DEVELOPING A METHODOLOGY TO IMPROVE SOIL C STOCK ESTIMATES FOR SCOTLAND & USE OF INITIAL RESULTS FROM A RESAMPLING OF THE NATIONAL SOIL INVENTORY OF SCOTLAND TO IMPROVE THE ECOSSE MODEL

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Final Report

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Contents

1. Executive Summary

Organic soils include true peats, and soils with a layer of organic material (less than 50 cm in depth) overlying mineral soil layers. Organic soils have a high organic matter content, holding huge quantities of carbon (C) and are particularly abundant in Scotland. When C is lost from these soils as carbon dioxide (the main greenhouse gas responsible for climate change) or as methane there may be implications for targets to reduce Scotland's emissions of greenhouse gases. Land use- and climate-change can both cause such losses from soils; in fact, land use change on organic soils has previously been estimated to be responsible for 15% of Scotland's total greenhouse gas emissions.

Because of the importance of organic soils, in a previous project funded by the Scottish Government and the Welsh Assembly (Smith et al., 2007), a computer model, ECOSSE, was developed to simulate greenhouse gas emissions from the organic soils of Scotland and Wales. This model has the capability to predict the impacts of changes in land use and future climate on greenhouse gas emissions from both mineral and organic soils. ECOSSE stands for Estimating Carbon in Organic Soils - Sequestration and Emissions.

The main objectives of the project were to explore approaches to improving data on soil C stocks, estimates and trends (in response to the lack of statistical confidence in our current estimates of total national soil C stocks), and to use ECOSSE to improve estimates of changes in soil C stock using data from the resampling of the National Soil Inventory of Scotland (NSIS2), and information derived from the Scottish Soils Knowledge and Information Base (SSKIB).

The main project outputs are:

1. An analysis of the minimum number of further samplings/analyses required to develop a more accurate estimate of soil C stock in Scotland.
   - The results suggest 600 additional depth and density measurements and further details on the scales of variation in peats are needed to provide an estimate with a high degree of statistical confidence

2. An analysis of the timescales, logistics and deliverables for targeted resampling to measure total depth and bulk density.
   - It is estimated that an adequate survey would have an estimated total cost of ca. £300k (at 2009 rates).

3. Retrospective use of archived dry bulk density data to determine C stocks for peat bogs.
   - Using a new pedotransfer function derived from the archived data, mean bulk density values were found to be comparable to those used for C stock estimates and on average were not found to vary significantly with depth.

4. A comparison of the costs and benefits in the measurement of peat depth and changes in soil C stocks in the peatlands of Scotland by ground penetrating radar, light detection and ranging, and other technologies.
   - Ground penetrating radar has the advantage of a continuous assessment of peat depth along a transect compared to the intermittent measurements achieved by probing, but is not very suitable for use on uneven terrain.
   - Using light detection and ranging to measure the C content of peats has potential as a tool to monitor development of peat gullies in areas of peat erosion, although currently it can only achieve depth accuracies in the order of ± 0.15m and a horizontal accuracy of 1–2m.

- Airborne gamma radiation has potential to differentiate peat from non peat soils and may add more information on soil type distribution in complex environments

5. Use of data from the National Soil Inventory of Scotland (NSIS1 & NSIS2) to evaluate and improve the accuracy of the ECOSSE model, and better define the uncertainty in national scale simulations.
   - Simulated values of percentage change in soil C are within the experimental error of the measurements (11% simulation error, 53% measurement error), are highly correlated to the measurements and show only a small bias in the simulations compared to the measured values, suggesting that a small underestimate of the change in soil C should be expected in the national simulations (-1 to -2%).

6. Improved national estimates of changes in soil C due to land use and climate change.
   - Increasing the area of land use change from arable to grass has the greatest potential to sequester soil C, and decreasing the area of grass to arable has the greatest potential to reduce losses of soil C.
   - Climate change alone is predicted to result in a decline in the soil C stocks that are nearly 50 times smaller than the losses due to land use change. This illustrates the potential for C losses due to climate change to be mitigated by changing land use.
   - Four mitigation options have been identified with high potential for achieving zero losses of C from Scottish soils:
     1) Decrease in the rate of conversion of grassland to arable to 28% of the current rate;
     2) Stop conversion of semi-natural land to arable or grassland and increase the conversion of grassland to semi-natural by 125% of the current rate;
     3) Stop conversion of semi-natural land to arable or grassland and increase the conversion of arable to grassland by 63% of the current rate; and
     4) Stop conversion of semi-natural land to arable or grassland and decrease the conversion of grassland to arable to 77% of the current rate.
   - At this stage, forestry has not been included as a soil C mitigation option as there is a paucity of good quality data for all soils in Scotland within the Scottish Soils Database for modelling land use changes to forestry. This reflects the historic development of the soil survey of Scotland where early mapping and data collection was mainly concerned with cultivated, agricultural soils. The process employed to generate typical profiles and C contents for afforested soils is, therefore, not yet sufficiently robust. Further work on the C content of forested soils and the changes occurring in soil C on change of land use to forestry is needed.
   - Note that when designing policies to reduce total greenhouse gas emissions, changes in C stocks in vegetation as well as in the soil should be considered. This project focuses on C losses from soils only; changes in greenhouse gas emissions associated with vegetation are beyond the scope of the project. Timber production can also bring additional emission reductions associated with substitution of high energy embedded materials and fossil fuels, which should also be included in any comprehensive analysis of greenhouse gas emissions from Scottish forests. The results of this project allow the design of policies to protect soil C stocks, but not to reduce total greenhouse gas emissions from the soil / plant system as a whole.

2. Background

Given the importance of soil carbon (C) in Scotland and the Ministerial commitment made in September 2006 to focus on this issue, it is important that we gain more reliable estimates of changes in soil C stocks. The recently completed ECOSSE project highlighted the uncertainties in our knowledge in this area (Smith *et al*., 2007a,b). This project has allowed us to further develop and improve the ECOSSE model, quantifying and reducing the uncertainty of the estimates of C stocks in Scottish soils. The Scottish Executive and Welsh Assembly Government funded the development of the ECOSSE model to predict the response of mineral and organic soils to both land use and climate change.

Whilst a few models have been developed to describe deep peat formation and soil organic matter turnover, before ECOSSE was constructed, none had been developed that were able to examine the impacts of land-use and climate change on the types of organic soils often subject to land-use change in Scotland and Wales. The organic soils subject to land-use change are often characterised by a shallower organic horizon than true peats (e.g. peaty podzols and peaty gleys). The main aim of ECOSSE was to simulate the impacts of land-use and climate change in these types of soils as well as in mineral and more highly organic soils. Driven by commonly available meteorological data and soil descriptions, the model predicts the impacts of land-use change and climate change on C and N stores in organic soils in Scotland and Wales.

ECOSSE uses a pool type approach, describing soil organic matter as pools of inert organic matter, humus, biomass, resistant plant material and decomposable plant material (figure 2.1). Material is exchanged between these pools according to first order rate equations, characterised by a specific rate constant for each pool, and modified according to rate modifiers dependent on temperature, moisture and pH of the soil. The N content of the soil follows the decomposition of the soil organic matter (figure 2.2), with a stable C:N ratio defined for each pool at a given pH, and N being either mineralised or immobilised to maintain that ratio. Mineral N may then be lost from the soil by the processes of leaching, denitrification, volatilisation or crop offtake, or C and N may be returned to the soil by plant inputs or organic amendments. The soil is divided into 5cm layers, so as to facilitate the accurate simulation of these processes down the soil profile. Each of the processes included in the model is simulated using only simple equations driven by readily available inputs, allowing it to be developed from a field based model to a national scale tool, without high loss of accuracy.

Previous evaluations of the model have focussed on field scale simulations, and provided estimates of the uncertainty in simulations at field scale. However, when the model is applied at the national scale, the uncertainty in simulations is likely to increase, due to increased uncertainty in the data available to run simulations at the national scale. Quantification of the uncertainties associated with national scale simulations is urgently needed, so that some estimate of the uncertainties in the national scale estimates of C change can be obtained. The increase in uncertainty in simulations at national scale over simulations at field scale is due to the inherent uncertainty in the input values at the larger scale, as well as increased uncertainty associated with the increased range of input drivers encountered at the national scale. This uncertainty can be quantified by evaluating the model at field sites but using only input drivers that are available at national scale, and by including the range of sites that encompass the full range of input drivers found at the national scale. This could be achieved by evaluating the simulation of change in soil C at all sites included in the full National Soil Inventory of Scotland.

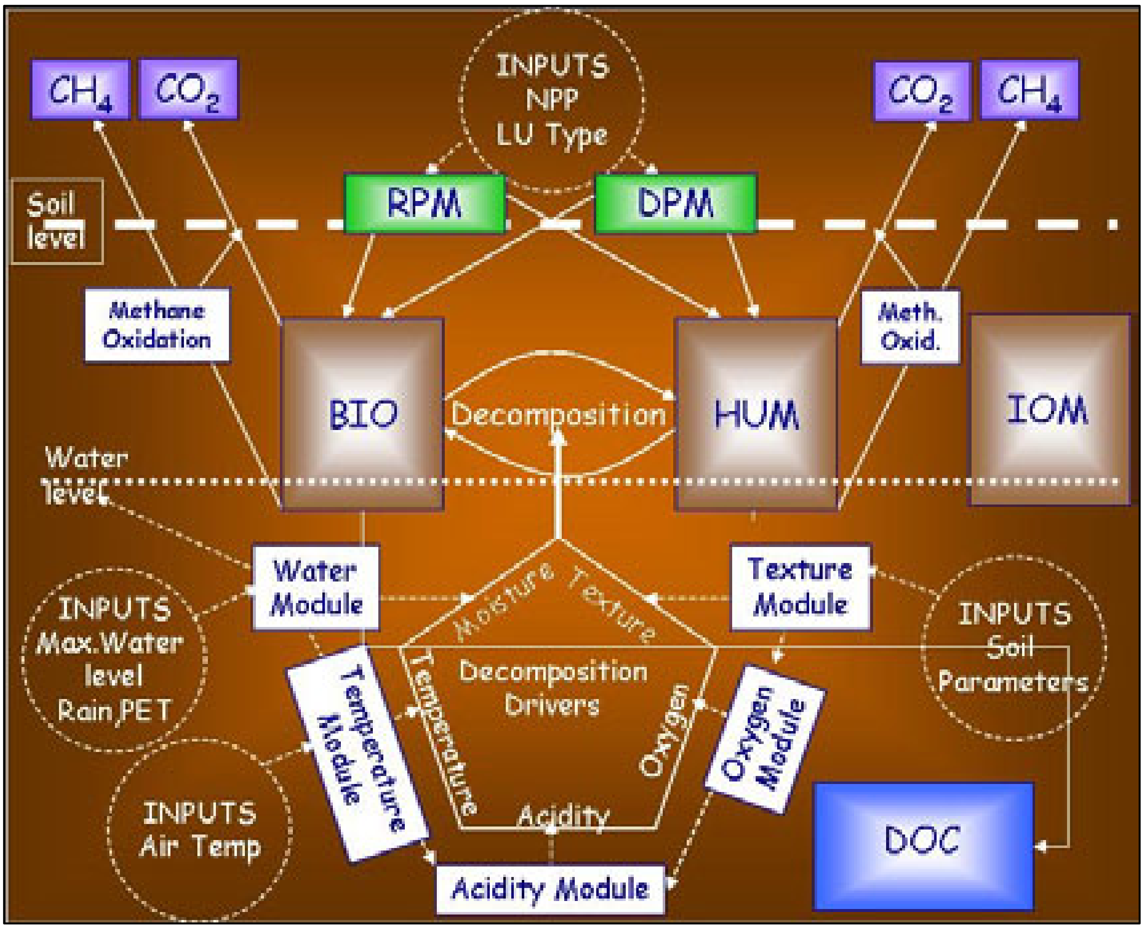

Figure 2.1 Structure of the carbon components of ECOSSE

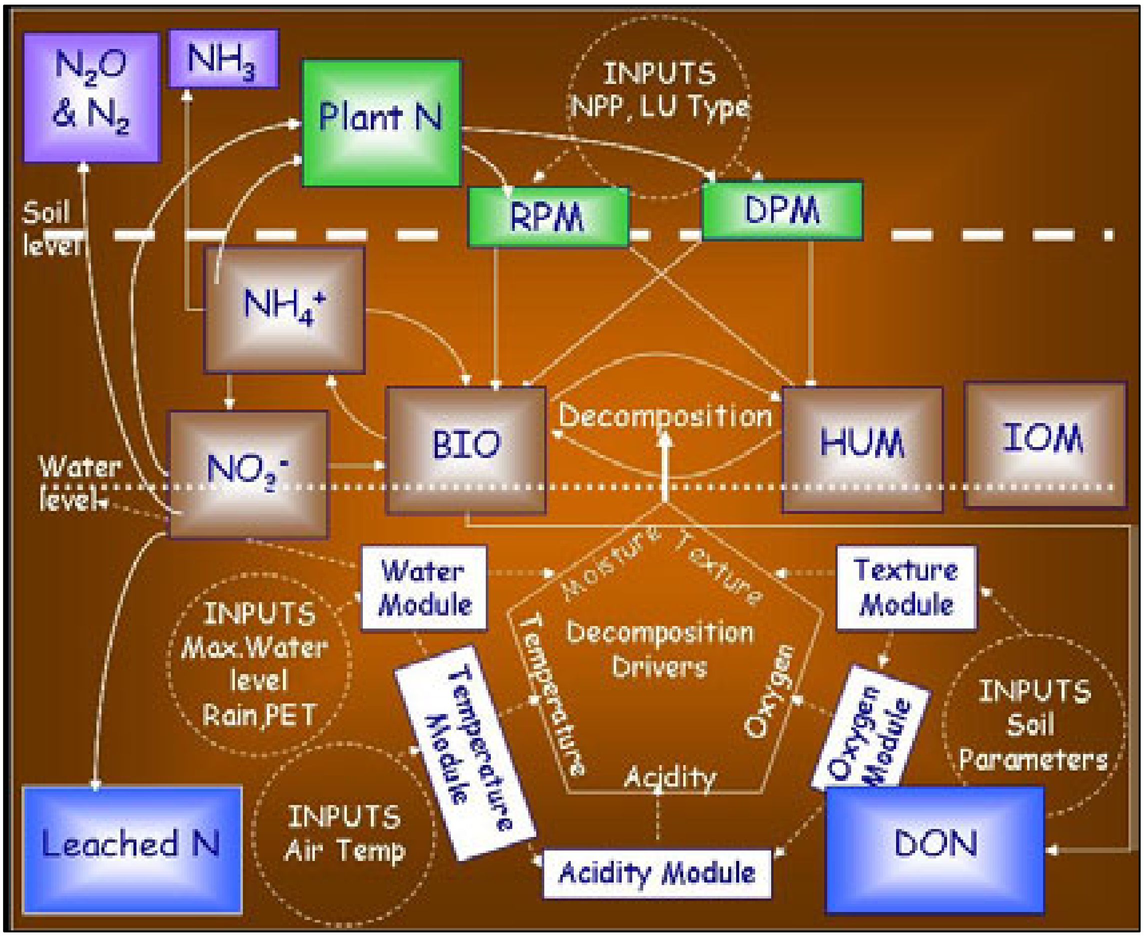

Figure 2.2 Structure of the nitrogen components of ECOSSE

Within current RERAD-funded work packages at the Macaulay Institute (MI), a resampling of the National Soil Inventory of Scotland (NSIS_2) is underway, which will allow the change in soil C stocks since the 1980s to be determined. The full National Soil Inventory of Scotland (NSIS_1) represents a point database collected on a 5km grid across Scotland (Lilly, *et al.*, 2009). The samples were collected in the 1980's and analysed for site and soil characteristics at that time. For each grid point (total = 3094), a range of site and soil characteristics is available. A subset of points on a 10 km grid also includes details of soil chemical analyses with physical and chemical details relevant to individual soil horizons rather than selected depths. For NSIS_1 this included a total of 721 points. NSIS_2 is a resampling of a subset of the NSIS_1 points (180 samples on a 20 km grid). This is being conducted in three phases over the years 2007-2009. Data is being collected that will permit the calculation of the C stock at each location along with estimates of uncertainty. This will allow the data from the original sampling, collected between 1978 and 1988 (NSIS_1), to be compared with data from the current NSIS_2 sampling. The resampling is limited to a depth of 1m, and so excludes soil C held in deeper peat layers, but will allow direct comparison of the changes in soil C between the NSIS_1 and NSIS_2 sampling times. The NSIS_2 resampling will:

i) Identify a statistically unbiased subset of the original 721 NSIS_1 locations that encompass the range of organic, organo-mineral and mineral soils found in Scotland, accurately recording the positions of sample sites for future relocation (using GPS), together with site and soil information.

ii) Measure the thickness and bulk density of soil horizons, following standard procedures and protocols, and record land use.

iii) Analyse the total C content and C:N ratios, archiving samples for future analysis.

iv) Calculate C stocks held within the top metre of Scottish soils.

Phase 1 of the resampling (62 sites) was completed in June 2007 and provides an opportunity to use this data to define the uncertainty in the ECOSSE national estimates of changes in soil C. Phase 2 of the sampling will be completed in 2008, and will be used as a blind test of simulations of changes in C stocks produced during this project. Phase 3 will be completed in 2009, and are not included in the simulations done, as the detailed descriptions of the sites are not yet available.

It is important to take account of the varying definitions of peatland. In the original peat surveys of Scotland, peat was taken as an organic layer containing less than 30% ash with a depth of over 30 cm (Robertson, 1971). Later, under the Soil Survey for Scotland definition, peat should have an organic layer or layers that exceed 50 cm depth from the soil surface. The peat will typically have an organic matter content of over 60%. In the classification for England and Wales peat soils should have an organic layer (or layers) over 40 cm deep (within the top 80 cm of soil) or over 30 cm deep if overlaying bedrock with an organic C content of at least 12-18% (depending on the clay content) (Avery, 1980). Thus, there is some difference between what is considered as peat in these countries. In addition, in Scotland there are considerable areas covered by organo-mineral soils: soils with a surface organic horizon less than 50 cm deep. Particular problems of assessment of C stocks arise where, commonly, organo-mineral soils and peat are intimately mixed within the landscape in varying proportions making estimates of the spatial extent of the different soil types difficult. Blanket, or hill, peat occurs mainly in hill and upland situations where formation is directly influenced by climate (low temperatures, high rainfall) while basin peat, encompassing raised bog, forms in valley or basin sites initially under the direct influence of groundwater. Semi-confined (or partly confined) peat is intermediate between blanket and basin, being generally located in valleys, on terraces or between ridges and drumlins (Hulme, 1980). In the following report, "Peat Polygons" refer to either blanket or basin peat where there is 100% coverage by peat. There are also further subdivisions depending upon whether the peat is deep or eroded or both. "QM units" refers to other soil map units on the 1:250,000 scale map that contain a proportion of peat; this may be blanket, basin or semi-confined in nature.

The aims of the project are

1. Use of data derived from NSIS_2 to improve the accuracy of ECOSSE and its ability to predict the response of Scotland's organic soils to external change.
   This will be achieved by the following objectives:

Objective 1: To undertake a geostatistical analysis of the minimum sample numbers required to produce a statistically significant value for **total** soil C stocks in Scottish peats.

Objective 2: To produce a short report on timescales, logistics and deliverables for a targeted resampling exercise to obtain a representative sub-sample of peats across Scotland (using a transect approach) to measure total depth and bulk density at 50 cm intervals. This will be undertaken after consideration of the results from objective 1.

Objective 3: To ensure that where feasible sites should be tied in with the NSIS_2 programme of work. Data derived from NSIS_2 should be used where appropriate such as depth of organic matter horizons where a probe has been used to gauge depths below 100 cm and any measures of bulk density made. Priority should be given to sites where there is limited historical data available.

Objective 4: To evaluate the possibility of using archived dry bulk density values for peat bogs to determine C stocks values retrospectively to supplement and enhance the estimate described in task 1.

Objective 5: To explore the costs and benefits of GPR and Lidar to measure peat depth and the potential for using these methods to monitor changes in soil C stocks in the peatlands of Scotland.

2. Use of ECOSSE to improve estimates of changes in soil C stock.
   This will be achieved by the following objectives:

   Objective 6: To feed in data derived from this project and NSIS_2 into the ECOSSE model to improve its accuracy and ability to predict the response of Scotland's organic soils to external change.

   Objective 7: To run a series of simulations using ECOSSE to address a number of policy questions from the Scottish Government such as specific land use change and climate change scenarios.

3. Exploring approaches to improve data used to derive changes in soil carbon stocks

3.1. Geostatistical analysis of the minimum sample numbers required to produce a statistically significant value for total soil C stocks in Scottish peats

3.1.1. Introduction

A geostatistical analysis requires a large number of geo-referenced measurements covering the study region, in this case Scotland. The data are used to inform geostatistical models (variograms) of spatial correlation, which provide estimates of spatial scales of variation. The variogram models can be used to estimate values at unsampled locations and the uncertainty in the estimates. A further application of the technique is to optimise the location of additional sample locations and to estimate how many additional samples are needed to improve the estimates in sparsely sampled areas.

Among the parameters required for C stock estimation, only peat depths were available at a suitable density for geostatistical analysis over Scotland as a whole. Depths were measured in individual peat bogs to characterise peat as a fuel, to aid reinstatement of opencast coal sites and to characterise proposed wind farm sites. The sampled areas were thus determined by factors other than the extents of the peat bogs. Additional information on peat extent over the whole country is provided by the 1:250,000 scale soil map of Scotland (Soil Survey Staff, 1981). The soil map delineates map polygons which provide estimates of the areas occupied by different soils, including the sampled peat bogs. A "peat bog" in this context may be a discrete area of peatland or it may be a named area that forms part of a larger peatland unit. The larger map polygons may include more than one sampled peat bog. The map polygons provide estimates of the areas covered by all soil types in Scotland.

Total C stocks within peatlands are the product of area, depth, bulk density and C concentration. From the available data described above, a suitable unit is chosen for the estimation of these parameters and these are then summed across the whole country. Generally, the unit is the "map polygon" defined by the 1:250,000 scale soil map unit and the component soils are further divided in the vertical plane into soil horizons. The basis of this summation, and the uncertainties associated with each of the components of area, depth, bulk density and C concentration were examined in turn, using all currently available data. It is recognised that the uncertainties in these parameters will vary across the country, and that there is a need for a means of expressing such uncertainty. Essentially, this objective will produce a sensitivity analysis of the parameters that lead to the estimation of peatland C stocks.

Uncertainties in area measurements may be determined by comparing soil map units covering peatland types at the 1:250,000 scale with the greater detail of areas available at larger cartographic scales (e.g. 1:500, 1:1,250, 1:5,000 and 1:25,000) where these are available for peatland areas. However, the national coverage at 1:25,000 or greater is very restricted, mainly to small lowland bogs. The feasibility of using other databases of peatlands and/or peatland vegetation cover was also examined.

Currently available data on peat depth varies considerably across the country and this has required the estimation of peat depth for polygons where no data exists. Gross C stock calculations were made for different bogs and the whole country by varying depth estimates and assessing the sensitivity of the output.

There is insufficient information on both peatland bulk densities and C concentrations to support any analysis or interpretation of regional variation. Rather, typical bulk densities and C concentrations are, in turn, ascribed to the various peatland types (i.e. basin peat, deep blanket peat, eroded blanket peat, etc.) and to the specific peat horizons (i.e. 0–30 cm, 30–100 cm, 100+ cm). Again, the uncertainties in these estimates are determined by varying the C concentration/bulk density used within the calculation and assessing the sensitivity of the predictions to these different input values.

We investigated the feasibility of using spatial statistical methods to enhance and characterize the variation in parameter values, particularly peat depth using available data. The calculation of variance and confidence limits enable estimation of the further sampling required to reduce uncertainties to any chosen level.

In summary, this geostatistical analysis follows a number of steps:

(i) An investigation of how peat depth varies spatially across a peatland area using sites which have been intensively sampled
(ii) A sensitivity analysis which examines the potential uncertainty in depth, area, bulk density and the proportion of C and how they impact C stock estimations
(iii) Utilization of a wider data set on peat depths in order to characterise typical variances and the application to a power analysis

3.1.2. Site descriptions of five typical peat bog areas

Peat depth measurements at many peat bogs were recorded prior to wide availability of computer hardware. Calculation of the mean depths for these bogs was carried out in the ECOSSE project (Smith *et al*., 2007b). A geostatistical study requires each data point to be captured electronically along with its location (grid reference). The limited availability of computer-stored data sets constrained the geostatistical study of peat bog depth measurements to five sites having detailed peat depth measurements with geographic coordinates. Data in this form were available for three main peatland types:

- lowland basin peat
- semi-confined valley-side peat
- hill (blanket) peat

The five sites with measurements of peat depths were:

- Site A: a lowland peat basin in central Scotland (Coalburn, NS8003400, 1985)
- Site B: valley-side peat in south-central Scotland (Libry Moor, NS710100, 1985)
- Site C: hill peat in north east Scotland (Commercial in confidence, 2003)
- Site D: hill peat in north east Scotland (ECOSSE project, Glensaugh, NO650800, 2005)
- Site E: hill peat in central Scotland (Commercial in confidence)

3.1.3. Data description

The distributions of sample points on each site are shown in Figure 3.1.1. The data comprise peat depth measurements on either regular grids or along proposed roadways. The original data for one of the sites also included observations where there were no peat layers (i.e. a peat depth of 0 cm). Since the focus of this study is peat depth, only observations with peat depths greater than zero were included in this analysis. Sites C and E differ from the others as the data points were preferentially sampled, i.e. neither regular grid or random. As described under heteroscedasticity, this is almost certain to have an effect on the sample statistics and an optimal treatment for estimation by geostatistics would involve thinning the points to approximate a regular pattern, although this was not done. The depth measurements on sites A, B and C were measured to the nearest 1 cm by hand augering and examining for mineral material in the auger screw. Measurements on sites C and E were made using a Macintosh probe and recorded to the nearest 10 cm on site C and to the nearest 1 cm on site E.

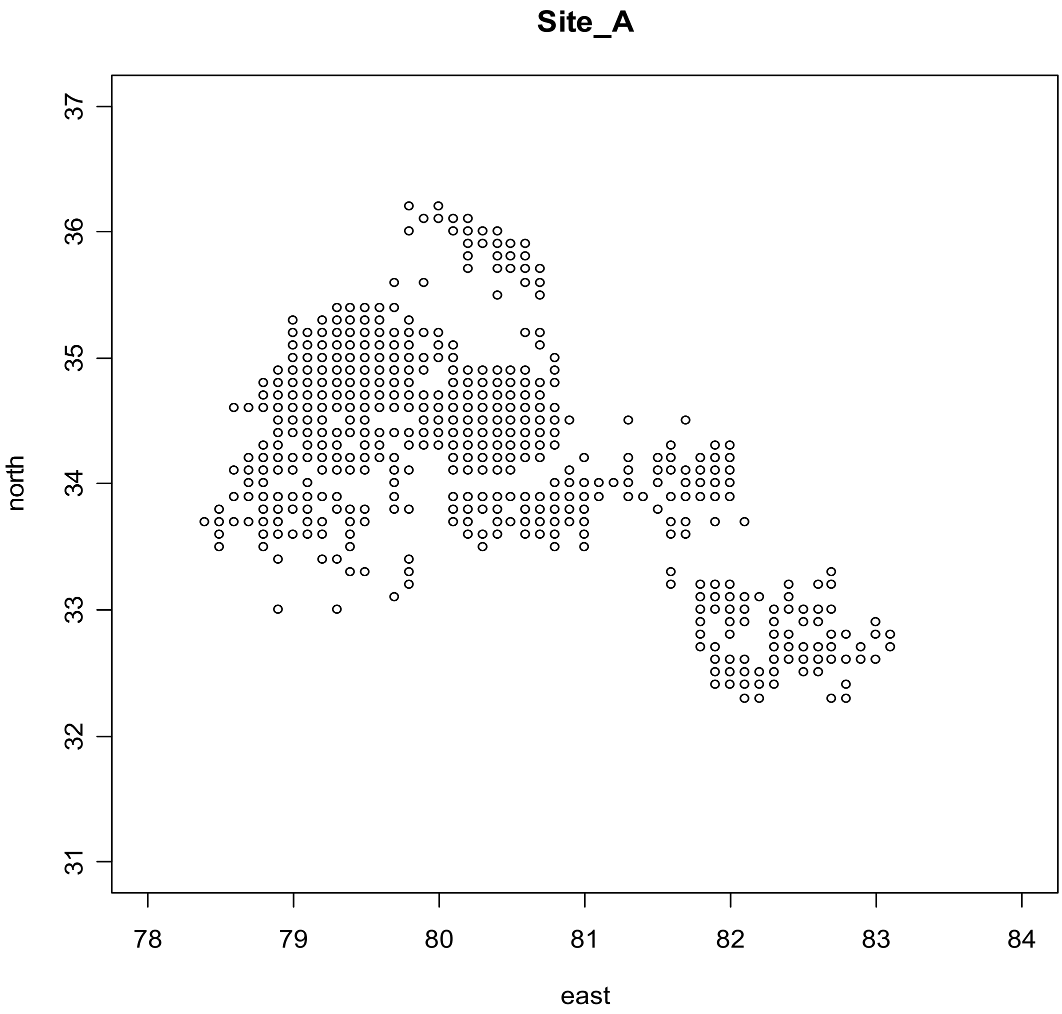

Figure 3.1.1.a

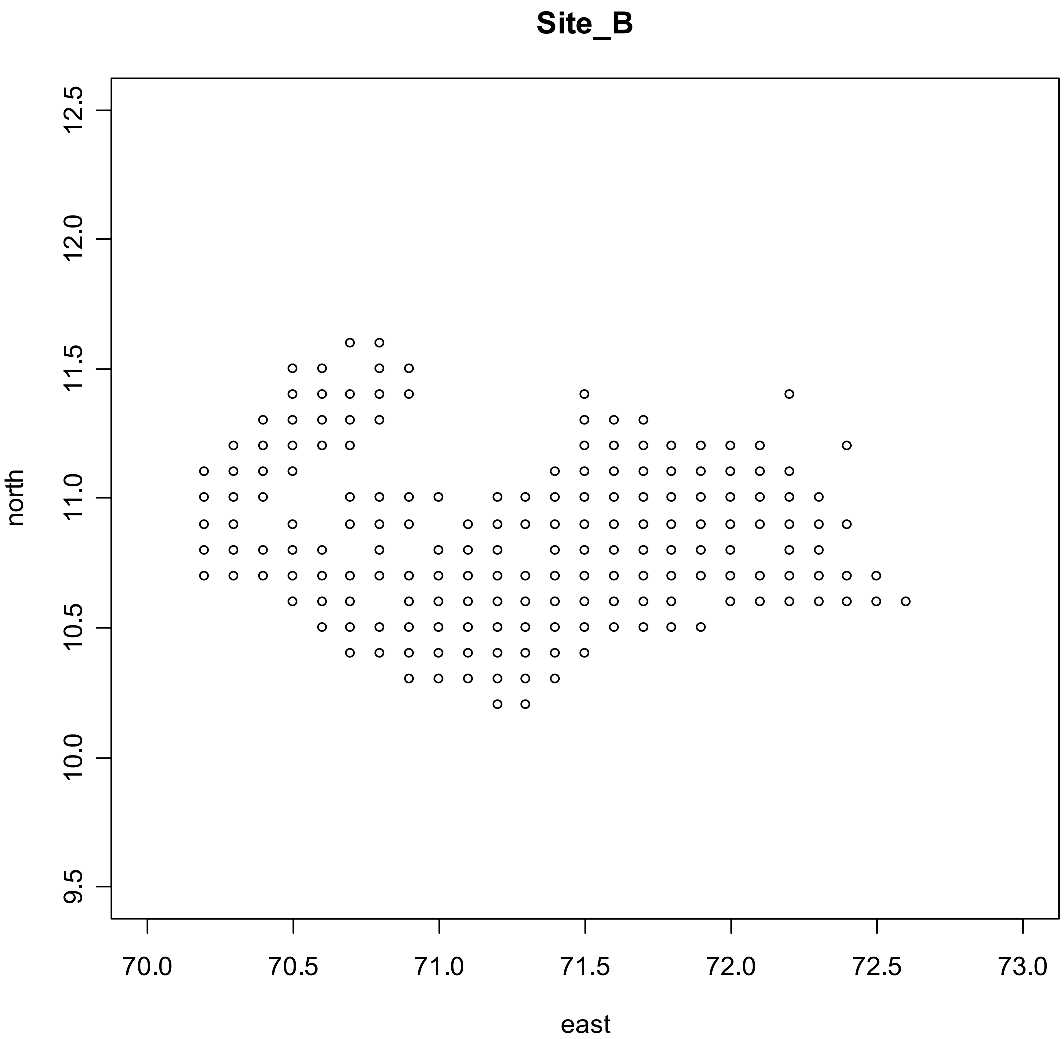
Site_B
north
east
9.5
10.0
10.5
11.0
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Figure 3.1.1.b

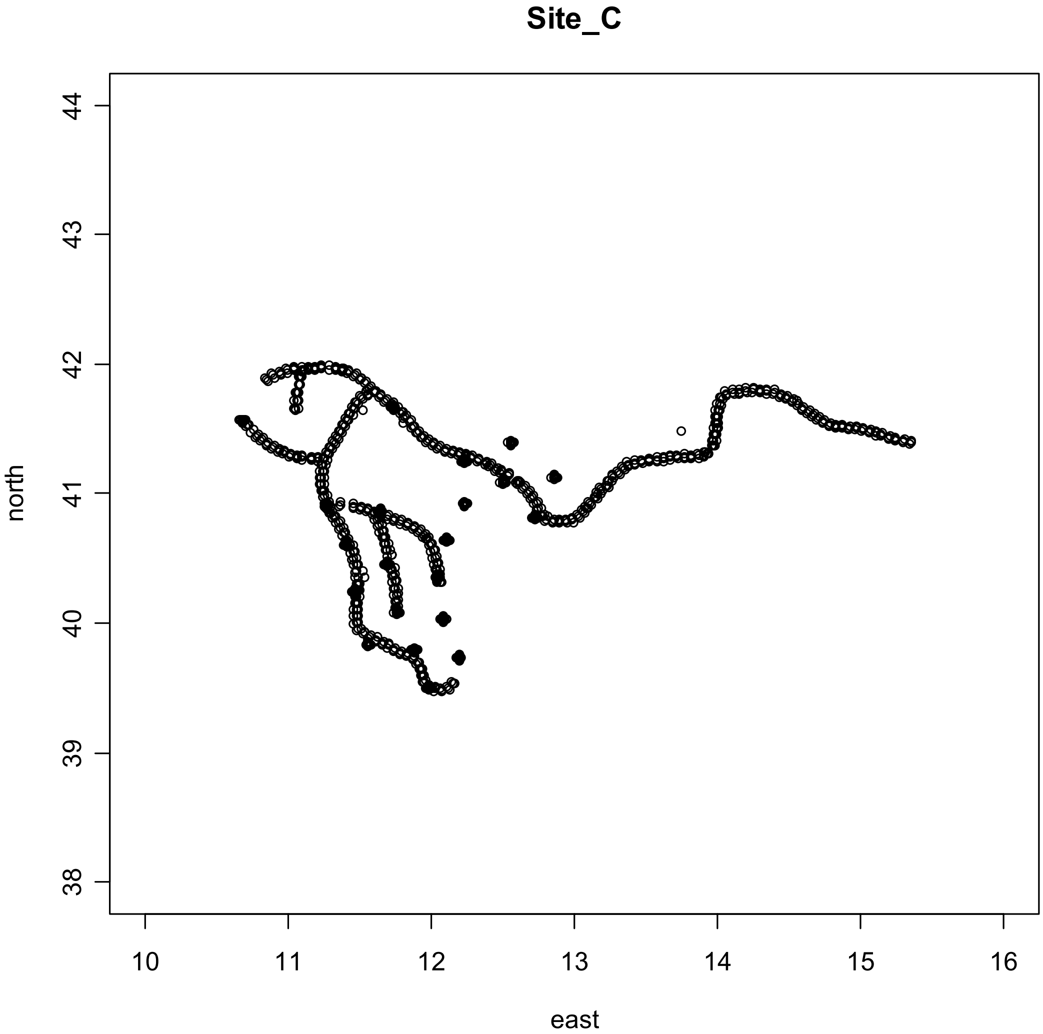


Figure 3.1.1.c

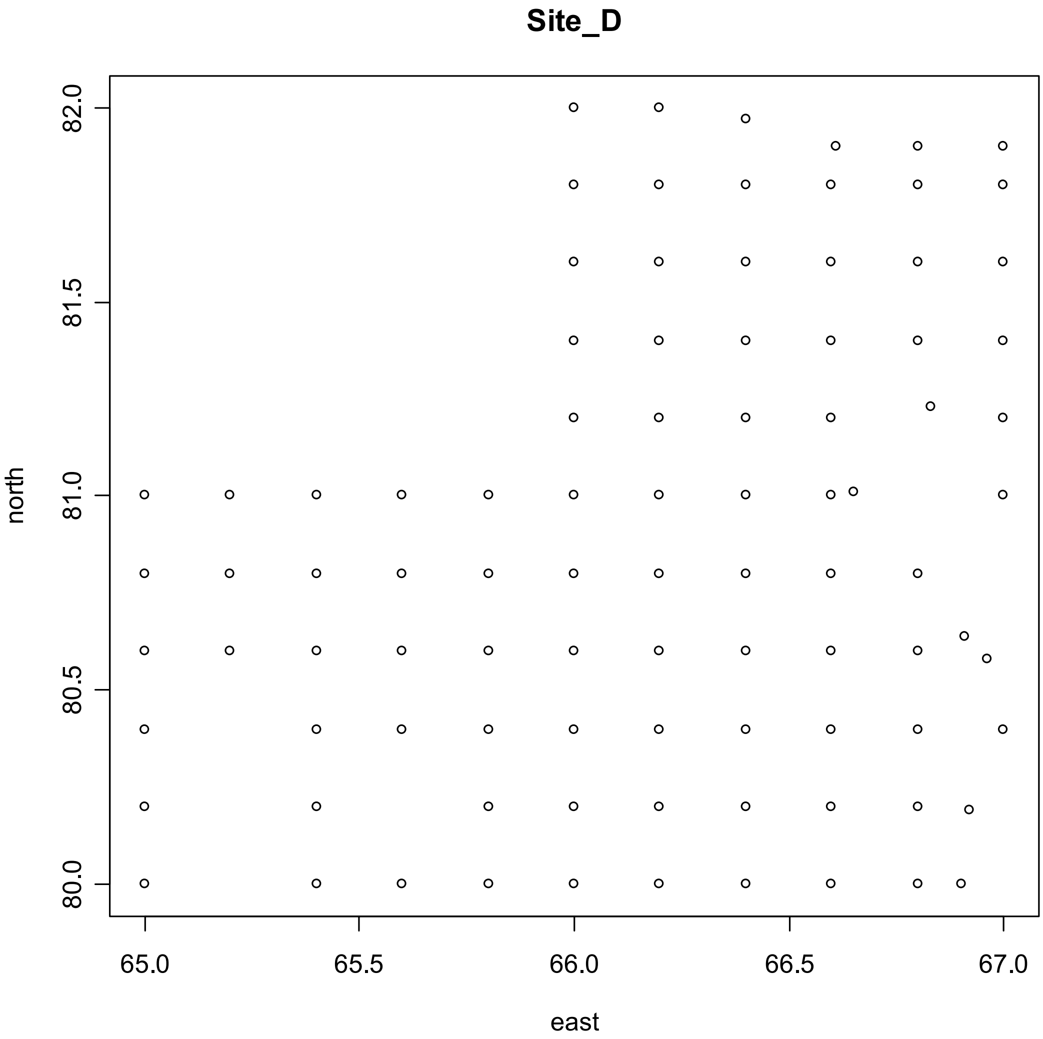


Figure 3.1.1.d

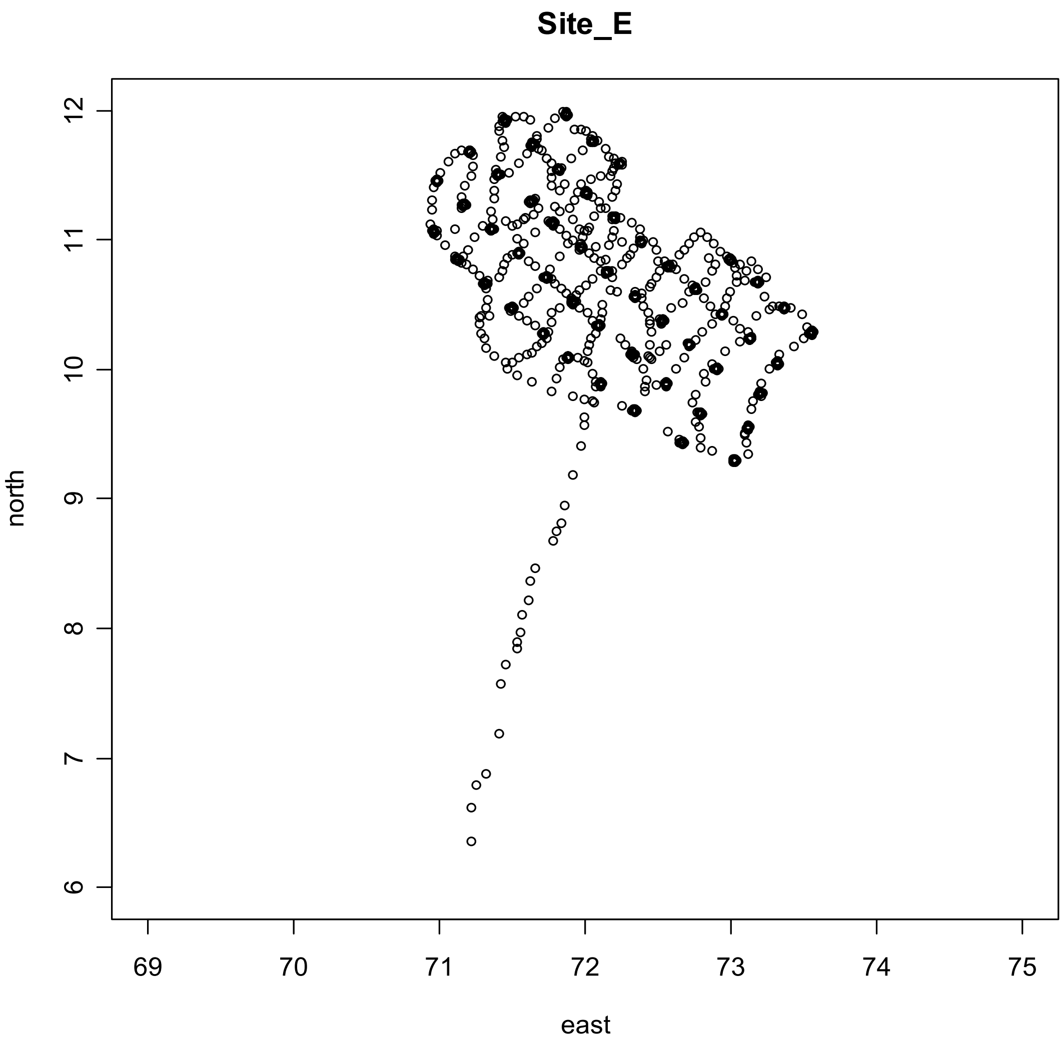


Figure 3.1.1.e

Figure 3.1.1. Locations of peat depth measurements at five sites (A–E) (scales in kilometres)

3.1.4. Data analysis methods

An exploratory analysis was done by calculating summary statistics for the five sites, along with histograms and boxplots. These are reported in the following two sections.

Data were analysed using the R statistical package (R Development Core Team, 2008) and libraries for geoR (Ribeiro and Diggle, 2001) and gstat (Pebesma et. al., 1998. Pebesma, 2004).

3.1.5. Exploratory plots

Histograms (Figure 3.1.2) and boxplots (Figure 3.1.3), backed up by normal q-q plots (not shown), of the raw data indicate that transformations are required. In particular, sites A, B and D have long tails of deeper peat. Transformation to natural logarithm or square root would be most appropriate, although this has not been done for the geostatistical analysis, since variograms of transformed data exhibit the same range characteristic. Computing local means and variances in a 1km square, non-overlapping, moving window was done on site A to check if local variability changes over the site. This effect of heteroscedasticity exists for site A where the local variances are directly proportional to the local means (Figure 3.1.4). This is, referred to as the proportional effect (Journel and Huigbregts, 1978) and data having the proportional effect is characteristic for a positive skew. If this proportional effect is present on sites C and E, and areas with low or high values were preferentially sampled, the effect on the variograms would be unpredictable.

The altitudes of the measurements were available for the hill peat sites, but had no effect on peat depths at the scales of investigation.

3.1.6. Descriptive statistics of peat depths

Summary statistics for the peat depths are given in Table 3.1.1. The mean depth of peat on site A, the basin peat site is 123 cm, although the median depth of 48 cm is probably a more accurate estimate of the average depth given there is long tail of depths greater than 100 cm. The valley-side mean depth of 53 cm is also substantially greater than the median of 29 cm. Only one of three hill peat sites, site D, has a median substantially less than the mean. The coefficients of variation were remarkably similar.

	Site A	Site B	Site C	Site D	Site E
Type of peat	Basin	Valley-side	Hill peat	Hill peat	Hill peat
Number of sites	464	179	943	92	804
Minimum	3	8	10	1	4
1st Quartile	27	19	40	10	107
Median	48	29	60	30	176
Mean	123	53	71	79	171
3rd Quartile	178	65	90	135	229
Maximum	630	325	510	300	521
Variance	20962	3261	3453	7125	7119
Coefficient of variation	1.18	1.08	0.83	1.07	0.49

Table 3.1.1. Summary of peat depths at five sites (A–E) (cm).

