Section 9

Incorporating effects of changes in climate, nitrogen deposition and CO_2 in projections of forest carbon budgets

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9. Incorporating effects of changes in climate, nitrogen deposition and CO_2 in projections of forest carbon budgets

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9.1. Summary

Methodology used in previous UK greenhouse gas inventories and projections for forestry-related C-sequestration did not consider the effects of environmental change. C-input into the forests was represented by constant site-specific values (yield classes). However, recent studies found significant effects of environmental change on C-dynamics in European forests. This showed the need to make inventory methodology environmentally responsive. To achieve this, we here employed the process-based forest model BASFOR. The model was parameterized by means of Bayesian calibration, which allowed quantifying the uncertainty in parameter values and the propagation of the uncertainty to model outputs. Application of the model to the UK showed large spatial variation in sequestration rates and in the effect of environmental change. Factor analysis for one forest site identified a key role for increasing atmospheric CO_2 and, to lesser extent, warming, but sensitivity to changes in N-deposition may have been underestimated by the use of a global soils database according to which UK soils have very high N-contents. We conclude that the methodology of using process-based models in combination with Bayesian calibration and uncertainty quantification works well and can be used to make inventory methodology environmentally responsive provided the quality of input data is increased.

9.2. Introduction

Methodology employed in previous UK greenhouse gas inventories and projections did not account for changes in forest carbon use caused by changes in the environmental drivers climate, nitrogen deposition and CO_2 (Milne *et al*. 2003). Projections were made for forest carbon use until the year 2020, using simple models like CFLOW that are based on yield tables derived from trees grown before 1990. However, European forests have been affected by changing growing conditions during the 20th century, invalidating the use of static yield tables (Spiecker *et al.* 1996). Studies using process-based modelling have estimated the effects of the changing environmental drivers on forest growth in Europe (project RECOGNITION: Milne & Van Oijen 2005) and the UK (Murray & Thornley, in Milne *et al*., 2003). The process-based models as such are too complex to be applied directly to mapping carbon budgets at high spatial resolution, but their output can be analysed to derive simplified relationships - linking environmental drivers and site conditions to forest carbon use - that can be incorporated in the simple models.

Although complex process-based models are attractive because of their capability to calculate the consequences of changes in various environmental factors, both soil-related and atmospheric, their use has been hampered by two practical problems. First, they require a large body of data both for driving the model and for quantifying their many parameters. Secondly, the data invariably are incomplete or imprecisely measured, which leads to an accumulation of uncertainty in model outputs (Levy *et al*., 2004). These two problems are significantly smaller when inventories are made using simpler and more robust models like CFLOW, which lump the effects of the growing environment together in the widely available measurement of yield class (*i.e.* average annual wood volume production). The data problem can not be overcome at short notice, but the present study does show how the inevitable uncertainty can be rigorously quantified and systematically reduced.

Here, we shall present results for UK-wide carbon sequestration in conifer plantation forests, derived using the relatively complex process-based forest model BASFOR. The method of quantifying and analysing uncertainties, involving Bayesian statistics, will be explained and areas of major uncertainty identified. Finally, we show an analysis of past and future forest growth at one particular Sitka spruce site, Dodd Wood, in which the contributions of changes in climate, CO_2 and N-deposition to changes in yield class and C-sequestration were quantified. This example shows how the input to CFLOW, *i.e.* yield class, could be made sensitive to actual and envisaged environmental change, thus making the inventory construction environmentally responsive.

9.3. Methods

9.3.1. Model

The BASic FORest simulator, BASFOR, is a process-based forest model that simulates carbon and nitrogen cycling in trees, soil organic matter and litter (Van Oijen *et al*., 2005). It simulates the response of trees and soil to radiation, temperature, precipitation, humidity, wind speed, atmospheric CO_2 and N-deposition, as well as tree thinning regime. The model has 11 state variables, representing carbon and nitrogen pools in trees and soil, and 32 parameters controlling the rate of physiological processes and morphological characteristics. Besides time series for the state variables, output may be produced of net primary productivity (NPP), tree height, ground cover, LAI, N-mineralisation and other tree and soil variables. BASFOR is built from well known process-representations. Light absorption is calculated by Beer's law. Gross primary productivity (GPP) is calculated as light absorption times a light-use efficiency (LUE). NPP is calculated as a fixed ratio of GPP. LUE is temperature- and CO_2-dependent and may be reduced if insufficient nitrogen is taken up by the plants. Potential nitrogen uptake scales with root system area. Actual nitrogen uptake is the minimum of demand, determined by tissue N-concentration, and potential uptake. Allocation of assimilates follows allometric rules, but water stress may limit leaf area index (LAI). Turnover of tree and soil components proceeds at constant relative rates.

The model is deterministic and is solved by Euler integration with a time step of one day.

