PUBLICATION INFORMATION

Chapter 9

Projecting soil C under future climate and land-use scenarios (modelling)

M. Dondini, M. Abdalla, F.K. Aini, F. Albanito, M.R. Beckert, K. Begun, A. Brand, K. Cheng, L.P. Comeau, K. Coleman, E.O. Jones, J.A. Farmer, D.M.S. Feliciano, N. Fitton, A. Hastings, D.N. Henner, M. Kuhnert, D.R. Nayak, J. Oyesikublakemore, L. Phillips, M.I.A. Richards, V. Tumwesige, W.F.A van Dijk, S.H. Vetter, J. Smith, P. Smith

Abstract

Soil carbon sequestration can be estimated from field to global scale using numerical soil/ecosystem models. In this chapter we describe the structure and development of models that have been widely used at international level, from simple models that include carbon only to model that include descriptions of the dynamics of a range of nutrients. We also present examples of the application from field to global scale of different models to answer a range of different questions on the impact of land use and climate changes on soil carbon sequestration.

A full discussion of the impact of soil carbon modelling on political and socio-economical aspects is included to emphasise the need of a close interaction between model developers, researchers, land owners/users and policy makers to ensure the development of robust approaches to climate change, food security and soil protection.

Whatever type of models are used to meet future challenges, it is important that they continue to be tested using appropriate data, and that they are used in regions and for land uses where they have been developed and validated.

Key words

First-order process; model pools; microbial mechanisms; process-based models; RothC; ECOSSE; DNDC; DAYCENT; field scale; global scale.

9.1. Introduction

Soils globally represent the most significant long term organic carbon (C) store in terrestrial ecosystems, containing 4.5 times as much C as all living biomass and 3.1 times as much as the atmosphere (McClean et al., 2015). Therefore, soil organic carbon (SOC) dynamics have become increasingly important in many research and policy areas (Manlay et al., 2007), ranging from small-scale projects to preserve or improve soil health, to large-scale climate change mitigation strategies (Lal 2004, Powlson et al., 2011). The soil system is heterogeneous and complex and direct SOC measurements alone do not easily support these types of efforts. Simulation models, however, provide the capacity for numeric evaluation of SOC after changes in land uses at different time and spatial scales. This has led to an expanding use of soil models specifically to predict SOC dynamics in order to apply policies or to make decisions on land use and management (Campbell and Paustian, 2015).

Different types of models have been developed in an attempt to quantify C in soil, including empirical and process-based multi-compartment models. These models have varying levels of complexity and their utility will depend on the data sets available to drive them (Dondini et al., 2009). In empirical modelling, there is no attempt to model the processes that result in changes in soil C; the model is a mathematical formula that has been fitted to reproduce the available data and can then be used to predict other values within similar environmental conditions (Lawson and Tabor, 2001). By contrast, process-based models have been developed from an understanding of how soil C is affected by soil properties, land management and weather fluctuations. These models have varying levels of complexity and the choice of model depends on the data available to drive the simulation as well as the conditions used to develop and test the model.

The objective of this work is to describe the structure and development of models that have been widely used at international level to assess the impact of land-use and climate change on SOC stocks. We also aim to describe the versatility of model applications and their importance to disentangle local and global socio-economic-environmental issues by reporting practical applications of such models from field to global scale.

9.2. Empirical models

Empirical models seek to parameterise a hypothesised relationship between variables, typically known as the dependent and independent variables. The structure of the model is determined by the statistical relationships observed within experimental data, where the hypothesis statement is translated into a simple mathematical representation. The goal in this case is prediction of the value of the dependent variable, not an explanation of the nature of the relationship between the variables (Hillier et al., 2016).

9.2.1 Greenhouse gas emissions calculators

The simplest empirical model is a linear one; this is used, for example, in the emission factor methods of the Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas (GHG) Inventories (IPCC, 2006). From this simple approach, several tools have been developed that integrate a number of such empirical equations into a complete model for C assessment; one example of this is the Cool Farm Tool developed by Hillier et al. (2011).

The Cool Farm Tool is a GHG emissions calculator which allows users to estimate annual GHG emissions associated with the production of crops or livestock products, following the emissions from production to the farm gate (Hillier et al., 2011). It comprises a generic set of empirical models that are used to estimate full farm-gate product emissions. The model has several sub-models breaking down the overall emission by GHG emitted and farm management practices. The GHG emissions from the production and distribution of a range of fertiliser types was taken from the Ecoinvent database (Ecoinvent Centre, 2007); for nitrous oxide and nitric oxide emissions related to fertiliser application, the multivariate empirical model of Bouwman et al. (2002) – which is based on a global dataset of over 800 sites – was used. Soil C stock changes were estimated using the IPCC Tier 1 method (IPCC, 2006). After changes in management practice related to tillage or soil C inputs, soil C stocks change by an amount determined in Ogle et al. (2005) for a period of 20 years. The effect of manure and compost addition on soil C stocks are derived from those of Smith et al. (1997), in which relationships were established using medium/long term data from EU15 countries. A simplified model was developed from ASABE technical standards (ASABE, 2006a,b) for fuel use as a function of machinery operation for tilling, drilling, seeding and harvest operations for differing soil types and crop yields.

The mitigation option tool, developed for the Climate Change, Agriculture and Food Security program of CGIAR, is another example of tool to estimate GHG from baseline management options in agriculture. The mitigation option tool accommodates a wide range of users, experts to non-experts, depending on objectives and issues such as time constraints and information available. It requires little input data and has the unique characteristic of suggesting management options that have the potential to further increase C sequestration in soils without risking crop yields. By providing a quick assessment of the C sequestration from current management practices, and of the practices that can increase the potential for soil C sequestration, these tools are extremely useful to inform policy-makers in the design of more effective policies to support the implementation of sustainable agricultural practices.

9.2.2 Models of changes in soil carbon

An example of an empirical model used to determine soil C stocks is the “C response function” (CRF) concept. The C response functions are representations of the average annual change in soil C following changes in land management, and they can also be used to show the cumulative change in soil C over time. The CRF curves are developed by using published reviews and analytical data, each describing a number of long-term, paired field experiments that quantify changes in soil C in response to changes in land use and management. The development of each CRF curve is based on analysis of one or more data sets, each describing a number of long-term, paired field experiments. The difference in soil C between the control and experimental plot for each field experiment in the data set is averaged across all experiments to estimate the mean change in soil C associated with a specific change in management. The CRF curves are developed by choosing a regression algorithm that best represents the estimated trend in soil C change over time, while ensuring that the sum of annual changes in soil C is equal to the previously estimated cumulative change in soil C (McClean et al., 2015; van der Weerden et al., 2012). In order to provide an estimate of the uncertainty surrounding mean changes in soil C, the 95% confidence intervals are given for each CRF curve. Standard error and sample size are also often given so that other confidence intervals can be calculated.

9.3. Process-based models

Process-based models focus on the processes mediating the movement and transformations of matter or energy. Each soil organic matter (SOM) pool within a model is characterized by its position in the model structure and its decay rate. Decay rates are usually expressed by first-order rate kinetics (Paustian, 1994) with respect to the concentration (Conc) of the pool

$$\frac{\mathrm{dConc}}{\mathrm{d}t} = -k\mathrm{Conc}$$

Where *t* is the time and *k* is the decay constant.

Here we give a description of the most common models based on the complexity of the process description and the types of nutrients modelled.

9.3.1 Simple models that include carbon only

The simplest approach used to model SOM turnover is to describe the SOC as pools with different turnover rates; these models predict SOC only and require minimal data inputs, including soil properties, meteorological data and land-use type, to initialise the simulations. The advantage of this approach is that the models can predict soil C sequestration under a wide range of ecosystems (e.g. from natural forest to managed arable land) and at different scales (from site to regional). Because of their simplicity and minimal input data requirements, these models are easily understood and used by non-expert users. However, because these models have been developed to describe only SOC in the soil, the impacts of nutrients on SOM turnover are not taken into account.

RothC is an example of a simple process-based model that includes C only. It simulates the turnover of organic C in non-waterlogged topsoil (Coleman and Jenkinson, 1996) using a monthly time step to calculate total SOC. The model has been widely tested and used at the plot, field, regional and global scales, using data from long-term field experiments throughout the world. The data required to run the model are: monthly rainfall and evaporation or potential evapotranspiration (mm), monthly air temperature (°C), clay content (%), an estimate of the decomposability of the incoming plant material, monthly soil cover (whether the soil is bare or vegetated), monthly input of plant residues (t C ha^{-1}) and monthly input of farmyard manure (t C ha^{-1}) if any. The model performs two types of simulations: "direct" that uses the known input of organic C to the soil to calculate the SOC, and "inverse" that evaluates the input of organic C required to maintain the stock of SOC.

RothC uses a pool type approach, describing SOC as pools of inert organic matter, humus, microbial biomass, resistant plant material and decomposable plant material (Fig. 9.1).

During the decomposition process, material is exchanged between the SOC pools according to first order rate equations. These equations are characterised by a specific rate constant for each pool, and are modified according to rate modifiers which are dependent on the temperature, moisture, and crop cover of the soil. The decomposition process results in gaseous losses of carbon dioxide (CO_2). In Figure 1 we report the original RothC structure (Coleman and Jenkinson, 1996) but other RothC model structures can been found in several publications, such as Liu et al., 2009.

FIGURE 9.1 HERE

9.3.2 Simple models that include carbon and nitrogen

The ECOSSE model (Estimate Carbon in Organic Soils –Sequestration and Emissions) is an example of a simple model that can be used for both C and nitrogen (N) simulation (Smith et al., 2010). It was developed by combining and adapting RothC (Coleman et al., 1996) and a mineral soil model (SUNDIAL, Bradbury et al., 1993) to allow organic soils in Scotland to be simulated, which were previously not well represented in models (Smith et al., 2007). Since its inception, it has been modified for use internationally (Bell et al., 2012) and evaluated using measurements in both organic and mineral soils.

