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Evaluation of the ECOSSE model for simulating soil carbon under short rotation forestry energy crops in Britain

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Abstract

Understanding and predicting the effects of land-use change to short rotation forestry (SRF) on soil carbon (C) is an important requirement for fully assessing the C mitigation potential of SRF as a bioenergy crop. There is little current knowledge of SRF in the UK and in particular a lack of consistent measured data sets on the direct impacts of land use change on soil C stocks. The ECOSSE model was developed to simulate soil C dynamics and greenhouse gas (GHG) emissions in mineral and organic soils. The ECOSSE model has already been applied spatially to simulate land-use change impacts on soil C and GHG emissions. However, it has not been extensively evaluated under SRF. Eleven sites comprising 29 transitions in Britain, representing land-use change from nonwoodland land uses to SRF, were selected to evaluate the performance of ECOSSE in predicting soil C and soil C change in SRF plantations. The modelled C under SRF showed a strong correlation with the soil C measurements at both 0–30 cm ($R = 0.93$) and 0–100 cm soil depth ($R = 0.82$). As for the SRF plots, the soil C at the reference sites have been accurately simulated by the model. The extremely high correlation for the reference fields ($R \geq 0.99$) shows a good performance of the model spin-up. The statistical analysis of the model performance to simulate soil C and soil C changes after land-use change to SRF highlighted the absence of significant error between modelled and measured values as well as the absence of significant bias in the model. Overall, this evaluation reinforces previous studies on the ability of ECOSSE to simulate soil C and emphasize its accuracy to simulate soil C under SRF plantations.

Keywords: ECOSSE model, energy crops, land-use change, process-based model, short rotation forestry, soil carbon

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Introduction

At the ecosystem scale the average total carbon (C) stock (including soil) of temperate forest biomes is approximately 280 t C ha^{-1} which is equivalent to 1030 t CO_2 ha^{-1}. (Saugier *et al.*, 2001; Grace, 2005). To quantify the Great Britain (GB) woodfuel resource McKay *et al.* (2003) carried out a thorough assessment of the standing biomass in GB forests. Based on the results presented by McKay *et al.* (2003), Morison *et al.* (2012) reported an average figure for UK woodland C stock in trees of approximately 209 t CO_2 ha^{-1}.

Average soil C for woodland in the UK varies greatly with soil type, but a GB average value is approximately 859 t CO_2 ha^{-1} (down to 1 m soil depth; Morison *et al.*, 2012). Morison *et al.* (2012) also reported that the C in the litter adds an additional 60 t CO_2 ha^{-1}, and that to this should be added the deadwood or coarse woody debris component, estimated at 3 t CO_2 ha^{-1} (Gilbert, 2007). Therefore, Morison *et al.* (2012) suggest that the average UK woodland C stock is 1131 t CO_2 ha^{-1}, about 10% more than the reported temperate biome value. This figure may be surprising, as much of the woodland area in the UK is relatively young, but it is largely because of the large soil C stock in peatland areas (Morison *et al.*, 2012). Morison *et al.* (2012) therefore concluded that the average soil C for GB is 778 t CO_2 ha^{-1}, and the average woodland C stock is then estimated at 1051 t CO_2 ha^{-1}, excluding the deep peat C stock and areas.

Forest soils usually contain more C than equivalent soils under cropland, due to repeated mechanical disturbance during cropping, fallow periods, reduced plant inputs under cropland compared with trees and the removal of a large fraction of C sequestered by crop

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production in grain (e.g. Mann, 1986; Grigal & Berguson, 1998). Forest soils also usually contain more C than soils under grassland (Guo & Gifford, 2002). Furthermore, forest C sinks play an important role in the Kyoto Protocol, both under article 3.3 for afforestation/reforestation/deforestation (ARD) activities, and article 3.4 for forest management activities (Smith *et al*., 2005). Therefore, increasing forest areas could help sequester C in the soil and providing accurate estimates of changes in forest soil C are of critical importance.

There has been long-standing interest in biomass fuel in the UK since the 1970s oil crisis. Willow grown as short rotation coppice (SRC) is the most common woody perennial crop (Hardcastle, 2006), but other species such as poplar and sycamore have also been investigated. The concept of short rotation forestry (SRF) is distinct from SRC. The underlying principle is to grow a plantation at close spacing (up to 5000 plants ha^{-1}) and then fell it when the trees reach a size that is easily harvested and handled (Mitchell *et al*., 1999). Short rotation forestry is considered as encompassing woody crops grown for between 8 and 20 years, i.e. much shorter than traditional forestry practice, but longer than SRC. The aim of SRF is to harvest the crop at an appropriate age and to remove only the stem wood. Leaving the plant residues on site may have a positive impact from the aspect of reduced nutrient removal as the wood contains less than 10% of the nutrients of the aboveground biomass of the trees (Hardcastle, 2006).

Following afforestation, changes occur in the quality and quantity of C inputs (Romanyá *et al*., 2000; Paul *et al*., 2002). The capacity of afforestation to increase soil C is highly variable, and is dependent on edaphic (e.g. soil type), climatic (e.g. precipitation) and biotic (e.g. species choice) factors, as well as land-use history (Paul *et al*., 2001; Laganière *et al*., 2010).

The balance between C inputs, in the form of litter and root exudates and/or fine root turnover, and losses through decomposition determines whether the ecosystem is a sink or a source of C. Evaluating the C dynamics of this type of system requires data on the size of the C pool, the magnitude of the C input and output fluxes, as well as information about the mechanisms involved in controlling flux dynamics. To promote the C sink status of tree plantations, it is therefore imperative to determine the mechanisms involved in controlling soil C dynamics and more specifically in the storage of C in the soil after afforestation (Laganière *et al*., 2010). Despite the considerable soil C sequestration potential that afforestation offers, many studies have reported contradictory findings (McKay, 2011). The magnitude and direction of the change in soil C after afforestation is strictly dependent to the previous land use (arable/grassland), the soil type (mineral/organo-mineral) and land preparation technique (Murty *et al*., 2002). Hence, afforestation could result in either a decrease (Ross *et al*., 1999; Farley *et al*., 2004) or an increase in soil C (Del Galdo *et al*., 2003), or had a negligible effect (Davis *et al*., 2007; Smal & Olszewska, 2008). Nevertheless, a trend appears to emerge: afforestation frequently shows an initial loss in soil C during the first few years, followed by a gradual return of C to levels comparable to those in the control soil, and then increasing to generate net C gains in some cases (Paul *et al*., 2002; Davis *et al*., 2007).