9.3.2. Data

This modelling study required the use of a considerable amount of data. The data were used for two different purposes. First, environmental data were used as drivers for the forest model simulations, as described in section 9.3.1. Secondly, literature data and data from UK forests were used to provide estimates of the model parameters. Both types of data are described in this section.

9.3.2.1 Weather

All weather data used in the study were taken from the climate scenarios provided by UKCIP (Hulme & Jenkins, 1998). For future weather, only the values in the "Medium-high" scenario were used. Figure 9-1 and Figure 9-2 show average temperature and rate of precipitation across the UK for the period 1920-2000. The data are given for a regular spatial grid of 655 cells of 20 by 20 km each. Spatial gradients for temperature and precipitation are dominated by latitudinal and longitudinal effects, respectively. Figure 9-3 shows the degree of warming predicted by the selected climate change scenario, expressed as the difference in temperature between the periods 2000-2080 and 1920-2000. Warming is expected to show a decreasing pattern from the South-East to the North-West.

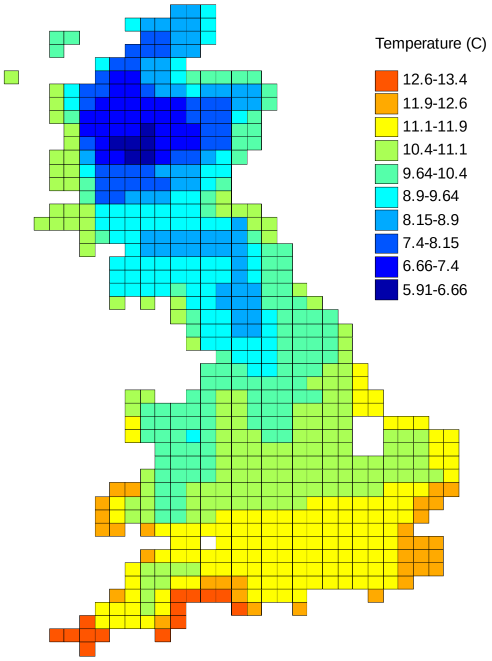

Figure 9-1 Mean temperature for 1920-2000. Data source: UKCIP

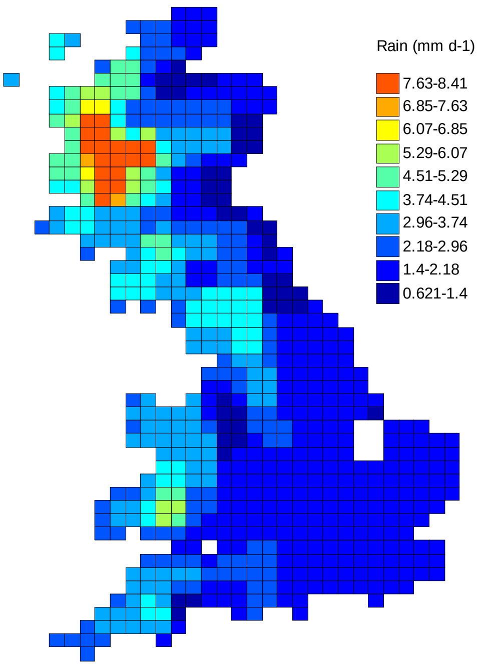

Figure 9-2 Mean precipitation for 1920-2000. Data source: UKCIP

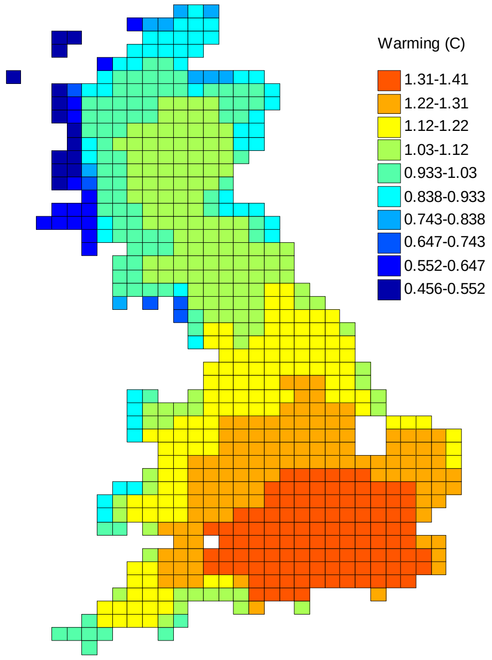

Figure 9-3 Change in mean temperature from 1920-2000 to 2000-2080. Data source: UKCIP

A summary of UK-average weather for the same two time periods but for all five variables used in the model (radiation, temperature, precipitation, vapour pressure and wind speed) is given in Table 9-1. According to the chosen UKCIP scenario, only temperature is expected to change significantly.

