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Toward Bayesian uncertainty quantification for forestry models used in the United Kingdom Greenhouse Gas Inventory for land use, land use change, and forestry

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Abstract The Greenhouse Gas Inventory for the United Kingdom currently uses a simple carbon-flow model, CFLOW, to calculate the emissions and removals associated with forest planting since 1920. Here, we aim to determine whether a more complex process-based model, the BASic FORest (BASFOR) simulator, could be used instead of CFLOW. The use of a more complex approach allows spatial heterogeneity in soils and weather to be accounted for, but places extra demands on uncertainty quantification. We show how Bayesian methods can be used to address this problem.

1 Introduction

Quantifying a greenhouse gas (GHG) inventory is a problem of incomplete information. As no amount of data collection will provide us with a full inventory of all fluxes in a region, additional calculations and assumptions are required. In the case of land use, land use change, and forestry (LULUCF) in the United Kingdom (UK), process-based models are used to quantify net carbon dioxide (CO_2) emissions associated with afforestation, reforestation, and deforestation, based on forestry data and soil type information (Thomson and van Oijen 2007). The model currently used for forests planted after 1920 is CFLOW (Dewar and Cannell 1992; Thomson and van Oijen 2007). CFLOW is a simple compartmental model for the carbon cycle which uses measured wood productivity as input and calculates the flows of carbon to tree parts and soil, with different turnover rates being used for the various compartments. A similar approach, with a similar model (CARBWARE), is used in the GHG Inventory for Ireland (Black, pers. comm. 2007). Here, we investigate

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the scope for partly or completely replacing CFLOW with a more complex process-based model, the BASic FORest (BASFOR) simulator, that can better take into account the spatial distribution of climate and soil properties across the UK—and how this replacement would affect the process of quantifying uncertainties in the UK Inventory. Besides spatial variation in environmental drivers, process-based models can also calculate the effects of inter-annual variation in weather conditions, such as the irregular occurrence of drought years. However, we shall focus on the spatial variation in this contribution.

A major problem with the use of complex models is incomplete knowledge of input variables as well as model parameters. This causes uncertainty in the model outputs which needs to be quantified and reported in an inventory. The basis of the method for uncertainty quantification used in this work is the Good Practice Guidance, Methodological Tier 2, of the Intergovernmental Panel on Climate Change (IPCC) (Penman et al. 2003). We first quantify the uncertainties associated with model parameters used in the inventory calculation by expressing them as probability distribution functions (PDFs). Then, representative samples are taken from the PDFs to propagate parameter uncertainty forward through the calculations. This results in representative samples of the desired output variables. There are excellent examples of the use of this method for uncertainty quantification (Monni et al. 2007; Peltoniemi et al. 2006). Although the method is relatively straightforward, it needs to be applied with caution. Knowledge about parameters is generally incomplete; they interact, and uncertainty may propagate nonlinearly in the calculations. If the only source of information utilized for the PDFs is direct measurement or expert opinion, the resulting output uncertainty may be overly high (van Oijen et al. 2005). To prevent the generation of inventory uncertainty estimates that are unrealistically high, or even unusable in practice, we need to reduce uncertainties where possible, but we also need to combine direct and indirect information when estimating uncertainties. Here, we use Bayesian calibration to incorporate as much information into our PDFs as possible (Patenaude et al. 2008; van Oijen et al. 2005). Bayesian calibration is the application to parameter pdf estimation of Bayes' Theorem:

$$\mathrm{p}(\theta|\mathrm{D}) = \mathrm{c}\,\mathrm{p}(D|\theta)\mathrm{p}(\theta), \tag{1}$$

where $p(\theta|D)$ is the so-called posterior pdf for our parameters θ after incorporating new direct or indirect information D, $p(\theta)$ is the prior pdf for θ that we had before arrival of the new information D, $p(D|\theta)$ is the likelihood of D for given values of θ, and c is proportionality constant. Bayes' Theorem is valuable for the inventory because it is often relatively easy to quantify the likelihood $p(D|\theta)$ of new information, in which case the Theorem tells us immediately how our uncertainty about the parameters θ decreases because of that information. Useful information D could be measurements of carbon stock changes or emissions (i.e., the key output variables of interest in the inventory), but also equally well measurements of any other variables that play a role in the inventory calculation such as litter fall rates or soil organic matter (SOM) decomposition rates that are intermediate variables in the calculations of the carbon pools and fluxes. The method thus not only propagates uncertainty in inputs and parameters to model outputs, but also uses data on output variables to reduce the uncertainty in inputs and parameters. Finally, an additional benefit of the method is that the posterior distribution generated by the Bayesian calibration includes appropriate correlations between all parameters—which would be hard to establish otherwise (Winiwarter and Muik 2010).

