Urban land classification and its uncertainties using principal component and cluster analyses: a case study for the UK West Midlands

S.M. Owen[a], A.R. MacKenzie[a], R.G.H. Bunce[b], H.E. Stewart[a], R.G. Donovan[a], G. Stark[b] and C.N. Hewitt[a]

Corresponding author: S.M. Owen, CREAF, Edifici C, Universitat Autònoma de Barcelona, 08193 BELLATERRA (Barcelona), SPAIN, sue.owen@creaf.uab.es; phone: +34 93 581 13 12; fax: +34 93 581 41 51

[a]Institute of Environmental and Natural Sciences, Lancaster University, Lancaster LA1 4YQ.

[b]Centre for Ecology and Hydrology, Lancaster Environment Centre, Lancaster University, LA1 4YQ.

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ABSTRACT

An urban land-cover classification of the 900 km^2 comprising the UK West Midland metropolitan area was generated for the purpose of facilitating stratified environmental survey and sampling. The classification grouped the 900 km^2 into eight urban land-cover classes. Input data to the classification algorithms were derived from spatial land cover data obtained from the UK Centre for Ecology and Hydrology, and from the UK Ordnance Survey. These data provided a description of each km^2 in terms of the contributions to the land-cover of 25 attributes (e.g. open land, urban, villages, motorway, etc). The dimensionality of the land-cover dataset was reduced using principal component analysis, and eight urban classes were derived by cluster analysis using an agglomeration technique on the extracted components. The resulting urban land-cover classes reflected groupings of 1 km^2 pixels with similar urban land morphology. Uncertainties associated with this agglomerative classification were investigated in detail using fuzzy-type analyses. Our study is the first report of a quantitative investigation of uncertainty associated with a classification of this type. The resulting classification for the UK West Midland metropolitan area offers an impartial basis for a wide range of environmental and ecological surveys. The methods used can be adapted readily to other metropolitan areas where generic urban features (e.g. roads, housing density) are gridded.

KEY WORDS

Land classification, stratified sampling and surveys, fuzzy analysis of uncertainty, urban land-cover.

1. INTRODUCTION

Urban land classification introduction

Land classification is essential for geographers, planners, and, increasingly, for environmental scientists. Lofvenhaft et al. (2002) remind us that there is “no single correct way to describe reality and solve practical questions” regarding the classification of land-cover, and that all classifications are subjective. Thus the quality of the classification depends on the skill of the interpreter even with globally applicable classification methods, such as the Food and Agriculture Organization of the United Nations (FAO, 2000) Land Cover Classification System (LCCS).

In the urban context, land classification is useful in a wide range of applications such as the study of urban land changes, urban ecology, illegal building development, urban expansion, etc. Around 49% of the world’s population live in metropolitan areas (FAOSTAT, 2004), and in some countries, a much higher percent of the population are concentrated in towns and cities, e.g. ~80% for England (Seymour, 2001) and 93% for Australia (FAOSTAT, 2004). The analysis of urban environments is therefore of direct relevance to a large proportion of the world’s population.

Many urban land classification systems have been based on interpretation of satellite imagery, which at one time was inadequate for urban applications, but has undergone rapid and sophisticated improvement in recent years (e.g. Karathanassi et al., 2000; Barr and Barnsley, 2000; Zhang and Foody, 1998; Hepner et al., 1998; Xiao et al., 2004; Lo and Choi, 2004). There are also reports of detailed urban classification from aerial photography. For example, Lofvenhaft et al. (2002) present a model to investigate the spatial aspects of biodiversity in urban planning for Stockholm, Sweden, based on the interpretation of colour infrared aerial photographs and laborious ground truthing. Lofvenhaft et al. (2002) conclude that urban planners sometimes have to deal with rapid and large-scale changes, so their basis for planning (for example an urban land-use classification) must be easy to use, and can never be regarded as complete. Modern satellite and aerial images can give very high resolution detail of urban land cover, but for applications requiring stratified sampling, aerial- and satellite-derived classifications need to be processed further to provide integrated information. Stratified sampling is commonly used to obtain samples more representative of a population than simple random sampling (e.g. Kaur et al., 1996).

In the UK, there have been regular reviews of urban land-use by the UK government environmental departments: the Department of the Environment (DoE), the Department of the Environment, Transport and the Regions (DETR), and now the Department of the Environment, Food and Rural Affairs (DEFRA; 2001-present) (e.g. Coppock and Gebbett, 1978; Stamp, 1947; DETR, 2000). However, as far as we are aware, there has been no urban classification system designed for stratified sampling at 1 km^2 resolution which attempts to describe the morphological characteristics of urban land within that 1 km^2 pixel. Bunce and Heal (1984) estimated that about 10% of land in Great Britain (GB) was “urban”, but they made no analysis of the nature of different urban land cover. They identified a need for stratified sampling strategies to improve databases for environmental description at national level, and suggested an approach for such a strategy based on work by Bunce and Smith (1978). This was developed by Bunce et al. (1996a), who described the land classification derived by the Institute of Terrestrial Ecology (ITE) (now Centre for Ecology and Hydrology (CEH)) of all 1 km-squares in Great Britain.

Although this was a successful tool for classifying the GB rural land cover for botanical survey (Bunce et al., 1996a), there were no detailed urban strata in the resulting classification. Therefore the method of Bunce et al. (1996a) was adapted in this study to classify the urban land comprising the UK West Midlands (UKWM) using land cover data stored as a raster dataset with Ordnance Survey coordinates.

The classification process used principal component analysis to reduce dimensionality of the input database and extract the dominant relationships between land-use variables, followed by cluster analysis to aggregate 1 km^2 pixels into classes. The classification that we generate differentiates between different grades of urbanisation, grouping together the most closely related 1 km^2 pixels in the same class. These classes (grades) of urbanisation then provide the basis for a range of applications that are not directly measurable from aloft. For example, a particular stratified class may give information about the amount of open space, open forest space and dwellings within any 1 km^2 pixel belonging to that class. This relationship inherent within all pixels of the same class is not captured with non-stratified classification, and is important for a range of applications, eg effects of different tree species on air quality or effects of urban environment on child health. Similarly, there are several applications where it is important to classify urban land beyond a single “urban” definition, for example in boundary-layer atmospheric chemistry, where there are steep gradients in air pollutants between heavy-industrial and suburban regions.