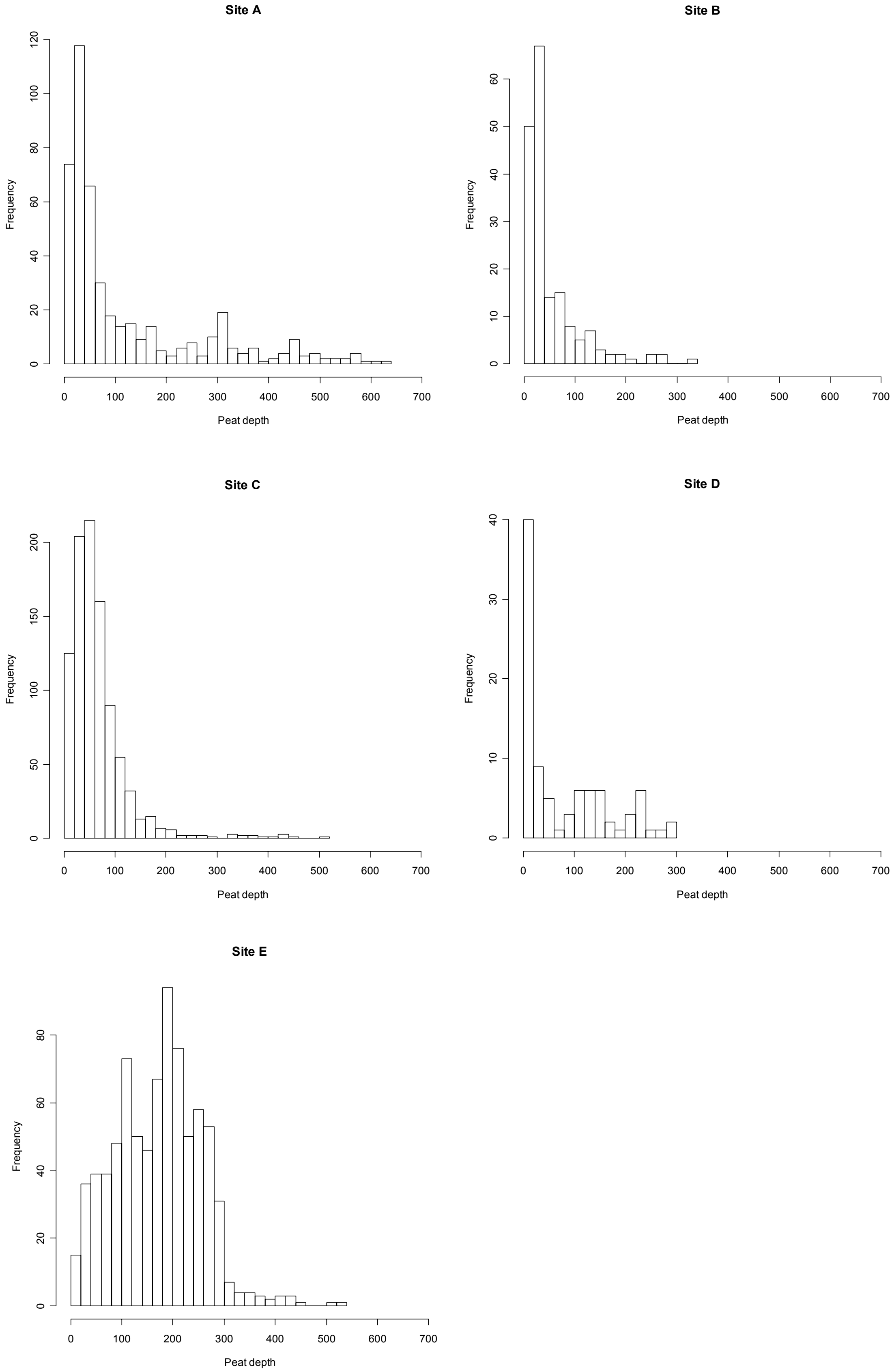


Figure 3.1.2. Histograms of raw data for peat depth for five sites (A–E) (cm)

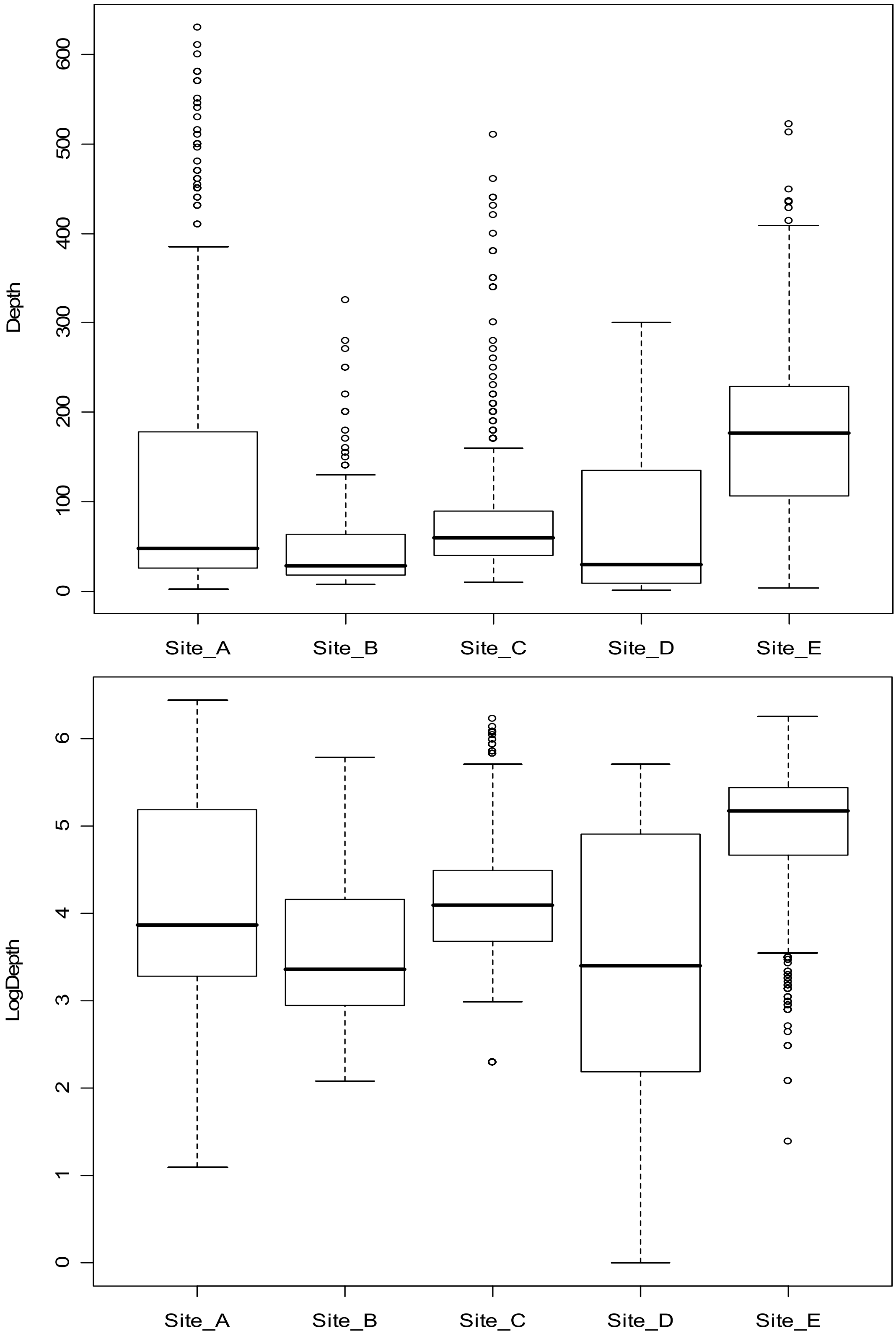


Figure 3.1.3. Boxplots (after Tukey) of peat depth and log depth at five sites (A–E) (cm). The bold line is the median, the box indicates the inter-quartile range and outliers (indicated by points) lie more than 1.5*IQR (inter-quartile range) away from the upper or lower quartile.

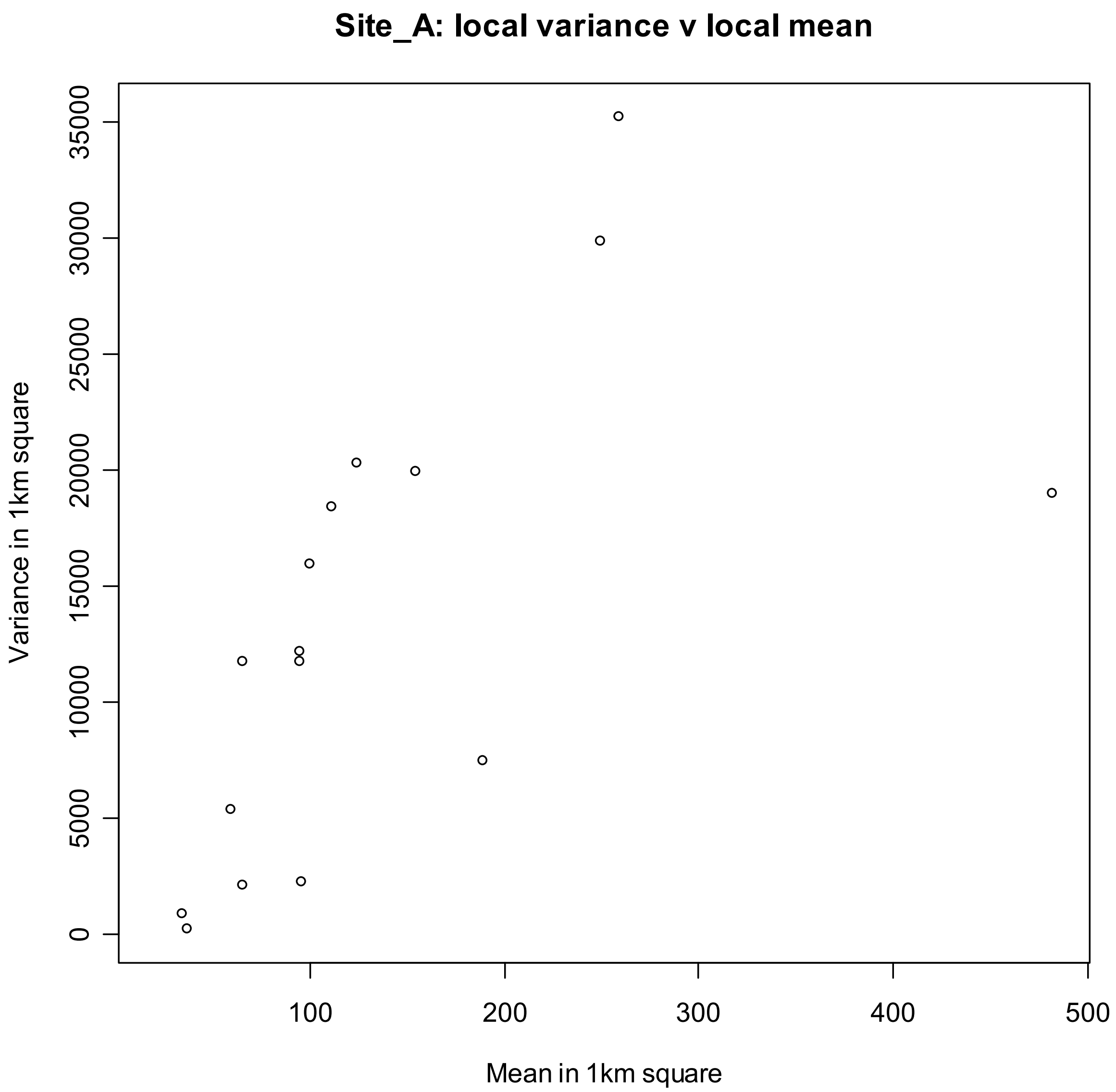


Figure 3.1.4. Site A. Moving (1km square) window variances plotted against means, confirming heteroscedasticity

3.1.7. Statistical tests

Comparing the raw data from the sites with t-tests showed that the differences in the mean peat depths were highly significant at 95% confidence levels for the basin peat compared to the valley side and hill peat. The same was true for the valley side peat compared to the hill peat sites. There was no significant difference between the three hill peat sites. However, since the distributions were skewed with heavy tails, t tests on the raw data should be interpreted with reservation. Computing t-tests with log-transformations of the raw data (Table 3.1.2) indicated that the geometric means were substantially lower than the mean depths computed with the raw data.

	Geometric Mean of Peat Depth (cm)	95% confidence interval
Site A	**63.8**	**57.3 – 71.0 [13.7]**
Site B	**35.3**	**31.1 – 40.0 [8.9]**
Site C	**55.3**	**52.8 – 57.8 [5]**
Site D	**32.7**	**23.7 – 45.0 [21.3]**
Site E	**143.7**	**137.1 – 150.6 [13.1]**

Table 3.1.2. Summary of t-test on log-transformed depth data at five sites (A–E) (back-transformed)

3.1.8. Geostatistical study

A guide to the number of samples required for robust estimation of variogram models (Webster and Oliver, 1992) indicates that, given certain assumptions, more than 225 data are needed to provide a reliable model The main assumptions are that the variable is normally distributed and isotropic (spatial variation is the same in all directions). This indicates that only site A, site C and site E have adequate numbers of samples for a geostatistical study. The issue of adequate sample numbers is further complicated by the skewed sample distributions on all sites. A further factor is that on site D there appears to be a trend in peat depths from west to east, which could be modelled using a trend function, although this was not attempted given the small sample numbers. Peat depths are thought to vary with external factors, e.g. slope, so a trend model is not unexpected.

Variography

The variogram indicates whether there is spatial dependence in a data set with geographical coordinates. There are three main parameters in a variogram model:

- Nugget – indicating short-range spatial components or measurement errors
- Sill – longer-range spatial components.
- Range – this indicates the spatial scale of correlation between sample points

In the absence of a spatial trend the sill and nugget combined approximate to the overall variance computed by standard statistics.

The spatial dependence can be independent of direction in which case it is isotropic, or dependent on direction – anisotropic. To check for anisotropic spatial dependence, variograms were computed in different directions. Only site C showed anisotropic spatial dependence, related to a trend in peat depths on this site from south to north. Accordingly variograms were computed, pooled for all directions, up to 1 km separation distance (Figure 3.1.5). The plots indicate differences in the spatial dependence on the five sites.

- Site A: depths are spatially correlated up to about 0.5 km
- Site B: no spatial correlation revealed (not studied further since the variogram matches the variance at all separation distances)
- Site C: spatial correlation up to 1 km
- Site D: spatial correlation up to 1 km
- Site E: spatial correlation up to about 0.3 km.

There appear to be differences in the form of the spatial correlation in the basin peat of site A as compared to the hill peat. The basin peat appears to show spatial correlation bounded at around 0.5 km. The hill peat on site C and site D appears to be unbounded up to 1 km distance. The peat depths on site D are greater in the eastern portion of the site so a trend model may be appropriate for these data. Site E appears to show a shorter range of spatial dependence than the other 2 hill peat sites, although this maybe due to an absence of trend here.

Variogram modelling

A weighted least squares approach was used to fit exponential and spherical models to the experimental variograms of peat depth, constrained to a different maximum distance for each site. The model parameters are reported in Table 3.1.3 and the models shown in Figure 3.1.5.

	Model	Nugget	Sill	Range (km)	Effective range (km)	Min sum of squares
Site A	Exponential	56	23970	0.238	0.717	5803265
Site A	Spherical	2482	20496	0.567	-	8709780
Site C	Exponential	1604	4052	0.678	2.034	1500671
Site C	Spherical	1912	4001	1.774	-	1579010
Site D	Exponential	0	7851	0.500	1.500	3357099
Site D	Spherical	518	5972	0.901	-	3058862
Site E	Exponential	2832	4062	0.186	0.558	2041525
Site E	Spherical	3067	3427	0.376	-	1997911

Table 3.1.3. Model parameters for variograms.

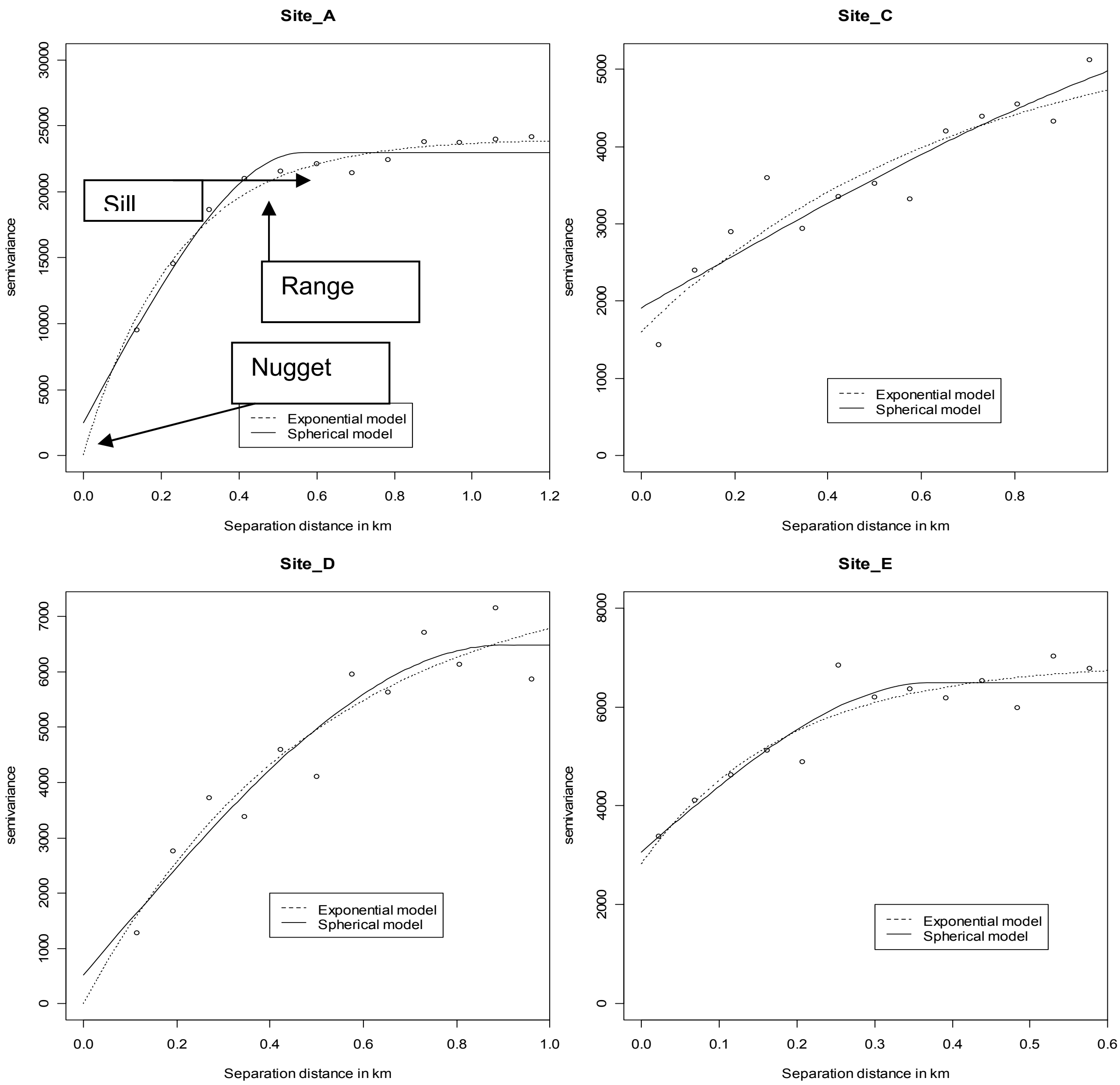


Figure 3.1.5 Models fitted for exponential and spherical variograms (no model for Site B due to lack of spatial correlation)

Kriging

Kriging uses the data values and the variogram model to estimate values at unsampled points. When the unsampled points are on a regular grid they produce a map. Computing the variance of estimation or carrying out a simulation using kriging is dependent on a reliable model for the variogram.

To exemplify the types of maps that can be produced by kriging, ordinary kriging was carried out on the basin peat (site A) and on of the hill peat sites (site E) (Figures 3.1.6 and 3.1.7).

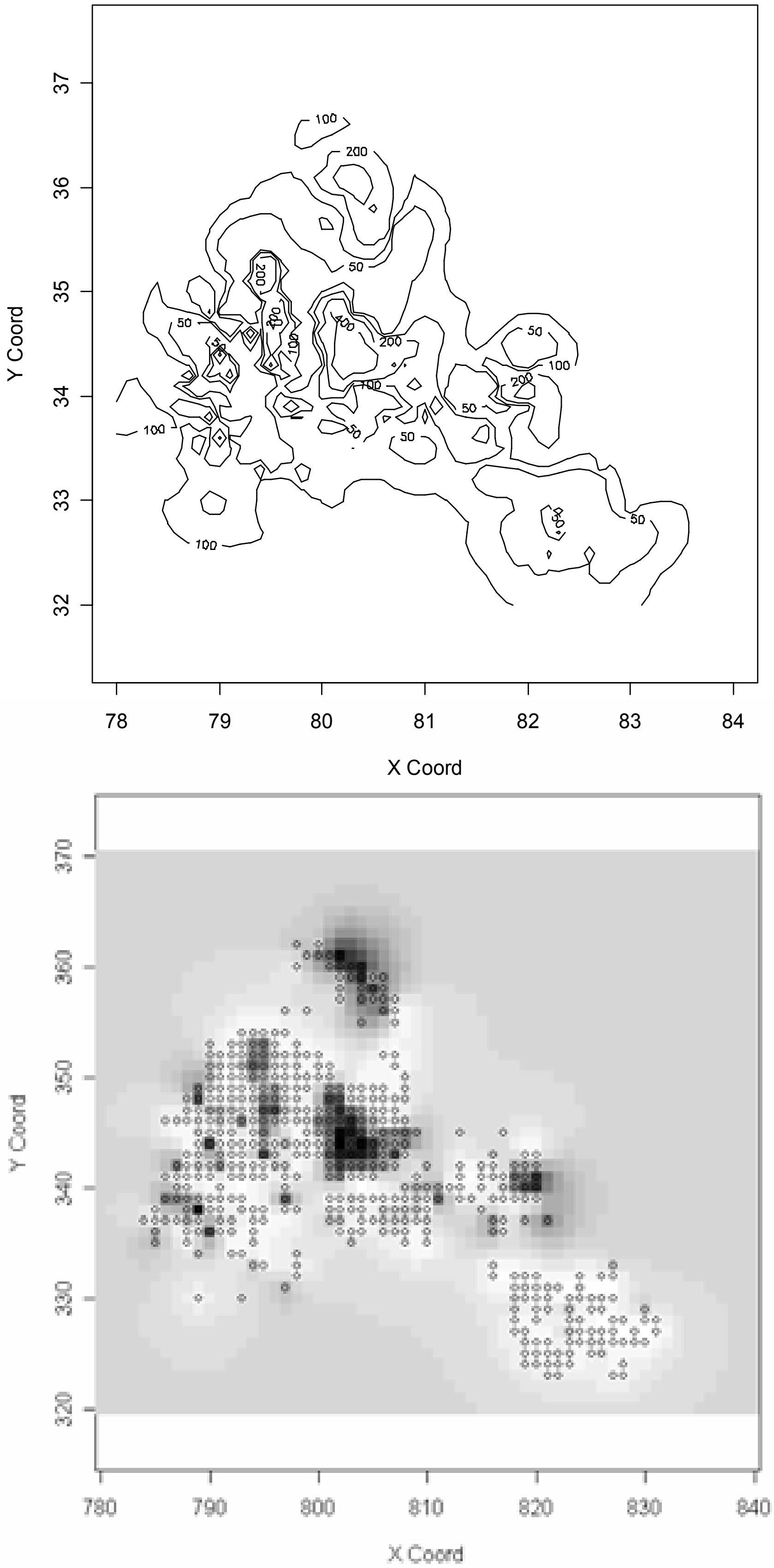


Figure 3.1.6. Contour plot and image plot of ordinary kriging estimates on site A

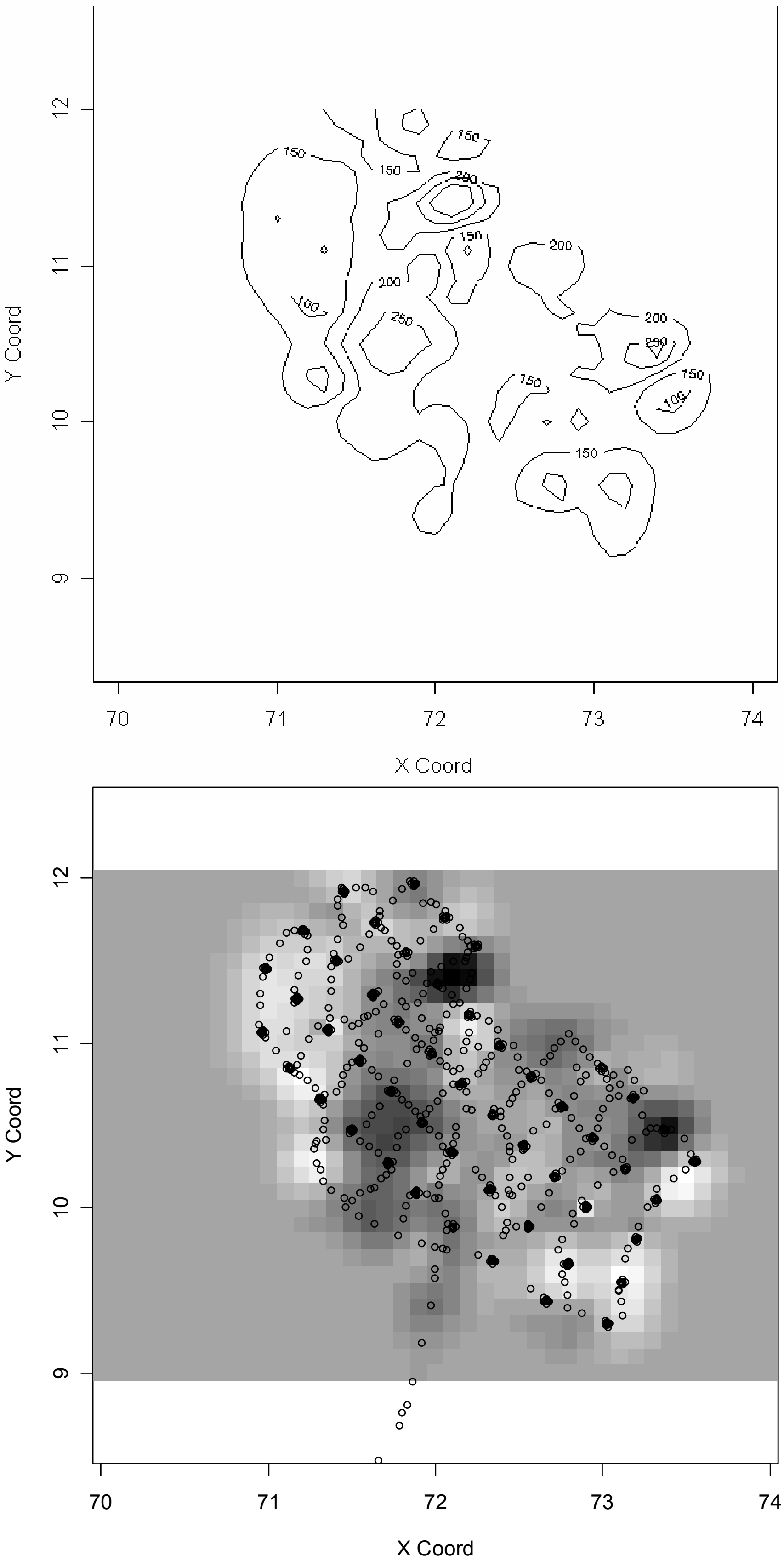


Figure 3.1.7. Contour plot and image of ordinary kriging on Site_E.

3.1.9. Sensitivity analysis on current carbon stock estimates

The ECOSSE project (Smith *et al*., 2007b) made some new calculations of the stock of C within Scotland's organic soils with particular emphasis on estimating the C stock below 100 cm in the soil profile by incorporating previously unused data on peat depth. While uncertainties in the estimates were acknowledged, a more precise quantification of the errors was not made. A set of analyses has now examined the variance associated with the component elements making up the current C stock estimate for peatlands. These parameters are depth, % C, bulk density and area with the total C stock being the product of all four, i.e.

Total C stock = area × depth × bulk density × %C

Usually %C is measured by analysis of the soil fine fraction (i.e. a sieved fraction) so a correction needs to applied for the proportion of stones removed. Since we are here concerned with peat the occurrence of stones is generally low or absent. Any large roots may also be removed by sieving so a correction may be required for these. It is a moot point whether roots, living or dead, are included. Logically, dead roots form part of the soil organic matter and are hence part of the peat while living roots are still part of the plant biomass, which is a separate entity; the practical difficulty is distinguishing the two. Inevitably, many fine roots will be included with the soil organic matter.

Since the total stock is a simple product, all parameters contribute equally to uncertainty. However the errors associated with each vary. Also there is variation between them in number of samples upon which they are based and in their spatial location. Each parameter has been examined in turn as to its origin or component data and estimates have been made of their respective standard errors or variances. The summation of variance was determined using simple error propagation equations, i.e. the combined variance is the sum of the component variances. Since the components were all in different units, relative standard errors had to be determined first.

Peatland Area

Estimating the error on the areas of peatland presented a special problem as these areas are on a map and not replicated in any sense. The irregular boundary on a soil map that encloses soil of a particular type, as determined by the soil surveyor, is denoted as a 'polygon', though in practice the term refers to the whole area thus enclosed. While some parts of Scotland are mapped at finer scales, coverage of the whole country has only been made at the 1:250,000 or one to quarter-million (QM) scale. Polygons on the QM map would be drawn based on survey data and notes in conjunction with aerial photography interpretation. The location of the polygons on the digitised QM map had been digitised using an automated laser light based system and hence unlikely to deviate much from the original QM map. The major error here was assumed to be in the delineation of a particular area on the ground at the time of survey. As a first approximation, the polygons were taken to be circular and the radius not to vary by more than 10% or by 250 m, whichever was less. The area was recalculated on this basis and this was taken to be the 95% confidence interval. Taking the additional assumption that there was no consistent error in determining the polygon boundary, assuming a normal distribution of possible errors and using a Monte Carlo simulation, overall errors on the peatland areas were estimated. These, together with the mean areas are given in Table 3.1.4.

	Area (km^2)	
	Mean	S.E.
QM UNITS		
Basin Peat	54	8
Semi-confined Peat	5423	360
Blanket Peat	4155	261
PEAT POLYGONS		
Basin Peat	673	6
Blanket Peat	3711	24
Eroded Basin Peat	8	1
Deep Blanket Peat	1679	16
Eroded Deep Blanket Peat	309	7
Eroded Blanket Peat	1259	14
TOTAL	17269	

Table 3.1.4 Mean Peatland areas used in the C stock calculations. Data shows means and estimated standard errors (S.E.).

	Depth (cm)					
	All data, measured + judged			Measured data only		
	Mean	S.E.	N	Mean	S.E.	N
QM UNITS						
Basin Peat	287	34	8			
Semi-confined Peat	128	9	71			
Blanket Peat	112	7	48			
PEAT POLYGONS						
Basin Peat	287	9	360	326	29	63
Blanket Peat	134	10	652	220	55	31
Eroded Basin Peat	272	39	4			
Deep Blanket Peat	230	15	166	253	43	19
Eroded Deep Blanket Peat	170	4	30			
Eroded Blanket Peat	132	8	116	173	54	4
All Peat types				241	44	117

Table 3.1.5 Variability in the area-weighted mean peat depth values used in the calculation of C stocks. Data shows means, standard errors (S.E.) and number of values (N).

Peat Depth

Estimating the error in the peat depth estimates is complicated by the fact that the peat depth values used in the final calculation were area-weighted averages rather than straight averages. This is necessary as the values are subsequently multiplied by the respective peat areas to give, effectively, a total peat volume. The variance in depth was calculated using the relationship:

$\mathrm{Var}(\sum w_i.x_i) = \sum w_i^2.\ \mathrm{Var}(x_i)$, where x_i is the depth and w_i = area of polygon i/total area.

The means and standard errors for depth given in Table 3.1.5 were calculated from all the peat depth estimates, both actual values and those assigned to areas without measured values by expert judgement. Including all values was judged appropriate since these are the actual depth values used in the C stock calculations. Note that the depths of 287 cm for basin peat in both the QM units and in the peat polygons are coincidental. In three cases, the number of values on which the peat depth is based was quite low; however, these were also categories that occupied the smallest areas, viz. basin peat in the QM units, eroded basin peat and eroded deep blanket peat.

Table 3.1.5 also gives the peat depths returned using actual measured values. Note that there were no data for eroded basin peat or for eroded deep blanket peat though these two types covered the smallest areas. Also there were no measured data for any of the QM units. This is particularly critical as the QM units accounted for 56% of the total peatland area (Table 3.1.4) and 45% of the final C stock (Table 3.1.9). **Hence the depth values for the QM units assigned in Table 3.1.5 are based solely upon expert judgement (although the judgement process did include recognition of a few scattered depths recorded in these areas in the survey reports)**. While this approach is not ideal, it is all that can be done in the absence of measured data; the broad agreement between the expert judgement and values obtained by kriging (see below, figure 3.2.5) give some confidence in the process used. There is clearly a trend for the peat depths including expert judgement to be less than those based on measured values. This is particularly so for blanket peat, which has been reduced from 2.20 m to 1.34 m. An explanation is given in that the measured data were biased towards the 'major peat deposits' with inherently greater depths while the country-wide value includes many peat deposits that are shallower for topological reasons.

Dry Bulk Density

This parameter was originally estimated using a pedotransfer function (PTF) which relates bulk density to %C. This function was based upon an analysis of 39 data pairs (See Smith *et al*., 2007b, appendix 1). However, further inspection of this relationship suggested that for peatland samples the relationship breaks down and that the positive regression originally obtained was based solely upon the inclusion of samples from organo-mineral soils, which contained varying additions of mineral material. Hence the dry bulk density values used (Table 3.1.6) were a compilation of the currently available data:

i) Samples taken from Red Moss (Netherley) and Middlemuir bogs as part of the project.
ii) Peat samples used in the original PTF calibration but removing those from organo-mineral soils.
iii) Peat samples from the NSIS_2 phases 1 and 2.
iv) Samples taken from Glensaugh as part of the ECOSSE project (Smith *et al*., 2007b). As the original dataset contained 145 values, to avoid over biasing this site these were consolidated by calculating mean values for each depth measured of the 3 one km^2 squares surveyed, giving 9 values.

In total, 104 bulk density values were obtained. Samples were stratified as being either basin or blanket peat and by depth at 0–30 cm, 30–100 cm and 100+ cm. Further division was not justified as sample numbers were already low in some categories or because further details (i.e. deep or eroded) were not known. Analysis on the data showed a difference between the mean for all basin peats (0.112 g cm^{-3}) and that for blanket peats (0.129 g cm^{-3}), which just failed to be statistically significant (P=0.054). There was no significant difference between 0–30 cm (0.134 g cm^{-3}), 30–100 cm (0.120 g cm^{-3}) and 100+ cm (0.109 g cm^{-3}). The greater bulk density values for 0–30 cm possibly reflects a tendency for these surface peats to dry out and compact; this was particularly clear at Glensaugh where samples with high bulk density were also low in moisture content. There was no significant interaction between peat type and depth. The samples were somewhat biased towards the north-east of Scotland with half coming from this region. In particular, there was a paucity of values from deeper peat horizons.

A summary of the bulk density data is given in Table 3.1.6. The value for basin peat was also applied to the eroded basin peat category and the value for blanket peat similarly applied to the other blanket peat categories. There were no independent values for the QM units and so peat polygon values were also ascribed to the respective peat types.

	Bulk Density ($g\ cm^{-3}$)								
	0-30 cm			30-100 cm			100+ cm		
	Mean	S.E.	N	Mean	S.E.	N	Mean	S.E.	N
QM UNITS									
Basin Peat	0.136	0.076	12	0.114	0.068	17	0.092	0.016	16
Semi-confined Peat	0.136	0.076	12	0.114	0.068	17	0.092	0.016	16
Blanket Peat	0.134	0.036	17	0.123	0.023	34	0.143	0.029	8
PEAT POLYGONS									
Basin Peat	0.136	0.076	12	0.114	0.068	17	0.092	0.016	16
Blanket Peat	0.134	0.036	17	0.123	0.023	34	0.143	0.029	8
Eroded Basin Peat	0.136	0.076	12	0.114	0.068	17	0.092	0.016	16
Deep Blanket Peat	0.134	0.036	17	0.123	0.023	34	0.143	0.029	8
Eroded Deep Blanket Peat	0.134	0.036	17	0.123	0.023	34	0.143	0.029	8
Eroded Blanket Peat	0.134	0.036	17	0.123	0.023	34	0.143	0.029	8

Table 3.1.6 Mean Bulk density values used in the C stock calculations. Data shows means, standard errors (S.E.) and number of values (N).

	Carbon (%)								
	0-30 cm			30-100 cm			100+ cm		
	Mean	S.E.	N	Mean	S.E.	N	Mean	S.E.	N
QM UNITS									
Basin Peat	51.1	1.0	25	48.6	1.1	43	60.8	3.4	2
Semi-confined Peat	51.1	1.0	25	48.6	1.1	43	60.8	3.4	2
Blanket Peat	50.6	1.8	21	52.9	0.7	49	54.6	3.2	7
PEAT POLYGONS									
Basin Peat	51.1	1.0	25	48.6	1.1	43	60.8	3.4	2
Blanket Peat	50.6	1.8	21	52.9	0.7	49	54.6	3.2	7
Eroded Basin Peat	51.1	1.0	25	48.6	1.1	43	60.8	3.4	2
Deep Blanket Peat	50.6	1.8	21	52.9	0.7	49	54.6	3.2	7
Eroded Deep Blanket Peat	50.1	3.5	10	57.1	0.4	8	54.2	1.2	2
Eroded Blanket Peat	53.0	0.9	40	55.2	1.0	33	54.0	3.2	9

Table 3.1.7 Mean %Carbon values used in the C stock calculations. Data shows means, standard errors (S.E.) and number of values (N).

Carbon content (%C)

Values for %C in peat were re-extracted from the Scottish soils analytical database in order to calculate the standard errors associated with the values as used. In total 240 values were used. These data are given in Table 3.1.7 with %C values for the three peat layers 0–30 cm, 30–100 cm and 100+ cm. The values were originally obtained from data for basin peat, deep blanket peat, eroded deep blanket peat and eroded blanket peat. Values for blanket peat were taken to be as for deep blanket peat (blanket peat in fact may include deep blanket peat as these areas are undifferentiated). Similarly, eroded basin peat was assumed to be the same as basin peat. For the QM units, where there were no data, basin and blanket peat was taken to be the same as their counterpart polygon values and semi-confined peat was taken to be the same as basin peat. It should be noted that there is a limited database of %C values and particularly so for the peat profiles below 100 cm.

Clearly this is not ideal though, in some mitigation, there is a limited range of values of %C for peat, which tend to cluster around 52%.

Relative uncertainties

Parameter	No. samples	Location	% Error in estimates
Depth	~6000	Country-wide but some areas under-represented	7.2
% C	240	Country-wide but mainly surface (0 – 100 cm)	3.4
Bulk density	104	Country-wide but weighted towards NE Scotland and few deep samples (>200cm)	8.3
Area	1455 polygons	Country-wide	4.5

Table 3.1.8 Basis of parameter estimates used in the calculation of total C stock and their relative errors

A summary of the relative uncertainties are given in Table 3.1.8. The %error in the estimates is the mean standard error as a percentage of the mean. Bulk density has the greatest uncertainty among the parameters, followed closely by depth, despite being based on the largest number of samplings. The number of samples for depth is an estimate based upon a limited recount: out of the total of 117 peat bogs with measured depths, 77 totalled nearly 4000 individual depthings (see section 3.1.10). These error values should be treated as being on the conservative side since they hide the fact that the underlying data is not randomly located but biased both in terms of position within the country as well as vertical position in the peat profile. The assumption is that the values currently obtained can be applied to other geographical regions and to other peat depths.

Peatland C stock

	C stock (Mt C)					
	0-100 cm		100+ cm		Profile	
	Mean	S.E.	Mean	S.E.	Mean	S.E.
QM UNITS						
Basin Peat	3.2	0.5	5.6	1.4	8.8	1.5
Semi-confined Peat	323.3	39.3	84.8	28.5	408.1	48.5
Blanket Peat	273.6	15.9	38.8	23.0	312.4	28.0
PEAT POLYGONS						
Basin Peat	40.1	4.5	70.4	6.1	110.5	7.5
Blanket Peat	244.4	8.2	98.2	30.3	342.6	31.4
Eroded Basin Peat	0.5	0.1	0.7	0.2	1.2	0.2
Deep Blanket Peat	110.6	3.8	169.9	25.1	280.4	25.4
Eroded Deep Blanket Peat	21.4	0.9	16.7	1.6	38.1	1.8
Eroded Blanket Peat	86.6	2.9	31.0	8.3	117.6	8.8
TOTAL	1104	44	516	55	1620	70

Table 3.1.9 Total peatland carbon stocks, means and standard errors, based upon error propagation of component parameters.

The resultant C stocks for the various peatland categories and at different depths, above and below 100 cm, as well as totals, are given in Table 3.1.9. It should be noted that the errors for the 0–100 cm horizon tend to be rather less than those for 100+ cm. This is because this horizon has a fixed cut-off. Hence all the variability in depth is incorporated into the 100+ figures. The total C stock value has a 95% confidence interval of 1482–1757

Mt C. However, it should be borne in mind that this is a minimum range in that the final figures are still dependant upon some of the underlying assumptions. As mentioned above, particularly significant is how far we can use %C and bulk density values from one peatland type and apply them to another. In the absence of further data, it is difficult to judge the overall impact of these assumptions.

3.1.10. Re-evaluation of peat depth data

A limited re-evaluation of the basis of the peat depth data obtained from the Scottish peat survey was carried out in order to determine the typical variability in depth across the peatland areas. Peat depth data was abstracted from five volumes of the hand-written survey notes held at the Macaulay Institute entitled:

- SURVEY NOTES 4/69 – 9/70
- SURVEY NOTES FROM: Mar 71 TO: Oct 72
- SURVEY NOTES (ATN) 1973 - 1976
- SURVEY NOTES (ATN) 1976 - 1978
- SURVEY NOTES (ATN) 1978 –

All depth data was recorded from a total of 77 ‘bogs’ and the period of recording was from April 1969 until September 1979. Two bogs were omitted from the notes as one had only one depth record and the other was in England. Some of the ‘bogs’ were transects across large tracts of peatland rather than being a discrete bog. In the calculation of mean depths and variances, values recorded as zero were omitted as (i) these were not peat but mineral soil, (ii) these tended to be values recorded at the start of transects and hence marked the edge of the bog, and (iii) this was consistent with the protocol used in the ECOSSE project. About 17% of the remaining values recorded an organic layer less than 0.5 m and hence technically were not peat. However, these values were retained in the dataset as they represented variation in the depth at a spatial scale below which these variations could be mapped on the 1:250,000 map and as such contributed to the mean depth of the overall peat polygon. A summary of the raw data for these peat bogs is given in Appendix 1. Across the 3924 non-zero depthings, the mean depth was 2.19 m with a maximum depth of 12 m though this was exceptional (Figure 3.1.8). Excluding one peat bog (Din Moss), which exhibited a very large variance in depth (14.9 m^2), the mean variance was 1.76 m^2, extending up to 6.1 m^2 (Figure 3.1.9).

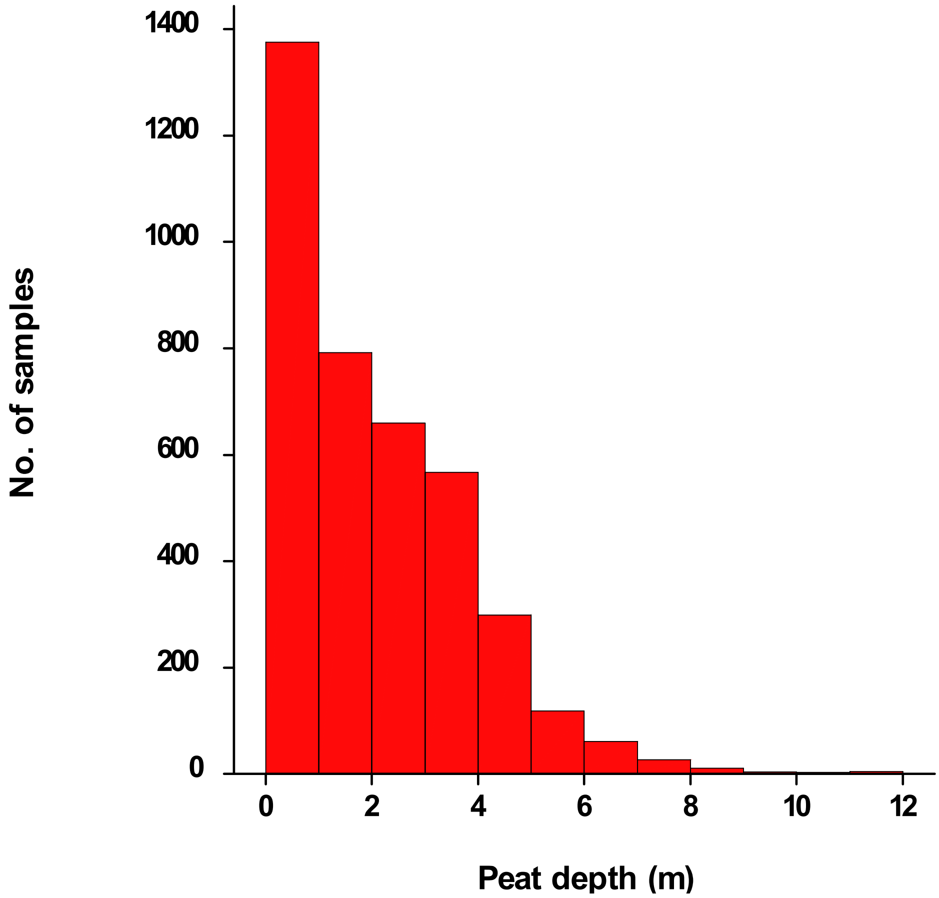


Figure 3.1.8 Histogram of peat depth distributions from survey data on 77 peat bogs

3.1.11. Power analysis

Using the data gathered in section 3.1.10, it is possible to perform a power analysis in order to estimate the number of samples required to obtain a value for a degree of precision in peat depth within those regions where data is missing. The results are summarised in Table 3.1.10. We have taken the mean depth of peat to be 2.28 m and the variance to be 1.93 m^2, which are the mean values for the 77 peat bogs (Appendix 1). The table gives the number of extra depthings required to give a set precision and to obtain that value with either 95 or 99% confidence. For example, to be 95% confident of obtaining a mean peat depth that is within 5% of the true value will require nearly 600 individual values. This assumes that the variance in unknown areas is same as that in the known areas.