Short rotation plantations do not usually replace undisturbed plant communities, but most often are established on previously cultivated land, either those presently under arable crops or under grass cover. In many cases, this is characterized as 'marginal crop land'. Such land is likely to have lost 30% or more of the original soil C through cultivation and associated erosion (Grigal and Berguson, 1998). The effect of land-use to short-rotation biomass plantations on soil C has become relevant because of links to atmospheric CO_2 enrichment, climate change, and related environmental issues. However, there is little current knowledge of SRF in the UK and the lack of consistent data sets on afforested SRF systems (Rowe *et al*., 2009), which in turn is mainly due to inconsistent experimental designs, sampling methods and/or soil analysis techniques, results in high uncertainty on the effect of land-use change to SRF on soil C.

Soil C sequestration is often estimated using numerical soil/ecosystem models. There are many types of soil C decomposition models including: (i) single pool first order decomposition rate models, (ii) food-web models using nitrogen (N) and C interchanges between soil organisms, (iii) cohort models describing decomposition as a continuum and (iv) process based multicompartment models such as RothC (Coleman & Jenkinson, 1999). These models have varying levels of complexity and their utility will depend on the data sets available for their parameterization (Dondini *et al*., 2010).

Several models have been developed in an attempt to quantify C from a vast range of mineral soils. Process-based models have been developed from an understanding of how soil C is affected by soil properties, land management and weather fluctuations. Incorporation of these detailed processes and levels of understanding means these process-based models are important, and often successful at predicting not just soil C but also greenhouse gas (GHG) emissions at site level (Bell *et al*., 2012). However, model testing is often limited by a lack of field data to which the simulations can be compared (Desjardins *et al*., 2010).

The requirement to simulate the C and N cycles using minimal input data on both mineral and organic soils led to the development of the ECOSSE model (Smith *et al.*, 2010a, b). ECOSSE is a process-based model designed to simulate soil C and N dynamics and GHG emissions from mineral and organic soils using only data that are commonly available at a regional scale (Bell *et al.*, 2012). The ECOSSE model has already been validated and applied spatially to simulate land-use change impacts on soil C and GHG emissions over different soil types, to simulate soil C change under energy crops and to simulate soil N and nitrous oxide (N_2O) emissions in cropland sites in Europe (Smith *et al.*, 2010b; Bell *et al.*, 2012). However, it has not previously been evaluated against a range of soils with varying organic content under SRF plantations across GB.

This article presents a field evaluation of ECOSSE and its suitability for estimating soil C from British SRF soils after land-use change from conventional nonwoody systems (grassland with the exception of one field site which was arable). If measured and modelled values are in agreement, the user can have more confidence that the model will correctly simulate the processes. Evaluation of process-based models is often made difficult due to lack of data from suitable study sites. The provision of data from eleven paired field sites in Britain means that the mechanistic processes of ECOSSE can be evaluated thoroughly in this study.

Materials and methods

ECOSSE model

The ECOSSE model includes five pools of SOM, each decomposing with a specific rate constant. Decomposition is sensitive to temperature, soil moisture and vegetation cover, and so soil texture, pH, bulk density and clay content of the soil along with monthly climate and land-use data are the inputs to the model (Coleman & Jenkinson, 1996; Smith *et al.*, 1997). The ECOSSE model simulates C and N cycle for four categories of vegetation: arable, grassland, forestry and seminatural. Short rotation forestry is commonly considered as encompassing woody crops, therefore it is included in the forestry category of the model.

The soil input of the vegetation (SI) is estimated by a modification of the Miami model (Lieth, 1972), which is a simple conceptual model that links the climatic net primary production of biomass (NPP) to annual mean temperature (T) and total precipitation (P) (Grieser *et al.*, 2006). Separate estimates are obtained for NPP as a function of temperature (NPPT) and precipitation (NPPP) according to empirical relationships, and the Miami estimate of NPP is found as the minimum of these two estimates. In the present study, NPP is rescaled for each land cover type; for forest the rescaling factor is 7/8 of the Miami NPP estimate (Del Grosso *et al.*, 2008) and the SI is then estimated as a fixed proportion of the NPP according to the land cover (value for forest is 0.15; Schulze *et al.*, 2010). The linear rescaling of the nonlinear Miami functions is reasonable given the near-linear behaviour of the Miami functions in the temperature and precipitation range of the UK.

For a full description of the ECOSSE model refer to Smith *et al.* (2010a).

The specific ECOSSE input requirements for large scale simulations are:

Climate/atmospheric data:

- 30 year average monthly rainfall, potential evapotranspiration (PET) and temperature,
- Monthly rainfall, temperature and potential evapotranspiration.

Soil data:

- Initial soil C content,
- Soil sand, silt and clay content,
- Soil bulk density,
- Soil pH.

Land-use data:

- Land-use for each simulation year.

The initialization of the model is based on the assumption that the soil column is at a stable equilibrium under the initial land use at the start of the simulation. The model uses estimated yearly plant inputs and measured initial soil C to estimate a soil turnover rate which would maintain this equilibrium. Estimated plant inputs were calculated from a combination of the net primary production (NPP) model MIAMI (Lieth, 1972, 1973) and land management practices of the initial land use. The decomposition rate modifier, required to modify the overall turnover rate, was estimated by numerically solving the analytical solution of the decomposition equations (Bradbury *et al.*, 1993). The solution was found using an iterative method, using long-term climate data, updating the decomposition rate modifier until the system converges to a stable equilibrium and the change in soil carbon was zero. This method produces relative carbon pool sizes of the decomposable plant material, resistant plant material, microbial biomass (BIO) and humified organic matter, which along with immobile soil C, is summed up to the measured soil C (Wong *et al.*, 2013).

Data

In 2011/2012, 11 sites were sampled in Britain using a paired site comparison approach (Keith *et al.*, 2013). The sites and the relative measurements contribute to the ELUM (Ecosystem Land Use Modelling & Soil Carbon GHG Flux Trial) project, which was commissioned and funded by the Energy Technologies Institute (ETI). Each site consisted of one reference field (arable or grassland, depending on the previous land-use of the SRF fields) and one or more adjacent SRF fields, for a total of 29 transitions to SRF (Table 1). The tree species included in the present study are: Alder (Alnus incana and A glutinosa), Ash (Fraxinus excelsior), Downy birch (Betula pubescens), Hybrid larch (Larix x eurolepis), Poplar (Populus spp.), Scots pine (Pinus Sylvestris), Shining gum (Eucalyptus nitens), Cider gum (Eucalyptus gunni), Silver birch (Betula pendula), Sitka spruce (Picea sitchensis) and Sycamore (Acer pseudoplatanus). A full description of the sites can be found in Keith *et al.*

Table 1 Details of vegetation type, duration of the SRF stands since transition and location of the study sites