The aims and objectives of this paper are to develop a classification system for the UKWM region, and characterise it as fully as possible by (1) interpreting the principal components, (2) testing the robustness of the classification, and (3) exploring thoroughly the uncertainties associated with the classification process. This work was carried out as part of Lancaster University's contribution to the NERC Urban Regeneration and the Environment (URGENT) programme

2. METHODS

2.1 Generation of urban classification for the UK West Midlands Metropolitan area

The method used to generate the urban classification was adapted from that used to generate a classification of the whole of GB (Bunce et al., 1996a), which was used for the CEH Countryside Information System (CIS) (http://www.cis-web.org.uk/). An overview of the methodology is shown in Figure 1. Quantitative spatial data were available at 1 km^2 resolution for each of the 900 km-squares comprising the West Midlands Metropolitan area in the UK (Table I; hereafter, km-square = "pixel"). These data were extracted from published sources (Crown Copyright Ordnance Survey; Fuller et al., 1994; and Wyatt et al., 1994.) and stored as tables in an EXCEL spreadsheet. Each 1 km^2 pixel occupied one row. The data consisted of 27 variables ("attributes") which occupied columns of the spreadsheet, with a value for each attribute for each of the 900 pixels. Twenty-five of the 27 attributes described land-cover (e.g. "urban", "motorways", etc; Table I). The remaining two of the 27 attributes did not contribute to land cover of the pixels, but were included as diagnostic attributes in the PCA. One of these was the first axis output from the CEH mean PCA values for the individual Land Classes of the GB land classification ("CIS axis 1"). This was used as an integrated environmental attribute for the urban land classification. The second diagnostic attribute "slope" described the gradient of land within the pixel was obtained from CEH data sources, and was included in case this physical parameter affected type of urban development (e.g. housing rather than heavy industry). The 25 land-cover attributes shown in Table I were spatial land-cover data which contributed a certain number of hectares to each 1 km^2 pixel of the UKWM, ie, the attributes were expressed as ha km^{-2} land-cover in each pixel.

Values for the 27 attributes for each 1 km^2 pixel were used in principal component analysis (PCA) and cluster analysis programs ('Minitab'; Minitab Inc., State College, Pennsylvania, USA). In the PCA, extracting uncorrelated, orthogonal components (factors) reduced duplication in the variability of the 27 attributes across the 900 pixels. In this way ~45% of the variability of the 27 attributes was accounted for by 6 extracted components (Table II). Further component extraction accounted for little extra variability (Figure 2). The extracted components were then used in the cluster analysis. Euclidean distance was used as the dissimilarity matrix coefficient, and Ward's method was used to minimise the increase in the error in sum of squares (variance) resulting from the clustering (Ward, 1963). This procedure uses an agglomerative hierarchical method that begins with all 900 pixels being separate, each forming its own "cluster". In the first step, the two pixels closest together (defined by the dissimilarity matrix) are joined. In the next step, either a third pixel joins the first two, or two other pixels join together into a different cluster. With Ward's method, every possible pair of pixels and existing clusters is tested iteratively, and the pair whose fusion results in the lowest increase of variance of the clusters are combined. This process continues until all clusters are joined into one, but output can be analysed to yield any number of clusters or groups. Initial visual interpretation of the components extracted from PCA (Table III) indicated that eight urban classes should be sufficient for the stratification of the 900 UKWM pixels (see below). The most widely used procedure for deciding on final number of classes in this type of analysis is to accept an ad hoc minimum size of group, guided by practicality and usability (Hall and Arnberg, 2002; Bunce et al., 1996b). The minimum and maximum number of squares in this UKWM classification were 7 and 218, respectively. Classes with large numbers could not be usefully subdivided, as they represented the extensive and homogenous farmland and open light suburban areas of the region (section 3.1). Similar use of PCA and cluster analyses have been reported by Huang et al. (2001) who classified energy flows in an urban region, reducing dimensionality of their input datasets from 19 variables to four factors. Cifaldi et al. (2004) performed PCA on two contrasting regions, one agricultural and one urban, to examine spatial patterns in land cover. The reduced the dimensionality of their data-sets of 25 variables to 5 extracted components which accounted for a large proportion of the variability in their original data.

2.2 Validating the method of generating urban classes using principal component and cluster analyses

The methodology was checked using different PCA and cluster analysis programs in two further software packages, "Clustan" (Clustan Ltd., Edinburgh, Scotland) and "Statistica" (Statsoft Inc., Tulsa, Oklahoma, USA). Clustan is a Fortran program running on a UNIX operating system. "Statistica" is a package available for Windows PC (StatSoft inc). Statistica was unable to run with the complete original 900-line dataset; therefore a subset of 300 lines was taken from the data file by extracting the first, then every third line of data. PCA and cluster analysis programs were run to produce eight classes from the subset of data, using Minitab and Statistica, with Euclidean distance and Ward's linkage. Minitab software generated the classification system directly, with eight classes and six components defined for the output. Statistica output produced a cluster dendrogram, and an amalgamation schedule from which eight classes were extracted. The data for the dendrogram indicated the linkage distance of the clusters that would result in 8 classes. Because the default dissimilarity coefficient for Clustan is squared Euclidean distance, a program was included in the Clustan syntax to define Euclidean distance as the dissimilarity coefficient. After processing output data, identical classifications were obtained using Minitab, Clustan and Statistica.

2.3 Analysis of uncertainty associated with the classification

All land cover data contributing to the analysis of a region the size of the UKWM is likely to carry uncertainties, irrespective of its source. When integrating land cover data to provide information at larger scales, more uncertainty is introduced as detail becomes sacrificed to average. When applications demand ground-truthing, surveying or sampling within a very large area, with view to extrapolating from the sampling domain to the entire study domain, uncertainties can become very large indeed. With this in mind, we undertook a rigorous analysis of uncertainty to make transparent the unavoidable and inherent sources of error when using a stratified sampling system.

2.3.1 Calculating fuzzy membership of each urban land class for each pixel

The vector of attribute values for any particular pixel will have some degree of similarity with all 8 urban class centroid properties, and therefore have some degree of membership to each of the 8 urban classes. To estimate the degree of membership of each pixel in each of the 8 urban classes, the Euclidean distance (d_E) between the pixel attribute vector, x, and that of each urban class mean (μ_c; Table IV) was calculated using:

$$d_E(x,\mu_c) = \sqrt{\sum_{j=1}^{n}(x_j - \mu_{cj})^2} \quad \ldots\ldots(1)$$

where $d_E(x,\mu_c)$ is the "distance" between pixel x and the class centroid μ_c for class c, $(x_j - \mu_{cj})$ is the distance between pixel and class centroid for attribute j, and n = number of attributes. This measures the similarity between the pixel vector of attribute values, and the class vector of centroid attribute values (Ahamed et al., 2000). The "distance" values $[d_E(x,\mu_c)]$ were used to calculate a vector of fuzzy class membership grades for each pixel using:

$$f_c(x) = \frac{\frac{1}{d_E(x,\mu_c)}}{\sum_{i=1}^{m} \frac{1}{d_E(x,\mu_i)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

where $f_c(x)$ is the membership grade of pixel "x" in class "c", with values between 0 and 1, $d_E(x,\mu_c)$ are calculated in equation (1), and m = number of urban classes (Ahamed et al., 2000). In this analysis, there are 8 urban classes (ie m=8), so a membership-grade vector of 8 values is calculated for each pixel (Table V). By definition, the sum of all membership values in a pixel's membership vector is 1.

2.3.2 Calculating uncertainty for pixel allocation to urban classes

Zhu (1997) described 2 stages in classification of spatial phenomena: (1) class definition and (2) class assignment. During class definition, the parameter space of a spatial phenomenon is discretised into regions (classes) with each region assigned a class name and represented by a centroid of that region, which is often the typical case for that class (Zhu, 1997). In the general case, the pixel is assigned to only one class based on a comparison of the observed attribute and the typical attributes of the classes. Once the pixel is assigned to that class, it assumes the centroid (mean) properties of that class, and thus loses its individuality. The loss of pixel individuality is the error introduced into the final classification product (Zhu, 1997). Zhu (1997) postulated that because no pixel is exactly identical to the class centroid in terms of attribute values, when a pixel is assigned to a class, an error of commission ("exaggeration uncertainty") is made, by allocating centroid properties to a pixel that does not "fully" qualify for it.