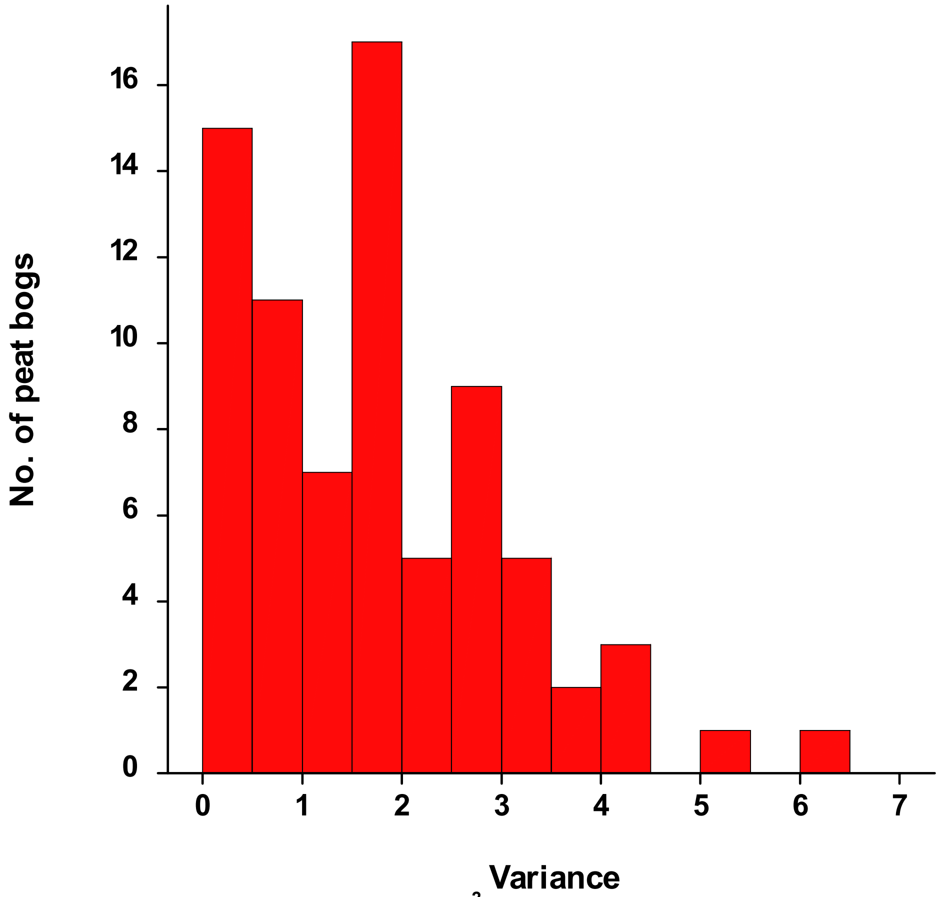


Figure 3.1.9 Histogram of variance (m^2) in peat depths for 76 peat bogs

Precision	Number of samples	
	@95%	@99%
± 20 %	38	65
± 10 %	145	250
± 5 %	<u>573</u>	989

Table 3.1.10 Power analysis: number of samples required to obtain depth data with a given precision and with a specified confidence

3.1.12. Conclusions

This study has used exploratory geostatistics to study the scales of variation in peat depths at five sites having three contrasting peatland types comprising:

- one basin peat
- one semi-confined valley side peat
- three sites with hill (blanket) peat.

The sampling designs on the sites used grid designs at 100 or 200 m with two of the hill peat sites sampled preferentially, along transects following proposed road construction routes. The basin peat has a range of spatial dependence between 400 and 650 m. The valley side peat studied apparently has no spatial dependence. Of the three hill peat sites, only site E has sufficient sample numbers for an estimate of a variogram model. This fact, combined with an inferred trend in peat depths on the other two peat sites leads to the conclusion that hill peats have a range of spatial dependence between 376 and 558 m. These variable results for fitting models indicate that there is not sufficient data for reliable modelling of the variogram.

We recommend that some effort should be made to identify the scales of variation in peat depths using sampling frames designed to capture different scales of spatial variation. The results suggest that a greater number of peatland examples should be examined over a wider geographical area to identify and separate regional components of spatial variation, which may be due to regional climatic differences, from local components of spatial variation, due to topographic or other short range factors which influence hydrology. Effort should be made to include study of the polygon boundaries between peaty and mineral soils, using for example, an indicator geostatistics approach with data on the presence and absence of a peaty layer.

A sensitivity analysis on the parameters needed to compute a total peatland C stock for Scotland showed decreasing uncertainty in the order dry bulk density > peat depth > peatland area > %C. Additional considerations were that both the available bulk density and %C values were not spatially explicit and that global values had to used based on limited data. Also, peat depth was partly reliant on measured values and partly on values estimated by expert judgement for areas of the country where depth values had not been determined. Accepting some assumptions about the country-wide applicability of values obtained from more restricted regions, the total C stock was estimated to be 1620 Mt with a 95% confidence interval of 1482–1757 Mt C.

A re-examination of archived data on peat depths revealed a wide range of variances across 77 peat bogs with a mean value of 1.93 m^2. Using this value, a power analysis was used to compute the additional number of depth measurements required to compute a mean peat depth with a given precision and level of confidence. For example, to be 95% confident of obtaining a mean peat depth that is within 5% of the true value will require a minimum of 573 individual values. As indicated above the current uncertainty in total C stock is about ±138 Mt C (95% confidence). If we assume no strong regional trends in bulk density or %C, then such improvements in peat depth would reduce the uncertainty to about ±81 Mt C.

3.2. Peat depth simulations

3.2.1. Introduction

The mean peat depths of 341 peat bogs in Scotland were computed from data contained in soil survey memoirs, peat survey reports and Forestry Commission site surveys as outlined in the ECOSSE Report (Smith *et al*., 2007b). Expert judgement used this data, together with information on topography and any additional survey notes, to make an informed guess of the average peat depth for each polygon on the 1:250,000 scale soil map of Scotland (see also section 3.1.9). There are 20720 polygons on the digital version of the map; the subset of 1328 polygons estimated to have a mean peat depth greater than zero is reported on in this simulation study.

3.2.2. Summary of the polygon and peat bog data

There are two data sets

- Peat bogs: measured mean depths (cm) calculated from site peat survey measurements and reported on in the ECOSSE report. This set has the coordinates of the centroid of the data measurements and a mean depth for the peat. This set is referred to in this report as the data.depth.
- Deduced peat depths (cm) of map polygons. This set has the coordinates of the polygon centroid and the mean depth deduced by an expert. Referred to in the report as expert.depth.

There is a difference in the geographical distribution of the two datasets (Figure 3.2.1). The data.depth map shows the location of peat polygons where we have actual measured depth data while the expert.depth map shows the location of those peat polygons for which we have no measured values and these have had to be derived from expert judgement. There are a large number of polygons in areas with few observed data for peat bogs, particularly in central Scotland and on the Inner and Outer Hebrides, i.e. the measured dataset tends to be rather patchy and not evenly distributed across the areas where peat occurs. The histograms of coordinates show different distributions in eastings and northings in more detail. The eastings plot shows that the measured data has been slightly biased towards the east while the northings plot indicates that there are data gaps around the centre of the country.

The mean depth of the peat bogs (data.depth) is 226 cm and the mean of the expert deduction for the peat polygons (expert.depth) is 169 cm (Table 3.2.1). A t-test, using the Welch approximation to degrees of freedom because of inequality in the variances, indicated that the difference in arithmetic means of 57 cm between these two sets is significant at the 95% confidence level. The same applies for the geometric means. The 95% confidence intervals in the arithmetic and geometric means are given in Table 3.2.2. These results indicate a significant difference in the global means (arithmetic and geometric) between the measured depths at peat bogs and the expert deduction for the polygons (Figures 3.2.2. and 3.2.3). The main reason for this is the mis-match in the spatial locations of the sampled peat bogs compared to that for the polygons (see on **depth** in section 3.1.9).

	data.depth	**expert.depth**
Type of data	**Mean depths in peat bogs**	**Deduced depths in peat polygons**
Number	**341**	**1328**
Minimum	**30**	**50**
1st quartile	**120**	**75**
Median	**206**	**150**
Mean	**226**	**169**
3rd quartile	**297**	**220**
Maximum	**843**	**702**
Variance	**16940**	**10080**

Table 3.2.1. Comparison of data.depth with expert.depth (cm)

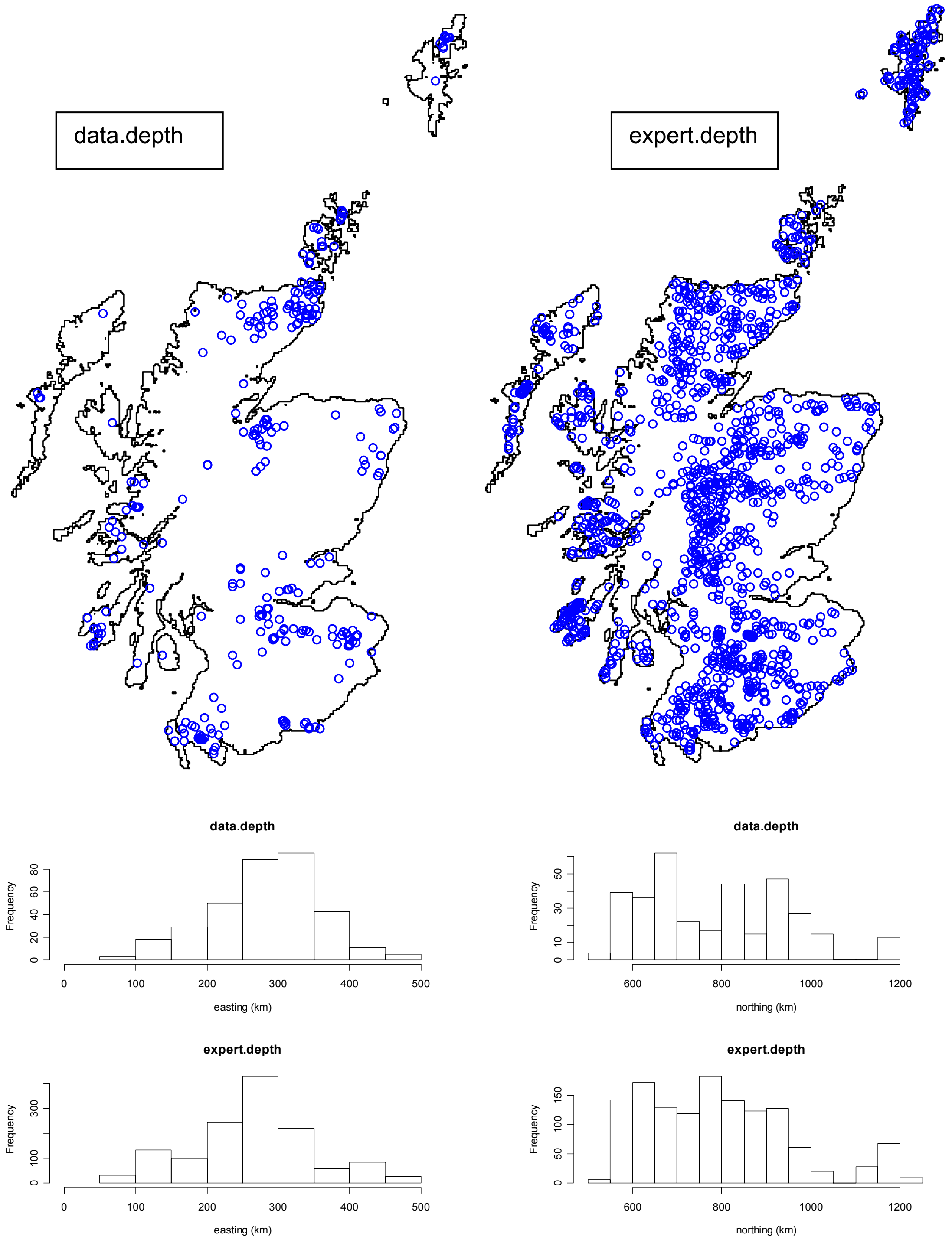


Figure 3.2.1. Geographical spread of sites and summary histograms for data.depth and expert.depth

	data.depth	expert.depth
Arithmetic mean and 95% confidence interval	**226.3 [212.4 – 240.1]**	**169.2 [163.7 – 174.6]**
Geometric mean and 95% confidence interval	**191.1 [179.2 – 203.8]**	**144.0 [139.7 – 148.5]**

Table 3.2.2. Arithmetic and geometric mean depths (cm)

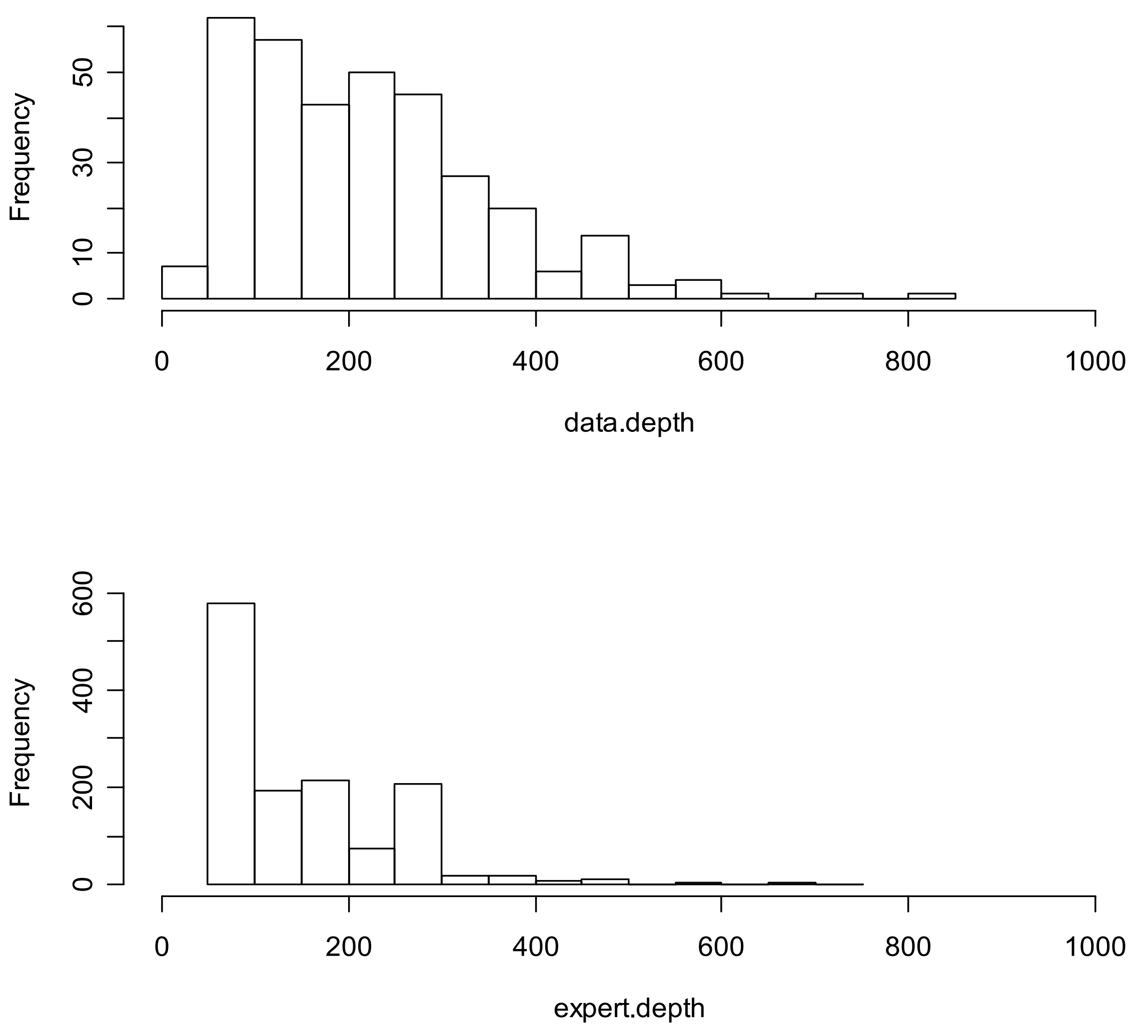


Figure 3.2.2. Histograms of data.depth and expert.depth (cm)

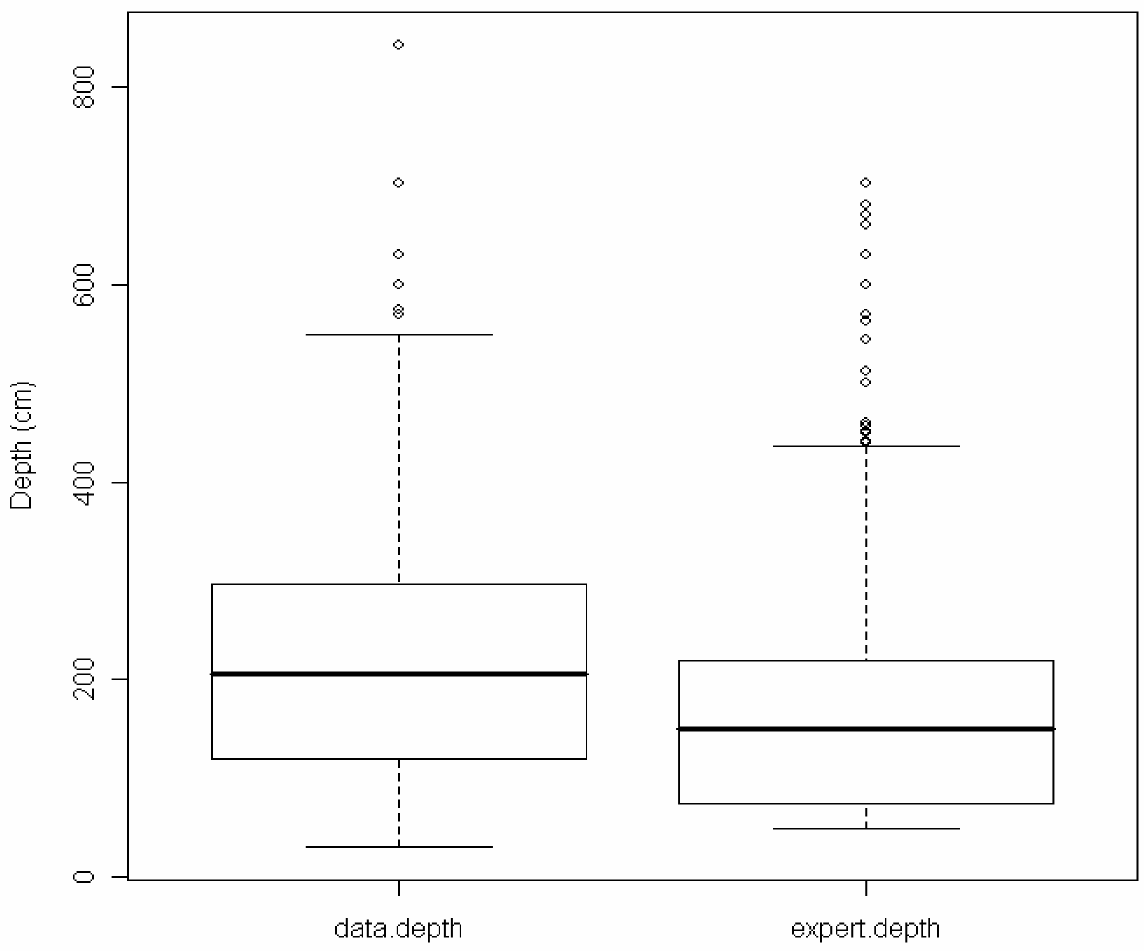


Figure 3.2.3. Boxplots of data.depth and expert.depth

3.2.3. Geostatistical study of peat depths in bogs and polygons

Variography of data.depth

Variograms were computed for the mean peat bog depths (Figure 3.2.4) and indicate a range of spatial correlation around 100 km. A spherical model was fitted, having range parameter of 95.2km, nugget value of 9695 cm^2 and sill of 8564 cm^2.

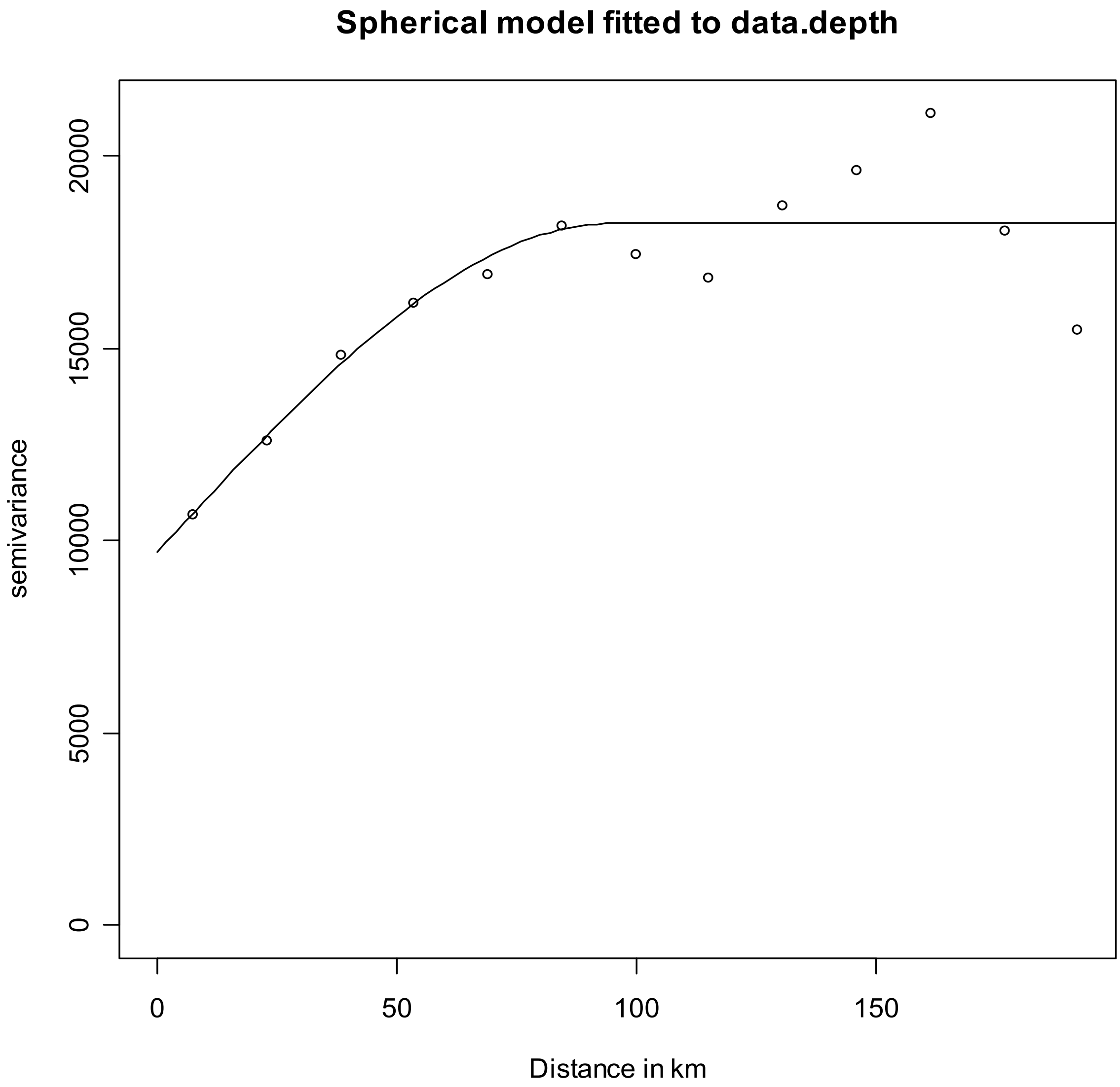


Figure 3.2.4. Variogram model for data depth

Comparison of kriged estimate with expert deduction at polygon centroids

The variogram model and the peat depth data for the peat bogs were used to predict a value for depth at each of the 1328 polygon centroids using ordinary kriging. The expert depth values at the polygon centroids were removed before the kriging estimation. The statistics for the kriged predictions are compared to the expert deductions in Table 3.2.3. A t-test indicated no significant difference in the mean values at the 95% level. However, when kriged.depth is plotted against the original expert.depth (Figure 3.2.5), differences in the values at each end of the depth scale become apparent.

	Kriged.depth	Expert.depth
Type of data	Kriged depths in peat polygons	Deduced depths in peat polygons
Number	1328	1328
Minimum	73	50
1st quartile	121	75
Median	158	150
Mean	172	169
3rd quartile	204	220
Maximum	514	702
Variance	4230	10080

Table 3.2.3. Kriged prediction and expert deduction for peat depth (cm)

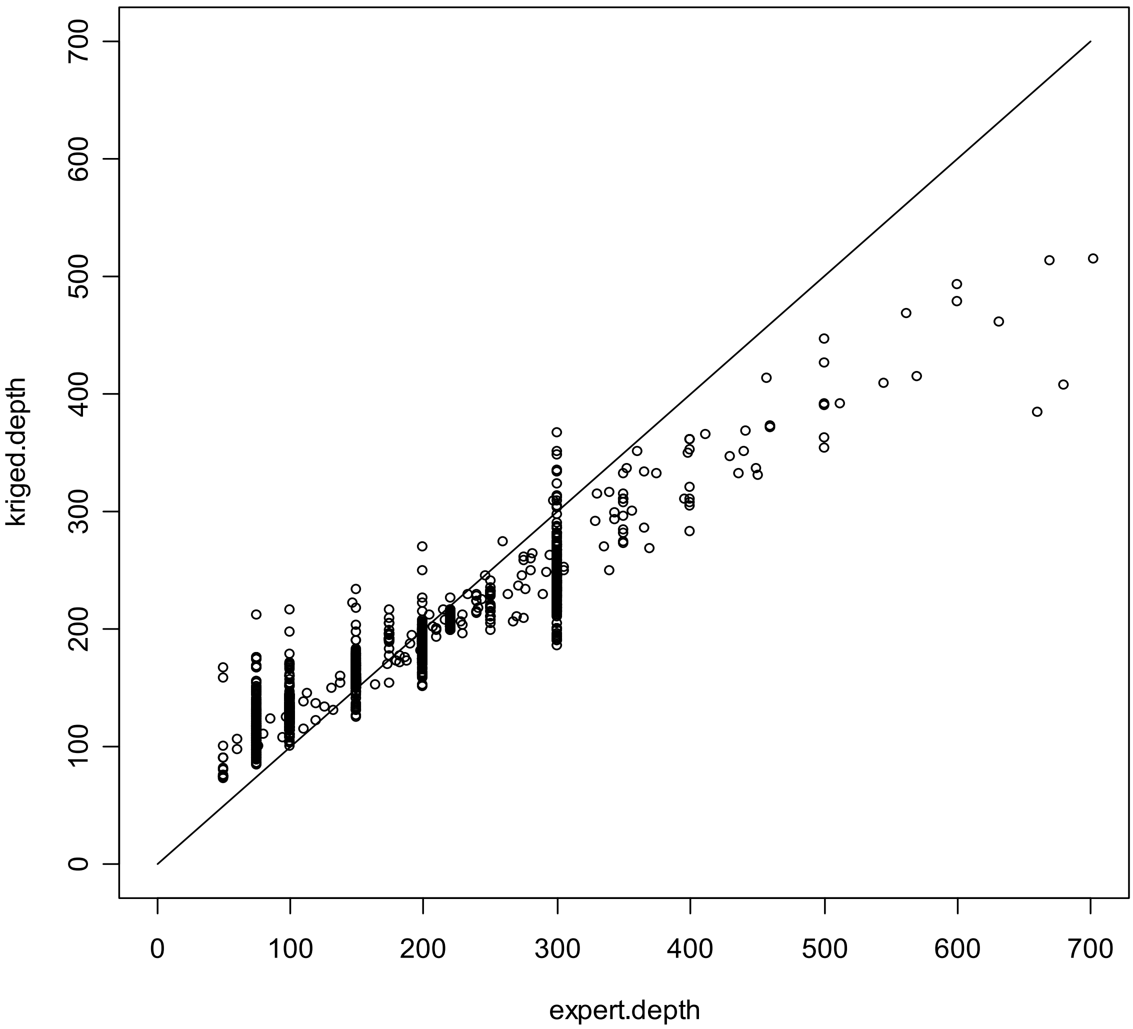


Figure 3.2.5. Kriged.depth plotted against expert.depth for polygon centroids

3.2.4. Bayesian geostatistical simulations

The model-based approach to geostatistics (Ribeiro and Diggle, 1998) was used in a simulation procedure to assess where the optimal sites for new samples would be. The measured peat depths (data.depth) were used to simulate 50 values at the polygon centroids. From these 50 simulations the mean depth and variance was calculated. The 24 polygons with the largest values for variance were selected. The simulated means were added to this set of 24 and a new simulation run performed using these additional 24 polygons as if they had been sampled. The procedure was repeated 3 times. Once 72 (3*24) bogs had been 'sampled' with simulated values, the variances were effectively reduced by around half (Figure 3.2.6). These results indicate that around 72 additional samples targeted at locations from the simulation effectively reduce the uncertainty in depth measurements by 50%.

3.2.5. Conclusions

The above study has demonstrated that using an analysis of the spatial statistics for peat depth it is possible to make a prediction of peat depth in areas where no measurements are available. Essentially, this relies upon distance to the nearest known values and clearly in areas where little data exists, the variance about the prediction increases. The expert judgement used in the original estimation of peat depths across the country similarly relies upon the depth in adjacent peat polygons where these are known. For this underlying reason, the agreement between the two approaches gives broadly similar results. However there was some consistent deviation, particularly at the deeper end where the expert system gave deeper peats. This is attributed to the expert system using additional information in its judgement, such as knowledge of the landscape and local topology and/or survey notes indicating 'deep' or 'shallow' peat. We conclude that the expert system gives a fair prediction for most peats and that the similarity in mean values indicates little difference in overall C stocks computed using either approach.

The simulation study has indicated that were 72 additional peat bogs sampled, targeted using the simulation results, the variances could be reduced by around 50%. This approach is also able to indicate the optimum location of these additional samplings, principally in the Western Isles and in central and north-west Scotland. While the current run considered increments of 24 additional bogs to give approximate locations, the optimum solution would be to use increments of one. However, the computational effort lies outwith the current project.

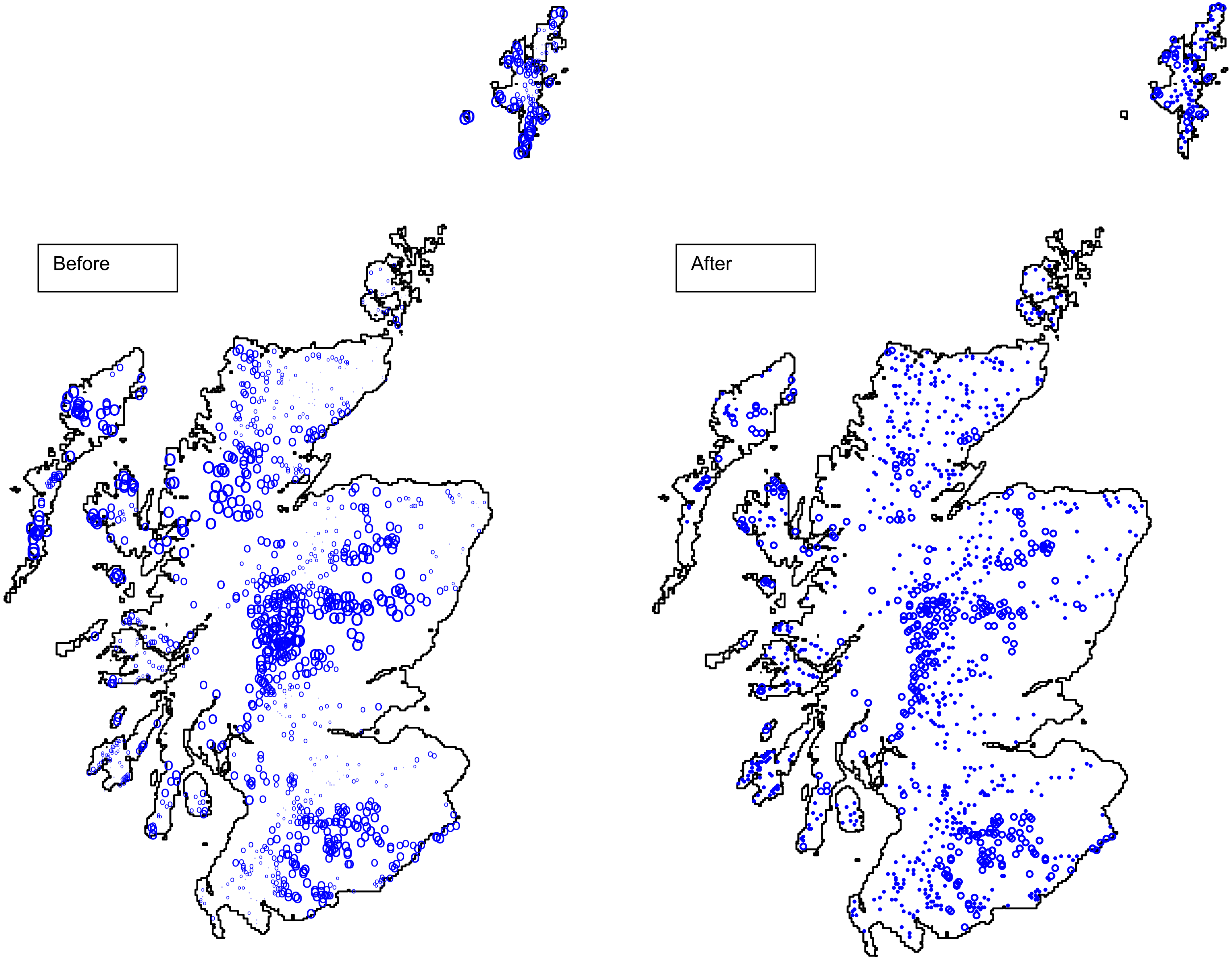


Figure 3.2.6. Variances of Bayesian simulations before and after first 24 samples added. Variances are proportional to the diameter of the plotted circles.

3.3. Report on targeted peat resampling

3.3.1. Introduction

This analysis is a general synopsis of the procedural and methodological considerations required when undertaking a survey of peat bogs, the logistical issues involved, the expected timescale and an estimate of costs when measuring the depth of peat and bulk density at 50 cm intervals, in a targeted sampling exercise.

3.3.2. Methodology

The standard and accepted methodology of measuring peat depths and sampling peat in order to characterise specific bogs involves two separate, but related stages – a) depthing on a grid pattern across the bog and b) sampling at 0.5 m vertical intervals, at between 5% and 10% of the observed depthing points.

Depthing

Following a reconnaissance survey of the area, a baseline is set out, usually along the longest axis of the bog. At fixed intervals along the axis, typically 100 m, the depth of peat is measured using interchangeable depthing rods of 1.5 m length which are inserted vertically into the peat until the underlying mineral or rock is encountered. Experience of staff in differentiating between mineral, rock and tree roots or wood fragments embedded in the peat is essential. The depth of peat is then recorded and the location of each point is also recorded using a Global Positioning System (GPS). Wooden pegs can be inserted at these points for relocation purposes when undertaking sampling. Extending from the baseline, depth and location measurements are made on a uniform grid across the bog. Variation of peat depth throughout the year because of differing hydrologic conditions is known to occur, but due to the relative accuracy and detection limits of the depthing rod technique and the measurements made, which relate specifically to the conditions on the day, little can be done to accommodate or assess this phenomenon, using the methodology discussed.

Sampling

At the selected depthing points, which are usually sited to give an even coverage of the area and to provide an agreed minimum sampling density, peat samples are taken using a Russian sampler at 0.5m intervals from the surface to the bottom of the peat deposit. This is a chamber of known volume which is attached to interchangeable rods and is inserted to specific depths within the peat profile from which a sample of peat is extruded. After removal of the chamber the peat is examined for degree of humification/decomposition (von Post classification) and samples are carefully extracted, bagged and labelled with site, location and depth range for bulk density and chemical analyses.

Additional characterisation

There could be added value to the resampling program to include additional characterization of the peatland at each sampling point. Such parameters might include a full peat profile description, a more detailed vegetation/plant species survey, assessment of peat erosion, assessment of local negative impacts such as grazing, peat cutting, fire incidence, as well as any additional chemical characterisation of the peat samples uplifted. Such further characterisation would incur additional costs, which are not included here.

3.3.3. Logistics

The logistics of undertaking such an exercise are considerable and are briefly outlined.

- The bogs/polygons to be sampled have to be identified.
- Construct agreed protocols and methodologies which meet the objectives of the project.
- List required of experienced personnel and equipment.
- Acquire/purchase relevant equipment.
- The ownership of the land relevant to the bog/polygon has to be acquired. This is not always readily available, may involve more than one owner and is often time consuming.

- Contact the owner by letter, explaining the reason for the work, how the work is to be undertaken, how long it will take and when the work is proposed to be carried out. Provide various options for replies e.g. stamped self-addressed envelope, telephone or email.
- Draw up provisional timetable of fieldwork taking into account available personnel, distribution and size of bogs/polygons.
- On receipt of replies granting access, finalise timetable of fieldwork, minimising travel and costs, and make arrangements for receipt and analyses of samples.
- Undertake fieldwork
  (i) Depth recording
  (ii) Sampling for bulk density, C/N analyses and humification assessments.
- Analyses of samples
- Data input into database
- Analyses of results
- Report and presentation of results.

3.3.4. Logistical Issues

Many issues arise when planning and undertaking such work, some of which can be foreseen and appropriate provision made, others are not e.g. inclement weather, unsafe ground conditions, breakage of equipment, rods becoming separated at depth. Some of the practical issues which would have to be taken into account when planning are:

- The scale of the 1:250,000 scale soil map which forms the basis of this work, does not allow a suitably accurate enough picture of the actual size of the bog when assessing timings and costings.
- Work is strenuous and requires at least two people for all field aspects of the work.
- Obtaining information on ownership of land and gaining access can be time consuming and problematic.
- The location and management of the bog may impose restrictions of access (nesting birds, shooting seasons and lambing) to times of the year, unsuitable for sampling.
- Accessibility of the bog from roads and the nature of the terrain can be difficult, curtailing the volume of work which can be undertaken. Previous peat surveys involved more staff and a tracked vehicle which is no longer available to traverse the bog.
- The depthing and sampling rods are difficult to manually carry over long distances and across steeply sloping land. For deep bogs more than two people may be required.
- Manufacture or acquisition of additional Russian samplers would be required if more than two teams were used (only two are extant which makes no allowance for loss or breakage).
- Variability across the bog in depth and nature of peat.
- Where root and wood fragments are present within the peat, several attempts may be necessary to ascertain the depth of peat to the underlying mineral substrate.

3.3.5. Timescales

This is dependent upon many factors - the size and number of bogs to be surveyed (Objective 1), the location, the grid size, distance to bog, the terrain and the depth of peat.

However it is estimated that once on site where depths do not exceed 3 m, a maximum of 22- depth recordings could be undertaken in one 8.5 hour day, allowing time for assembling rods, measuring the depth, recording location, dissembling rods and walking to the next recording point. Where depths exceed 3 m, a maximum of 17 points would be a realistic figure.

This assumes 9.5 hours daylight, weather is dry, there are no obstacles such as ditches to traversing the site and there is no walk in time from the vehicle.

Sampling is more time consuming than the depthing stage because of:

- heavier and more cumbersome equipment that has to be assembled and dissembled at each sampling site
- the process of sampling, bagging and labelling,

- undertaking and recording humification/decomposition assessments
- distance between sampling sites will be greater

It is estimated therefore, that a maximum of 6 sampling points across a bog could be visited in one day. This would be reduced if the depths encountered typically exceed 3–4 m.

Depending on location and distance from Aberdeen, travelling to and from many of the bogs will entail a minimum of 1 day but often two days. In a normal working week this equates with a maximum of 68-88 depth recordings (bog area of 68-88 ha if a 100 m grid is adopted) or 24 sample sites.

Taking into account the issues mentioned previously, 34-44 points and sampling 12 points on one bog per week would seem to be a realistic expectation. Reducing the depthing points to 17-22 and the sampling points to 3, could enable two bogs to be covered per week, provided that the travelling distance between the two was minimal.

3.3.6. Deliverables

Adopting the methodology described would allow the following deliverables:

- A map detailing depths across the bog on a grid basis with sampling sites located.
- Tables of location, sample depth, humification/decomposition assessments, bulk density and %C and N at each of the sampling sites.
- Estimate of C stocks for the bog.
- Report of work and results.

3.3.7. Costs

The costs are dependent upon many of the issues raised previously, but particularly the distance from Aberdeen, the size of bog, depth of peat and the number of samples. Outsourcing of work might reduce travel costs, but the need for training and equipment to ensure consistent results would offset any benefit of subcontracting.

However, assuming a week's fieldwork (depthing 44 points and sampling 12 points) for two staff (Band E @ £479 per day and Band C @ £392 per day), with associated travel and subsistence, analyses of 72 samples (peat 3 m depth, 6 samples per point) for loss on ignition and total C and nitrogen with the necessary drying, sieving and milling, plus office time for preparatory and data manipulation work, an estimated minimum cost associated with one week's fieldwork is approximately £8700. The number of weeks' fieldwork and total costs are based upon the outcomes of Sections 3.1 and 3.2 whilst the need for additional staff, more samples, ferry trips and the purchase or manufacture of equipment will increase costs accordingly.

A provisional estimate is that an additional 72 spatial locations would reduce the variance on the depth estimates by 50% (see Section 3.2.5). At the same time, power analysis indicates that a total of ca. 600 depth values should give an acceptably precise mean depth (see Section 3.1.12). Hence the indication is that it is better to have fewer depth samplings, say 8–10, at a greater number of locations (peat polygons). However, the results of the spatial analysis (Section 3.1.8) would suggest that sample points should be at least 500 m apart rather than the traditional 100 m to avoid spatial autocorrelation. (To some extent this might need to be adjusted to take into account practicalities and the size of the particular peat area.) As result there would be an offset between fewer sampling points and more walking between points. Hence total costs, assuming 36 weeks of field work would be of the order of £313k.

3.3.8. Conclusions

To undertake a comprehensive targeted peat sampling programme will be time consuming and costly in terms of salaries, equipment acquisition and analytical costs. The costs and timescale involved should be considered against the benefits ensuing from collecting such data. The data collected during the current NSIS_2 resampling programme will provide some information on the thickness and depth of horizons, which combined with bulk density analysis and %C values, will allow C stocks for the soil profiles sampled to be calculated, enhancing the national soil datasets and the associated variability studies will also give an insight into the range of values around a point. The NSIS_2 work will also provide information on the thickness of organic horizons within organo-mineral soils and using hand held augers, the *thickness* of peat deposits at each site can be assessed to 2m depth, again enhancing previous information and C stocks. However to transport actual peat depthing rods to each site in conjunction with the required NSIS_2 equipment, is not thought a feasible proposition within current budgets and any additional *sampling* of peat below 1 metre should be undertaken as a separate exercise as outline above. Such an exercise would allow the known uneven distribution of data, both across the country (east to west) and between peat types (basin and blanket) to be built into the sampling programme, and would reduce the uncertainty in C stock measurements by at least 50% (equivalent to ca. 50 MtC), as well as providing some validation (or otherwise) for some of the assumptions used in the current C stock estimates about more locally-obtained parameters being applicable across the country. Using the data from geo-statistical analyses (Section 3.1), the necessary work is estimated to cost of the order of £313k.

3.4. Evaluation of use of archived dry bulk density values for peat bogs to determine C stocks values retrospectively

3.4.1. Introduction

There exists in the archived records of the surveys of the Scottish Peat Committee some data on what is termed "bulk density" but what is actually a laboratory bulk density, or particle packing density, of dried and milled peat, together with recorded peat moisture contents, ash content and humification indices on the von Post scale. Here we investigate the possibility of using this data to reconstruct the actual field dry bulk density using pedotransfer functions. The benefit of this approach is that the archived data extends to the base of many peat deposits and so could give data on bulk density at depths greater than 100 cm, as well as giving an indication of how bulk density may vary (or not) with depth in different peatland forms. This exercise includes some limited sampling of different peat sites in order to verify the relationships between the laboratory bulk densities and field bulk densities. We also utilise data from the first phase of the NSIS_2 resampling, where there is sufficient sample volume available for this project.