Table 9-1 Mean weather conditions for 1920-2000 and 2000-2080. Averages, standard deviations and extremes of global radiation (GR), temperature (T), precipitation (RAIN), vapour pressure (VP) and wind speed (WN), for 655 grid cells of 20 x 20 km (see Figure 9-1 to Figure 9-3) covering Great Britain. Data source: UKCIP.

		GR	T	RAIN	VP	WN
		MJ m^{-2} d^{-1}	°C	mm d^{-1}	kPa	m s^{-1}
1920-2000	Mean	9.54	9.46	2.80	1.00	7.01
	Standard deviation	1.17	1.04	0.80	0.07	1.31
	Minimum	6.58	5.71	0.61	0.79	4.27
	Maximum	12.79	12.30	5.41	1.20	8.73
2000-2080	Mean	9.58	10.30	2.83	1.06	6.97
	Standard deviation	1.27	0.98	0.81	0.07	1.29
	Minimum	6.53	6.74	0.62	0.84	4.28
	Maximum	13.00	13.06	5.42	1.26	8.63

9.3.2.2 Atmospheric CO_2 concentration.

Measurements of [CO_2] are more precise than those of most other environmental variables, and spatial variation is limited. Hence the literature is quite unanimous in its estimates of past CO_2 levels, with values of about 300 ppm in 1920 increasing to current levels of around 380 ppm. The average CO_2 level for the whole period 1920-2000 has been about 325 ppm. There is less unanimity regarding future CO_2 levels. We employed the predictions of the Bern model (Joos *et al*., 1996) for the mid-range IPCC emission scenario IS92a. This predicts an average CO_2 concentration for the period 2000-2080 of 480 ppm.

9.3.2.3 N-deposition

The time course of yearly total atmospheric N-deposition for the years 1920–2080 was estimated using three sources of information (Van Oijen *et al*. 2006). First, literature information suggested very low levels of N-deposition (< 3 kg N ha^{-1} yr^{-1}) across Europe in the year 1900 (Galloway, 1985). Second, data and calculations by the Co-operative Programme for Monitoring and Evaluation of the Long-Range Transmission of Air Pollutants in Europe (EMEP) show increasing N-deposition values during most of the 20th century with maxima reached around 1990. Third, the 1999 Gothenburg Protocol to Abate Acidification, Eutrophication and Ground-level Ozone sets emission ceilings for 2010 for NO_x, ammonia and other pollutants. Hence further reductions of N-deposition until the year 2010 were assumed and deposition was assumed to remain constant thereafter. These temporal patterns with overlaid with the spatial distribution determined for deposition on 2004 across the UK (R.I. Smith, pers. comm., Figure 9-4).

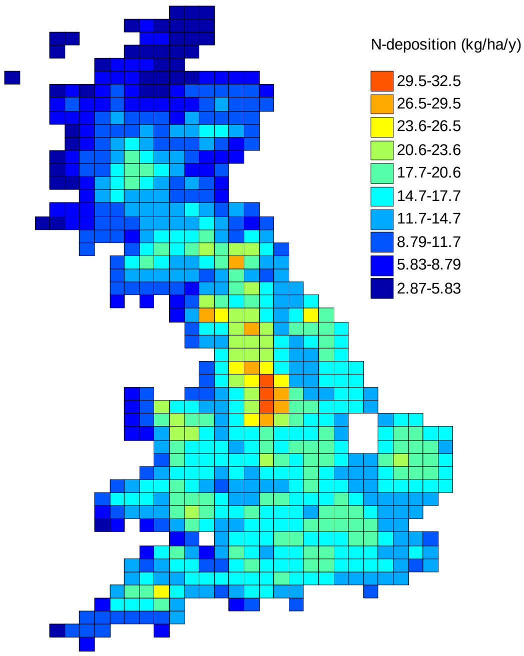

Figure 9-4 Atmospheric N-deposition in 2004. Data provided by R. Smith, CEH-Edinburgh

9.3.2.4 Soils

All soil information used in this study was taken from the global soils database produced by the Data and Information Services of the International Geosphere-Biosphere Programme (IGBP-DIS, Global Soil Data Task 2000). The IGBP-DIS database was used primarily because of its data on soil nitrogen content (Figure 9-5), but for consistency its data on soil carbon (Figure 9-6) and on plant available soil water content (PAWC, Figure 9-7) were used as well.