Similarly, by allocating a pixel to a class, similarities between it and the other classes are ignored, thus introducing an error of omission (“ignorance uncertainty”).

The classification method employed here does not pre-define class centroid properties, but generates them in the process of agglomeration. The centroid properties are then defined as the class means of the attributes, and the fuzzy membership functions described above are based on this process-derived centroid definition for each of the 8 urban classes.

2.3.3 Exaggeration Uncertainties

Zhu (1997) describes exaggeration uncertainty as inversely related to the membership saturation in the class to which an object is assigned. Here we define an exaggeration uncertainty vector for a pixel’s possible assignation to each of the 8 urban classes. For any pixel x, possible allocation to class c with centroid μ_c, carries an exaggeration uncertainty which we define as:

$$E_c[x,\mu_c] = \frac{d_E(x,\mu_c)}{\max[d_E(x,\mu_c)]} \quad (3)$$

where $E_c[x,\mu_c]$ is a measure of exaggeration uncertainty with values ranging between 0 and 1, $d_E(x,\mu_c)$ are calculated in equation (1) and $\max[d_E(x,\mu_c)]$ is the maximum value of the distance $d_E(x,\mu_c)$ from the centroid μ_c for pixels previously calculated to be in that class. By calculating E for possible assignation to each of the 8 urban classes, a vector of class exaggeration uncertainty values was generated for each pixel (Table VI).

2.3.4 Ignorance Uncertainties

The uncertainty associated with ignoring the similarities between a pixel and the classes to which it was not allocated is related to the fuzziness of the pixel compared with the definition of the class centroids (Zhu, 1997). The fuzzier a pixel’s relationship to the classes, the more evenly distributed is the membership in the vector and the greater is the ignorance uncertainty. Ignorance uncertainty can be defined in several ways, but a method adopted by Zhu (1997) is based on the level of membership of a pixel in classes to which it was not assigned. The sum of values in a pixel's membership vector is 1 (section 2.3.1 and equation (2)), therefore we define a measure of ignorance uncertainty

$$I(x) = 1 - f_c(x) \quad \text{.....(4)}$$

where $f_c(x)$ is the membership value for the class to which a pixel x is assigned. $I(x)$ was calculated for each pixel, and the mean (I_c) and standard deviation calculated for each class (Table VII).

3. RESULTS

3.1 The urban land classification

The distribution of Eigenvalues derived from the PCA is presented in Figure 2. Eigenvalues represent the relative contribution of each component to total variation in the data. Figure 2 shows clearly that most of the variation in the data was accounted for by the first six components. The percentage of total variation explained by each component is calculated as (eigenvalue x 100/number of attributes). Thus ~45% of the variability was accounted for by successive extraction of the first six components (Table II). Eigenvectors are sets of scores representing the weighting of each of the original land-cover attributes on each extracted component (Table III). The Eigenvector scores give information for the interpretation of the principal component analysis (Cifaldi et al., 2004). The first component (or factor) describes a gradient between (a) built-up and (b) non built-up areas; the second component distinguishes between (a) wooded areas /heathland, and (b) farmed land; the third component, between (a) water/bare ground, and (b) suburban built-up areas; the fourth component, between (a) urban built-up areas/major transport corridors, and (b) suburban areas/minor transport corridors; the fifth, between (a) wooded areas, and (b) heathland countryside; and the sixth between (a) less dense built-up areas, and (b) major transport corridors (Table III). The extracted components' spectra of attribute weightings suggested, therefore, that eight classes would be an optimum number of classes to specify in the output from the cluster analysis, and that the classes would broadly reflect wooded areas, water, transport corridors, urban built-up areas, different density suburban built-up areas, open land, and farmland. Cluster analysis was then used to generate the classes, and class centroids were found by calculating the mean hectare-age of each of the 25 land-cover attributes in each urban class (Table IV). The distribution and brief interpretation of urban classes in the UKWM region is shown in the maps in Figure 3. The classes generated were named subjectively according to their dominant centroid attributes (Figure 3; class 1 – villages/farms; class 2 –suburban; class 3 – light suburban; class 4 – dense suburban; class 5 – urban/transport; class 6 – urban; class 7 – light urban/open water; class 8 – woodland/open land). Representative aerial view photographs of pixels representative of each land class are shown in Figure 4 (Cities Revealed (R) photography © 1998 The Geoinformation Group (R) Ltd). The interpretation of each class was confirmed by visual inspection of OS maps (1:50000, nos. 139 and 140).

3.2 Fuzzy analysis of uncertainty of the urban land-cover classification

3.2.1 Fuzzy membership of each urban land class for each pixel

Mean membership grade vectors for each class are presented in Table V. Figures in bold depict the mean membership value in the membership-grade vectors (*fc*) for the class to which the member pixels are allocated. For example, the average membership value of class 1 pixels for class 1 is 0.32±0.10, which is higher than the average membership values of these pixels for the other classes (Table V).

3.2.2 Exageration uncertainties

Mean exaggeration uncertainties are presented in Table VI. The bold figures describe the exaggeration uncertainty of allocating pixels to their own class, and the non-bold figures describe the exaggeration uncertainty of allocating pixels to other classes. Thus, for the pixel members of class 1, the mean exaggeration uncertainty associated with assuming class 1 pixels possess the class 1 centroid properties is 0.20±0.11.

3.2.3 Ignorance Uncertainties

Table VII lists the ignorance uncertainties for each class. For example, the mean uncertainty associated with lost information about an individual pixel allocated to class 1 is 0.68±0.10. This is lower than the mean exaggeration uncertainties associated with allocating these pixels to any other class.

4. DISCUSSION

4.1 The classification system

The classification procedure reduced the number of input variables to the principal component analysis from 25 land-cover types to 6 factors, resulting in 8 urban morphology classes. The classification was robust in that different software packages generated identical classifications based on the same input data. Mean class characteristics were derived by interpreting the principal components (Table IV). While the characteristics of most classes are distinct, there is at first glance a close similarity between classes 5 and 6. However, the distinction between class 5 and 6 is real. Class 5 is characterised by high density of transport corridors in an urban, rather than suburban or rural environment. Class 6 is high density urban with few transport corridors. This type of distinction is important if we are considering eg communication, ecology corridors for encouraging biodiversity, linear sources of anthropogenic pollutant gases, tree planting, etc.

4.2 Fuzzy membership of each urban land class for each pixel

As described above, the vector of attribute values for any particular km^2 "pixel" will have some degree of similarity with all 8 urban class centroid properties, and therefore have some degree of membership to each of the 8 urban classes. In theory, the largest fuzzy class membership grade of the 8 urban classes for any individual pixel should correspond to the urban class allocated to that pixel. In fact, there is a satisfactory 65% correspondence for all pixels, between allocated class and largest value in the class membership vector. The remaining 35% non-correspondence highlights the difference between the original clustering process (in which the mean properties of the cluster change as the cluster forms), and a post-hoc test using the final cluster-mean properties. In joining a new pixel to a growing class, it is possible that the pixel that minimizes overall variance at that point in the agglomerative clustering process is not necessarily the pixel whose attribute values are nearest to the final class centroid.