3.4.2. Methodology

The initial step in this exercise was to translate the archived data into computer format. The data exists as figures within the reports (Volumes I to IV) of the Scottish Peat Committee (Department of Agriculture and Fisheries for Scotland, 1964; 1965a; 1965b; 1968). While scanning the data or using a digitizing tablet was considered, the most efficient way was to measure the length of the bars on the figures with a ruler, measure the scale and enter the figures into an Excel spreadsheet. From this the actual values could be computed. The data entered were the "bulk density" (henceforth referred to as "laboratory bulk density"), moisture content, ash content and humification index on the von Post scale. Values were recorded typically every 50 cm down the peat profile to the bottom of the peat layer (for the deepest this was 9.5 m) and the dataset contained over 80 profiles.

The second step was to derive a pedotransfer function whereby the archived data could be used to give values of dry bulk density down the peat profiles. Laboratory bulk density is not normally measured in contemporary analysis; its value related more to peat extraction for fuel use and so was of relevance to the post-war Scottish Peat surveys but not so any longer. The precise protocol for its measurement is unfortunately no longer available. Even interviewing a number of contacts with considerable history in peat survey (R.A. Robertson, P.D. Hulme and J. Anderson) did not bring to memory its exact nature except that the dried and milled peat was compacted by shaking it on a ratchet-like device on a wheel that was turned. Comparison with the literature (Päivänen, 1969) revealed that there were several variants on the methodology. It was decided to adopt the following protocol:

1) The peat was air-dried at 27˚C and subsequently at 105˚C.
2) The dried sample was hammer-milled using a 1 mm grid on the mill.
3) A sample of 20-30 ml was placed into an adapted 50 ml syringe body and tapped 30 times by hand on the bench from a height of 3 cm (A preliminary test indicated that this consolidated the sample to a constant volume).
4) Both the volume and weight of the sample was recorded and from these the laboratory bulk density could be calculated.

The laboratory bulk density was determined for a number of peat samples for which (field) dry bulk density had also been determined:

1) Samples (28) from two basin peats (Middlemuir and Red Moss, Netherly) collected using a Russian sampler to a maximum depth of 5 m. The humification index and moisture content was also recorded.
2) Samples (20) from eleven NSIS_2 sites which were peat. These were necessarily only to a maximum depth of 1 m. Humification index and moisture content were not available.

A further set of data from Shetland, Allt Mharcaidh and Glensaugh (supplied by Zoë Frogbrook) were added where both bulk density and moisture content values were known. The original samples were not available for laboratory bulk density determination.

Linear regression and multiple linear regression between the various parameters were performed using Genstat 8.

3.4.3. Results

The results of regression analysis revealed a significant but not particularly strong relationship between dry bulk density and laboratory bulk density (Figure 3.4.1). The relationship could be improved by removing one or two data points which had come from near surface samples and which had particularly high dry bulk density values, e.g. the value over 0.2 came from a sample that represented an old cut-over surface that had previously been dried and consolidated. However, the regression was still not very good (data not shown).
During the process of regression analysis, it was found that that the relationship between dry bulk density and moisture content was much closer (Figure 3.4.2). The figure gives the regression for the values obtained from the two basin peats; a quadratic (polynomial) fit was slightly better than a simple linear regression and an r-squared in excess of 0.99 was obtained. A second larger dataset from blanket peat (Shetland, Allt Mharcaidh and Glensaugh) gave different regression line having greater scatter and with an r-squared of 0.61 (data not shown). It was decided to combine the two datasets to give a general regression that could be applied to the archived moisture content values (Figure 3.4.3). The combined dataset also had an r-squared of 0.61 and only a linear fit was justified. Some samples showed lower moisture contents than might be expected. Closer inspection indicated that these samples had lower wet bulk density values also and hence were from unsaturated horizons that contained an appreciable air-space.

Further regression analysis was performed to ascertain if the relationships between dry bulk density and peat moisture content could be improved further by the addition of the humification index or of laboratory bulk density (in a multiple linear regression analysis). The results indicated that the addition of the laboratory bulk density gave some improvement but not the addition of the humification index. However, the number of samples where these additional parameters were known was limited and hence it was preferred to use the larger dataset of moisture content alone as the predictor of dry bulk density.

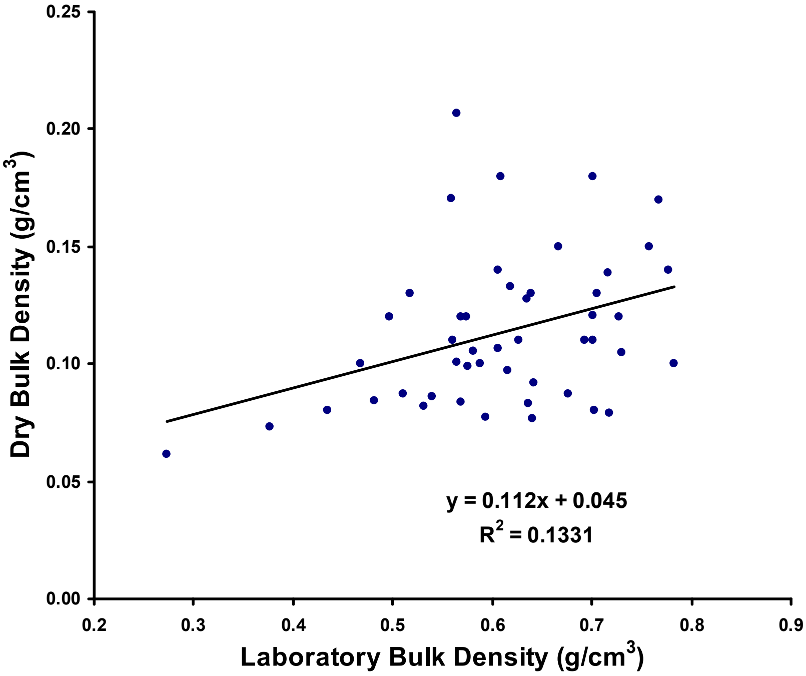


Figure 3.4.1 Regression of dry bulk density on laboratory bulk density for a set of peat samples

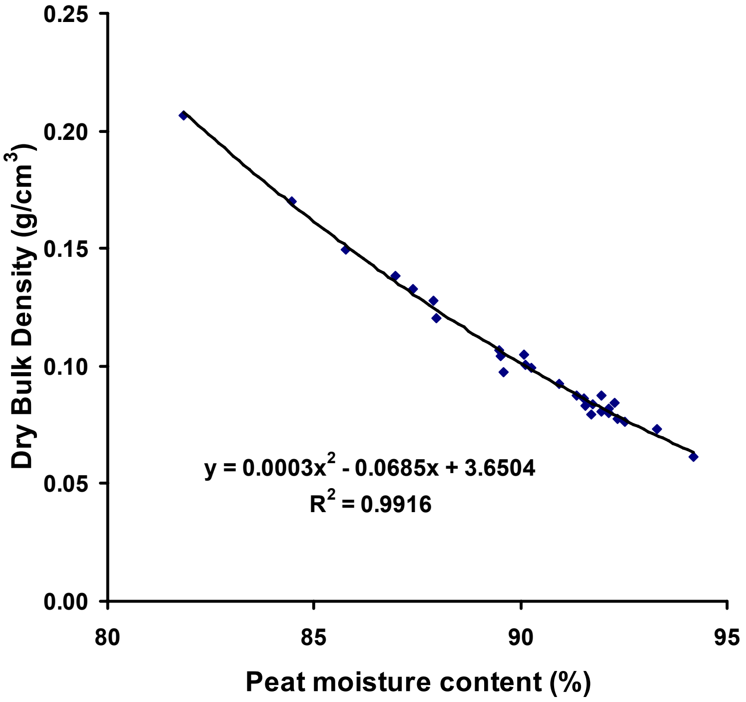


Figure 3.4.2 Regression between dry bulk density and moisture content using data from two basin peats.

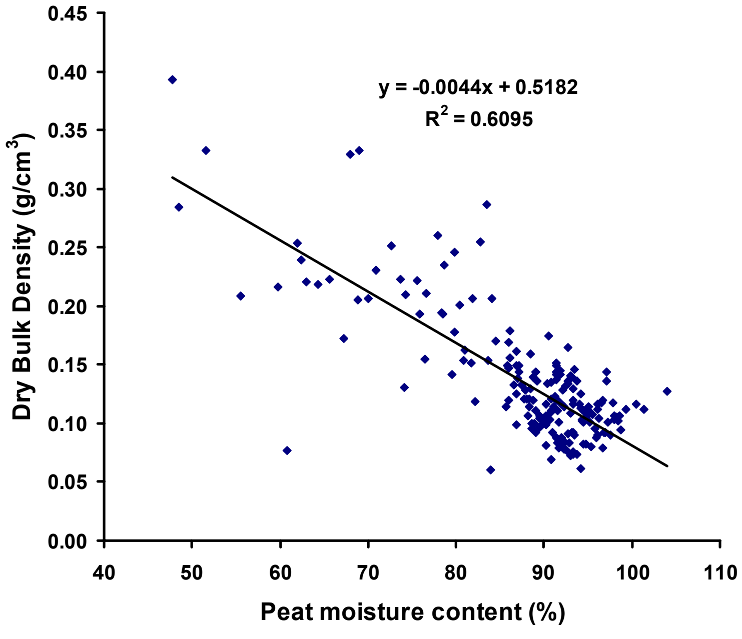


Figure 3.4.3 Regression between dry bulk density and moisture content using data from both basin and blanket peats.

The final step was to apply the regression relationship obtained from Figure 3.4.3 to the archived data on peat moisture content in order to calculate a dry bulk density. This would enable characterization of how this parameter may vary with depth. Figure 3.4.4 shows the variation in bulk density with depth using 918 datapoints from 86 peat profiles taken from a total of 32 peat bogs. There is an underlying assumption that the pedotransfer function that was obtained using data from shallower peat profiles can be applied to the deeper peat profiles of the archived dataset; the regression dataset had a mean depth of only 48.7 cm (range 7.5–485 cm) while the archived data goes down to nearly 10 m. However, if this is accepted then the data shows little variation of bulk density with depth. There is slight evidence of a minimal decrease with depth; the fitted line is a cubic polynomial which is a significantly better fit than a linear regression. The suggestion is a slight increase in bulk density at the surface and a slight decrease below 8 m though the data points here are few. Taking means over the depth ranges as used for the C stock calculations gives estimated bulk density values (g cm^{-3}) of 0.125 (0–30 cm), 0.118 (30–100 cm) and 0.118 (100+ cm). These are very close to the mean bulk density values actually used in the C stock calculations from a more limited set of measured bulk density data, 0.134, 0.120 and 0.109, respectively, and give some confidence to the application of these values.

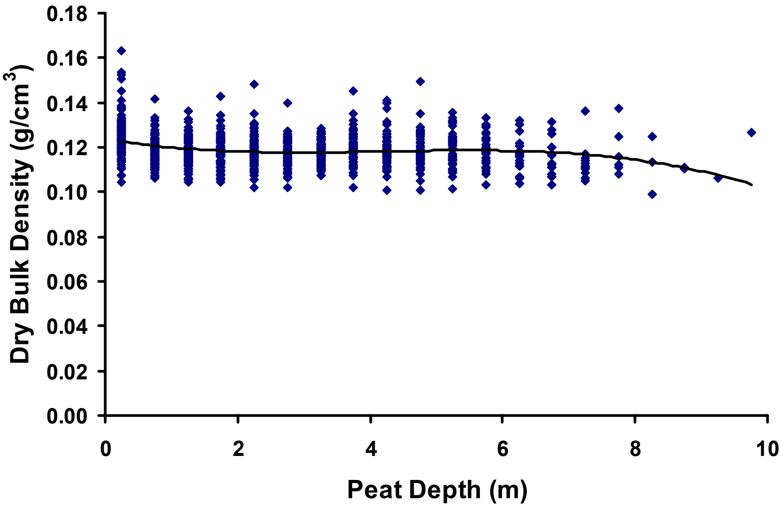


Figure 3.4.4 Predicted dry bulk density, using the regression against moisture content, and its variation with peat depth.

3.4.4. Conclusions

A pedotransfer function may be derived that enables dry bulk density to be estimated from peat moisture content. A restriction is that the peat samples should be from the saturated zone or at least have a wet bulk density in excess of 0.85. Since we are here interested in bulk density changes at depth, this restriction does not interfere too much with its application. The application of this function to a set of archived peat moisture content data yields bulk density data that is comparable to that actually used in the national C stock calculations and gives some credibility to these bulk density values. Additionally, it suggests that bulk density does not vary markedly with depth in these peat deposits so that surface values may be used with more confidence for deeper deposits where measured values are largely absent.

3.5. *Costs and benefits of GPR and Lidar to measure peat depth and the potential for using these methods to monitor changes in soil carbon stocks in the peatlands of Scotland*

3.5.1. Introduction

The collection of data related to the measurement of peat depth and monitoring of peat stocks has been traditionally carried out by intensive and expensive field work. Whilst field work will remain an important component of any future work in this area, not least for validation purposes, new remote techniques may enable more measurements to be undertaken at less cost. This short analysis reviews the use and potential of the Ground Penetrating Radar (GPR) and LIDAR (Light Detection and Ranging) technologies both for measuring peat depth and to monitor changes in peat depth in Scotland. The Scottish Government is currently funding two pilot projects to evaluate the feasibility of using satellite derived information to measure the extent of erosion and greenhouse gas emissions from Scottish peatlands. This work is due to complete in 2009 and will help to inform the Scottish Government on the value of this new technology in supplementing more traditional and costly field measurements.

3.5.2. Ground Penetrating Radar (GPR)

Ground Penetrating Radar (or GPR for short) is the general term applied to techniques which employ radio waves, typically in the 1 to 1000 MHz frequency range, to map structure and features buried in the ground. It is often used in the building industry to determine and inspect the general arrangement of construction, changes in material type, location of structural steelwork and layer thickness.

It is a high resolution, field-portable geophysical method that produces graphic sections of subsurface structure. Typical site investigation applications include accurate location of voids and buried obstructions; mapping subsurface soil and rock interfaces and defining buried archaeological structures. The method can also identify ancient landfill sites and detect buried hazardous waste. In man made built environments, use of GPR is quite straightforward and machine use and data capture can be at rates not much slower than normal walking pace, but ease of access could be a significant constraint in peatland environments. This will be discussed more fully later.

Applications in Soils Research

The performance of ground-penetrating radar (GPR) in soils strongly depends on soil electrical conductivity (Doolittle *et al*., 2007). Electrical conductivity is the ability of a material to transmit (conduct) an electrical current and is expressed in the units milliSiemens per meter (mS/m). Soil electrical conductivity measurements may also be reported in units of dS/m which is equal to the reading in mS/m divided by 100. Soils having high electrical conductivity rapidly attenuate radar energy, which restricts penetration depths and severely limits the effectiveness of GPR. GPR can offer a number of advantages over traditional methods of digging soil pits as these are destructive, time consuming and only provide single point sources of information (Knight 2001, Holden *et al.,* 2002). For specific applications such as measuring and mapping soil water content, GPR is a technique that is intermediate in resolution between the detailed scale of time domain reflectometry (TDR) and the small scales that remote sensing using air photographs or satellites can handle (Huisman *et al.,* 2002).

A number of soil properties are known to affect electrical conductivity in soils (Geonics Limited 1980). These include:

- **Pore Continuity** – Soils with water-filled pore spaces that are connected directly with neighbouring soil pores tend to conduct electricity more readily. Soils with high clay content have numerous, small water-filled pores that are quite continuous and usually conduct electricity better than sandier soils. Compaction normally increases soil electrical conductivity, presumably by reducing air space within the soil matrix.
- **Water content -** Dry soils are much lower in conductivity than moist soils.
- **Salinity level** – An increasing concentration of electrolytes (salts) in soil water will dramatically increase soil electrical conductivity. The salinity level in most humid regions such as the Corn Belt is normally

very low. However there are areas that are affected by Ca, Mg or other salts that will have elevated electrical conductivity.

- **Cation exchange capacity (CEC)** – Mineral soils containing high levels of organic matter (humus) and/or 2:1 clay minerals such as montmorillonite, illite or vermiculite have a much higher ability to retain positively charged ions (such as Ca, Mg, K, Na, NH4, or H) than soils lacking these constituents. The presence of these ions in the moisture-filled soil pores will enhance soil EC in the same way that salinity does.
- **Depth** – The signal strength of EC measurements decreases with soil depth. Therefore, subsurface features will not be expressed as intensely by EC mapping as the same feature if it were located nearer to the soil surface.
- **Temperature** – As temperature decreases toward the freezing point of water, soil EC decreases slightly. Below freezing, soil pores become increasingly insulated from each other and overall soil EC declines rapidly.

Ground penetrating radar (GPR) has been used as a pedological tool in the United States since 1978 (Doolittle and Collins 1995). Principal uses have been to estimate the variability and taxonomic composition of soils, chart the lateral extent, and estimate the depth and thickness of soil horizons and geologic layers and to map and interpret soils. All soils are not equally suited to GPR techniques. A Ground-Penetrating Radar Soil Suitability Map has been produced for the United States based on taxonomic criteria, clay content, salinity, sodium absorption ratio, and calcium Cate content (Doolittle *et al.,* 2007). The map is based on over twenty-five years of field observations made throughout the United States and soil attribute data contained in the State Soil Geographic (STATSGO) database. The map limits areas that are rated as being "Unsuited" for GPR to saline and sodic soils, reassesses calcareous and gypsiferous soils, and provides a mineralogy override for soils with low activity clays. This map can be used to assess the relative appropriateness of GPR for soil investigations within comparatively large areas of the conterminous United States. No similar analysis has been undertaken nor map produced for the UK.

Many of the specific GPR applications have been in relation to soil water content in mineral soils (rather than peat soils, which is the focus of this report). Weihermueller *et al.* (2007) used two ground penetrating radar (GPR) techniques to estimate the shallow soil water content at the field scale. The first technique is based on the ground wave velocity measured with a bistatic impulse radar connected to 450 MHz ground-coupled antennas. The second technique is based on inverse modelling of an off-ground monostatic TEM horn antenna in the 0.8-1.6 GHz frequency range. The aim of the study was to test the applicability of the ground wave method and the off-ground inverse modelling approach at the field scale for a soil with a silt loam texture. Both methods produced disappointing results and did not provide adequate spatial information on soil water content variation at the field scale. The main reason for the deviating results of the ground wave method was the poor data quality due to high silt and clay content at the test site. Additional reasons were shallow reflections and the dry upper soil layer that cannot be detected by the ground wave method. In the case of off-ground GPR, the high sensitivity to the dry surface layer is the most likely reason for the observed deviations. The off-ground GPR results might be improved by using a different antenna that allows data acquisition in a lower frequency range.

Strobbia and Cassiani (2007) used GPR as a tool to quickly obtain soil moisture content over large areas. The technique was applied to a mountain slope with a 1-m soil cover where repeated measurements over time, inverted by conceptualizing the soil as a single guiding layer, lead to estimates of the GPR wave velocity and thickness varying over time. They developed a multilayer GPR waveguide model and although this did partly overcome the model error arising from using a single-layer forward model – it underestimates the total soil thickness because the inversion is sensitive mainly to the layer with the lowest velocity (the wettest layer) – it did not fully overcome it. They then used a multilayer forward model to invert the actual field data. There was still some uncertainty about the position of such a layer in the layer sequence.

Other studies in the area of soil water content include that of Lunt *et al.* (2005) who concluded that GPR has the potential for monitoring soil water content over large areas and under variable hydrological conditions. This was done by comparing volumetric water contents from calibrated neutron probe logs with estimates produced from GPR reflections. Although they do not state it explicitly, they do not seem to advocate the technique as a substitute for field studies but rather to complement and provide a focus for them. GPR can provide continuous high-resolution data that chart depth to water tables in coarse textured soils (Doolittle *et al*., 2006).

GPR has also proved useful in soil pollution monitoring and in contributing towards describing the spatial distribution of pollutants in an industrial area in Southern Italy (Chianese *et al*., 2006). In a study investigating its potential use in identifying soil compaction, Petersen *et al*., (2005) demonstrated that loamy soils that have a higher risk of compaction could be differentiated by GPR from those with a lower risk, for example, sandy soils. However, they did not demonstrate whether compacted soils could be identified as the deeper soil horizons (below 30 cms) in the study area showed only uniformly strong compaction with little contrasts.

Applications in peat soils

Applications of GPR in peat soils have been carried out largely by Finnish and Canadian researchers in the measurement of peat depth and measurement of gas accumulation and release in peats, whilst work on the location and analysis of the connectivity of underground pipes in peat has largely been carried out in England.

Comas *et al*., (2007) reported that that GPR is a useful tool for assessing the spatial distribution, temporal variation, and volume of biogenic gas deposits in peatlands. They found that (1) changes in the two-way travel time from the surface to prominent reflectors allow estimation of average gas contents and evolution of free-phase gas (FPG); (2) peat surface deformation and gas flux measurements are strongly consistent with GPR estimated changes in FPG content over time; (3) rapid decreases in atmospheric pressure are associated with increased gas flux; and (4) single ebullition events can induce releases of methane much larger (up to 192 g m^{-2}) than fluxes reported by others. The same authors subsequently found that GPR in combination with other techniques provided insights into the spatial and seasonal variability in production and emission of biogenic gases from northern peatlands (Comas *et al*., 2008).

Natural underground soil pipes are common in peat and can play a significant role in catchment drainage where peat forms a significant component. Holden *et al.* (2002) compared data on pipes identified by GPR and verified by manual measurement and found that that pipes can be located in the soil profile with a depth accuracy of 20 to 30 cm. Generally pipes smaller than 10 cm in diameter could not be identified using the technique although modifications could allow enhanced resolution. GPR demonstrated that pipe network densities were much greater than could be detected from surface observation alone. Thus, GPR provides a non-destructive fast technique which can produce continuous profiles of peat depth and indicate pipe locations across survey transects. Subsequent work (Holden 2004) has demonstrated that GPR in combination with a tracer solution can identify connectivity within the pipe network and travel times within that network.

Most GPR applications on peat have been to test how well the technique can identify different layers within it, in other words its stratigraphy, and whether it can measure the total depth of peat to the underlying mineral material. Research by Comas *et al.* (2005) suggest that GPR and terrain conductivity measurements reveal a close correlation between the location of water-filled pools and stratigraphic/lithologic features in Caribou Bog, a 2200-hectare peatland in central Maine. The geophysical profiles, supported by coring, define the general peatland stratigraphy as till underlain by glacio-marine sediment overlain by organic-rich lake sediment transitioning into terrestrial peat. Similarly Slater and Reeve (2002) working on the same bog integrated GPR with direct measurements of peat stratigraphy from probing, fluid chemistry, and vegetation patterns in the peatland. They concluded that GPR was an excellent method for delineating peatland stratigraphy and prominent reflectors from the peat-lake sediment and lake sediment-mineral soil contacts were precisely recorded up to 8 m deep. Comparison of the bulk conductivity images with peatland vegetation revealed a correlation between confining layer thickness and dominant vegetation type, suggesting that stratigraphy exerts a control on hydrogeology and vegetation distribution within this peatland. Their understanding of the hydrogeology, stratigraphy, and controls on vegetation growth in this peatland was much enhanced from the geophysical study.

Thiemer and Nobes (1994) carried out geophysical surveys and chemical analyses on cores in three Ontario peatlands. They found that the dielectric permittivity in peats is largely controlled by the bulk water content and that GPR can detect changes in water content greater than 3%, occurring within a depth interval less than 15 cm. The principal peatland interfaces detected by GPR are the near-surface aerobic to anaerobic transition and the peat to mineral basement contact. The potential for the successful detection of the basement contact using the radar can be predicted using the radar instrument specifications, estimates of the peatland depth, and either the bulk peat or the peat pore water electrical conductivities. Predicted depths of penetration of up to 10 m exceed the observed depths of 1 to 2 m so the full capability of the technique was not fully tested in this study.

At the third one, on the other hand, it was observed that, as predicted, a 100 MHz signal will penetrate to the base of a 2 m thick peat but a 200 MHz signal will not.

Jol and Smith (1995) used GPR in site assessment for the placement of pipelines crossing peatland. This built on previous work that demonstrated the use of GPR in the assessment of the thickness and volume of peat as a fuel resource and horticultural material in Scandinavia and Canada. Several GPR surveys assessed the thickness of the peat along two oil pipeline right-of-ways. Results show the peat-sand contact as irregular and undulating, ranging from 0 to 3.7 m deep. Each survey, 460 and 550 m long, was completed in two hours. Such results from 1 m station spacings (sampling interval) can considerably reduce the uncertainties in planning and placement of oil, gas, and water pipelines crossing peatlands. Significantly the authors argue that the results indicate that thickness variations of peat can be detected more effectively in terms of quality of results, lower cost, and less time with GPR than with a peat probe or by coring.

Hanninen (1992) wrote a major review of the applicability of ground penetrating radar (and radio wave moisture probe techniques) in practical research work between 1983 and 1990. The primary aim was to examine the practicability of ground penetrating radar antennae. Their main findings were that

- Ground penetrating radar provides continuous cross-sectional data on the depth of a mire, a good picture of the quality of its bottom and indications of the underlying mineral soil type. Together with location data, such a cross-section allows extremely accurate depth maps to be constructed for the site concerned.
- The method also constitutes a rapid means of examining open, unditched peatland areas, but is slower to use in forested mires with a dense network of ditches.
- Of the antennae available at that time, those of frequency 80, 100, 120 and 500 MHz lend themselves best to peatland investigations. The first three types are best suited for measuring peat layer thickness in extensive unditched peatland areas, while a 500 MHz antenna provides accurate data on the mire surface and moisture fluctuations inside the peat. The results can be improved markedly by digital processing of the radar cross-section, especially if a 500 MHz antenna has been employed.
- Possibly most significantly, the authors claim that the depth data obtained using ground penetrating radar are markedly more accurate and detailed than those obtained by traditional means.

Wastiaux *et al.* (2000) and Doolittle *et al.* (1990) have also undertaken peat bog surveys using GPR. Wastiaux *et al.*, working on a 800 ha area of drained peatlands in the Hautes-Fagnes (Belgium), found that GRP ‘provided very accurate information about the subsurface relief and the thickness and extent of the peat deposit, as well as stratigraphical information and suggestions of possible links between subsurface, hydrology and present vegetation’. Doolittle *et al.* used GPR to estimate peat thickness and peat volume within a kettle bog in Plymouth County, Massachusetts, USA.

3.5.3. Light Detection and Ranging technology (LIDAR)

LIDAR is a remote sensing technique that uses laser light in much the same way that sonar uses sound, or radar uses radio waves**.** The journey time of the laser beam, from leaving the instrument to its return after reflection, is measured and – knowing the speed of light – a distance can be computed between the aircraft and the ground**.** It produces very high resolution surfaces and has been used in a number of ecological applications for example in forestry for measuring tree height and in flood risk studies. Applications in the study of soils and particularly in peat are very scarce but those that have been sourced are referenced here. Two good sources of information on the technical and applied aspects of LIDAR can be found at

http://www.forestry.gov.uk/forestry/INFD-6RVC9J and
http://www.snh.org.uk/pdfs/publications/commissioned_reports/F02LG15.pdf

In terms of quantifying peat resources, LIDAR [or as it is sometimes termed Airborne Laser Scanner (ALS)] produces a very detailed and accurate representation of the ground surface. However this information has to be used alongside peat depth data collected by traditional (e.g. coring or drilling) or remote methods such as GPR in order to generate a 3 dimensional representation of bogs. From this, total volume of peat can be estimated and when combined with data on soil C content and bulk density, C stocks can be derived.

A case study from Ireland (Lenihan 2008) used three steps:

1. process LIDAR data in GIS software to create a top surface for a particular bog. The data are accurate to 0.075m.
2. peat depth measurements collected in 1950 were entered into the GIS software to create a bottom surface.
3. using modelling functions in ESRI ArcGIS 9.2, subtract the one from the other to create a predicted peat depth map.

A similar study has already taken place in Indonesia within a tropical peatland (Boehm and Frank 2008). The ALS data were accurate to +/- 15 cm in elevation and to 0.5 m in the x and y directions and, the authors argue that 3-5% of the laser beams penetrate the peat swamp forest. This allowed them to produce a true topographic surface of the peat. Each flight track was GPS recorded. Peat depth readings were taken on a 500 x 200 m grid and GPS reading recorded at each point on the grid. In another part of the peatland, cores were taken every 700 m though access through the peat swamp forest was very difficult. Two georeferenced datasets were thus obtained albeit with radically differing levels of resolution and accuracy. Considerable computing power and expertise are required to analyse these data and to produce the 3 dimensional representation of the bog. Although the extent of the bog is not stated explicitly, from data presented it is of the order of 40 km long. Given the difficulties of access on this site, the obtaining of ALS data probably was the difference between the project being feasible at all.

An on-going project in the Peak District National Park in England is investigating the use of LIDAR along with other remotely sensed data to predict catchment sediment flux (Evans and McMorrow, pers. comm.). The overall aim is to assess the usefulness of pattern analysis of remotely sensed data to assess connectivity between peat gullies and their role in sediment flux. Clearly the capability of LIDAR data to produce accurate DEMs and therefore the degree of connectivity between gullies is fundamental to the success of this initiative.

LIDAR has also been used by Haycock *et al.* (2004) to classify the morphology and dynamics of the peat surface within a National Trust estate and then apply new topographically derived flow and network propagation models to map the drainage network of the landscape. From this information and the ability to classify the depth and drainage information of the gullies they were able to identify the critical gullies within the estate, select appropriate gully blocking techniques and then develop operational working plans that assist in the air-drop of materials to key locations.

3.5.4. Other methods

Although this report was asked to focus on the potential of GPR and LIDAR in peatland survey and monitoring, some other techniques emerged during the literature search and perhaps should be considered as part of the portfolio of techniques available. It should be recognised that most of the examples cited below have not been tested in peatland but are reported here as potential non-destructive techniques.

Radio wave moisture probes

Radio wave moisture probes have been used with the aim of examining their application in the measurement of peat moisture, bulk density and energy content in hydrologically different mires (Hanninen *et al.,* 1992). The practicability of the radio wave moisture probe was examined by comparing the probing results with those obtained using a volumetric piston sampler and analysed under laboratory conditions. Following the collection of 4434 probe measurements and 739 volumetric samples taken from mires in 13 local government districts they were analysed for peat type, humification, moisture content, bulk density, ash content, heating value, and in some cases sulphur content. A radio wave moisture probe was used to measure attenuation, frequency and quality factor (Q value) in peat, of which the first can be used to calculate moisture content, bulk density and energy content. It was concluded that the method allows more accurate measurement of energy content and bulk density in peatland areas, as the number of measurements required in the latter case can be increased essentially without any rise in research costs. For example a group of 2-3 persons can perform 3-4 times more bulk density measurements in a day than by the traditional method, and the number of volumetric samples needed can be reduced by 30-50%. Cross-sections describing the moisture, solid matter and energy content in peat can be created and mire-specific maps printed on the basis of the results obtained.

Electromagnetic induction (EMI)

Electromagnetic induction has been compared and contrasted with GPR with respect to its capability in rapid, extensive and non-destructive mapping of diagnostic subsurface features and soil series map unit boundaries (Stroh *et al.,* 2002). In contrast to GPR, EMI consistently distinguished boundaries of soil map units. In several instances, gradients or contrasting inclusions within map units were also identified. In addition, the location and boundary of calcic or cambic-horizon inclusions embedded within a laterally co-extensive and well-developed argillic horizon were consistently predicted. However, correlations between EMI assessments of apparent conductivity (ECa) and soil properties such as CEC, pH, particle size distribution and extractable bases were low (i.e., explained <6% of the variance), or non-significant. As a result, EMI has a high prospecting utility, but cannot necessarily be used to explain the basis for edaphic contrasts. Results suggest EMI can be a cost-effective tool for soil survey and exploration applications in plant ecology. As such, it is potentially useful for rapidly locating and mapping subsurface discontinuities, thereby reducing the number of ground truth soil samples needed for accurate mapping of soil map unit boundaries. There is no evidence that the technique has been used on peatland soils.

Time domain reflectometry

In a similar fashion, GPR was compared with time domain reflectometry (TDR) by Huisman *et al.* (2002). They demonstrated that GPR can measure soil water content variation as expressed in a variogram produced by the heterogeneous irrigation of ground using sprinklers of various intensities. Additionally they have demonstrated GPR is better that TDR for mapping features > 5 m in soil water content. GPR has also been utilised to investigate its utility in identifying depth to a ground water table. Roth *et al.* (2004) demonstrated that discontinuities in soil could be identified and a local water table located, all verified by soil coring and water table measurement in the field. They advocate its use as a initial screening tool to help find optimal locations for field based measurements.

Magnetic susceptibility measurements

Chianese and colleagues (2006) demonstrated that magnetic susceptibility measurements in combination with GPR can be useful in soil pollution and monitoring. Magnetic susceptibility measurements in topsoil can define the spatial distribution of superficial pollution phenomena in an area whilst detailed and integrated measurements based on high-resolution magnetic mapping and ground penetrating radar (GPR) profiling have been applied to investigate the subsurface in two more polluted sites that were identified during the first phase.

Metje *et al.* (2007) report on a major UK initiative called Mapping the Underworld (MTU). Whilst the driver for this work is a completely different context from peatland - the social, environmental and economic consequences arising from an inability to locate accurately and completely the buried utility service infrastructure without resorting to excavations – the ultimate findings may identify some wider applications in soils. One of the four MTU projects aims to develop and prove the efficacy of a multi-sensor device for accurate remote buried utility service detection, location and, where possible, utility identification. The three essential technologies that are to be combined in the device are ground penetrating radar (GPR), low-frequency quasi-static electromagnetic fields and acoustics.

Virtanen and Lersii (2008) have demonstrated that airborne gamma radiation detection can differentiate shallow and deep peatland areas and help identify areas for further research and survey. The method is based on the natural radioactivity of the mineral soil underlying the peat. There is no signal from areas where the peat is greater than 0.5 metres thick and the signal is strongest from mineral soils. The method is best at separating peat from other soils but cannot be used for assessing peat stocks.

3.5.5. Discussion and recommendations

From this review it would appear that GPR technology has been used much more in peat studies than LIDAR. This is probably a reflection on the maturity of the technology and of the software requirements required to process the output rather than it being seen purely as a better technique. Nevertheless, from the information obtained in this review, GPR could be used on its own to measure peat depth (although it would be ill advised to do so) whereas Lidar could not. In contrast, Lidar perhaps offers the better option for measuring changes in C stocks in peat.

Ground penetrating radar

Some of the work cited here (e.g., Hanninen 1992) suggests that 'the depth data obtained using ground penetrating radar are markedly more accurate and detailed that those obtained by traditional means'. It is unclear upon what evidence this is based and intuitively it appears to be a very ambitious statement. Certainly probing peat depth by rod can be ambiguous in that there is some uncertainty as to precisely what is being impacted by the rod; it could be a woody remain or perhaps a lens of mineral material within the peat. Similarly, Jol and Smith (1995) contend that their results indicate that thickness variations of peat can be detected more effectively in terms of quality of results, lower cost, and less time with GPR than with a peat probe or by coring.

One clear advantage of GPR is that it can provide a continuous assessment of peat depth along a transect compared to the intermittent measurements achieved by probing. Whether or not this is important would depend on the specific application and no matter what the method is, some interpolation of data is required to produce a representation of the bottom surface of a peat mire. GPR therefore does offer advantages over probing along a pipe line, but if the objective is to measure the total volume of a bog, then the advantages are marginal.

Most small GPR devices currently available can, in theory, be operated by a single operator, but for practical and safety reasons, a two man team is preferable particularly when consideration of the type of terrain that the equipment would be used in is taken into account. Most GPR devices on sale or for hire today are very suitable for use in the built environment but the logistics of using them on the much more uneven terrain of blanket bog vegetation is more taxing. Many of them are wheeled devices, resembling small lawn mowers and there may be practical difficulties of access. Another issue may be the potential damage that the operation might cause to the surface vegetation particularly on designated sites; accessing the bog on foot with depthing rods is likely to cause less damage.

The costs associated with GPR will in general terms be similar to those associated with traditional surveying methods in that much of the expenditure is associated with obtaining field data. There will be additional software costs but these are liable to be minor compared to the total costs. Depending on the complexity of the raw output, more specialised interpretation skills may be required but the overall costs to adapt processing and analysis are likely to be similar.

There are a number of bogs with detailed depth measurements including the detailed survey at Glensaugh in the ECOSSE project (Smith *et al*., 2007b). Testing a GPR device on this site, where the organic surface horizon varies in depth from a few centimetres to three metres plus would provide an indication

- of the accuracy of the technique in measuring peat depth compared to traditional methods
- of whether the results obtained would radically change the C stock estimate of the study area.

LIDAR

Research in this field using Lidar is in its infancy and very much at the experimental phase and it is recommended that the Scottish Government keep a watching brief on the ongoing study in the Peak District in England. Lidar does appear to have potential as a tool to monitor development of peat gullies in areas of peat erosion, and therefore depletion of the resource. However, even though the highest quality laser scanner systems are capable of achieving height accuracies in the order of +/- 0.15m and with a horizontal accuracy of 1-2 metres, it would a significant erosion event for this to be picked up using this technology. Studies using erosion pins have demonstrated that an average erosion rate *where it is actually on going*, is of the order of 10-30 cms/annum and significantly that continuing erosion tends to be in the vertical rather than horizontal direction (Smith *et al*., 2007b), i.e. gullies get deeper rather than wider. It may take several years of erosion for the process to be identified and quantified by Lidar with much confidence.

Lidar has the capacity to generate very accurate representations of the ground surface and when combined with depth to the peat bottom in a GIS, 3 D models of the peat resource can be generated. This has been done by Lenihan (2008) and Boehm and Frank (1980). Peat volumes have been calculated for a number of Scottish bogs based on the depth data alone combined with the bog area (for example DAFS 1968). It may prove instructive to consider how these calculations compare with ones generated using Lidar data for the bog surface and a modelled interpolation of the bog/mineral interface based on the much sparser data obtained by coring. If both results are within 10% of each other, Lidar probably does not add sufficient value for it to be used more widely.

Lidar data costs proved difficult to obtain but costs for 200 square kilometres varied from £17,000 (M Evans pers. comm.) to £55,000 (web). As far as is known, this is the cost of raw data and there are additional costs associated with data processing before it could be used. Current Lidar coverage is very scarce in Scotland and apart from the major cities, it is only available if a mission is specifically flown in the area.

Other methods with potential in peatland applications

Accurate estimates of C stocks rely on good quality bulk density data and radio wave moisture probes offer an alternative to the destructive method of obtaining soil cores (Hanninen *et al*., 1992). Obviously there would be a need for cross validation between the methods

Virtanen and Lersii (2008) have demonstrated that airborne gamma radiation can differentiate shallow and deep peatland areas and help identify areas for further research and survey. The method is based on the natural radioactivity of the mineral soil underlying the peat. There is no signal from areas where the peat is greater than 0.5 metres thick and the signal is strongest from mineral soils. The method is best at separating peat from other soils but cannot be used for assessing peat stocks. Therefore airborne gamma radiation may have a use in distinguishing between the peat and non peat components of soil complexes where at present only standard approximations of the different proportions of different soils are available.

4. Using ECOSSE to improve estimates of changes in soil carbon stock

4.1. Use NSIS data to improve the accuracy of ECOSSE and its ability to predict the response of Scotland's organic soils to external change

4.1.1 Introduction

The ECOSSE model was run at all phase 1 and phase 2 National Soil Inventory of Scotland (NSIS) sites (see section 2 for a detailed account of these data), using real weather data and the limited soil, land use and management data that would be available in the large scale national simulations (see figure 4.1.1). By comparing the simulated values with the measurements of soil C at the resampling date, these simulations were used to test the accuracy with which the model simulates changes in C content associated with the changes in climate as well as land use change over the ~30 year period between sampling dates. This assessment was done using data from the 62 phase 1 sites that have already been re-sampled. The model was modified and the improved simulations reassessed with respect to the NSIS_2 data. Subsequently, in a blind test, the model will be used to predict the changes in C contents expected in the phase 2 NSIS_2 sites (to be verified at a later date, when the samples have been taken).

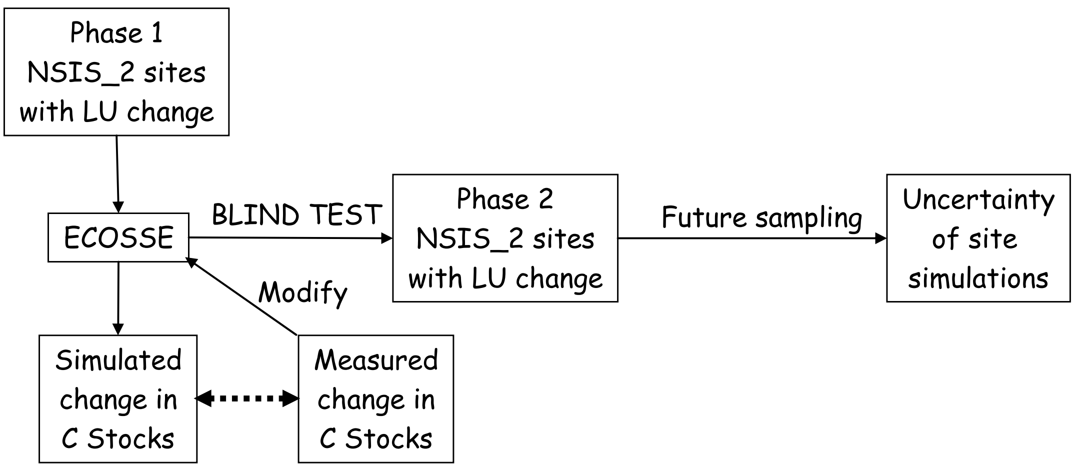


Figure 4.1.1. Approach to evaluating performance of ECOSSE against NSIS_2 data

Good model performance is indicated statistically by simulations and measurements that are both coincident (indicating a close fit) and associated (indicating the trends in measurements are replicated). Where measurements are replicated, the coincidence between simulated and measured values is best expressed as the lack-of-fit statistic, and the significance of the coincidence determined using an F-test (Whitmore, 1991). However, replicates are not provided in the NSIS data, so the degree of coincidence was instead determined by calculating the total error as the root mean squared error and the bias in the error as the relative error (Loague & Green, 1991; Smith *et al*., 1996; 1997). The association between simulated and measured values was calculated as the correlation coefficient, and the significance of the correlation was determined using a t-test (e.g. Chatfield, 1983). Sources of model error were also examined using graphical plots.

Because the detail in the input data was limited to that available at the national scale, these simulations provide an estimate of the uncertainty associated with simulations when the model is run using the national soils database to estimate changes in soil C stock for all of Scotland. This result is used in the description of the national scale simulations.

4.1.2. Input data

Soil

The Macaulay Institute provided the data from the NSIS sites that is required to run ECOSSE. The NSIS_2 sites follow a 20 km^2 grid, based on a sampling round carried out ~30 years ago (NSIS_1). Data from both NSIS_1 and NSIS_2 resampling times for the 62 phase 1 sites were used in the evaluation of ECOSSE. Data from the NSIS_1 sampling time only were also made available at a further 120 phase 2 sites. These data were used to predict changes in C at the NSIS_2 resampling time and could be used in future work in a blind test of ECOSSE when the NSIS_2 resampling is complete.

Land use change

The original land use at the NSIS_1 sites and any changes in land use occurring before the NSIS_2 resampling were used as inputs to the simulations. Note that no exact dates of land use change are available, and it was assumed that land use change occurred half way through the simulation period. This introduces uncertainty in the model inputs, which will be discussed later.

Weather

The weather data were downloaded as a grid of 5 km^2 from the climate monitoring service of the MetOffice UK: http://www.metoffice.gov.uk/research/hadleycentre/obsdata/ukcip/index.html. Long term average monthly data are based on the period of 1961-1990. Actual monthly data are only available up to 2005. This restricts the evaluation period to 2 years before the NSIS_2 resampling time, which was spring 2007.

4.1.3. Data preparation

Data from 62 NSIS (1+2) sites were reformatted as inputs to ECOSSE and used to run ECOSSE simulations at each site. The C contents measured in the NSIS_1 sampling were used to initialize the model run using long-term average weather data and assuming the soil organic C is in a steady state. The simulation was then run forward to 2005 using actual monthly data for the simulation period. NSIS_2 measurements of soil C were used to evaluate the model performance.

For litter layers, such as “L”, “F” or “LF”, C data were mostly missing. Since the data were missing, the model simulations in these layers could not be evaluated. Therefore, they were omitted from the simulation and horizon depths of layers below were adjusted so the first layer in the simulation would always start with 0 cm. Note that the national simulations (section 4.2) included all layers in the soil profile as given in the national soils database and did not omit litter layers. Layers of rock were defined as the bottom of a profile and water impermeable and iron pan layers were defined as fully water impermeable. Some layers included two entries in the database as the horizon showed different attributes across its depth. The average of the two attributes was used in the simulations.

The total C was calculated for each depth using bulk density and % C. The amount of C was corrected for the percentage of stones in the soil. In some instances, NSIS_2 did not have the same percentage of stones as recorded in NSIS_1. This is likely to be due to spatial variability at the site coupled to errors in locating the original sampling point plus error in locating the resample (reduced by use of GPS). To allow a fair comparison between C contents at the two sampling times, the NSIS_2 C contents were adjusted to assume the percentage of stones found in NSIS_1. Horizon depths were corrected similarly.