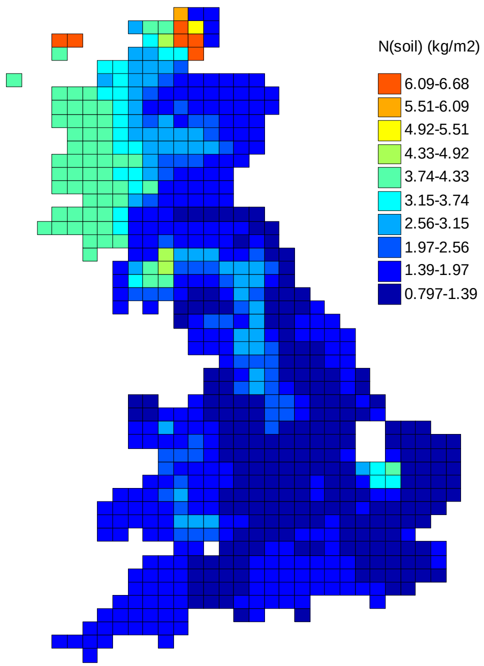

Figure 9-5 Total nitrogen in top 100 cm soil.
Data source: IGBP-DIS

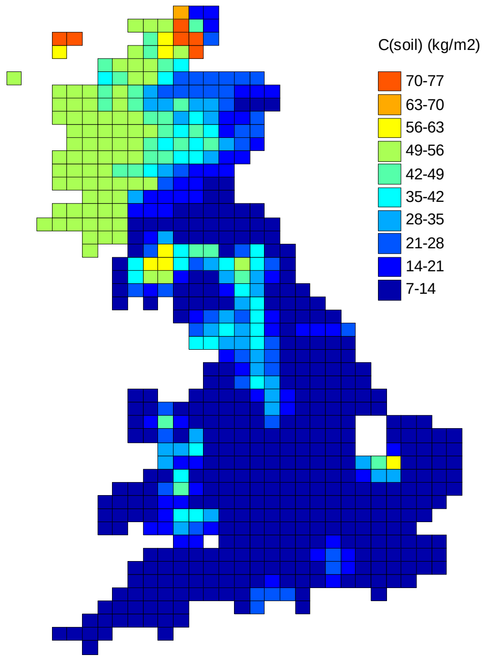

Figure 9-6 Total carbon in top 100 cm soil.
Data source: IGBP-DIS

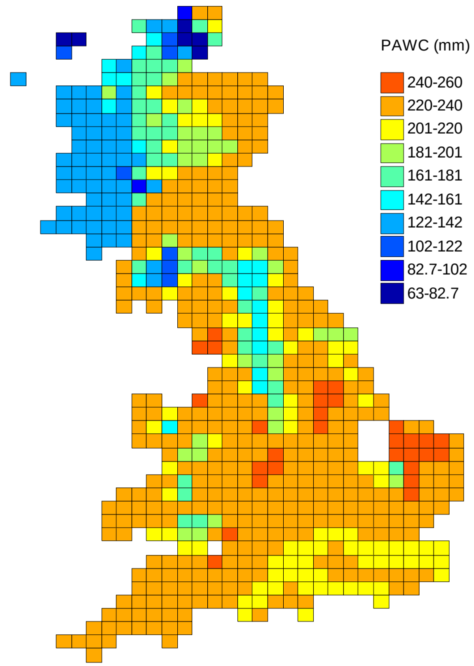

Figure 9-7 Maximum plant available water in top 100 cm soil. Data source: IGBP-DIS

9.3.2.5 Trees

Forest Research provided data on tree growth and soil characteristics from two Sitka spruce stands, for use in model calibration (R. Matthews & P. Taylor, pers. comm.). The sites were Dodd Wood (54.64 °N, 3.17 °W, alt. 381 m., indurated brown earth sandy soil) and Rheola (51.74 °N, 3.68 °W, alt. 220 m., brown earth soil) (Figure 9-8). Trees were planted in 1927 and 1935, respectively, and management followed a 5-year thinning cycle on both sites.

Figure 9-8 Model calibration data sites (Forest Research, UK)

9.3.2.6 Bayesian calibration and uncertainty quantification

The parameters of the BASFOR model were quantified by means of Bayesian calibration, using the Forest Research data for Dodd Wood and Rheola (see 9.3.2.5). Bayesian calibration provided estimates of the parameters of BASFOR, with measures of their uncertainty and correlations. The procedure began with quantifying the uncertainty about the parameter values in the form of a prior probability distribution. The prior information was taken from the literature on conifer growth. The Forest Research data on model output variables were used to update the parameter distribution by application of Bayes' Theorem. This yielded a posterior, calibrated probability distribution for the parameters. The predictive uncertainty of the model was then quantified by running the model with different parameter settings, sampled from the posterior distribution (n=5). Because Bayesian calibration of process-based models like BASFOR cannot be performed analytically, the posterior parameter distribution was approximated in the form of a representative sample of parameter values. This was achieved by means of Markov Chain Monte Carlo simulation. For further details of the Bayesian calibration procedure, see Van Oijen *et al*. (2005).

One limitation of the present study was that only the uncertainty in model parameters was quantified. Uncertainty in model drivers (climate, soils) was not quantified, nor was the uncertainty relating to the structure of the BASFOR model itself assessed.