Site no.	Transition unit (previous land use in bold)	Duration of the SRF stands since transition to year of sampling (years)	Latitude, Longitude
1	Arable		55.2, −1.5
	Eucalyptus gunnii	8	
	Eucalyptus nitens	8	
2	Pasture		52.0, −3.6
	Hybrid larch	23	
	Sycamore	23	
3	Rough pasture		54.3, −0.5
	Alder	56	
	Scots pine	58	
	Silver birch	56	
	Beech	56	
4	Rough pasture		53.34, −1.0
	Eucalyptus gunnii	6	
	Eucalyptus nitens	6	
5	Rough pasture		57.6, −3.2
	Downy birch	13	
	Silver birch	13	
	Sitka spruce	12	
6	Pasture		57.7, −3.3
	Poplar	17	
	Alder	15	
	Ash	15	
7	Rough pasture		54.0, −2.4
	Alder	55	
	Scots pine	55	
	Sitka spruce	20	
8	Pasture		56.9, −2.6
	Sycamore	23	
	Scots pine	23	
	Hybrid larch	23	
9	Pasture		55.8, −3.6
	Alder	21	
	Poplar	21	
	Sitka spruce	21	
10	Pasture		54.7, −2.8
	Ash	4	
	Sycamore	4	
	Alder	4	
11	Rough pasture		56.1, 3.6
	Scots pine	4	

(2013). The change in soil C was assumed to be the difference in the forested and nonforested pair.

Measurements of soil C, soil bulk density and soil pH, as well as information on the land-use history, were collated for each field. A full description of the field sampling approach is described in Keith *et al.* (2013). Briefly, for each field, 15 soil cores to 30 cm depth were taken using a split tube soil sampler with an inner diameter of 4.8 cm. A further, three deep cores to 1 m were taken using a window sampler system with an inner diameter of 4.4 cm. Samples were analysed for %C using a LECO Truespec CN analyser.

Air temperature and precipitation data at each location were extracted from the E-OBS gridded data set from the EU-FP6 project ENSEMBLES, provided by the ECA&D project (Haylock *et al.*, 2008). This data set is known as E-OBS and is publicly available (http://eca.knmi.nl/). For each location, monthly air temperature and precipitation for each simulated year was collated and a long-term average was also calculated (Table 2). Monthly PET was estimated using the Thornthwaite method (Thornthwaite, 1948), which has been used in other modelling studies when direct observational data has not been available (e.g. Smith *et al.*, 2005; Yokozawa *et al.*, 2010; Bell *et al.*, 2012).

Soil texture data for the sites (Table 3) were extracted from the 'Falloon' soil database (1 km resolution) which is a collated soils data set for England and Wales, Scotland and Northern Ireland described in Bradley *et al.* (2005), and termed 'Falloon' as it was first used to run RothC in support of the Land-Use Change and Forestry (LULUCF) inventory (Falloon *et al.*, 2006).

Model evaluation

At each site, each transition from conventional crop (arable or grassland) to SRF was modelled and the simulated soil C was compared with the measured soil C. Based on the site information provided, the measured soil C at each reference arable/grassland site was used as the starting C input to the model, assuming that the soil at the reference site had been in equilibrium before the transition to SRF. All model parameters have been maintained unvaried; therefore, the presented results are a test of the ability of the model to simulate soil C under SRF as well as change in soil C from grassland/arable.

The model was evaluated using input data of measured soil C at the start of the simulation, bulk density and soil texture from the 'Falloon' soil database. The simulations were done for 0–30 cm and 0–100 cm soil depth.

A quantitative statistical analysis was undertaken to determine the coincidence and association between measured and modelled values, following methods described in Smith *et al.* (1997) and Smith & Smith (2007). The statistical significance of the difference between model outputs and experimental observations can be quantified if the standard error of the measured values is known (Hastings *et al.*, 2010). The standard errors (data not shown) and 95% confidence intervals around the mean measurements were calculated for all field sites.

The degree of association between modelled and measured values was determined using the correlation coefficient (R). Values for R range from −1 to +1. Values close to −1 indicate a negative correlation between simulations and measurements, values of 0 indicate no correlation and values close to +1 indicate a positive correlation (Smith *et al.*, 1996). The significance of the association between simulations and measurements was assigned using a Student's t-test as outlined in Smith & Smith (2007).

The average size of the error was calculated as the root mean squared deviation (RMS) (Smith *et al.*, 2002). This is the average total difference between measured and modelled

Table 2 Long-term (30 years) monthly rainfall and temperature at the location of the study sites

	Rainfall (mm/month)										
Month	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9	Site 10	Site 11
January	52.6	134.5	61.2	48.3	52.0	57.1	142.7	70.2	126.0	138.9	102.7
February	44.3	104.7	47.8	37.3	51.1	53.8	102.9	61.5	96.9	98.7	72.6
March	48.4	96.5	48.6	40.6	45.9	45.3	107.8	54.5	85.2	101.1	74.2
April	47.2	82.1	47.9	45.4	44.9	47.7	82.9	54.2	61.8	68.3	52.6
May	46.1	75.7	49.3	45.2	49.1	51.3	81.3	53.7	61.8	69.4	60.9
June	58.4	75.4	55.9	60.3	55.5	57.2	87.4	58.2	67.0	72.6	60.2
July	59.3	96.4	58.5	46.6	57.2	63.0	96.6	60.6	76.6	83.8	66.6
August	62.6	97.9	68.0	53.0	62.9	63.7	117.0	66.8	86.2	94.9	76.9
September	58.1	95.3	59.4	49.2	61.9	68.2	120.3	62.7	85.2	101.2	84.4
October	62.4	144.9	60.7	55.9	79.6	80.7	141.2	97.7	121.5	134.5	100.1
November	69.0	141.8	69.5	52.6	65.8	72.0	142.6	84.4	113.0	136.0	93.8
December	58.5	138.5	64.7	52.0	55.4	58.9	150.5	67.5	112.2	138.1	91.1
	Temperature (°C $month^{-1}$)										
Month	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9	Site 10	Site 11
January	6.6	3.9	2.9	4.1	3.6	3.3	2.2	2.9	3.4	2.3	2.9
February	7.0	4.1	3.0	4.4	3.8	3.5	2.3	3.1	3.9	2.6	3.13
March	9.2	5.5	4.8	6.5	5.2	4.9	4.0	4.5	5.5	4.1	4.88
April	11.5	7.3	6.9	8.6	7.3	7.3	6.3	6.4	7.8	6.3	7.16
May	14.2	10.5	9.9	11.6	9.7	9.6	9.3	9.0	10.5	9.4	9.9
June	17.0	12.8	12.8	14.5	12.3	12.3	12.1	11.8	13.0	12.0	12.8
July	19.4	14.7	14.8	16.7	14.3	14.3	13.8	13.7	14.7	14.0	14.4
August	19.2	14.7	14.9	16.5	14.1	14.1	13.6	13.5	14.6	13.6	14.2
September	16.7	12.6	12.9	14.1	12.0	12.1	11.6	11.4	12.3	11.3	11.9
October	12.9	9.7	9.7	10.6	9.0	9.0	8.6	8.2	9.0	8.3	8.9
November	9.2	6.5	5.8	6.9	5.8	5.8	5.0	5.0	5.9	5.0	5.3
December	6.9	4.1	3.7	4.4	3.2	2.9	2.9	2.6	3.0	2.8	3.2