Except for class 7, the highest membership value in the average membership-grade vectors (*fc*) is for the class to which the member pixels are allocated (Table V). The membership values in the average vector for class 7 are all very similar, indicating a very high degree of membership fuzziness for these pixels. These pixels were clustered together in the analysis on the strength of the large area of inland water land-cover which these pixels share, but apart from inland water, their land-cover attribute composition is similar to that of other classes. Figure 5A illustrates how a pixel can have different degrees of membership in more than one class.

4.3 Exaggeration Uncertainties

Individual pixel exaggeration uncertainties associated with allocating each pixel to its urban class ranged from 0.04 to 1.00. The fuzzy class vectors of the mean and standard deviation of the exaggeration uncertainties for each class ranged from 0.11±0.05 to 0.50±0.13 (bold type, Table VI). Surprisingly, allocation of a mean class-5 pixel to its own class carries slightly higher mean exaggeration uncertainty than allocating the pixel to class 6 (0.30±0.15 cf 0.29±0.17). Similarly, allocating a mean class 7 pixel to its own class carries exaggeration uncertainty (0.50±0.13) equivalent to the exaggeration uncertainty associated with allocating this square to some of the other classes. The values of the mean class exaggeration uncertainty vectors are a relative measure of how much each pixel is different from the centroid of its allocated class compared with how much the same pixel is different from the centroids of other classes (Figures 5A, 5B). Assuming that a feature we wish to ascribe to a class (e.g. biogenic emission rates, see below) varies linearly with d_E, exaggeration uncertainty can be interpreted as the extra false pixel information acquired as each pixel in a class assumes the identity of the class centroid. This could be up to 50% (Table VI). Exaggeration uncertainties reflect the complex nature and broad scope of land-cover within each class.

4.4 Ignorance Uncertainties

Individual mean class ignorance uncertainties range from 0.65±0.11 to 0.87±0.04 (Table VII) and the overall average ignorance uncertainty is 0.73±0.11. As for the exaggeration uncertainties, ignorance uncertainty values are not absolute measures of uncertainty, but indicate the amount of information lost when classifying pixels using the agglomerative cluster analysis methodology, and assigning each pixel to a single class (Figures 5A, 5B). Again, this assumes a linear relationship between some feature assigned to the class and pixels' d_E values. Although the results of the uncertainty analysis appear to be cause for concern, all comparable systems of stratification, whether in ecology, social science or environmental studies, have comparable problems. The most important feature to emerge from the analysis of uncertainty of the classification described here, is that the allocation of pixels to classes is satisfactory for practical purposes, even for those pixels with very fuzzy membership grade vectors. However, the cluster test with f_c (equation 2) broadly justifies the classes that have been formed using PCA and cluster techniques, but indicates that categorical statements regarding class membership, class behaviour and properties should be avoided.

4.5 Specific Applications

The classification can now be used as a structure for surveys and sampling, to answer questions such as "What is the total tree cover in the UK metropolitan region and what are the uncertainties associated with the estimates?"; "How much space is available for future tree planting in the UKWM?"; "What is the effect of the present and possible future tree populations on air quality in the UKWM?". Given that the classification methodology can be applied to other metropolitan areas where gridded data is available, the same kind of questions may be addressed in metropolitan areas around the world.

The classification described here has already been used in a desk study to estimate biogenic volatile organic compound (BVOC) emissions from the UKWM conurbation (Owen et al., 2003). It has also been used in a field survey study to estimate tree cover and tree biomass for the UKWM conurbation (Donovan, 2004), and in a modelling study to investigate the effect of pollutant deposition and biogenic VOC emissions on air quality in the UKWM (Donovan et al, 2005). In the field study (Donovan, 2004), a survey of trees in the UKWM was undertaken by stratified recording of all individual trees in sample plots in randomly selected 1 km^2 pixels. A total of 22 pixels were surveyed, the number of squares sampled for each of the eight urban land-cover classes was proportional to the area occupied by each class in the 900 pixels comprising the UKWM. Data for each urban land-class pixel were extrapolated to the total area of each of the classes in the UKWM to obtain an integrated estimate for the tree population for the whole region based on the survey work, rather than on previously published tree data (c.f. Owen et al*.,* 2003). Because the sampling was stratified, i.e. based upon the urban classification, there was compensation for the relatively small percentage of the total region that it was possible to sample with the available time and manpower.

4.6 Wider Applications

This type of urban land classification could facilitate first estimates of:

- **overall land resources of an urban region.** This would be useful for features that are not recorded on a systematic basis by other agencies and that are not a simple linear sum or difference of standard recorded features, e.g. area occupied by transport corridors, commercial land suitable for tree planting.
- **the distribution of land resources throughout urban classes**. For example, urban land class 5 is designated "urban/transport" here, and each UKWM pixel which is classified as "urban/transport" has a mean of ~20 ha km^{-2} grassland/open land. This information could be of interest to planners, recreation and amenity officers and conservation bodies, to conduct more detailed survey of each pixel according to the application of interest (e.g. housing, creation of playing fields, new woodland planting etc) and to identify, for example, those "urban/transport" squares whose proportion of open space is detrimentally low.

- **land-use potential**. Survey work based on the classification can identify further land-use attributes for sample survey pixels (for example, future tree planting potential, derelict sites, sites suitable for recreational development etc.), which can be extrapolated to the whole UKWM region.
- **changes in the urban infrastructure**. For example, removal of railway lines from a pixel in class 5 (urban transport) will result in re-classification of that square, bringing it into a class with less railway, but with other attributes similar to class 5 (e.g. class 2; Table IV), and therefore subject to monitoring or policies for the new class. Of course, when pixel re-classification exceeds some threshold (e.g.10%), then the basis of the original classification becomes obsolete and the region should be re-classified. The procedure described here ensures that updating the classification is a straightforward and time-efficient process.
- **policy options**. For example, the classification provides an estimate of the spatial distribution of high-density transport corridors (i.e. class 5 squares). It is therefore possible to make a first estimate of the concentration of associated features and potential facilities (e.g. lighting, street tree planting, pollutant emissions), and their costs, without resorting to detailed survey in the first instance.
- **assessment and costings for scaling-up policies.** Classification of urban land-use for all major cities would assist planners and policy-makers in the task of larger-scale assessments and costings.

These are examples of the wide range of potential applications for an urban land-cover classification system, of interest and use to Local Authority planners, property developers, environmental researchers, utility companies and policy makers. The classification system described here is “robust enough”, and useful for stratified sampling and extrapolation where time and resources are scarce. It is easy to apply to other UK conurbations, and indeed to any region for which there exists a spatial dataset consisting of attribute data to describe the component land-covers of each pixel. It is also easy to reapply using updated datasets, to monitor land-use changes at pixel and regional scales.