ECOSSE uses a pool based approach with C and N transferred between pools. As in RothC, the soil pools used are described as biomass (active), humus (stabilised) and inert organic matter, and plant litter is described as decomposable and resistant plant material. The base rate of exchange between the pools is specific to the pools in question and is then adjusted according to rate modifiers that describe the impact of environmental factors on the processes; these include pH, moisture and temperature. Soil texture is used to determine the efficiency of the decomposition (i.e. the amount of CO_2 lost on decomposition). Under aerobic conditions, the decomposition process results in gaseous losses of CO_2; under anaerobic conditions losses as methane dominate. Nitrogen released from decomposing SOM as ammonium or added to the soil may be nitrified to nitrate. Carbon and N may be lost from the soil by the processes of leaching, denitrification, volatilisation or plant uptake, or C and N may be returned to the soil by plant inputs, inorganic fertilizers, atmospheric deposition or organic amendments.

9.3.3 Models that include complex descriptions of carbon and nitrogen dynamics

More complex models have been developed using the pool concept described above, with extra complexity to provide scope for the model to be applied at ecosystem level. These models couple descriptions of decomposition and denitrification processes, as influenced by the soil environment, to predict C and N turnover. Often such models are used to examine the impacts of management and climate change in agriculture at site and regional scale. These type of models are highly amenable, allowing the user to describe the effect of various management and climate scenarios on a wide range of ecosystems. The user has full control of a large number of parameters, which need to be accurately determined to allow a successful simulation.

The DeNitrification DeComposition (DNDC) model is an example of a model that includes detailed descriptions of the processes of C and N dynamics. It was first described by Li et al. (1992). The first versions (1.0–7.0) of DNDC consisted of three main sub models for simulating nitrous oxide and N emissions; (1) soil-climate/thermal-hydraulic flux sub-model, (2) decomposition sub-model, and (3) denitrification sub-model. During the following two decades many additions were made to the early version of DNDC. In 2000, Li (2000) reorganised the model into two components incorporating six sub-models (Fig. 9.2) and this new structure formed the basis of many DNDC-based models. Component 1 links ecological drivers to soil environmental variables and consists of the soil climate, crop growth and decomposition sub-models. Component 2 links soil environmental factors to trace gases and consists of the already known denitrification sub-model and two additional sub-models for nitrification and fermentation.

FIGURE 9.2 HERE

The DNDC model can be run on a site specific or regional basis. For most input variables, default values are set but many can and should be changed by the user in order to adequately describe the particular situation. Some input variables are mandatory and need to be set with individual values. These are location (latitude), weather data (daily mean air temperature and precipitation as minimum), soil bulk density, pH and SOC at the surface (0-10 cm). The mandatory input variables together with land use and crop type, soil texture and management practices will be sufficient to run the model. Among the most important output values for DNDC are daily reports on weather, soil climate, and soil C to N ratio in the pools, C and N fluxes, water balance, crop yields and field management for the modelled site for each simulated year.

Over the last 20 years, many versions of DNDC have been developed and published, both for regional application (e.g. UK-DNDC) and for specific uses (e.g. Crop-DNDC, Wetland-DNDC, Forest-DNDC). In some cases, DNDC has been coupled with market management models to include economic impacts of policy (e.g. DNDC-Europe). Due to the default values that are provided, DNDC is relatively easy to use and can easily be used by inexperienced modellers. The model is freely available.

9.3.4 Models that include descriptions of the dynamics of a range of nutrients

Quantifying nutrient availability is crucial to understanding the interaction between plant and soil processes; these mechanisms relate to litter quantity and quality, and so are important drivers for SOM accumulation. The prediction of nutrient cycling aims to quantify the availability in time and space of nutrient elements in soil and to assess likely effects on plant growth and on nutrient fluxes, which can affect water and air quality. Quantifying nutrient availability requires an understanding of the rates of nutrient input, transformation and loss from the soil. The most appropriate approach to modelling nutrient interactions may vary with the ecosystem and with the data available to run the model.

DAYCENT is an example of a C model that includes simulation of the dynamics of a range of nutrients. It was developed by a team at the Natural Resource Ecology Laboratory at Colorado State University in Fort Collins (Parton et al., 1998). It is the daily time step version of the 1994 monthly CENTURY model (Parton, 1996), also developed by the Natural Resource Ecology Laboratory at Colorado State University. The DAYCENT model is a terrestrial ecosystem model that simulates C and N cycles for forest, arable and grassland ecosystems. There is also an option to consider the phosphorous and sulphur cycles, if needed. Fluxes from the atmosphere to plant and soil are considered in simple approaches as atmospheric CO_2 concentration and N deposition. Sub-models are included that describe plant productivity, phenology, decomposition of dead plant material and SOC, soil water and temperature dynamics, and GHG fluxes; these are described in detail by Del Grosso et al. (2001). Required input variables are physical soil properties (e.g. soil texture, field capacity, wilting point, bulk density, pH), climate data and management information. The management information provided depends on the land use simulated; for grassland it includes grazing, for forests it includes thinning and fire (forest); for cropland it includes tillage, fertilizer inputs, irrigation and sowing and harvest dates. DAYCENT is a one-dimensional model developed for site simulations, but it can also be applied on a regional scale.

9.3.5. Microbial mechanisms and soil process-based models

A key similarity across all of the process-based models discussed above is the representation of organic matter decomposition as a first-order process. First-order models assume that the activity of decomposers only depends on temperature, pH, clay content and moisture. This assumption implies that the microbial biomass and composition are not directly represented in the models, but only indirectly via the outcome of temperature and moisture effects on the rate of decomposition (Pagel et al., 2016). One limitation of this approach is that the effects of the changes in microbial community composition due to new conditions are not directly represented in the models. Recent evidence from empirical studies suggests microbial communities may shift in composition, adapt physiologically, or evolve in response to environmental changes, such as warming, N addition, and altered precipitation (Allison and Martiny, 2008; Hawkes et al., 2011). Furthermore, management techniques, such as ploughing or no-till, and organic amendments, such as manure or straw incorporation, change the composition of the soil biota ecosystem and hence the SOM decomposition rate.

Van Groenigen et al. (2011) attempted to compare direct measurements of soil C to predictions made by RothC and a cohort model. They reported on soil C sequestration beneath a 9 year old tillage and straw management experiment in an Irish winter wheat field, to estimate the decomposition rate of crop residue under different tillage management practices. Correlation between modelled and observed SOC were achieved by varying the size and decay rate of each pool and for each treatment, therefore not developing a mathematical function to describe the effects of different management practices on the soil biota ecosystem and processes. However, insufficient experimental evidence have been provided from various environments to enable robust process-based modelling of these affects. Salinity also effects the soil biota and again SOC and input decomposition rates have to be modified in models such as RothC to implicitly model the effect, although again the actual soil biota processes are not explicitly modelled. Despite the drawbacks in describing soil decomposition by first-order process, all of the models used to assess SOC stocks in the most recent IPCC assessment (IPCC, 2014), use the same first-order assumption. Including models which can represent microbial mechanism in soils would increase the diversity of model predictions. This would help to prevent the biases which can arise from averaging the predictions of an ensemble of models that all make the same first-order assumptions (Knutti et al., 2008).

One of the main challenges in including microbial mechanisms in process-based models is to define which of these mechanisms should be scaled up from plot to regional level. One approach would be to use plot data to inform the models, which could then be modified by new mechanistic equations for including microbial processes before validating the model developed using independent data. However, this approach could lead to at least two sources of error on the simulated values at both the spatial and temporal scales. Many large-scale models operate with a spatial resolution that could potentially include high levels of microbial diversity and heterogeneity. Also, soil models at a large spatial scale are generally used to simulate soil processes over time (decades). It is unclear if plot-scale measurements, which are meant to describe microbial responses on a short-term basis, could be applied to a higher temporal scale without loss of accuracy in the model predictions (Todd-Brown et al., 2012). In the future, the increased use of new technologies, such as remote sensing and precision farming, will help in reducing the granularity of our knowledge of the spatial variability of soil, soil water, plant yields and GHG emissions. The application of remote sensing will improve the accuracy and resolution of land use maps to less than 10 m resolution (current land use maps are available at 100 m x 100 m resolution); these new maps could be then used for models parameterization. Precision farming, and the associated sensors that enable 1 m x 1 m resolution detail of field soil and crop condition, will allow maps of crop yield to be made. This information can be used with new informatics technology, which will enable these large spatial data sets to be used to drive high spatial and temporal resolution models.

Another approach to better represent soil C cycling processes in current models would be to quantify functional trait in microbial communities and to link these traits to key factors controlling the soil decomposition and degradation processes. There is a body of research, particularly in India investigating the impact of soil biota on fertility and the use of different biological inoculates to increase crop yields (e.g. Pandya and Saraf, 2010a,b), and hence organic input and SOC. This will lead to a better understanding of the function of different taxa of soil biota. Consequently, a few models have been proposed to explore possible microbial roles in SOC dynamics (Wieder et al., 2015) but these models need rigorous evaluation with observations before they can be incorporated into large-scale soil process-based models (Luo et al., 2016).

9.4. Examples of model application for predicting soil organic carbon changes

Soil models are useful tools to estimate the effect of 'disturbance' events on soil C dynamics; disturbances such as climate change, land management, land cover and land use change have been widely represented in models, while soil erosion and extreme events have been found difficult to model and are not directly used in soil process-based model (Box 1). Here we present a selection of studies where soil models have been applied from field to global scale to predict SOC changes under different vegetation types.

[[Text Box 1]] Impact of soil erosion and extreme events on SOC

This text box shows relevant aspects of SOC modelling, which are not yet well represented in SOC model approaches. Two of these aspects are the impact of soil erosion and the impact of extreme events on SOC. Extreme event is a general term and there are several definitions available to define an event as extreme. Here we refer to extreme events as "an episode or occurrence in which a statistically rare or unusual climatic period alters ecosystem structure and/or functions well outside the bounds of what is considered typical or normal variability" (Reichstein et al., 2013). In the context of soil C, these are mainly extreme climate and weather events.