Table 3 Measured soil C, measured bulk density, percentage of clay, silt and sand at 0–30 cm and 0–100 cm soil depth for the reference fields

		0–30 cm soil depth					0–100 cm soil depth				
Site	Reference field	Soil C (t C ha^{-1})	Bulk density (g cm^{-3})	Clay (%)*	Silt (%)*	Sand (%)*	Soil C (t C ha^{-1})	Bulk density (g cm^{-3})	Clay (%)*	Silt (%)*	Sand (%)*
1	Arable	112.0	1.3	23	33	44	151.9	1.3	39	33	29
2	Pasture	76.2	0.9	23	49	29	81.0	1.0	23	51	26
3	Rough Pasture	101.4	0.6	6	29	64	115.3	1.1	4	25	71
4	Rough Pasture	54.0	1.2	8	17	75	64.5	1.4	4	9	87
5	Rough Pasture	94.6	0.8	10	24	66	169.6	1.0	10	24	66
6	Pasture	39.3	1.1	8	22	70	58.0	1.2	6	15	79
7	Rough Pasture	117.2	0.7	23	33	44	239.6	1.2	23	36	42
8	Pasture	80.7	0.7	9	33	58	90.6	0.9	8	29	62
9	Pasture	122.9	1.0	20	27	52	285.5	1.2	25	29	46
10	Pasture	83.0	1.0	19	30	51	164.8	1.0	29	32	39
11	Rough Pasture	83.2	1.2	5	56	39	123.9	1.2	5	58	37

*Data extracted from 'falloon' soil database.

values and is expressed in the same units as the analysed data. The lower the value of RMS, the more accurate was the simulation.

The bias was expressed as a percentage using the relative error, *E*. The significance of the bias was determined by comparing to the value of *E* that would be obtained at the 95%

confidence interval of the replicated values (E_{95}). If the relative error $E < E_{95}$, the model bias cannot be reduced using these data.

Analysis of coincidence was undertaken to establish how different the measured and modelled values were. The degree of coincidence between the modelled and measured values was determined using the lack of fit statistic (LOFIT) and its significance was assessed using an *F*-test (Whitmore, 1991) indicating whether the difference in the paired values of the two data sets is significant. All statistical results were considered to be statistically significant at $P < 0.05$.

Results

The model simulations of soil C showed a good fit against the measured soil C, for both reference (Fig. 1) and SRF fields (Fig. 2), at 0–30 cm soil depth.

All the reference sites have been simulated for a time-period of ≥30 years without any land-use change and using the field measurements as inputs to the model. Based on the site histories, we assumed that all the reference sites were in equilibrium at the time of sampling. The *R* value (1) of the reference sites at 0–30 cm soil depth showed a significant ($P < 0.05$) association between modelled and measured values, as well as no significant model bias ($E < E_{95}$).

Figure 2 shows the correlation between modelled and measured soil C at the SRF fields, at 0–30 cm soil depth. Overall, the modelled soil C is highly correlated with the measured C (Table 4). The *R* value (0.93) showed a significant ($P < 0.05$) association between modelled and measured values.

The ECOSSE model simulates SRF as a single woodland vegetation type, but at all sites, with the exception of Site 11, more than one SRF species was sampled. Therefore, for each site, a single model simulation has been correlated with more than one measurement. To avoid the lack of consistency between the number of model simulations and site measurements, the results of each SRF species sampled at the same site have been averaged and the results of the 0–30 cm soil depth presented in Figure 3.

At most of the sites, the modelled soil C at 0–30 cm soil depth was within the 95% confidence interval of the measured soil C (error bars in Fig. 3). At Site 1 and Site 4, the model estimated a higher soil C content compared with the measured values (112.1 t C ha^{-1} vs. 95.8 t C ha^{-1}, 52.5 t C ha^{-1} vs. 43.1 t C ha^{-1}, respectively), while for Site 10 the model simulated a lower accumulation of C compared with the site measurements taken 4 years after conversion from pasture (82.2 t C ha^{-1} vs.

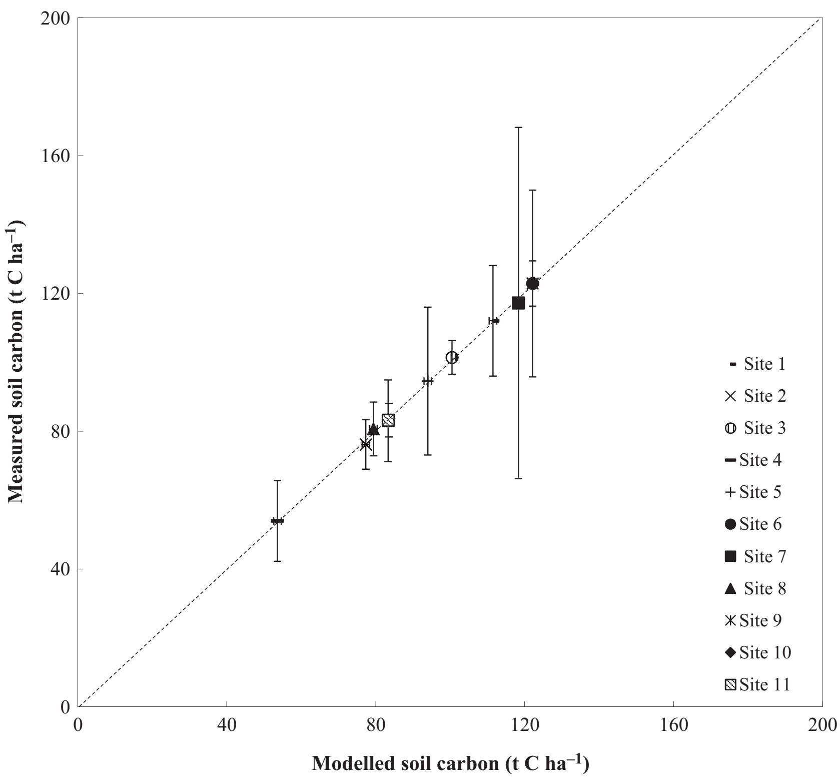

Fig. 1 Correlation between measured and modelled soil C at the reference sites at 0–30 cm soil depth. Error bars represent 95% CI of measured values. Dotted line represents 1 : 1 correlation between measured and modelled values.