Here we will demonstrate the application of Bayesian calibration to BASFOR and show predictions of carbon sequestration, including their uncertainty for the time periods 1920–2000 and 2000–2080. From the model results, we calculate coefficients of sensitivity to environmental change. We discuss how the coefficients could be added to the model currently used in the UK Inventory (i.e., CFLOW), as a possibly simple way of sensitizing that model—and thereby the Inventory—to spatio-temporal patterns of atmospheric CO_2, nitrogen (N) deposition, and climate.

2 Methods

In this study, the parameters of the BASFOR model were calibrated using data for two Sitka spruce plantations in the UK. After calibration, the model was run for the whole of the UK at 20 × 20 km resolution for both current and future environmental conditions. For each of the 655 grid cells, flux rates per unit of forested area were calculated. The study did not quantify total fluxes per grid cell, which would have required information about planting areas, as the primary objective was to quantify uncertainties at the level of the forest stand. This section describes the different elements in the approach: the model (Section 2.1), the data (Section 2.2), and the method of Bayesian calibration (Section 2.3).

2.1 BASFOR 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, 2010). It simulates the response of trees and soil to radiation, temperature, precipitation, humidity, wind speed, atmospheric CO_2 and N deposition, and 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. Net carbon uptake by the trees is simulated by multiplying light absorption, calculated using Beer's Law, with a light-use efficiency that depends on temperature and the water and nitrogen status of the trees. Uptake of water and nitrogen depends on the balance between tree demand and soil supply. The model is deterministic and is solved by Euler integration with a time step of 1 day.

BASFOR is more complex than CFLOW, the model currently being used in the UK GHG Inventory. CFLOW simulates the pools and fluxes of carbon in the tree–soil system, whereas BASFOR also simulates pools and fluxes of nitrogen and water. The input requirements of the two models also differ. Forest volumetric yield class is input to the CFLOW model, and information on wood density and biomass expansion factors is needed to convert yield class into carbon uptake rates. BASFOR does not require tree productivity as input, but calculates net primary productivity (NPP) dynamically as a function of the current state of the trees and the environmental conditions, including the thinning regime of the stands.

2.2 Data

2.2.1 Weather data

Weather data for the periods 1920–2000 and 2000–2080 were taken from the *UK Climate Impacts Programme* (UKCIP) climate scenarios (Hulme and Jenkins 1998). For future weather, only the "medium–high" scenario was used. The data are given for a regular spatial grid of 655 cells of 20 × 20 km each. The scenarios show that current spatial gradients in the UK for temperature and precipitation are dominated by latitudinal and longitudinal effects, respectively. Future warming is expected to show a decreasing pattern from the southeast to the northwest.

2.2.2 Atmospheric CO_2

Atmospheric CO_2 concentration has increased from around 300 ppm in 1920 to current levels of close to 380 ppm, with an average for the period 1920–2000 of 325 ppm. For the average CO_2 level in the period 2000–2080 under the Special Report on Emissions Scenarios (SRES) IS92a, the Bern model (Joos et al. 1996) predicts a value of 480 ppm.

2.2.3 N deposition

Early twentieth century levels of N deposition were low across Europe (<3 kg N ha^{-1} year^{-1}) (Galloway 1985). 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 twentieth century, with maxima reached around 1990 (van Oijen et al. 2008). 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, we assumed continued reductions of N deposition until the year 2010, with deposition remaining constant thereafter. These temporal patterns were spatially disaggregated using the 2004 UK deposition map (R.I. Smith, personal communication).

2.2.4 Soils

Data on soil nitrogen, carbon, and plant-available water content were taken from the global soils database produced by the Data and Information Services of the International Geosphere–Biosphere Programme (Global Soil Data Task 2000). The data are at a resolution of 5 × 5 arc minutes.