Soil erosion results from extreme precipitation and storm events, and includes both wind and water erosion. Here we focus on the erosion by water, which affects a larger area (751 Mha *vs* 296 Mha land affected by water and wind erosion, respectively) and erodes more sediment compared to wind erosion (Lal, 2003). The scientific debate about the impact of soil erosion on the SOC is controversial; while some studies come to the conclusion that erosion causes C losses, others show that it enhances soil C accumulation (Doetterl et al., 2016). Despite its high relevance for global C dynamics, the impact of soil erosion on the global C budget is not yet quantified (Lal, 2003; Müller-Nedebock and Chaplot, 2015) and it is rarely considered in biogeochemical models. EPIC (Williams, 1990) and CENTURY (Lugato et al., 2016) are biogeochemical models that contains an erosion routine, the RUSLE model (Renard, 1997), a revised version of the universal soil loss equation (USLE; Wischmeier and Smith, 1978). The USLE model, and its modifications, simulates sediment detachment using empirical approaches based on relative simple factors such as precipitation, soil properties, slope and tillage. The disadvantage of this approach is that sediment deposition is not simulated.

Extreme events are not explicitly considered in SOC model approaches. Thresholds in the models consider limitations or impacts affected by soil water content, soil temperature or nutrient concentration in the soil without considering these explicitly as extreme event. Therefore, some direct impacts (e.g. drought might reduce respiration rates) can be simulated, whereas indirect impacts (e.g. a lag effect of respiration as the soil microbial community might be affected by a drought) won’t be considered in the model approach (Frank et al., 2015). The limitations in modelling extreme events include a lack of observations describing large scale impacts and a lack of standardisation of experimental designs. Moreover, several processes may be too sensitive or too detailed to be implemented within a model – e.g. microorganisms are responsible for C sequestration, but the specific communities or activity are not directly considered in the models.

As extreme events and soil erosion are hardly considered in SOC model, more experimental data are needed to understand their impacts on SOC and to calibrate and validate soil process-based models. A standardized experimental and observational framework would be beneficial so that the collection of comparable modelling-friendly data sets may be realised.

9.4.1 Simulation of carbon sequestration at field plot scale

9*.4.1.1 Impact of land use change from grassland to woodland at Glensaugh*

The Glensaugh Research Station in rural Aberdeenshire is an experimental site where conversion from grassland to woodland was undertaken almost 30 years ago. The site was set up to investigate the impact of afforestation of pasture on animal output (Sibbald et al., 2001). Three tree species, namely scots pine, hybrid larch and sycamore were planted at a 400 trees ha^{-1} silvopastural configuration, which allows for animal grazing between the rows of trees. The same species were also planted at 2500 trees ha^{-1} in farm woodland plots that have received no thinning since the site was established. Both approaches integrate trees into farmland, either spatially segregated in farm woodland or integrated as silvopasture. The site was sampled for total soil C and labile, stabilized and inert C fractions in 2012 (Beckert, 2016). In both silvopasture and farm woodland, SOC was found to be greater compared to the pasture treatment. While woodland and silvopasture plots had similar levels of total SOC, silvopasture showed levels of stabilized C comparable to pasture.

The RothC model was used to investigate how C stocks will develop in the different land use systems at the Glensaugh site, assuming that land management remains constant. The RothC model was first run from the year of tree planting (1988) to the year of sampling (2012), assuming equilibrium at each site. Comparison with measured fractions showed that this assumption only holds true for the pasture site, which had seen no change in management. To investigate how C stocks will develop up to the year 2040 taking actual C quality into account, the model was initialized with measured fractions to replace equilibrium pools. Initializations with fractionation data resulted in the prediction of an increase in C stocks at all wooded sites, particularly in the silvopastoral systems, which showed evidence of combined pasture/forest C stabilization mechanisms. The initialization revealed a slightly increased accumulation rate after 2020 compared to 2012-2020 before it levels off in ca. 2030, indicating that initial increase in respiration is negated when the systems reach a more mature age. The results at site level agree with the results of large scale modelling (Section 9.4.3.1), showing that afforestation of grassland soils could have a positive impact on SOC in the long term.

9.4.1.2 Impact of climate change on grassland and arable systems in Ireland

Grasslands represent an effective option for C sequestration in soils. However, predictions of increase in SOC are associated with a great uncertainty (Freibauer et al., 2004; Vleeshouwers and Verhagen, 2002). Croplands have less SOC than grassland (Cole et al., 1993) as a result of several factors including soil disturbance, less return of plant residues to the soil, less below-ground biomass and no grazing (Franzluebbers et al., 2000). Here we present a study where measured and simulated net ecosystem exchange (NEE) values from a managed grassland and a spring barley field, in Ireland, were compared with simulated NEE to validate the latest version (9.5) of the DNDC (the DeNitrification-DeComposition; www.dndc.sr.unh.edu; Li et al., 1992) model and to estimate present and future NEE and SOC (Abdalla et al., 2013). The averages measured NEE for the grassland during the experimental period (2003-2006) was calculated as -212 g C m^{-2}. The DNDC model predicted seasonal trends of NEE effectively for 2003 and 2004 but overestimated carbon losses in 2006 (Fig. 9.3a).

FIGURE 9.3 HERE

The root mean square error (RMSE) values were small and ranged from 0.20 to 0.22 g C m^{-2} with an overall RMSE of 0.21 g C m^{-2}. The relative deviation (RD) between the measured and simulated NEE values was also small (+30%) except in the year 2006 when it was +45%. The average annual values of NEE, GPP and Reco, over the measurement period (2003-2007) were -189, 906 and 715 g C m^{-2}, respectively. The DNDC model effectively predicted the seasonal trend of NEE at the spring barley field (Fig. 9.3b). The RMSE values from the comparison between daily simulated and measured NEE are small, ranging from 0.09 to 0.16 g C m^{-2} indicating a good fit between the model and simulated values. The RD values between the measured and predicted NEE values ranged from -13 to +100%, with the highest RDs in 2004 (+100%) and 2005 (+92%). These poor RD were mainly due to the DNDC overestimation of NEE peaks during the growing seasons.

In future simulations to 2060, SOC at the grassland site was predicted to decrease by 2-3% by the year 2060 for all climate scenarios. At the arable site, the SOC was also predicted to decrease, but only by 1-2%. This indicates that the soil C systems for the two ecosystems are not in equilibrium. The cropland was historically under grassland prior to 1990 and, therefore, continues to lose C. The grassland had been tilled and reseeded with perennial ryegrass in 2001 and, therefore, will take time to reach a new equilibrium after the tillage disturbance. In both the arable and grassland case water stress would affect crop yields (Hastings et al., 2010) and thereby, the amount of carbon input. The model effectively predicted seasonal and annual changes in NEE at both sites, and responded appropriately to changes in air temperature, timing of precipitation events and management, which have a strong influence on the seasonal net ecosystem exchange. These results suggest that the DNDC model is a valid tool for predicting the consequences of climate change on net ecosystem exchange and SOC from arable and grassland ecosystem.

9.4.1.3 Impact of rice management in Bangladesh

In Bangladesh, rice occupied 70% of all agricultural land in 2016, accounting for 7% of the world's total harvested area (FAOSTAT, 2016). Due to different physiological characteristics, such as the need of continuous flooding of water to provide the best growth environment, rice can sequester more C relative to upland crops and offers substantial mitigation potential (Smith et al., 2008). The DAYCENT model was used to simulate SOC sequestration potential under different N management and mitigation options applied at two rice sites in Bangladesh. In this study, all model parameters, except for the plant growth, were set to default values based on previous literature (Cheng et al., 2013). Values of the plant growth parameter, were adjusted to 3.50 for rice while for wheat it was set to 2.00, and was fixed for all treatments. Annualized C stock changes were calculated as the difference of the SOC stock of the mitigation scenario and the SOC of the baseline scenario normalized by time period. The management treatments at the sites included application of N as mineral N, organic manure alone and in combination with N applications (Karim et al., 1995; Egashira et al., 2003; Egashira et al., 2005). There was a significant agreement between measured and simulated SOC at both sites under single nutrient management practices (Fig. 9.4a,b). A systematic underestimation of SOC was observed at Site 1 (combination of manure and N treatments), which could be attributed to a reduction of plant inputs and suggesting that less N application through manure was limiting plant production.

Mitigation options considered including reduced tillage (sowing with less disturbance to the topsoil in place of tractor ploughing), a reduction in residue removal, replacement of mineral fertilizer by manure, combined application of fertilizer and manure, and an integrated scenario of inorganic fertilizer, manure addition, less residue removal and reduced tillage. All tested mitigation options increased SOC in comparison to the standard procedures, except for the scenario with lower N application, which shows a slight decrease in SOC contents (Fig.

9.4c). The integrated scenario, which combines mineral N and manure applications with reduced tillage and increased residue incorporation, appears to be the best management practice for both sites. Despite the limited availability of long term field data for tropical rice cropland, the results suggest that the DAYCENT model could be a powerful tool for exploring mitigation potentials of rice in Bangladesh.

FIGURE 9.4 HERE

9.4.2 Simulating carbon sequestration at farm scale

Whole farm modelling attempts to simulate not only C sequestration, but also to determine the impact of C sequestration on crop and animal production, water use, fuel availability, labour and finances, so that the feedback of these factors on the potential for C sequestration can be accounted for. Whole farm modelling is particularly important in low input, close-to-subsistence farming, where the potential for external inputs to the farm from inorganic fertilisers and organic resources is minimal. Such systems are often also severely limited in organic resources, with important competing uses for the organic resources that are available, such as for household energy provision, animal feeds and building. In such situations, it becomes important to model, not only the impact of the different types of organic amendment on potential C sequestration, but also to estimate the amount of material that is left over and can be added to the soil. Whole farm modelling of C sequestration attempts to account for these competing uses, and works through the impact of using resources in different ways on the quality and quantity of C inputs to the soil (Fig. 9.5). One example of this is seen in Hawassa, Ethiopia, where soils are often highly depleted in SOM, and so C sequestration is important, not only for the environment, but also to improve soil fertility and hence productivity.