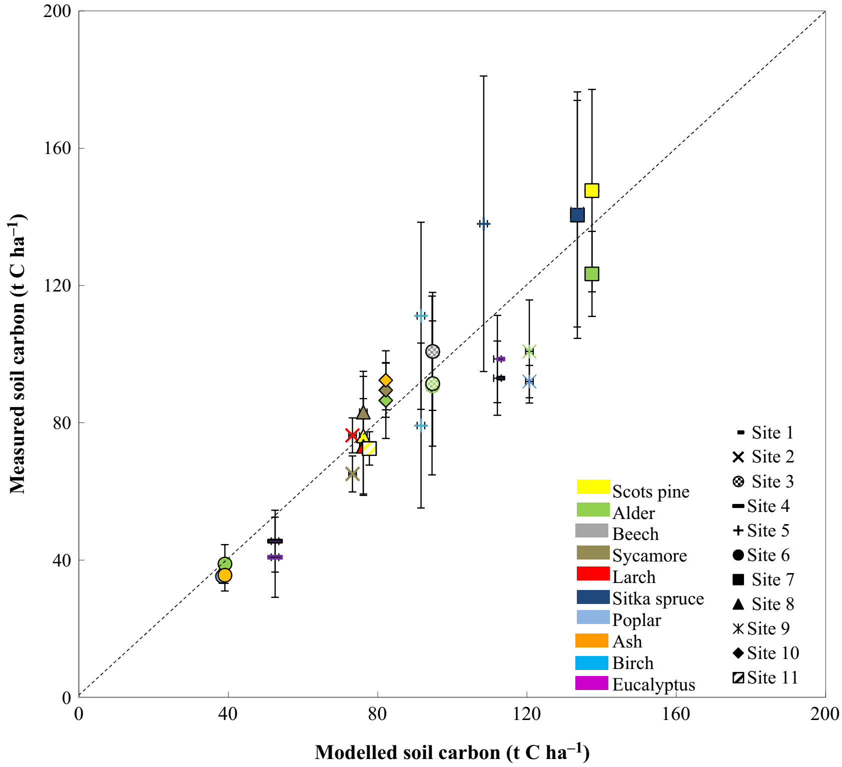

Fig. 2 Comparison between modelled and measured soil C at the SRF sites at 0–30 cm soil depth. Error bars represent 95% CI of measured values. Dotted line represents 1 : 1 correlation between measured and modelled values. SRF species are represented by different colours.

Table 4 ECOSSE model performance at simulating soil C and soil C changes (ΔC) at the reference, SRF and averaged SRF fields for two soil depths (0–30 cm and 0–100 cm). Averaged SRF represents statistical analysis on averaged soil C values of the SRF fields at each site. Averaged ΔC represents averaged change in soil C of the SRF fields at each site. Association is significant for $t > t$ (at $P = 0.05$). Model bias is not significant for $E < E_{95}$. Error between measured and modelled values is not significant for $F < F$ (critical at 5%)

		R	t value	t value at $P = 0.05$	E	E (95% Confidence Limit)	F value	F value (Critical at 5%)
0–30 cm	Reference	1.00	52.02	2.26	0	24	0.00	2.03
	SRF	0.93	13.48	2.05	−4	27	0.00	1.55
	Averaged SRF	0.96	10.58	2.26	−4	16	0.00	2.03
	Averaged ΔC	0.66	2.61	226	93	−2003	0.18	2.03
0–100 cm	Reference	0.99	17.84	2.26	0	58	0.00	2.03
	SRF	0.82	7.23	2.06	−3	72	0.01	1.56
	Averaged SRF	0.87	5.39	2.26	−13	52	0.02	2.03
	Averaged ΔC	0.72	3.15	2.26	91	−1068	0.07	2.03

89.5 t C ha^{-1}). However, modelled soil C under SRF showed a good fit against soil measurements, with an overall correlation value of $R = 0.93$ (Table 4).

The calculated statistical analysis of the model performance indicated that there is no significant model bias ($E < E_{95}$) to simulate SRF and averaged SRF data. Similarly, the *LOFIT* values showed that the model error was within (i.e. not significantly larger than) the measurement error (*F < F (critical at 5%)*).

The model simulations of the soil C at 0–100 cm soil depth again showed a good correlation with the measured soil C, for both reference ($R = 0.99$, Fig. 4) and SRF fields ($R = 0.82$, Fig. 5). Although the correlation between modelled and measured soil C at the SRF sites

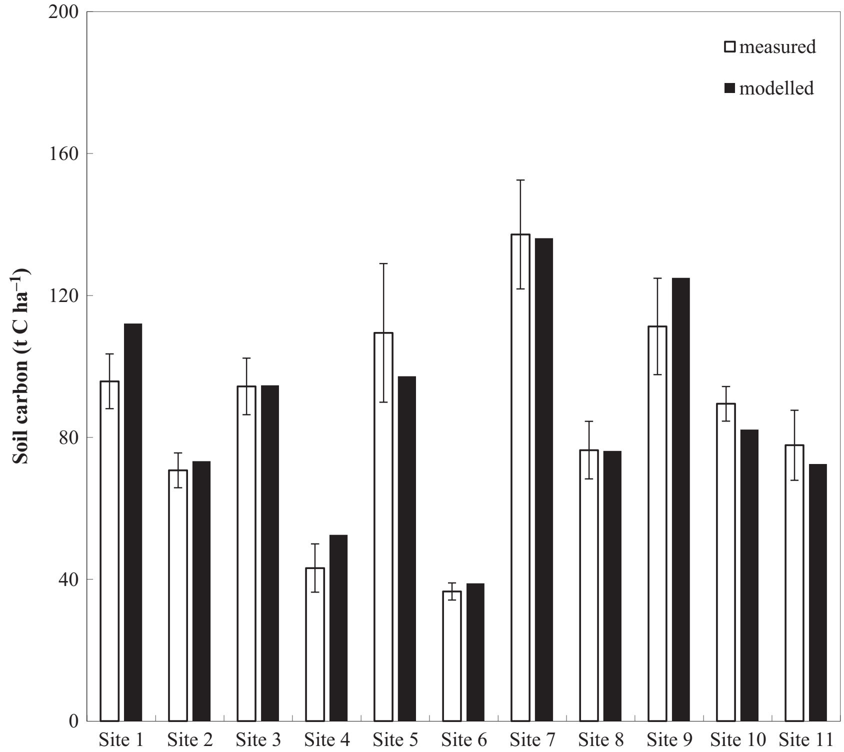

Fig. 3 Modelled and measured soil C at the study sites (0–30 cm soil depth). Results are averaged soil C values for the SRF fields at each site. Error bars represent 95% CI of measured values.