2.2.5 Tree data from Dodd Wood and Rheola sites

Forest Research UK provided data on soil characteristics and destructive measurements of tree growth from two Sitka spruce stands for use in model calibration (Fig. 1) (R. Matthews and P. Taylor, personal communication). 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). Trees were planted in 1927 and 1935, respectively, and management followed a 5-year thinning cycle on both sites, starting 24 and 28 years, respectively, after planting. In each thinning year, data were gathered on standing and removed stem volume and on standing and removed whole tree biomass. At the last thinning, biomass fractions in leaves, branches, stems, and

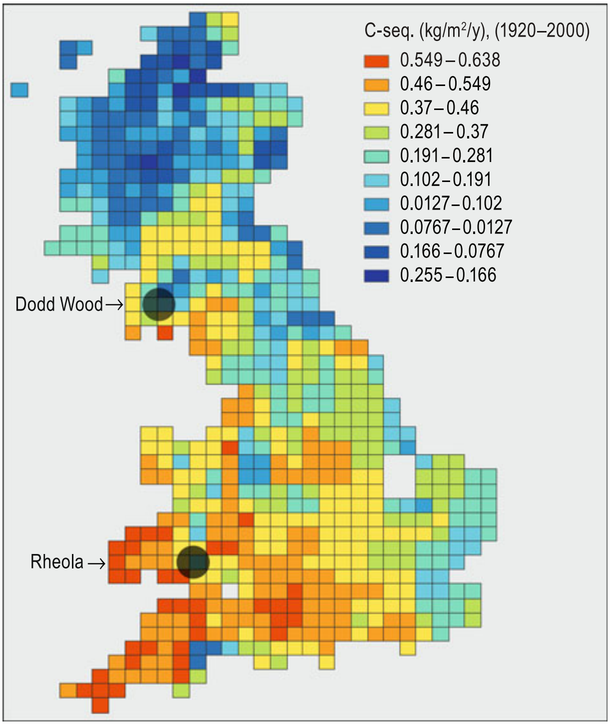

Fig. 1 Simulated average annual C-sequestration (in soil, living trees and wood products) for 1920–2000. Results from model BASFOR following Bayesian calibration on data from Sitka spruce plantations at Dodd Wood and Rheola

roots were estimated using site-specific biomass expansion factors. In total there were 52 data points for Dodd Wood and 44 for Rheola, for each of which a measurement uncertainty of 20% was estimated.

2.3 Bayesian calibration and uncertainty quantification

The parameters of the BASFOR model were quantified by means of Bayesian calibration (van Oijen et al. 2005), using the Forest Research UK data for Dodd Wood and Rheola. The procedure began with quantification of the uncertainty about the parameter values in the form of a prior probability distribution. In the absence of detailed data on Sitka spruce, the prior distribution was based on literature data on conifer growth (Table 1) (Levy et al. 2004; van Oijen et al. 2005). The Forest Research data on model output variables were used to update the parameter distribution by application of Bayes' Theorem (Eq. 1). This yielded a posterior, calibrated probability distribution for the parameters. As BASFOR is a nonlinear model, the posterior distribution could not be determined analytically. We therefore used a Markov Chain Monte Carlo (MCMC) approach, the Metropolis algorithm (Robert and Casella 1999), to generate a representative sample from the posterior distribution (for computer code, see http://nora.nerc.ac.uk/6087/). The calibration was carried out in two steps. In the first MCMC, the prior distribution was updated using the Dodd Wood data. The parameter sample generated by this step was approximated by a truncated normal distribution which was further modified

