Programme Area: Bioenergy

Project: ELUM

Title: Land-use Change and the Bioenergy Crop Management Model Report

Abstract:

The ELUM project was commissioned to provide greater understanding on the GHG and soil carbon changes arising as a result of direct land-use change (dLUC) to bioenergy crops, with a primary focus on the second-generation bioenergy crops Miscanthus, short rotation coppice (SRC) willow and short rotation forestry (SRF). The project was UK-bound, but with many outcomes which could be internationally relevant. Indirect land-use change impacts were out of scope.

The aim of Work Package 4 (WP4) was to develop a bioenergy spatial modelling tool (ELUM software package) to allow non-specialist users to explore the consequences of land-use and land-management change arising from planting of energy crops on soil carbon and greenhouse gas emissions in the UK. This deliverable tests the accuracy of the ECOSSE model (from which the ELUM software package is derived) to simulate soil carbon and greenhouse gas fluxes, describes the uncertainties in the simulations and describes the ELUM meta-model itself.

Context:

The ELUM project has studied the impact of bioenergy crop land-use changes on soil carbon stocks and greenhouse gas emissions. It developed a model to quantitatively assess changes in levels of soil carbon, combined with the greenhouse gas flux which results from the conversion of land to bioenergy in the UK. The categorisation and mapping of these data using geographical information systems allows recommendations to be made on the most sustainable land use transition from a soil carbon and GHG perspective.

Some information and/or data points will have been superseded by later peer review, please refer to updated papers published via www.elum.ac.uk

ETI Project code: BI1001

Ecosystem Land Use Modelling & Soil C Flux Trial (ELUM)

Management & Deliverable Reference: PM07.4.3

Report on Land-use Change and the Bioenergy Crop Management Model

REPORT

V2.3

01/10/2014

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EXECUTIVE SUMMARY

The ultimate purpose of Work Package 4 (WP4) is to develop a bioenergy spatial modelling tool (ELUM software package) to allow non-specialist users to explore the consequences of land-use and land-management change arising from planting of energy crops on soil carbon (C) and greenhouse gas (GHG) emissions in the UK.

The results of the ELUM software package are based on the ECOSSE model, a process-based model capable of simulating soil C and GHG fluxes at site level as well as spatially. In order to generate reliable outputs, it is therefore crucial to test the model accuracy to describe soil processes adequately. Spatial results from ECOSSE are stored in a look-up table within the ELUM software package, which are processed according to user inputs; this combination of look-up table and processing is referred to as the ‘meta-model’.

The objective of this report is to test the accuracy of the ECOSSE model to simulate soil C and GHG fluxes, describe the uncertainties in the simulations and finally to describe the meta-model.

The model evaluation has been conducted at site level, with detailed information on soil characteristics, GHG fluxes and environmental data collected as part of the ELUM Work packages, WP1, WP2 and WP3. This opportunity to validate the model against a large and comprehensive dataset is extremely valuable, as the lack of experimental data (and site replicates) is often a limiting factor for model development.

The results of the present study show that the ECOSSE model is extremely accurate in predicting soil C after land-use change (LUC) from arable/grassland to Willow, *Miscanthus* and short-rotation forest (SRF), to a soil depth of 1 metre. Soil CO_2 emissions from bioenergy and conventional crops have been measured using three different techniques, all showing a good correlation with the modelled values. Continuous measurements on root-exclusion plots appear to be the most comprehensive dataset to test model performance in simulating soil CO_2 fluxes.

The ECOSSE model is also capable of simulating small GHG fluxes such as N_2O and CH_4 from conventional and bioenergy crop regimes. High variability in the measured non-CO_2 fluxes led to a low correlation between measured and modelled values, but the model outputs were within experimental error, resulting in no error in the description of the simulated processes.

A sensitivity analysis of the spatial results was carried out to determine the effects of variations in bioenergy crop yield and nitrogen fertiliser application rates on the output variables. In general, increases in yield of 50% are insufficient to alter the qualitative impact of land-use transitions from grassland and forest to bioenergy crops on soil C, with the exception of grassland to SRF. Here, a 50% increase in SRF yield is sufficient to transform a negative change in mean soil C to approximately no change in mean soil C.

Insufficient data exist to identify spatial variation in model uncertainty. Uncertainty is therefore assumed uniform, calculated from comparison of model results against field measurements,

and reported in the ELUM software package as error bars in the time series. The uncertainties around the use of a large soil database for spatial simulations have also been quantified and found to be minimal, and we therefore concluded that the Harmonized World Soil Database (HWSD), used for the spatial simulations, provides a reliable source of soil input to run the model for the whole UK.

Finally, an extensive description of the meta-model is given in this report, describing assumptions and constraints, as well as the structure of the look-up table. The benefits and limitations of the look-up table approach for the meta-model are reported below.

Benefits:

- Results are as reliable as possible, since results from the ECOSSE model are directly reported (except for non-default fertiliser and yield improvement)
- Comparatively fast to use
- Future modifications are relatively straightforward, since results for different transitions, climates and regions, for example, can be obtained from the underlying model and used to create a new look-up table, without further modelling work to approximate the results of the ECOSSE model

Limitations:

- The data storage space for the meta-model is comparatively large
- Results are restricted to those considered by the model (although use of regression equations for non-default options works around this).