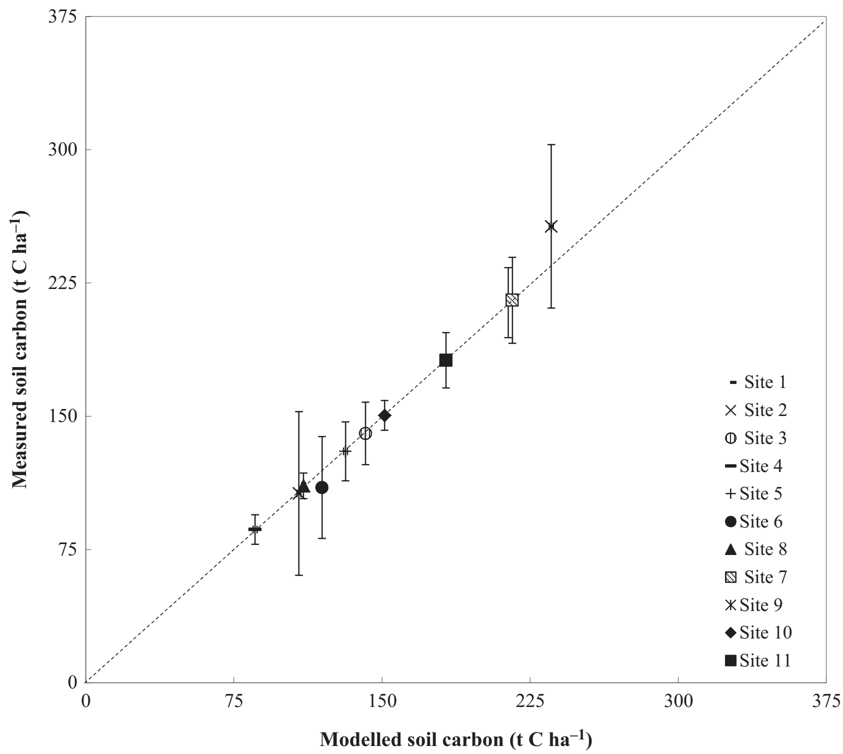

Fig. 4 Comparison between measured and modelled soil C at the reference sites at 0–100 cm soil depth. Error bars represent 95% CI of measured values. Dotted line represents 1 : 1 correlation between measured and modelled values.

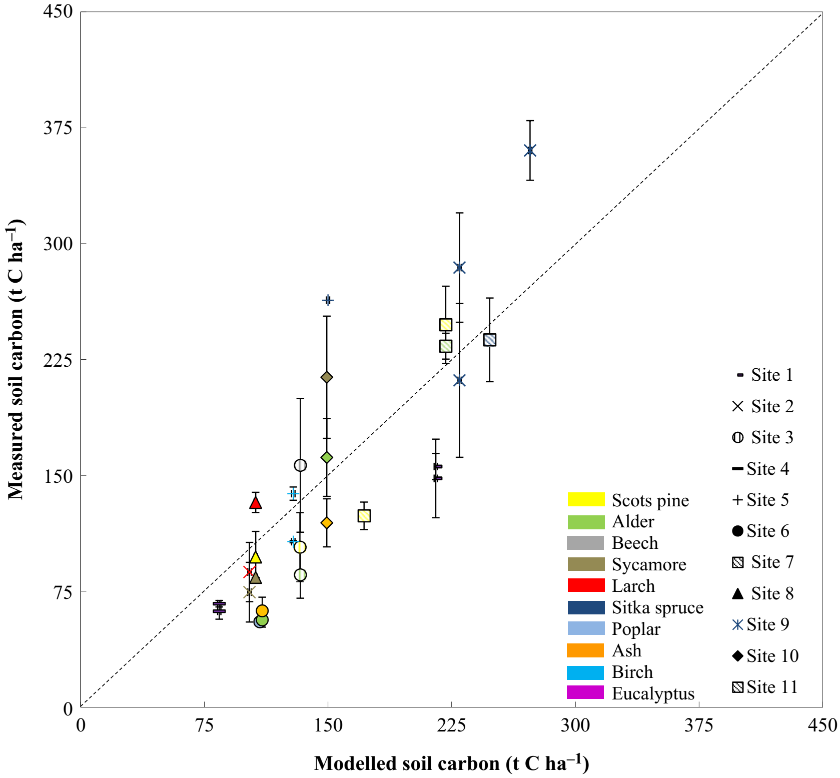

Fig. 5 Comparison between modelled and measured soil C (0–100 cm soil depth) at the SRF sites. Error bars represent 95% CI of measured values. Dotted line represents 1 : 1 correlation between measured and modelled values. SRF species are represented by different colours.

was lower for the whole 100 cm soil profile compared with the 0–30 cm soil depth (Table 4), the statistics of the soil C at the 0–100 cm soil depth reflected the good model performance found for the top soil layer, with a high correlation between modelled and measured values and no significant bias (Table 4).

The results of each SRF species sampled at the same site have been averaged and the results are presented in Figure 6; the modelled and measured soil C at 0–100 cm soil depth followed the same correlation among sites as for the 0–30 cm soil depth. The only exceptions are Site 5, Site 6, Site 9 and Site 11. The model underestimates the soil C at Site 5 and 9 by about 15–20% of the measured values; whereas for Sites 6 and 11 the model overestimates the soil C at 0–100 soil depth by about 50% and 30%, compared with the measured values.

The change in soil C (ΔC) has been calculated as the difference between the soil C at the SRF and the soil C at the reference site and the results are presented in Figures 7 and 8. These results are important as they directly show the effect of the land-use transition itself. At 0–30 cm soil depth, the ΔC was within the 95% confidence intervals of the measured values (Fig. 7). Site 1 was the only site where the ΔC was not accurately simulated by the model. At Site 1, the land-use change from arable has led to a decrease in soil C (16.3 t C ha^{-1}) after 8 years of land-use conversion to SRF; whereas, the results of the model simulations at Site 1 showed a small increase in soil C (0.6 t C ha^{-1}) after the transition.

Overall, at 0–100 cm, the ΔC simulated by the model followed the same direction of soil C change as the simulated values (Fig. 8). The ΔC simulated by the model is within the 95% confidence intervals of the measured values at four sites (Site 3, Site 7, Site 8 and Site 9; Fig. 8). The seven sites where the model did not match the measurements have all been established recently (2004–2008).

Despite a lower correlation between modelled and measured soil C changes compared with the soil C, the simulated changes in soil C are well-associated with the measured values, with a correlation factor of 0.66 and 0.72, at 0–30 cm and 0–100 cm soil depth, respectively. Furthermore, the statistical analysis on the ΔC showed no model bias ($E < E_{95}$) and a good coincidence [$F < F$ (*critical at 5%*)] between modelled and measured changes in soil C after transition to SRF (Table 4).