FIGURE 9.5 HERE

Whole farm modelling of C sequestration starts with some form of accounting; what goes where and how is it used? The nature of this depends on the input variables available to the user; when working with data provided by subsistence farmers the number of animals that must be fed is usually known, but the amount of home-produced crop fed to each animal may not be known. In this case, a simple model or look-up table of feed requirements can be used (e.g. Herrero et al., 2013). Similarly, the farmer knows what crops are grown, but the yield may not be measured as it is mainly consumed within the household. Therefore, a simple crop model is needed to estimate yield and the impact of different management decisions on crop production (e.g. Leith, 1972; Reid, 2002; Zaks et al., 2007).

Having accounted for the different uses of organic resources, a SOM model is then used to determine the impact of adding differently treated organic wastes to the soil. This was simulated by Smith et al. (2014) using a variant of RothC (Coleman and Jenkinson, 1996), showing more rapid C sequestration per unit of starting material if the organic wastes are added as compost or biochar, rather than applying it fresh or as bioslurry (Fig. 9.6). After application of organic materials stops (after 20 years in this example), the C content of the soil returns to the starting position within 100 years for the fresh residue, compost and bioslurry amended soils. However, if the biochar contains a high proportion of inert organic material (currently an area of uncertainty), then the C sequestered by biochar application remains in the soil. Long-term experiments on impact of biochar on SOC dynamics and soil fertility are still limited and there are very few simulation studies on biochar and its effect on agricultural soil. Moreover, only few models have been developed to account for the effects of biochar on SOC, as discussed in Box 2.

FIGURE 9.6 HERE

The real value of the whole farm model is to then use these simulations to try out different options. For example, if organic wastes are composted rather than applying them as fresh farmyard manure, how will this affect C sequestration? Identifying these positive feedbacks will provide important information for better management of subsistence farms. Similarly, identifying negative feedbacks will highlight practices that result in a reduction in the overall productivity of the farm, so helping to reduce soil degradation.

[[Text Box 2]] Modelling impact of biochar application on soil organic carbon

Biochar is a more stabilized form of C obtained from thermal decomposition of raw biomass. Because of its high recalcitrant nature and slow turnover rate, biochar has been identified as one of the promising option to mitigate climate change. However, modelling biochar is still in its infancy and only few models have been recently developed, or modified, to account for the effects of biochar on SOC. For example, Woolf and Lehmann (2012), and Smith et al., 2014, modified the turnover rates of the labile organic C (LOC) pool in the RothC model to simulate impact of biochar on SOC sequestration. Priming effects of biochar on LOC was also included in the model by altering the decomposition rate coefficients of the resistant plant material (RPM) and decomposable plant material (DPM). Positive priming effect – i.e. the increase in mineralization of LOC – was modelled by increasing RPM and DPM decomposition rate coefficients by an amount proportional to the concentration of biochar C in the soil. Negative priming effect – i.e. an increase in the fraction of LOC transferred to the stable organo-soil-mineral fraction – was modelled as an increase in the fraction of DPM and RPM that is transferred to the humus pool (HUM) rather than mineralised to CO_2.

Lychuk et al. (2015) modified the Environmental policy Integrated Climate (EPIC) model by developing a set of new algorithms to determine the impact of biochar amendment on SOC sequestration, as well as other soil and crop parameters (e. g. CEC, pH , bulk density and corn yield). In the EPIC model, SOC is split into three compartments – i.e. microbial biomass, slow humus and passive humus. To account for biochar applications, the total biochar C is allocated to the three pools as follows: 60% to the slow humus pool, 38% to the passive humus pool and only 2% to the metabolic pool. Recently, Archontoulis et al. (2016) developed a biochar sub-model within the Agricultural Production Systems sIMulator (APSIM) model. The APSIM model divided the SOC into three pools – i.e. microbial biomass pool, humic pool and inert pool – but the fresh organic matter is accounted as a separate pool, which is also divided in three sub-pools. Archontoulis et al. (2016) introduced an additional biochar C pool to the model, which represents both labile and recalcitrant components and varies according to the type of biochar; a new double exponential decay function has been also introduced to calculate the biochar decomposition rate. Priming effects of biochar and the impact of biochar on N mineralization, soil CEC, soil pH, ammonium adsorption and desorption, soil water and bulk density have also been included in the biochar sub-model.

Despite the late developments in modelling biochar at field scale, more long-term field trials are required to better understand the relationship between soil C sequestration and biochar applications and to consequently develop, calibrate and validate soil models.

9.4.3 Regional scale

9.4.3.1 Potential for carbon sequestration with land use change

Currently the Scottish Government has committed to increase the amount of forest by approximately 100,000 hectares per year as part of a national strategy of reducing GHG emissions by 42% by 2020 and 80% by 2050. Several models (e.g. RothC, Century) have been used to study C sequestration due to land use change. This section describes the application of the ECOSSE model (Smith et al., 2010) to analyse the long term change in soil C stocks with afforestation of non-forest soils, aiming to identify regions that would provide most C benefit if reforested.

To achieve this, high resolution (1 ha grid) land use data from the Integrated Administrative and Control System was used to identify the dominant land use; cropland, grassland, forestry and semi-natural land. Masks of productive agricultural land and current forest were applied to the land use database and this was then combined with the Scottish Soils Knowledge and Information Base (SSKIB) and long term climate input data from the UK Metrological Office. Each land use change to forestry was assumed to take place in this decade (2010's). Suitability masks of 12 different forest compositions were applied and soil C was simulated only for areas where land use change was deemed suitable.

Figure 9.7 details the change in soil C after land use conversion from crop, grass and semi-natural land to native conifer forest, which is the forest type with the greatest extent of suitability in Scotland. Values outline the average annual loss in soil C for the first 20 years after planting. Across Scotland, conversion from arable and grassland to forest typically resulted in an increase in soil C where in some cases, after conversion, C accumulated up to 0.69 t C ha^{-1} yr^{-1} on mineral soils. By contrast, land use change to semi-natural soils, which typically were defined as occurring on peaty soils, lead to an emission of soil C at a rate of up to 5 t C ha^{-1} yr^{-1} in the most extreme cases. While changing to forest tends to enhance C sequestration in arable and grassland soils, mass conversion may not be economically viable or sustainable as removal of productive land can increase Scotland's reliability on food or cereal imports. While un-managed semi-natural land may be an obvious alternative, in some cases the management involved in converting these soils into a forest may lead to long term losses in soil C, despite any increases in plant C inputs. These results suggest that while, theoretically, conversion to forest maybe a long term approach to enhancing C removals, to implement such a mitigation strategy, especially in Scotland, detailed analysis on the impacts on soil C losses in different areas should be undertaken. A similar approach was used by Pogson et al. (2016) and Richards et al. (2016) to investigate the impact on SOC of land use change across the UK. Pogson et al. (2016) developed the ELUM Software Package, which is based on the ECOSSE model, to spatially predict the net soil GHG balance of land use change to grow energy crops in the UK up to 2050. The results of the model application demonstrated that wood and perennial grass production on arable land sequestered SOC, on grassland it was neutral and on forest it emitted CO_2.

FIGURE 9.7 HERE

9.4.3.2 Carbon losses from tropical peatlands undergoing land use change to oil palm

Tropical peatlands are hugely under-researched compared to their temperate counterparts, with approaches to sampling and interpretation of peat properties still evolving to more "tropically" appropriate methods (Farmer et al., 2011). As such, there are considerable data limitations when it comes to modelling scenarios of climate and land use change on tropical peats. Some process-based models, such as RothC and ECOSSE could potentially be used to model C dynamics in tropical peats (Farmer et al., 2011), and are currently undergoing modification to be made more applicable in scenarios where the soil is accumulating C (i.e. an intact peatland scenario) before undergoing land use change. The HPMTrop (Kurinato et al., 2015) is the first process-based model to simulate long-term (decadal to millennial) C accumulation dynamics in tropical peat ecosystems. It has been applied to simulate peat accumulation in Indonesian peat swamp forests and to study the impact of land use change of these areas to oil palm plantations (Kurinato et al., 2015). The modelled average peat accumulation rates and the mean annual C losses due to conversion to oil palm were comparable to literature values; however the limited published values restricted model evaluation (Dommain et al., 2011).

Hooijer et al. (2012) measured and then modelled subsidence rates in oil palm plantations on Sumatran peatlands and an empirical model, the Tropical Peatland Plantation-Carbon Assessment Tool (TROPP-CAT), was developed from this data to provide a user friendly tool to predict soil C and CO_2 emissions from drained tropical peat soils (Farmer et al., 2014). The model uses simple input values to determine the rate of subsidence, of which the oxidising proportion results in CO_2 emissions. Although based on a number of assumptions, evaluation across sites of various ages showed simulations of net CO_2 fluxes from the soil to be within 6% of measured CO_2 emissions and within the range of measurement error.

In tropical peat soils, positive correlation has been observed between mean water table depth and net C loss, heterotrophic emissions and total emissions (Carlson et al., 2015) which is also observed in Northern peat soils (Abdalla et al., 2016). This relationship can be used to make predictions on emissions under future drainage scenarios. However, several studies have found discrepancies between empirical model outputs and experimental data (e.g. Allison et al., 2010; Davidson et al., 2012; Wieder et al., 2013), likely to be due to the omission of key factors, such as direct microbial control of soil C dynamics and brief soil respiration increase due to warming. To partially remedy these discrepancies, annual rhythm oscillation models have been suggested (Comeau, 2016). The novelty and advantage of a rhythm oscillation method over the traditional empirical approaches is that it automatically provides the annual flux amplitude and the peak emission time. In addition, the oscillation curves are not biased due to possible delay in microbial activity response to temperature change and other environmental variables that affect soil C dynamics. As tropical peatland research continues to develop with more datasets becoming available, an enhanced understanding of the dynamics of tropical peat formation and soil properties and characteristics will make for improved modelling of the impacts of land use change on these soils.

