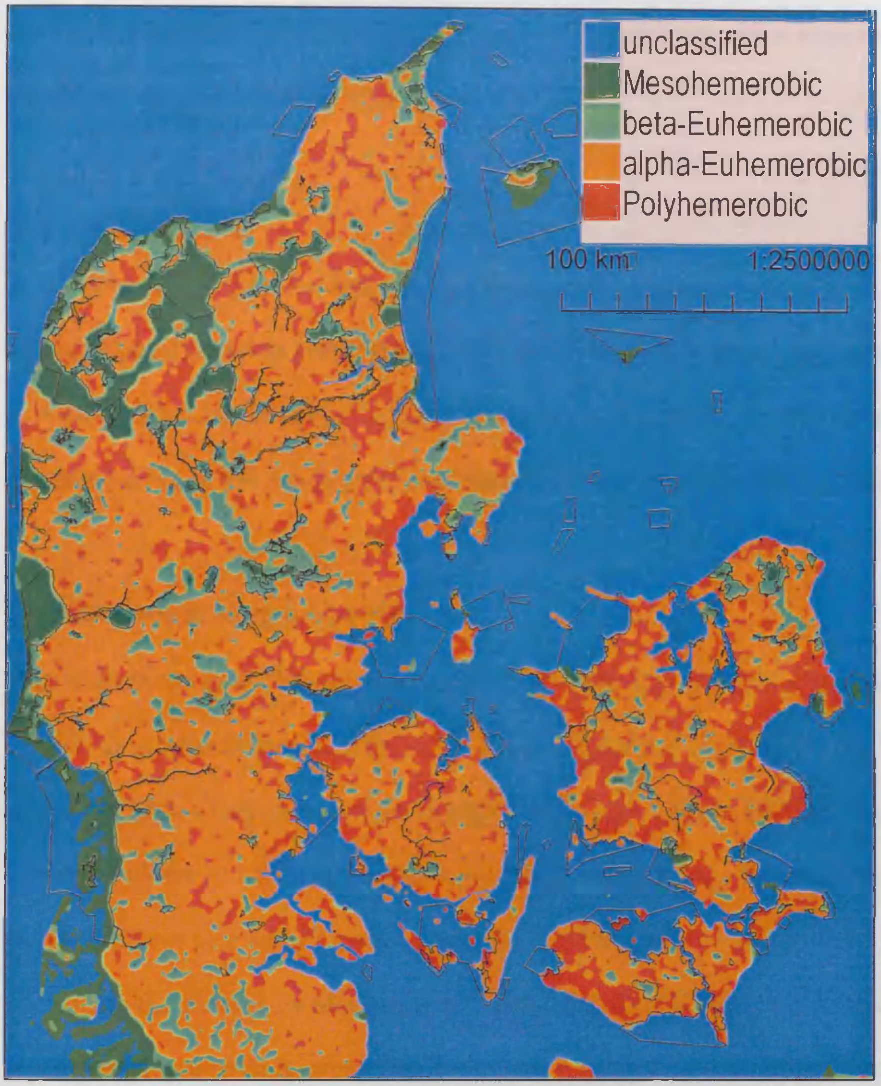

Figure 5.26 "Hemeroby map" of Denmark based on CLC data, extracted with 'smooth' averaging in circular windows (with diameter 13 pixels, corresponding to an area of 8.3 km^2), classification by intervals and clean-up filtering. The vector theme shows appointed EU habitat areas (Bertelsen 2003), acquired from AIS, updated July 2003. These areas constitue the Danish contribution to the Natura2000 network (European Commission 1999).

Figure 5.26 shows one of many possible approaches to map the distribution of Hemeroby classes at the national level. For the study area in Vendsyssel, it is clearly areas with low Hemeroby index values that have been appointed, like heath lands, forest areas and the raised undisturbed bog area in Store Vildmose. For the rest of the country, it can be noted that areas with a long history of intense agricultural use like western Zealand and the plain west of Copenhagen stand out as being polyhemerobic, while suburban zones like the forested area north of Copenhagen does not seem to be under pressure. In general, the objective of producing a map that would highlight the parts of Denmark that are most intensively used by agriculture and dense settlement was met.

5.6 Discussion

In this section, the questions that emerged from the cultural environment project are addressed, using the data sets available and the landscape ecological – spatial metrics approach. The points stated in the Objectives section will thus be addressed in the light of the results obtained in this study, and the questions answered as far as it is possible.

1) Thematic scaling properties

Data from the three test blocks showed the values of diversity metrics to increase with increasing number of classes in the input images (higher thematic resolution). As expected, the values of structural metrics such as edge length and patch number were observed to increase with the inclusion of more classes. Metrics values were also notably influenced by the exclusion or inclusion of matrix, as expected in the methodological considerations, and confirming the warning by McGarigal and Marks (1995), that metrics values will differ significantly, as also demonstrated by Gallego et al (2000). This was especially seen for the diversity metrics SHDI and SIDI, where comparisons were made at the forest and landscape thematic levels and the highest values were found for calculations with matrix excluded – typically resulting in a greater evenness of the class distribution.

2) Influence of spatial resolution

Changing spatial scale influenced metrics values, though in different ways for different types of metrics. The cover proportion metrics showed practically no response, and (as a consequence) the also the diversity metrics showed very little response. Patch count metrics, in terms of total patch numbers as well as counts of background/matrix patches decreased linearly with increasing grain size, but with different slopes of the scalogram curves for different classes. This is in line with the observations by Wu (2003), who compared landscape and class level metrics for different types of landscapes and found distinct differences in scalogram shapes. Fragmentation metrics increased in a linear or logarithmic way. Some artificial fragmentation effects were observed for the AAK data when converted to grids with 25m grain size (see also the scalograms in Figure 5.13), a resolution which is otherwise practical for comparison with LCM and LCP data. Thus it would be advisable to either use images with smaller grain size or to apply a more sophisticated aggregation method that preserves or rapidly removes linear elements during aggregation of classes and map generalisation, such as those described by Goffredo (1998) and Büttner et al (2002). Preserving object shapes and thereby values of structural metrics is not always possible. However, with increased availability of computer speed and memory, there is no practical reason why land use data should be aggregated to larger grain sizes (before spatial metrics are calculated) – apart from needs to compare metrics values from images with similar grain size or to save computation time for very large area calculations.

3) Comparability of data for landscape characterisation

Moving-windows analyses showed that the different data sets to a large extent are comparable, even when they have differences in the absolute values of the metrics. For instance, the total number of patches counted within each window would be four times higher for LCM data than for AAK data, even with the same number of classes present (Table 5.17 and Table 5.18). Also diversity and fragmentation metrics were twice as high or more from LCM and LCP data relative to AAK data, and even higher relative to the CLC data. The main reason for these differences lies in the origin of the data: the AAK coming from vectors based on existing topographic maps and interpretation of aerial photos, and the LCM/LCP data from semi-automated classifications of satellite imagery. The AAK and LCM/LCP data agreed well for the forest thematic level, especially on cover proportions, and less so at the nature thematic level. For the diversity metrics, the best agreements were found at the landscape level. The edge length metric appears to be quite robust, and good agreements are found between these data sources at all window sizes and thematic resolutions. Thus, basic elements of forest structure can be derived from for instance the land cover maps (potentially updated on a yearly basis) and used to predict (changes in) metrics values from the AAK land use data, which potentially serve as a base map for environmental monitoring.

4) Comparisons between maps at different thematic resolutions

Agreements between metrics values at different thematic levels are reported for AAK and LCP data, since they represent "end points" in terms of number of classes and in where the focal points of classification have been (land use vs. vegetation types). The pattern of agreements and disagreements were however very similar, compare Table 5.22 and Table 5.23. Some metrics 'translate' well between thematic levels, in particular the patch count metric NP and the closely related (highly correlated) metric of edge density. In general the best agreements are found between the forest and the nature level, and the worst between the forest and the landscape levels, where the disparity is the largest in terms of number of classes.

5) Influence of terrain features on metrics values

The inclusion of the (averaged) terrain parameters slope and elevation showed that some metrics were highly correlated with these, and that it may be possible to predict (average) metrics values from terrain, at least at some window sizes and thematic resolutions. For the AAK data at forest thematic level, all metrics values turned out to be positively, and with two exceptions, significantly correlated with elevation and slope; the total number of patches and edge length having the highest coefficients. For the LCP-forest data, such relationships were not apparent and negative coefficients arose for the relationships between slope and M and between slope and SqP. At the landscape thematic level for the AAK data, edge length and total patch number again agreed well with both elevation and slope, diversity metrics only with slope. For the LCP data at the landscape level, only vague relations appear.

The use of basic geomorphological types as a mask for stratification showed some significant differences between the strata in terms of metrics values. As expected, most nature was found in the Dunes stratum, which also had the highest diversity metrics values for the LCP data. The AAK data also pointed to Dunes as having most nature content, but for this data type the highest diversity - and fragmentation - values were found for Young Moraine. These results and possible visualisations of 'structural separability' like in Figure 5.22 show the feasibility of characterising landscape types with spatial metrics and points to the possibility of predicting vegetation patterns and the appearance (texture) of landscapes from their three dimensional shape or their geomorphological history.

6) Options for description of landscapes using spatial metrics

The results presented so far show the potential of spatial metrics to characterise and classify landscapes according to their composition and structure of their land use/land cover classes. For instance, a combination of a diversity metric, a fragmentation metric (at the landscape level an edge length metric) and cover proportion (or at the landscape level a patch count metric which is normally highly correlated with cover proportion) together span the 'space' of most possible landscape configurations, and should thus be sufficient to characterise the landscapes within the windows. This could be in the form of summary statistics or artificially coloured images with the mentioned parameters controlling image display parameters Red, Green and Blue (RGB) or Intensity, Saturation and Hue (ISH). The exact choice of metrics would depend on the preferred grain size of the map, the size of the M-W in the calculations and the data type and thematic resolution used, and be guided by the correlations between metrics values found here. These methods remain to be tested for applicability in the DACE project.

7) Use of the Hemeroby index

A Hemeroby index as proposed by Steinhardt et al (1999) was implemented using a M-W approach and the Naturalness Degradation Potential (NDP) coefficients defined by Brentrup et al (2002) for CLC classes, which could also be applied to AAK data. A good agreement was observed between the values of the Hemeroby index derived from AAK and CLC data respectively. Visually expressive illustrations can be made using the reclassification-averaging approach described in section 5.5.3.3, see also Table 5.11. Given that Hemeroby has been defined as a measure of unnaturalness, it is considered a satisfying result, that the Hemeroby index used here shows strong negative correlation with the coverage fraction of the classes appointed to the nature theme. The Hemeroby index is however only positively correlated with metrics of fragmentation for the nature theme from AAK data, for the CLC data the coefficients are significantly negative for both the nature and landscape themes, but this can partly be attributed to the small window sizes in terms of pixels.

Based on the apparent usefulness of a Hemeroby index, it is proposed to generalise the Hemeroby index to an Integrated Hemeroby Index: IHI_{Dx} where D denotes the diameter of the window and x is either S for square or C for circle. As shown in Table 5.30, average values of the IHI will be almost identical even though different window sizes are used. It is rather the variability within the study area that will change with window size and overlap. These relations discussed here were established for the test area, but later on it would be worth comparing CLC and AAK data from other parts of Denmark. To that end the 25*25km blocks of AAK vector data represent good samples – also for instance for looking into the relations between Hemeroby indices and spatial metrics.

5.7 Conclusions – implications for landscape monitoring

For this study, the moving-windows method was useful for further investigation of the behaviour of spatial metrics in response to changing resolution and window size as well as thematic resolution. The M-W approach also proved to be well suited for creating maps to illustrate large-area landscape patterns. Scalograms showing metrics values as function of grain size proved to be useful tools for assessment of individual metrics in limited areas such as the test blocks used in this study. In this study scalograms were used to confirm that landscape pattern is spatially correlated and dependent on scale (Wu 2003, Wu et al 2002) also on the thematic level.

The AIS data were well suited for the analyses carried out in this study, the AAK data especially fulfilled their purpose. When these were transformed to raster format, realistic land use maps were obtained, which could be used not only for monitoring/change detection (Groom and Stjernholm 2001) but also for landscape characterisation. However the CLC data of lower resolution (250m grain size) can substitute the AAK raster data (at 25 m grain size) for calculation of Hemeroby index values over large areas, as index values from these two sources are strongly correlated. The Hemeroby index itself turned out to be a useful indicator of pressure on landscapes from human activity. While AAK and CLC data are well suited for creating maps of unnaturalness (which is one definition of Hemeroby), LCP data might be useful for creating contrasting maps of naturalness. Where these coincide with high values, potential areas with conflicting interest and/or nature under pressure have been identified. Thematic maps of Hemeroby index values can provide background information for planning in the open land, although how it is best implemented on landscape management remains to be tested. The inclusion of terrain parameters can provide supplementary spatial information for landscape stratification (before metrics are calculated) as well as segmentation (when used together with spatial metrics).

For characterisation of smaller areas, such as individual cultural environments, a combination of contextual and patch/object specific metrics can possibly be used. In raster-GIS analyses it would even be possible to combine metrics derived with different window sizes, as long as the output cell size remains the same. This approach is likely to provide landscape indicators that supplement those proposed by Fry et al (2003) and required for selection and management of cultural environment areas in Denmark. It will thus be applied within the framework of the DACE project. The Hemeroby index, based on AAK maps will be used in the following chapter, to assess landscape-level changes in naturalness following different afforestation scenarios.

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6 Applications of spatial metrics for environmental monitoring and planning, exemplified by afforestation scenarios for Vendsyssel, Denmark

6.1 Introduction/background

In the previous chapter, methods for quantification and visualisation of forest- and landscape structure were described. As an example of the possible use of spatial metrics and moving-windows methods in planning at regional level, the impact on landscape structure of different afforestation strategies is assessed in the present chapter. A number of common GIS and image processing operations were used to create different scenarios that represent very different afforestation strategies. Changes in spatial metrics and Hemeroby index values were compared with the present situation.

In Europe, afforestation has become an important issue during the last few decades. Partly as a response to changing conditions for agriculture, partly following a demand for nature conservation, environmental protection and recreational facilities. The national goal for Denmark is a doubling of the current forest cover of 11% in a "tree generation", i.e. 80 to 120 years, as expressed in the Forest Act of 1989 (Jensen 1999).

The study site used in this study is similar to the area used in chapter 5, Vendsyssel in Northern Jutland. Today, the average forest cover within the study area is 9.5 per cent, but even within this limited area forests are very unevenly distributed. The western part of Vendsyssel is poor in forest, a situation that dates back to pre-historic times, when the forest were cleared for cropping and grazing, mostly on the Yoldia plains (Hansen 1964, p. 13). Some less fertile areas soon turned into heathlands, most of which have later been reclaimed for agriculture or turned into plantations, mostly spruce. On the other hand, parts of the extensively used, hilly areas are though to have remained more or less constantly forested.

The main agents for actually planting new forest are farmers/land owners and public authorities. The tools for control of the afforestation activities on private land are grants and tax deductions (Jensen 1999). They are given when forest is established in designated afforestation areas, which are outlined at the national level and incorporated as parts of the regional development plans. Other areas are considered neutral, and planting of forest is allowed but not encouraged, and finally some 'negative areas' have been pointed out, where afforestation is unwanted. The criteria for selection of afforestation areas include protection of ground water resources, where the quality of these is threatened, for instance through leaching of manure and pesticides from intensive agriculture (Nordjyllands Amt 2001, p. 159). Also outdoor life activities have high priority, and it is thus attempted to create larger coherent forest areas rather than forest patches on small and difficultly accessible marginal agriculture areas. Negative areas include cultural environments, in particular around churches, but also areas designated for wind farms should have a distance of up to 2 km from forests (ibid, p. 161).

Given the potential of thematic mapping and application of moving windows for extraction and display of spatial metrics, it was considered appropriate to use such metrics as indicators of structural change for different afforestation scenarios, as an example of the potential use of landscape-ecological spatial analysis in a real-world setting.