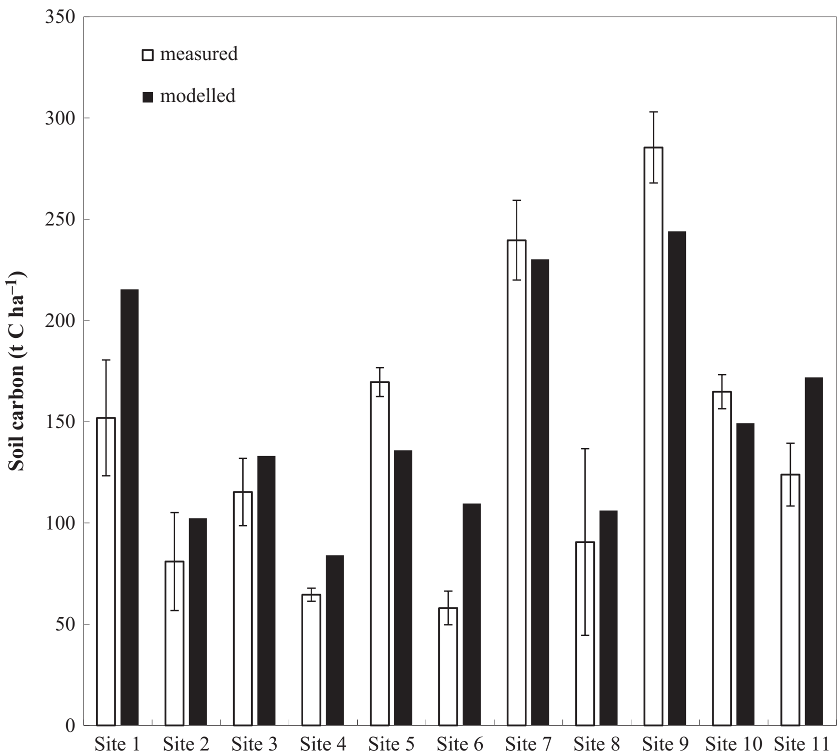

Fig. 6 Modelled and measured soil C at the study sites (0–100 cm soil depth). Results are averaged soil C values for the SRF fields at each site. Error bars represent 95% CI of measured values.

Discussion

The results of the present work revealed a strong correlation between modelled and measured soil C and soil C changes to SRF plantations, at two soil depths (Table 4). Smith *et al.* (2010a) presented an evaluation of the ECOSSE model to simulate soil C at national-scale, using data from the National Soil Inventory of Scotland. This data set provided measurements of soil C and soil C change for the range of soils, climates and land-use types found across Scotland. The results of the present work are in agreement with the publication of Smith *et al.* (2010a), which reported a high degree of association of the ECOSSE modelled values with the measurements in both total C and change in C content in the soil.

As for the SRF plots, the soil C at the reference sites have been accurately simulated by the model. The extremely high correlation for the reference fields shows a good performance of the model spin-up. The spin-up is used by the model to reach a state of equilibrium under the specified inputs. However, it is important to stress that it does not confirm that the reference sites are in an equilibrium condition. Together, these results confirm the good performance of the initialization method and the efficiency of the ECOSSE model in simulating soil C under SRF.

Previous studies on ECOSSE have used large spatial data sets (Smith *et al.*, 2009, 2010a, b) to evaluate the model accuracy to simulate soil C. The present work is the first study to utilize measured soil C at 11 different paired-sites in GB, to accurately test the ECOSSE model performance in simulating soil C and soil C changes to SRF plantation. The statistical analysis on results at both soil depths (0–30 cm and 0–100 cm soil depths) revealed no significant error between modelled and measured soil C and soil C changes, as well as no model bias, which suggests that the model cannot be further improved with the available data.

This is a promising result, given that this work is an independent evaluation of ECOSSE and therefore, the model had not been further improved or parameterized to produce the outputs presented in this article.

Despite the good overall results, the analysis of the correlation between modelled and measured soil C at specific sites showed that the model under/overestimated the measured soil C at some of the SRF sites (Fig. 3 and 6). Since the change in soil C was determined as the difference between the soil C at the SRF sites and the paired reference sites, such error was also propagated in the soil C changes values (Fig. 7 and 8). This low correlation between measured and modelled soil C is particularly manifested when comparing the

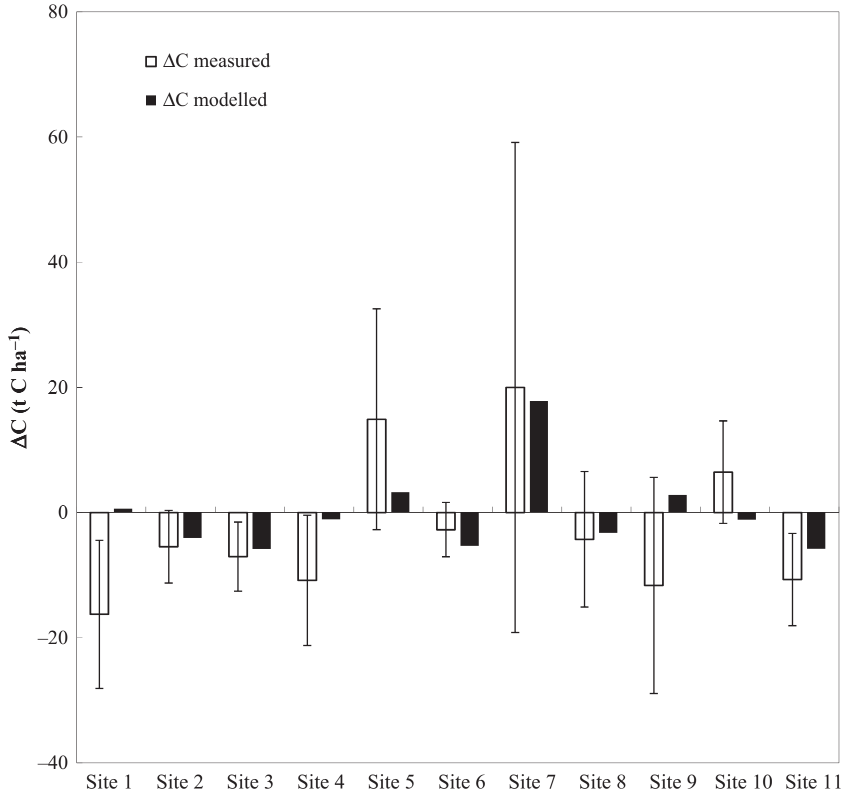

Fig. 7 Measured and modelled change in soil C at 0–30 cm soil depth. Results are averaged change in soil C values between the SRF fields at each site. Error bars represent 95% CI of measured values.