9.4.4 Global scale

9.4.4.1 The impact of growing bioenergy crops on carbon stocks

Quantitative and qualitative global datasets on the environmental effects of land use and land use change are still scarce, making climate mitigation analysis difficult. In addition, there is still a lack of information on where, at what rates, and what type of land cover is affected by land use change. In that respect, highly productive food croplands are unlikely to be used for bioenergy, but in many regions of the world a proportion of cropland is being abandoned, particularly marginal croplands, and some of this land is now being used for bioenergy. Recently, Albanito et al. (2015) used a number of harmonized geographically explicit datasets and process-based biogeochemical models to assess the global climate change mitigation potential of cropland when converted to bioenergy production (C_4 grass, short rotation coppice woody crops as willow and poplar) or reforested. This study, in particular, identified areas where cropland is so productive that it may never be converted, and assess the potential of the remaining cropland to mitigate climate change by identifying which alternative land use provides the best climate benefit: C_4 grass bioenergy crops, coppiced woody energy crops, or allowing forest regrowth to create a C sink.

The average cropland C loss resulting from land use change was calculated as the difference in C between annual bioenergy crop yields and cropland yields aggregated over 20 years. The global forest C stocks scenario was developed using the IPCC 2006 Tier-1 method for estimating vegetation C stocks. The potential distribution and forest vegetation C stocks were obtained using the LPJmL-DGVM v3.1 model simulations. In the comparison with cropland, the C sequestration in forests was calculated by applying the factors representing percentage of final biomass C stock accumulated after 20 years (F_{20}). F_{20} was estimated by integrating, over a 100 year timescale, the IPCC default dry matter biomass annual increments in aboveground biomass in naturally regenerated forest classified below and above 20 years of age (IPCC-GPG-LULUCF, 2006). Total SOC change in reforested cropland was assumed to be equal to 53% of the initial SOC occurring in cropland (Guo and Gifford, 2002) adjusted by the percentage of biomass stock accumulated after 20 years.

Across 1.11 billion hectares of global agricultural land, Albanito et al. (2015) reported that approximately 420.1 Mha would be more suitable for food crop production and therefore excluded from conversion to bioenergy crops or reforestation. Over a 20 year rotation horizon, 597.7 Mha of croplands could potentially be converted to bioenergy crops or forest, sequestering approximately 13.8 Pg C in soil (Fig. 9.8). An area of 384.9 Mha has annual extractable C of C_4 bioenergy crops that is equal to or lower than cropland, but nevertheless sequesters approximately 10.3 Pg C in soil. In Asia (continental and insular) the replacements of croplands with C_4 bioenergy crops have the potential to sequester 3.6 Pg C in soil across 66.1 Mha of cropland. On approximately 26.3 Mha of cropland, short rotation of woody crops has greater or equal C mitigation potential to C_4 bioenergy crops and forest, giving a potential sequestration in soil of 0.8 Pg C (Fig. 9.7). Finally, approximately 186.5 Mha reforestation of cropland would be the best climate mitigation option, saving a total of ~ 8.4 Pg C in biomass and ~ 2.7 Pg C in the soil (Fig. 9.7). It is important to note, however, that this study does not present these projections as a scenario of land use change where bioenergy crops or forests should replace cropland, which will depend on many other factors, not least of which is the need to produce food; rather it is to show where there could be a climate benefit if this land were to be converted.

FIGURE 9.8 HERE

9.5. Political aspects and concluding remarks

In 2015, the world defined and committed itself to striving toward the UN Sustainable Development Goals (UN SDG) (UNDP, 2015), in which the historic Paris Climate Agreement (PCA) was signed under the UN Framework Convention on Climate Change (UNFCCC, 2015), and was also the UN International Year of Soils (UN, 2015).

The agreement of the UN SDG and the PCA could not have set up a better legacy for the UN International Year of Soils, since soils are recognised as being critical to the delivery of both. A number of the UN SDG are underpinned by healthy soil C stocks, including the following Sustainable Development Goals (SDGs), among them: SDG 1 – no poverty – in developing countries, a large proportion of the population rely on the land for their livelihoods, and productive land relies on healthy soils (Smith et al., 2013), SDG 2 - zero hunger – soils underpin the production of safe and nutritious food (Keestra et al., 2016), SDG 13 – climate action – soil C sequestration offers climate mitigation (Smith, 2016) and makes ecosystems more resilient to future climate change (Smith et al., 2016a), and SDG 15 – life on land – healthy ecosystems are founded on healthy soils (Smith et al., 2015).

By linking international, national and local policies, and action frameworks to the PCA, governments can develop more comprehensive and robust approaches to climate change, food security, soil protection, sustainable land management, water management and energy generation (Chan et al., 2015; Casado-Asensio et al., 2016). However, there is often a difference in objectives between practitioners at various levels and policy makers, particularly in the agricultural sector, with respect to priorities for resource and land management (Casado-Asensio et al., 2016; Bodansky et al., 2014). This disconnect requires robust institutional support to encourage inclusivity in decision making, increase the dissemination of policies, offer financial assistance and access to markets and provide insurance for climate risks. These actions will require collaborative action from both the public and the private sector. In this context it is crucial to explore the relationship between farmers' attitudes and their farming practices, as well as informing decision makers regarding the social impacts of their decisions. This aspect is discussed in more details in Box 3.

[[Begin Text Box 3]] Translating scientific soil carbon models to the farming community

Scientific models predicting the effects of farming practice and land use change on C emissions and sequestration provide a very valuable tool that can guide policy-makers, industry and individual farmers to make changes for a more sustainable agricultural sector. Greenhouse gas calculator tools such as the Cool Farm Tool, C-Plan and CCAFS-Mitigation option tool are currently being used as a platform to translate scientific models to the daily farming practice (Hillier et al., 2011; Whittaker et al., 2013). These tools aim to encourage farmers to change their behaviour by raising awareness of the negative outcomes of their farming practice on GHG emissions and help them to take informed decisions on alternatives. This approach has for a long time been a popular strategy in promoting pro-environmental behaviour in various contexts (Stern, 2011). Although it has been proven to be effective in increasing people's knowledge, it has minimal effects changing actual behaviour (Abrahamse et al., 2005; Gardner and Stern, 2002; Stern, 2011). To effectively motivate farmers to take up mitigation measures, it is recommended that information provision from GHG calculators be combined with other psychological interventions. To effectively create a bespoke intervention aiming at a specific psychological factor, it is recommended to first assess which factors underlie the willingness of farmers to take up mitigation measures. Psychological models, such as the Theory of Planned Behaviour (Ajzen, 1991), can provide a good starting point to assess the significance of a number of factors such as attitude towards pro-environmental measures, social pressure, group pressure or self-identity (Van Dijk et al., 2015, 2016). For example, if the model indicates that peer pressure is related to the motivation of farmers to take up mitigation measures, benchmarking would be an effective intervention. This can be done by organising plural workshops in which farmers collectively run a GHG calculator for their farms and receive information on how their outcomes compare to their peers. Benchmarking has been proven to be effective at increasing farmers' intentions and uptake of pro-environmental measures (Lokhorst et al., 2010). However, combining different interventions can further increase the uptake of measures. For example, combining benchmarking with public commitment making, in which farmers commit themselves in front of fellow participants of the workshop to certain measures, has been demonstrated to even further increase the willingness and uptake of these measures (Lokhorst et al., 2010). In conclusion, GHG calculator tools are very valuable tools to translate scientific carbon models to the farming community by providing information on how to decrease GHG emissions, but to successfully establish a change in the daily practice it is recommended to combine these tools with other psychological interventions and communication strategies.

Given the role of soils, and soil C, in delivering the UN SDGs and the PCA, the accurate modelling of soil C stocks has never been more important. There is a pressing need to develop, test and challenge our soil C models to meet the challenges facing humanity in the 21st Century. Whatever type of models are used to meet future challenges, it is important that they continue to be tested using appropriate data, and that they are used in regions and for land uses where they have been developed and validated. As new uses of land are developed, models should continue to be validated and modified if necessary, so that they are still appropriate. In addition, in many situations the type of model used, will be dependent on the input data available. Models such as DAYCENT, ECOSSE and the Cool Farm Tool are ideal for assessing soil C sequestration under future climate and land use, but if insufficient data is available, then less data intensive models (e. g. RothC, statistical techniques) should be used.

It is also important that the best data available are readily accessible, whether this is decomposition pot experiments, long-term experiments, soil maps, or satellite data. The development of the technologies of remote sensing and precision farming will provide high resolution data and advances in informatics will enable their use in developing higher resolution and more detailed process-based models. It is extremely important that experimentalists/data curators are involved in the modelling process, as modellers need to know if analytical methods have changed over time or between different counties, what quality control has been used on the data, and how missing data has been addressed.

With good quality data and timely modifications, soil C models will be able to help meet the challenges of the future.

[[Text Box 4]] Take home message

- Soil models are essential tools to understand the effects of land and climate change, from field to global scale.
- Soil models are crucial tools to up-scale and interpolate point/site/field information to larger scales in a quantitative way.
- In order to provide meaningful and useful soil C predictions, uncertainties in model outputs should always be quantified.
- Whatever type of models are used to meet future challenges, it is important that they continue to be tested using appropriate data.
- As new uses of land are developed, models should continue to be validated and modified if necessary, so that they are still appropriate.
- It is extremely important that experimentalists/data curators are involved in the modelling process, as modellers need to know if analytical methods have changed

over time, what quality control has been used on the data and how missing data has been addressed.

- Calibrated and validated models can be used by experimentalists to provide information on data acquisition and to develop new research hypothesis.
- GHG calculator tools are very valuable tools to translate scientific carbon models to the farming community by providing information on how to decrease GHG emissions, but to successfully establish a change in the daily practice it is recommended to combine these tools with other psychological interventions and communication strategies.
- By linking international, national and local policies, and action frameworks to the Paris Climate Agreement, governments can develop more comprehensive and robust approaches to climate change, food security, soil protection, sustainable land management, water management and energy generation.
- There is often a difference in objectives between practitioners at various levels and policy makers with respect to priorities for resource and land management. This disconnect requires robust institutional support to encourage inclusivity in decision making.