In order to process the large number of data, R scripts were developed to assist in input and output generation and create graphical and tabular output. The script can be used with a small modification to the standalone version of ECOSSE.

Note that although the model was run at all 62 sites, due to the size of the inherent experimental error, the results were only used for model evaluation at the 9 sites where land use change had occurred. This is explained further below.

4.1.4. Results

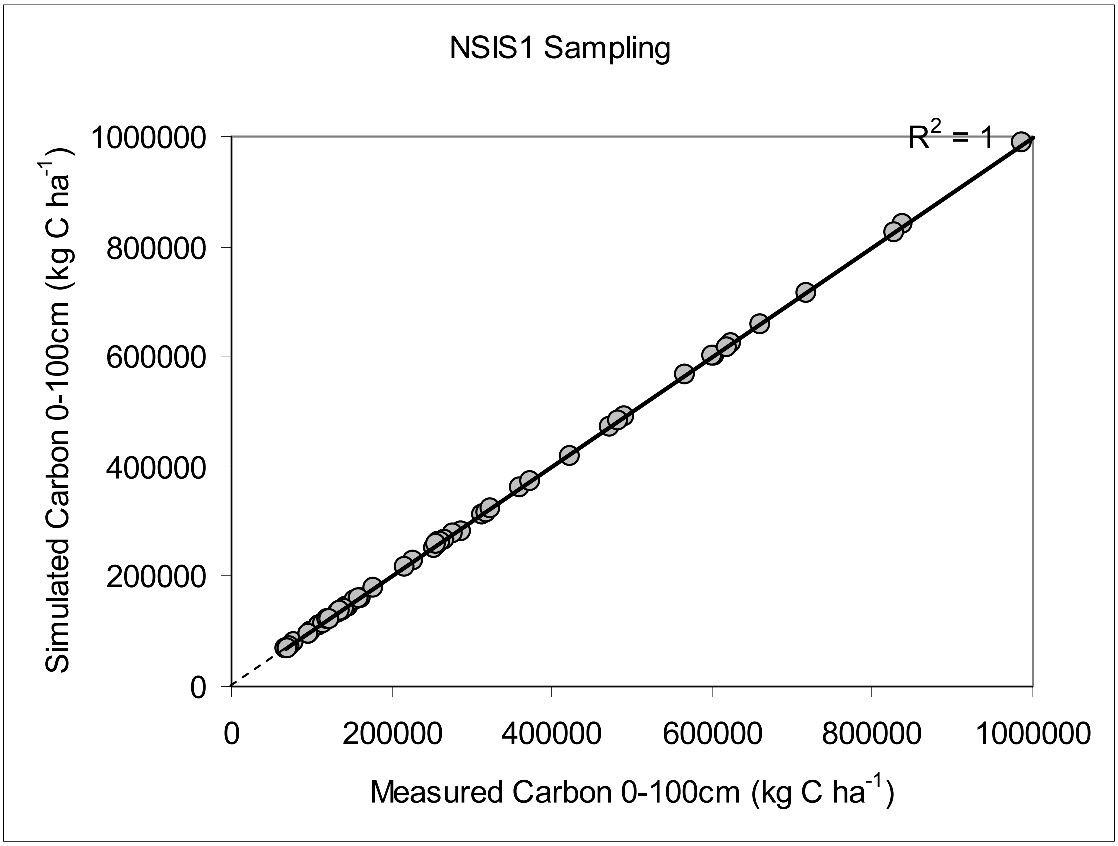
Figure 4.1.2 shows the simulated soil C plotted against the measured data at the time of NSIS_1 and NSIS_2 samplings. The 1:1 line is given in the plots, and represents perfect agreement between the simulations and the measurements. The close agreement between the points and the 1:1 line in the NSIS_1 plot indicates that the model is correctly initialised using the NSIS_1 data. The spread of points around the 1:1 line increases in the NSIS_2 plot, indicating some errors in the simulation of changes in soil C with time. However, over all sites, the correlation between the simulated and the measured values is high and statistically significant (r^2 = 0.94; P < 0.001).

As indicated in table 4.1.1, the correlation between simulations and measurements is statistically significant for all land uses. Overall, the total error between the simulated and measured values of C at the NSIS_2 resampling time is 20% of the average measurement. The accuracy of the simulations decreases in the order natural/semi-natural > forestry > arable > grassland. As will be discussed below, errors between simulations and measurements occur in some simulations. These are associated with inaccuracies in the measurement inputs, as well as being due to the errors in the model. However, because these errors are all part of the uncertainties encountered in the simulations at large scale, it could be argued that these values of uncertainty should be used to represent the potential uncertainty in the simulations at national scale.

Since it is the change in C content that is of interest in these simulations, the simulated change in C content was compared to the measured C change. This is expressed as a percentage change to normalise the impact of C change at high and low C content sites (Smith *et al*., 1996). Unfortunately, the errors in the measurements with this type of resampling exercise can be extremely high. This is due to inherent spatial variability especially at unmanaged sites as well as the time period of unrecorded management between the first and second sampling dates and the difficulty in relocating sampling sites. As illustrated in figure 4.1.3, at sites where no land use change has occurred, the errors in the measurements are larger than the variation in soil C, and so no meaningful statistical analysis is possible. The sites where land use change has occurred are shown in figure 4.1.4. It is only these sites, where land use change has occurred, that are included in the following analysis.

	Association		Lack of Coincidence
Land Use	**r^2**	**P-value**	**RMSE (%)**
Arable	**0.91**	**<0.001**	**21**
Grassland	**0.93**	**<0.001**	**39**
Forestry	**0.97**	**<0.001**	**19**
Natural/semi-natural	**0.94**	**<0.001**	**15**
Over all land uses	**0.94**	**<0.001**	**20**

Table 4.1.1. Evaluation of degree of association and coincidence between values simulated by ECOSSE using the limited data input available at national scale and measurements at the 62 first phase NSIS sites



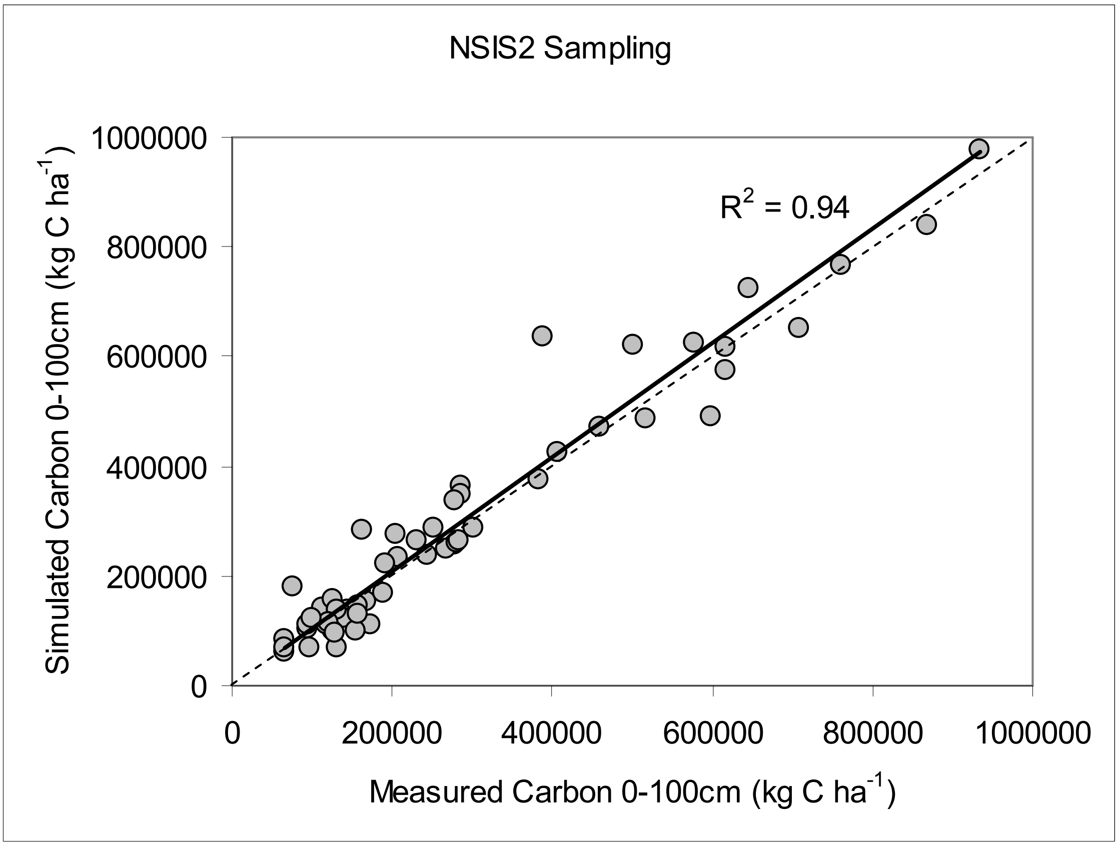


Figure 4.1.2. Simulated vs measured values of soil organic carbon in the soil profile 0-100cm at the time of the NSIS1 and NSIS2 samplings

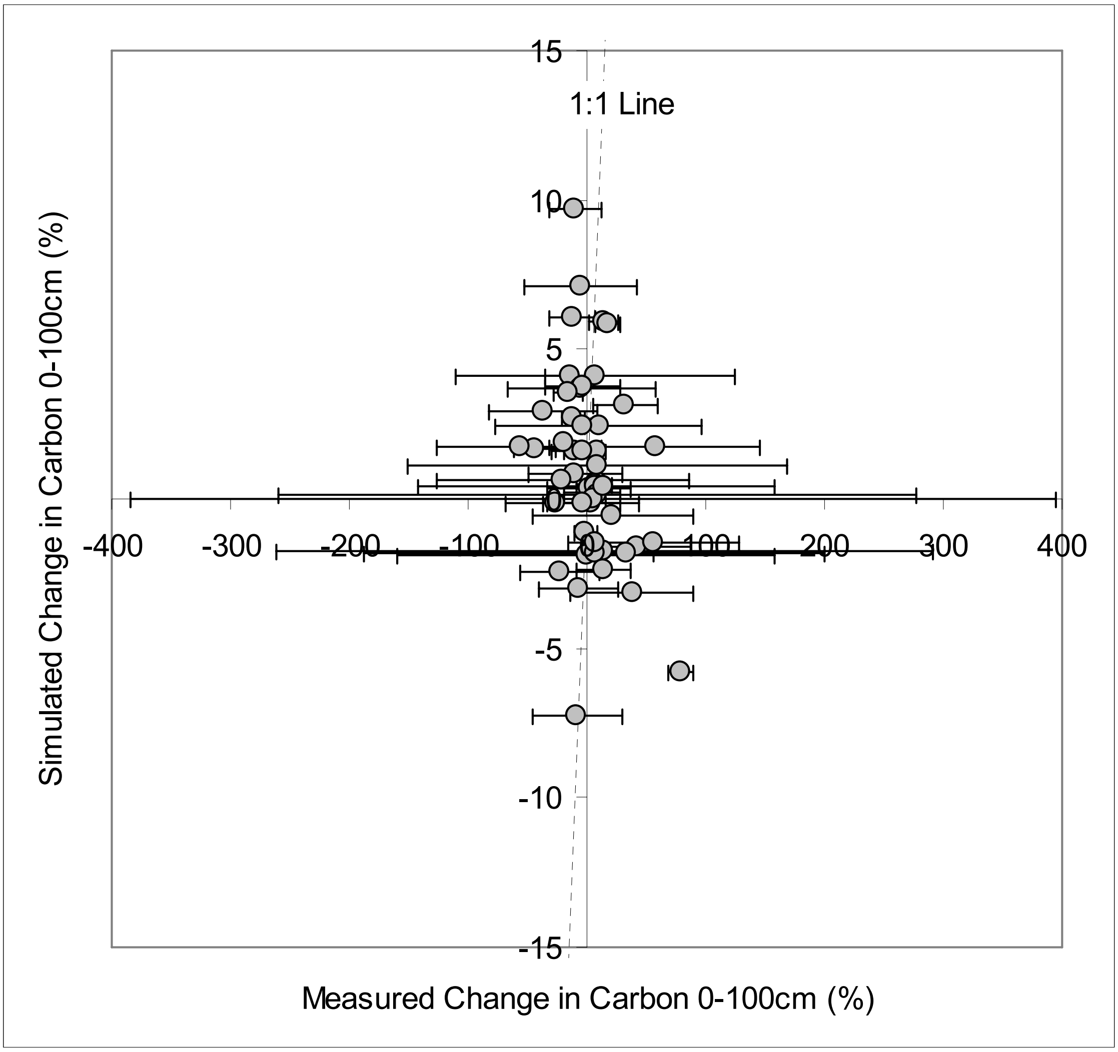


Figure 4.1.3. ECOSSE simulated values against measured values of change in carbon content for the NSIS sites where no land use change has occurred. The error bars show the 95% confidence interval for the measured values.

Land use change	Site	Soil association / series / type	95% confidence interval for % change in soil C
Arable to grassland	**NJ200600**	Alluvial / Traquair	**68**
	NN600000	Alluvial / Lochside	**35**
	NO000200	Balrownie / Balrownie / Brown forest soil with gleying	**69**
Grassland to arable	**NJ400600**	Tynet / Aulthash	**19**
	NJ800200	Tarves / Thistlyhill / Brown forest soil with gleying	**38**
	NK000600	North Mormond / North Mormond	**13**
	NO800800	Auchenblae / Auchenblae	**31**
Natural to forestry	**NN600600**	Arkaig / Kildonan / Peaty podzol	**21**
	NO000600	Strichen / Strichen / Humus iron podzol and iron podzol	**180**
		Average	**53**
		Average excluding sites with 95% CI over 35%	**24**

Table 4.1.2. Estimated errors in measurement at the 9 NSIS sites where land use change occurs

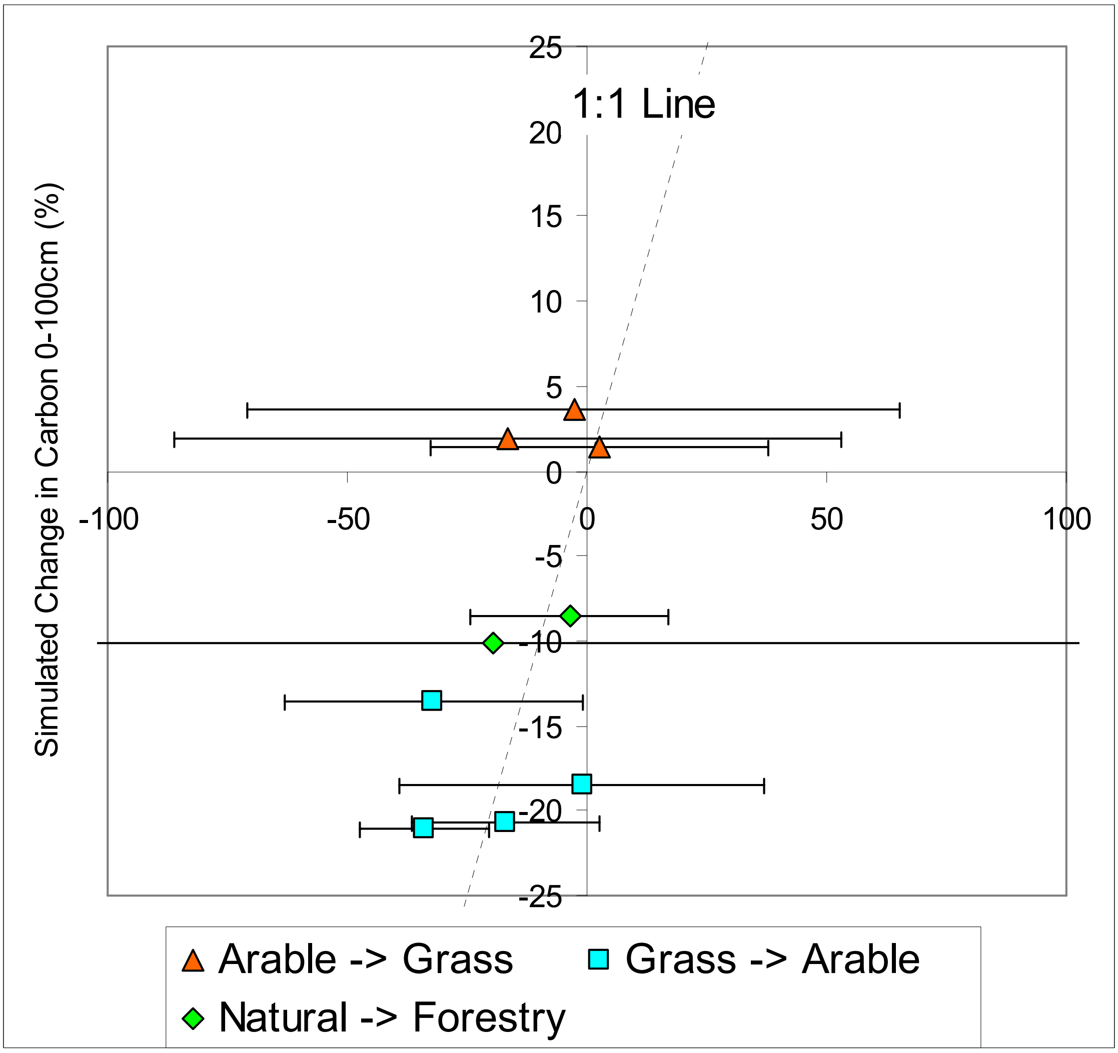


Figure 4.1.4. ECOSSE simulated values against measured values of change in carbon content for the 9 NSIS sites where land use change has occurred. The error bars show the 95% confidence interval for the measured values.

Simulation of change in C content is a more stringent test of the model than the simulation of total C content. Over all sites where land use change has occurred, the correlation between the simulated and the measured values is given by r^2 = 0.25. This is not significant, suggesting the simulations and measurements are not highly associated. However, the picture changes when the experimental error is taken into account. The 95% confidence intervals of the measured values are shown on the plot, and are also given for each land use change site in table 4.1.2. For four sites, the 95% confidence intervals of the measurements are very high; greater than 35%. If these sites are excluded from the analysis, the correlation coefficient increases to r^2 = 0.80. Although the r^2 value is high, this is still not significant, due to the low number of measurements now included in the comparison (only 5). However, the simulated values are all within the measured 95% confidence interval of the 1:1 line between simulations and measurements, suggesting the association between simulations and measurements is within experimental error.

The average deviation between the simulations and the measurements is only 11% if all points are included and 7% if the measurements with high experimental error are excluded. This is less than the average measured deviation at the 95% confidence interval (53% for all points and 24% when measurements with high experimental errors are excluded). Therefore, the coincidence between the simulations and the measurements is also well within experimental error; the model cannot be improved further against this data (Smith *et al.*, 1997). The bias in the simulations is very low; -4% for all measurements. Therefore, only a small systematic underestimate (-4%) is expected in the national simulations.

The simulations at the sites where land use change have occurred are all within the experimental error, but at 25% of the sites without land use change (22% of all sites), the simulated values show a greater deviation from the measurement than the recorded experimental error (see figure 4.1.5).

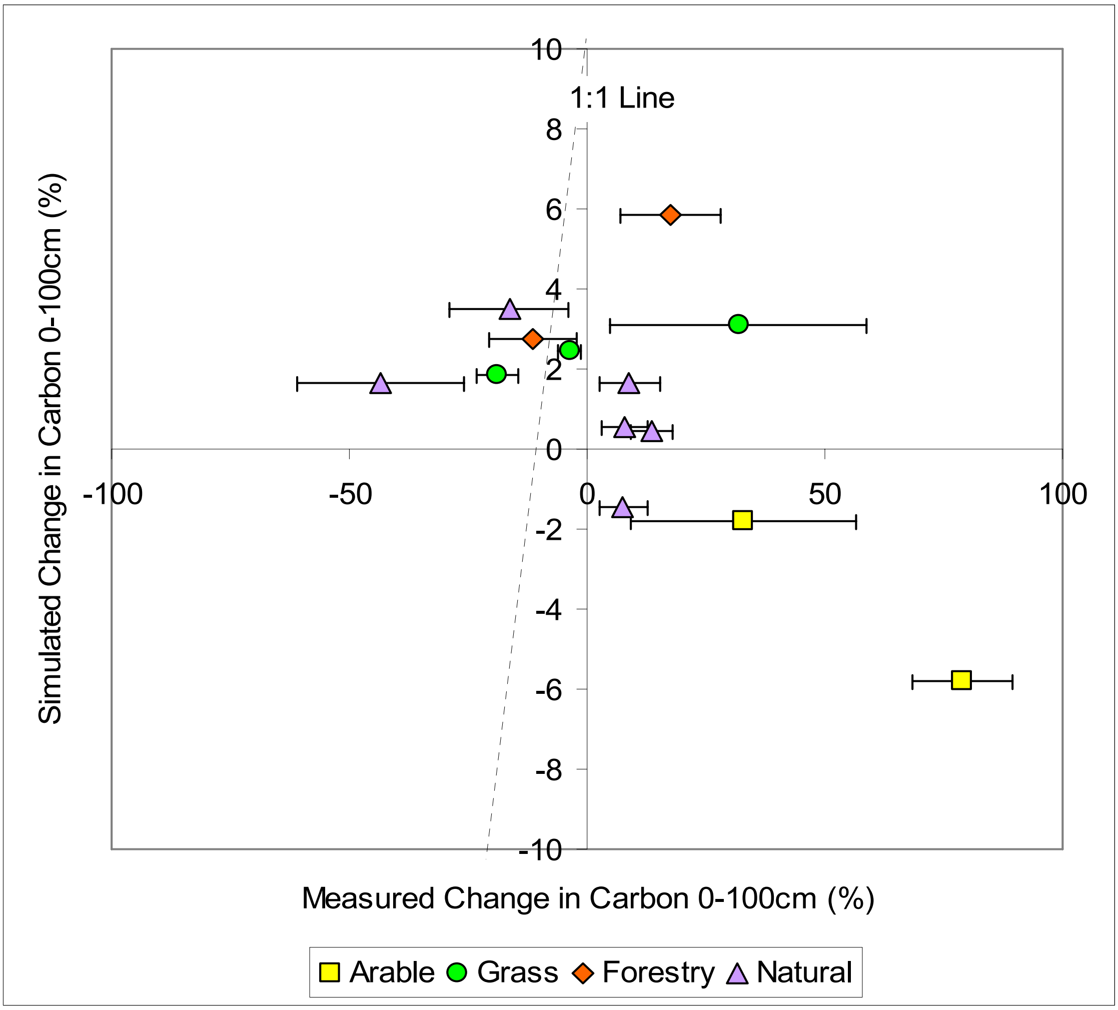


Figure 4.1.5. ECOSSE simulated values against measured values of change in carbon content for the NSIS sites where no land use change has occurred and the simulations deviate from the measurements by more than the 95% confidence interval in the measured values. The error bars show the 95% confidence interval for the measured values.

The sites where the error between simulations and measurements exceeds the recorded experimental error include all land use types, so no systematic error due to including a particular land use type has been identified. At two arable sites, ECOSSE simulates a small decline in soil C (-2% and -6%), whereas a large increase is measured (+33% and +79% respectively). It is unlikely that such a large increase in soil C would occur without some change in land use or management. This illustrates one type of error that occurs due, not to the failure of the model, but rather due to the shortage of information available to run the model (as would be the case at the national scale). These errors may have been attributable to the use of improved crop varieties, changes in cropping practice (such as straw incorporation), or an interim period of grassland resulting in a build up of soil C before the land is converted back to arable. Similarly, at two grassland and two semi-natural, a relatively large decline in soil C is measured (grass = -19% and -4%; semi-natural = -43% and -16%), whereas the model simulates a small increase (grass = +2% and +3%; semi-natural = +2% and +4%). This again could be due to an interim period of land use change, resulting in the reduction in soil C, before the land is converted back to grassland or semi-natural use. At one forestry site, a relatively large decline in soil C is observed (-12%), whereas an increase is simulated (+3%). This may be attributable to disease, drainage of a highly organic site or incorrect assumptions about the age class of the forestry. At the remaining sites, the simulated values have the same sign as the measurements, and are usually only slightly outside the reported experimental error.

4.1.5 Conclusions

Simulations have been run at all 62 sites included in the first phase of the NSIS_2 analysis. The simulated values show a high degree of association with the measurements in both total C and change in C content of the soil. The uncertainty in the simulations is 20% of the average C content over all land use types, uncertainty increasing in the order natural/semi-natural < forestry < arable < grassland. Over all sites where land use change occurred, the average deviation between the simulated and the measured values of percentage change in soil C was less than the experimental error (11% simulation error, 53% measurement error). This was still the case if measurements with very high experimental error were excluded (7% simulation error, 24% measurement error). The correlation between simulations and measurements was not significant (r^2 = 0.25 for all sites; r^2 = 0.80 if sites with high errors were excluded). However, simulated values were within the 95% confidence interval of the 1:1 line between simulated and measured values, so the simulated values were again within experimental error with respect to correlation. Only a small bias in the simulations compared to the measured values was observed, suggesting that a small underestimate of the change in soil C should be expected in the national simulation (-4%).

A large proportion of the uncertainty is associated with uncertainty in the input data: these include uncertainties in

1. timing of land use change,
2. actual management of arable land, grassland and forestry, and
3. unrecorded land use change before the start of and during the simulation.

These factors are also likely to be unknown at national scale, and so the erroneous results due to uncertainty in the input data are included in the estimate of uncertainty in the simulations. There is potential to greatly decrease the uncertainty associated with unrecorded land use change in the national simulations by developing algorithms to estimate the likely rate of C accumulation or loss at the start of the simulation. These algorithms could be developed from long term experiments on the basis of climate, land use and soil type and would be used to set up a standard soil organic matter pool structure for each soil / land use type at the start of the simulation, which then determines the subsequent rate of soil organic matter turnover.

Note that a major limitation of these estimates of uncertainty is the small number of sites included in the first phase of the NSIS re-sampling where land use change had occurred. Improved estimates of uncertainty at the national scale could be achieved by including more land use change sites in the next phase of resampling. Sub-sampling all land use units within >20 x 1km^2 grid squares across the country and repeating the simulations of changes in C content done here would greatly improve estimates of uncertainty. This would require changes to the long term soil sampling strategies. The costs /benefits of such a change in land use monitoring should be considered further.

4.2. Use national scale simulations of ECOSSE to address policy questions

4.2.1. Introduction

The ECOSSE model was used together with soils, land use and weather data to simulate changes in soil C content across the whole of Scotland. Soils and climate data were available on a 1km^2 grid across Scotland, whereas land use and land use change data were only available on a 20km^2 grid. The land use and land use change data were interpolated, allowing results to be reported on a 1km^2 grid.

Simulations were of three types:

1. Historical simulations to determine changes in soil C content each decade since 1950, apportioning the losses to different soil types and changes in land use. These address the policy questions: “What C emissions can be attributed to Scottish soils?”, “Which land use changes are responsible for the losses in soil C?” and “On which soil types do most losses in soil C occur?”.
2. Future simulations using projected changes in land use and climate. These address the policy questions: “What are the changes in soil C due to projected land use change over the next decade?” and “What are the changes in soil C due to projected climate change during this century?”.
3. Calculations of the potential of different mitigation options to reduce soil C losses. These address the policy question: “Which mitigation options are most likely to reduce losses of soil C?”.

The revised national estimates of changes in soil C stocks not only determine the total change in soil C, but also apportion the observed change to specific changes in land use, management or climate. This is of crucial importance if we are to implement effective mitigation measures to protect vulnerable soil C sinks (Reay *et al*., 2007). Bellamy *et al*. (2005) suggest a link to climate change to explain the observed mean loss of soil organic C of 0.6% yr^{-1}, between 1978 and 2003 in England and Wales. The attribution to climate change has been questioned (Smith *et al.,* 2007b). The findings also contradict evidence that the UK and Europe as a whole is a net CO_2 sink (Janssens *et al*., 2003) and data from another long term study of soil organic C in British woodlands (Kirkby *et al*., 2005) suggesting a small increase in soil organic matter over 30 years (0.094% increase y^{-1}). Other repeated sampling studies in Europe have shown contrasting results, with some showing loss of soil organic C (e.g. for Flemish cropland soils; Sleutel *et al*., 2003), attributed to changing manure application practices, and others showing no loss of soil organic C (in Danish croplands; Heidmann *et al*., 2002 and in Austrian soils; Dersch & Boehm, 1997). Our results provide modelling evidence that will allow the observed C changes in Scottish soils to be attributed to different drivers, and will provide an important contribution to this debate.

4.2.2. Adaptation of ECOSSE to use new data

Changes completed in ECOSSE to allow it to run with the new data include the following:

- Initialisation of C pools and plant input
  - Optimisation of plant input to achieve zero C change under steady state conditions
  - Analytical solution of initialisation of C content and plant input under equilibrium conditions (Hillier solver)
  - Initialisation of C pools for soils that are not at equilibrium, but accumulating C (note, standard soil pool structures derived from long term experiments for each land use / soil type would be needed to simulate soils that are already loosing C).
  - Weighting of soil variables according to proportions coming from each SOM layer.
- Changes to description of soil water
  - Description of impermeable soil layer
  - Changes to use wetness class in model runs
  - Changes to allow water content below wilting point
- Improvement of simulation of methane production and oxidation
  - Adjusted pH effect on methane oxidation

- Improved diffusion routine
- Changes to input/output
  - Changes to format to include soil pH and soil wetness class
  - Changes to allow a variable number of layers in the soil profile
  - Hole filling of missing data
  - Changes to allow simulation of future projections in land use
  - Changes to use UKCIP weather data scenarios for future simulations

4.2.3. Historical Simulations

Soil Data

The national soil spatial dataset

The soil attribute dataset is based on the component soils that are delineated on the national scale 1:250 000 scale soil map. This soil map covers the whole of Scotland and comprises 580 soil map units. The vector dataset has been converted to raster format into 100m grid cells. The mapping took place between 1978 and 1982 and incorporated existing 1:63 360 scale mapping to give complete coverage of Scotland with a common framework. The nature of this reconnaissance scale mapping means that soil/landscape units were identified and mapped rather than individual soil types as is common with greater resolution mapping.

The soils are mapped by a procedure known as 'free survey' in which the soil surveyor selects the soil profile sites by using his field knowledge of soil forming processes in relation to the factors he observes in the landscape. As the mapping was done at a reconnaissance scale, landform units that recur throughout Scotland were used as the basis for delineating soil/landscape units (Soil Survey Staff, 1984). These soil/landscape units were also found to contain a similar set of soils although the type of parent material varied. A combination of parent material (soil association) and landform was used to construct a numeric soil key which contained 580 soil units (plus some subdivision of the organic soil units). This approach means that individual map units are likely to contain more than one soil type. The soils were mapped at the major soil subgroup taxonomic unit (mssg) rather than at the soil series level, which is used in more detailed mapping.

Subsequent work identified the component soil series of each of these 580 map units (that is, a specific mssg with a specific drainage category developed on similar parent materials) and the approximate proportion of each soil series within the soil map unit was determined by expert judgment (and partial validation). Because of the broad scale approach of this mapping, only 530 soil series were delineated within this spatial dataset. This set of soil series and their proportions is the basis of the national scale spatial dataset.

The 1:250 000 scale soil map has been digitised and the resulting vector dataset has been converted to raster format to a resolution of 100m grid cells. The proportion of each soil map unit in each of these 100m cells was determined within a GIS, multiplied by the proportion of individual soil series within each map unit and summed to derive the proportion of each soil series within each grid cell. The results were then ranked by areal extent and the top 5 most extensive soils and their proportions selected to represent the component soils of that grid cell. This resulted in a spatial dataset of approximately 80 000 geo-referenced grid cells with the top 5 most extensive soil series and their proportions.

Soils data requirement of the GIS version of ECOSSE

The data requirements of the model are summarised below.

Soil distribution (1 km^2 Grid)

- 20km^2 gridID
- 1km^2 gridID
- Easting
- Northing
- Area (m^2)
- Series 1-5

- % of cell under series (note, total of all 5 series may be less than 100%)
- Soil depth for series (cm)
- Soil wetness class for series

Soil characteristics

For each horizon and for each of arable, grassland, forestry and semi-natural soils:

- Top depth (cm)
- Bottom depth (cm)
- % C
- C (kg x 10^6 km^{-2})
- % Clay
- % Silt
- % Sand
- Bulk density (g cm^{-3})
- pH

An existing attribute dataset which is linked to the soil spatial dataset via the soil series was used to derive the soil data required for the model. SSKIB (Scottish Soils Knowledge and Information Base; Lilly *et al.*, 2004) holds statistical summary data for a set of typical soil horizons for each soil series delineated on the 1:250 000 soil map of Scotland.

Derivation of data for cultivated and semi-natural soils

Using expert knowledge, typical horizon sequences and depths were derived for each of the 530 soil series in the national spatial dataset. These were based on the central concepts of each series and took account of the information contained within the Scottish soil morphological database. A distinction was made between cultivated and uncultivated versions of the same soil series as both the soil chemistry and horizon sequences differ. Once the typical horizon sequence had been derived, summary statistics were derived from the Scottish soil analytical database. Only soil horizons that matched those selected as being typical for that series were used in the derivation of the summary statistics. Certain criteria were applied; for example, where a horizon nomenclature matched the typical horizon but the organic C content was outside normal limits, the horizon would be eliminated from the statistical analyses. Similarly, data for horizons sampled at depth below 1m were ignored. Where horizons could be designated with more than one horizon, for example, Bsh or Bhs, these were treated as being synonymous.

SSKIB contains, amongst other attributes and contextual information, summary data on the number of horizons used in the calculations, the geometric mean, the mean, the median and standard deviation, minimum and maximum values for a wide range of physical and chemical attributes derived from the Scottish soil analytical database. An example of the range of these soil attributes is shown in Table 4.2.1. Where no values were determined as there were no data for the specific series, data from an analogous series were used. Where a specific attribute had no data, this was generally due to very low values which were below the detection limit. In these cases, the detection limit was applied as the attribute value. In some cases there were limited soil profiles available and so the standard deviation of some or all soil properties could not be determined.

HOR_SYMB	Soil horizon notation
SERCODE	Soil Survey of Scotland 5 figure numeric code applied to each Soil Series
LOI	Loss on Ignition (percentage)
CA	Calcium content (meq/100g)
MG	Magnesium content (meq/100g)
NA	Sodium content (meq/100g)
K	Potassium content (meq/100g)
H	Hydrogen and Aluminium content: Exchangeable acidity (meq/100g)
SUM	Sum of the Mean values of all exchangeable cations (Ca, Mg, Na, K and H)
SATN	Percentage saturation of Mean values of base cations (Ca, Mg, Na and K) as a proportion of the Sum of exchangeable cations.
PHW	pH in water
H(ueq/L)	H ion equivalent of soil pH
C	Elemental Carbon content (percentage)
N	Elemental Nitrogen content (percentage)
DER_OM	Organic Matter content derived from Mean value of C*1.724
TOTP	Total Phosphate (mg P2O5/100g)
CLAY	Percentage clay (<2microns)
SILT	Percentage silt (2- 50/60 microns)
SAND	Percentage sand (50/60- 2000 microns) calculated from (100-(clay+silt))

Table 4.2.1. The physical and chemical soil attributes contained within SSKIB

The dataset supplied for use in ECOSSE modelling contains a subset of SSKIB. Mean values for a range of attributes were derived from SSKIB along with contextual information. These are shown in Table 4.2.2.

SERIES	Soil Survey of Scotland Soil Series name
SERCODE	Soil Survey of Scotland 5 figure numeric code applied to each Soil Series
LANDUSE	Whether the soil profile is from arable, grassland, forestry or semi-natural land cover types
HOR_SYMB	Soil horizon notation
UPPER_DEPTH	Upper depth of the soil horizon
LOWER_DEPTH	Lower depth of the soil horizon
MEAN_PHW	Mean value of pH in water
MEAN_C	Mean value of elemental Carbon content (percentage
MEAN_CLAY	Mean value of the percentage clay (<2microns)
MEAN_SILT	Mean value of the percentage silt (2- 50/60 microns)
MEAN_SAND	Mean value of the percentage sand (50/60- 2000 microns)
SD_PHW	Standard deviation value of pH in water
SD_C	Standard deviation value of elemental Carbon content (percentage)
SD_CLAY	Standard deviation value of the percentage clay (<2microns)
SD_SILT	Standard deviation value of percentage silt (2- 50/60 microns)
SD_SAND	Standard deviation value of percentage sand (50/60- 2000 microns)
Db	Dry bulk density of <2mm fraction predicted by pedotransfer functions based on clay, silt and organic carbon contents
STONE_CONTENT	Estimate of the percentage of stones in each horizon

Table 4.2.2. SSKIB contextual and attribute data derived for the ECOSSE project

Translation of data into arable, grassland, forestry and natural / semi-natural categories

As previously described, SSKIB summary statistics were calculated for cultivated and semi-natural soils. However, data were required for arable, grassland, forestry and semi-natural land uses. Soil profiles under afforested land often acquire an LF layer which is either thin or absent from many semi-natural soils. This has implications for the estimated C content of these soils. Similarly, there are generally differences in organic C contents and pH of soils under arable compared with those under grassland. In order to derive estimates of C and pH for the 4 land uses, correction factors had to be derived as the C contents and pH values of soils in SSKIB were averages of both arable and grassland soils (cultivated) and of both semi-natural and afforested soils (semi-natural).

Values for both pH and C content of cultivated topsoils from the Scottish Soils Analytical Database were classified according to whether the land use was recorded as arable or grassland (soils with rotational grassland, which is part of an arable rotation, were treated separately). The mean C content and pH were then determined for arable (n=2055 and 2009) soils and for grassland soils (n=152 and 142) where C contents were less than or equal to 15% (mineral and humic soils only). The mean C content of all cultivated soils was 3.8% while the mean for arable soils was 3.6% and 5% for grasslands. Therefore, 0.2% was subtracted from all SSKIB topsoil C mean values to derive a value for arable soils while 1.2% was added to derive a value for C contents of grassland soils. For pH, arable topsoils were increased by 0.04 pH units while grassland topsoils were decreased by 0.46.

There were only slight differences in organic C contents of surface organic layers under forestry compared with semi-natural soils with some horizons having greater organic C contents in afforested soils compared with semi-natural and *vice versa* so no adjustment was made. Instead, the average thickness of an 'LF' horizon (which also included F, FH and L horizons) under afforested soils was determined along with average C content and its standard deviation. This horizon was added to all semi-natural soil profiles to derive an afforested soil profile. The bulk density of the LF horizon was taken from a number of measured LF horizons rather than being derived by pedotransfer functions.

Stone Content

Stone content is included so that estimates of volume of C can be adjusted for stony soil horizons. Each data field is labelled according to the horizon number (up to 9) and by land use e.g. A1 is the first arable horizon, SN1 is the first semi-natural horizon.

Soil Wetness class

The soil wetness class was determined for each of the 5 most extensive soil series in each 1 km grid cell. Soil wetness class was determined by combining soil and climate data (Lilly *et al*., 2003). Soil Wetness Class is an attribute that has been used in UK national land evaluation systems for many years (Bibby *et al*., 1982; MAFF 1988) and allows all soils in the UK to be assigned to one of six classes based on the depth to, and duration of, saturated conditions as indicated by the presence of a water table (Table 4.2.3). By definition, it represents long term, typical conditions (Hodgson, 1997). Soil Wetness Class can be predicted using pedotransfer rules (Jarvis *et al*., 1984; Lilly and Matthews, 1994) based on the attributes of depth to a slowly permeable layer (Ks < 10 cm day $^{-1}$) and depth to gleying. In essence, Soil Wetness Class uses basic soil information to refine the climate attribute 'Field Capacity Days'. This attribute is derived from modelled predictions of evaporation from standardised conditions; a deep, loamy soil under a short grass crop with no inhibition to drainage and a large store of water. Differences in soil drainage and soil texture from these standardised conditions will alter the number of days that a soil is saturated.

Wetness Class	Duration of Waterlogging
I	**The soil profile is not waterlogged within 70 cm depth for more than 30 days in most years.**
II	**The soil profile is waterlogged within 70 cm depth for 30-90 days in most years.**
III	**The soil profile is waterlogged within 70 cm depth for 90-180 days in most years.**
IV	**The soil profile is waterlogged within 70 cm depth for more than 180 days, but not waterlogged within 40 cm for more than 180 days in most years.**
V	**The soil profile is waterlogged within 40 cm depth for 180-335 days, and usually waterlogged within 70 cm for more than 335 days in most years.**
VI	**The soil profile is waterlogged within 40 cm depth for more than 335 days in most years.**

[1] **The number of days specified is not necessarily a continuous period.**
[2] ***In most years* is defined as more than 10 out of 20 years.**
After Jarvis *et al.* (1984)

Table 4.2.3. Definition of Soil Wetness Classes

Figure 4.2.1 gives an indication as to how soil wetness can be temporally distributed. This assumes that the greatest potential soil moisture deficit occurs at the end of July and the dry period is evenly distributed around this date.

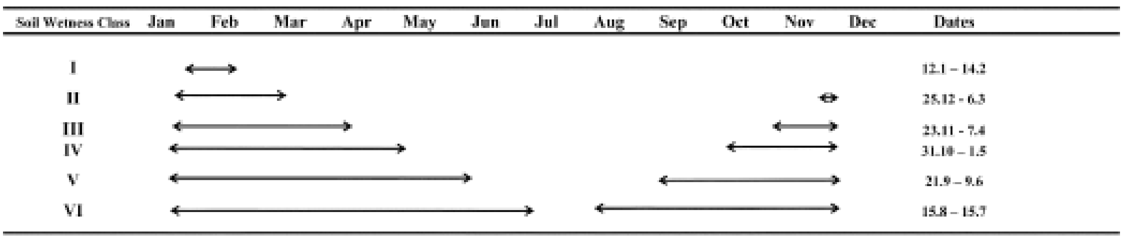


Figure 4.2.1. Periods of the year when soil is deemed wet for each Soil Wetness Class

Land use data

<u>The CEH land use and land use change database</u>

The database includes
- 20km^2 grid cells covering Great Britain (cell ID, northing, Easting)
- 1km^2 cells covering Great Britain (cell ID, northing, Easting)
- Historical decadal land use change (average annual in kha yr^{-1} allocated in each 20 km^2 cell) for 1950-59, 1960-69, 1970-79, 1980-1989, 1990-1999.
- Predicted decadal land use change (average annual in kha yr^{-1} allocated in each 20 km^2 cell) for 2000-2009, 2010-2019.

<u>Land use and land use change data requirement of the GIS version of ECOSSE</u>

The land use and land use change data requirements are as follows:
- 20km^2 gridID
- Easting
- Northing
- In each decade, land use change from…
    - Arable
    - Grassland
    - Forestry
    - Natural / Seminatural

…to

- Arable
- Grassland
- Forestry
- Natural / Seminatural

Derivation of land use data required by the model

The land use change matrices were provided by CEH (A.Thompson, pers. comm.) in a format that can directly be read by ECOSSE and does not need any modifications

Preparation of land use data for use in ECOSSE

Land use change files are the same as used in the ECOSSE project (Smith *et al*., 2007b).

Weather data

The retrospective run of the model uses monthly long-term average data. Data were downloaded as a grid of 5 km^2 from the climate monitoring service of the MetOffice UK: http://www.metoffice.gov.uk/research/hadleycentre/obsdata/ukcip/index.html. Monthly long term average data are based on the period of 1961-1990.

The weather data requirements of ECOSSE are as follows:

- 20km^2 gridID
- Easting
- Northing
- Rainfall (mm $month^{-1}$) Jan to Dec
- Air Temperature (mm $month^{-1}$) Jan to Dec
- Longitude
- Latitude

Results and discussion of historical simulations

Simulated values of changes in soil C were output both on a 1km^2 and a 20km^2 grid. The higher resolution results provide a more accurate estimate of the distribution of results. The lower resolution output allows direct comparison to the CEH estimates of CO_2 emissions.

A comparison of the average changes in soil C content across Scotland as estimated by ECOSSE and by CEH (D.Mobbs & A.Thompson, CEH Edinburgh, summary given in Smith *et al*., 2007b) is shown for 1990-1999 in figure 4.2.2 and for 2000-2009 in figure 4.2.3. The results show the changes in soil C content calculated using a simulation started in 1950. Changes in soil C stocks due to land use change occurring between 1950 and the end of the time slice all contribute to the changes in soil C stocks estimated in the given time slice. The effects on soil C of any land use change that occurred before 1950 will be omitted from the results, but the effect of land use change on soil C diminishes with time, so this is not anticipated to introduce a large error in the estimates.

The results from the two decades are similar. The correlation between the ECOSSE and CEH estimates is given by $r^2 = 0.97$ and $r^2 = 0.93$ for 1990-1999 and 2000-2009 respectively, which is highly significant ($P < 0.001$). A *t*-test also indicates that the mean values estimated by the two approaches are not significantly different in either decade. This provides confidence in the results are these two very different approaches are able to provide broadly similar results. The results do, however, differ in the detail.