9.4. Results

9.4.1. Bayesian calibration and uncertainty quantification

The results of model parameterisation using the method of Bayesian calibration are summarized in Table 9-2. The table lists the major parameters of BASFOR, with their prior uncertainty before application of data from UK forests. For most parameters, prior uncertainty was quite large, as is evident from wide ranges of possible values, *i.e.* lower and upper limits being far apart. The high level of prior uncertainty is typical whenever forest parameter values need to be quantified from the literature (Levy *et al.*). Figure 9-9 (black dotted lines) shows for four model output variables (tree and soil carbon, height and total produced wood volume) how the prior parameter uncertainty effected uncertainty in model outputs at the Dodd Wood site. For example, the uncertainty interval (2 standard deviations wide) for tree carbon at the end of the eighty-year rotation ranged from below 40 to above 80 ton carbon ha^{-1}. Table 9-2 and Figure 9-9 also show to what extent uncertainties were reduced by the Bayesian calibration using the data from the Dodd Wood and Rheola sites, described in section 9.3.2.5. The marginal posterior probability distributions were much narrower than the prior distributions, as can be seen from the small coefficients of variation. The data from Dodd Wood were not equally informative for all parameters, with CVs for three parameters – initial leaf and stem carbon content and N/C ratio of wood – exceeding 20%. However, Figure 9-9, red unbroken lines, show that overall parameter uncertainty had been reduced enough to significantly reduce output uncertainty for the four selected variables.

Table 9-2 Prior and posterior probability distributions for parameters of BASFOR. The prior is beta-distributed between specified lower and upper limits. The posterior, derived using data from Dodd Wood and Rheola, is not analytical and is characterized here by the mean values of the marginal parameter probability distribution and the coefficients of variation (CV = standard deviation / mean) (correlation matrix not shown).

Parameter vector			Prior probability distribution		Posterior probability distribution	
Symbol	Unit	Meaning	Lower limit	Upper limit	Mean	CV
$C_{B,0}$	($kg\ m^{-2}$)	Initial value branch C	0.00005	0.005	0.0010	0.18
$C_{L,0}$	($kg\ m^{-2}$)	Initial value leaf C	0.0001	0.01	0.0015	0.38
$C_{R,0}$	($kg\ m^{-2}$)	Initial value root C	0.0001	0.01	0.0017	0.16
$C_{S,0}$	($kg\ m^{-2}$)	Initial value stem C	0.00005	0.005	0.00090	0.34
B	(-)	CO_2-response factor	0.4	0.6	0.52	0.06
$CO_{2,0}$	(ppm)	CO_2-response base level	320	380	362	0.02
f_B	(-)	Allocation to branches	0.25	0.30	0.29	0.02
$f_{L,max}$	(-)	Maximum allocation to leaves	0.27	0.37	0.29	0.03
f_S	(-)	Allocation to stem	0.25	0.3	0.28	0.01
Γ	(-)	Respiration fraction	0.4	0.6	0.48	0.06
k_{CA}	(m^2)	Crown area allometric normalisation constant	5	15	11	0.12
$k_{CA,exp}$	(-)	Crown area allometric exponent	0.3	0.45	0.36	0.07
k_h	(m)	Tree height allometric normalisation constant	4	12	7.5	0.07
$k_{h,exp}$	(-)	Tree height allometric exponent	0.2	0.3	0.26	0.04
LAI_{max}	($m^2\ m^{-2}\ mm^{-1}$)	Maximum LAI	4	10	6.3	0.06
LUE_0	($kg\ MJ^{-1}$)	Light-Use Efficiency	0.001	0.003	0.0014	0.10
$NC_{L,\ max}$	($kg\ kg^{-1}$)	Maximum C/N ratio leaves	0.02	0.05	0.028	0.12
$NC_{R,con}$	($kg\ kg^{-1}$)	C/N ratio roots	0.02	0.04	0.023	0.06
$NC_{W,con}$	($kg\ kg^{-1}$)	C/N ratio woody parts	0.0005	0.002	0.00080	0.23
SLA	($m^2\ kg^{-1}$)	Specific Leaf Area	5	40	6.0	0.05
T_{opt}	(°C)	Temperature optimum	12	28	19	0.12
$TC_{L,max}$	(d)	Maximum survival time coefficient leaves	365	1460	1048	0.09
δ	($kg\ C\ m^{-3}$)	Wood density	150	250	182	0.04