5. CONCLUSIONS

We generated a successful classification system for the UKWM region using land cover data stored as a raster dataset with Ordnance Survey coordinates. Our approach is supported by other workers who have also used PCA and cluster analyses to generate a classification relevant to urban land-cover (e.g. Huang et al., 2001; Cifaldi et al., 2004).

We believe that this is the first time that an attempt to quantify uncertainties has been presented alongside an agglomerative land-cover classification. The same analysis of uncertainty could be applied to any application of PCA and clustering in landscape science, with similar uncertainty results. In view of the process of agglomeration and the associated errors, we expected a very large degree of uncertainty associated with the classification and therefore the results of the uncertainty analyses were encouraging.

The methodology is statistically robust and reproducible and enables standard errors to be estimated. By including a posteriori tests of the classification, its limits become more clearly defined, and the tendency to make categorical statements based on the classes is reduced. The statistical procedures used can vary according to the availability of algorithms in PCA packages. Even though the decision about the number of classes to allow the cluster analysis to generate is subjective, the principal feature of our approach is the use of objective procedures to construct the classification, and to facilitate subsequent estimation of environmental parameters. Similar data for the generation of an urban land classification are available in most European countries so that the approach could be adapted to many other situations.

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Table I Attributes used in the principal component analysis to generate eight urban classes

From ITE land cover database:	From OS data:
urban	OS A roads
suburban	OS B roads
tilled land	OS towns
managed grassland	OS villages
rough grassland	OS canals
bracken	OS minor roads
heath grassland	OS motorway
open heathland	OS open countryside
dense heathland	OS railway
coniferous woodland	OS rivers
inland bare ground	OS inland waters
inland water	OS woodland
deciduous woodland	
slope	CIS Axis 1*

* First axis scores (upland/lowland weighting) of the principal component analysis used to generate the CIS land classes.

Table II Eigenvalues from successive extractions of Principal Components from 27 land cover attributes

Component	Eigenvalue	% of total variance	Cumulative eigenvalue	Cumulative %
1	4.62	17.10	4.62	17.10
2	2.49	9.22	7.11	26.33
3	1.93	7.15	9.04	33.48
4	1.49	5.52	10.53	39.00
5	1.09	4.04	11.62	43.04
6	0.55	2.05	12.18	45.09

Table III Eigenvector scores for each of the urban land-cover attributes

	Component (factor)[1]					
	1	2	3	4	5	6
Slope	-0.001	0.064	0.058	-0.05	-0.079	**-0.473**
Bracken	0.04	0.084	0.05	-0.002	**0.324**	-0.212
Inland bare	-0.001	-0.088	**-0.181**	0.165	-0.045	-0.153
OS[2] village	0.05	-0.047	0.007	0.023	-0.048	**-0.123**
Urban	-0.125	-0.02	-0.189	**0.212**	0.09	-0.119
OS[2] canals	-0.047	-0.038	-0.113	**0.176**	0.14	-0.078
OS[2] open country	**0.187**	-0.094	-0.026	0.071	0.034	-0.049
OS[2] B road	-0.044	0.053	0.041	-0.015	-0.02	**-0.046**
Heath grass	0.106	0.166	0.102	-0.04	**0.31**	-0.045
OS[2] A road	-0.086	-0.017	-0.083	**0.155**	0.111	-0.032
Deciduous wood	0.077	**0.279**	-0.039	0.072	-0.03	-0.017
Managed grass	**0.163**	-0.091	0.053	-0.012	0.048	-0.009
Rough grass	0.038	-0.003	0.029	0.033	**0.226**	0.016
Inland water	0.02	0.023	**-0.374**	-0.324	0.06	0.017
OS[2] inland water	0.018	0.027	**-0.37**	-0.328	0.06	0.018
OS[2] rail	-0.064	0.026	-0.141	**0.177**	0.175	0.02
Tilled land	0.12	**-0.165**	-0.029	0.048	-0.12	0.022
Dense heath	0.054	**0.24**	-0.063	0.074	-0.083	0.04
OS[2] minor road	0.059	-0.061	0.102	**-0.18**	-0.146	0.043
OS[2] towns	**-0.189**	0.079	0.066	-0.074	-0.013	0.048
Open heath	0.042	**0.237**	0.074	-0.044	0.17	0.069
OS[2] wood	0.052	0.184	-0.105	0.16	**-0.305**	0.07
Coniferous wood	0.043	0.128	-0.114	0.149	**-0.317**	0.07
Suburban	-0.155	0.058	**0.157**	**-0.172**	-0.076	0.093
OS[2] motorway	0.004	-0.03	-0.073	0.146	0.162	**0.228**
OS[2] rivers	0.052	-0.018	0.012	0.064	0.131	**0.316**
CIS axis1[3]	-0.005	-0.013	0.003	0.016	0.041	**0.549**

[1]component 1=built-up (-ve scores) vs non-built up (+ve scores); 2=farmed land (-ve scores) vs wooded and heathland (+ve scores); 3=urban built-up, water and wooded areas (-ve scores) vs suburban built-up (+ve scores); 4=suburban built-up and water (-ve scores) vs major transport, built-up urban and wooded areas (+ve scores); 5=wooded areas and farmland (-ve scores) vs heathland countryside and transport corridors (+ve scores); 6=less dense built-up (-ve scores) vs major transport corridors (+ve scores). Bold type indicates high scores contributing to interpreting components; [2]OS Ordnance Survey data; other attributes from ITE database (see text); [3]First axis scores (upland/lowland weighting) of the principal component analysis used to generate the CIS land classes.

Table IV Mean cover (ha km^{-2}) of 25 attributes in each of eight urban classes*