Table 1 Prior and posterior probability distributions for parameters of BASFOR

Parameter vector			Prior probability distribution			Posterior probability distribution	
Symbol	Unit	Meaning	Lower limit	Upper limit	Mean	Mean	CV
$C_{B,0}$	(kg m^{-2})	Initial value branch C	0.00005	0.005	0.0012	0.0010	0.18
$C_{L,0}$	(kg m^{-2})	Initial value leaf C	0.0001	0.01	0.0024	0.0015	0.38
$C_{R,0}$	(kg m^{-2})	Initial value root C	0.0001	0.01	0.0024	0.0017	0.16
$C_{S,0}$	(kg m^{-2})	Initial value stem C	0.00005	0.005	0.0012	0.00090	0.34
B	(–)	CO_2-response factor	0.4	0.6	0.50	0.52	0.06
$CO_{2,0}$	(ppm)	CO_2-response base level	320	380	350	362	0.02
f_B	(–)	Allocation to branches	0.25	0.30	0.28	0.29	0.02
$f_{L,max}$	(–)	Maximum allocation to leaves	0.27	0.37	0.31	0.29	0.03
f_S	(–)	Allocation to stem	0.25	0.30	0.28	0.28	0.01
Γ	(–)	Respiration fraction	0.4	0.6	0.50	0.48	0.06
k_{CA}	(m^2)	Crown area allometric normalization constant	5	15	10	11	0.12
$k_{CA,exp}$	(–)	Crown area allometric exponent	0.30	0.45	0.38	0.36	0.07
k_h	(m)	Tree height allometric normalization constant	4	12	6.6	7.5	0.07
$k_{h,exp}$	(–)	Tree height allometric exponent	0.2	0.3	0.25	0.26	0.04
LAI_{max}	(m^2 m^{-2} mm^{-1})	Maximum LAI	4	10	5.7	6.3	0.06
LUE_0	(kg MJ^{-1})	Light-use efficiency	0.001	0.003	0.0020	0.0014	0.10
$NC_{L,max}$	(kg kg^{-1})	Maximum N/C ratio leaves	0.02	0.05	0.038	0.028	0.12
$NC_{R,con}$	(kg kg^{-1})	N/C ratio roots	0.02	0.04	0.030	0.023	0.06
$NC_{W,con}$	(kg kg^{-1})	N/C ratio woody parts	0.0005	0.002	0.0011	0.00080	0.23
SLA	(m^2 kg^{-1})	Specific leaf area	5	40	14.2	6.0	0.05
T_{opt}	(°C)	Temperature optimum	12	28	20	19	0.12
$TC_{L,max}$	(d)	Maximum survival time coefficient leaves	365	1460	791	1048	0.09
δ	(kg C m^{-3})	Wood density	150	250	203	182	0.04

The prior is skewed or symmetrically 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). The posterior correlation matrix is not shown in the second MCMC using the Rheola data. Note that, in Bayesian calibration, the order in which two or more data sets are processed does not affect the final posterior distribution. After calibration, the predictive uncertainty of the model was quantified by running the model with different parameter settings sampled from the posterior distribution ($n = 5$). The sample size was kept small to allow uncertainty quantification for each of the 655 grid cells covering the UK. It was verified that deleting any of the five parameter vectors from the sample changed the average value of sequestration by <2%.

The calibration was applied only to model parameters. Uncertainty associated with model drivers (CO_2, temperature, N deposition) was assessed in only a preliminary way by varying their values for the Dodd Wood site and quantifying forward propagation of the variation to model output. Model drivers consist of long time series, and formally including them in the Bayesian calibration would have required determination of a joint prior distribution encompassing daily values of each variable, which was beyond the scope of this study. Moreover, no attempt was made to quantify uncertainty relating to the structure of the model itself.

3 Results

3.1 Bayesian calibration and uncertainty quantification

Table 1 lists the major parameters of BASFOR, with their prior uncertainty before application of data from UK forests, and their posterior uncertainty after Bayesian calibration. For most parameters, prior uncertainty was large (i.e., lower and upper limits were far apart). Figure 2 (black dotted lines) shows for four model output variables (tree and soil carbon, tree height, and total produced wood volume) how the prior parameter uncertainty caused uncertainty in model outputs at the Dodd Wood site. For example, the uncertainty interval (two standard deviations wide) for tree carbon at the end of the 80-year rotation ranged from below 40 to above 80 tonnes carbon ha^{-1}. Table 1 and Fig. 2 also show to what extent uncertainties were reduced by the Bayesian calibration using the data from the Dodd Wood and Rheola sites, described above. The marginal posterior probability distributions for the parameters were much narrower than the prior distributions, as can be seen from the small coefficients of variation. The data from the two forest sites were not equally informative for all parameters, with coefficients of variation (CV) for three parameters—initial leaf and stem carbon content and the nitrogen to carbon (N/C) ratio of wood—exceeding 20%. However, the red unbroken lines in Fig. 2 show that overall parameter uncertainty had been reduced enough to significantly reduce output uncertainty for the four selected variables.