For this study, only the base map area is used (see Figure 5.2), not the entire area of the region Nordjyllands Amt, thus this is not a full investigation of the effects of afforestation at region level. Four different scenarios have been established, based on the following criteria:

1. All of the designated areas are afforested;
2. Connectivity between existing forest areas are improved through planting of forest corridors;

3. Hemeroby is minimised through planting of forest in the areas with highest Hemeroby index values;
4. Public access to forest is optimised through planting of forest on the available lands closest to urban concentrations.

These imaginary afforestation scenarios represent extreme cases of weighting interests, and are not to be taken as recommendations for future land use.

6.2 Objectives

Objectives for this study include:

- Creation of afforestation scenarios in the form of modified AAK land use/land cover maps with 25 m grain size, based on existing AAK maps, assumptions on afforestation strategies and supplementary data on terrain and population.
- Assessment of the resulting changes in landscape structure expressed through variations in spatial metrics and Hemeroby values, and display of the results for overview of where the most significant changes take place.
- Comparison of Forest Concentration (FC) profiles from the current situation and the different scenarios.

6.3 Data

The data used for this study are basically same as in chapter 5, supplemented by information on soil texture, population density and location of areas designated for afforestation. Each of the additional data sets are briefly described below.

6.3.1 Soil type maps

The data on topsoil types were acquired (for the cultural environment atlas project) as vector data at a nominal resolution of 1:50,000 and converted to a raster image with 25m grain size. Twelve soil classes are defined, according to texture/grain size distribution but normally only eight classes or colour codes are used (Breuning-Madsen et al 1999). The definition of the classes are shown in Table 6.1.

Colour code	SOIL TYPE	JB nr.	Clay	Silt	Fine Sand	Total Sand	Humus
1	Coarse sand	1	0-5	0-20	0-50	75-100	<= 10
2	Fine sand	2			50-100		
3	Clayey sand	3	5-10	0-25	0-40	65-95	
		4			40-95		
4	Sandy clay	5	10-15	0-30	0-40	55-90	
		6			40-90		
5	Clay	7	15-25	0-35		40-85	
6	Heavy clay or silt	8	25-45	0-45		10-75	
		9	45-100	0-50		0-55	
		10	0-50	20-100		0-80	
7	Organic soils	11					> 10
8	Atypic soils	12					

Table 6.1 Definition of soil types and colour codes for the soil classification of Denmark (after Breuning-Madsen et al 1999).

6.3.2 Dwellings density maps

One of the base maps for the Danish Area Information System (AIS) is a classification of the built environment (Nielsen et al 2000a). Here data from the national Building and Dwelling Register are aggregated to 100*100m (one hectare) grid cells, for use with other applications (Hvidberg 2001). One type of information herein is the density of floor space in the buildings within the grid cell. This area is used as a proxy of population density. The data are available from the National Environment Research Institute (DMU) in vector Arc-View or MapInfo format[36]. Using the Vertical Mapper (R) module of MapInfo, these data could be converted to a 'building density' raster map of Denmark, from which a subset for the study area was extracted. The data and the procedure for creation of an image to be used in scenario building is illustrated in Figure 6.1. The apparent 'cutting off' of the northernmost part of the region owes to the output from filtering including only pixels within the filter radius from the edges.

[36] From this URL address: http://www.dmu.dk/1_viden/2_miljoe-tilstand/3_samfund/ais/4_Download/MIdownload/aisdownload.htm (accessed 19/2 2004)

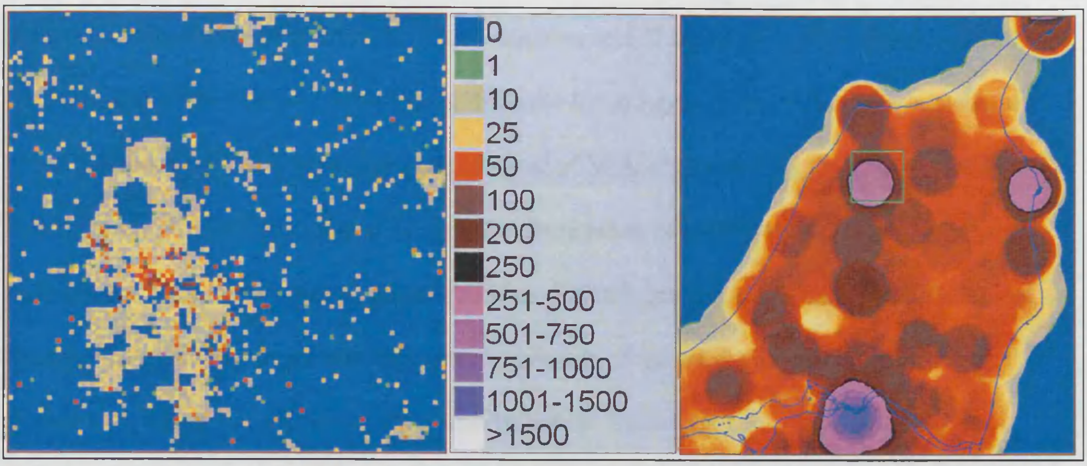

Figure 6.1 Creation of dwellings/floor space density surface with 25m grain size. To the left the density grid imported to image at 100m grain size. In the middle the legend for colour coding of density values, applied to both images. To the right the density image re-sampled to 25m grain size and filtered using a circular 'kernel' with radius 5km. Coasts inserted as blue lines, the sub-area of 10*10 km around Hjørring, used in Figure 6.2, is marked by the light green box.

6.3.3 Designated afforestation areas

These areas can be viewed on the regions web site[37], but the data are not yet available for download. However, data were available on request, and were delivered as Arc-Info shape files, and ready for use in the image processing routines for generation of the hypothetical forest maps.

6.4 Methods

Simple ways to create theoretical maps of future land cover are described, along with the approach to comparison of derived spatial metrics with similar metrics from the current situation.

6.4.1 Creating afforestation scenarios

The four different criteria for development of the scenarios are listed in the introduction. Common to all the scenarios, is that the forest cover is increased to 14.4 per cent. This figure is reached by using all of the area, which is available for afforestation within the designated zones where afforestation is promoted – i.e. Scenario 1, using the designated areas. This

[37] Interactive map available at: http://www.gis.nja.dk/lodsejerjava/default1.htm. Implementation in "ESRI Map Café", Java must be installed. Tick "Skovrejsning" to activate afforestation layer. Accessed 8/3 2004.

corresponds to establishing forest on 17226 hectares or 172 square km. Also common to all the scenarios is the relative proportion of different forest types, measured as area (number of pixels). According to the generally accepted goal of Multi-Purpose Forestry (Jensen 1999, Nordjyllands Amt 2001, section 5.2), an even distribution of coniferous and deciduous forest is aimed for, with some areas of mixed forest as well and small areas of the bush-forest class, though still relatively larger than the current presence of these land cover types. The distribution within the afforested areas thus becomes: Bush-forest 2%, Coniferous 44%, Deciduous 44% and Mixed 10%.

The AAK classes which were used as possible afforestation sites include:
Mineral extraction areas (being mostly gravel pits), Arable land, Pastures, Grass in urban areas, Sparsely vegetated areas and the 'unclassified' class, which by comparison the LCM data appeared to be mostly arable land. These classes were used to create a (mask) layer representing possible 'target areas' for afforestation. No patch size limit was applied, thus patches of one or a few pixels could be identified as potential afforestation sites.

It was furthermore assumed that current forest areas remain as they are, i.e. that they keep the current land use/cover, so the natural (managed) dynamics of these areas are not modelled. The same applies to other land use types, so for instance urban sprawl and nature restoration is not modelled either.

A generalised method for creation of a scenario map can be summarised as follows:

- Create potential surface (e.g. proximity to corridor, population density, Hemeroby)
- Multiply by potential afforestation area mask
- RANK result in order to find areas best suited for afforestation
- RECLASS to select overlay (selecting pixels with highest ranking)
- Multiply overlay (true) with forest index
- RANK to sort according to forest type index (defined below)

- RECLASS to assign to resulting forest classes
- Assign non-zero values to original AAK-map, result: selected forest classes replaces 'suitable classes' (agriculture etc.).

Where RANK and RECLASS are Idrisi functions (Eastman 1997), image arithmetic operations were performed in WinChips (Hansen 2000). The creation of potential surfaces and the forest index is described below.

Forest type index:

In order to make the most realistic map of future forest scenarios, a simple model for prediction of forest type from landscape parameters was applied. A "Forest type index" was defined as:

$$\mathbf{FTI = GMT + ST + ALT/15}$$

where GMT is the "textural equivalent" of the geomorphological landscape type (i.e. moraines have high clay content, dunes low), ST is the textural soil class (low values = gravel/sand, high values=silt/clay, range from 1 to 8, see Table 6.1) . ALT is the altitude from the 25m-cell DEM, where the maximum value in the test area is 130.4 m. The composition of the index is based on the following assumptions:

- Deciduous forest is mostly found at higher elevations on finer soils (moraine hills).
- Coniferous forest is mostly found at lower elevations on coarser soils (near the coast, plantations in dune areas).

The assignment of 'afforestation pixels' to different forest types, as described above, should thus be possible according to their FTI value. The distribution of the current forest types found in the AAK maps was tested against a model based on ranking of pixels based on FTI values and the results are shown in Table 6.2. Though the agreement is not truly convincing numerically, application of the FTI was found to produce realistic patterns within the areas assigned for afforestation, see Figure 6.2.

	0: Non-forest	2: Bush-forest	3: Deciduous	4: Coniferous	5: Mixed	Total
1:Land/matrix	5106122	0	0	0	0	5106122
2: Bush-forest	0	**0**	78	479	1	558
3: Deciduous	0	26	**30104**	85058	312	115500
4: Coniferous	1	530	85006	**333176**	1049	419762
5: Mixed	0	0	313	1049	**0**	1362
99: Background	5588694	2	0	0	0	5588696
Total	10694817	558	115501	419762	1362	**11232000**

Table 6.2 Cross-tabulation of test image with forest types assigned according to pixel ranking by FTI (columns) against actual forest map from AAK at 25m (rows). Kappa index of agreement for class 3 is 0.252, for class 4 it is 0.786.

Improved Connectivity is modelled by manually drawing centre lines for forest corridors to connect existing large forest areas. The lines are converted to a raster image and the DISTANCE function of Idrisi (Eastman 1997) is used to assign highest values to pixels closest to the lines. Thus, an image of proximity to corridor centres functions to determine priority for afforestation. The total length of the proposed corridor lines was 384 km, This approach turned out to produce broad corridors with a width of 800 to 850m in open land, making them forest habitats in their own right to most species, rather than merely corridors for movement.

Proximity to population centres was modelled by creating a 'building density surface', through application of an average filter with a radius of 5km or 50pixels in the 100m-grain image. The choice of such a large filter size was based on the intention to include areas around the larger centres in the region, especially Hjørring and Aalborg. This approach also contributes to segregation of residential/recreational areas from agricultural ones. More advanced models have been developed, that take into account accessibility (Skov-Petersen 2001).

Highest current Hemeroby was found using the smoothed Hemeroby index map produced for illustration purposed in the precious chapter, based on averaging of NDP values in a circle with radius 1.25km or 50 pixels in the 25m-grain AAK-based image. It is assumed here, that establishing forest in the areas with current highest Hemeroby index values will lead to the greatest possible over-all decrease in Hemeroby index values for the region as a whole. The possible high costs associated with using the best (most intensively used) arable land and areas close to urban centres are not considered, though in reality some cost-benefit analysis would be carried out in the context of such a radical land-use change.

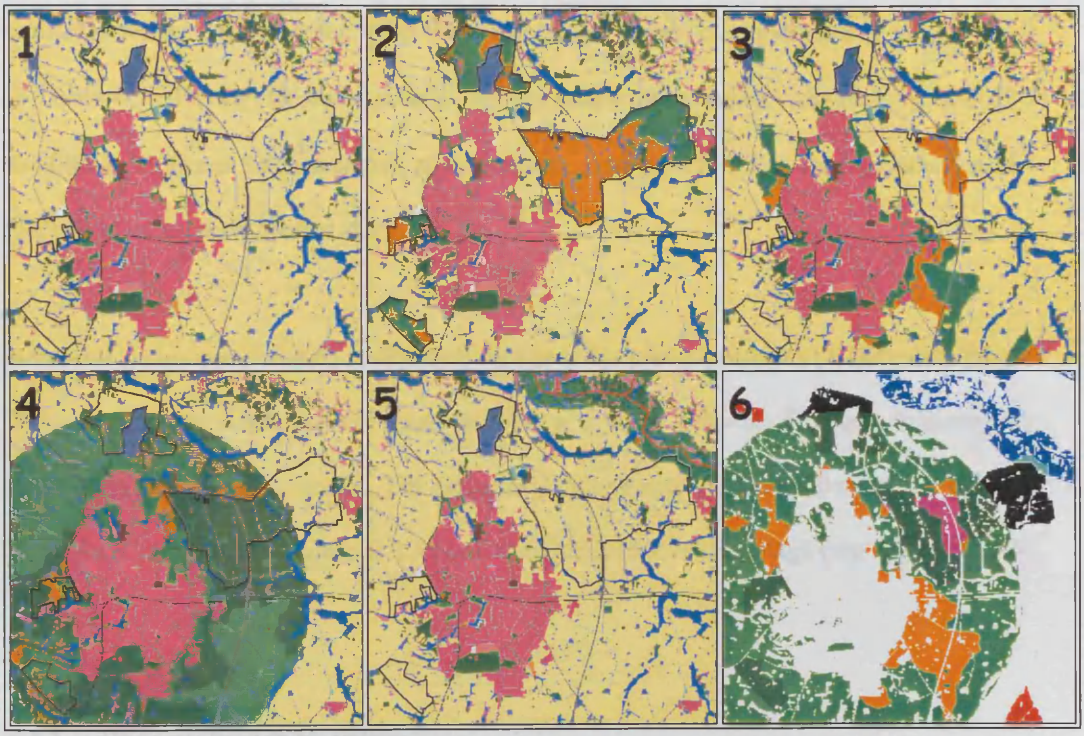

Figure 6.2 Local effects of different theoretical afforestation scenarios around regional centre town Hjørring. Image 1 shows the current situation, image 2 afforestation of the designated areas, image 3 the minimised Hemeroby scenario, image 4 the proximity to urban centres scenario, image 5 the connecting-corridor scenario and image 6 a combination of the appointed areas in image 2 to 5, indicating only little overlap between the different scenarios. Image 1-5 follows the standard AAK legend, shown in Figure 5.4, in image 6 the afforestation areas from image 2 are black, from image 3 red, from image 4 green and from image 5 blue, other colours indicate overlaps of two or more scenarios.

6.4.2 Calculating and comparing metrics

Moving-windows calculations of spatial metrics were performed on the scenario-maps, using the methods and IDL-scripts described in the previous chapter. In this study, focus was on the 1*1 km output cells, as it was found that this resolution gave the best basis for comparing the effects of the different scenarios and most significant changes. Change was assessed in two ways: by comparing average metrics values for the entire test area and by creation of change images by subtraction of the M-W image representing the current situation from the scenario-based M-W output (so that positive values come to represent increases in metrics values and negative values decreases). For extraction of these change values, degraded versions of the afforestation maps for the different scenarios were used as masks, in order to work only on cells affected by 'afforestation' (this is the reason that forest cover increases in all instances in Table 6.3). Finally, the cover metrics were calculated for window sizes ranging from 500 to 5000 or 5500m at 500m increase, and the results were used to create forest concentration (FC) profiles for the different scenarios.

Hemeroby maps were created in the same way as in the previous chapter. NDP value maps were created from AAK land use maps, with the new forest imposed. This was done through an Idrisi re-classification routine. The Hemeroby index maps were created using the IDL-script for averaging byte values and returning an Idrisi real-values image (see Appendix 1.5).