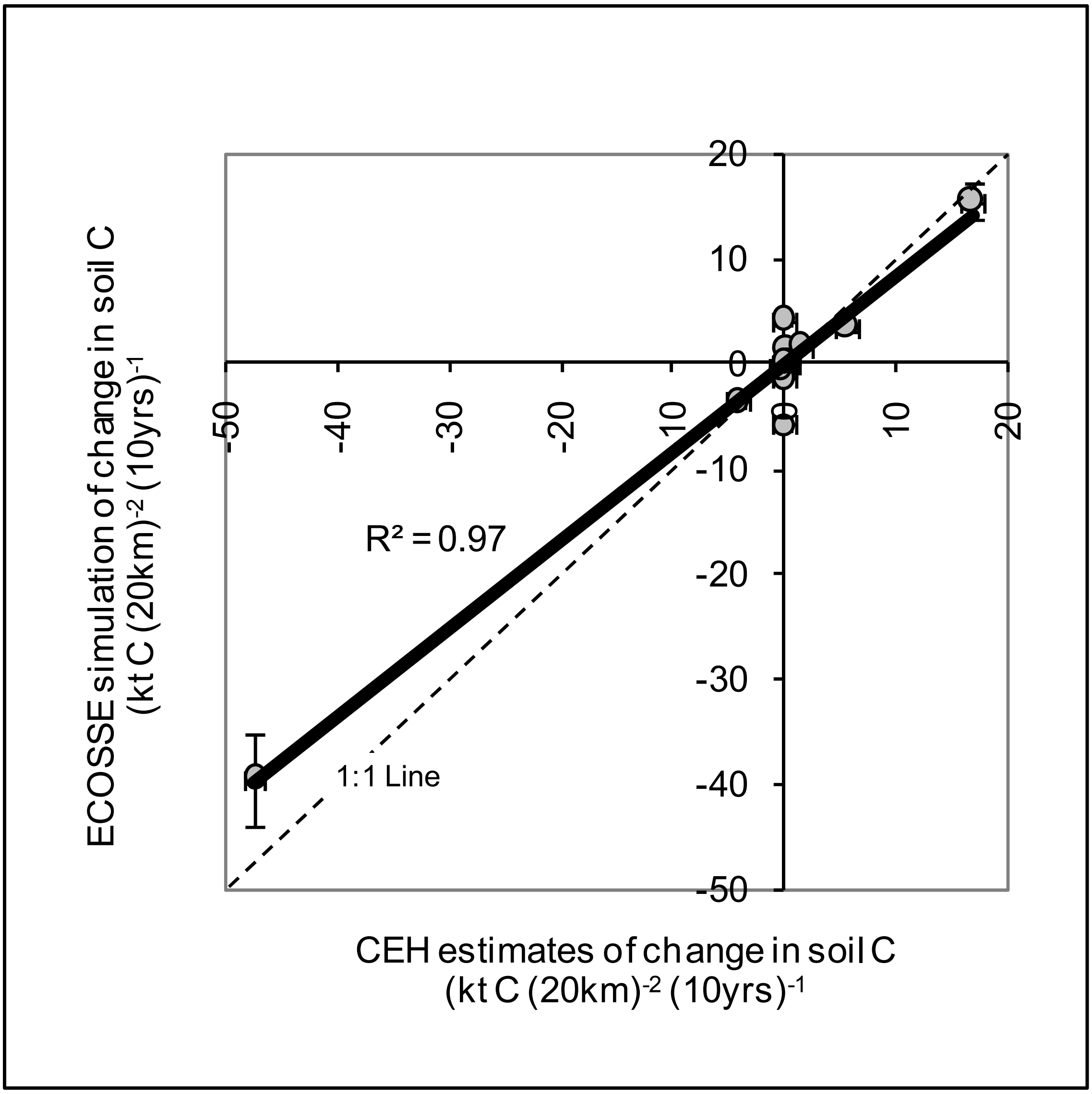


Figure 4.2.2. Comparison of changes in soil carbon content from 1990-1999 due to a range of different land use changes as estimated by ECOSSE and by CEH. Values are averaged across Scotland. Error bars indicate the uncertainty in the simulations calculated from the simulation of NSIS sites as the average deviation of the simulations from measurements (root mean squared deviation = 11%).

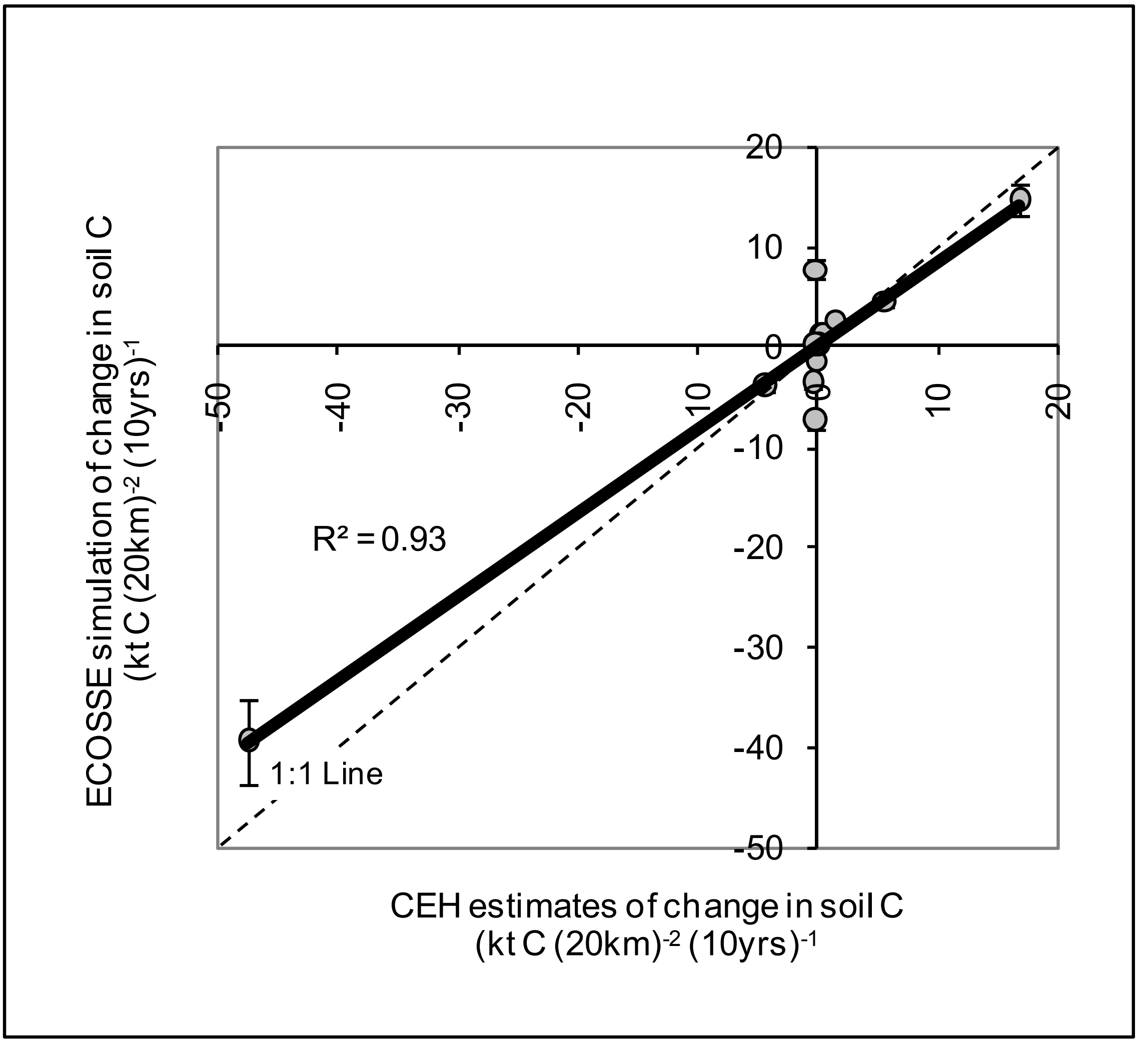


Figure 4.2.3. Comparison of changes in soil carbon content from 2000-2009 due to a range of different land use changes as estimated by ECOSSE and by CEH. Values are averaged across Scotland. Error bars indicate the uncertainty in the simulations calculated from the simulation of NSIS sites as the average deviation of the simulations from measurements (root mean squared deviation = 11%).

The simulated changes in soil C attributed to the different land use changes between 2000 and 2009 are shown in figure 4.2.4. Values are averaged across Scotland. Similar results were obtained between 1990 and 1999. Most land use changes produce changes in soil C estimated by the two methods that are of a similar magnitude and sign. The estimates of changes in soil C made by ECOSSE on land use change semi-natural to grassland show a larger loss of soil C than estimated by the CEH method. Similarly, ECOSSE estimates a larger gain in soil C on land use change grassland to semi-natural. Correspondingly, a larger loss of soil C is estimated by ECOSSE than by the CEH method for the land use change forestry to semi-natural and a smaller gain in soil C for the land use change semi-natural to forestry. These differences occur due to processes that are included in ECOSSE but not in the CEH approach associated with soil disturbance and reduced plant inputs when vegetation is immature. Carbon losses due to soil disturbance and an initial reduction in the plant input result in a loss of soil C or a smaller gain than estimated by CEH for land use changes between semi-natural land and grassland or forestry.

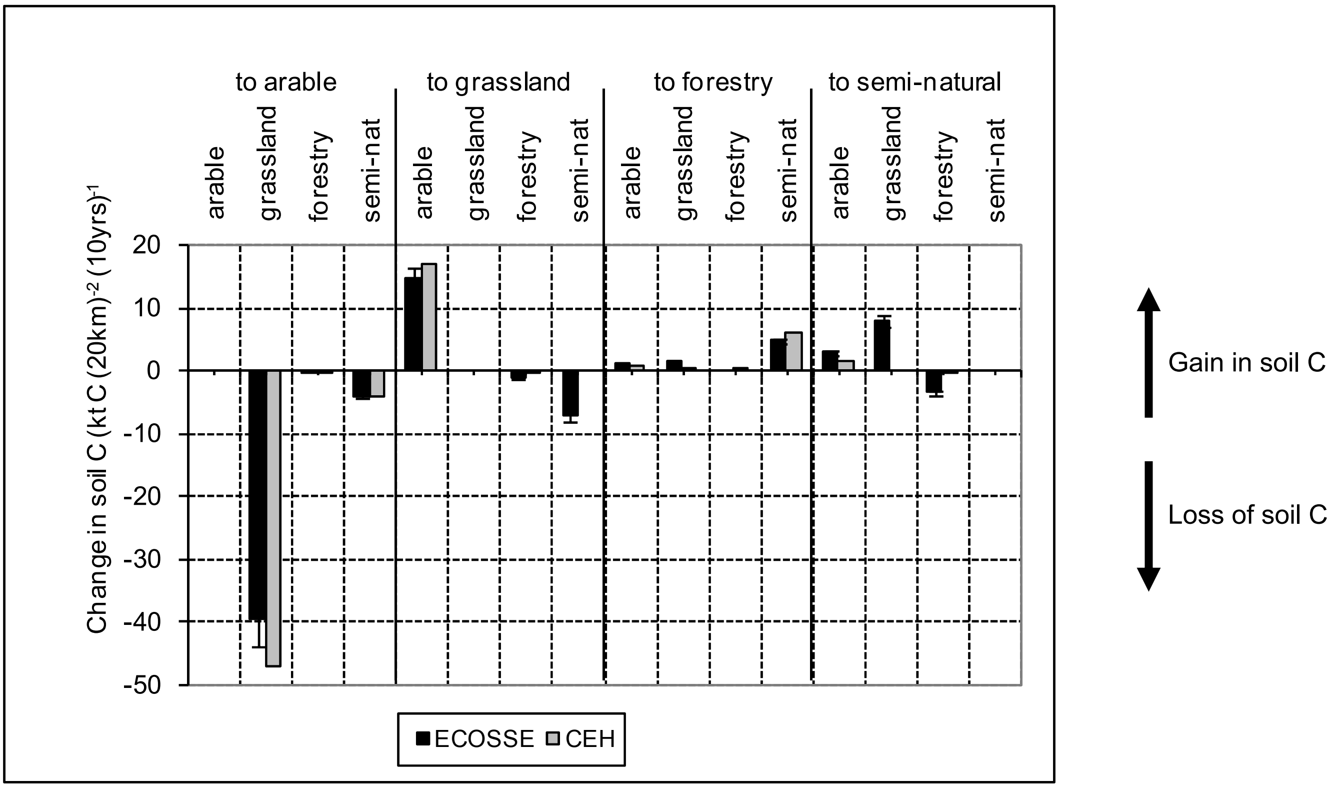


Figure 4.2.4. Comparison of simulated changes in soil carbon content from 2000-2009 divided according to land use change as estimated by ECOSSE and by CEH. Values are averaged across Scotland. Error bars indicate the uncertainty in the simulations calculated from the simulation of NSIS sites as the average deviation of the simulations from measurements (root mean squared deviation = 11%).

The CEH approach uses the observed C contents of Scottish soils under the different land uses (Milne *et al.*, 2004). The CEH approach estimates the change in soil C, $X_{T2\text{-}T1}$ (t C), between land use change times T_2 and T_1 from the area of land undergoing the given land use change, A_T (ha), the equilibrium soil C content under the initial land use, C_0 (t C ha^{-1}), the equilibrium soil C content under the final land use, C_f (t C ha^{-1}), and a time constant for the change, k.

$$X_{\mathrm{T2\text{-}T1}} = \sum_{T_0}^{T_2} A_{\mathrm{T}}\left(C_{\mathrm{f}} - C_0\right)\left(1 - \exp\left(-k\left(T_2 - T\right)\right)\right) - \sum_{T_0}^{T_1} A_{\mathrm{T}}\left(C_{\mathrm{f}} - C_0\right)\left(1 - \exp\left(-k\left(T_1 - T\right)\right)\right)$$

where T_0 is the start of the simulation, and T is the time of any land use change.

(adapted from Milne *et al.*, 2004).

This equation describes the changes in soil C using exponentially declining rates of change, the difference between the equilibrium soil C contents under the final and initial land uses, $\left(C_{\mathrm{f}} - C_0\right)$ (t C ha^{-1}), determining the asymptote of the curve, and the time constant, *k*, determining the rate of loss or gain, as shown for the example of land use change between semi-natural and forestry in figure 4.2.5. These terms are cumulated across all land use changes occurring since time T_0 to give the total change in soil C in the given year or decade. Note that the rate of loss is more rapid than the rate of gain, so describing the time required to stabilise soil C during the process of C sequestration. The values of C_{f} and C_0 are determined for each type of land use from measurements of the equilibrium C contents of Scottish soils divided into the soil categories aquic, high activity clay, low activity clay, sandy and organic. Because a higher equilibrium C content is usually observed under forestry than semi-natural, this inevitably results in an increase in soil C content with the land use change semi-natural to forestry even in the first years following land use change.

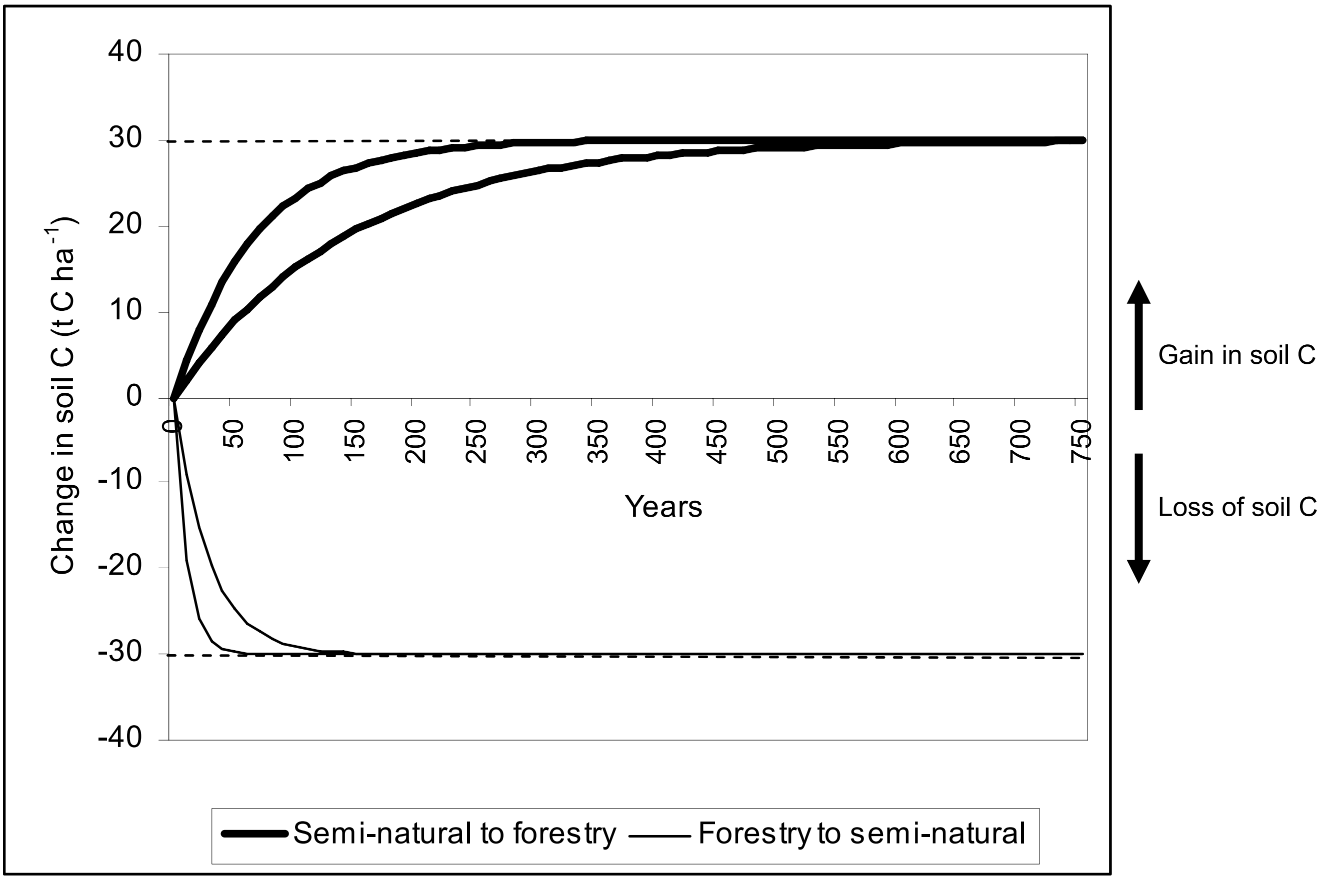


Figure 4.2.5. CEH estimates of change in soil carbon on land use change semi-natural to forestry and forestry to semi-natural in Scotland. Note a gain in soil carbon occurs more slowly than a loss of soil carbon. The two lines represent the minimum and maximum rate of change assumed.

ECOSSE also uses the equilibrium soil C content under different land uses to determine the change in soil C associated with each land use change. It does this by using the equilibrium soil C content to determine the amount of plant input and the distribution of soil pools under the different land uses at steady state. The plant input is assumed to be reduced from the rate calculated in the equilibrium run during the initial period of semi-natural or forestry growth up to the time when the plants mature, but then increases to its full rate after this time. On disturbance of the soil due to land use change, a proportion of the slowly decomposing soil humus pool is passed back to the more rapidly turning over soil organic matter pools of biomass, resistant plant material and decomposable plant material. This simulates the reduction of physical protection of soil organic matter that would occur when long term uncultivated soil is disturbed by management operations. The proportion passed back from the humus pool for long term uncultivated land uses (grassland, forestry and semi-natural) is currently set to 0.5, following an analysis by West and Post (2002) of global data on the effects of tillage on losses of C from the soil. An initial loss of soil C can occur even where the steady state soil C content used to initialise the model is higher under the new than the original land use if the period since the land use change occurred is not sufficient for the soil and vegetation to have reached steady state. If for example the area of land use change to forestry was to significantly increase over the next decades, as planned in the Climate Change (Scotland) Bill 2009 [as passed], an initial decline in soil C could be observed, especially if this was to come from semi-natural land which has a steady state soil C content close to that of forestry.

The observation of a decline in simulated soil C immediately after afforestation of grassland and semi-natural land is supported by experimental evidence both globally and from the UK. In a meta-analysis of 74 publications including data from 16 different countries on the impact of land use change on soil C stock, Guo and Gifford (2002) found a reduction in soil C when pasture was converted to plantation (-10%). This is consistent with the decline (of 50%) in total soil C observed by Zerva *et al.* (2005) during the first rotation following afforestation of a peaty gley soil in the NE of England. The extent of the decline in soil C content is highly dependent on soil type, the management of the land, and the nature of the disturbance. An ECOSSE simulation of changes in soil C stocks on afforestation of a semi-natural NSIS site, NN600600 (see section 4.1), is shown in figure 4.2.6. Two simulations are shown (see table 4.2.4); a simulation assuming disturbance of the site on afforestation (proportion passed from humus pool = 0.5 as used above), and a simulation assuming the minimal disturbance that might be associated with optimum minimum intervention management and longer rotations (proportion passed from humus pool = 0).

	Definition of forestry management	**Definition in ECOSSE**
Disturbance on afforestation	**Standard practices of land preparation for forestry**	**Proportion of C passed from humus pool to more rapidly decomposing pools (DPM,RPM, BIOMASS) = 0.5**
Minimal disturbance on afforestation	**Optimum minimum intervention management and longer rotations**	**Proportion of C passed from humus pool to more rapidly decomposing pools (DPM,RPM, BIOMASS) = 0**

Table 4.2.4. Summary of forestry management and ECOSSE characteristics associated with different levels of disturbance on afforestation

The initial reduction in soil C simulated by ECOSSE is 15% in the simulation assuming disturbance, and only 3% in the minimal disturbance simulation. The C losses associated with the simulation assuming disturbance are well within the reported range, whereas losses from the minimal disturbance simulation are too low, suggesting that some effect of soil disturbance should be assumed. If the proportion of material passed from the humus pool were 0.35, the reduction in soil C stocks would be 10% as obtained by Guo and Gifford (2002) in their review (see "Fitted" on figure 4.2.6). Guo and Gifford (2002) attributed the decline in soil C content on land use change grassland to forestry to

- the shallower distribution of soil C in forestry as compared to grassland resulting in less soil C in the profile as a whole despite a higher surface soil C stock under trees,
- the persistent tree root system resulting in the annual turnover of organic matter from dying tree roots being less than from grass roots, and
- woody plants depositing a larger fraction of organic matter on the surface than grasses resulting in less formation of stabilised soil organic matter.

Our results would suggest that soil disturbance could also be a factor. Note the Guo & Gifford results suggested a permanent decline in soil C of 10%, whereas this simulation would give a temporary dip. The recovery of the soil C levels is dependent on management of the forestry following afforestation.

Guo and Gifford (2002) found that tree type and precipitation had a significant impact on soil C losses; planting broadleaf trees on pasture had no significant impact on the soil C stocks, but planting conifer trees (mostly *Pinus radiata*) significantly reduced soil C stocks by 12%. However, by contrast, a review of forest CO_2 fluxes from temperate, boreal and Mediterranean regions (Law *et al.*, 2002) found no significant difference in stand-scale CO_2 fluxes between deciduous broadleaf forests and evergreen coniferous forests. In low rainfall areas (<1200mm year^{-1}), Guo and Gifford (2002) observed the land use change had little impact on the soil C stocks, but in higher rainfall areas with precipitation over 1500 mm year^{-1}, soil C stocks were significantly reduced (-

23%). With annual precipitation of 1300 to 1400 mm year^{-1}, Scotland as a whole is intermediate between Guo and Gifford's definition of a low and high rainfall area. Within Scotland, annual rainfall ranges from 600 to 4000mm, so the impact of the land use change will also depend on the location.

Many authors report a relationship between stand age and change in soil C content. In a review of UK BioSoil sites (a large EU soil and biodiversity survey in forestry), Morison *et al*. (2008) reported that growing conifer forests, especially in peaty soils and in their first rotation, can decrease soil C stocks by as much as 30%. Measurements of soil C stocks following afforestation of unplanted natural grassland with Sitka spruce (*Picea sitchensis)* on a peaty gley soil at Harwood Forest in N.E. England showed significant changes in both the total amount and the distribution of soil C (Zerva and Mencuccini, 2005a; Zerva *et al*., 2005). The total C stocks declined significantly during the first 40 year rotation, with the lowest soil C content at the time of clear felling, but then increased to levels approaching the unplanted grassland by the end of the second rotation (80 years) due to the incorporation of brash during clear felling. The vertical distribution of soil C changed with a higher proportion of the C stored in the litter layer O_L and A layers after afforestation. Zerva and Mencuccini (2005a) attributed this to the input of persistant woody material to the litter layer under trees and the mixing of the soil during clear felling at the end of the first rotation. The ECOSSE simulation of the NSIS site, NN600600, undergoing land use change semi-natural to forestry was extended to 160 years using long term average weather data (figure 4.2.6). No attempt was made to explicitly simulate the processes of clear felling and brash incorporation, although these are implicitly included in the values of total soil C content under forestry used to initialise the model. If the site is assumed to be disturbed on afforestation, the time to net sequestration of soil C is 140 years. If minimal disturbance of the site is assumed, the time until net sequestration of soil C can be as low as 15 years. With disturbance fitted to the 10% soil C losses observed by Guo and Gifford (2002), the time to net sequestration of soil C is between 70 and 80 years. This suggest that at Harwood Forest, the level of disturbance simulated should be intermediate between the simulation assuming the site is disturbed and the simulation assuming minimal disturbance, at around the level of the fitted simulation (proportion of humus released to other pools = 0.35). If sufficient national information were available on practices of felling and brash incorporation, it would be useful to explicitly simulate these processes, so that the national implications of changing practices could be ascertained.

Within each rotation, changes in the direction of soil C fluxes are observed. In an analysis of CO_2 flux measurements from Scottish peatlands that were drained, ploughed and afforested with conifer plantation dominated by Sitka spruce (*Picea sitchensis)*, Hargreaves *et al*. (2003) observed an initial loss of C from peat and ground vegetation up to 5 years after afforestation, followed by a period up to 10 years when the peat plus ground vegetation started to sequester C. After 15 years, canopy closure resulted in less ground vegetation and the peat became an increasing source of C (~1 t C ha^{-1} year^{-1}). This is equal to in a cumulative change in the C held in soil and ground vegetation as shown in figure 4.2.7. Note the similarity in the shape of the curve calculated by ECOSSE (figure 4.2.6) and the changes in C held in soil and ground vegetation calculated from the data of Hargreaves *et al.* (2003), both curves showing an initial sharp decline, followed by an increase that levels off at around 15 years after afforestation. In a second rotation stand, Ball *et al*. (2007) measured lower annual loss of soil C from the 20 year old stand than from the 30 year old stand and clear-felled sites on the peaty-gley soil at Harwood Forest, and attributed the differences to changes in soil temperature. Soil conditions and soil type have a significant impact on the extent of losses. By comparison to the Scottish peatland studied by Hargreaves *et al.* (2003), Zerva & Mencuccini (2005b) calculated a higher rate of C loss from the peaty gley at Harwood forest (3.5 t C ha^{-1} year^{-1}), whereas the losses calculated from a review of available data by Reynolds (2007) suggest that losses from an organo-mineral soil are much lower at 0.5 t C ha^{-1} year^{-1} (although Reynolds notes the results are inconclusive). The ECOSSE simulation of NN600600 estimates no long term decline in soil C as this is an undrained site.

The study of Hargreaves *et al*. (2003) only considered stand age up to 26 years, so the accumulation of C noted by Zerva and Mencuccini (2005a) in the second rotation was not observed, and the C losses from the soil and ground vegetation were extrapolated to the future at a rate of 1 to 2 t C ha^{-1} year^{-1}.The longer term losses described are largely attributable to the drainage of the peat, but the short term losses were attributed to the reduced inputs associated with the land use change. Despite this conclusion of long term loss from the soil and ground vegetation, the results presented by Hargreaves *et al*. (2003) also showed that the C fluxes from peat, ground vegetation and trees when all taken together become negative after only 10 years, and the system would remain a net sink for 90 to 190 years. This result is consistent with simulations of long term rates of C sequestration in the timber of British woodlands ranging from 1.0 to 5.4 t C ha^{-1} yr^{-1} (Morison et al, 2008), which would exceed the C losses from the soil. While this illustrates the need to consider the changes in C stocks in vegetation as well as in the soil when designing policies to reduce total C emissions, this project focuses on C losses from Scottish soils; changes in greenhouse gas emissions associated with vegetation are beyond the scope of the project. Timber production can also bring additional emission reductions associated with substitution of high energy embedded materials and fossil fuels, which should also be included in any comprehensive analysis of greenhouse gas emissions from Scottish forests.

Although the results are highly variable, it is clear that the afforestation of semi-natural land leads to some initial reduction in soil C, due to reduced inputs of plant C and the disturbance of the soil on planting, but that this may change to a net increase in soil C after the forestry has become established. The different conclusions published from different studies reflect the influence on the extent of soil C loss of soil type, previous land use, nature of land preparation, management of the stand and the species included in the study. The disturbance of the soil and its effect on the extent of C loss is perhaps the largest source of uncertainty. Schmidt *et al.* (1996) and Mallik and Hu (1997) found significant loss of soil C associated with mechanical site preparation, whereas Paul *et al.* (2002) found no significant effect of disturbance level. The Forest Research draft Carbon Review (Morison *et al*., 2008) concluded that soils under forestry stands with minimum intervention management and longer rotations can sequester significant amounts of C, whereas shorter rotations with frequent disturbance may result in net loss of soil C. The information used to determine the ECOSSE parameters that describe the impact of soil disturbance on conversion to forestry is largely based on shorter term rotations. If a larger proportion of forestry in Scottish soils uses minimum intervention management and longer rotations, the simulated increase in soil C on conversion to forestry may have been under-estimated, and the recovery time simulated by the model may be too long. These uncertainties illustrate the urgent need for further experimentation for evaluation and development of models to simulate physical protection and disturbance of the soil on land use change semi-natural to forestry.

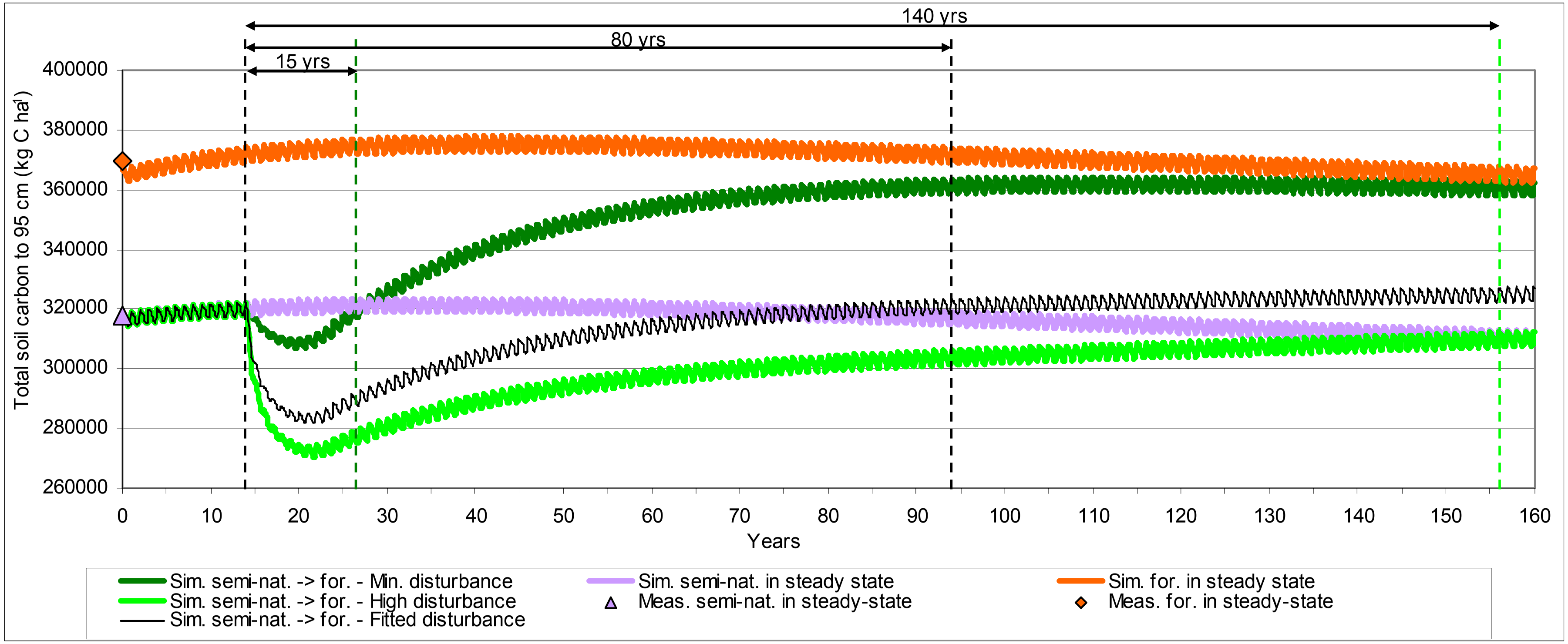


Figure 4.2.6. Simulation of total soil carbon (0-95cm) at NSIS site NN600600 with land use change semi-natural to forestry on a peaty podzol (association = Arkaig, series = Kildonan). Extrapolation of results over the 160 years using long term average weather data. Simulation of the time before net accumulation of soil C occurs following afforestation. Assuming minimal disturbance, time to net soil C sequestration = 15 years. Assuming the soil is disturbed on afforestation, time to net soil C sequestration = 140 years.

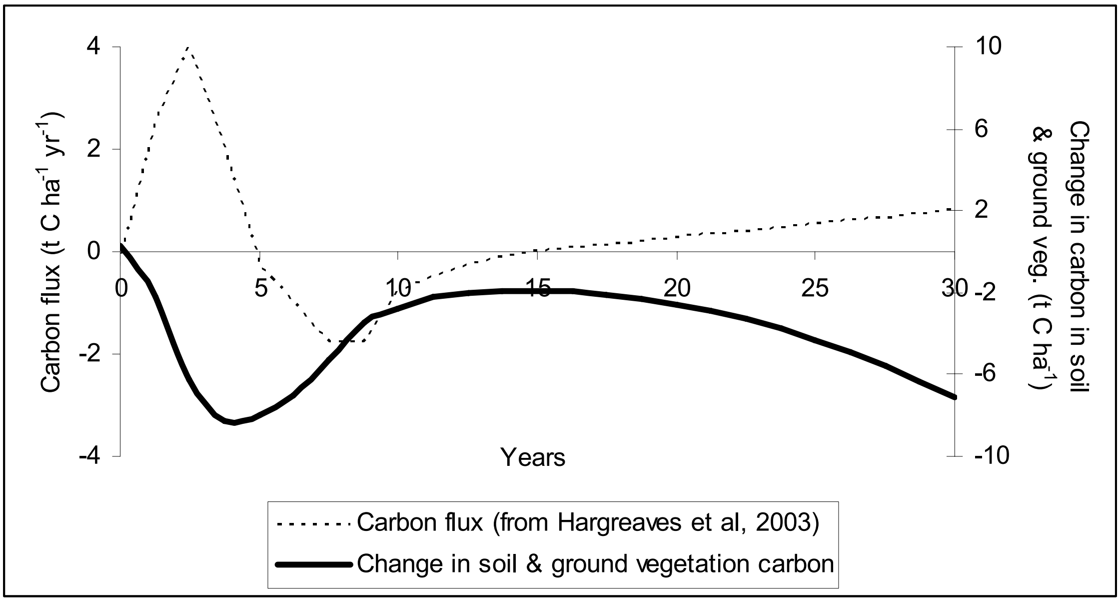


Figure 4.2.7. Change in carbon held in soil and ground vegetation calculated from data from Hargreaves *et al.*, 2003.

A comparison of the distribution of simulated results across Scotland is shown for 2000-2009 in figure 4.2.8. Similar results were observed in 1990-1999. Notice a similar pattern in the emissions estimated by the two approaches, following the distribution of changes in land use across the country, but higher variability in the emissions estimated by ECOSSE, reflecting the impact of the more detailed soil information used. Some grid squares are empty in the 1km^2 map. This is due to a land use change being recorded in the 20km^2 scale land use change data, but no soil characteristics being defined under the soil types found in that particular 1km^2 cell. This is due to the mismatch of the 20km^2 and 1km^2 data and is currently recorded as an error so the results are not included in the output. In future simulations, an alternative method for dealing in this mismatch in the data will be sought. Note that because of the way the simulations are run, this introduces no error in the overall results for Scotland or the 20 km^2 maps.

The highest losses in soil C are simulated in the land use change grassland to arable (see figure 4.2.4). A comparison of the distribution of simulated results across Scotland for the land use change grassland to arable is shown for 2000-2009 in figure 4.2.9. Again, a similar overall distribution is observed, but with notable differences associated with the soil type. Note, in particular, that ECOSSE simulates an area of lower emissions in the borders than was estimated by CEH, due to the land use change grassland to arable not occurring in this region. If the soil characteristics are not defined for a particular land use, this land use change will be excluded from the ECOSSE simulation. This means that unrealistic changes in land use are filtered out, providing an additional check for realism in the simulations.

The highest simulated sequestration of C occurs due to land use change arable to grassland (see figure 4.2.4). A comparison of the distribution of results across Scotland for the land use change arable to grassland is shown for 2000-2009 in figure 4.2.10. The overall distribution estimated by the two approaches is similar, but again with greater variability in the ECOSSE results, reflecting the soil characteristics.

Policy Relevant Questions

What total carbon emissions can be attributed to Scottish soils?

The total changes in soil C across Scotland as estimated by CEH and ECOSSE are given in table 4.2.5. While the estimates in changes in soil C stocks are very similar in 1990-1999, the ECOSSE simulations estimate soil C losses that are a little lower than the CEH estimates in 2000-2009.

	CEH estimate of annual changes in soil C for Scotland (kt year^{-1})	ECOSSE estimate of annual changes in soil C for Scotland (kt year^{-1})	Difference (CEH-ECOSSE) (kt year^{-1})
1990-1999	**-913**	**-822**	**-9**
2000-2009	**-878**	**-810**	**-68**

Table 4.2.5. Simulated changes in soil carbon across Scotland as estimated by CEH and by ECOSSE

Which land use changes are responsible for the emissions?

The ECOSSE simulated annual changes in soil C for Scotland between 1950 and 2009 for the different land use changes are shown in figure 4.2.11. The land use changes that result in these changes in soil C are shown in figure 4.2.12. The changes in soil C stocks are the soil C changes occurring during given decade only, but are the effect of land use changes occurring from the 1950s up to the given decade, so will account for the long-term as well as the short-term impacts of land use change. The simulated total change in C stocks becomes more negative (i.e. increased emissions) up to the end of the 1970s when the change in C stocks increases sharply (i.e. decreased emissions), although remaining negative (net C emissions). The increase occurs due to a levelling off of the losses associated with the land use change grassland to arable and forestry to semi-natural, and increased sequestration associated with conversion of arable land to grassland. Conversion of forestry to semi-natural results in net emissions up to the 1970s, because the plant communities have not had time to reach maturity. After this time, the greater maturity of the earlier converted land results in decrease in emissions. Increasing the area of land use change from arable to grass has the highest potential to sequester soil C, and decreasing the area of grass to arable has the highest potential to reduce losses of soil C. Note that changes in the 1950s and 1960s may have been underestimated due to omission of land use changes that occurred before the start of the simulation, but the trends from the 1970s to 2000s show a clear effect.

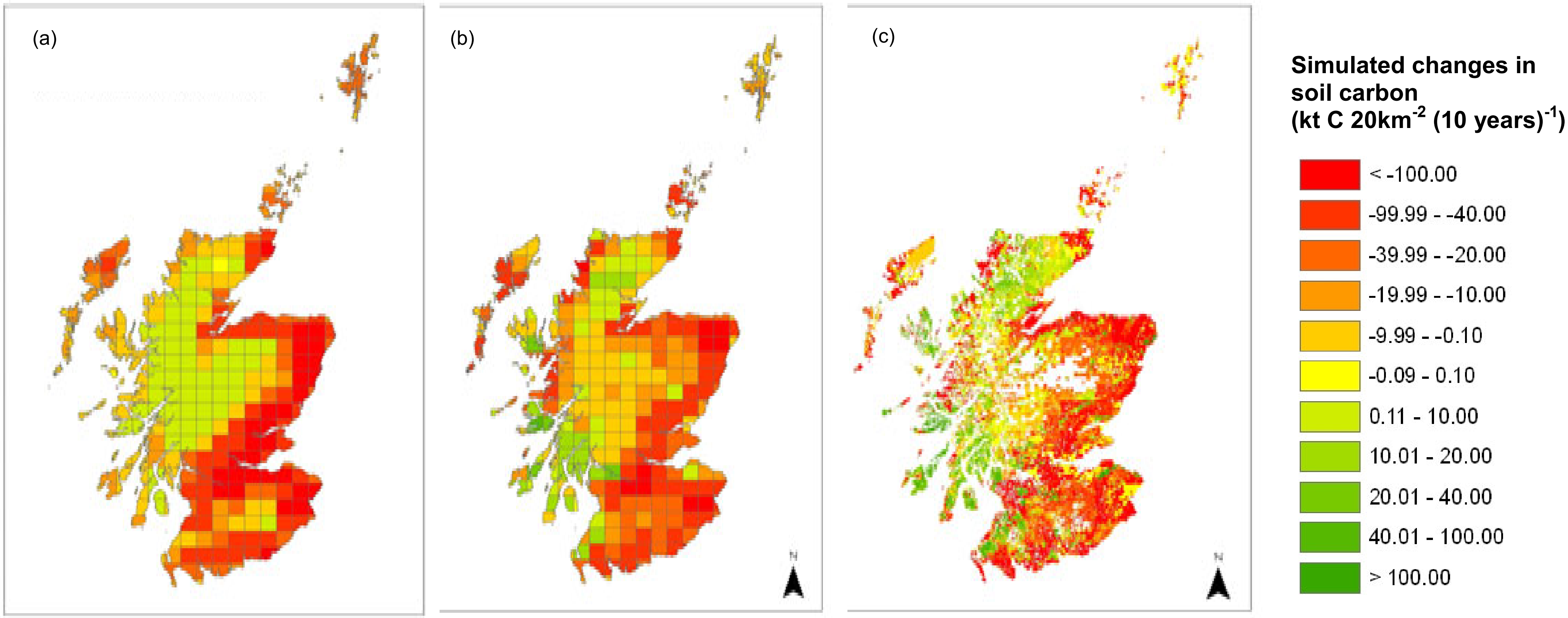


Figure 4.2.8. Simulated change in soil carbon stocks due to all land use changes occurring in Scotland 2000-2009 (a) CEH estimates (b) ECOSSE simulations (20km^2 resolution) (c) ECOSSE simulations (1km^2 resolution)

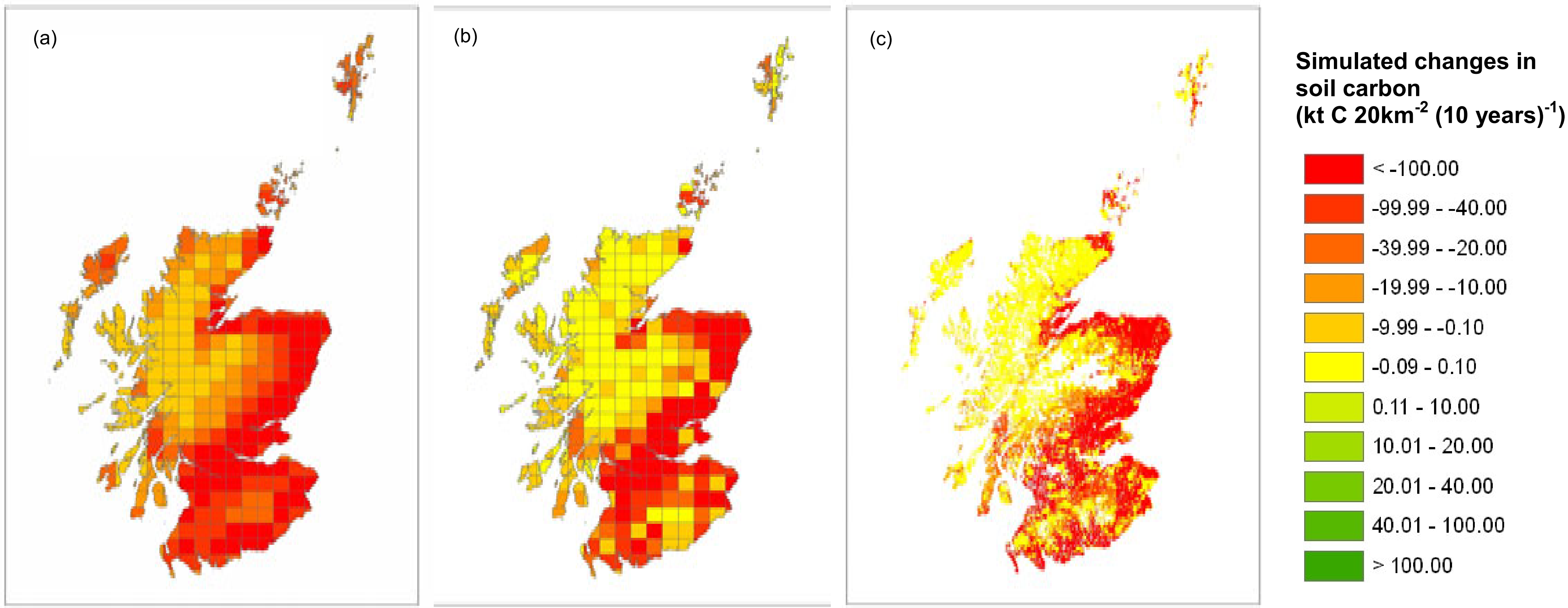


Figure 4.2.9. Simulated change in soil carbon stocks due to land use change grassland to arable occurring in Scotland 2000-2009 (a) CEH estimates (b) ECOSSE simulations (20km^2 resolution) (c) ECOSSE simulations (1km^2 resolution)

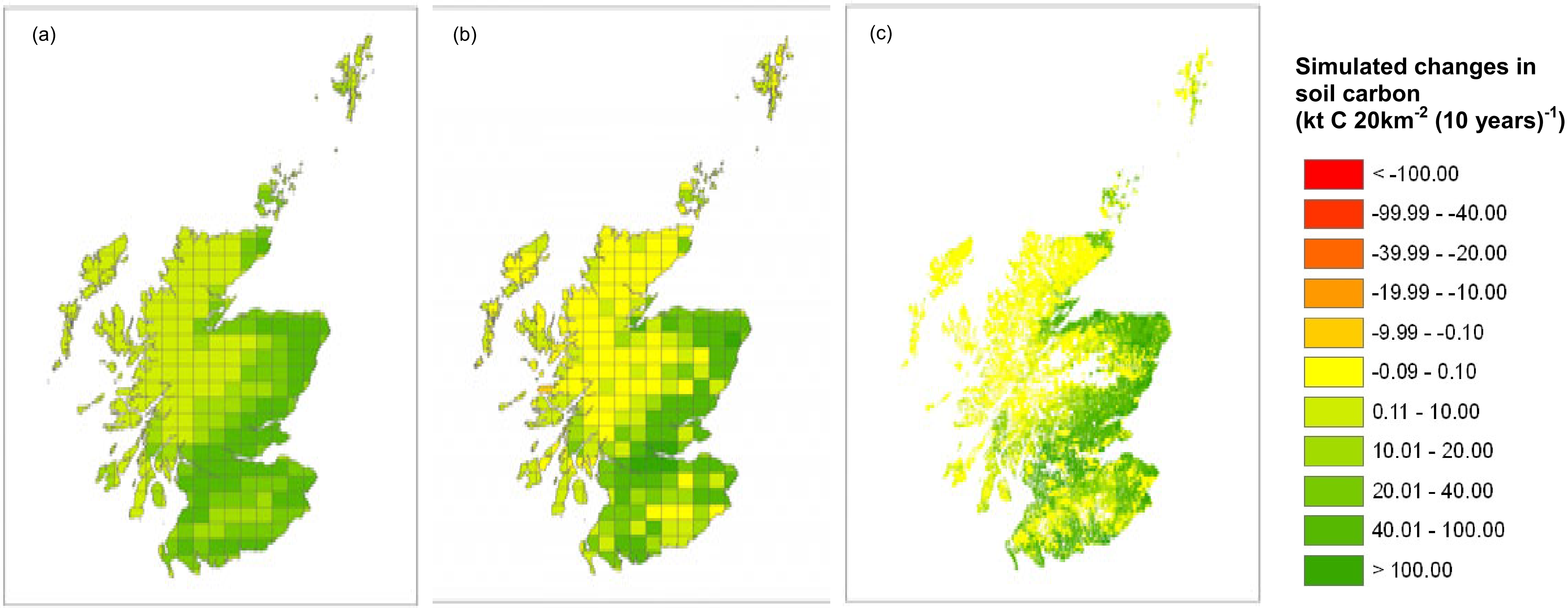


Figure 4.2.10. Simulated change in soil carbon stocks due to all land use change arable to grassland occurring in Scotland 2000-2009 (a) CEH estimates (b) ECOSSE simulations ($20km^2$ resolution) (c) ECOSSE simulations ($1km^2$ resolution)

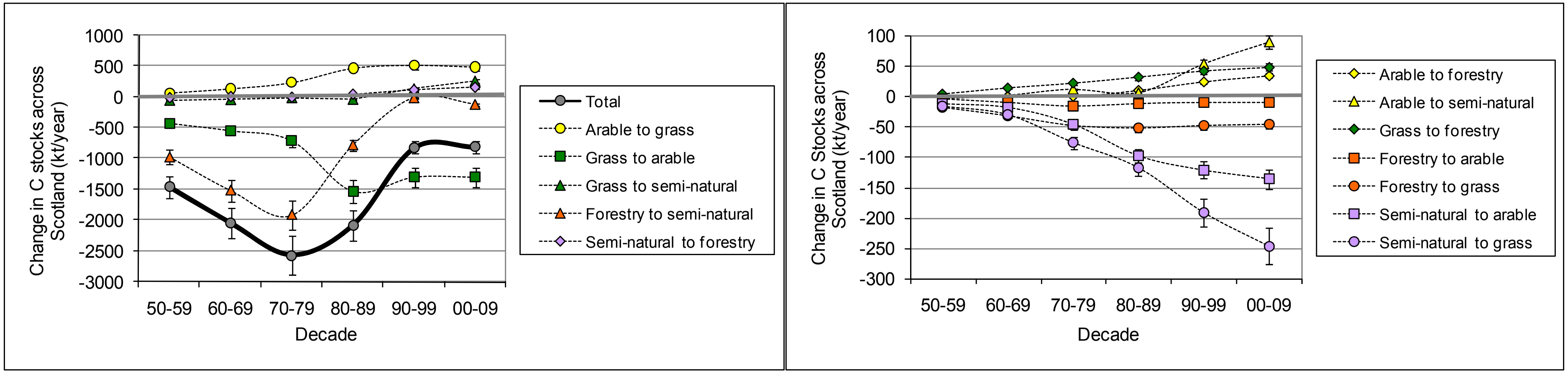


Figure 4.2.11. Simulated total changes in soil carbon stocks across Scotland from 1950-2009 for different land use changes as simulated by ECOSSE. Note the change scale in the two graphs.