3.2 C sequestration 1920–2000

The calibrated model was applied to calculate UK-wide C sequestration between 1920 and 2000 for a standardized Sitka spruce rotation with a five-yearly thinning interval (Fig. 1). C sequestration was defined as the average annual total accumulation of carbon in soil, standing biomass, and wood removed at thinnings. Product decay was not accounted for. Calculated sequestration rates were highest

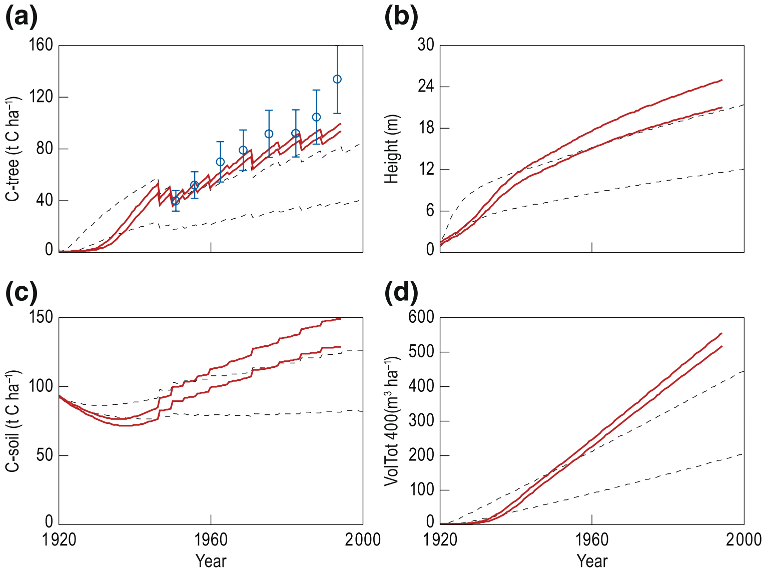

Fig. 2 Prior (*black*, *dotted lines*) and posterior (*red*, *unbroken lines*) model output uncertainty for conifer forests planted in 1920 under Dodd Wood environmental conditions. Pairs of lines are separated by two standard deviations. Output variables are tree and soil carbon content, tree height and cumulative wood volume production. *Blue circles and vertical lines* data with estimated measurement error

in the southwest of the country, which combines moderately high temperature and precipitation. The far north is identified by the model as an area of net C source rather than a sink (Fig. 1). The spatial pattern of C sequestration was not closely related to the spatial distribution of atmospheric N deposition and soil nitrogen. The propagation of parameter uncertainty to uncertainty about C sequestration rates was calculated by randomly taking five parameter vectors from the posterior parameter probability distribution (Table 1) and calculating the standard deviation for the five resulting output sets. Figure 3 shows the resulting map of sequestration uncertainty. The spatial pattern of sequestration uncertainty differed strongly from that of sequestration itself, with Figs. 1 and 3 showing only a weak correlation ($r = -0.25$). This means that the coefficient of variation for carbon sequestration, induced by parameter uncertainty alone, varies among different growing conditions.

3.3 C sequestration, 2000–2080

The same calculations of C sequestration were repeated for the environmental conditions expected for the period 2000–2080. Figure 4 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 their spatial patterns differ. However, some degree of warming is expected across the whole country, causing C sequestration to increase mainly in the higher, colder regions of Wales, northern England, and Scotland, and to decrease in southern England.

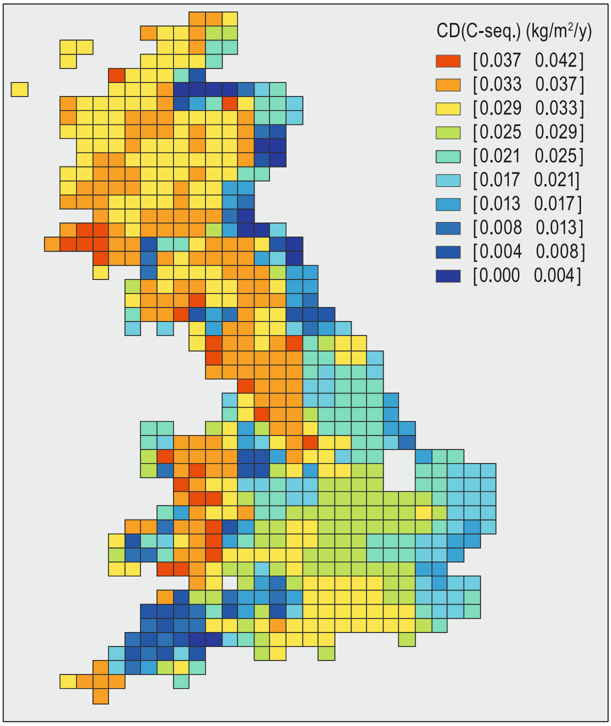

Fig. 3 Uncertainty (standard deviation) in simulated average annual C-sequestration (in soil, living trees and wood products) for 1920–2000. Results from model BASFOR