6.5 Results

6.5.1 Changes in metrics values

Table 6.3 shows the differences between the spatial effects of the different scenarios, compared to the present. In all cases 172 km^2 of additional forest was created, but how concentrated they are differs widely. For the Near Urban (NU) scenario only 373 windows of 1km^2 are affected, corresponding to adding 46 hectares of forest per km^2, while for the Maximum Hemeroby (MH) cells scenario the number is 808, corresponding to adding 21 hectares of forest per km^2. These differences are not surprising, since there was no mechanism for spatial concentration of the selected pixels in the MH scenario. Still, the structure of the new forest areas is surprisingly spatially coherent – distinctively non-random. The Improved Connectivity (IC) scenario falls between the NU and MH scenarios in terms of number of windows affected. Here the elongated shape of the new forest areas, stretches the effect across a number of windows. The changes in cover percentage seen in Table 6.1 also reflect this.

	Designated Areas N = 492			Improved Connectivity N = 668		
	Min.	Max.	**Mean**	Min.	Max.	**Mean**
Cover	1	95	**35.197**	1	100	**26.171**
Edge	-1800	20750	**5742.683**	-8550	23950	**5122.193**
M	-3.743	1.625	**-0.153**	-2.711	31	**-0.11**
NP_back	-2	31	**4.242**	-6	30	**3.846**
NP_total	-3	43	**6.366**	-7	29	**5.79**
Richness	0	3	**0.677**	0	3	**0.531**
SHDI	-0.931	1.096	**0.17**	-0.619	1.08	**0.165**
SIDI	-0.567	0.665	**0.1**	-0.472	0.655	**0.103**
SqP	-0.961	0.562	**-0.042**	-0.943	0.717	**-0.036**
	Maximum Hemeroby cells N = 808			**Near urban/popultaion N = 373**		
	Min.	Max.	**Mean**	Min.	Max.	**Mean**
Cover	1	100	**21.402**	1	100	**48.432**
Edge	-500	29050	**5377.042**	-3150	29850	**9341.22**
M	-3.613	2.971	**0.355**	-3.357	4.419	**0.302**
NP_back	-1	19	**2.079**	-3	22	**4.957**
NP_total	0	37	**4.663**	-1	56	**10.257**
Richness	0	4	**1.053**	0	4	**1.097**
SHDI	-0.647	1.348	**0.231**	-0.708	1.345	**0.261**
SIDI	-0.484	0.73	**0.138**	-0.458	0.729	**0.149**
SqP	-0.979	0.748	**-0.085**	-0.894	0.723	**-0.009**

Table 6.3 Observed values of *changes* in metrics values per 1*1 km window for the four different scenarios – compared with the current situation. N describes the number of windows/output cells changed under the scenario.

The greatest change in Edge Length is seen for the near urban scenario, where the greatest increase in patch count metrics is also found. This is because new forest is placed in the smaller patches that characterise the near-urban landscape, compared with the open land where agriculture dominates, giving fewer and larger patches (a more coherent landscape matrix). The Matheron fragmentation index decreases for the Designated Areas (DA) and the improved connectivity scenarios, where forest is placed in rural areas, whereas increases are seen for the MH and NU scenarios. The greatest change in NP_back, the count of background patches *within* forest is seen for the NU scenario, but the greatest increases relative to the NP metric is seen for the IC and DA scenarios. This is because land use elements like small biotopes and rural settlements that currently seem like 'islands' in the agricultural matrix will appear as gaps in a modelled coherent forest cover.

The forest type *richness* increases the most for the MH and NU scenarios, where new forest is placed in areas with low forest cover and relatively low diversity, whereas for the DA and IC scenarios, additional forest is placed in areas already diverse and 'natural', leading to falling diversity at forest and possibly landscape thematic level. The diversity metrics change in a way similar to richness, most for areas that previously had little forest. The SqP metric shows a slight decrease on average for all scenarios, most for the MH scenario, indicating that the afforestation leads to more natural (more complex/less square) shapes of the (lower thematic level) layer consisting of the combined forest classes.

The visual appearance of the changes in metrics values and their distinct spatial distribution is shown in Figure 6.3. The changes in the Matheron index (M) and Shannon's Diversity Index (SHDI) are used for illustrations, as these metrics are practically un-correlated (see section 4.5.3) and indicate different aspects of forest structure. It should be noted that an 'inverted' look-up table is used for M – positive values indicate more fragmented landscapes, negative values less fragmented.

The spatial distribution of changes in metrics values shows some distinct patterns, especially for the IC scenario. Here afforestation leads to decreasing diversity in areas which already has high proportions of forest and nature classes. Finally, it should be noted that the quantification of the changes in metrics values, summarised in Table 6.3, are calculated only for the cells that are affected – thus *not* the values for the entire landscape[38]

[38] That could readily be done using Fragstats or similar software, for evaluation of all sorts of consequences of the scenarios.

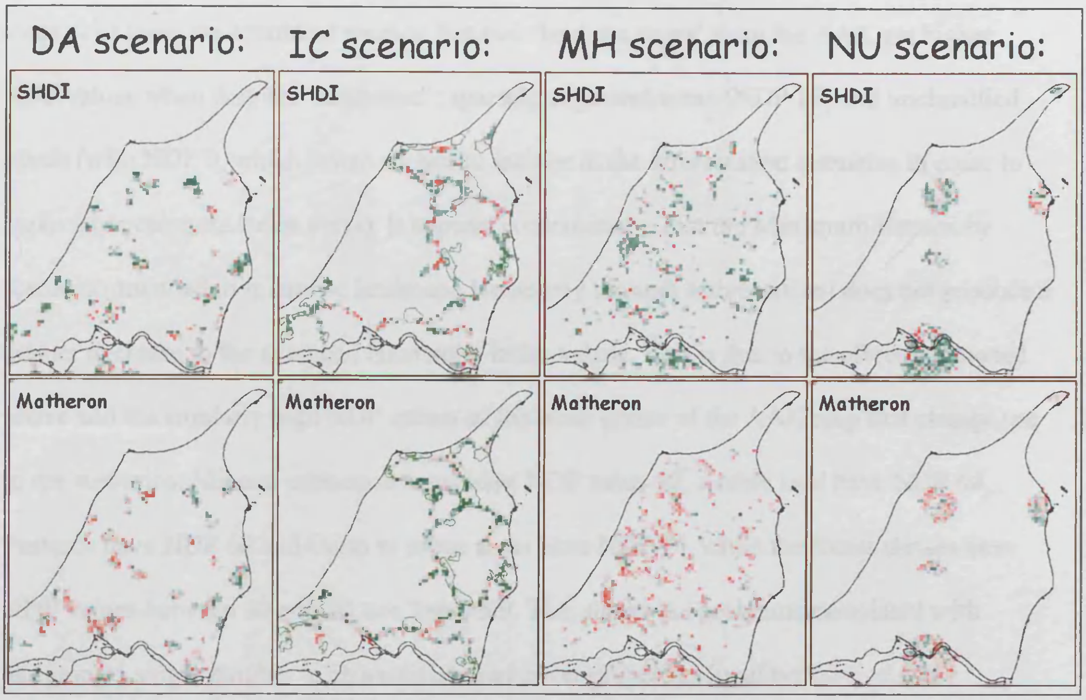

Figure 6.3 Summary of effects on spatial metrics from different afforestation scenarios. Red colours indicate decreasing diversity (SHDI values) and increasing fragmentation (Matheron index values), green colours indicate increasing diversity and decreasing fragmentation, white indicate no change or pixels outside the actual afforestation zone. In addition to coastlines, existing larger forest areas are shown for the 'connectivity' scenario.

6.5.2 Changes in Hemeroby

Average Hemeroby index values from the four different afforestation scenarios are very similar, as seen from Table 6.4, which shows a decrease in the average index value from 67 to 65.

1*1 km windows	Values for entire scene (non-background)					Change in affected windows			
	current	DA	IC	MH	NU	DA	IC	MH	NU
Min.	15	15	15	15	15	-46.15	-37.34	-47.89	-48.13
Max.	90	90	90	90	90	-0.025	0.094	1.297	12.075
Mean	67.079	65.045	65.048	65.049	65.035	15.308	11.129	8.877	20.012
Std. Dev.	15.483	16.176	16.352	14.96	16.329	12.126	9.353	9.857	14.197
N.obs.			3808			506	695	871	389

Table 6.4 Changes in Hemeroby values following implementation of different afforestation scenarios.

All scenarios apart from DA produce some cells with increasing Hemeroby index values. This is surprising, since afforestation is normally meant to increase naturalness, thus lowering the Hemeroby values. The reason that it is possible to have higher Hemeroby index values in some cells from the simulated maps is that two 'land use types' from the AAK get higher NDP values when they are 'afforested': sparsely vegetated areas (NDP 15) and unclassified pixels (with NDP 0, which it was chosen to include in the afforestation scenarios in order to make more coherent forest areas). It appears contradictory, that the Maximum Hemeroby scenario (intended to minimise landscape Hemeroby through afforestation) does not produce a greater decrease in the averaged Hemeroby index values. This is due to the effect mentioned above and the similarly high NDP values of the other grains of the AAK map that change use in the scenarios: Mineral extraction areas have NDP value 90, Arable land have NDP 80, Pastures have NDP 60 and Grass in urban areas have NDP 70, while the forest classes have NDP values between 30 and 40, see Table 5.9. This shows the problems associated with assigning a single number to characterise land cover properties (quality).

The changes in Hemeroby index values are illustrated in Figure 6.4, where the current Hemeroby pattern is also seen. For the DA scenario, clear differences are seen between sites, with the most marked decreases in large areas where agriculture dominates. This is also apparent for the MH areas, where the largest decreases are seen in the western parts of the study area, where reclamation of heaths, lakes and wetlands have produced a landscape of large fields with little interruption – which following the scenario will be turned into large forests with little interruption. The DA scenario has appointed a number of smaller forest areas in this part of the region, as well as a larger area between Aalborg and the rural town Aabybro, which could possibly function as a stepping-stone for connecting existing forests and plantation. In the DA scenario this area stands out with great decrease in Hemeroby index value. The change image for the NU scenario shows the difficulties with simulation afforestation near urban centres (red colours indicating increased Hemeroby) but also illustrates the creation of (recreational) land use buffer zones between the towns and the surrounding open land.

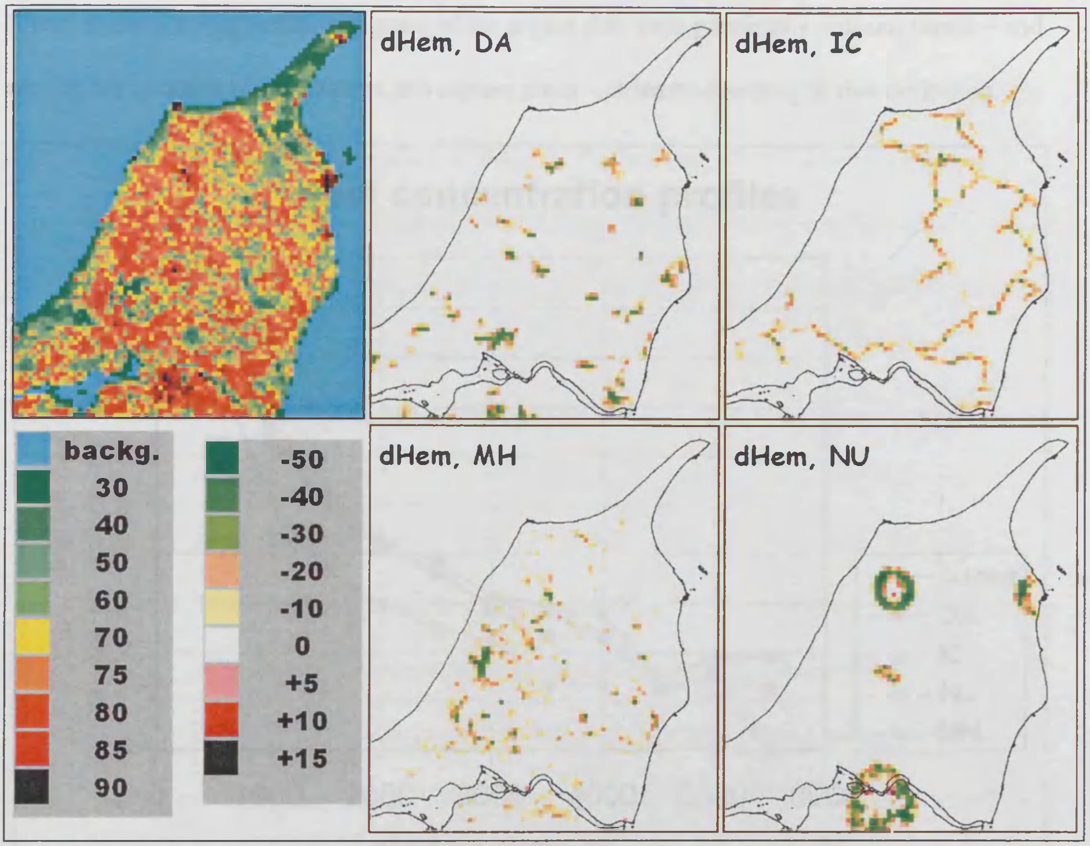

Figure 6.4 Changes in Hemeroby index values (averages within 1*1 km windows) with the different scenarios. The upper left image shows the current situation, according to the legend to the lower left, while the legend to the right of that shows the colours assigned to the changes.

6.5.3 Forest Concentration profiles

In the previous chapter, the choice of window sizes for the calculation of F.C. values resulted in a logarithmic-like x-axis for the F.C. profiles. Since this was not possible to do in a similar way here, due to the larger number of window sizes, at smaller intervals, a more linear shape of the profile curves was obtained by plotting the square root of the F.C. values. The result is seen in Figure 6.5. The F.C. curves appear very similar for the different scenarios, mostly because they represent the entire study area, where the existing forests and their spatial distribution are included in the scenario-based forest maps from which the curves are made. The current forest pattern thus influences the position and shape of all of the scenario curves. The FC curve for the MH scenario however stands out from the rest and shows the more scattered/less concentrated distribution of the forest patches across the study area. The current situation has the highest FC-values, thus all the afforestation scenarios contribute to spreading forest across the study area, into parts of the region that were previously without forest – and reduce the concentration of forest into certain areas – at least according to this definition.

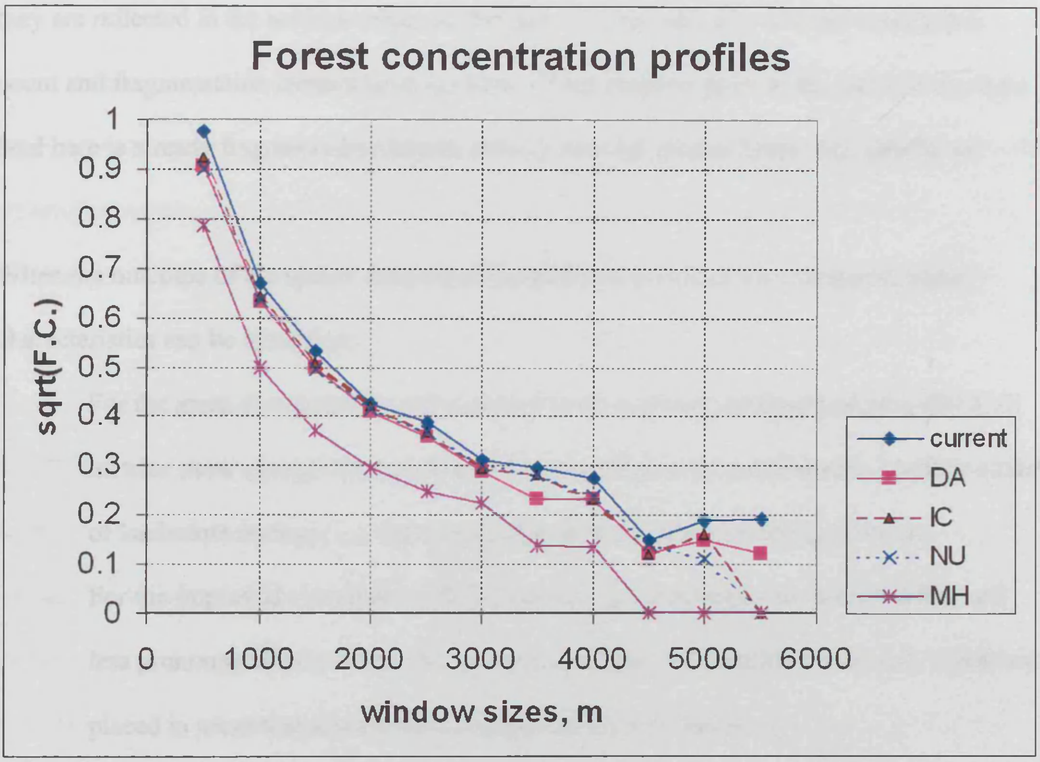

Figure 6.5 FC profiles for the different scenarios used in this study, with the abbreviations defined in the text.