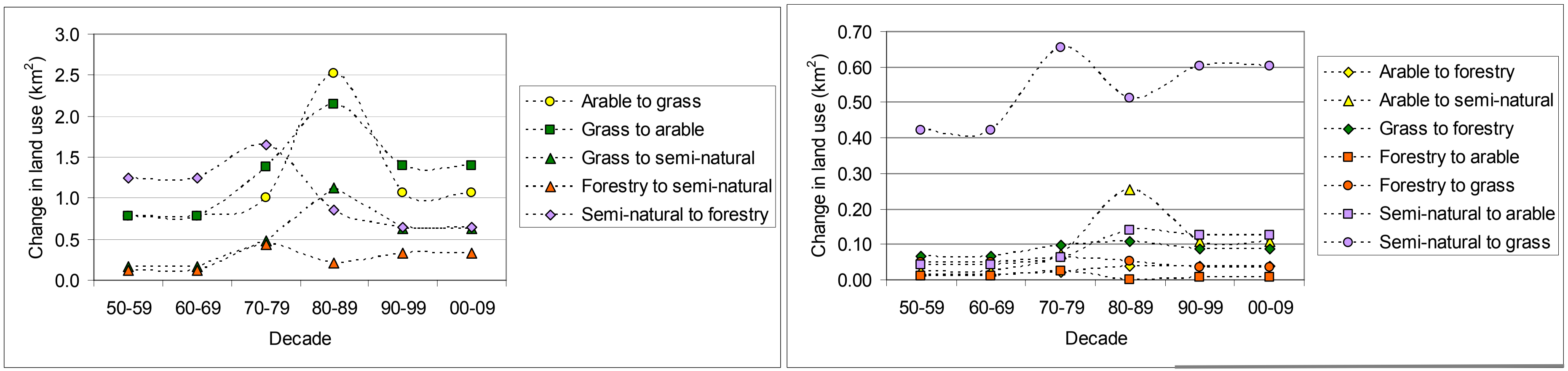


Figure 4.2.12. Simulated total changes in land use across Scotland from 1950-2009 as specified by CEH land cover map. Note the change in scale of the two graphs.

On which soil types do most emissions occur?

The ECOSSE simulated changes in soil C since 1950 across Scotland for organic and mineral soils are shown in figure 4.2.13. Organic soils are defined here as soils with a C content of over 6% (Smith *et al*., 2007b). On average, losses from organic soils represent 64% of the total losses. Across Scotland, the simulated change in soil C from organic soils between 1950 and 2009 is -62512 kt, compared to -35351 kt from mineral soils.

The distribution in the simulated changes in soil C stocks in organic soils is shown from 1950-2010 in figure 4.2.14. Note the high losses of C from organic soils up to 1980, when the losses decline to a lower level as plant communities from the earlier land use changes mature.

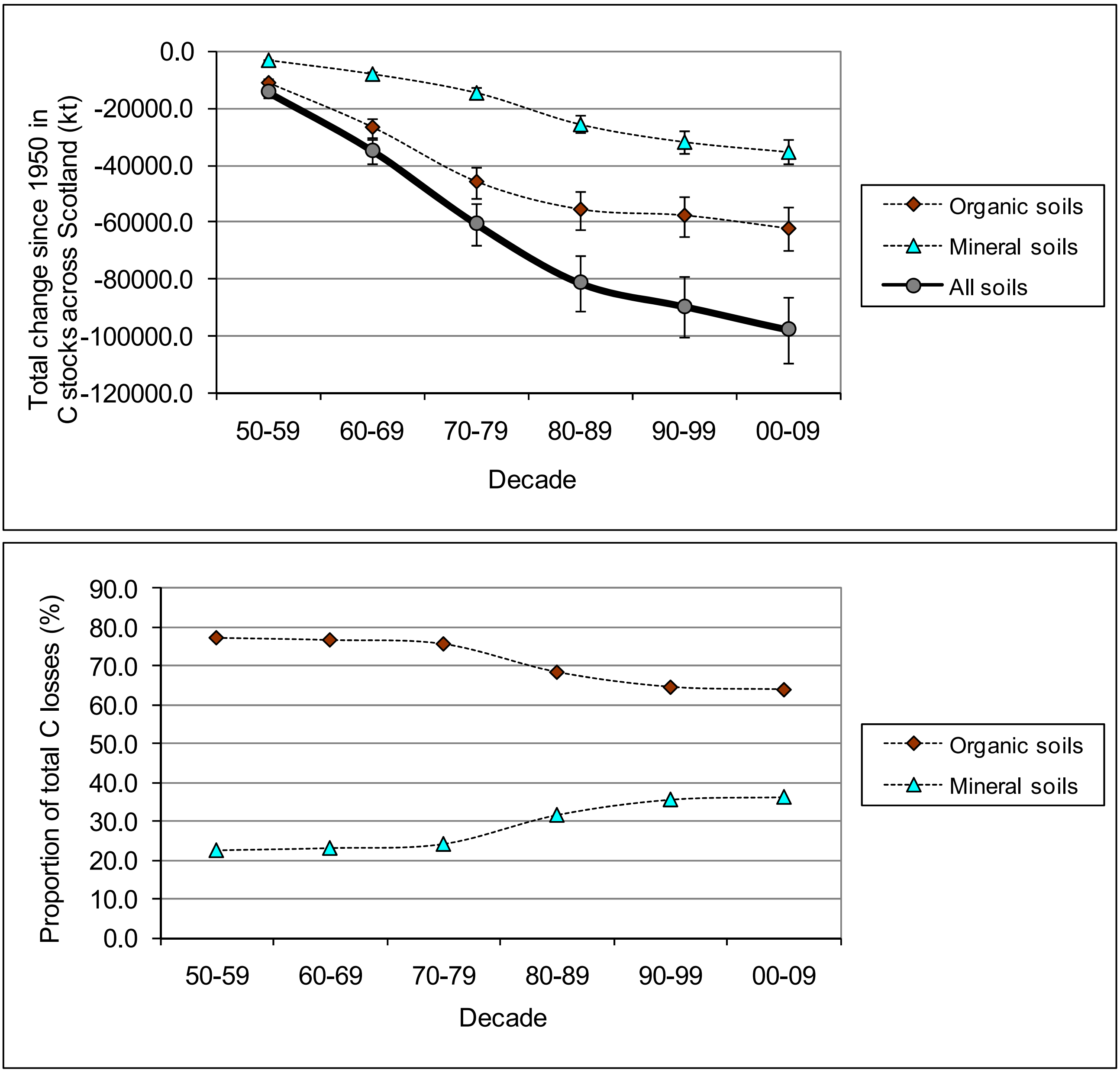


Figure 4.2.13. Simulated total changes in carbon stocks across Scotland from 1950-2009 for different soil types as simulated by ECOSSE assuming soil disturbance on afforestation.

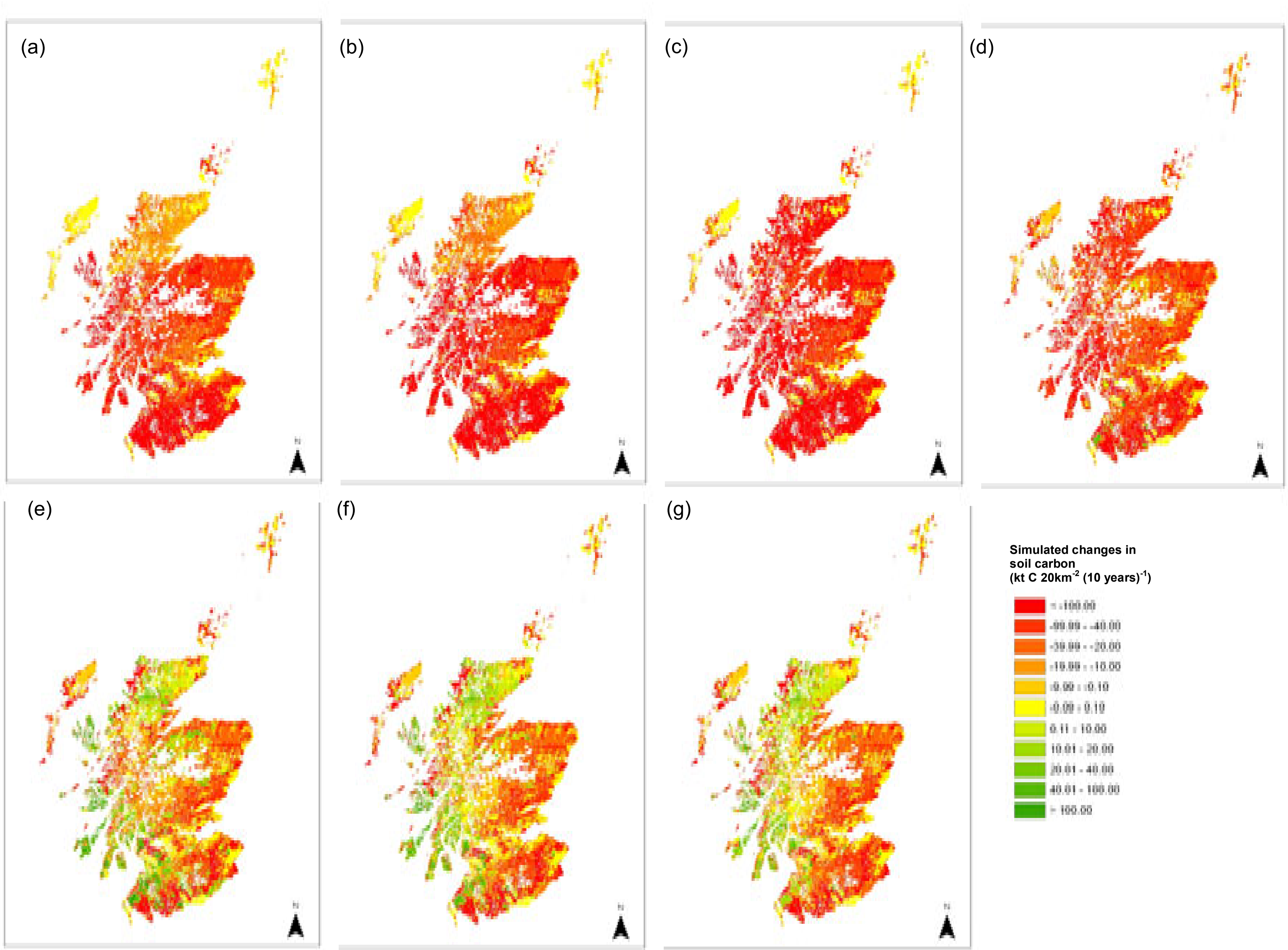


Figure 4.2.14. ECOSSE simulations of changes in soil C stocks on organic soils across Scotland due to all land use changes occurring between 1950 and 2010. Simulations assume soil disturbance on afforestation (a) 1950s; (b) 1960s; (c) 1970s; (d) 1980s; (e) 1990s; (f). 2000s; (g) 2010s

The distribution of losses between organic and mineral soils associated with the different land use changes that have occurred since 1950 as simulated by ECOSSE are shown in figure 4.2.15. The results represent the emissions that occur between 2000 and 2009, but show the impact of land use changes occurring between 1950 and 2009. The largest losses in soil C are associated with the conversion of mineral soil from grassland to arable, while the largest gains in soil C are associated with the conversion of mineral soil from arable to grassland. Other large losses in soil C are observed due to conversion of organic soils from grassland to arable, and from semi-natural to grassland. Whereas the changes in soil C in mineral soils are largely compensatory, the changes in organic soils are not, resulting in an average loss of soil C from organic soils of 19 kt (20 km)$^{-2}$ (10 years)$^{-1}$, compared to an average loss from mineral soils of only 5.5 kt (20 km)$^{-2}$ (10 years)$^{-1}$. **This emphasizes the importance of organic soils in any national estimates of greenhouse gas emissions.** These results suggest that mitigation options to reduce losses of soil C might recommend different policies for land use change on mineral and organic soils.

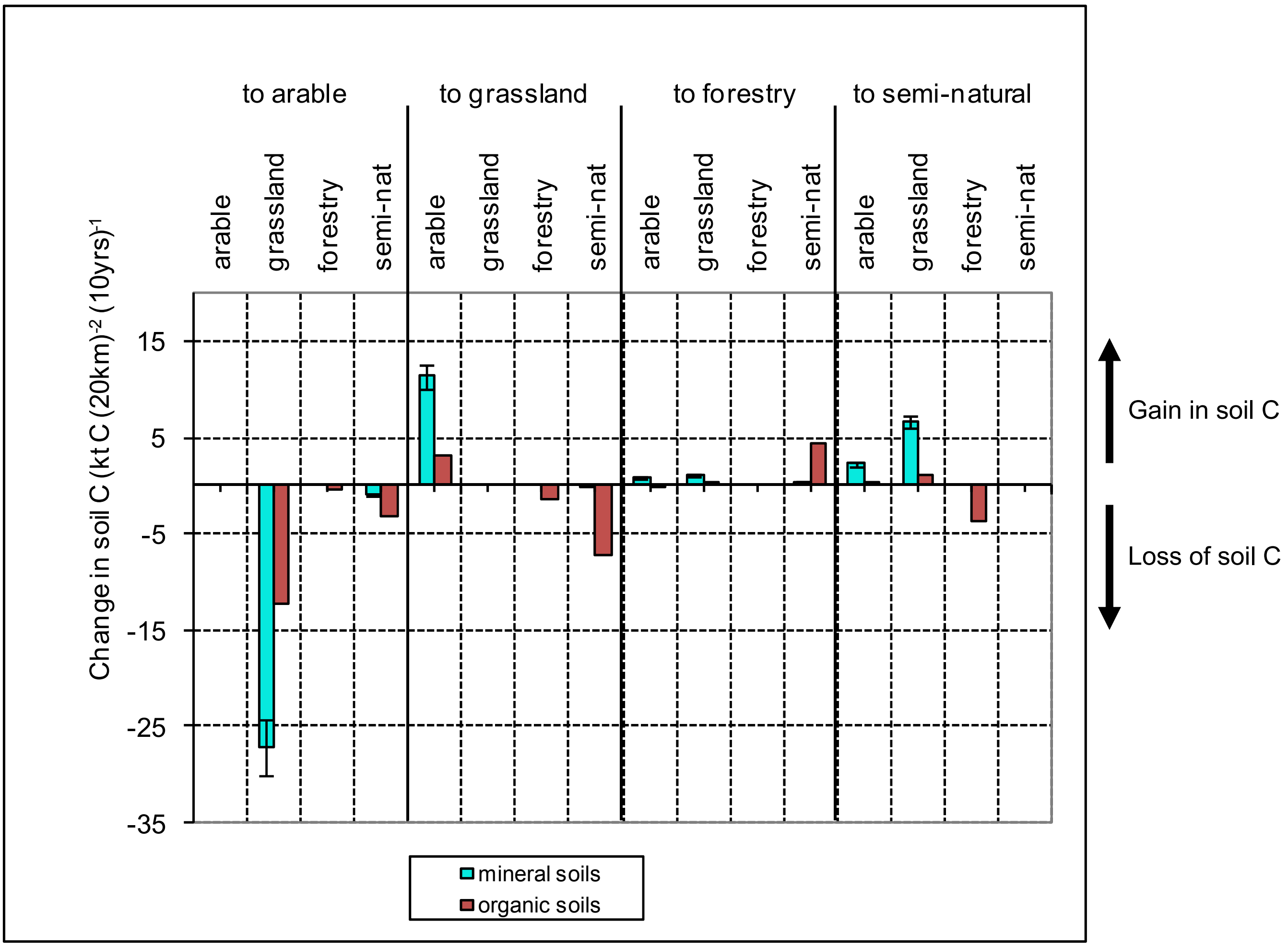


Figure 4.2.15. Comparison of simulated changes in soil carbon content from 2000-2009 divided according to land use change on organic and mineral soils as estimated by ECOSSE. Values are averaged across Scotland. Error bars indicate the uncertainty in the simulations calculated from the simulation of NSIS sites as the average deviation of the simulations from measurements (root mean squared deviation = 11%).

4.2.4. Future Simulations

Soils data

Soils data were obtained from the national soil database, as described in section 4.2.3.

Land use data

In the original plan of the work, land use scenarios were to be obtained from future predictions provided by Rounsevell *et al*. (2005). The scenarios provided by Rounsevell *et al*. (2005) are Europe-wide land-use change scenarios for each of the IPCC future scenarios, based on the IPCC emission scenario narratives (IPCC, 2000), at a resolution of 10′ x 10′ (Rounsevell *et al*., 2005). These narratives are likely to be of reasonable accuracy at the European scale, but at national resolution, local political and sociological factors could introduce a high degree of inaccuracy. During the period of the project, new scenarios for Scotland were made available by Thompson *et al*. (pers. comm., CEH Edinburgh). Therefore, the model was run using these scenarios to 2020. Historical land use and land use change data were obtained from CEH projections (A.Thompson, CEH, Edinburgh, pers.comm).

Weather data

Future weather data was obtained from UKCIP02 database. These data are derived from the HadCM3 model for 4 scenarios based on the predicted cumulative CO_2 emissions between 1990 and 2100: the 'low' emissions scenario assumes that the cumulative emissions will be less than 1100 Gt C, the 'medium–low' scenario assumes emissions between 1100 and 1450 Gt C, the 'medium–high' scenario assumes emissions between 1450 and 1800 Gt C, while the 'high' scenario assumes that the cumulative emissions will exceed 1800 Gt C over the period. The data includes rainfall and temperature predictions for each scenario, for three future time steps: 2020, 2050 and 2080. These data are in 5km^2 grids covering the whole of Scotland.

Results and Policy Questions

<u>What are the predicted changes in soil carbon due to projected land use change over the next decade?</u>

Figure 4.2.16 shows the predicted changes in soil C due to projected land use change over the next decade as simulated by ECOSSE. The results shown are the changes in soil C stocks occurring in 2000 – 2009 and 2010 - 2019, but include the carry-over effects of land use changes that occurred from 1950 to the reported decade. The difference between the two decades in the changes in soil C stocks is small compared to the total change in soil C. The largest difference is associated with the land use change forestry to semi-natural, and is an additional loss of C from the soil of 80 kt C yr^{-1}. The overall trend is towards increased emissions, with a total additional loss of 135 kt C yr^{-1} from the soil due to the projected scenarios of land use change in Scotland.

<u>What are the predicted changes in soil carbon due to projected climate change during this century?</u>

The UKCIP02 scenarios suggest the climate of Scotland will become warmer and drier as shown in Figure 4.2.17. The effect of the drying of the soil is exacerbated by a change in the distribution of rainfall, with a higher proportion of the rain projected to fall during the colder winter months when decomposition is already reduced by low temperatures (Figure 4.2.18). The changes in temperature and rainfall have opposing effects on the rate of soil organic matter decomposition. As the temperature increases, the rate of decomposition also increases, whereas as the rainfall declines, the soil dries out and the rate of decomposition slows down. The increasing annual temperatures result in more rapid decomposition of soil organic matter and so increased loss of soil C, whereas the drier summers slow the rate of decomposition, tempering the increase in soil C loss. Climate change alone is predicted to result in a decline in the soil C stocks of only -93 to -125 kt between 1990 and 2060 (-1.3 to -1.8 kt year^{-1}). The largest changes in soil C are seen under unmanaged semi-natural land, -38 to -60 kt between 1990 and 2060 (-0.5 to -0.9 kt year^{-1}). The model assumes that the C inputs from plants are maintained under climate change. If plant inputs are not maintained, as may be the case especially in semi-natural land uses, the losses of soil C will be greater than predicted.

Projected changes in land use result in larger predicted changes in soil C stocks than climate change: in 1990-1999, changes in climate result in C losses across Scotland of up to 181 kt C (10 years)$^{-1}$, whereas projected land use change results in C losses nearly 50 times greater, up to 8222 kt C (10 years)$^{-1}$. This is encouraging, as it illustrates the great potential for C losses due to climate change to be mitigated by changing land use.

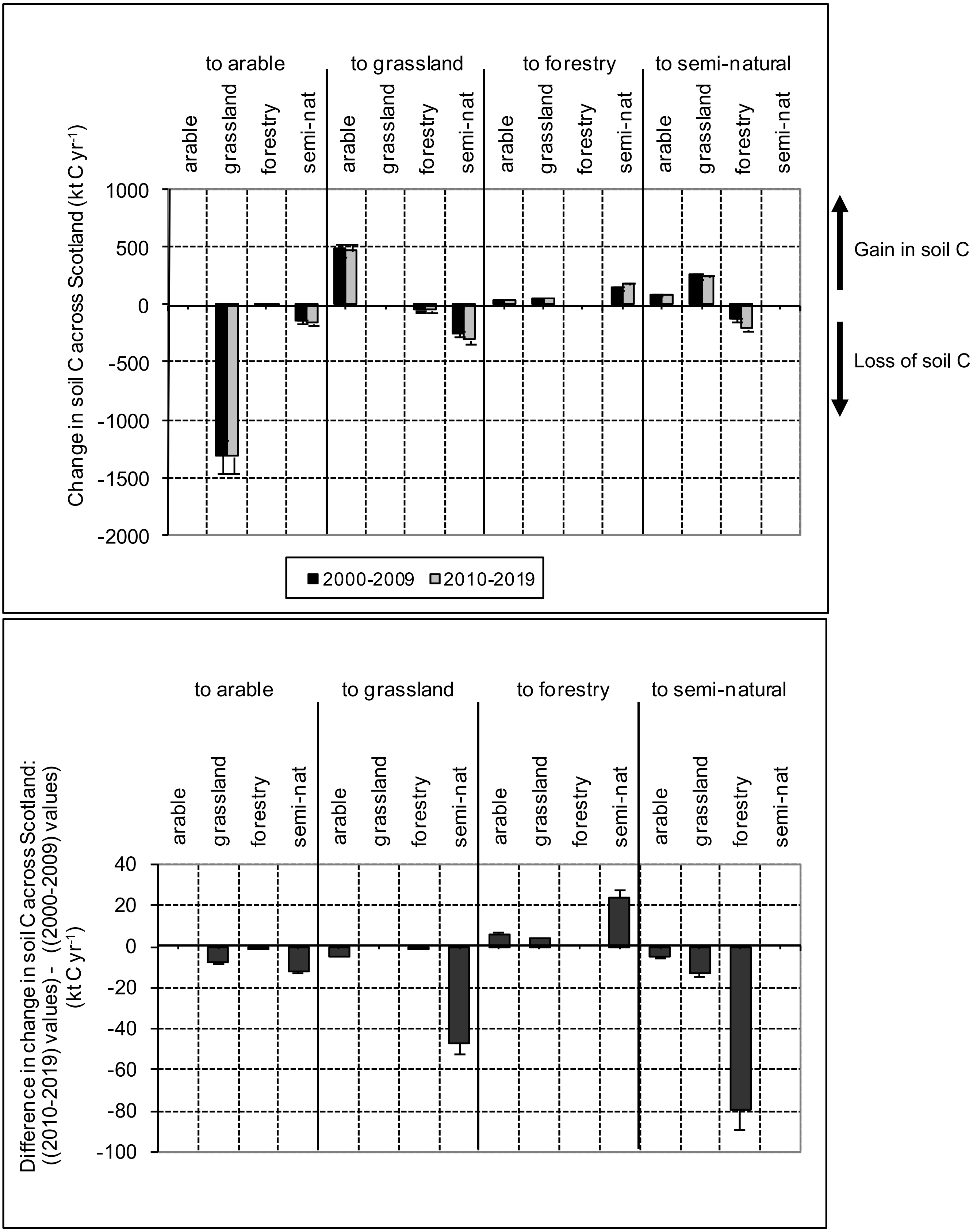


Figure 4.2.16. Predicted changes in soil carbon stocks across Scotland for different land use changes as simulated by ECOSSE assuming soil disturbance on afforestation. Comparison of 2000-2009 and 2010-2019

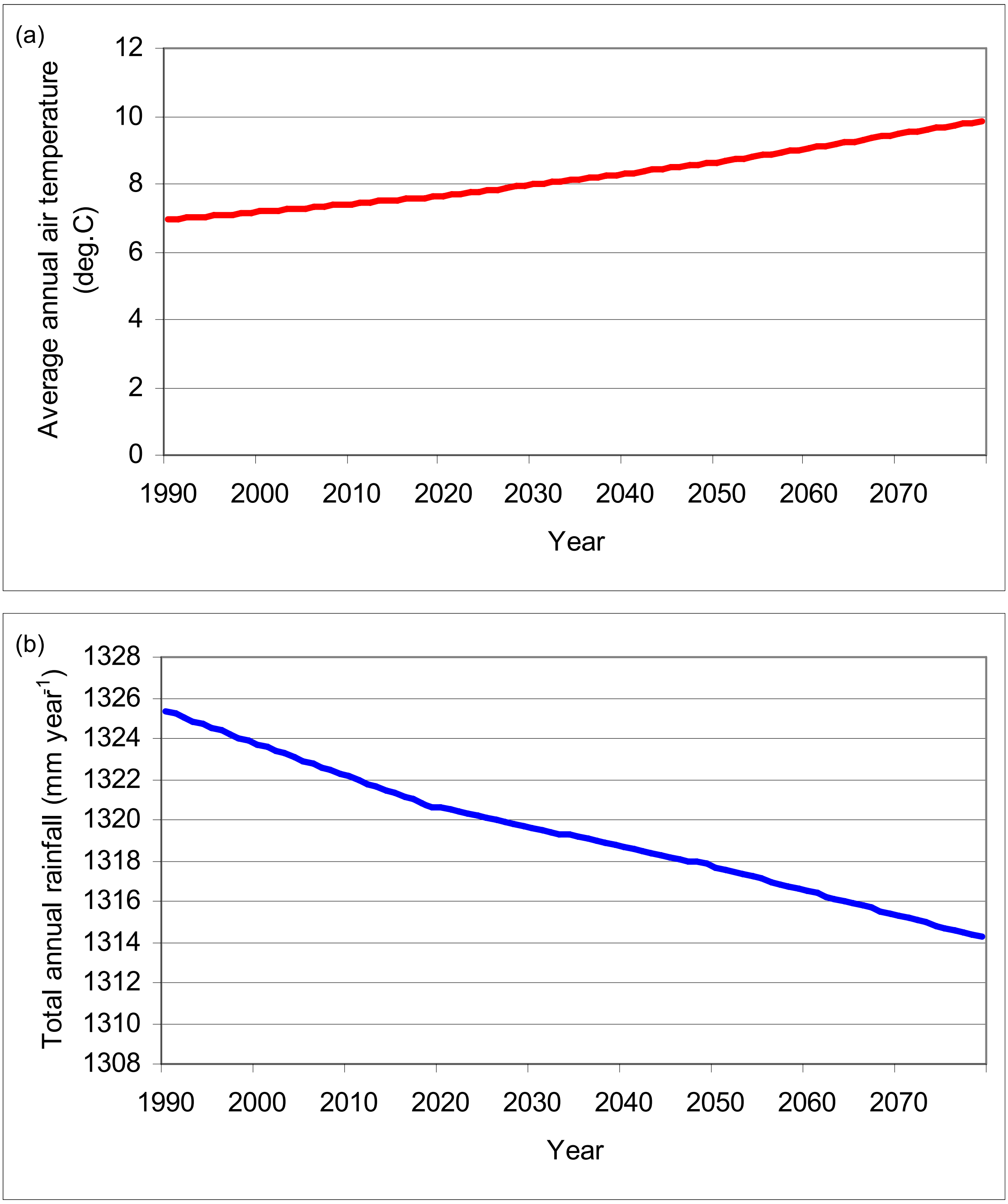


Figure 4.2.17. Predicted changes in climate across Scotland from UKCIP02 high scenario (a) average annual air temperature (b) total annual rainfall. Average across all 5km^2 cells.

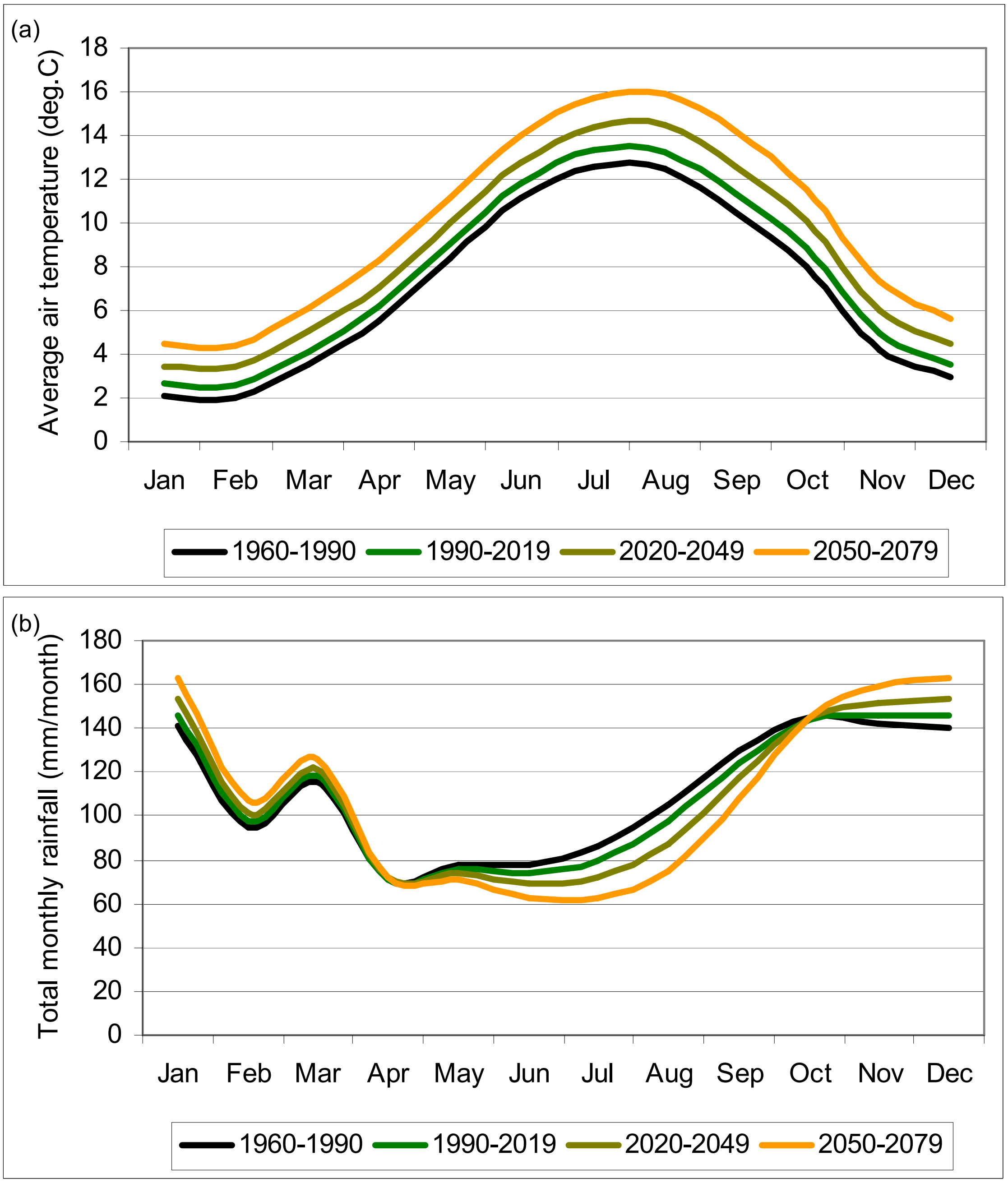


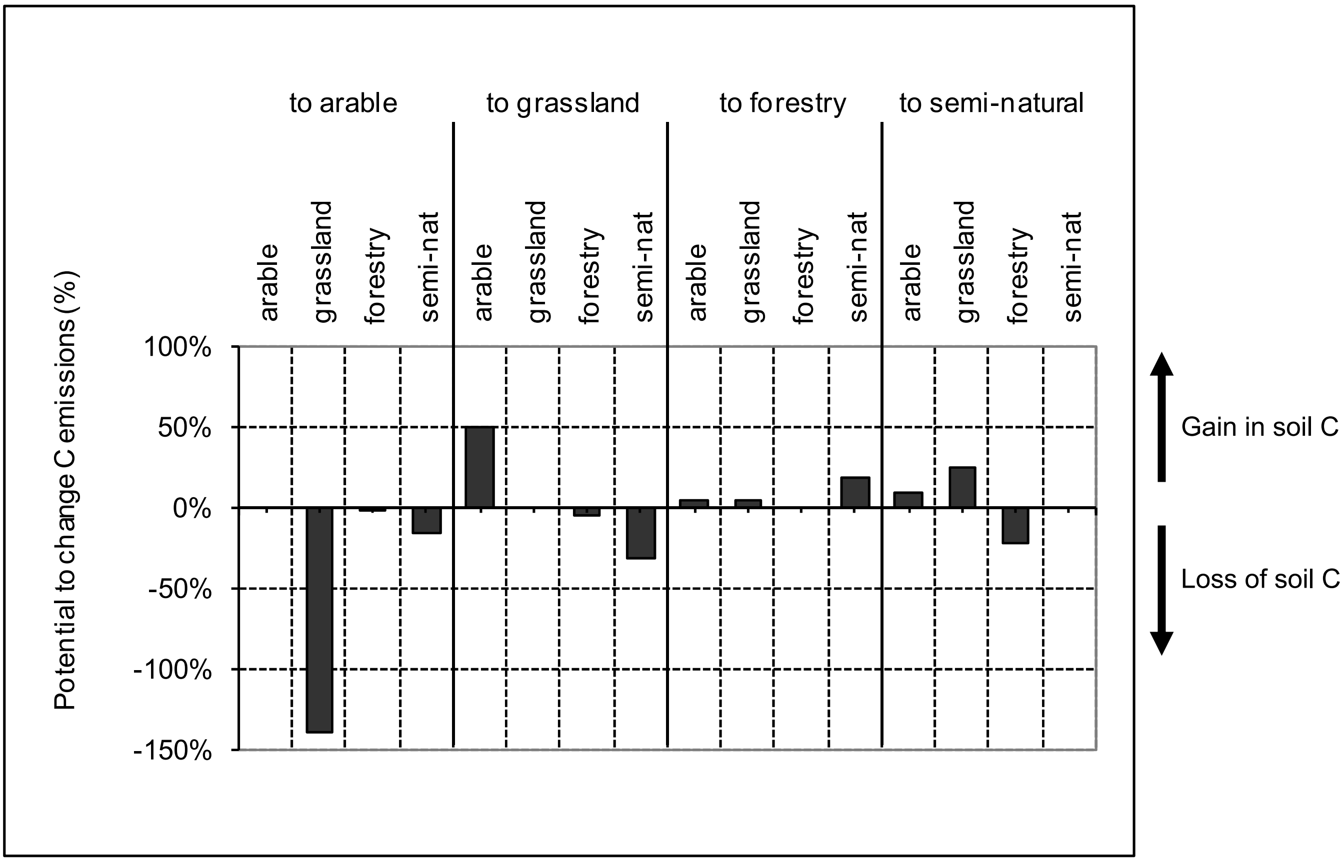
Figure 4.2.18. Predicted changes in climate across Scotland from UKCIP02 high scenario (a) average monthly air temperature (b) total monthly rainfall. Average across all 5km^2 cells.

These simulations have assumed no land use change, and no changes to the plant C inputs to the soil. Changes in plant inputs will be superimposed on the effects of climate change. Note UKCIP02 scenarios were used because the UKCIP08 scenarios have not yet been published. In early 2009, the revised UKCIP scenarios are expected to be published, providing improved spatial resolution and updated climate scenarios. Simulations should be rerun with and without changes in land use and plant input when the new climate scenarios become available.

4.2.5. Mitigation options to reduce losses of soil C

Which mitigation options are most likely to reduce losses of soil C?

Figure 4.2.19 shows the potential of each land use change to impact the C emissions of Scotland. The potential to impact C emissions is calculated from the simulated change in total C emissions that occur when the given land use change is reduced to zero, and so accounts for both the area of predicted land use change and the size of the impact of the land use change on soil C stocks.



4.2.19. The impact of land use change on the carbon emissions of Scotland as estimated by ECOSSE.

The land use change grassland to arable has most potential to reduce soil C losses. If the area of land converted from grassland to arable was reduced to 28% of its current rate of conversion, the soil C losses across Scotland would be reduced to zero; i.e. if in a given grid square the CEH prediction for conversion of arable to grassland from 2010 to 2019 was 100 ha, reducing the area of land converted from arable to grassland to 28 ha would reduce the losses of soil C such that the net losses of soil C across Scotland would be zero. However, given the current agricultural market, such a mitigation option may be unrealistic.

Other significant losses of soil C occur due to the conversion of semi-natural land to arable or grassland. The results suggest that if policies were designed to reduce conversion of semi-natural land to arable or grassland while maintaining the rate of conversion of semi-natural land to forestry, net losses of soil C could be reduced to as low as 53% of the current emissions. If this were coupled with an increase in the conversion of grassland to semi-natural land by 125% of the current rate of conversion (i.e. increase 100ha conversion of grassland to semi-natural to 225ha), net losses of soil C would be reduced to zero. Alternatively, a 63% increase in the current rate of conversion of arable to grassland (i.e. increase 100ha conversion of arable to grassland to 163ha) would also result in zero net losses of soil C when coupled with the reduced conversion of semi-natural land to arable or grassland. This could also be achieved by decreasing the current rate of conversion of grassland to arable to 77% of its current rate (i.e. decrease 100ha conversion of grassland to arable to 77ha).

The results also suggest that conversion of semi-natural land to forestry would sequester additional soil C. However, the data in the national soils database does not currently account for the detail of changes in soil C likely to occur due to drainage and disturbance of semi-natural soils following afforestation. Due to the absence of better information, forested soils are described in the national soils database as a semi-natural soil (of the same soil type) with an additional litter layer added to the top of the soil profile. The analysis of NSIS data occurring as part of the core MLURI programme is providing a more accurate picture of the soil C content of forested soils. This information will be used in future work to revise the national soils database. Therefore, in the current study, conversion of semi-natural land to forestry was not included as a potential method to sequester soil C. Further work on the C content of forested soils and the changes occurring in soil C on afforestation is urgently needed.

Similarly, the results suggest that conversion of forestry to semi-natural land results in a loss of soil C, and so this land use change should be reduced. While a short-term loss of soil C is consistent with a reduction in soil C on disturbance of the soil as discussed in the previous sections, the data that provided this result is the estimate of the C content of forested soils from the C content of soil under semi-natural land use with a litter layer added to the top. No account is taken of the impact of possible changes in soil hydrology if drains are blocked on restoration of the land to its semi-natural state. Therefore, this result should not be used to suggest reduced conversion of forestry to semi-natural land as a mitigation measure. Further work is urgently needed on the C content of forested soils and the changes in soil C occurring on restoration of forested to semi-natural land.

These results suggest four mitigation options that would be effective tools for achieving zero net losses of C from Scottish soils:

1. Decrease in the rate of conversion of grassland to arable to 28% of the current rate;
2. Stop conversion of semi-natural land to arable or grassland and increase the conversion of grassland to semi-natural by 125% of the current rate;
3. Stop conversion of semi-natural land to arable or grassland and increase the conversion of arable to grassland by 63% of the current rate; and
4. Stop conversion of semi-natural land to arable or grassland and decrease the conversion of grassland to arable to 77% of the current rate.

The mitigation options were applied as a multiplication factor to the predicted land use changes for 2010 – 2019. The impact on the distribution of change in soil C stocks of applying these mitigation options is shown in figures 4.2.20 to 4.2.23.

Mitigation option 1 (reduce conversion of grassland to arable land) results in a reduction in the loss of soil C across the East coast and Central belt, while the losses on the West coast remain relatively unchanged.

Mitigations options 2, 3 and 4 (stop conversion of semi-natural land to arable or grassland and either increase grassland to semi-natural, increase arable to grassland, or reduce grassland to arable) all result in reduced loss of soil C across the West coast and smaller reductions on the East coast and Central belt.

These mitigation options represent simple changes to the amount of land use change occurring. In future work, more subtle changes in land use (such as changes in the distribution of crops, management of forestry, grazing of animals) could be applied in a similar way through modification of the land use types selected.