Class	1	2	3	4	5	6	7	8
total pixels	216	218	37	155	71	183	13	7
CIS land cover (LC) attributes								
urban	2.6±5.4	5.7±6.6	3.6±5.0	6.3±6.7	39.6±22.7	27.6±15.0	8.8±8.6	3.7±8.1
suburban	15.5±10.6	50.5±12.4	32.7±12.3	71.1±10.3	38.1±11.5	51.2±11.0	33.2±22.0	7.2±5.8
tilled	30.2±16.2	14.4±8.8	9.9±5.9	9.3±5.0	10.1±6.4	9.7±5.2	19.8±13.2	10.8±14.9
managed grassland	41.4±18.3	19.5±11.6	23.5±13.4	9.8±6.3	8.2±12.1	7.0±6.2	19.0±13.0	15.5±15.0
rough grassland	0.1±0.3	0.02±0.08	0.4±1.0	0.01±0.06	0.03±0.11	0.01±0.09	0.01±0.04	0.1±0.1
bracken	0.01±0.03	0.00±0.02	0.1±0.3	0.00±0.00	0.00±0.00	0.00±0.01	0.01±0.04	0.04±0.09
heath grassland	2.6±2.3	2.1±1.8	7.7±6.9	0.8±0.8	0.4±0.7	0.5±0.7	1.1±1.8	5.0±5.1
open heath	1.2±1.2	2.1±2.3	7.2±5.2	0.9±1.1	0.5±0.8	0.7±0.7	1.2±2.2	6.0±5.0
dense heath	0.2±0.6	0.2±0.4	0.9±1.1	0.05±0.3	0.02±0.08	0.03±0.1	0.2±0.5	7.1±7.6
coniferous wood	0.1±0.3	0.1±0.2	0.1±0.2	0.02±0.1	0.04±0.2	0.01±0.04	0.1±-.3	4.6±4.1
inland bare ground	1.4±2.4	0.9±1.1	0.4±0.6	0.4±0.5	1.8±1.5	1.2±1.2	1.8±2.0	1.2±2.6
inland water	0.1±0.4	0.1±0.6	0.2±0.6	0.01±0.1	0.2±0.5	0.05±0.2	10.2±14.2	0.9±1.5
deciduous wood	4.3±4.9	4.3±4.5	13.0±8.6	1.3±1.6	1.1±1.7	2.0±3.0	4.2±7.2	37.9±22.3
OS attributes								
A roads	0.5±1.0	0.8±1.1	0.8±1.0	0.9±1.1	2.9±2.2	2.1±1.7	1.0±1.6	0.1±0.2
B roads	0.2±0.4	0.3±0.7	0.5±0.7	0.6±0.9	0.4±0.6	0.5±0.7	0.4±0.7	0.6±0.6
towns	6.4±13.8	65.0±22.9	48.5±31.3	90.6±9.3	73.4±26.5	87.3±14.3	41.0±37.1	6.4±11.8
villages	3.8±9.7	0.1±1.0	0.00±0.00	0.00±0.02	0.04±0.3	0.00±0.00	0.00±0.00	1.7±4.6
canals	0.2±0.4	0.1±0.3	0.1±0.2	0.1±0.2	0.8±0.6	0.4±0.5	0.2±0.4	0.00±0.00
minor roads	1.0±0.8	0.9±0.8	0.6±0.6	1.0±0.8	0.2±0.3	0.5±0.6	0.9±0.9	0.4±0.4
motorways	0.3±1.0	0.1±0.5	0.1±0.7	0.1±0.5	1.8±2.2	0.2±0.8	0.3±0.9	0.00±0.00
open countryside	86.4±16.1	32.0±22.5	48.4±31.1	6.7±9.0	19.5±26.2	8.6±14.1	41.0±33.8	58.9±17.1
railways	0.1±0.3	0.1±0.3	0.3±0.4	0.1±0.2	0.9±0.7	0.5±0.5	0.2±0.5	0.2±0.3
rivers	0.4±0.5	0.3±0.5	0.4±0.5	0.2±0.4	0.5±0.6	0.2±0.4	0.5±0.5	0.3±0.4
inland waters	0.02±0.2	0.2±1.1	0.2±1.0	0.01±0.1	0.1±0.3	0.00±0.00	14.5±17.4	1.2±1.9
woodland	0.7±3.4	0.00±0.02	0.3±1.6	0.03±0.4	0.00±0.00	0.00±0.00	0.4±1.5	30.5±18.8

*attributes slope and CIS axis1 did not contribute to "land cover" (see text)

Table V Mean class membership vectors

Mean membership $f_c(x)$ of class:-	Allocated to class:- 1	2	3	4	5	6	7	8
1	**0.32±0.10**	0.09±0.02	0.12±0.03	0.07±0.02	0.08±0.02	0.07±0.02	0.12±0.02	0.12±0.02
2	0.07±0.05	**0.20±0.09**	0.14±0.06	0.16±0.10	0.11±0.02	0.13±0.06	0.13±0.04	0.06±0.02
3	0.12±0.09	0.14±0.04	**0.19±0.08**	0.10±0.06	0.10±0.02	0.10±0.05	0.14±0.03	0.09±0.04
4	0.04±0.01	0.14±0.06	0.08±0.02	**0.35±0.11**	0.10±0.02	0.17±0.05	0.08±0.01	0.04±0.01
5	0.08±0.06	0.13±0.04	0.11±0.04	0.12±0.03	**0.19±0.06**	0.19±0.08	0.11±0.04	0.07±0.02
6	0.05±0.02	0.13±0.05	0.08±0.03	0.19±0.10	0.17±0.05	**0.26±0.09**	0.08±0.03	0.05±0.01
7	0.15±0.11	0.14±0.07	0.12±0.03	0.13±0.11	0.11±0.04	0.13±0.07	**0.13±0.04**	0.10±0.05
8	0.15±0.05	0.10±0.01	0.13±0.01	0.07±0.01	0.09±0.01	0.08±0.01	0.13±0.01	**0.25±0.04**

Table VI Mean class exaggeration uncertainties

	Allocated to class:- 1	2	3	4	5	6	7	8
Member of class:-								
1	**0.20±0.11**	0.78±0.16	0.62±0.14	0.84±0.13	0.81±0.14	0.83±0.14	0.64±0.13	0.48±0.07
2	0.58±0.19	**0.28±0.14**	0.39±0.16	0.31±0.17	0.38±0.10	0.32±0.15	0.42±0.15	0.64±0.14
3	0.46±0.22	0.43±0.20	**0.36±0.20**	0.50±0.22	0.50±0.17	0.48±0.21	0.45±0.17	0.52±0.16
4	0.83±0.09	0.37±0.10	0.62±0.11	**0.11±0.05**	0.38±0.07	0.22±0.05	0.65±0.11	0.86±0.08
5	0.71±0.23	0.48±0.17	0.58±0.20	0.40±0.14	**0.30±0.15**	0.29±0.17	0.59±0.19	0.74±0.17
6	0.80±0.12	0.39±0.12	0.59±0.13	0.23±0.11	0.26±0.07	**0.16±0.09**	0.61±0.13	0.81±0.10
7	0.51±0.25	0.52±0.25	0.54±0.14	0.51±0.30	0.53±0.23	0.50±0.29	**0.50±0.13**	0.59±0.18
8	0.45±0.15	0.80±0.11	0.63±0.11	0.81±0.08	0.78±0.09	0.79±0.08	0.68±0.12	**0.27±0.05**

Table VII Mean Class Ignorance uncertainties (I_c)

class	
1	0.68±0.10
2	0.80±0.09
3	0.81±0.08
4	0.65±0.11
5	0.81±0.06
6	0.74±0.09
7	0.87±0.04
8	0.75±0.04

Figure 1 Schematic presentation of urban land classification methodology

Figure 2 Results of extracting principal components from 27 urban land-cover attributes. Columns represent the relative contribution of each component to total variation in the land cover data (Eigenvalue)

Figure 3 Distribution of urban land classes in the West Midlands

Figure 4 Aerial photographs of pixels (square km) typical of each urban class

Figure 5A Allocating urban class membership to a pixel

Figure 5B Exaggeration and Ignorance uncertainties in terms of centroid and pixel attributes