6.6 Discussion/conclusion

The use of the Forest Type Index (FTI) for assignment of forest type to selected afforestation areas ensured that large coherent patches of the different forest types were created, but did not give a completely realistic picture, as seen by the forest patches created in the scenarios being relatively larger and more compact, i.e. less scattered and with larger patch size than existing forest (as they appear in the AAK maps, see Figure 6.2). This is possibly because altitude was too dominating a factor in the FTI, and it must be concluded that this method does not yet provide fully realistic forest patterns - different definitions should be tested and applied to structurally different regions. An alternative might be the use pattern generating software such as SimMap (Saura and Martinez-Millan 2000) or RULE (With and King 1999) for distributing different forest types into the 'designated' areas.

In general, a clear advantage of using this kind of scenario "modelling" is that a planner is forced to consider not only the immediate structural effects of changed land use, but also *why* they are reflected in the metrics values as they are. For instance, does the increased patch count and fragmentation metrics from the Near-Urban scenario point to the fact that the open land here is already fragmented by human activity and that planted forest will also be so?

When the outcome of the spatial analysis of the different scenarios are compared, some characteristics can be identified:

- For the areas designated for afforestation in the regional development plan (DA), all metrics show changes that are beneficial according to the patch-matrix-corridor model of landscape ecology, i.e. decreasing fragmentation and increasing diversity.
- For the improved connectivity (IC) scenario, the same trends are seen, but they are less pronounced than for the DA scenario, probably because here more new forest are placed in areas that already have a certain amount of forest.
- The Maximum Hemeroby areas (MH) scenario places forest near towns, which assures a radically new distribution of forest across region and increased diversity, although the pseudo-random placing of new forest patches result in increased fragmentation. An argument against using this method to assign areas for afforestation could be that it takes the best (most intensively used) agricultural lands out of use.
- The Near Urban (NU) scenario creates large, apparently coherent forests around the largest towns, and result in the greatest increase in forest diversity in the affected areas. These forest areas however turn out to be relatively fragmented by roads, railways etc.

The suite of metrics that was used to quantify landscape structure turned out to be useful for characterisation of current and future patterns as well as detection of changes. The combination of reporting metrics values in tables and showing their spatial distribution on (groups of) maps can aid identification of zones undergoing large changes, following different scenarios for land use planning.

The scenarios approach has proven useful in this study, which was limited in extent, spatially as well as thematically. For the purpose of describing basic changes in landscape structure, the relatively simple spatial metrics used were found appropriate. Analyses of temporal developments in metrics values, using statistical methods similar to the ones described by Luque (2000) would allow monitoring of structure and diversity of the afforested areas. However, if more detailed assessments of the influence of the changes in land use and land cover following the different scenarios are needed, correspondingly advanced techniques should be applied. Spatial analyses methods as implemented in common GIS systems allow calculation of parameters of ecological importance such as distance of forest patches to roads or towns, as well as incorporation of information from ecological inventories such as the small biotopes database described by Brandt et al (2002). If provision of habitats for species which are endangered or otherwise of special interest is included in the goals of afforestation, Gap Analysis approaches are relevant to identify that kind of forest/woodland to establish – and where they would be most beneficial (Scott el al 1993, Smith and Gillet 2000).

Furthermorel, for evaluation of the impacts of new forest for particular species, detailed ecological modelling that incorporates knowledge about mobility and feeding ranges might be needed (Verboom 1996, Petit and Usher 1998). If land cover information is available at relevant scales (Dreschler and Wissel 1998), meta-population models could help assess the viability of forest dwelling species (Wu and Vancat 1995, Hanski and Ovaskainen 2000), assuming that the established forests will provide habitats of a quality similar to existing areas (Diamond 1988). For the current study of land use in Vendsyssel, the single most important factor influencing environmental quality and development of forests is undoubtedly agricultural practices, which are again strongly influenced by socio-economic factors such as the Common Agricultural Policy (CAP) of the EU (Gallego, ed. 2002). In order to predict future developments in forest structure and quality, it might thus be necessary to include economic and social science (Roe 1996, Jensen 1999).

The study described in this chapter serves as an example of, how spatial metrics and the moving-windows method can be applied in regional planning, and the results point to subjects worth studying more in-depth. For instance, the impacts of the different scenarios could be analysed at the landscape as well as the forest thematic level; the changed pattern of metrics values could be reported and mapped at different window sizes (besides what was already done for the FC-profiling), and finally efforts could be directed towards creation of more realistic afforestation scenarios, following dialogue with foresters, biologists and regional planners.

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7 Conclusions

7.1 Summary of key findings

In this thesis, new approaches to calculation and communication of metrics of landscape structure have been defined and implemented. Use of the 'moving-windows' approach has made it possible to calculate metrics values throughout the study areas and to visualise and statistically analyse regional differences. At the same time, it was shown that spatial metrics have the potential to function as indicators of landscape structure and diversity.

Shape metrics, especially the Matheron index, proved usable for quantification of fragmentation, while it was found that patch count metrics should be used with care due to sensitivity to grain size, and that the SqP index appeared to be highly sensitive to extent (window size). Which specific metrics to use for a particular environmental assessment will depend on the issues of monitoring and the management objectives for the landscape, forest or nature area of interest. However, all outputs from the moving-windows approach could be used in geo-referenced image format, and combined with data from other sources (ground based mapping and observations) using standard GIS software.

An example of a possible application was shown with the creation of different afforestation scenarios for the study area in northern Jutland, reflecting different land use strategies. Maps showing the changes in selected metrics values were found to well illustrate the effects of different strategies and point to potential management conflicts, such as decreased forest fragmentation leading to decreased landscape diversity.

The Hemeroby concept was quantified through assignment of 'Nature Degradation Potential' values to land cover classes and a spatial dimension added through the use of 'moving-windows' for creation of Hemeroby (naturalness) maps. These were found to provide a useful overview of land use intensity, with potential for use in landscape level environmental management and planning.

7.2 Limitations to the study

An obvious limitation to the use of spatial metrics (of landscape structure) as indicators is the quality of the input data, i.e. maps or satellite images. Often a higher thematic resolution, than what is normally available from Land Use and Land Cover data, is needed for meaningful comparisons for assessment of forest and nature/habitat diversity. It was however found that binary forest-non-forest maps constitute a sufficient input for analysis of forest fragmentation.

In this study it was not possible to establish relations between metrics values and observed biological diversity, due to lack of ground reference data and biological records. Once such data become available, preferably from observation grids, an approach taken in some ongoing botanical and wildlife inventories, it should be possible to statistically relate species richness and other measures of biological diversity to metrics values from moving-windows calculations.

In the calculation of metrics of landscape structure, information on absolute or relative edge length is utilised. Metrics values are thus affected by boundary and edge effects, in particular at map borders and where different data sources are combined (overlaid/merged). It was also found necessary to distinguish between the internal external and 'background classes', the latter being excluded from calculation of metrics values. This was particularly done in order to eliminate the effects of having large windows include relatively large sea areas, causing edge effects at the coasts as well as apparently lower forest cover with increasing window size. Further development is needed to fully overcome such potential sources of error and provide un-biased and scale-independent metrics values and maps.

7.3 Possible future work

The methods described in this thesis could without difficulty be integrated into a broader land classification system, where for instance cultural and socio-economic factors are included. This is typically required for assessment of agri-environmental issues, potential afforestation or nature protection. In such a land classification system, moving-windows outputs should be used as layers of geo-referenced maps, where different aspects of landscape structure are depicted. This also seems the best way to integrate landscape metrics and Hemeroby (index) values. When maps of metrics values are combined with data from ecological inventories, more advanced statistical approaches, than the ones used here, will be needed, especially if the aim is to relate metrics at different levels of a spatial hierarchy to Alpha, Beta and Gamma diversity (see Figure 2.2) respectively. Combining the calculated metrics values with biological observations will also help define *threshold values* for spatial metrics, to be applied for planning purposes and assessment of alternative scenarios.

Metrics of forest structure can be used to evaluate a country's compliance with international conventions of sustainable forest or landscape management. For this to be applied operationally, image processing must be standardised, with regards to (amongst other things) resolution and quality of input data, classification algorithms used and verification through use of ground control data.

In these studies, raster images of real-world landscapes have been used throughout, based on the assumption that biological diversity and ecological functions are related to landscape structure, as it appears in land use/land cover maps. However, modelling of different species response to changes in forest and landscape structure is possible using spatially explicit meta-population models, preferably in combination with simulated land cover maps derived using neutral models. This will directly provide examples of habitat maps or high-resolution land cover maps, help establish mathematical links between ecological theory and applied landscape ecology, and minimise errors from the sensor-to-map processing chain for research of metrics (scaling) behaviour *per se*. Individual- or population based ecological models and neutral landscape simulated maps also have the potential to evaluate the use of classified imagery from new EO data sources with high spatial and/or spectral resolution.

The temporal scale/dimension is only included here to a lesser extent, through afforestation scenarios. There is however a strong potential to perform comparison with historical maps and data in the form of archived aerial photographs back to (early 20th century) and satellite images (back to 1972). The relation between changing land use practices and development of landscape structure remains a challenging subject, that calls for further studies, which will be carried out for example within the framework of the cultural environment atlas (DACE) project. In this project, a central task is identification of areas with particular spatial structures, reflecting modes of production and land use strategies, in past as well as present landscapes. Thus, topographic maps from the 19th and 20eth century are being digitised and interpreted, with a standardised (land cover) legend, and one of the next steps of the project involves calculation of relevant spatial metrics, possibly supplemented by Hemeroby index values from contemporary land use data. This will allow changes to be quantified and regional differences to the identified.

Some strengths and limitations of spatial metrics have been identified in this study. The knowledge gained can assist in the selection of data and indicator metrics in **monitoring frameworks** such as those outlined in Figure 2.6 and 2.7. Outputs in map format from moving-windows analysis can be combined with vector GIS data and can thus serve as input to (for instance) environmental impact analysis. The examples provided by the interlinked studies carried out for this thesis have proven the separate steps of the landscape analysis proposed in Figure 2.7 to be feasible. The choice of data sources, classification approaches and the suite of spatial metrics to use will however ultimately depend on the objectives of the actual monitoring initiative.

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9 Epilogue and Acknowledgements

This thesis results from work done at the Joint Research Centre (JRC) in Ispra, Italy where I was post-graduate grant holder from 1998 to 2001 and at the University of Southern Denmark (SDU) in Esbjerg, where I have been employed as research worker from January 2003. Meanwhile, I have been working part-time on the Ph.D. thesis under the supervision of Dr. Blackburn, first at King's College, London, and from October 2000 at Lancaster University.

At the JRC, I was affiliated with the Eurolandscape project at Space Applications Institute (SAI), a project where one of the objectives was to develop methods for large-area monitoring of sustainability in forest management, as a contribution to the forest policy of the European Union (EU). Thus, from the onset the purpose of my project was to develop **criteria and indicators** for sustainability of forest in Europe. Focus soon came to be on biological and structural diversity – and the relation between these. During the project monitoring of landscapes and indicators of sustainable land use and measures of multi-functionality was included as well.

Given the easy access to various types of Earth Observation data at the SAI, research was directed towards extraction of relevant thematic maps, in particular forest maps from satellite data, followed by calculation of spatial metrics to characterise forest structure. A rich literature was found to exist on the relations between biological diversity and spatial structure, and this became the focus of the literature survey that was carried out from the onset of the project. Here, **Fragmentation** was identified as a key concept in forest ecology, and attention turned to develop metrics for quantification of this process/state. Also the concept of **scale**, was found to be central in issues concerning EO and GIS in general and calculation and use of spatial metrics in particular. Besides its geographical and cartographic applications the term scale also has an ecological meaning and thus it was found worthwhile to quantify the effects of changes in spatial as well as thematic scale, especially since the correct scale(s) for environmental monitoring is still an issue of discussion.

During my employment at SDU, focus turned to the use of Land Use and Land Cover (LUC) data for landscape characterisation and use of spatial metrics as contextual information for cultural environment sites and areas. This followed from an objective to evaluate the utility of data from the Danish Area Information System (AIS) in the framework of an Internet-based database and atlas of cultural environments in Vendsyssel, Northern Jutland. For these parts of the study, the importance of incorporating the historical dimension of landscape development into description of current state became clear to me, and on-going work within the DACE project is aimed at that. Similar to the work done at JRC was calculation and display of spatial metrics values with a moving-windows approach and selection of a suite of metrics as indicators of landscape naturalness.

During the preparation of this thesis, I have been so fortunate as to work with geographers, foresters, engineers, historians and archaeologists, who have all given me indispensable advice, hopefully making this a somewhat cross-disciplinary study. I have learned that forests are not just groups of trees, landscapes are more than what appears on maps and biological diversity is indeed a complex and fascinating issue, much more than counting and comparing genes and species. Apart from the technical skills and insights gained (GIS, image processing, data and reference management, writing academic English), much of what I have learned in Ispra, Umbria, Lancaster and Esbjerg is beautifully summarised in this quotation from one of the 'grand old men' of landscape ecology:

Neotechnological landscape degradation, like other syndromes of the severe global environmental crisis, must be addressed as part of a far-reaching environmental and cultural revolution, aiming at the reconciliation of human society with nature. For this new symbiosis landscape ecology should provide a new conception of cultural landscapes and practical, holistic methods and tools, combing scientific knowledge with ecological wisdom and ethics.

Zev Naveh, at the IALE world congress - Ottawa, July 1991, published in Landscape and Urban Planning 32 (1995) pp. 43-54.

Acknowledgements:

I stand as the author of this thesis, but it would never have been possible to write it without the help and support of a number of people from all over Europe.

At the JRC in Ispra, Sten Folving made contacts with the Institute of Geography in Copenhagen and together with Pam Kennedy helped me apply for the grant at SAI, and then during my stay provided professional and practical guidance. I had three wonderful years in Italy, not least thanks to boys with whom I shared an office in the old building 25 during my first year at JRC: Bram de Bot, Thomas Kemper, Andreas Brink and Dino de Simone. In what came to be the EGEO unit I had some very nice and highly competent colleagues, of which I remember Niall McCormick, Janna Puumalainen, Jürgen Vogt, Javier Gallego, Maria Luisa Paracchini and Francesca Bertolo particularly well (and thus omit all the skilful IT-people, secretaries, librarians, trainees etc.). We soon got in touch with the forestry department of Regione dell'Umbria, and thanks to Franz Grohmann, Paola Savini and Mauro Frattegiani, the stays in Perugia and the field trips in the beautiful mid-Italian landscapes will never be forgotten.

Back in Denmark I found myself situated in Esbjerg, where by good fortune I got to work at the local branch of University of Southern Denmark. I am now surrounded by learned historians, in a fruitful academic environment, and I'm very grateful to have been accepted here. Special thanks go to my colleagues in the DACE project: Per Grau Møller, Morten Stenak, Mette Thøgersen, and most of all Bo Ejstrud with whom I've had the most inspiring discussions, and who pushed me ahead even when moving on with the PhD work seemed almost hopeless.

Finally and most of all I want to thank my parents for being there for me whenever needed, Monica for never-ending patience and for making us a family, even under stress, and Erik for just being with us.