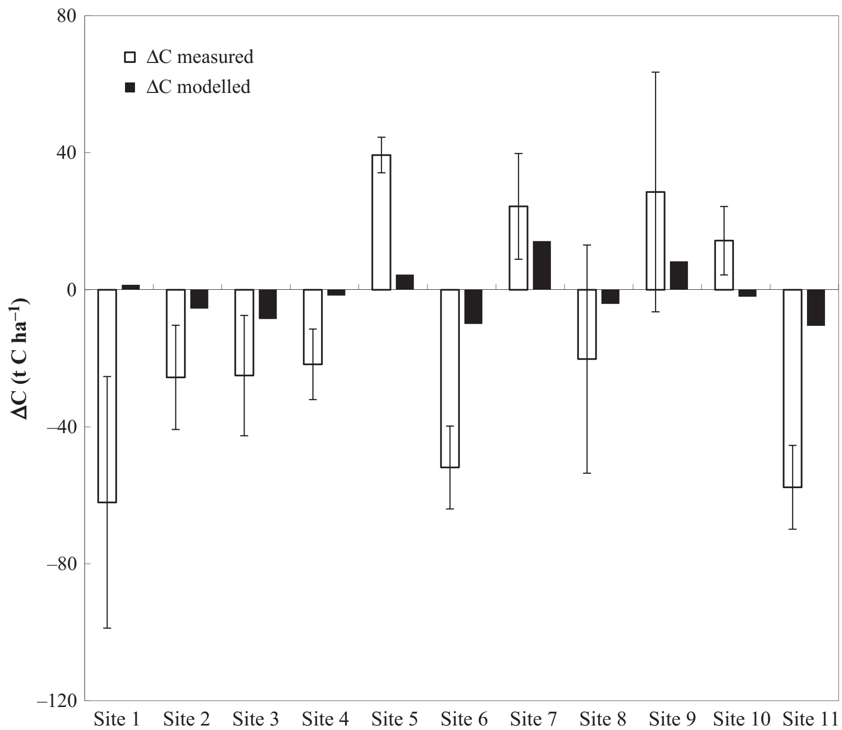

Fig. 8 Measured and modelled change in soil C at 0–100 cm soil depth. Results are averaged change in soil C values between the SRF fields at each site. Error bars represent 95% CI of measured values.

soil C values of the whole soil profile (0–100 cm soil depth). One reason of the higher model inaccuracy at 0–100 cm compared with the 0–30 cm soil depth is the difference between the soil sampling procedures. In fact, only three soil replicates were taken at one meter depth, which generated a higher measurement uncertainty compared with data presented for the 0–30 cm soil depth (n = 15).

The young age of SRF plantations is also a factor that affected the simulation of the soil C. The majority of transitions were less than 24 years old and four of the eleven sites were less than 9 years old (e.g. Site 1, 4, 10 and 11). The decrease in the model accuracy to simulate the soil C at some sites could therefore be caused by the imprecision of the processes described in the model to capture the fast decrease in soil C that occurs during the first years of cultivation. Similar issues to capture the decrease in soil C after afforestation were reported for the parent model, RothC, by Romanyá *et al.* (2000). Romanyá *et al.* (2000) concluded that the soil organic C that has become physically protected before land-use change loses its protection from decomposition when the soil is converted to a new vegetation cover.

This process is not sufficiently described in the ECOSSE model, and could explain the loss in soil C after land-use change measured at some experimental sites. It is important to notice that at each sampled site, different SRF species have been sampled and this could have also led to differences in soil C accumulation/depletion compared with the model simulations, which in turn led to differences in soil C changes values. At Site 5, for example, the soil was sampled on a Sitka spruce site together with two birch sites. The Sitka spruce site accumulated an extremely high amount of soil C in 11 years, especially at the 30–100 cm soil depth (122 t C ha^{-1}), but such high C content in deep soil layers was not captured by the model. Previous studies on the effect of conversion from pasture to forest on soil C have shown contrasting results on the direction and rate of change in soil C after land-use change (Guo & Gifford, 2002; Poeplau *et al*., 2011; Poeplau & Don, 2013). A meta analysis on the influence of land use change on soil C concluded that when established pastures switch to forest, soil C stocks decline under pine plantation, but are unaffected by broadleaf plantations and that the time since conversion occurred influences the soil C stocks (Guo & Gifford, 2002). A recent review of 95 studies on the dynamics of soil C after land use change in temperate zone (Poeplau *et al*., 2011) reported that the cultivation of grassland or forest caused rapid soil C losses and the accumulation of soil C was a slow and continuous process after establishment of grassland and afforestation of cropland. Finally, Poeplau & Don (2013) used a paired side approach on selected sites across Europe to measure changes in soil C after different land use change types. In particular, they found a significant accumulation of soil C after conversion of cropland to forest and no significant effect on the soil C converting grassland to forest.

Another common source of error when studying soil C, and particularly soil C changes after transition to a new vegetation system, is the selection of paired sites (Davis and Condron, 2002). Inexact pairing is a frequent source of discrepancy, which is mainly due to the lack of information on the land-use history of fields (Goidts *et al*., 2009). In our study, 29 transitions have been simulated based on extended information on the selected sites. The only improper pair was found at Site 6. At this site the reference field was an arable crop, which was converted to pasture in 1994. The pasture site was sampled as a reference site, but was planted at the same time as the SRFs (1994–1996), therefore it is not a good reference for this site. In fact, the measurements showed a lower soil C under the SRFs compared with the reference site, while the model predicted around the same C content at the two paired sites.

In the present study, a range of SRF species has been modelled, including Eucalyptus (Site 1 and 4). However, the results of the modelled soil C did not agree with the measured values at either Eucalyptus sites or at either soil depth. In addition, at site 1, the establishment of Eucalyptus species involved the use of strip plastic mulch mats for weed suppression, which may have led to a reduction in volume of leaf litter material being incorporated into the humic soil horizon. There is very little research from Europe and GB on Eucalyptus litter and soil chemistry effects (Hardcastle, 2006). It has, however, been reported that the various species of Eucalyptus have widely different canopy density and potential growth rate (Pryor, 1976), which affect the soil C behaviour under this SRF species. The ECOSSE model has previously been parameterized for forest as a land use category (Smith *et al*., 2010a), but no parameterization have been made for exotic species such as Eucalyptus. It is therefore likely that the model does not describe the soil C behaviour under Eucalyptus as well as under the other SRF species reported in the present work. Further model developments are therefore needed to include this vegetation type in the model parameters.

This article reinforces previous studies on the ability of ECOSSE to simulate soil C and N and test its accuracy to simulate changes in soil C after land-use change to SRF. The use of this process-based model is an improvement on empirical models, with simulations of aggregate monthly data producing high degrees of association with measured data. With further modification to capture the decrease in soil C which often occurs in the early stage of a new transition and with better parameterization for Eucalyptus and coniferous species, ECOSSE would be expected to be a very useful tool for quantitatively predicting the impacts of future land-use on soil C, GHG emissions and climate change.

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