9.6. References

ASABE, 2006a. Agricultural Machinery Management Data. American Society of Agricultural and Biological Engineers Standard ASAE EP496.3. ASABE, St Joseph, MI, USA, pp. 385–390.

ASABE, 2006b. Agricultural Machinery Management Data. American Society of Agricultural and Biological Engineers Standard ASAE EP496.3. ASABE, St Joseph, MI, USA, pp. 391–398.

Abdalla, M., Jones, M., Yeluripati, J., Smith, P., Burke, J., Williams, M., 2010. Testing DayCent and DNDC model simulations of N_2O fluxes and assessing the impacts of climate change on the gas flux and biomass production from a humid pasture. Atmos. Environ. 44, 2961–2970.

Abdalla, M., Saunders, M., Hastings, A., Williams, M., Smith, P., Osborne, B., Lanigan, G., Jones, M.B., 2013. Simulating the impacts of land use in Northwest Europe on Net Ecosystem Exchange (NEE): The role of arable ecosystems, grasslands and forest plantations in climate change mitigation. Sci. Tot. Environ. 465, 325–336.

Abdalla, M., Hastings, A., Truu, J., Espenberg, M., Mander, Ü., Smith, P., 2016. Emissions of methane from northern peatlands: a review of management impacts and implications for future management options. Ecol. Evol. 6, 7080–7102.

Abrahamse, W., Steg, L., Vlek, C., Rothengatter, T., 2005. A review of intervention studies aimed at household energy conservation. J. Environ. Psychol. 25, 273–291.

Ajzen, I., 1991. The Theory of Planned Behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.

Albanito, F., Beringer, T., Corstanje, R., Poulter, B., Stephenson, A., Zawadzka, J., Smith, P., 2016. Carbon implications of converting cropland to bioenergy crops or forest for climate mitigation: a global assessment, GCB-Bioenergy 8, 81–95.

Allison, S.D., Martiny, J.B.H., 2008. Resistance, resilience, and redundancy in microbial communities. Proc. Natl. Acad. Sci. USA 105 (Suppl 1), 11512–11519.

Allison, S.D., Wallenstein, M.D., Bradford, M.A., 2010. Soil-carbon response to warming dependent on microbial physiology. Nat. Geosci. 3, 336–340.

Archontoulis, S.V., Huber, I., Miguez, F.E., Thorburn, P.J., Rogovska, N., Laird, D.A., 2016. A model for mechanistic and system assessments of biochar effects on soils and crops and trade-offs. GCB-Bioenergy 8, 1028–1045.

Beckert, M.R., Smith, P., Lilly, A., Chapman, S.J. 2016. Soil and tree biomass carbon sequestration potential of silvopastoral and woodland-pasture systems in North East Scotland. Agrofor. Syst. 90**,** 371–383.

Bell, M., Jones, E., Smith, J., Smith, P., Yeluripati, J., Augustin, J., Juszczak, R., Olejnik, J. & Sommer, M., 2012. Simulation of soil nitrogen, nitrous oxide emissions and mitigation scenarios at 3 European cropland sites using the ECOSSE model. Nutri. Cycl. Agroecosyst. 92, 161–81.

Bodansky, D., Hoedl, S.A., Metcalf, G.E., Stavins, R.N., 2014. Facilitating linkage of heterogeneous regional, national, and sub-national climate policies through a future international agreement. Cambridge, Mass.: Harvard Project on Climate Agreements.

Bouwman, A.F., Boumans, L.J.M., Batjes, N.H., 2002. Modeling global annual N_2O and NO emissions from fertilized fields, Global Biogeochem. Cycles 16, 1080.

Bradbury, N.J., Whitmore, A.P., Hart, P.B.S., Jenkinson, D.S., 1993. Modelling the fate of nitrogen in crop and soil in the years following application of ^{15}N-labelled fertilizer to winter wheat. J. Agric. Sci. 121, 363–379.

Campbell, E., Paustian K., 2015. Current developments in soil organic matter modeling and the expansion of model applications: a review. Environ. Res. Lett. 10, 123004.

Carlson, K.M., Goodman, L.K., May-Tobin, C.C., 2015. Modeling relationships between water table depth and peat soil carbon loss in Southeast Asian plantations. Environ. Res. Lett. 10, 074006.

Casado-Asensio, J., Drutschinin, A., Corfee-Morlot, J., Campillo, G., 2016. Mainstreaming Adaptation in National Development Planning. OECD Development Co-operation Working Papers, No. 29, OECD Publishing, Paris.

Chan, S., Asselt, H., Hale, T., Abbott, K.W., Beisheim, M., Hoffmann, M., Guy, B., Höhne, N., Hsu, A., Pattberg, P., Pauw, P., 2015. Reinvigorating international climate policy: A comprehensive framework for effective nonstate action. Global Policy 6, 466–473.

Cheng, K., Ogle, S. M., Parton, W. J., & Pan, G. (2014). Simulating greenhouse gas mitigation potentials for hinese croplands using the DAYCENT ecosystem model. Glob. Change Biol. 20, 948–962.

Cole, C.V., Flach, K., Lee, J., Sauerbeck, D., Stewart, B., 1993. Agricultural sources and sinks of carbon. Water Air Soil Pollut. 70, 111–122.

Coleman, K., Jenkinson, D.S., 1996. RothC-26.3 - A model the turnover of carbon in soil. In: Powlson, D.S., Smith, P., Smith, J.U. (Ed.), Evaluation of soil organic matter models using existing long-term datasets. NATO ASI Series I, Springer, Berlin, pp 237–246.

Comeau, L.P., 2016. Carbon dioxide fluxes and soil organic matter characteristics on an intact peat swamp forest, a drained and logged forest on peat, and a peatland oil palm plantation in Jambi, Sumatra, Indonesia. Ph.D. thesis, University of Aberdeen.

Davidson, E.A., Samanta, S., Caramori, S.S., Savage, K., 2012. The Dual Arrhenius and Michaelis–Menten kinetics model for decomposition of soil organic matter at hourly to seasonal time scales. Glob. Chang. Biol. 18, 371–384.

Del Grosso, S.J., Parton, W.J., Mosier, A.R., Hartman, M.D., Brenner, J., Ojima, D.S., Schimel, D.S., 2001. Simulated interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. In: Schaffer, M., Ma, L., Hansen, S. (Eds.), Modeling Carbon and Nitrogen Dynamics for Soil Management. CRC Press, Boca Raton, FL, pp. 303–332.

Doetterl, S., Berhe, A.A., Nadeu, E., Wang, Z., Sommer, M., Fiener, P., 2016. Erosion, deposition and soil carbon: A review of process-level controls, experimental tools and models to address C cycling in dynamic landscapes. Earth-Sci. Rev. 154, 102–122.

Dommain, R., Couwenberg, J., Joosten, H., 2011. Development and carbon sequestration of tropical peat domes in south-east Asia: links to post-glacial sea-level changes and Holocene climate variability. Quat. Sci. Rev. 30, 999–1010.

Dondini M., Hastings, A., Saiz, G., Jones, M.B., Smith, P., 2009. The Potential of *Miscanthus* to sequester carbon in soils: comparing field measurements in Carlow, Ireland to model predictions. GCB-Bioenergy 1, 413–425.

Ecoinvent Centre, 2007. Ecoinvent data v2.0. Ecoinvent reports No. 1e25, Swiss Centre for Life Cycle Inventories, Dübendorf, Switzerland.

Egashira, K., Han, J., & Karim, A., 2003. Evaluation of long-term application of organic residues on accumulation of organic matter and improvement of soil chemical properties in a clay terrace soil of Bangladesh. Journal of the Faculty of Agriculture, Kyushu University 48, 227–236.

Egashira, K., Han, J. Satake, N., Nagayama, T., Mian, M.J.A., & Moslehuddin, A.Z.M. 2005. Field experiment on long-term application of chemical fertilizers and farmyard manure in floodplain soil of Bangladesh. Journal of the Faculty of Agriculture, Kyushu University 50, 861–870.

FAOSTAT 2016. Food and agriculture organization of the United Nations. <http://faostat3.fao.org/browse/D/FS/E> (accessed 05.10.16).

Farmer, J., Matthews, R., Smith, J.U., Smith, P., Singh, B.K., 2011. Assessing existing peatland models for their applicability for modelling greenhouse gas emissions from tropical peat soils. Curr. Opin. Environ. Sustain. 3, 339–349.

Farmer, J., Matthews, R., Smith, P., Smith, J.U., 2014. The Tropical Peatland Plantation-Carbon Assessment Tool: Estimating CO_2 emissions from tropical peat soils under plantations. Mitig. Adapt. Strateg. Glob. Chang. 19, 863–885.

Frank, D., Reichstein, M., Bahn, M., Thonicke, K., Frank, D., Mahecha, M.D., Smith, P., van der Velde, M., Vicca, S., Babst, F., Beer, C., Buchmann, N., Canadell, J.G., Ciais, P., Cramer, W., Ibrom, A., Miglietta, F., Poulter, B., Rammig, A., Seneviratne, S.I., Walz, A., Wattenbach, M., Zavala, M.A., Zscheischler, J., 2015. Effects of climate extremes on the terrestrial carbon cycle: concepts, processes and potential future impacts. Global Change Biol. 21, 2861–2880.

Franzluebbers, A.J., Stuedemann, J.A., Schomberg, H.H., Wilkinson, S.R., 2000. Soil organic C and N pools under long-term pasture management in the Southern Piedmont USA. Soil Biol. Biochem. 32, 469–478.

Freibauer, A., Rounsevell, M.D.A., Smith, P., Verhagen, J. 2004. Carbon sequestration in the agricultural soils of Europe. Geoderma 122, 1–23.

Gardner, G.T., Stern, P.C., 2002. Environmental Problems and Human Behavior, 2nd edn ed. Pearson Custom Publishing, Boston.

Hastings, A.F., Wattenbach, M., Eugster, W., Li, C., Buchmann, N., Smith, P. 2010. Uncertainty propagation in soil greenhouse gas emission models: An experiment using the DNDC model and at the Oensingen cropland site. Agric. Ecosyst. Environ.136, 97–110.