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10 Appendices 1 – IDL scripts for image processing

In this appendix, examples are given of the main types of image processing scripts developed for calculations in the chapters 4 to 6. Each script is followed by an example of the accompanying parameter file.

10.1 Appendix 1.1 - Calculation of cover percentage, diversity, edge and fragmentation metrics

```
pro cover_div_frag040130
; This program should be applied to land-cover data in ERDAS 7.5 (.gis) format
;  or similar formats like CHIPS, assuming single band
; It is meant to complement outputs from Moving Windows Fragstats (a la GAF)
; Input : images, list with image and moving windows data in the following format :
;                       (once)
;                       no. of images
;                       number of land cover classes
;                       initial window size, increase in winsize, no. of diff. windows, initial step, increase in step
(once)
;                       (then for each image)
;                       filename (.gis file)
;                       For each image: headerlength (no. of pixels to be skipped), cols, rows, pixelsize
;                       (no. of classes of interest)
;                       (outfile - created automatically in this version)
;
;  Output are comma separated ASCII (.csv) files with each of the cover classes'
; - percentage of sublandscape area, richness'=no. of classes present in last column
; - percentage of edge pixels
; - a simple per class "edge index"
; - per class Matheron "fragmentation" indices + 'landscape Matheron index' in last column of outfile!


; Modified 4 september 2003 to read input UTM coordinates for image and output coordinates for centre
of esch cell/window
; 18 september bug fixed in block-edge-count

                others=7                        ; No. of other div. metrics to be calculated, pt. SIDI,
SHDI, richness
                filelist='m:\IDL_test\aak_div25m_fill2.txt' ; where the run parameters are kept
                n=0b ; number of files in list
                noclasses=0  ; read from info-file
                backval=0    ; read from info-file
                landval=1b   ; read from info-file
                inclback=0 ; read from info-file
                coverland=1 ; read from info-file
                cols=0l             ; etc.
                rows=0l
                headersize=0l
                grainsize=0.0
                ws_ini=0l
                winstep=0l
                step_ini=0l
                step_incr=0l
                openr,lun3,filelist, /get_lun
                readf,lun3,n

                ; Read over-all parameter(s): number of inpuit images
```

```
                image='' ; strings for filenames

                for inputfiles=0,n-1 do begin
                readf,lun3, image                              ; reading image-specific parameters
                readf,lun3, headersize, cols, rows, grainsize, UL_E, UL_N
                readf,lun3, noclasses, backval, landval
                readf,lun3, inclback ; should background pixels be included in calculations (yes if
inclback <> 0)?
                readf,lun3, coverland ; is there a class for non-background, non-forest (context/matrix)
land ?
                readf,lun3, ws_ini, win_incr, winss, step_ini, step_incr ; initial window size, increment in
window size,
                                                               ; number of different windows, inital
step size
                                                               ; incenrement of stepsize with larger
window..
                divs=others
                wins=winss-1
                maxwin=ws_ini+(win_incr*wins)
                 winstep=step_ini ; stepsize must be reset before each new image is processed
                winsize=ws_ini

for rounds=1, winss do begin ; new image - varying window sizes

; create (meaningful?) NAMES for output files:

sizestr=string(winsize)
stepstr=string(winstep)
suf1='_w'+strcompress(sizestr, /remove_all)
suf2='s'+strcompress(stepstr, /remove_all)
split=str_sep(image,'.')
origimagename=split[0]
imagename=origimagename+suf1+suf2
outfile1=imagename+'_cover.csv'
outfile2=imagename+'_edgelength.csv'
outfile3=imagename+'_edgeindex.csv'
outfile4=imagename+'_matheron.csv'
outfile5=imagename+'_diverse.csv'
outfile6=imagename+'_sqp.csv'
outfile7=imagename+'_mathallmap.csv'

openr, lun, image, /get_lun  ; read input image
image_arr=bytarr(cols*rows+headersize)
readu, lun, image_arr
free_lun,lun ; Close input image

print, 'reading ',image
print, 'output to ', outfile1
print, 'output to ', outfile2
print, 'output to ', outfile3
print, 'output to ', outfile4
print, 'output to ', outfile5
print, 'output to ', outfile6
print, 'output to ', outfile7
print, 'Background value: ', backval
if (inclback EQ 0) then print, 'Background pixels ignored in Diversity calculations'
print, 'Land value      : ', landval

pixcount=headersize ; store input image as 2-D matrix
image_mtx=bytarr(cols,rows)
for rc=0,rows-1 do begin
        for cc=0,cols-1 do begin
                image_mtx(cc,rc)=image_arr(pixcount)
                pixcount=pixcount+1
        endfor ; cc
endfor ; rc
```

```
winsz=float(winsize)
blocksize=float(winsz*winsz)
block_cols=fix((cols-winsize+winstep)/winstep)
block_rows=fix((rows-winsize+winstep)/winstep)
geo_E=fltarr(block_cols)
geo_N=fltarr(block_rows)


x=0u
y=0u
value=0
outedgect=0l
blockedgect=0l
prob=fltarr(256)
percent=0.0
MI=0.0

covercount=lonarr(256)
edgecount=lonarr(256)
edgelengths=fltarr(block_cols, block_rows, noclasses+3)
countpct=intarr(block_cols, block_rows, noclasses+3) ; array for percentage of cover & richenss (no. of
classes in window)
edgepct=intarr(block_cols, block_rows, noclasses+1) ; array for simple edge ratio
edgeprop=intarr(block_cols, block_rows, noclasses+1) ; array for edge to covertype area ratio
MIA=fltarr(block_cols, block_rows, noclasses+1)  ; Matheron Index Array
sqp_mtx=fltarr(block_cols, block_rows,2)         ; Squareness of Patches Array
divind=fltarr(block_cols, block_rows,divs)       ; matrix for various diversity metrics

; Define output coordinates
outsize=winsize*grainsize
outstep=winstep*grainsize
UL_E_out=UL_E+((outsize-outstep)/2)
UL_N_out=UL_N-((outsize-outstep)/2)
for east=0,block_cols-1 do Geo_E(east)=UL_E_out+outstep*(east+0.5)
for north=0,block_rows-1 do Geo_N(north)=UL_N_out-outstep*(north+0.5)

for a=0,(block_rows-1) do begin ; calculation starts, runs through blocks - a counts rows (Y values)
	print, 'img', inputfiles+1,' / ',n,'Iteration ',rounds,', ws: ',winsize, ' step: ', winstep,', now analysing
row ',a+1,' of', block_rows
	print, 'blocksize :', blocksize, ' pixels = ', blocksize*grainsize*grainsize/10000,' ha'
	aa=(block_rows-1)-a ; lowerleft coordinate system - better for Surfer import! ignored for the
moment!!
	for b=0,(block_cols-1) do begin          ; = overlapping windows - b counts columns (X values)
		for c=0,255 do covercount(c)=0 ; reset covercounter
		for ee=0,255 do edgecount(ee)=0 ; reset edgecounter
		blockedgect=0.0
		outedgect=0.0
		totedgect=0.0
		isobject=0
		notback=0

		; count of object - "outside window" edges (only) for combined M and SqP values :
		for xo=1,winsize-2 do begin ; counting along outer rows:
			blockedgect=blockedgect+(image_mtx(b*winstep+xo,a*winstep) NE landval)
*(image_mtx(b*winstep+xo,a*winstep) NE backval); counting for top row in block
			blockedgect=blockedgect+(image_mtx(b*winstep+xo,a*winstep+winsize-1) NE
landval) *(image_mtx(b*winstep+xo,a*winstep+winsize-1) NE backval); counting for bottom row in block
		endfor; xo
		for yo=1,winsize-2 do begin ; counting along outer columns:
			blockedgect=blockedgect+(image_mtx(b*winstep,a*winstep+yo) NE landval)
*(image_mtx(b*winstep,a*winstep+yo) NE backval); counting for left column in block
			blockedgect=blockedgect+(image_mtx(b*winstep+winsize-1,a*winstep+yo) NE
landval) *(image_mtx(b*winstep+winsize-1,a*winstep+yo) NE backval); counting for right column in block
		endfor; yo
		blockedgect=blockedgect+2*(image_mtx(b*winstep,a*winstep) NE landval)
*(image_mtx(b*winstep,a*winstep) NE backval) ; top left corner of block
```

```
            blockedgect=blockedgect+2*(image_mtx(b*winstep,a*winstep+winsize-1) NE landval)
*(image_mtx(b*winstep,a*winstep+winsize-1) NE backval) ; top right corner of block
            blockedgect=blockedgect+2*(image_mtx(b*winstep+winsize-1,a*winstep) NE landval)
*(image_mtx(b*winstep+winsize-1,a*winstep) NE backval) ; bottom left corner of block
            blockedgect=blockedgect+2*(image_mtx(b*winstep+winsize-1,a*winstep+winsize-1) NE
landval) *(image_mtx(b*winstep+winsize-1,a*winstep+winsize-1) NE backval) ; bottom right corner of
block

            for d=0,(winsize-1) do begin    ; counting inside window
                  for e=0,(winsize-1) do begin
                        x=(b*winstep+e)
                        leftx=(x-1)
                        rightx=(x+1)
                        y=(a*winstep+d)
                        upy=(y-1)
                        downy=(y+1)
                        value=image_mtx(x,y)                    ; reading of pixel value
                        covercount(value)=covercount(value)+1    ; THIS is where the actual counting
takes place - directly in the array

; "Internal edges" (between all LC types):

; "Landscape edges" (forest - background)
                        isobject=((value NE landval)*(value NE backval))
                        notback=(value NE backval)
                        if coverland NE 0 then begin ; the 'object of structural interest' is anything not
matrix or background (e.g. all forest):
                        if (e GT 0) then outedgect=outedgect+(isobject*((image_mtx(leftx,y) EQ
landval)+(image_mtx(leftx,y) EQ backval)))  ; checks for edges in horizontal direction
                        if (e LT winsize-1) then outedgect=outedgect+(isobject*((image_mtx(rightx,y)
EQ landval)+(image_mtx(rightx,y) EQ backval)))
                        if (d GT 0) then outedgect=outedgect+(isobject*((image_mtx(x,upy) EQ
landval)+(image_mtx(x,upy) EQ backval)))    ; checks for edges in vertical direction
                        if (d LT winsize-1) then
outedgect=outedgect+(isobject*((image_mtx(x,downy) EQ landval)+(image_mtx(x,downy) EQ backval)))
                        endif else begin ; the 'object of structural interest' is anything not background
(e.g. all land):
                        if (e GT 0) then outedgect=outedgect+(notback*(image_mtx(leftx,y) EQ
backval)) ; checks for edges in horizontal direction
                        if (e LT winsize-1) then outedgect=outedgect+(notback*(image_mtx(rightx,y)
EQ backval))
                        if (d GT 0) then outedgect=outedgect+(notback*(image_mtx(x,upy) EQ
backval)) ; checks for edges in vertical direction
                        if (d LT winsize-1) then outedgect=outedgect+(notback*(image_mtx(x,downy)
EQ backval))
                        endelse
                  endfor ;e
            endfor ;d

; INDEX CALCULTATION:
            richn=0s
            richslot=0s
            shannon_f=0.0
            shannon_l=0.0
            simpson_f=0.0
            simpson_l=0.0
            sqp_obj=0.0
            sqp_land=0.0
            landscpix=float(blocksize-covercount(backval)) ; Greater than 0 if there in this window are
pixels different from background
            forestpix=float(landscpix-covercount(landval)) ; Greater than 0 if there in this window are
pixels different from non-forest land
            if (landscpix GT 0) then forestfraction=(forestpix/landscpix) else forestfraction=0
            sum_pf=0.0
            sum_pl=0.0
            totel=0.0
```

```
		for f=0,noclasses-1 do begin		; only go through the classes that are defined and
meant for output

			proportion=0.0 ; to be used for this class in this window
			prop_forest=0.0
			prop_land=0.0
			edgelength=0.0
			present=float(covercount(f))			; coverdata from array of counts
			; to be used for sevaral indices
			if (inclback NE 0) then proportion=float(present/blocksize) else if (landscpix GT 0)
then proportion=float(present/landscpix)
			if (f EQ backval) then proportion=proportion*(inclback NE 0); background-
proportion set to zero if flag is up
			richn=richn+(present GT 0)			; checks for presence of pixel value =
land cover type
			countpct(b,a,f)=round(100*proportion)
			edge=float(edgecount(f))			; edgedata written to matrix for output
			edgelength=edge*grainsize
			totel=totel+edgelength
			edgelengths(b,a,f)=edgelength		; real world edge-length
			edgepct(b,a,f)=round(100*(edge/blocksize)) ; edge realtive to TOTAL AREA in
window
			edgeprop(b,a,f)=round(100*(edge/present))  ; edge relative to AREA of the
CLASS within the window

			; the original MATHERON index calculated and written to matrix - per class:
			if (present GT 0) then MI=float(edgecount(f)/(sqrt(present)*sqrt(blocksize))) else
MI=-0.1
			MIA(b,a,f)=10*MI
			rif=f ; to be used for where to insert extra values

			if (present GT 0) then begin
				if (forestpix GT 0) then prop_forest=(f NE landval)*(f NE backval)
*float(present/forestpix) else prop_forest=0
				prop_land=(f NE backval)*float(present/landscpix)
			end

			; the classic diversity metrics are summed:
			if (prop_forest GT 0) then begin
				shannon_f=shannon_f+(prop_forest*alog(prop_forest))
				simpson_f=simpson_f+prop_forest^2
				sum_pf=sum_pf+prop_forest
			end
			if (prop_land GT 0) then begin
				shannon_l=shannon_l+(prop_land*alog(prop_land))
				simpson_l=simpson_l+prop_land^2
				sum_pl=sum_pl+prop_land
			end

		endfor;  f - same output cell, LC classes was run through

		countpct(b,a,noclasses)=round(100*forestfraction) ; forest fraction written to array
		if landscpix EQ 0 then begin
		  edgedens_land=0
		  edgedens_block=0
		endif else begin
		  edgedens_land=totel*10000/(landscpix*grainsize^2)
		  edgedens_block=totel*10000/(blocksize*grainsize^2)
		endelse
		edgelengths(b,a,noclasses)=totel
		edgelengths(b,a,noclasses+1)=edgedens_land
		edgelengths(b,a,noclasses+2)=edgedens_block
		richslot=noclasses+2			; outputs richness = "species number"
		countpct(b,a,richslot)=richn
		divind(b,a,0)=richn

		totedgect=outedgect+blockedgect
```

```
                ; the 'non-empty' criterion:
                if (landscpix GT 0) then begin
countpct(b,a,noclasses+1)=round(100*(landscpix/blocksize)) ; landscape fraction to array
                                        ; now calculate forest-non-forest (landscape) Matheron index
                                        mathout=10*float(totedgect/(sqrt(forestpix)*sqrt(landscpix)))
                endif else begin mathout = -1
                endelse

                MIA(b,a,rif)=mathout ; aggregated Matheron written to matrix

                ; calculate "Squareness of Patches", sensu Frohn(1998), index for forest-nonforest:
                if outedgect GT 0 then sqp_obj=1-(4*(sqrt(forestpix))/totedgect) else sqp_obj=1
                if sqp_obj LT 0 then sqp =0
                if outedgect GT 0 then sqp_land=1-(4*(sqrt(landscpix))/totedgect) else sqp_land=1
                if sqp_land LT 0 then sqp_land =0
                ; write to matrix:
                sqp_mtx(b,a,0)=sqp_obj
                sqp_mtx(b,a,1)=sqp_land

                ; now close diversity indices:
                if (richn GT 1) then divind(b,a,1)=-shannon_f else divind(b,a,1)= 0
                if ((richn GT 1) and (forestpix GT 0)) then divind(b,a,2)=1-simpson_f else divind(b,a,2)=
0
                if (richn GT 1) then divind(b,a,3)=-shannon_l else divind(b,a,3)= 0
                if (richn GT 1) then divind(b,a,4)=1-simpson_l else divind(b,a,4)= 0
                divind(b,a,5)=sum_pf
                divind(b,a,6)=sum_pl
                ; to give higher values (tow. 1) of SIDI /Simpson's for more diverse compositions

                endfor ;b - next block (next colum)
endfor ;a - next line of blocks (next row)

; end of counting/calculation sequence

; start output sequence

openw,lun,outfile1, /get_lun        ; output results for each window cell = ASCII line
print, 'now writing cover results'
for aaa=0,(block_rows-1) do begin        ; count through rows - increase Y values
        aaah=(block_rows-1)-aaa; modified Y coordines for 'lower left style'
        for bbb=0,(block_cols-1) do begin             ;
                outline1=''
                for classes=0, noclasses+2 do begin
                   outline1=outline1+strcompress(countpct(bbb, aaa, classes))+', '
                endfor; classes
                outline1=outline1+strcompress(bbb)+',
'+strcompress(aaah)+','+string(Geo_E(bbb))+','+string(Geo_N(aaa))
                printf, lun, outline1
        endfor ;bbb

endfor ;aaa                             ; useful for e.g. Surfer(R)

free_lun,lun  ; _cover written
; Column (noclasses)   : Forest fraction (of landscape)
; Column (noclasses+1) : Landscape fraction (of entire window)
; Column (noclasses+2) : Land cover class Richness
; Column (noclasses+3) : Image X-coordinate
; Column (noclasses+4) : Image Y-coordinate
; Column (noclasses+5) : UTM X-coordinate
; Column (noclasses+6) : UTM Y-coordinate

openw,lun,outfile2, /get_lun        ; output results for each window cell = ASCII line
print, 'now writing edge count results'
print, '...writng header line'
outline0=''
writtenclasses=0b
```

```
for head=0,noclasses-1 do begin
        if (writtenclasses GT 0) then outline0=outline0+', '
        outline0=outline0+'cl'+strcompress(head, /remove_all)
        writtenclasses=writtenclasses+1
endfor
outline0=outline0+', total, ED_land, ED_block, X, Y, X_geo, Y_geo'     ; Header line!
printf, lun, outline0

for ccc=0,(block_rows-1) do begin       ; writings to files..
ccch=(block_rows-1)-ccc
        for ddd=0,(block_cols-1) do begin               ;
                outline2=''
                for edgeclasses=0, noclasses+2 do begin
                        outline2=outline2+strcompress(edgelengths(ddd, ccc, edgeclasses))+', '
                endfor ;edgeclasses
                outline2=outline2+strcompress(ddd)+', '+strcompress(ccch)+', '+string(Geo_E(ddd))+',
'+string(Geo_N(ccc))
                printf, lun, outline2 ;
        endfor ;ddd

endfor ;ccc
free_lun,lun ; _edgepct written

openw,lun,outfile3, /get_lun                    ; output results for each window cell = ASCII line
print, 'now writing edge proportion results'
for eee=0,(block_rows-1) do begin       ; writings to files..
        eeeh=(block_rows-1)-eee
        for fff=0,(block_cols-1) do begin               ;
                outline3=''
                for edgepclasses=0, noclasses do begin
                   outline3=outline3+strcompress(edgeprop(fff, eee, edgepclasses))+', '
                endfor ;edgepclasses
                outline3=outline3+strcompress(fff)+', '+strcompress(eeeh)
                printf, lun, outline3 ; write array for this window to output file
        endfor ;fff

        ; plus block coordinates
endfor ;eee     useful for e.g. Surfer(R)
free_lun,lun ; _edgeindex written

openw,lun,outfile4, /get_lun                    ; output results for each window cell = ASCII line
print, 'now writing Matheron results'
for ggg=0,(block_rows-1) do begin       ; writings to files..
        gggh=(block_rows-1)-ggg
        for hhh=0,(block_cols-1) do begin               ;
                outline4=''
                for edgeMIclasses=0, noclasses do begin
                        outline4=outline4+strcompress(MIA(hhh, ggg, edgeMIclasses))+', '
                endfor ;edgeMIclasses
                outline4=outline4+strcompress(hhh)+', '+strcompress(gggh)+', '+string(Geo_E(hhh))+',
                '+string(Geo_N(ggg))
                printf, lun, outline4 ;, hhh,', ', gggh  ; write array for this window to output file
        endfor ;hhh                                             ; plus block coordinates
endfor ;ggg

free_lun,lun ; Matheron written

openw,lun,outfile5, /get_lun                    ; output results for each window cell = ASCII line
print, 'now writing Diversity results'
; Column 1(A) : Class richness
; Column 2(B) : SHDI object
; Column 3(C) : SIDI obejct
; Column 4(D) : SHDI landscape (object+matrix)
; Column 5(E) : SIDI landscape (object+matrix)
; Column 6(F) : coversum forest = forest mask
; Column 7(G) : coversum landscape = land mask
for iii=0,(block_rows-1) do begin       ; writings to files..
```

```
        iiih=(block_rows-1)-iii
        for jjj=0,(block_cols-1) do begin             ;
              outline5=''
              for divindtypes=0, divs-1 do begin
                    outline5=outline5+strcompress(divind(jjj, iii, divindtypes))+', '
              endfor ; divindtypes
              outline5=outline5+strcompress(jjj)+', '+strcompress(iiih)+', '+string(Geo_E(jjj))+',
              '+string(Geo_N(iii))
              printf, lun, outline5 ;, hhh,', ', gggh   ; write array for this window to output file
        endfor ; jjj
endfor ; iii

free_lun,lun ; Diversities written

openw,lun,outfile6, /get_lun                    ; output results for each window cell = ASCII line
print, 'now writing SQP results'
outline0='SqP_object, SqP_land, X_Image, Y_Image, X_Geogr, Y_Geogr' ; Header line!
printf, lun, outline0
for kkk=0,(block_rows-1) do begin     ; writings to files..
        kkkgb=(block_rows-1)-kkk
        for lll=0,(block_cols-1) do begin            ; write array for this window to output file:
              outline6=strcompress(sqp_mtx(lll,kkk,0))+', '+strcompress(sqp_mtx(lll,kkk,1))+', '
              outline6=outline6+strcompress(lll)+', '+strcompress(kkkgb)+', '+string(Geo_E(lll))+',
              '+string(Geo_N(kkk))
              printf, lun, outline6
        endfor ; lll
endfor ; kkk
free_lun,lun ; SqP values written

; openw,lun,outfile7, /get_lun ; output 'total'Matheron index as ASCII image
print, 'writing Matheron map'
for mmm=0,(block_rows-1) do begin     ; writings to files..
                outline7=''
                ; mmma=(block_rows-1)-mmm - no inversing of y-values here!
                for nnn=0, (block_cols-1) do begin              ;
                            outline7=outline7+strcompress(MIA(nnn,mmm,noclasses))+', '
                endfor ; nnn
;               outline7=outline7+strcompress(MIA(block_cols-1,mmm,noclasses))
;               printf, lun, outline7
endfor; mmm

; free_lun,lun ; 'Total M map' written
; end of output sequence

winstep=winstep+step_incr; ready with next stepsize
winsize=winsize+win_incr ; ready with next windowsize
winsize=fix(winsize)

endfor ; rounds - to next winodw/step size

endfor ;inputfiles - to next image

free_lun,lun3 ; close parameter file
print, 'finito'

end
```