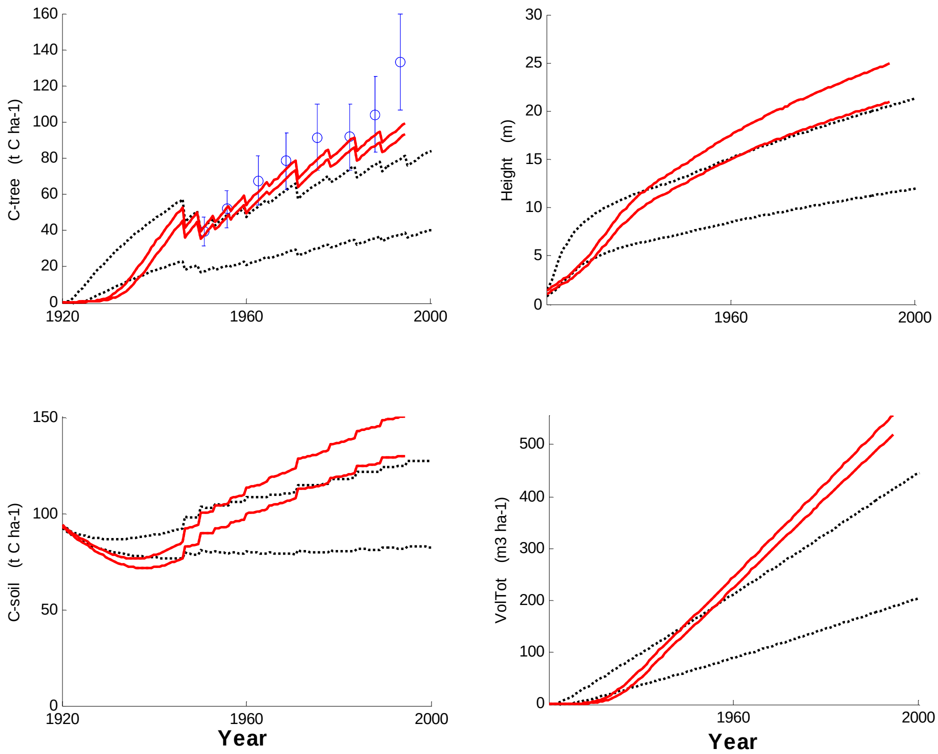

Figure 9-9 Prior (black,dotted lines) and posterior (red, unbroken lines) model output uncertainty for Dodd Wood. Output variables are tree and soil carbon content, tree height and cumulative wood volume production. Blue circles and vertical lines: data with estimated measurement error

9.4.2. Past and future UK-wide C-sequestration

9.4.2.1 C-sequestration 1920-2000

The calibrated model was applied to calculate UK-wide C-sequestration between 1920 and 2000 for a standardized conifer rotation with a 5-yearly thinning interval (Figure 9-10). C-sequestration was defined as the average annual total accumulation of carbon in soil, standing biomass and wood removed at thinnings. Calculated sequestration rates were highest in the South-West of the country, which is the area which combines moderately high temperature and precipitation (Figure 9-1, Figure 9-2). In the far North, possibilities for forestry-related C-sequestration may even be non-existent, as the model identifies these areas as being a net C-source rather than a sink (Figure 9-10). The spatial pattern of C-sequestration was not closely related to the spatial distribution of atmospheric N-deposition and soil nitrogen (Figure 9-4, Figure 9-5).

The propagation of parameter uncertainty to uncertainty about C-sequestration rates was calculated by taking five samples from the posterior parameter probability distribution (Table 9-2) and calculating the standard deviation for the five different results. Figure 9-11 shows the resulting map of sequestration uncertainty. The spatial pattern of sequestration uncertainty differs strongly from that of sequestration itself (Figure 9-10), indicating that the coefficient of variation varies between different growing conditions.

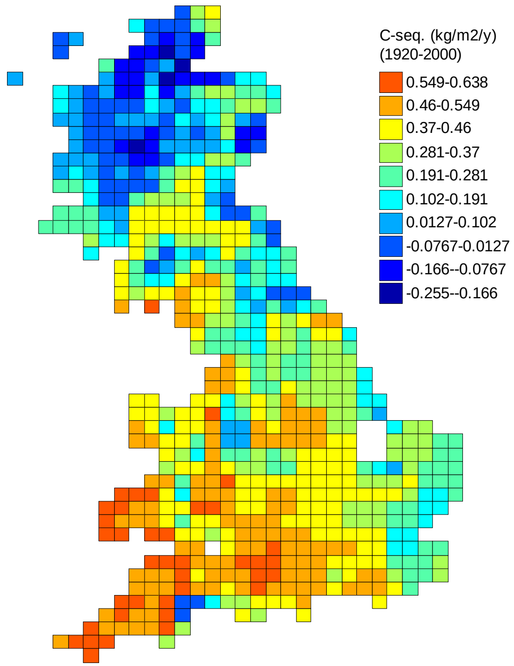

Figure 9-10 Simulated average annual C-sequestration (in soil, living trees and wood products) for 1920-2000. Results from model BASFOR