Hawkes, C.V., Kivlin, S.N., Rocca, J.D., Huguet, V., Thomsen, M.A., Suttle, K.B., 2011. Fungal community responses to precipitation. Glob. Change Biol. 17, 1637–1645.

Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blümmel, M., Weiss, F., Grace, D., Obersteiner, M., 2013. Biomass use, production, feed efficiencies and greenhouse gas emissions from global livestock systems. PNAS 110, 20888–20893.

Herrero, M., Henderson, B., Havlík, P., Thornton, P.K., Conant, R.T., Smith, P., Wirsenius, S., Hristov, A.N., Gerber, P., Gill, M., Butterbach-Bahl, K., 2016. Greenhouse gas mitigation potentials in the livestock sector. Nat. Clim. Chang. 6, 452–461.

Hillier, J., Walter, C., Malin, D., Garcia-Suarez, T., Mila-i-Canals, L., Smith, P., 2011. A farm-focused calculator for emissions from crop and livestock production. Environ. Modell. Softw. 9, 1070–1078.

Hillier, J., Abdalla, M., Bellarby, J., Albanito, F., Datta, A., Dondini, M., Fitton, N., Hallett, P., Hastings, A., Jones, E. Kuhnert, M., 2016. Mathematical modeling of greenhouse gas emissions from agriculture for different end users. In: Del Grosso, S., Ahuja, L., Parton, W. (Ed.), Synthesis and modeling of greenhouse gas emissions and carbon storage in agricultural and forest systems to guide mitigation and adaptation. Advances in Agricultural Systems Modeling 6, 197–228.

Hollis, J.M., 2008. Unpublished internal report prepared by Cranfield University for the Defra PS2225 project.

Hooijer, A., Page, S., Canadell, J.G., Silvius, M., Kwadijk, J., Wösten, J.H.M., Jauhiainen, J., 2010. Current and future CO_2 emissions from drained peatlands in Southeast Asia. Biogeosciences 7, 1505–1514.

Hooijer, A., Page, S., Jauhiainen, J., Lee, W.A., Lu, X.X., Idris, A., Anshari, G., 2012. Subsidence and carbon loss in drained tropical peatlands. Biogeosciences 9, 1053–1071.

IPCC, 2006. Agriculture, Forestry and Other Land Use. In: Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds), IPCC Guidelines for National Greenhouse Gas Inventories. National Greenhouse Gas Inventories Programme. Vol. 4, IGES, Japan.

IPCC, 2014. Climate Change 2014–Impacts, Adaptation and Vulnerability: Regional Aspects. Cambridge University Press, Cambridge, UK.

Karim, A., Egashira, K., Yamada, Y., Haider, J., Nahar, K., 1995. Long-term application of organic residues to improve soil properties and to increase crop yield in terrace soil of Bangladesh. Journal of the Faculty of Agriculture Kyushu University 39, 149–165.

Keesstra, S.D., Bouma, J., Wallinga, J., Tittonell, P., Smith, P., Cerdà, A., Montanarella, L., Quinton, J., Pachepsky, Y., van der Putten, W., Bardgett, R., Molenaar, S., Mol, G., Fresco, L.O., 2016. The significance of soils and soil science towards realization of the UN sustainable development goals. SOIL 2, 111–128.

Knutti, R., Allen, M.R., Friedlingstein, P., Gregory, J.M., Hegerl, G.C., Meehl, G.A., Meinshausen, M., Murphy, J.M., Plattner, G.-K., Raper, S.C.B., Stocker, T.F., Stott, P.A., Teng, H., Wigley, T.M.L., 2008. Review of Uncertainties in Global Temperature Projections over the Twenty-First Century. J. Clim. 21, 2651–2663.

Kurinato, S., Warren, M., Talbot, J., Kauffman, B., Murdiyarso, D., Frolking, S., 2015. Carbon accumulation of tropical peatlands over millennia : A modeling approach. Glob. Chang. Biol. 21, 431–444.

Lawson, D.A., Tabor, J.H., 2001. Stopping distances: an excellent example of empirical modelling. Teach. Math. Appl. 20, 66–74.

Lal, R., 2003. Soil erosion and the global carbon budge. Environ. Int. 29, 437–450.

Lal, R., 2004. Soil carbon sequestration impacts on global climate change and food security. Science 304, 1623–1627.

Leith H., 1972. Modelling the primary productivity of the world. Nature and Resources, UNESCO VIII 2, 5–10.

Li, C., Frolking, S., Frolking T. A., 1992. A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity, J. Geophys. Res. 97 (D9), 9759–9776.

Li, C.S., 2000. Modeling trace gas emissions from agricultural ecosystems. Nutr. Cycl. Agroecosys. 58, 259–276.

Lokhorst, A.M., van Dijk, J., Staats, H., van Dijk, E., de Snoo, G., 2010. Using tailored information and public commitment to improve the environmental quality of farm lands: an example from the Netherlands. Hum. Ecol. 38, 113–122.

Lugato, E., Paustian, K., Panagod, P., Jones, A., Borelli, P., 2016. Quantifying the erosion effect on current carbon budget of European agricultural soils at high spatial resolution. Glob. Chang. Biol. 22, 1976–1984.

Li Liu, D., Chan, K.Y., Conyers, M.K., 2009. Simulation of soil organic carbon under different tillage and stubble management practices using the Rothamsted carbon model. Soil & Till. Res., 104, 65–73.

Luo, Y., Ahlström, A., Allison, S.D., Batjes, N.H., Brovkin, V., Carvalhais, N., Chappell, A., Ciais, P., Davidson, E.A., Finzi, A. and Georgiou, K., 2016. Toward more realistic projections of soil carbon dynamics by Earth system models. Glob. Biogeochem. Cycles 30, 40–56.

Lychuk, T.E., Izaurralde, R.C., Hill, R.L., McGill, W.B., Williams, J.R., 2015. Biochar as a global change adaptation: predicting biochar impacts on crop productivity and soil quality for a tropical soil with the Environmental Policy Integrated Climate (EPIC) model. Mitig. Adapt. Strateg. Glob. Change 20, 1437–1458.

Manlay. R.J., Feller, C., Swift, M.J., 2007. Historical evolution of soil organic matter concepts and their relationships with the fertility and sustainability of cropping systems Agric. Ecosyst. Environ. 119, 217–233.

McClean, G.J., Rowe, R.L., Heal, K.V., Cross, A., Bending, G.D., Sohi, S.P. 2015. An empirical model approach for assessing soil organic carbon stock changes following biomass crop establishment in Britain. Biomass Bioenerg. 83, 141–151.

Müller-Nedebock, D., Chaplot, V., 2015. Soil carbon losses by sheet erosion: a potentially critical contribution to the global carbon cycle. Earth Surf. Process. Landforms 40, 1803–1813.

Nijbroek, R.P., Andelman, S.J., 2016. Regional suitability for agricultural intensification: a spatial analysis of the Southern Agricultural Growth Corridor of Tanzania. Int. J. Agr. Sustain. 14 (2), 231–247.

Ogle, S.M., Breidt, F.J., Paustian, K., 2005. Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperature and tropical regions. Biogeochemistry 72, 87–121.

Pagel, H., Poll, C., Ingwersen, J., Kandeler, E., Streck, T., 2016. Modeling coupled pesticide degradation and organic matter turnover: From gene abundance to process rates. Soil Biol. Biochem. 103, 349–364.

Pandya, U. Saraf, M., 2010a. Application of fungi as a biocontrol agent and their biofertilizer potential in Agriculture. Journal of Advances in Developmental Research 1, 90–99.

Pandya, U. Saraf, M., 2010b. Role of single fungal isolates and consortia as plant growth promoters under saline conditions. Res. J. Biotechnol. 5, 5–9.

Parton, W.J., Hartman, M.D., Ojima, D.S., Schimel, D.S., 1998. DAYCENT: its land surface submodel: description and testing. Glob. Planet. Change 19, 35–48.

Parton, W.J., 1998. The CENTURY model. In: Powlson, D.S., Smith, P., Smith, J.H. (Eds.), Evaluation of Soil Organic Matter Models. Springer Berlin Heidelberg. pp. 283–291.

Paustian, K., 1994. Modelling soil biology and biochemical processes for sustainable agriculture research. In: Pankhurst, C.E., Doube, B.M., Gupta, V.V.S.R., Grace, P.R. (Eds.), Soil Biota: Management in Sustainable Farming Systems. CSIRO, Australia, pp. 182-193.

Powlson, D.S., Gregory, P.J., Whalley, W.R., Quinton, J.N., Hopkins, D.W., Whitmore, A.P., Hirsch, P.R., Goulding, K.W.T., 2011. Soil management in relation to sustainable agriculture and ecosystem services. Food Policy 36, S72–87.

Pogson, M., Richards, M., Dondini, M., Jones, E.O., Hastings, A., Smith, P., 2016. ELUM: a spatial modelling tool to predict soil greenhouse gas changes from land conversion to bioenergy in the UK. Environ. Model. Softw. 84, 458–466.

Reichstein M, Bahn M, Ciais P Frank, D.,Mahecha, M.D., Seneviratne, S.I., Zscheischler, J., Beer, C., Buchmann, N., Frank, D.C., Papale, D., Rammig, A., Smith, P., Thonicke, K., van der Velde, M., Vicca, S., Walz, A., Wattenbach, M., 2013. Climate extremes and the carbon cycle. Nature 500, 287–295.

Reid, J.B., 2002. Yield response to nutrient supply across a wide range of conditions 1. Model derivation. Field Crops Res. 77, 161–71.

Renard KG., 1997. Predicting soil erosion by water: a guide to conservation planning with the revised universal loss soil equation (RUSLE). USDA-ARS, Washington DC.

Richards, M., Pogson, M., Dondini, M., Jones, E.O., Hastings, A., Henner, D.N., Tallis, M. J., Casella, E., Matthews, R. W., Henshall, P. A., Milner, S., Taylor, G., McNamara, N. P., Smith, J. U., Smith, P., 2016. High-resolution spatial modelling of greenhouse gas emissions from land-use change to energy crops in the United Kingdom. GCB-Bioenergy, doi:10.1111/gcbb.12360.