Parameter file:

```
3
m:\divind\LC_Vends\AAK25LND.RST
0, 3120, 3600, 25, 522000, 6405000
25, 99, 1
0
1
20, 40, 6, 20, 40
```

```
m:\divind\LC_Vends\AAK25NAT.RST
0, 3120, 3600, 25, 522000, 6405000
18, 99, 1
0
1
20, 40, 6, 20, 40
m:\divind\LC_Vends\AAK25FOR.RST
0, 3120, 3600, 25, 522000, 6405000
6, 99, 1
0
1
20, 40, 6, 20, 40
```

10.2 Appendix 1.2 – Patch counting in M-W

```
pro patchcount_mw031129
; mw = moving windows = multiple classes

; 17/8 2001: now works with images up to about 1000*1000 pixels,  for bigger ones -> too slow.
; 18/8 2001: moving windows implemented
; april 2003: multiple window/step sizes implemented
; september 2003 - UTM-georef. option added
; november 2003 - header row added, total NP now minus background patches

filelist='m:\idl_ting\patchcount\nj_lcp_themes_bw.txt' ;  ; pointing to "parameter file", where the run
parameters are stored
n=0b ; number of files in list
image=''
noclasses=0
incols=0l
inrows=0l
headersize=0l
ws_ini=0l
win_incr=0l
winstep=0l
step_ini=0l
step_incr=0l

openr,lun3, filelist, /get_lun
readf,lun3, n

for inputfiles=0,n-1 do begin ; needs modifications to work with >1 files

readf,lun3, image; name of input image
readf,lun3, headersize, incols, inrows, grainsize, UL_E, UL_N
readf,lun3, landscvalue, backval ; pixelvalue for landscape-class, resp. background
readf,lun3, ws_ini, win_incr, winss, step_ini, step_incr ; initial window size, increment in window size,
                                                          ; number of different windows, inital step size
                                                          ; incenrement of stepsize with larger window..
print, 'input image ',image
print, 'columns : ', incols, ' rows: ', inrows

wins=winss-1
winstep=step_ini ; stepsize must be reset before each new image is processed
winsize=ws_ini

openr, lun, image, /get_lun  ; read input image
imagesize=incols*inrows+headersize
image_arr=bytarr(imagesize)
readu, lun, image_arr

print, 'reading input:   ',image

histotal=lonarr(256) ; histogram for entire image
```

```
for byt=0,255 do histotal(byt)=0; reset count array - using pixel value from image array as index in historgram table
for his=headersize, imagesize-1 do histotal(image_arr(his))=histotal(image_arr(his))+1
types=0b
for bytt=0,255 do if histotal(bytt) GT 0 then types = types + 1; counts number of different types
print, 'land cover types (different pixel values) : ', types
histotab=lonarr(types, 2)
actualtype=0b
for bytval=0,255 do begin
        if histotal(bytval) GT 0 then begin
                histotab(actualtype,0)=bytval
                histotab(actualtype,1)=histotal(bytval)
                if (bytval EQ backval) then backslot=actualtype
                print, ' type ',bytval,' : ',histotal(bytval)
                if (bytval NE backval) then maxtype=bytval
                actualtype=actualtype+1
        endif ; histotab
endfor; bytval

pixcount=headersize                    ; store input image as 2-D matrix
wholeimage_mtx=bytarr(incols,inrows)
for rc=0,inrows-1 do begin
        for cc=0,incols-1 do begin
                wholeimage_mtx(cc,rc)=image_arr(pixcount)
                pixcount=pixcount+1
        endfor ; cc
endfor ; rc

for rounds=1, winss do begin ; new image - varying window sizes

; create (meaningful?) NAMES for output files:
sizestr=string(winsize)
stepstr=string(winstep)
suf1='_w'+strcompress(sizestr, /remove_all)
suf2='s'+strcompress(stepstr, /remove_all)
split=str_sep(image,'.')
origimagename=split[0]
imagename=origimagename+suf1+suf2
outfile1=imagename+'np_geo.csv'

print, 'output to  ',outfile1

winsz=float(winsize)

blocksize=float(winsz*winsz)
block_cols=fix((incols-winsize+winstep)/winstep)
block_rows=fix((inrows-winsize+winstep)/winstep)
geo_E=fltarr(block_cols)
geo_N=fltarr(block_rows)

pns=intarr(block_cols, block_rows, types+1); defines array for results

rowpatch=0l

; Define output coordinates
outsize=winsize*grainsize
outstep=winstep*grainsize
UL_E_out=UL_E+((outsize-outstep)/2)
UL_N_out=UL_N-((outsize-outstep)/2)
for east=0,block_cols-1 do Geo_E(east)=UL_E_out+outstep*(east+0.5)
for north=0,block_rows-1 do Geo_N(north)=UL_N_out-outstep*(north+0.5)

;START OF MOVING WINDOWS :

for a=0,(block_rows-1) do begin ; calculation starts, runs through blocks - a counts rows (Y values)
print, 'img', inputfiles+1,' / ',n,', ws: ',winsize, ' step: ', winstep,', now analysing row ',a+1,' of', block_rows
print, 'blocksize :', blocksize
```

```
rowpatch=0

for b=0,(block_cols-1) do begin  ; = overlapping windows possible  - b counts columns (X values)
                                 ; extract sub-image for patch-counting:

image_mtx=bytarr(winsize,winsize)
for rc=0,winsize-1 do begin
        for cc=0,winsize-1 do begin
                image_mtx(cc,rc)=wholeimage_mtx((b*winstep+cc),(a*winstep+rc))
        endfor ; cc
endfor ; rc

totpatch=0l

for typenr=0,types-1 do begin ; inside each output cell, run through "patch types"

        landval=histotab(typenr,0) ; classtype/pixel value to count patches for!

        patch_mtx=intarr(winsize,winsize)          ; for storage of assigned patch-number values of each
        pixel
                                                   ; X-Y cordinate system, upper left corner = 0,0
        patchcount=1l
        cols=winsize
        rows=winsize

        ; PATCH COUNTING STARTS:
        foundn=0b

        ; first (horisontal) row - with nothing above:
        for pccol=0, cols-2 do begin ; presence check:
                if (image_mtx(pccol,0) NE landval) then patch_mtx(pccol,0)=0 else begin
                        patch_mtx(pccol,0)=patchcount  ; and if nothing to the right, increase patch number:
                        if (image_mtx(pccol+1,0) NE landval) then patchcount=patchcount+1
                endelse
        endfor; pccol
        ; checking last pixel in first row:
        if (image_mtx(cols-1,0) NE landval) then patch_mtx(cols-1,0)=0 else begin
                patch_mtx(cols-1,0)=patchcount
                patchcount=patchcount+1
        endelse

        ; then for the rest of the (horisontal) rows of the matrix
        for pcrow=1, rows-1 do begin
        ; (1) for first pixel in each row:
        if (image_mtx(0,pcrow) NE landval) then patch_mtx(0,pcrow)=0 else begin; presence check
                patch_mtx(0,pcrow)=patchcount
                foundn=0; no negihbours this far
                ; compare with pixel above:
                if (image_mtx(0, pcrow-1) EQ landval) then begin
                        patch_mtx(0,pcrow)=patch_mtx(0, pcrow-1)
                        foundn=1
                endif
                ; compare with pixel above-right:
                if (image_mtx(1, pcrow-1) EQ landval) then begin
                        patch_mtx(0,pcrow)=patch_mtx(1, pcrow-1)
                        foundn=1
                endif; for cols except the rightmost
        endelse

        ;  (2) then for the rest of the pixels in the row, except the last
        for pccol=1, cols-2 do begin
                if (image_mtx(pccol,pcrow) NE landval) then patch_mtx(pccol,pcrow)=0 else begin;
                presence check
                        foundn=0
                        if (image_mtx(pccol-1, pcrow-1) EQ landval) then begin; compare with pixel above
                   left
                                patch_mtx(pccol,pcrow)=patch_mtx(pccol-1, pcrow-1);
```

```
                    foundn=1
            endif  ; above-left
            if (image_mtx(pccol, pcrow-1) EQ landval) then begin ; compare with pixel above
                    patch_mtx(pccol,pcrow)=patch_mtx(pccol, pcrow-1)
                    foundn=1
            endif ; above
            if (image_mtx(pccol+1, pcrow-1) EQ landval) then begin; compare with pixel above-
            right - exception for last pixel in each row
                    patch_mtx(pccol,pcrow)=patch_mtx(pccol+1, pcrow-1)
                    foundn=1
            endif  ;  above-right
            if (image_mtx(pccol-1, pcrow) EQ landval) then begin ; compare with pixel to the left
                    patch_mtx(pccol,pcrow)=patch_mtx(pccol-1, pcrow)
                    foundn=1
            endif  ; left
            if (foundn EQ 0) then begin
                    patchcount=patchcount+1
                    patch_mtx(pccol,pcrow)=patchcount
            endif ; no neighbours
        endelse; case of pixel in the landscape category
endfor; pccol

; (3) checking last pixel in row:
if (image_mtx(pccol,pcrow) NE landval) then patch_mtx(pccol,pcrow)=0 else begin; presence
check
        foundn=0
        if (image_mtx(pccol-1, pcrow-1) EQ landval) then begin; compare with pixel above left
                patch_mtx(pccol,pcrow)=patch_mtx(pccol-1, pcrow-1);
                foundn=1
        endif  ; above-left
        if (image_mtx(pccol, pcrow-1) EQ landval) then begin ; compare with pixel above
                patch_mtx(pccol,pcrow)=patch_mtx(pccol, pcrow-1)
                foundn=1
        endif ; above
        if (image_mtx(pccol-1, pcrow) EQ landval) then begin ; compare with pixel to the left
                patch_mtx(pccol,pcrow)=patch_mtx(pccol-1, pcrow)
                foundn=1
        endif
        if (foundn EQ 0) then begin
                patchcount=patchcount+1
                patch_mtx(pccol,pcrow)=patchcount
        endif
endelse; case of pixel in the landscape category

endfor; pcrow

; end of preliminary 'classification'

patches=lonarr(patchcount+2); checks presence of patches before/after filtering
for reset=0,patchcount+1 do patches(reset)=0

;trick1 - to avoid filter being affected by backgrond pixels:
for aa=0,winsize-1 do begin
        for bb=0,winsize-1 do begin
                if (image_mtx(bb,aa) NE landval) then patch_mtx(bb,aa)=patchcount+1
                patches(patch_mtx(bb,aa))=patches(patch_mtx(bb,aa))+1
                ; plus counting for initial histogram of patch 'areas'
        endfor; bb
endfor; aa

change=0l
runs=0l
filter_mtx=intarr(winsize,winsize)          ; for storage of assigned patch-number values of each
pixel
                                            ; X-Y cordinate system, upper left corner = 0,0
ul_corner=intarr(4)
top_row=intarr(6)
```

```
ur_corner=intarr(4)
leftside=intarr(6)
kernel=intarr(9)
rightside=intarr(6)
ll_corner=intarr(4)
bottom_row=intarr(6)
lr_corner=intarr(4)

;FINDING MINIMUM PATCH NUMBERS for coherent patches (8-directions):

cols=winsize
rows=winsize

repeat begin

	change=0
	runs=runs+1

	ul_corner=[patch_mtx(0,0),patch_mtx(0,1),patch_mtx(1,0),patch_mtx(1,1)]
	filter_mtx(0,0)=min(ul_corner)

	for top=1,cols-2 do begin
		top_row=[patch_mtx(top-1,0), patch_mtx(top-1,1),patch_mtx(top,0),
		patch_mtx(top,1), patch_mtx(top+1,0), patch_mtx(top+1,1)]
		filter_mtx(top,0)=min(top_row)
	endfor

	ur_corner=[patch_mtx(cols-2,0),patch_mtx(cols-2,1),patch_mtx(cols-1,0),patch_mtx(cols-
	1,1)]
	filter_mtx(cols-1,0)=min(ur_corner)

	for down=1, rows-2 do begin
		leftside=[patch_mtx(0,down-1),patch_mtx(1,down-
		1),patch_mtx(0,down),patch_mtx(1,down),
		patch_mtx(0,down+1),patch_mtx(1,down+1)]
		filter_mtx(0,down)=min(leftside)
		for across=1,cols-2 do begin
			kernel=[patch_mtx(across-1,down-1),patch_mtx(across,down-
			1),patch_mtx(across+1,down-1),patch_mtx(across-
			1,down),patch_mtx(across,down),patch_mtx(across+1,down),
			patch_mtx(across-
			1,down+1),patch_mtx(across,down+1),patch_mtx(across+1,down+1)]
			filter_mtx(across,down)=min(kernel)
		endfor ; across

		rightside=[patch_mtx(cols-2,down-1),patch_mtx(cols-1,down-1),patch_mtx(cols-
		2,down), patch_mtx(cols-1,down),patch_mtx(cols-2,down+1),patch_mtx(cols-
		1,down+1)]
		filter_mtx(cols-1,down)=min(rightside)
	endfor ; down

	ll_corner=[patch_mtx(0,rows-2),patch_mtx(0,rows-1),patch_mtx(1,rows-
	2),patch_mtx(1,rows-1)]
	filter_mtx(0,rows-1)=min(ll_corner)

	for bottom=1,cols-2 do begin
		bottom_row=[patch_mtx(bottom-1,rows-2), patch_mtx(bottom-1,rows-
		1),patch_mtx(bottom,rows-2), patch_mtx(bottom,rows-1),