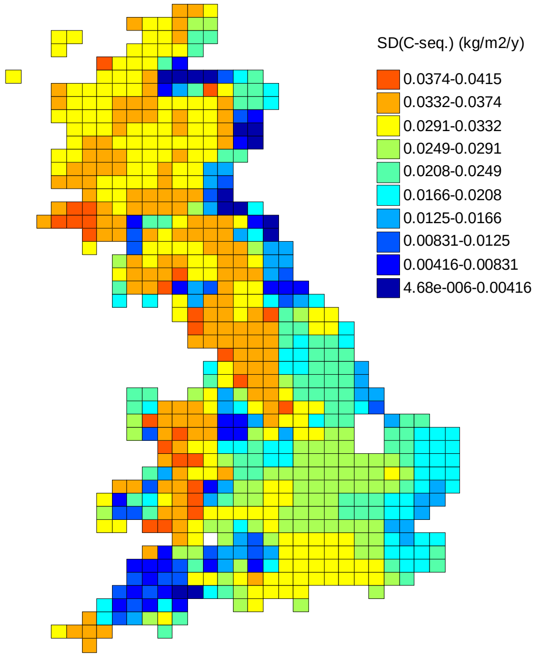

Figure 9-11 Uncertainty in simulated average annual C-sequestration (in soil, living trees and wood products) for 1920-2000. Results from model BASFOR

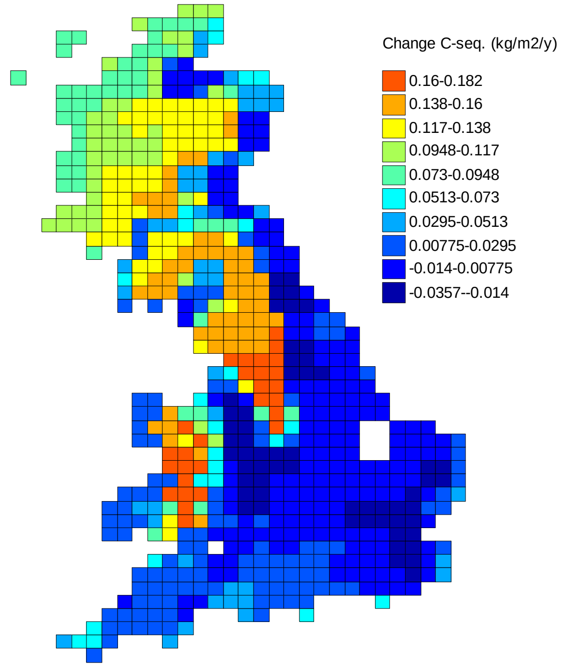

Figure 9-12 Simulated change in average annual C-sequestration (in soil, living trees and wood products) from 1920-2000 to 2000-2080. Results from model BASFOR

9.4.2.2 C-sequestration 2000-2080

The same calculations of C-sequestration were repeated for the environmental conditions expected for the period 2000-2080 (see section 9.3). Figure 9-12 shows the spatial distribution of expected changes in sequestration, relative to 1920-2000. The changes are not closely related to the magnitude of expected changes in temperature, as the spatial patterns differ (compare Figure 9-3 and Figure 9-12). However, some degree of warming is expected across the whole country, causing C-sequestration to change mainly in the higher, colder regions of Wales, North-England and Scotland.

9.4.3. Analysis in terms of environmental change factors: climate, CO_2, N-deposition

The preceding UK-wide assessments of the effects of environmental change on expected C-sequestration rates in conifer forests did not separate out the effects of the different environmental factors subject to change. For the purpose of such analysis, we ran simulations for the Dodd Wood site with a range of temperatures, atmospheric CO_2 concentrations and N-deposition rates, in a full-factorial set-up. Average temperature was varied from 6.8 to 9.9 °C (which amounts to expanding the UKCIP-estimates for the site for 1920-2000 and 2000-2080 with one degree on either side of the range), atmospheric CO_2 was varied from 320 to 480 ppm (corresponding to changes estimated by the Bern model using the IS92a emissions scenario for 1920-2000 and 2000-2080), and N-deposition was varied from 0 to double the 1920-2000 average value of 8.0 kg N ha^{-1} y^{-1}.

Table 9-3 summarizes the results of application of the model for these environmental conditions. The first data column of the table lists the average values of yield class and annual C-sequestration rate across the considered set of environmental conditions, with standard deviations indicating the uncertainty arising from both the variation in environmental conditions as well as the parametric uncertainty determined before (section 9.4.1). The final thee data columns of Table 9-3 give the average effect on yield class and sequestration of changes in temperature, CO_2 and N-deposition, with uncertainties. On the examined site, Dodd Wood, changes in each of the three environmental factors has an effect on the output variables, but with the strongest effect (relative to its expected degree of change) for CO_2. The analysis further suggests that C-sequestration rates are likely to increase to similar extent in soils and in tree biomass.