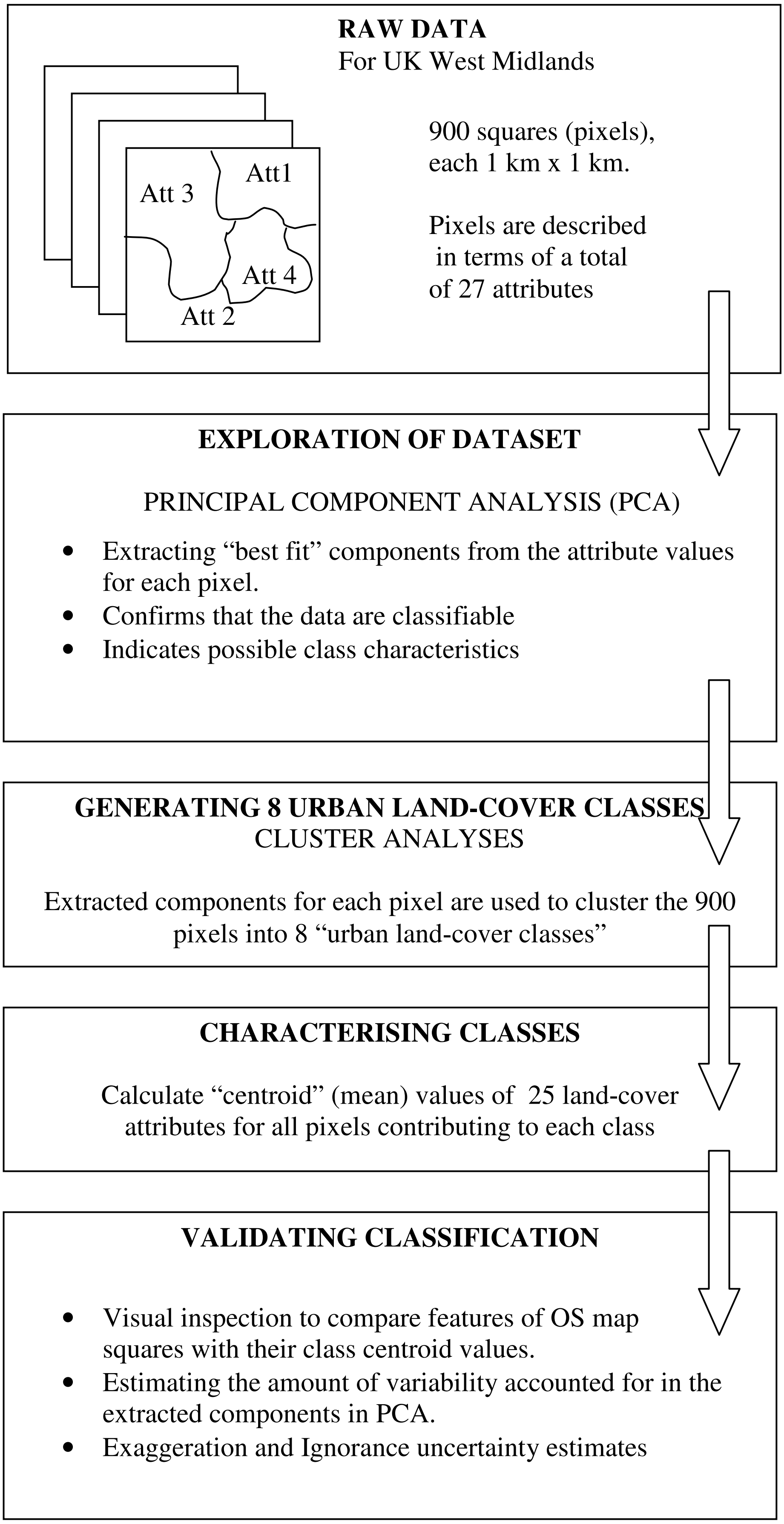

Figure 1 Schematic presentation of urban land classification methodology

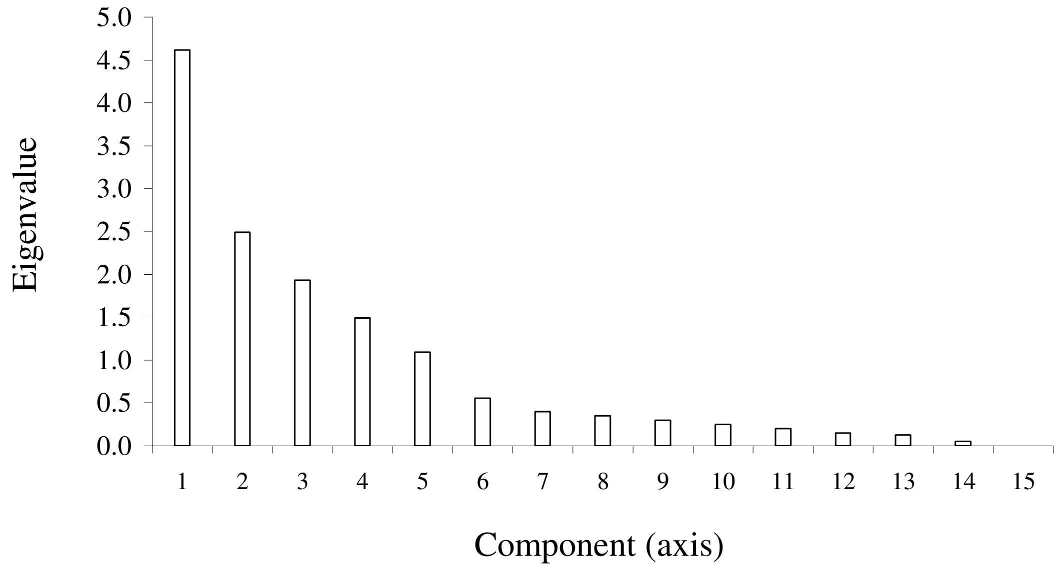

Figure 2 Results of extracting principal components from 27 urban land-cover attributes. Columns represent the relative contribution of each component to total variation in the land cover data (Eigenvalue)