		patch_mtx(bottom+1,rows-2), patch_mtx(bottom+1,rows-1)]
		filter_mtx(bottom,rows-1)=min(bottom_row)
	endfor

	lr_corner=[patch_mtx(cols-2,rows-2),patch_mtx(cols-2,rows-1),patch_mtx(cols-1,rows-
	2),patch_mtx(cols-1,rows-1)]
	filter_mtx(cols-1,rows-1)=min(lr_corner)

	;count changes in landscape pixels:
```

```
            for aa=0,cols-1 do begin
                for bb=0,rows-1 do begin
                    if (image_mtx(bb,aa) EQ landval) then begin
                        if not(filter_mtx(bb,aa) EQ patch_mtx(bb,aa)) then change=change+1
                    end ; if
                endfor ; bb
            endfor ; aa

            ;swap before going back:
            for aa=0,cols-1 do begin
                for bb=0,rows-1 do begin
                    patch_mtx(bb,aa)=filter_mtx(bb,aa)
                endfor; bb
            endfor; aa

            ;trick2 - to avoid influence of patches spreading over background:
            for aa=0,cols-1 do begin
                for bb=0,rows-1 do begin
                    if not(image_mtx(bb,aa) EQ landval) then patch_mtx(bb,aa)=patchcount+1
                endfor; bb
            endfor; aa

        endrep until (change EQ 0)

        ; check possible patches for existence after filtering


        for reset=0,patchcount+1 do patches(reset)=0

        for aa=0,cols-1 do begin
            for bb=0,rows-1 do begin
                patches(patch_mtx(bb,aa))=patches(patch_mtx(bb,aa))+1
            endfor; bb
        endfor; aa

        ;count number of different patches in (sub)landscape:
        count_filtered=0l
        for cc=0,patchcount do begin
            count_filtered=count_filtered+(patches(cc) GT 0)
        endfor; cc

        totpatch=totpatch+count_filtered

        pns(b,a,typenr)=count_filtered ; storing result from this window/block

    endfor  ; typenr; next land cover type

    totpatch=totpatch-pns(b,a,backslot)

    pns(b,a,typenr)=totpatch
    rowpatch=rowpatch+totpatch

    endfor  ;b - next block (next colum)

    print, 'Row ',a,' Column ',b, ', Summed no. of Patches: ', rowpatch
    endfor   ;a - next line of blocks (next row)

    ; END MOVING WINDOWS

    openw,lun,outfile1, /get_lun                ; output results for each window cell = ASCII line
    print, 'now writng header line'
    outline0=''
    writtenclasses=0b
    for head=0,255 do begin
        if (histotal(head) GT 0) then begin
            if (writtenclasses GT 0) then outline0=outline0+', '
            outline0=outline0+'cl'+strcompress(head)
```

```
		writtenclasses=writtenclasses+1
	end; if
endfor ; head
outline0=outline0+', total, X, Y, X_geo, Y_geo'
printf, lun, outline0

print, 'now writing patch numbers'
for aaa=0,(block_rows-1) do begin	; count through rows - increase Y values
	aaah=(block_rows-1)-aaa ; modified Y coordines for 'lower left style'
	for bbb=0,(block_cols-1) do begin		;
		outline1=''
		for classes=0, types do begin
			outline1=outline1+strcompress(pns(bbb, aaa, classes))+', '
		endfor; classes
		outline1=outline1+strcompress(bbb)+', '+strcompress(aaah)+','+string(Geo_E(bbb))+',
		'+string(Geo_N(aaa))
		printf, lun, outline1			; write array for this window to output file
	endfor ;bbb					; plus block coordinates
endfor ;aaa

free_lun,lun ; _np written

winstep=winstep+step_incr ; ready for next stepsize
winstep=fix(winstep)
winsize=winsize+win_incr ; ready for next window size
winsize=fix(winsize)

endfor ; rounds - to next winodw/step size

endfor ;inputfiles - to next image

free_lun,lun3 ; close parameter file

print, 'THE END'

end
```

Parameter file:

```
3
m:\divind\LC_Vends\LCP25LND.RST
0, 3120, 3600, 25, 522000, 6405000
1, 99
40, 40, 5, 40, 40
m:\divind\LC_Vends\LCP25NAT.RST
0, 3120, 3600, 25, 522000, 6405000
1, 99
200, -40, 5, 200, -40
m:\divind\LC_Vends\LCP25FOR.RST
0, 3120, 3600, 25, 522000, 6405000
1, 99
200, -40, 5, 200, -40
```

10.3 Appendix 1.3 – Spatial degradation of binary maps

```
pro binary_degprop_030317
; reads list of files to spatially degrade, plus maximal degradation factor
; then degrades each file to a number of cell sizes and writes to output files
; this version for ERDAS 7.5 (.gis) files with 128 bytes header
; assumes one-byte pixels !
; NO OVERLAP in this version.
; Input, list in the following format:
;   number of files to treat (and then for each file)
;   name and path of input image file
;   columns and rows in input image
;   maximum degrade factor
;   cut or threshold value of cover percentage for inclusion in output image

filelist='c:\NCN\IDL_ting\AIS\degraster.txt'
nfiles=0b ; number of files in list  alt. read, nfiles, prompt='number of files : '
openr, lun3, filelist, /get_lun
readf, lun3, nfiles
print, nfiles, ' files to treat'

infile=''
rows=0l
cols=0l

for i=0,nfiles-1 do begin   ; goes through input files in list

        readf, lun3, infile
        readf, lun3, cols, rows
        readf, lun3, maxdegrade
        readf, lun3, cut

        openr, lun, infile, /get_lun  ; read input image
        image_arr=bytarr(cols*rows+128)
        readu, lun, image_arr

        print, 'reading ',infile

        pixcount=128l                           ; store input image as 2-D matrix
        image_mtx=bytarr(cols,rows)
        for rc=0,rows-1 do begin
                for cc=0,cols-1 do begin
                        image_mtx(cc,rc)=image_arr(pixcount)
                        pixcount=pixcount+1
                endfor ; cc
        endfor ; rc

        for degfactor=2,maxdegrade do begin

                degcols=0
                degrows=0
                degcols=long(fix(cols/degfactor))
                degrows=long(fix(rows/degfactor))
                deg_img=bytarr(degcols,degrows)
                prop_img=bytarr(degcols,degrows)
                degsize=0.0
                degsize=float(degcols*degrows)

                ; start of actual degradation:
                for k=0,(degrows-1) do begin    ; going through blocks = output cells/pixels
                        for l=0,(degcols-1) do begin
                                cellsum=0.0
                                average=0
                                result=0b
                                for n=0,degfactor-1 do begin            ; collect/sum values over output cell
```

```
                    for p=0,degfactor-1 do begin
                        x=l*degfactor+n
                        y=k*degfactor+p
                        cellsum=cellsum+(image_mtx(x,y) GT 0) ; add to sum
                    endfor ; p
                endfor ; n
                average=float(cellsum/(degfactor*degfactor))
                proppct=average*100
                deg_img(l,k)=1*(proppct GT cut)
                prop_img(l,k)=proppct
            endfor ; l
        endfor ; k

        print, 'finished degrading ', infile, ' with deg. factor', degfactor, 'with threshold', cut

        deg_arr=bytarr(degsize)
        for r_row=0,(degrows-1) do begin                ; back to array for export - import
            for s_col=0,(degcols-1) do begin
                deg_arr((r_row*degcols)+s_col)=deg_img(s_col,r_row)
            endfor ; s_col
        endfor ; r_row

        prop_arr=bytarr(degsize)
        for r_row=0,(degrows-1) do begin                ; back to array for export - import
            for s_col=0,(degcols-1) do begin
                prop_arr((r_row*degcols)+s_col)=prop_img(s_col,r_row)
            endfor ; s_col
        endfor ; r_row

        dsuffix='.d_'+strcompress(degfactor, /remove_all)
        psuffix='.p_'+strcompress(degfactor, /remove_all)
        degoutfile=infile+dsuffix                       ; write to export files
        propoutfile=infile+psuffix
        openw,lun,degoutfile, /get_lun
        writeu,lun,deg_arr
        free_lun,lun
        openw,lun,propoutfile, /get_lun
        writeu,lun,prop_arr
        free_lun,lun

        print, 'output to ', degoutfile, propoutfile

    endfor ; degfactor

endfor ; i

print, 'THE END'

end
```

Parameter file:

```
1
c:\NCN\IDL_ting\AIS\aak_natt.lan
1560, 1800
60
40
```

10.4 Appendix 1.4 – Spatial degradation of thematic maps

```
pro degrweight040106
; FOR DEGRADATION OF LAND COVER (Choropleth) MAPS and similar data...
; reads list of files to spatially degrade and weight file (if available)
; then degrades each file to a number of cell sizes and writes to output files
; this version for ERDAS 7.5 (.gis) files with 128 bytes header
; assumes one-byte pixels !

filelist='m:\idl_ting\deg_jord.txt'
nfiles=0b ; number of files in list  alt. read, nfiles, prompt='number of files : '
openr, lun3, filelist, /get_lun
readf, lun3, nfiles
print, nfiles, ' files'
infile=''
rows=0l
cols=0l
header=0l
minclass=0l
maxclass=0l
weightfile=''
degfactor=0l
suffix=''

for i=0,nfiles-1 do begin   ; goes through input files in list
	readf, lun3, infile
	readf, lun3, header, cols, rows, maxclass
	readf, lun3, mindegrade, maxdegrade
	readf, lun3, weightfile
	openr, lun, infile, /get_lun  ; read input image
	image_arr=bytarr(cols*rows+header)
	readu, lun, image_arr
	print, 'read ',infile

	pixcount=header               ; store input image as 2-D matrix
	image_mtx=bytarr(cols,rows)
	for rc=0,rows-1 do begin
		for cc=0,cols-1 do begin
			image_mtx(cc,rc)=image_arr(pixcount)
			pixcount=pixcount+1
		endfor ; cc
	endfor ; rc
	; convert to include histogram creation, check for min-max values ?

	for degfactor=mindegrade,maxdegrade do begin ; start new degradation size
		cwtab=fltarr(2,256) ; table for class weights
		count=0
		classno=0
		classwt=0.0
		for j=0,255 do begin ; reset cw-table (all classes equal weight)
			cwtab(0,j)=j
			cwtab(1,j)=1
		endfor ;

		if not (weightfile eq 'x') then begin
			openr, lun1, weightfile, /get_lun   ; assign name to weight-tablefile
			while not eof(lun1) do begin
				readf, lun1, classno, classwt
				cwtab(0,count)=classno
				cwtab(1,count)=classwt
				count=count+1
			endwhile
		endif

		dc=0
		dr=0
```

```
        dc=long(fix(cols/degfactor))
        dr=long(fix(rows/degfactor))
        deg_img=bytarr(dc,dr)
        histotab=fltarr(2,256)
        select=0
        degsize=0l
        degsize=long(dc*dr)
        ; start of actual degradation
        for k=0,(dr-1) do begin    ; going through blocks = output cells/pixels
            for l=0,(dc-1) do begin
              for m=0,maxclass do begin ; reset histogram
                  histotab(0,m)=0
                  histotab(1,m)=0
              endfor ; m
              for n=0,degfactor-1 do begin                ; build histogram for block
                  for p=0,degfactor-1 do begin
                      x=l*degfactor+n
                      y=k*degfactor+p
                      histotab(0,image_mtx(x,y))=histotab(0,image_mtx(x,y))+1 ; incr value
                  endfor ; p
              endfor ; n
              maxwtd=0.0
              select=0
              for q=1,maxclass do begin                   ; find highest value = output
                  histotab(1,q)=histotab(0,q)*cwtab(1,q) OBS - ignore counts of zero-values!
                  if (histotab(0,q) gt maxwtd) then begin
                      maxwtd=histotab(0,q)
                      select=q
                  endif
              endfor ; q
              deg_img(l,k)=select
            endfor ; l
        endfor ; k

        degfactorprint=round(degfactor)
        print, 'finished degrading ', infile, ' with deg. factor', degfactorprint

        deg_arr=bytarr(degsize)
        for r_row=0,(dr-1) do begin                       ; back to array for export - import
        for s_col=0,(dc-1) do begin
        deg_arr((r_row*dc)+s_col)=deg_img(s_col,r_row)
        endfor ; s
        endfor ; r
        suffix='.d_'+strcompress(degfactorprint, /remove_all)
        outfile=infile+suffix                             ; write to export file
        openw,lun,outfile, /get_lun
        writeu,lun,deg_arr
        free_lun,lun

        print, 'output to ', outfile

    endfor ; degfactor - next (smaller) image
endfor ; i

print, 'THE END'
end
```