Table 9-3 Simulated change in average yield class and annual C-sequestration at the Dodd Wood site due to changes in temperature, CO_2 and N-deposition. The standard deviations are due to uncertainty in parameterisation and to variation in interacting environmental factors, but not including soil characteristics.

		Impact of environmental change		
Ecosystem variable	Dodd Wood value	Effect of temperature (per °C)	Effect of [CO_2] (per 100 ppm)	Effect of N-deposition (per 10 kg N ha^{-1} y^{-1})
Yield class (m^3 ha^{-1} y^{-1})	7.91 ± 1.11	0.18 ± 0.05	1.32 ± 0.38	0.74 ± 0.26
C-sequestration (t C ha^{-1} y^{-1})	3.99 ± 0.64	0.10 ± 0.03	0.76 ± 0.21	0.41 ± 0.14
C-sequestration, soil (t C ha^{-1} y^{-1})	1.58 ± 0.31	0.05 ± 0.01	0.36 ± 0.10	0.18 ± 0.07
C-sequestration, trees and products (t C ha^{-1} y^{-1})	2.41 ± 0.34	0.05 ± 0.02	0.40 ± 0.12	0.23 ± 0.07

9.5. Discussion and Conclusions

9.5.1. Methodology

This study has tried out a range of methods that may be used to improve the construction of the UK carbon inventory. The process-based forest model BASFOR was parameterised efficiently using Bayesian calibration, allowing for uncertainty quantification when using the model to calculate UK-wide conifer forest C-sequestration and yield class. However, the procedure likely suffered from low quality of some data, in particular those on soils. We used the IGBP-DIS global soils database to quantify soil nitrogen content, but the values seemed high in comparison to values reported commonly for North-West European soils (Van Oijen *et al*., 2006). Weather data seemed sufficient, but more data on tree growth need to be incorporated and the study needs to be expanded to different evergreen and deciduous tree species.

9.5.2. Uncertainties

Throughout our study we found relatively little sensitivity of UK forest C-sequestration rates and yield class to soil nitrogen content and atmospheric N-deposition, as opposed to the calculated sensitivities to changes in temperature and atmospheric CO_2 concentration. This finding may be an artefact from the use of the IGBP-DIS dataset with its possibly overestimated values of nitrogen contents of UK soils, leading to apparent nitrogen saturation (Van Oijen & Jandl, 2004). In follow-up research there is an urgent need to identify better soil data sources and to quantify the uncertainty associated with the soils data. In fact, uncertainties in all environmental factors, soil-related and atmospheric, need to be included in the Bayesian procedure, in order to give a realistic estimate of current uncertainties regarding C-sequestration.

9.5.3. The impacts of changes in environmental factors

The use of a process-based model for calculating C-sequestration, rather than a semi-empirical model like CFLOW, allowed us to analyse the contributions of changes in temperature, CO_2 and N-deposition to changes in sequestration. The analysis for the Dodd Wood site identified changing CO_2 as the major factor expected to affect sequestration. However, this finding should be seen as a proof of concept for the methodology rather than as a high-probability identification of a key environmental variable. This caution is needed because of the likely poor quality of the soils data, as mentioned above, but also because the factor analysis needs to be repeated for the whole of the UK first. Our analysis showed that the impact of environmental change varies across the country depending on the starting condition upon which the change was superimposed. For example, temperature increase only had a significant effect in the colder areas. Besides such nonlinear effects of individual factors like temperature, this study also suggests that important interactive effects, e.g. CO_2 x N-deposition, need to be taken into account. Even the spatial pattern of uncertainties, both expressed in absolute terms and as coefficients of variation showed distinct spatial trends across the country, so not only the calculation of main effects, but also uncertainty quantification needs to be calculated country-wide.

The presence of nonlinear individual and interactive effects limits the usefulness of response factors as calculated in Table 9-3. For example, the yield class temperature response factor of 0.18 ± 0.05 (m^3 ha^{-1} y^{-1}) (°C)$^{-1}$ does not necessarily apply outside the Dodd Wood area. This has implications for the way in which we can use results from the process-based modelling to derive modifiers for the yield class values that are used as input for the carbon inventory calculations using CFLOW. In short, the yield class modifiers should be complex multivariate functions of the set of different environmental factors. However, we can calculate such functions if we redo the current factor analysis at a UK-wide scale and with improved input information. This needs to be accompanied by quantification of the uncertainties from incomplete knowledge of parameters, environmental drivers and model structure.

9.6. Acknowledgments

We thank Robert Matthews and Paul Taylor (Forest Research, Alice Holt) for providing information about the Sitka spruce stands at Dodd Wood and Rheola, and Ron Smith (CEH-Edinburgh) for the data on UK-wide atmospheric N-deposition.

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