3.4 Analysis in terms of environmental change factors: climate, CO_2, N deposition

The above-mentioned 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 that are subject to change. For the purpose of such analysis, we ran additional simulations for the Dodd Wood site with a range of temperatures, atmospheric CO_2 concentrations, and N deposition rates in a full-factorial setup. The ranges of these factors were not intended to represent uncertainty; they served only as input to a sensitivity analysis encompassing the full range of conditions from 1920 to 2080. Average temperature was varied from 6.8°C to 9.9°C (which amounts to expanding the UKCIP estimates for the site for 1920–2000 and 2000–2080 by 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 emission scenarios 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} year^{-1}. Table 2 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 set of environmental conditions considered, with standard deviations indicating the uncertainty arising from both the variation in environmental conditions and the parametric uncertainty determined previously. The final three data columns of Table 2 give the average effect on yield class and sequestration of changes in temperature, CO_2, and N deposition, with uncertainties. At the site examined, Dodd Wood, changes in each of the three environmental

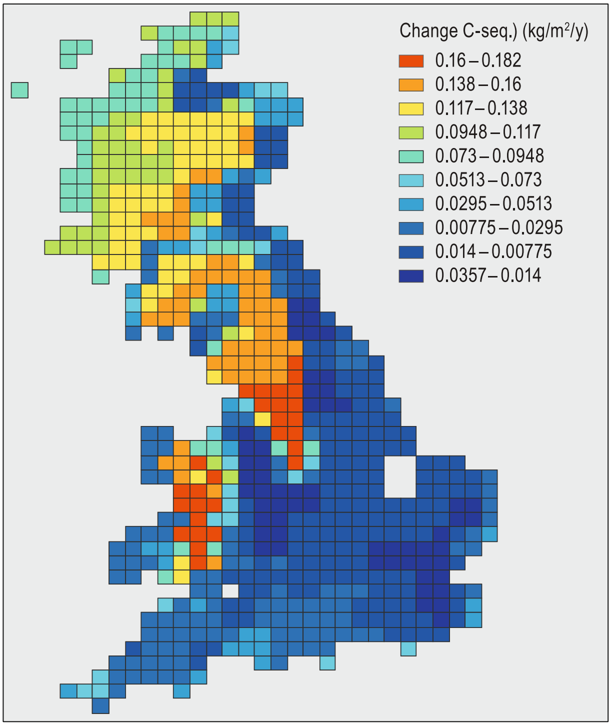

Fig. 4 Simulated change in average annual C-sequestration (in soil, living trees, and wood products) from 1920–2000 to 2000–2080. Results from model BASFOR

factors have an effect on the output variables, but with the strongest effect (relative to its expected degree of change) being for CO_2. The analysis further suggests that C sequestration rates are likely to increase to a similar extent in soils and in tree biomass.

Table 2 Simulated change in average yield class and annual C sequestration at the Dodd Wood site due to changes in temperature and CO_2 and N deposition

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

The standard deviations are due to uncertainty in parameterization and to variation in interacting environmental factors, but not including soil characteristics

4 Discussion and conclusions

4.1 Bayesian calibration and data quality

This study has investigated methods that may be used to improve the construction of the UK GHG Inventory. The process-based forest model BASFOR was parameterized efficiently using Bayesian calibration. The method is probabilistic in that it uses information from data to update the probability distribution for parameters. The calibration thus allowed subsequent uncertainty to be quantified when the model was used to calculate UK-wide conifer forest productivity and C sequestration.

The Bayesian procedure depends on the availability of good data. Data for which measurement uncertainty is considered to be high are not very informative, for example, the likelihood $p(D|\theta)$ is a relatively flat function of the parameters θ. In the calibration, such data will not strongly modify the parameter distribution. As there was considerable uncertainty in the forest data used here, posterior model outputs tended to be intermediate between the prior outputs and the data (Fig. 2). The prior information helps prevent overfitting of the data.