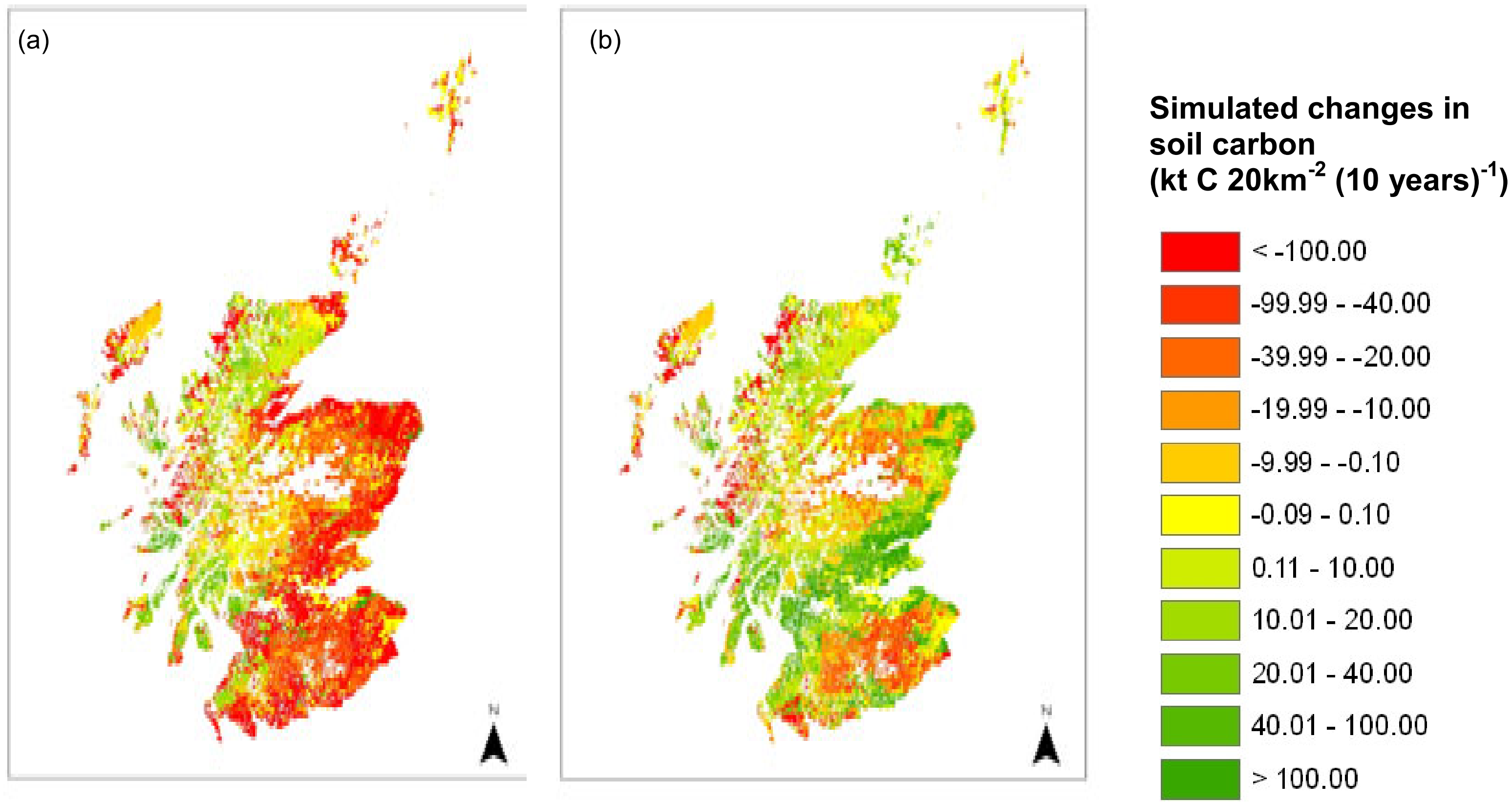


Figure 4.2.20. Simulated changes in soil C stocks in 2010 to 2019 as predicted by ECOSSE (a) no mitigation options applied; (b) rate of conversion of grassland to arable decreased to 28% of the current rate (mitigation option 1)

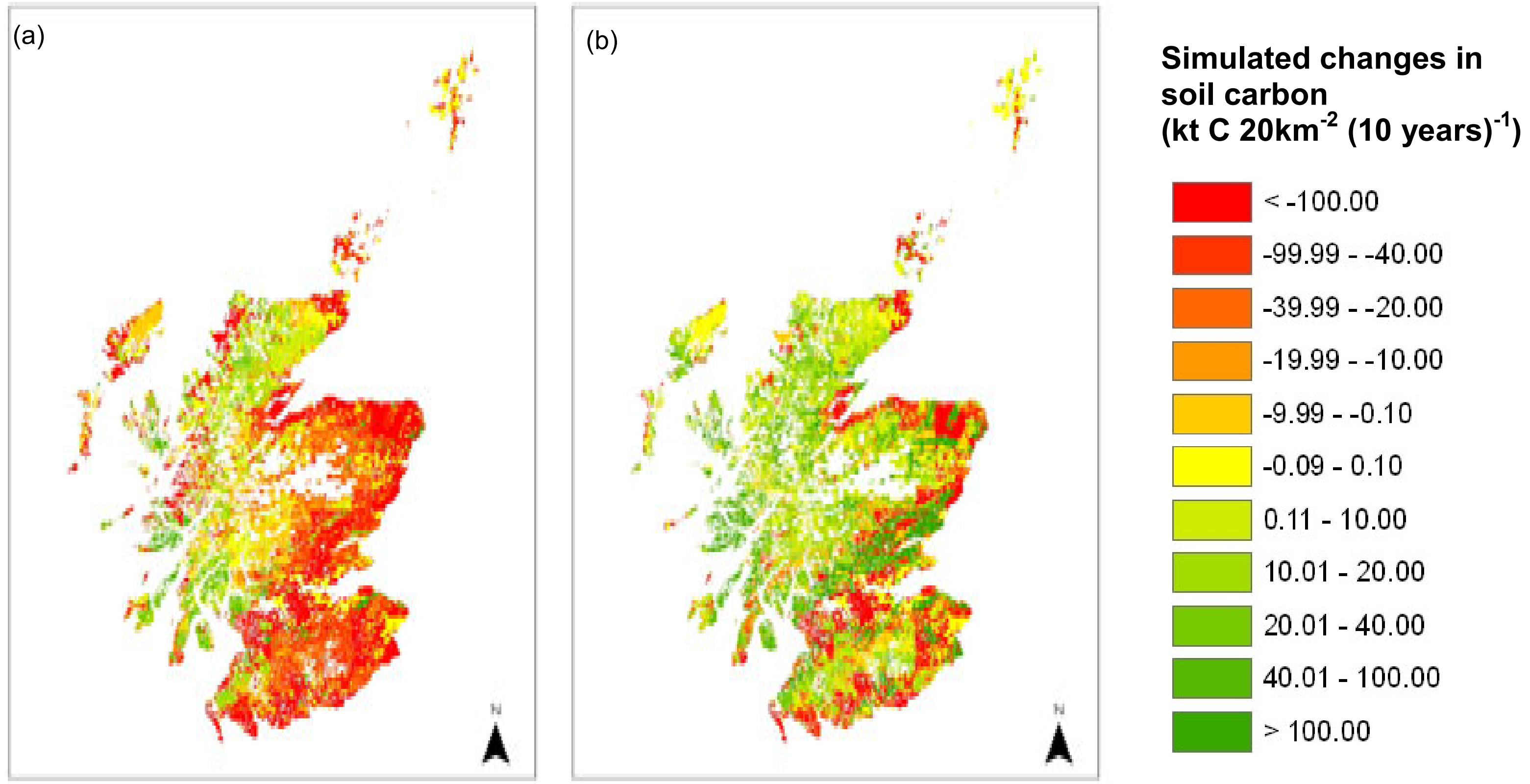


Figure 4.2.21. Simulated changes in soil C stocks in 2010 to 2019 as predicted by ECOSSE assuming a disturbance of the soil on afforestation (a) no mitigation options applied; (b) conversion of semi-natural land to arable or grassland and stopped and conversion of grassland to semi-natural increased by 125% of the current rate (mitigation option 2)

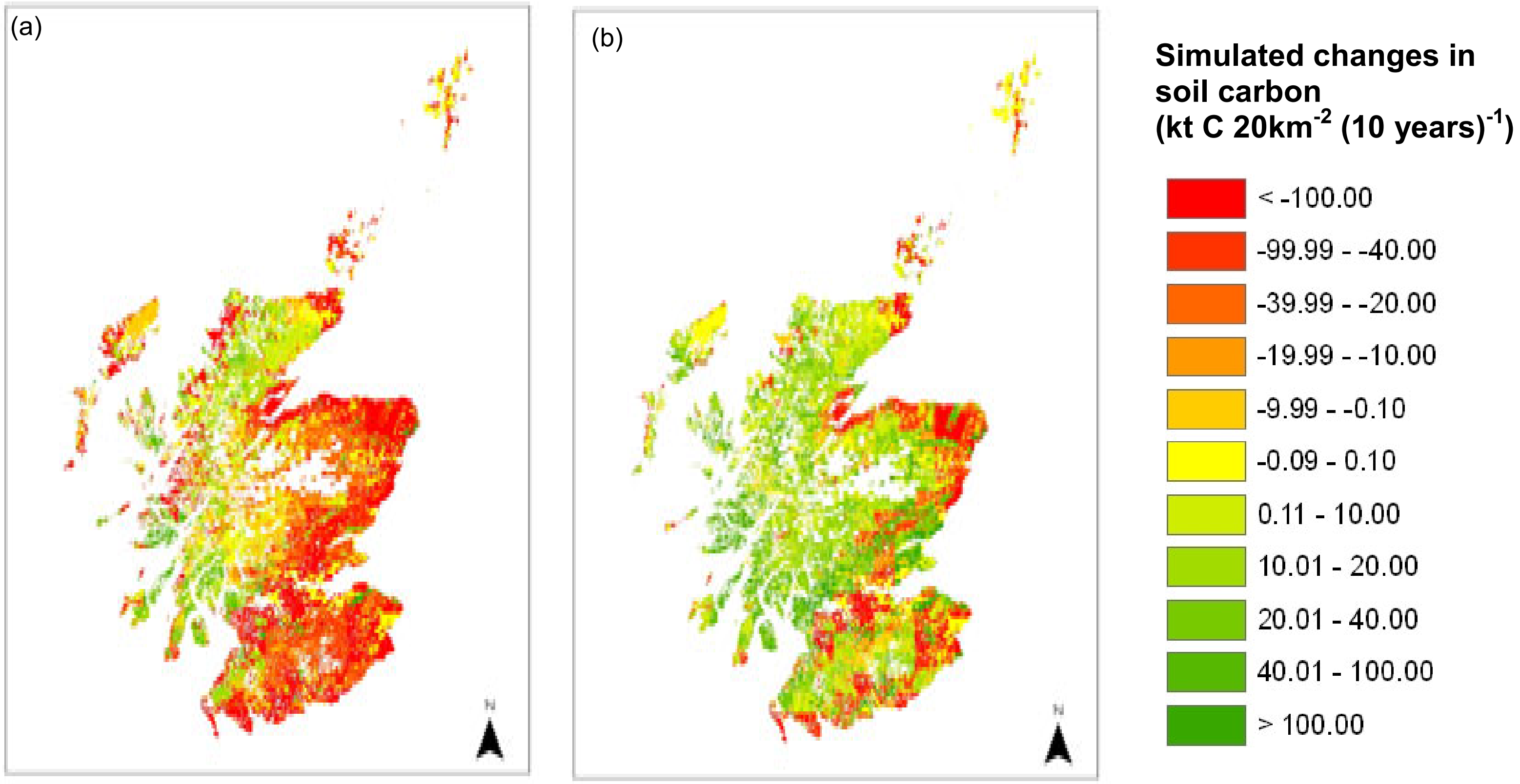


Figure 4.2.22. Simulated changes in soil C stocks in 2010 to 2019 as predicted by ECOSSE assuming a disturbance of soil on afforestation (a) no mitigation options applied; (b) conversion of semi-natural land to arable or grassland stopped and conversion of arable to grassland increased by 63% of the current rate (mitigation option 3)

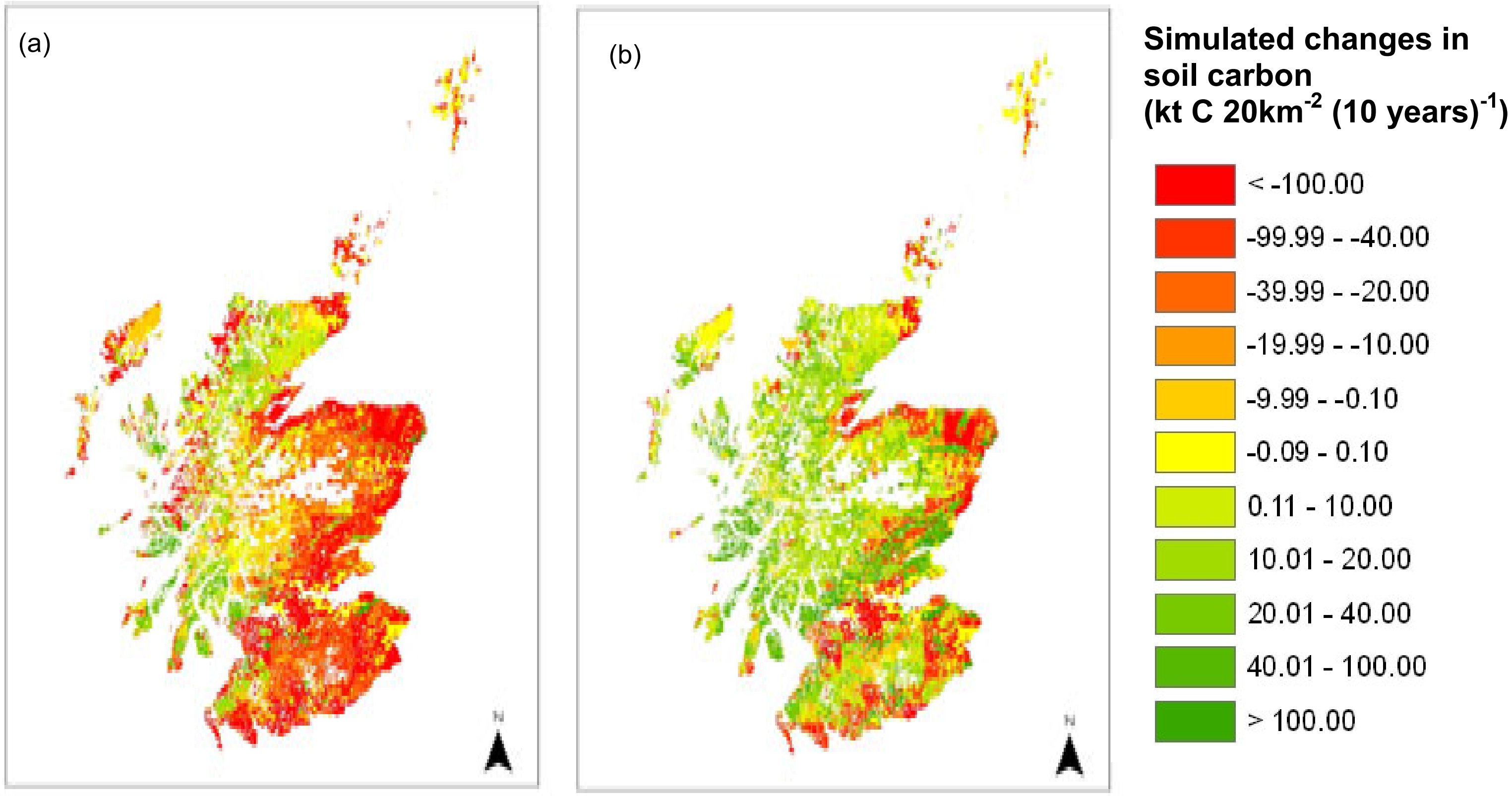


Figure 4.2.23. Simulated changes in soil C stocks in 2010 to 2019 as predicted by ECOSSE assuming a high level of disturbance on afforestation (a) no mitigation options applied; (b) conversion of semi-natural land to arable or grassland stopped and conversion of grassland to arable decreased to 77% of the current rate (mitigation option 4)

4.2.6 Conclusions

Comparison of CEH and ECOSSE estimates of change in SOC

The correlation between the ECOSSE and CEH estimates is given by $r^2 = 0.97$ and $r^2 = 0.93$ for 1990-1999 and 2000-2009 respectively, which is highly significant ($P < 0.001$). A *t*-test also indicates that the mean values estimated by the two approaches are not significantly different in either decade. This provides confidence that these two very different approaches are able to provide broadly similar results.

Soil disturbance and reduced plant inputs

The estimates of changes in soil C made by ECOSSE on land use change semi-natural to grassland show a larger loss of soil C than estimated by the CEH method. Similarly, ECOSSE estimates a larger gain in soil C on land use change grassland to semi-natural. Correspondingly, a larger loss of soil C is estimated by ECOSSE than by the CEH method for the land use change forestry to semi-natural and a smaller gain in soil C for the land use change semi-natural to forestry. These differences occur due to processes that are included in ECOSSE but not in the CEH approach associated with soil disturbance and reduced plant inputs when vegetation is immature. Carbon losses due to soil disturbance and an initial reduction in the plant input result in a loss of soil C or a smaller gain than estimated by CEH for land use changes between semi-natural land and grassland or forestry. A literature review provides evidence for the need to include soil disturbance and reduced plant inputs in simulations.

Changes in carbon attributable to Scottish soils

In 1990-1999, the ECOSSE estimate of the annual change in soil C stocks for Scotland is -822 kt year^{-1}, differing from the CEH estimates by -9 kt year^{-1}. In 2000-2009, the ECOSSE estimate of the annual change in soil C stocks for Scotland is -810 kt year^{-1}, differing from CEH estimates by -68 kt year^{-1}. These estimates show a high degree of agreement.

Land use changes responsible for the emissions

The simulated total change in soil C stocks becomes more negative (i.e. increased emissions) from 1950s up to the end of the 1970s when the change in soil C stocks increases sharply (i.e. decreased emissions), although remaining negative (net C emissions). The increase occurs due to a levelling off of the losses associated with the land use changes grassland to arable and forestry to semi-natural, and increased sequestration associated with conversion of arable land to grassland. Conversion of forestry to semi-natural results in net emissions up to the 1970s, because the plant communities have not had time to reach maturity. After this time, the greater maturity of the earlier converted land results in decrease in emissions. Increasing the area of land use change from arable to grass has the highest potential to sequester soil C, and decreasing the area of grass to arable has the highest potential to reduce losses of soil C.

Soils responsible for the emissions

Across Scotland, the simulated change in soil C from organic soils (defined here as soils with a C content of over 6%; Smith *et al*., 2007b) between 1950 and 2009 is -62512 kt, compared to -35351 kt from mineral soils; losses from organic soils are 64% of the total soil C losses. This emphasizes the importance of organic soils in any national estimates of greenhouse gas emissions, and the need to avoid C emitting land use changes on these soils. These results also suggest that mitigation options to reduce losses of soil C might recommend different policies for land use change on mineral and organic soils.

Changes in soil carbon due to projected land use change over the next decade

The largest difference in the C losses from the soil estimated for the next decade is associated with the land use change forestry to semi-natural, and is an additional loss of C from the soil of 80 kt C yr^{-1}. The overall trend is towards increased loss of soil C, with a total loss of an extra 135 kt C yr^{-1} from the soil due to the projected scenarios of land use change in Scotland.

Changes in soil carbon due to projected climate change during this century

Climate change alone is predicted to result in a decline in the soil C stocks of only -93 to -125 kt between 1990 and 2060 (-1.3 to -1.8 kt year^{-1}). The largest changes in soil C are seen under unmanaged semi-natural land, -38 to -60 kt between 1990 and 2060 (-0.5 to -0.9 kt year^{-1}). If plant inputs are not maintained, as may be the case especially in semi-natural land uses, the losses of soil C may be greater than predicted. Projected changes in land use result in losses of soil C stocks that are nearly 50 times greater than the losses due to climate change. This illustrates the potential for C losses due to climate change to be mitigated by changing land use.

Mitigation options to reduce losses of soil C

Four mitigation options were identified as potential tools for achieving zero net losses of C Scottish soils:

1. Decrease in the rate of conversion of grassland to arable to 28% of the current rate;
2. Stop conversion of semi-natural land to arable or grassland and increase the conversion of grassland to semi-natural by 125% of the current rate;
3. Stop conversion of semi-natural land to arable or grassland and increase the conversion of arable to grassland by 63% of the current rate; and
4. Stop conversion of semi-natural land to arable or grassland and decrease the conversion of grassland to arable to 77% of the current rate.

5. Future Work

5.1. Geostatistical analysis of sampling required to estimate total soil C stocks in Scottish peats

The geostatistical analysis of variation in peat depth suggests that more work is needed on the scales of variation in peat. A greater number of peatland types and examples should be examined over a wider geographical area in order to identify and separate regional components of spatial variation, which may be due to regional climatic differences, from local components influenced by topography, such as slope, or other short range factors which influence hydrology.

5.2. Targeted resampling of map polygons containing peat to measure total depth, bulk density and %carbon

Geostatistical analysis should be used to highlight the areas of Scotland and the relevant peat-containing polygons where additional information would be beneficial. This particularly applies to those QM units where peat is a component but where data is lacking. A depthing and sampling strategy should be undertaken on the prescribed areas to enable better estimates of the average depth, bulk density, % C and ultimately the C stocks, both at a local and national level. Use of this data as well as data from the current NSIS_2 resampling programme will allow estimates of C stocks for soil profiles to be improved, so enhancing the national soil datasets.

5.3. Explore the costs and benefits of Ground Penetrating Radar (GPR) and Light Detection and Ranging (LIDAR) to measure peat depth and monitor changes in soil C stocks in the peatlands of Scotland

The use of GPR should be tested in the field at sample peatland sites with detailed depth measurements (e.g. Glensaugh, Smith *et al*., 2007b).This would indicate whether the results obtained agree with the depth measurements and whether these methods would be likely to significantly enhance the estimates of C stocks of areas where the depth was unknown.

5.4. Use data derived from NSIS_2 to improve accuracy of ECOSSE and its ability to predict the response of Scotland's organic soils to external change

Simulations of the soil C stocks from phase 2 and phase 3 of the NSIS_2 resampling programme should be compared to experimental measurements, when they become available. This will further refine the estimate of uncertainty associated with the national scale simulations. Additional resampling to include more land use change sites would greatly improve the evaluation of the model simulations.

5.5. Use of ECOSSE to address policy questions

There is a degree of uncertainty in the simulations of changes in soil C associated with the level of disturbance occurring on afforestation of Scottish soils. The uncertainties in the simulations would be greatly reduced by coupling the model to national scale data on past, present and alternative afforestation practices in Scotland. Further work is also needed to develop and evaluate the simulations of soil C turnover on land use change and soil disturbance, possibly explicitly including simulation of practices such as clear-felling, brash incorporation. This could be facilitated by linking ECOSSE to existing forestry models. In particular, these evaluations should focus on soil C losses following afforestation of semi-natural land, but could also include simulation of changes in physical protection of soil organic matter following other land use changes. These evaluations may require further measurements to be made at appropriate sites.

The simulations included here report changes in soil C stocks only. Changes in C stocks in vegetation and emissions of other greenhouse gases (methane and nitrous oxide) are not reported here. Simulations of changes in C held in vegetation would require ECOSSE to be coupled to a simple vegetation model such as BIOTA (Wang and Polglase, 1995); this would be a useful advance. ECOSSE already provides simulations of other greenhouse gas emissions (methane, nitrous oxide). The results were not included in this report as the evaluations at the NSIS sites only provided estimates of the uncertainties associated with national scale simulations of total C loss. Analogous national scale evaluations of uncertainty in methane and nitrous oxide emissions should be done to allow the full greenhouse gas balance to be reported.

The future climate simulations presented above used the UKCIP02 climate scenarios. The UKCIP08 scenarios have not yet been published. In early 2009, the revised UKCIP scenarios are expected to be published, providing improved spatial resolution and updated climate scenarios. Simulations should be rerun with and without changes in land use and plant input when the new climate scenarios become available.

Four simple mitigation options to reduce C losses from Scottish soils were identified in the reported work. In future work, more detailed mitigation options should be considered, refined separately for mineral and organic soils. These could include

1. Including biomass and biofuel crops
2. Changing from high disturbance to low disturbance forestry operations
3. Changing from till to no-till arable management
4. Changing the intensity of grazing
5. Peatland restoration and maintenance

Brown *et al.* (2008a, 2008b) recently produced a revised map of land capability for agriculture in Scotland based on potential future climate. Future work should use this modelled land capability map as a filter for possible land use changes. The impact on national emissions of other potential land use changes, such as siting wind farms on peatlands, could also be considered.

6. Conclusions

The work in this project included a number of different objectives, all aimed at improving national estimates of soil C and soil C change. The focus of the geostatistical analysis is to improve estimates of peat depths and total soil C stocks in Scottish peats using more targeted sampling approaches. The exploration of GPR and LIDAR assesses the potential of new methods to measure peat depth and monitor changes in soil C stocks in the peatlands of Scotland. The data derived from the NSIS_2 resampling is used to improve the accuracy of the ECOSSE model and its estimates of C change given a range of land use and climate change scenarios. This project provides a significant contribution to improved estimates of C stocks and C change in Scottish soils.

The geostatistical analysis of variation in peat depth suggests that more work is needed on the scales of variation in peat. A greater number of peatland examples should be examined over a wider geographical area to identify and separate regional components of spatial variation, which may be due to regional climatic differences, topographic factors or other short range factors which influence hydrology. Effort should be made to include a study of the polygon boundaries between peaty and mineral soils, using data on the presence and absence of a peaty layer.

The analysis of technologies available for improved determination of peat depth and C content, indicates GPR technology has been used much more in peat studies than LIDAR. Ground penetrating radar could be used on its own to measure peat depth whereas LIDAR could not, but LIDAR perhaps offers the better option for measuring changes in C stocks in peat. One clear advantage of GPR is that it can provide a continuous assessment of peat depth along a transect compared to the intermittent measurements achieved by probing. Most small GPR devices currently available can be operated by one or two personnel, but are not very suitable for use on uneven terrain, being wheeled devices that are cumbersome to use and may cause damage to the surface vegetation. Accessing sites on foot and measuring depths with depthing rods is likely to cause less damage to the site. There are a number of bogs with detailed depth measurements (eg. Glensaugh, Smith *et al*., 2007b) where testing a GPR device would provide an indication of the accuracy of the technique in measuring peat depth compared to traditional methods. This would indicate whether the results obtained would significantly impact the C stock estimates of the study area.

By contrast, research using LIDAR to measure the C content of peats is still at the experimental phase. LIDAR appears to have potential as a tool to monitor development of peat gullies in areas of peat erosion, but can only achieve height accuracies in the order of +/- 0.15m and with a horizontal accuracy of 1-2 metres. LIDAR has the capacity to generate very accurate representations of the ground surface, and when combined with depth to the peat bottom in a GIS, 3D models of the peat resource can be generated. A comparison of peat volumes calculated using depth data combined with the bog area to those obtained using LIDAR would indicate whether LIDAR adds sufficient value for it to be used more widely.

The study suggests that it is possible to make a prediction of peat depth in areas where no measurements are available using an analysis of the spatial statistics for peat depth. This relies on distance to the nearest known values and clearly in areas where little data exists, the variance about the prediction increases. The expert judgement used in the original estimation of peat depths across the country similarly relies upon the depth in adjacent peat polygons where these are known. For this reason, there is broad agreement between the two approaches, but there was some consistent deviation, particularly at the deeper end where the expert system gave deeper peats. This is attributed to the expert system using additional information in its judgement. We conclude that the expert system gives a fair prediction for most peats and that the similarity in mean values indicates little difference in overall C stocks computed using either approach.

To undertake a comprehensive targeted peat sampling programme will be time consuming and costly and should be considered against the benefits ensuing from collecting such data. However the data collected during the current NSIS_2 resampling programme will provide information on the thickness and depth of horizons, which combined with bulk density analysis and % C values, will allow C stocks for the soil profiles sampled to be calculated, enhancing the national soil datasets and the associated variability studies will also give an insight into the range of values around a point. The NSIS_2 work will also provide information on the thickness of organic horizons within organo-mineral soils and using hand held augers, the thickness of peat deposits at each site can be assessed to 2 metre depth, again enhancing previous information and C stocks. However to transport actual peat depthing rods to each site in conjunction with the required NSIS_2 equipment, is not thought a feasible proposition within current budgets and any additional sampling of peat below 1 metre should be undertaken as a separate exercise. Such an exercise would allow the known uneven distribution of data, both across the country (east to west) and between peat types (basin and blanket) to be built into the sampling programme.

The evaluation of the use of archived dry bulk density values for peat bogs to determine C stocks values retrospectively suggests that a pedotransfer function may be derived that enables dry bulk density to be estimated from peat moisture content. A restriction is that the peat samples should be from the saturated zone or at least have a wet bulk density in excess of 0.85. Since we are here interested in bulk density changes at depth, this restriction does not interfere too much with its application.

Simulations have been run at all 62 sites included in the first phase of the NSIS_2 analysis. The simulated values show a high degree of association with the measurements in both total C and change in C content of the soil. The uncertainty in the simulations is 20% of the average C content over all land use types, uncertainty increasing in the order natural/semi-natural < forestry < arable < grassland. Over all sites where land use change has occurred, the average deviation between the simulated and the measured values of percentage change in soil C is less than the experimental error (11% simulation error, 535% measurement error). Simulated values are within the 95% confidence interval of the 1:1 line between simulated and measured values, so the simulated values are within experimental error with respect to correlation. Only a small bias in the simulations compared to the measured values is observed, suggesting that a small underestimate of the change in soil C should be expected in the national simulation (-4%). A large proportion of the uncertainty is associated with uncertainties in the input data: these include uncertainties in

1. timing of land use change,
2. actual management of arable land, grassland and forestry, and
3. land use change before the start of the simulation.

There is potential to greatly decrease the uncertainty in the national simulations by developing algorithms to estimate of the likely rate of C accumulation or loss at the start of the simulation. Improved estimates of uncertainty at the national scale could also be achieved by sub-sampling all land use units within >20 x 1km^2 grid squares across the country and repeating the simulations of changes in C content done here. This would require changes to the long term soil sampling strategies.

The national simulations using ECOSSE have been improved during this project by the extensive developments in the model and by using improved data to drive the simulations. Data required for the national simulations have been collated from a number of different sources and prepared into files that can be used to drive the ECOSSE model. ECOSSE has been adapted to use the new data, to improve the initialisation of the model and to incorporate improved descriptions of processes. Comparison of estimates of changes in soil C stocks by CEH and ECOSSE for 1990-1999 and 2000-2009 show a highly significant correlation ($P < 0.001$), and mean values estimated by the two approaches that are not significantly different in either decade. This provides confidence in the results because these two very different approaches provide broadly similar results. The estimates of changes in soil C made by ECOSSE on land use change semi-natural to grassland show a larger loss of soil C than estimated by the CEH method. Similarly, ECOSSE estimates a larger gain in soil C on land use change grassland to semi-natural. Correspondingly, a larger loss of soil C is estimated by ECOSSE than by the CEH method for the land use change forestry to semi-natural and a smaller gain in soil C for the land use change semi-natural to forestry. These differences occur due to processes that are included in ECOSSE but not in the CEH approach associated with soil disturbance and reduced plant inputs when vegetation is immature. Carbon losses due to soil disturbance and an initial reduction in the plant input result in a loss of soil C or a smaller gain than estimated by CEH for land use changes between semi-natural land and grassland or forestry. A literature review provides evidence for the need to include soil disturbance and reduced plant inputs in simulations. In 2000-2009, the ECOSSE estimate of the annual change in soil C stocks for Scotland is -810 kt year^{-1} (differing from CEH estimates by -68 kt year^{-1}).

The results suggest that increasing the area of land use change from arable to grass and grass to semi-natural is likely to sequester more C, and decreasing the area of grass to arable and forestry to semi-natural is likely to reduce losses of soil C. However, note that these simulations have assumed no difference in the drainage status of the soil when converted to semi-natural; if the soil becomes less drained, a different pattern of changes in soil C would be expected.

Across Scotland, the simulated change in soil C from organic soils (defined here as soils with a C content of over 6%; Smith *et al*., 2007b) between 1950 and 2009 is -62512 kt, compared to -35351 kt from mineral soils; losses from organic soils are 64% of the total soil C losses. This emphasizes the importance of organic soils in any national estimates of greenhouse gas emissions, and the need to avoid C emitting land use changes on these soils. These results also suggest that mitigation options to reduce losses of soil C might recommend different policies for land use change on mineral and organic soils.

Climate change alone is predicted to result in a decline in the soil C stocks of only -93 to -125 kt between 1990 and 2060 (-1.3 to -1.8 kt year^{-1}). The largest changes in soil C are seen under unmanaged semi-natural land, -38 to -60 kt between 1990 and 2060 (-0.5 to -0.9 kt year^{-1}). If plant inputs are not maintained, as may be the case especially in semi-natural land uses, the losses of soil C may be greater than predicted. Projected changes in land use result in losses of soil C stocks that are nearly 50 times greater than the losses due to climate change. This illustrates the potential for C losses due to climate change to be mitigated by changing land use.

Four mitigation options have been identified with high potential for achieving zero net losses of C from Scottish soils:

1. Decrease in the rate of conversion of grassland to arable to 28% of the current rate;
2. Stop conversion of semi-natural land to arable or grassland and increase the conversion of grassland to semi-natural by 125% of the current rate;
3. Stop conversion of semi-natural land to arable or grassland and increase the conversion of arable to grassland by 63% of the current rate; and
4. Stop conversion of semi-natural land to arable or grassland and decrease the conversion of grassland to arable to 77% of the current rate.

Possible ways of incentivising these changes may come about through improving implementation of existing good agricultural and environmental condition (GAEC) standards for soil protection, through strengthening rural development policy, or though redesign of CAP to encourage the maintenance of existing C stocks (Frelih-Larsen et al., 2008).

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9. Appendices

9.1. Appendix 1. Summary data on peat depth (m) for 77 peat bogs, collated from the Scottish peat survey notes

BOG NAME	NOBS	MEAN	MEDIAN	MIN	MAX	RANGE	Q1	Q3	SD	SEM	VAR	%CV	SKEW
All Bogs	3924	2.19	1.80	0.10	12.00	11.90	0.70	3.30	1.74	0.028	3.04	79.5	1.16
Alvie	38	1.98	1.45	0.20	8.00	7.80	0.60	2.00	1.94	0.314	3.76	97.7	1.51
Ardnamurchan	63	1.06	0.60	0.10	3.80	3.70	0.30	1.38	1.05	0.132	1.10	98.9	1.31
Aultnaslanach	19	0.58	0.50	0.10	1.30	1.20	0.25	0.85	0.36	0.082	0.13	61.6	0.58
Baddengorm	316	1.13	0.70	0.20	5.30	5.10	0.30	1.60	1.06	0.060	1.12	94.0	1.58
Balmurie Fell	10	1.25	1.05	0.20	3.30	3.10	0.50	1.50	1.01	0.319	1.02	80.7	0.89
Bansras Road	23	2.65	3.00	1.40	4.50	3.10	2.00	3.08	0.84	0.174	0.70	31.5	0.36
Bogach Nan Sgadan	257	2.79	2.80	0.30	6.00	5.70	1.60	3.90	1.39	0.086	1.92	49.8	0.18
Boindarg Store and Ditch Line near Camster to Hill of Yarrow	16	1.73	1.35	0.50	4.80	4.30	0.55	2.55	1.37	0.343	1.88	79.3	1.10
Brabstermire to Hollandmey Farm	15	2.42	2.60	0.20	4.90	4.70	1.65	3.45	1.39	0.359	1.93	57.5	-0.24
Braid Fell	203	1.80	1.00	0.20	8.00	7.80	0.50	2.65	1.62	0.114	2.63	90.4	1.33
Cairn Muir	62	1.37	1.00	0.20	5.50	5.30	0.50	2.00	1.15	0.146	1.32	83.6	1.35
Carnock	69	1.41	1.00	0.10	5.40	5.30	0.50	2.00	1.23	0.148	1.52	87.2	1.50
Coladoir	11	1.04	0.80	0.30	3.00	2.70	0.50	1.33	0.82	0.247	0.67	78.9	1.46
Craiquerow Bog	35	1.47	0.90	0.20	4.50	4.30	0.50	2.53	1.30	0.219	1.68	88.3	0.90
Crosswood Hill	45	1.27	0.90	0.20	9.50	9.30	0.30	1.50	1.67	0.249	2.79	131.8	3.16
Dalemore (near Shepards Cairn)	423	2.48	2.50	0.10	6.50	6.40	1.40	3.50	1.37	0.066	1.87	55.1	0.10
Dalmagarry	43	2.45	1.80	0.20	7.50	7.30	1.00	3.53	2.06	0.314	4.24	84.1	1.13
Dalriach	47	2.92	2.70	0.20	6.50	6.30	1.03	4.50	2.04	0.297	4.15	69.8	0.23
Din Moss	10	9.58	11.25	1.80	12.00	10.20	10.00	12.00	3.86	1.220	14.89	40.3	-1.40
Drumbow	41	3.52	3.00	1.00	7.00	6.00	3.00	4.43	1.24	0.193	1.53	35.2	0.55
Drumbreck Moss	106	3.32	3.20	0.10	7.80	7.70	2.50	4.00	1.52	0.148	2.31	45.8	0.34
Drummoddie Moss	9	7.02	7.90	4.20	8.70	4.50	5.63	8.30	1.73	0.576	2.98	24.6	-0.72
Dunnet Hill	96	0.81	0.80	0.10	2.00	1.90	0.50	1.05	0.40	0.041	0.16	49.7	0.46
Eldrig Moss	14	2.96	3.05	0.10	6.00	5.90	2.30	3.80	1.59	0.425	2.53	53.8	-0.26
Feith Shalach	10	2.99	3.10	0.50	5.50	5.00	0.70	4.80	1.85	0.584	3.41	61.8	-0.24
Freeburn Hotel	14	0.66	0.45	0.10	2.10	2.00	0.10	0.80	0.67	0.178	0.45	101.6	1.14
Giar Hill	83	1.57	1.20	0.20	5.80	5.60	0.50	2.18	1.29	0.141	1.66	82.0	1.17
Glen Geirisdale	127	1.99	1.70	0.10	4.40	4.30	0.80	3.40	1.27	0.113	1.61	63.7	0.17
Glengyre	12	3.28	3.55	0.80	6.80	6.00	1.75	4.20	1.80	0.521	3.26	55.0	0.36
Glims	8	3.74	4.25	0.20	5.50	5.30	2.85	5.00	1.75	0.620	3.08	47.0	-1.02
Greenhead Moss	45	3.53	3.50	0.30	5.20	4.90	3.18	4.30	0.95	0.142	0.90	26.9	-1.10
Grey Carin of Camster West to Badryie	18	2.42	2.60	0.10	4.50	4.40	1.20	3.10	1.31	0.308	1.71	54.1	-0.15
Hecken	6	1.85	1.65	0.70	3.10	2.40	1.50	2.50	0.84	0.344	0.71	45.6	0.23
HeldaleWater	40	1.90	1.65	0.80	4.20	3.40	1.25	2.45	0.87	0.137	0.75	45.5	0.83
Highpark Farm	49	1.89	1.70	0.20	5.00	4.80	0.78	2.80	1.31	0.187	1.71	69.1	0.67
Hill of Bomo	19	2.61	3.00	0.50	4.40	3.90	1.38	3.45	1.26	0.288	1.58	48.1	-0.40
Hill of Harley (Cont'd)	19	1.78	1.20	0.40	4.60	4.20	0.55	2.93	1.41	0.324	2.00	79.2	0.84
Hill of Harley to Brabstermire	33	2.16	1.80	0.30	4.70	4.40	0.95	3.55	1.41	0.245	1.98	65.0	0.34
Hill of Stoupster (Cont'd)	30	2.29	2.40	0.50	3.80	3.30	1.50	3.00	0.88	0.161	0.78	38.6	-0.21
Hill of Stroupster - Ruthers of Howe	52	2.36	2.40	0.30	5.00	4.70	1.60	3.05	1.07	0.149	1.15	45.6	0.01
Hoy - Rackwick	6	0.53	0.65	0.20	0.70	0.50	0.30	0.70	0.23	0.092	0.05	42.2	-0.68
Linkertaing	22	2.93	2.95	0.50	5.30	4.80	1.50	4.50	1.56	0.332	2.42	53.1	-0.05
Loch Bunachton	34	2.92	3.35	0.20	6.50	6.30	1.30	4.50	1.77	0.304	3.14	60.6	-0.20
Loch Mave to Shinvall	37	3.16	3.20	0.10	5.90	5.80	2.18	4.13	1.49	0.245	2.22	47.1	-0.03
Loch Nan Clach	19	1.46	1.20	0.20	3.20	3.00	0.80	2.10	0.92	0.211	0.84	62.8	0.65
Loch Nan Gabhar	20	6.39	6.20	4.50	8.10	3.60	5.85	7.10	0.94	0.209	0.87	14.6	-0.06
Loch Rangag to Trig an Hill	16	1.51	1.20	0.50	3.50	3.00	0.50	2.50	1.05	0.262	1.10	69.2	0.59
Loomachuns	13	3.56	3.60	1.00	5.50	4.50	2.38	5.05	1.51	0.418	2.27	42.3	-0.26
Lower Camster West to Nursery Cottage	15	2.27	1.50	0.40	5.30	4.90	0.85	3.65	1.67	0.432	2.80	73.9	0.65
Luchan	34	2.19	2.20	1.00	4.40	3.40	1.50	2.80	0.78	0.135	0.62	35.9	0.56
Machrie Burn Arran	77	0.61	0.40	0.10	4.00	3.90	0.30	0.50	0.63	0.072	0.39	102.2	2.98
Marl Moss (Achingills)	4	1.25	1.00	1.00	2.00	1.00	1.00	1.50	0.50	0.250	0.25	40.0	1.15
Methven Moss	46	5.45	5.50	3.00	7.80	4.80	4.50	6.60	1.30	0.191	1.68	23.8	-0.10
Millbuie to Coulvid Wood	20	1.90	1.80	0.10	5.30	5.20	0.80	2.65	1.28	0.287	1.64	67.5	0.86
Moss Morran	83	3.25	3.30	0.10	8.00	7.90	2.03	4.30	1.93	0.212	3.72	59.3	0.23
Moss of Greenland	15	1.07	1.10	0.30	1.60	1.30	0.83	1.43	0.37	0.096	0.14	34.8	-0.24
North Shielton Bog	224	2.34	2.25	0.10	7.00	6.90	0.70	3.50	1.71	0.114	2.91	72.8	0.62
P.O. @ Westdale to Dwight House	10	2.51	2.80	0.40	4.90	4.50	0.50	3.70	1.61	0.509	2.59	64.2	-0.18
Pegal Hill	17	0.88	1.00	0.20	1.40	1.20	0.50	1.20	0.39	0.095	0.15	44.8	-0.39
Quarter Fell	8	0.65	0.50	0.10	1.50	1.40	0.40	0.90	0.43	0.154	0.19	66.8	0.82
Refaithy	11	2.37	2.70	0.20	5.00	4.80	0.65	3.80	1.66	0.502	2.77	70.1	0.05
Riskaman to Cuocan Canachreag	20	2.94	2.70	0.30	5.60	5.30	1.50	4.60	1.76	0.393	3.08	59.8	0.10
Scorrie Moss	6	1.70	1.70	1.00	2.30	1.30	1.30	2.20	0.54	0.219	0.29	31.6	-0.09
Sheuchan Hill	10	0.42	0.35	0.20	1.00	0.80	0.20	0.50	0.27	0.084	0.07	63.3	1.08
Slochd	76	1.93	1.45	0.10	7.00	6.90	0.60	3.10	1.70	0.195	2.89	88.3	1.12
Slochd (Cont.)	76	1.00	0.85	0.10	3.00	2.90	0.30	1.60	0.78	0.089	0.60	77.9	0.55
Spurlens Rig	148	2.88	2.70	0.20	9.00	8.80	0.60	4.40	2.25	0.185	5.04	77.9	0.65
Stab Hill	12	2.56	2.80	0.20	6.00	5.80	0.50	4.00	2.12	0.612	4.49	82.8	0.26
Strompster (North)	20	3.08	3.25	0.50	5.00	4.50	2.00	4.00	1.16	0.260	1.36	37.9	-0.38
Todholes	30	1.00	1.00	0.20	2.50	2.30	0.50	1.50	0.59	0.108	0.35	59.2	0.69
Traigh Farm	34	2.51	2.30	0.80	5.50	4.70	1.50	3.50	1.27	0.218	1.62	50.6	0.39
Trig on Tannach Hill West to Loch of Cavalia	23	1.77	1.20	0.20	5.80	5.60	0.53	3.20	1.58	0.329	2.48	89.0	1.03
Ulbster bog	81	3.52	3.00	0.20	10.80	10.60	1.60	5.10	2.48	0.275	6.14	70.4	0.85
Wartle Moss	19	1.09	1.00	0.30	2.00	1.70	0.90	1.30	0.43	0.099	0.19	39.6	0.12
West Freugh	71	2.06	2.00	0.50	4.10	3.60	1.20	2.90	0.98	0.116	0.96	47.6	0.18
Weydale	14	0.88	0.85	0.30	1.60	1.30	0.60	1.00	0.37	0.098	0.13	41.7	0.49
Yellow Moss	17	0.96	1.00	0.10	2.00	1.90	0.60	1.20	0.50	0.121	0.25	51.6	0.32
Mean	51	2.28	2.19	0.49	5.02	4.53	1.33	3.12	1.25	0.250	1.93	61.2	0.45
Min	4	0.42	0.35	0.10	0.70	0.50	0.10	0.50	0.23	0.041	0.05	14.6	-1.40
Max	423	9.58	11.25	4.50	12.00	10.60	10.00	12.00	3.86	1.220	14.89	131.8	3.16

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