Sibbald, A.R., Eason, W.R., Mcadam, J.H., Hislop, A.M. 2001. The establishment phase of a silvopastoral national network experiment in the UK. Agrofor. Syst., 53, 39–53.

Smith, J.U., Gottschalk, P., Bellarby, J., Chapman, S., Lilly, A., Towers, W., Bell, J., Coleman, K., Nayak, D.R., Richards, M.I., Hillier, J., Flynn, H.C., Wattenbach, M., Aitkenhead, M., Yeluripurti, J.B., Farmer, J., Milne, R., Thomson, A., Evans, C., Whitmore, A.P., Falloon, P., Smith, P., 2010. Estimating changes in national soil carbon stocks using ECOSSE – a new model that includes upland organic soils. Part I. Model description and uncertainty in national scale simulations of Scotland. Clim. Res. 45, 179–192.

Smith, J., Abegaz, A., Matthews, R., Subedi, M., Orskov, R., Tumwesige, V., Smith, P., 2014. What is the potential for biogas digesters to improve soil carbon sequestration in Sub-Saharan Africa? Biomass Bioenerg. 70, 73–86.

Smith, P., Powlson, D.S., Glendining, M.J., Smith, J.U., 1997. Potential for carbon sequestration in European soils: preliminary estimates for five scenarios using results from long-term experiments. Global Change Biol. 3, 67–79.

Smith, P., 2016. Soil carbon sequestration and biochar as negative emission technologies. Glob. Chang. Biol. 22, 1315–1324. doi: 10.1111/gcb.13178.

Smith, P., Cotrufo, M.F., Rumpel, C., Paustian, K., Kuikman, P.J., Elliott, J. A., McDowell, R., Griffiths, R.I., Asakawa, S., Bustamante, M., House, J.I., Sobocká, J., Harper, R., Pan, G., West, P.C., Gerber. J.S., Clark, J.M., Adhya, T., Scholes, R.J., Scholes, M.C., 2015. Biogeochemical cycles and biodiversity as key drivers of ecosystem services provided by soils. SOIL 1, 665–685.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C. and Scholes, B., 2008. Greenhouse gas mitigation in agriculture. Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 363 (1492), 789–813.

Smith, P., Smith, J., Flynn, H., Killham, K., Rangel-Castro, I., Foereid, B., Aitkenhead, M., Chapman, S., Towers, W., Bell, J., 2007. ECOSSE: Estimating Carbon in Organic Soils-Sequestration and Emissions: Final Report.

Smith, P., Ashmore, M., Black, H., Burgess, P.J., Evans, C., Quine, T., Thomson, A.M., Hicks, K., Orr, H., 2013. The role of ecosystems and their management in regulating climate, and soil, water and air quality. J. Appl. Ecol. 50, 812–829.

Smith, P., House, J.I., Bustamante, M., Sobocká, J., Harper, R., Pan, G., West, P.C., Clark, J.M., Adhya, T., Rumpel, C., Paustian, K., Kuikman, P., Cotrufo, M.F., Elliott, J.A., McDowell, R., Griffiths, R.I., Asakawa, S., Bondeau, A., Jain, A.K, Meersmans, J., Pugh, T.A.M., 2016a. Global change pressures on soils from land use and management. Glob. Chang. Biol. 22, 1008–1028.

Smith, P., Davis, S.J., Creutzig, F., Fuss, S., Minx, J., Gabrielle, B., Kato, E., Jackson, R.B., Cowie, A., Kriegler, E., van Vuuren, D.P., Rogelj, J.. Ciais, P.. Milne, J., Canadell, J.G., McCollum, D., Peters, G., Andrew, R., Krey, V., Shrestha, G., Friedlingstein, P., Gasser, T., Grübler, A., Heidug, W.K., Jonas, M., Jones, C.D., Kraxner, F., Littleton, E., Lowe, J., Moreira, J.R., Nakicenovic, N., Obersteiner, M., Patwardhan, A., Rogner, M., Rubin, E., Sharifi, A., Torvanger, A., Yamagata, Y., Edmonds, J. & Yongsung, C., 2016b. Biophysical and economic limits to negative CO_2 emissions. Nat. Clim. Chang. 6, 42–50.

Stern, P.C., 2011. Contributions of Psychology to Limiting Climate Change. Am. Psychol. 66, 303–314.

Tilman, D., Clark, M., 2015. Food, Agriculture & the Environment: Can We Feed the World & Save the Earth?. Daedalus 144, 8–23.

Todd-Brown, K.E.O., Hopkins F.M., Kivlin S.N., Talbot J.M., Allison S.D., 2012. A framework for representing microbial decomposition in coupled climate models. Biogeochemistry 109, 19–33.

UNFCCC, 2015. Framework convention on climate change. <http://unfccc.int/paris_agreement/items/9485.php> (accessed 28.11.16).

United Nations, 2015. International year of soils. <http://www.fao.org/soils-2015/en/> (accessed 28.11.16).

United Nations Development Programme, 2015. Sustainable Development Goals. <http://www.undp.org/content/undp/en/home/sustainable-development-goals.html> (accessed 28.11.16).

Van der Weerden, T.J., Kelliher, F.M., de Klein, C.A.M., 2012. Influence of pore size distribution and soil water content on nitrous oxide emissions. Soil Res. 50, 125–135.

van Dijk, W.F.A., Lokhorst, A.M., Berendse, F., de Snoo, G.R., 2015. Collective agri-environment schemes: How can regional environmental cooperatives enhance farmers' intentions for agri-environment schemes? Land Use Pol. 42, 759–766.

van Dijk, W.F.A., Lokhorst, A.M., Berendse, F., de Snoo, G.R., 2016. Factors underlying farmers' intentions to perform unsubsidised agri-environmental measures. Land Use Pol. 59, 207–216.

van Groenigen, K.J., Hastings, A., Forristal, D., Roth, B., Jones, M, Smith, P., 2011. Soil C storage as affected by tillage and straw management: An assessment using field measurements and model predictions. Agric. Ecosyst. Environ. 140, 218–225.

Vleeshouwers, L.M., Verhagen, A., 2002. Carbon emissions and sequestration by agricultural land use: a model study for Europe. Glob. Chang. Biol. 8, 519–530.

Watson, J.E., Iwamura, T., Butt, N., 2013. Mapping vulnerability and conservation adaptation strategies under climate change. Nat. Clim. Chang. 3, 989–994.

Whittaker, C., McManus, M.C., Smith, P., 2013. A comparison of carbon accounting tools for arable crops in the United Kingdom. Environ. Model. Softw. 46, 228–239.

Wieder, W.R., Bonan, G.B., Allison, S.D., 2013. Global soil carbon projections are improved by modelling microbial processes. Nat. Clim. Change 3, 909–912.

Wieder, W.R., Allison, S.D., Davidson, E.A., Georgiou, K., Hararuk, O., He, Y., Hopkins, F., Luo, Y., Smith, M.J., Sulman, B., Todd-Brown, K., 2015. Explicitly representing soil microbial processes in Earth system models. Global Biogeochem. Cycles 29, 1782–1800.

Williams J.R., 1990. The erosion productivity impact calculator (EPIC) model: A case history. Phil. Trans. R. Soc. Lond. 329,421–428.

Wischmeier, W.H., Smith, D.D., 1978. Predicting rainfall erosion losses - A guide planning. U.S. Department of Agriculture, Agriculture Handbook No. 537.

Woolf, D., Lehmann, J., 2012. Modelling the long-term response to positive and negative priming of soil organic carbon by black carbon. Biogeochemistry 111, 83–95.

Zaks, D.P.M., Ramankutty, N., Barford, C.C., Foley, J.A., 2007. From Miami to Madison: Investigating the relationship between climate and terrestrial net primary production. Glob. Biogeochem. Cycles 21, GB3004.

FIGURE CAPTIONS

Figure 1: Structure of the RothC carbon sequestration model. Key: DPM is Decomposable Plant Material; RPM is Resistant Plant Material; BIO is Microbial Biomass; HUM is Humified Organic Matter; and IOM is Inert Organic Matter, and α, β and (1-α-β) are the proportions of BIO, HUM and CO_2 produced on aerobic decomposition. Adapted from Bradbury et al. (1993) and Coleman and Jenkinson (2014).

Figure 2: Structure of the two-component DNDC model with six sub-models: soil climate, crop growth, decomposition, denitrification, nitrification and fermentation. Adapted from Li, (2000).

Figure 3: Measured (dark circle) and simulated (light circle) NEE for (a) the grassland and (b) arable fields during the experimental period (grassland experimental period: 2003-2006; arable experimental period: 2003-2007). Adapted from Abdalla et al. (2013).

Figure 4: Simulated (line) and measured (points) SOC values at 20 cm depth over 20 years under different treatment for the period of 1978-2015 and 1988-2008 for site 1 (Fig. 1a) and site 2 (Fig. 1b) respectively. Fig. 1c indicates modelled annualised SOC stock changes under different mitigation scenarios of two test sites for the period of 1988-2008. [MN-Mineral N, FYMN-Farmyard manure + mineral N, CD-Cowdung, CDN-Cowdung+mineral N, RSD20-20% residue return, RT-Reduced tillage, BMP-Best management practice, RSD20+RT+less N+CD].

Figure 5: Whole farm modelling, accounting for the feedback between soil organic matter on crop and animal production, water use, fuel availability, labour and finances.

Figure 6: Rate of carbon sequestration for application continued over 20 years of differently treated organic residues derived from 1 t ha^{-1} y^{-1} of carbon in fresh residue. Adapted from Smith et al. (2014).

Figure 7: Change in soil C (t C ha^{-1} y^{-1}) after conversion from grass, crop or semi – natural land to Forestry. Values represent the average annual change in soil C for the first 20 years after conversion.

Figure 8: Potential contribution (%) of soil C sequestration to the total C savings occurring from the conversion of rainfed and irrigated high-input croplands to C_4 bioenergy crops, short rotation coppice wood land (SRCW) and forests.