Parameter file:

```
1
m:\mapinfo\Vendsyssel\jord\degrade\jordtype.rst
0, 3120, 3600, 10
2, 40
x
```

* * *

10.5 Appendix 1.5 – Per-window averaging of continuous field value images

```
pro MW_average040202coord_realidr

; This program should be applied to land-cover data in ERDAS 7.5 (.gis) format
; or similar formats like CHIPS, assuming single band
; Input : images, list with image and moving windows data in the following format :
; (once)
; no. of images
; number of land cover classes
; initial window size, increase in winsize, no. of diff. windows, initial step, increase in step (once)
; (then for each image)
; filename
; For each image: headerlength (no. of pixels to be skipped), cols, rows, pixelsize
; (no. of classes of interest)
; (outfile - created automatically in this version)
;
; Output are comma separated ASCII (.csv) files with each of the cover classes'
; - percentage of sublandscape area, richness'=no. of classes present in last column

; Created  21/10 2003, based on older script (2001-2003) for extraction of spatial metrics in moving
windows
; Modified 22/10 2003 to read input UTM coordinates for image and output coordinates for centre of esch
cell/window
; Modified 22/10 2003 to output Idrisi header (v 2.0, = .doc file) along with binary (.rst) image
; 24/10 outputs area proportion file, calc on area corresp. to output window, for use as mask
; NB. Check settings for file extensions in Idrisi/Environment

filelist='m:\IDL_ting\CLC_avg2coord.txt'; where the run parameters are stored
n=0b ; number of files in list
noclasses=0  ; read from info-file
backval=0    ; read from info-file
inclback=0   ; read from info-file
subst=0
cols=0l                              ; etc.
rows=0l
headersize=0l
grainsize=0.0
ws_ini=0l
winstep=0l
step_ini=0l
step_incr=0l

openr,lun3,filelist, /get_lun
readf,lun3,n      ; Read over-all parameter(s): number of input images
image='' ; initiating strings for filenames

for inputfiles=0,n-1 do begin  ; read list of ID-images, valuetables and outputimages (to be implemented)
readf,lun3, image                  ; reading image-specific parameters
readf,lun3, headersize, cols, rows, grainsize, UL_E, UL_N
readf,lun3, noclasses, backval, inclback, subst ; should background pixels be included in calculations
(yes if inclback <> 0)?
; if yes then use assigned (substitute) number for the background pixels in calculations of average
values
if (inclback GT 0) then print, 'Background value pixels included in calculations'
print, 'Background value is : ',backval
readf,lun3, ws_ini, win_incr, winss, step_ini, step_incr ; initial window size, increment in window size,
                                                          ; number of different windows, inital
                                                          step size
                                                          ; incenrement of stepsize with larger
window..
wins=winss-1
```

```
maxwin=ws_ini+(win_incr*wins)

winstep=step_ini ; stepsize must be reset before each new image is processed
winsize=ws_ini

for rounds=1, winss do begin ; new image - varying window sizes

sizestr=string(winsize)  ; Create names for output files
stepstr=string(winstep)
suf1='x_w'+strcompress(sizestr, /remove_all)
suf2='s'+strcompress(stepstr, /remove_all)
split=str_sep(image,'.')
origimagename=split[0]
imagename=origimagename+suf1+suf2
outfile1=imagename+'_avg.csv'
outfile1img=imagename+'_avg.rst'
outfile1prop=imagename+'_incl.rst'
outfile1doc=imagename+'_avg.doc'
outfile1pdoc=imagename+'_incl.doc'
outfile2=imagename+'_cov.csv'


openr, lun, image, /get_lun  ; read input image to memory
print, 'Now reading ',image
image_arr=fltarr(cols*rows+headersize)
readu, lun, image_arr
free_lun,lun ; Close input image

print, 'output to ', outfile1

pixcount=headersize                    ; store input image as 2-D matrix
image_mtx=fltarr(cols,rows)
for rc=0,rows-1 do begin
        for cc=0,cols-1 do begin
                image_mtx(cc,rc)=image_arr(pixcount)
                pixcount=pixcount+1
        endfor ; cc
endfor ; rc

block_cols=0l
block_rows=0l
winsz=float(winsize)
blocksize=float(winsz*winsz)
block_cols=fix((cols-winsize+winstep)/winstep)
block_rows=fix((rows-winsize+winstep)/winstep)
x=0u
y=0u

; Define output coordinates
geo_E=fltarr(block_cols)
geo_N=fltarr(block_rows)
outsize=winsize*grainsize
print,'Calculation window size : ',outsize
outstep=winstep*grainsize
print,'Output window size : ',outstep
UL_E_out=long(UL_E+((outsize-outstep)/2))       ; Upper Left corner coordinates of output image
UL_N_out=long(UL_N-((outsize-outstep)/2))
LR_E_out=long(UL_E_out+outstep*block_cols)  ; Lower Right corner coordinates of output image
LR_N_out=long(UL_N_out-outstep*block_rows)
for east=0,block_cols-1 do Geo_E(east)=UL_E_out+outstep*(east+0.5) ; writing coordinates for each
output pixel to array
for north=0,block_rows-1 do Geo_N(north)=UL_N_out-outstep*(north+0.5) ; for use when .csv file is
imported to Surfer-grid

; Define and reset count parameters
value=0.0
minimum=99.99
```

```
maximum=0.0
prob=fltarr(256)
percent=0.0
avg_mtx=fltarr(block_cols, block_rows) ; average value for outout cells
prop_mtx=fltarr(block_cols, block_rows) ; proportion of non-background in area corresp. to output cells
average=0.0

for a=0,(block_rows-1) do begin ; calculation starts, runs through blocks - a counts rows (Y values)

	aa=(block_rows-1)-a ; lowerleft coordinate system - better for Surfer import! ignored for the
	moment!!
	for b=0,(block_cols-1) do begin			; = overlapping windows - b counts columns (X values)
		inclpix=0.0
		cellsum=0.0
		for d=0,(winsize-1) do begin	; counting inside window - d counts rows
			for e=0,(winsize-1) do begin ; counting inside window - e counts columns
				x=(b*winstep+e)
				y=(a*winstep+d)
				value=image_mtx(x,y)
				if (inclback GT 0) then begin
					if (value EQ backval) then value=subst
					cellsum=cellsum+value; adds to sum
					inclpix=inclpix+1
				endif else begin if (image_mtx(x,y) NE backval) then begin
					cellsum=cellsum+value; adds to sum
					inclpix=inclpix+1
					endif
				endelse
				; covercount(value)=covercount(value)+1	; THIS is where the actual
				counting takes place - directly in the array
			endfor ;e
		endfor ;d

		startbox=fix((winsize-winstep)/2)
		endbox=fix((winsize-winstep)/2+(winstep-1))
		inclsum=0.0
		inclprop=0.0
		for i=startbox, endbox do begin
			for j= startbox, endbox do begin
				x=(b*winstep+j)
				y=(a*winstep+i)
				value=image_mtx(x,y)
				if (value NE backval) then inclsum=inclsum+1
			endfor ; j
		endfor ; i
		inclprop=inclsum/(winstep*winstep)
		prop_mtx(b,a)=inclprop

		; INDEX CALCULTATION:
		richn=0s
		richslot=0s
		average=0.0

		if (inclpix GT 0) then average=(cellsum/inclpix) else average=0 ; average value in block
		calculated as floating point number
		avg_mtx(b,a)=average			; and stored in matrix for subseq. output
		if (average LT minimum) then minimum=average
		if (average GT maximum) then maximum=average

	endfor ;b - next block (now go to next colum)
endfor ;a - next line of blocks (now go to next row)

; Finished Moving-Windows, start output

openw,lun,outfile1, /get_lun			; output results for each window cell = ASCII line
print, 'now writing average values to .csv'
for aaa=0,(block_rows-1) do begin	; count through rows - increase Y values
```

```
aaah=(block_rows-1)-aaa                          ; modified Y coordines for 'lower left style'
for bbb=0,(block_cols-1) do begin                ;
outline1=''
outline1=outline1+strcompress(avg_mtx(bbb, aaa))+', '
outline1=outline1+strcompress(bbb)+', '+strcompress(aaah)+', '+string(Geo_E(bbb))+',
'+string(Geo_N(aaa))
printf, lun, outline1 ;                ; write array for this window to output file
   endfor ;bbb
endfor ;aaa


free_lun,lun  ; _averages written to file

block_col2=long(block_cols)
block_row2=long(block_rows)
outsize=long(block_col2*block_row2)
avg_arr=fltarr(outsize)
prop_arr=fltarr(outsize)

for r_row=0,(block_row2-1) do begin                        ; back to arrays for export - import
  for s_col=0,(block_col2-1) do begin
                                    avg_arr((r_row*block_col2)+s_col)=avg_mtx(s_col,r_row)
                                    prop_arr((r_row*block_col2)+s_col)=prop_mtx(s_col,r_row)
                 endfor ; s_col
endfor ; r_row

openw,lun,outfile1img, /get_lun ; write to export file
print, 'now writing average values to binary image (.rst) file'
writeu,lun, avg_arr
free_lun,lun

openw,lun,outfile1prop, /get_lun ; write to export file
print, 'now writing land proportion values to binary image (.rst) file'
writeu,lun, prop_arr
free_lun,lun

openw,lun,outfile1doc, /get_lun ; write to export file
print, 'now writing average parameters Idrisi documentation (.doc) file'

printf,lun,'file title  : '
printf,lun,'data type   : real'
printf,lun,'file type   : binary'
outline='columns     :'+strcompress(block_cols)
printf,lun, outline
outline='rows        :'+strcompress(block_rows)
printf,lun, outline
printf,lun,'ref. system : utm-32n'
printf,lun,'ref. units  : m'
printf,lun,'unit dist.  : 1.0000000'
outline='min. X      :'+strcompress(UL_E_out)
printf,lun, outline
outline='max. X      :'+strcompress(LR_E_out)
printf,lun, outline
outline='min. Y      :'+strcompress(LR_N_out)
printf,lun, outline
outline='max. Y      :'+strcompress(UL_N_out)
printf,lun, outline
printf,lun,'pos''n error : unknown'
outline='resolution  :'+strcompress(outstep)
printf,lun, outline
outline='min. value  :'+strcompress(minimum)
printf,lun, outline
outline='max. value  :'+strcompress(maximum)
printf,lun, outline
printf,lun,'value units : undefined'
printf,lun,'value error : unknown'
printf,lun,'flag value  : none'
```

```
printf,lun,'flag def''n  : none'
printf,lun,'legend cats : 0'

free_lun,lun

openw,lun,outfile1pdoc, /get_lun ; write to export file
print, 'now writing average parameters Idrisi documentation (.doc) file'

printf,lun,'file title  : '
printf,lun,'data type   : real'
printf,lun,'file type   : binary'
outline='columns     :'+strcompress(block_cols)
printf,lun, outline
outline='rows        :'+strcompress(block_rows)
printf,lun, outline
printf,lun,'ref. system : utm-32n'
printf,lun,'ref. units  : m'
printf,lun,'unit dist.  : 1.0000000'
outline='min. X      :'+strcompress(UL_E_out)
printf,lun, outline
outline='max. X      :'+strcompress(LR_E_out)
printf,lun, outline
outline='min. Y      :'+strcompress(LR_N_out)
printf,lun, outline
outline='max. Y      :'+strcompress(UL_N_out)
printf,lun, outline
printf,lun,'pos''n error : unknown'
outline='resolution  :'+strcompress(outstep)
printf,lun, outline
outline='min. value  :  0'
printf,lun, outline
outline='max. value  :  1'

printf,lun, outline
printf,lun,'value units : undefined'
printf,lun,'value error : unknown'
printf,lun,'flag value  : none'
printf,lun,'flag def''n  : none'
printf,lun,'legend cats : 0'

free_lun,lun

winstep=winstep+step_incr; ready with next stepsize
winsize=winsize+win_incr ; ready with next windowsize
winsize=fix(winsize)

endfor ; rounds - to next winodw/step size

endfor ;inputfiles - go to next image

free_lun,lun3 ; close parameter file
print, 'finito'
end
```

Parameter file:

```
1
c:\ncn\geodata\AIS\divind\IDRIS\250m\CLCDKHEM.rst
0, 1208, 1480, 250, 441000, 6408000
100, 0, 0
20, 10, 4, 4, 2
```

11 Appendix 2 - Software used during the study

The programs are listed alphabetically, when appropriate the reference to the entry in the list of References is given.

Fragstats for Windows: Calculation of spatial metrics from raster images at patch, class and landscape level. Academic freeware, maintained at University of Massachusetts, Amherst. Version 3.3, 2002. Available through project web site: http://www.umass.edu/landeco/research/fragstats/fragstats.html

Hovey's Idrisi MapWalker (Hovey 1998): Smoothed averaging of raster images. Freeware, currently not available for download. Created for Research Branch, Ministry of Forests, Revelstoke, British Columbia, Canada, by Fred Hovey who can be contacted by e-mail at: ursus_soft@yahoo.com

IDL (Research Systems Inc. 1999): Interactive Data Language - implementation of matrix/image processing calculations. Version 5.2.1. Commercial software, company site: www.rsinc.com

Idrisi (Eastman 1997): GIS/image processing. Reclassification, ranking, Moran's I etc. Version 2.010, compiled 1998. Commercial software, educational discounts, information at: http://www.idrisi.clarku.edu

MapInfo Professional: Gridding of vector data to raster format (using the "Vertical Mapper" extension). Version 7.0, 2002. Commercial software, manufactured by Clark Labs, educational discounts, information at: http://www.mapinfo.com/

Microsoft Office for Windows 2000 package: commercial software, manufactured by Microsoft. Version SR-1 (9.0.3821) Product web site: http://www.microsoft.com/uk/office/ Includes

MS Excel: Used for basic statistics, drawing graphs

MS Access: Literature database

MS Power Point: Illustrations (diagrams, text)

Paint Shop Pro: Illustrations (images). Version 7.04. Commercial software, manufactured by Jasc Software, product web site: http://www.jasc.com/products/paintshoppro/

SILVICS (Satellite Image Land Vegetation Integrated Classification System): Topographic normalisation, ortho-rectification, image segmentation. Freeware, developed by Niall McCormick under contract to JRC-SAI for the Irish Forest Inventory and Planning System Project. Available from http://eurolandscape.jrc.it/forest/silvics/

Surfer (Keckler 1997): Import and display of GRID-files. Version 6.04 (Win32). Commercial software, manufactured by Golden Software. Information at: http://www.goldensoftware.com/products/surfer/surfer.shtml

WinChips (Hansen 2000): image processing, statistics, arithmetic operations. Version 4.7, January 2000. Available from http://www.geogr.ku.dk/chips/index.htm

All web sites were accessed between 1 and 3 March 2004.