Data that are biased will lead to bias in parameterization. Our soil nitrogen data in particular were taken from a global database of low resolution (Global Soil Data Task 2000) and they showed surprisingly high values for the UK, suggesting that forests tend to be nitrogen-saturated and therefore unresponsive to N deposition. As these data were the only source of information on soil nitrogen content available to us, we were unable to decide if they represented overestimates. Using these data, we found relatively low sensitivity on the part of UK forest productivity and C sequestration rates to soil nitrogen content and atmospheric N deposition, as opposed to the high values calculated for sensitivity to changes in temperature and atmospheric CO_2 concentration. As explained, this finding may be an artifact 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 and Jandl 2004).

Although our joint prior pdf reflected uncertainty about conifer forests in general, the posterior pdf—as well as the sequestration values shown in Figs. 1, 3 and 4—are specific to Sitka spruce, as only data from this species were used in the Bayesian calibration.

4.2 Spatial distribution of uncertainties

Uncertainties, expressed both in absolute terms (Fig. 3) and as coefficients of variation (compare Figs. 1 and 3) showed distinct spatial trends across the country. Uncertainty with regard to carbon sequestration was highest in northern and western parts of the country. Spatial variation in inventory uncertainty is a well known phenomenon, typically associated with spatial variation in economic activity (Bun et al. 2010). However, our study is restricted to a single activity, forestry, and the spatial distribution is exclusively the result of heterogeneity in environmental conditions. This is a finding of significance for the UK GHG Inventory, as it suggests that a simple approach to forestry-related uncertainty (e.g., assuming uncertainty to be a fixed percentage of the absolute flux rate) is unfeasible across regions of this magnitude. Thus, when a GHG Inventory is being determined for forestry GHG fluxes, not only the calculation of main effects, but also uncertainty quantification needs to be carried out in a spatially disaggregated manner.

4.3 The impacts of changes in environmental factors

The use of a process-based model for calculating C sequestration, rather than the semi-empirical model CFLOW currently used in the UK GHG Inventory, allowed us to analyze the contribution of changes in temperature and CO_2 and N deposition to changes in sequestration. Elevated CO_2 was found to have a particularly strong effect on sequestration. In the future, C sequestration is expected to decrease in southern England and increase in the currently coldest parts of the country, which is consistent with studies by Broadmeadow et al. (2005) using a different model. However, given the likely poor quality of the soils data our analysis should be seen as a proof of concept for the methodology rather than as a high-probability identification of a key environmental variable. Furthermore, the factor analysis was applied only to a single site and should be repeated for the whole of the UK.

4.4 The use of process-based models in GHG inventories

Relatively complex models like BASFOR provide more detailed outputs than simple compartmental carbon models can provide. These outputs include fluxes of carbon within trees and how they respond over time to the changes in the environment at different locations. Furthermore, this study has shown that Bayesian calibration may be an efficient method of calibrating such parameter-rich models, while simultaneously quantifying uncertainties in parameters and outputs. In our test of the approach, we used the model BASFOR, but many process-based forest models exist that simulate the carbon cycle (for one comparison of such models see van Oijen et al. 2008), and could be selected for this purpose. Using process-based models in a GHG inventory may therefore be an attractive proposition. However, this study has also shown how the extra demand that complex models place on input information may lead to biased outputs if no good-quality data are available—with soil fertility being a prime example.

Instead of using the complex models directly in the UK Inventory, we were able to restrict ourselves to using their output. From the output of BASFOR, we calculated response factors that quantify the impact of environmental change on flux rates (Table 2). Black (pers. comm. 2007) found that uncertainties in the Irish Inventory—whose calculation scheme is similar to that of the UK Inventory—were mainly associated with incomplete information about annual biomass increments as derived from yield tables. The yield class response factors we calculated (Table 2) could conceivably be added to the currently used CFLOW model to provide a more realistic spatial distribution and inter-annual variability of the annual increments. However, the presence of nonlinear individual and interactive effects limits the scope for using the response factors. For example, because of nonlinearity, the yield class temperature response factor of 0.18 ± 0.05 (m^3 ha^{-1} $year^{-1}$) ($^\circ$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 modeling to derive modifiers for the yield class values that are used as input for the carbon inventory calculations using CFLOW. The yield class modifiers likely need to be complex multivariate functions of the set of different environmental factors. However, we may calculate such functions if we redo the current factor analysis at a UK-wide scale and with improved input information. We aim to do this alongside quantification of the uncertainties from incomplete knowledge of parameters, environmental drivers, and model structure.

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