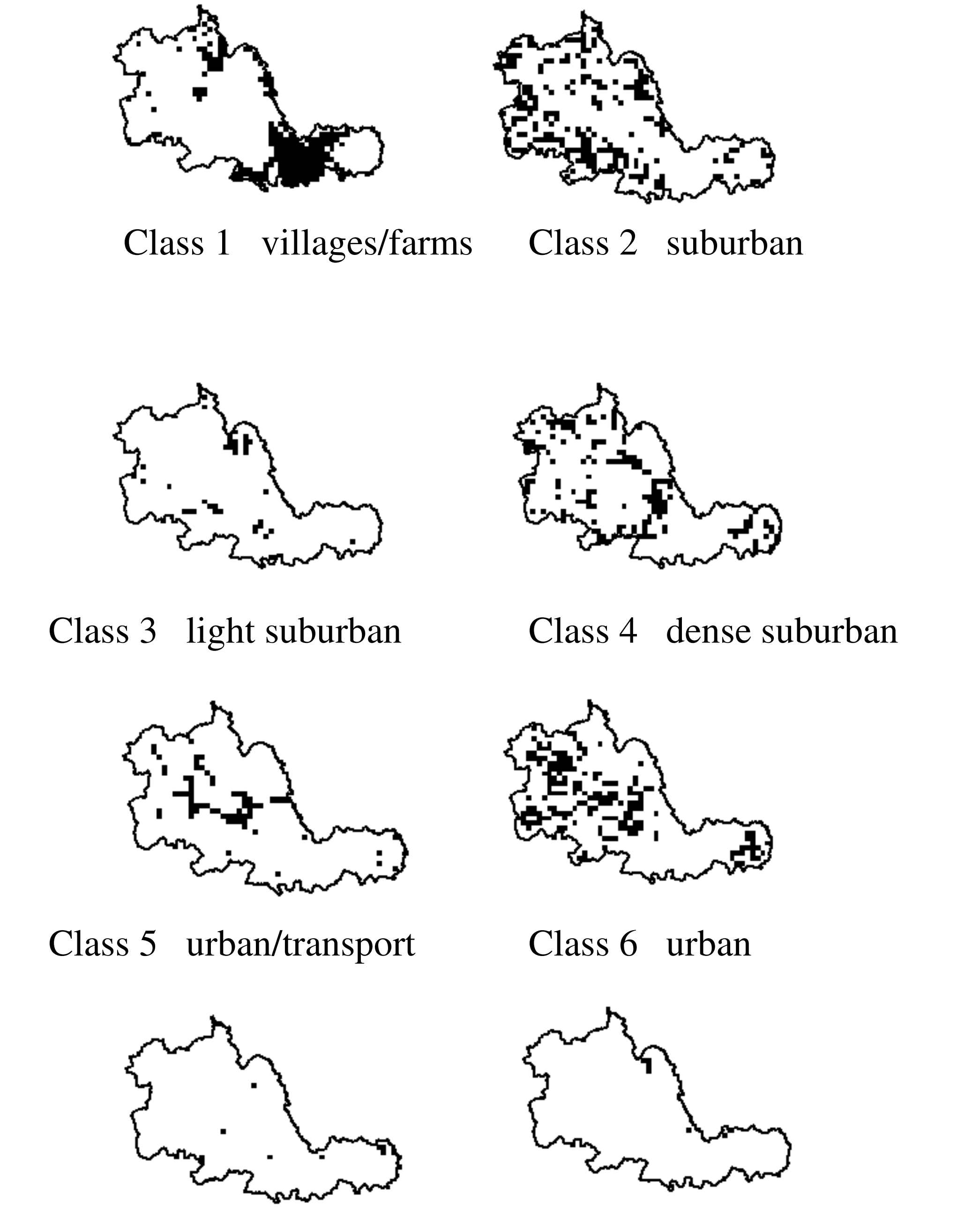

Figure 3 Distribution of urban land classes in the West Midlands

Class 1 villages/farms
OS reference 410277

Class 2 suburban
OS reference 414277

Class 3 light suburban
OS reference 400283

Class 4 dense suburban
OS reference 402278

Class 5 urban/transport
OS reference 409290

Class 6 urban
OS reference 401277

Class 7 urban
OS reference 400280

Class 8 woodland/mixed open land
OS reference 418284

Figure 4 Aerial photographs of pixels (square km) typical of each urban class

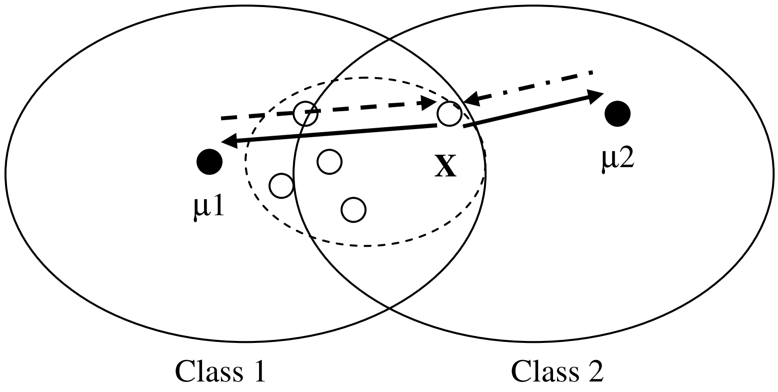

Figure 5A Allocating urban class membership to a pixel. ○ pixels; ● class centroids. Pixel X has attribute values that are close to those of the centroids of class 1 (μ_1) and class 2 (μ_2). During the process of clustering, it is likely that the pixel will be allocated to class 2, whose centroid is "closer" to the pixel. However, pixel X may be allocated to class 1 if, early in the clustering process, it is linked with nearby pixels which form a cluster which is nearer to μ_1, than to μ_2 (small cluster delineated within dashed line). All pixels have some degree of membership in each of the generated urban classes. Generally, a pixel is allocated to the class whose centroid is closest. After allocating to a class, the pixel assumes the characteristics of the class centroid. This results in an exaggeration uncertainty due to false pixel information acquired (solid arrows), and an ignorance uncertainty due to loss of individual pixel information (dashed arrows). Further explanation of these uncertainties is illustrated in Figure 5B below.

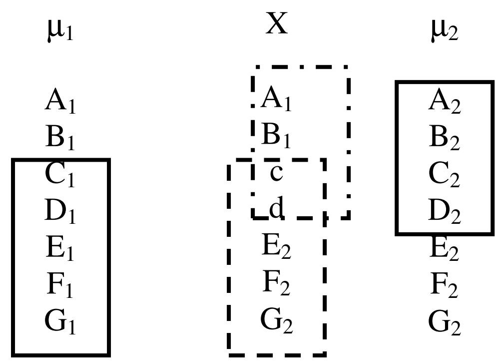

Figure 5B Exaggeration and Ignorance uncertainties in terms of centroid and pixel attributes. A – G represent different attributes for class 1 and class 2 centroids (μ_1 and μ_2, respectively), and pixel X. Pixel X has similar values to μ_1 for attributes A and B, and similar values to μ_2 for attributes E, F and G. Exaggeration uncertainties associated with allocating pixel X to classes 1 and 2, respectively, are represented by the attribute values enclosed in the solid line boxes. Ignorance uncertainties associated with allocating pixel X to classes 1 and 2, respectively, are represented by the pixel X attribute values enclosed in the dashed line box (for class 1 allocation) and in the dot-dash line box (for class 2 allocation).

Author biographies:

Susan (Sue) M. Owen is interested in the effects of environmental stress and land-use change on trace gas emissions from man-made and natural vegetation canopies. With several publications on emissions from Mediterranean and urban ecosystems, she completed a NERC Research Fellow at Lancaster University, UK studying emissions from tropical habitats. She is now working at CREAF, University Autonoma de Barcelona, to investigate the effects of biotic and abiotic stresses on isoprenoid emissions from urban and natural vegetation. Robert (Bob) G.H. Bunce is a "retired" senior scientist (CEH Merlewood). A major contributor to the CEH land classification and Countryside Information System, he is now engaged in a large European land classification program based in the Netherlands. Hope E. Stewart was a post-doctoral researcher at Lancaster, and is now an Atmospheric Scientist with the UK Environment Agency. R. Donovan was a NERC-funded PhD student at Lancaster, studying the effect of urban trees on air quality, and is now a Research Fellow at Birmingham University studying the benefit of greening cities. R.A. MacKenzie is a senior lecturer in atmospheric chemistry studying stratospheric processes, and C.N. Hewitt is Professor of atmospheric chemistry at Lancaster University investigating a wide range of biosphere-atmosphere interactions.