References to other ELUM Reports

The reader's attention is drawn to the following additional ELUM reports and documents which are referred to in this report:

- PM04.2.2_Year 1 Report for WP2 Chronosequence Sampling Activities
- PM04.3.2_Year 1 Report for Work Package 3 – Network of field sites to measure soil C dynamics and GHG emissions
- PM06.2.3_WP2 Year 2 Chronosequence Report v1.1
- PM06.3.3_Year 2 report for Work Package 3_ Network of Field Sites to Measure Soil Dynamics and GHG Emissions
- PM06.4.2_Report on Existing Models and Spatial Meta-Model Test v2.0
- PM07.2.4_WP2_Year 3 Chronosequence Report v1.0
- PM07.4.4_WP4_ELUM Meta-model source code
- PM07.4.6_WP4_Effects on LUC into Bioenergy v1.0

CONTENTS

1. INTRODUCTION

1.1 Overview

This report describes the work undertaken within Work Package 4 (WP4) on the land-use change (LUC) / bioenergy crop management model.

The deliverable and acceptance criteria for this report are as follows:

Deliverable D4.3:	One report which details the LUC/crop management model - methodology and validation/parameterisation approaches/ sensitivities/assumptions etc., including description of all input data from existing sites and network sites used in ETI project (all input data to be provided in excel format (or other appropriate database format if exceeds 64,000 points) to be provided on DVD with written report.
Acceptance Criteria:	Report provides detailed description of meta-model methodology, detailed design, assumptions and limitations; sensitivity analyses, verification and validation activities. Report contains meta-data description of all inbuilt data and any input data required to run the models. Any data required for running the model is provided in excel database format, on DVD and electronically via VPN. The report will be provided in both Microsoft Word and Adobe pdf formats. The report will also have a clear executive summary, contents page, next steps (linking it to previous and future deliverables) and a complete 'references' section (references to be provided in form of Global Change Biology Journal).

This report documents the work done to-date to integrate experimental results from WP2-3 to the models and to develop the spatial and meta-model.

The site modelling has been performed to test the model accuracy to simulate soil carbon (C) and greenhouse gas (GHG) fluxes from grassland, arable, *Miscanthus*, Short-Rotation Forestry (SRF) and Short-Rotation Coppice (SRC) Willow. After proving the statistical association between measured and modelled values and the absence of model bias, the model has been run spatially for the all UK (results of spatial simulations are presented and discussed in report PM07.4.6_WP4_Effects on LUC into Bioenergy). The results of the spatial modelling have been then used to build the ELUM software package, which include the meta-model and a graphical user interface (GUI). The latter is used by the end-user to obtain results according to their interests.

Specifically, in accordance with the acceptance criteria, we report on:

- Evaluation and validation of the process-based model against field sites for soil C and GHG fluxes, incorporating new soil texture data from WP2. Model evaluation of simulating the effects of transition to SRF on soil C have been extensively discussed in report PM06.4.2_Report on Existing Models and Spatial Meta-Model Test. Therefore we will present only the key findings on the current report.
- Description of spatial and meta-model
- Report uncertainties in spatial simulations

1.2 Site-specific Modelling

A model can only be properly evaluated against independent data: i.e., data that was not used to develop the model itself. The procedures of model development, involving derivation of equations, parameter fitting or other data-dependent methodologies, amalgamate the effects of any processes that have not been included in the model into the description of those processes that are included. If the model is evaluated against independent data, it is likely that the effect of the missing process will be different with respect to the process it has been amalgamated into, so the model evaluation will show an error, exposing this fault. Therefore a quantitative analysis of model performance should use independent measurements for the full range of conditions in which the model is to be used, providing assessments of both association and coincidence between simulations and measured data.

The evaluation process is therefore crucial to assess if the model requires further implementation. Such implementation may take the form of inclusion of new processes not currently included in the models, or more likely, an improved description of a process already included within the model. The improved model is then tested again using independent data (i.e. again, data not used for the model evaluation).

1.3 Spatial Simulation and Meta-Model

In order to consider the effects of land-use transitions anywhere in the UK, and to investigate the effects of converting large areas to grow bioenergy crops, results from the process-based model are obtained spatially for the whole UK. The model is the same as used for site-specific simulations, but using national datasets for soil and meteorological inputs. Methodology, results and discussions on the effects of land-use transition to bioenergy crops in UK can be found in the report PM07.4.6_WP4_Effects on LUC into Bioenergy v1.0.

The spatial modelling tool (ELUM software package) is intended to allow users to obtain information gained from the spatial simulations, but faster and easier to use and interpret than a process-based model. Users will be able to obtain results according to their interests, such as geographic region, time period, land-use transition and climate-change scenario. User documentation is provided in the ELUM software package.

The spatial modelling tool uses a 'meta-model' to obtain results. The meta-model is built around a look-up table, which is generated directly from results from the ECOSSE model. The results provided by the spatial modelling tool are therefore exactly the same as the ECOSSE results. The only exception to this is for non-default choices of fertiliser application and yield improvement, in which case results in the look up table are adjusted according to equations obtained from statistical analysis of ECOSSE results.

2. METHODOLOGY

2.1 Evaluation and validation of the ECOSSE model

2.1.1 ECOSSE model

The soil carbon (C) model, ECOSSE, was developed to simulate highly organic soils from concepts originally derived for mineral soils in the RothC (Jenkinson et al., 1987; Coleman and Jenkinson, 1996) and SUNDIAL (Smith et al. 1996) models. Building on these established models, ECOSSE uses a pool-type approach, describing Soil Organic Matter (SOM) as pools of inert organic matter, humus, biomass, resistant plant material and decomposable plant material.

The ECOSSE model includes five pools of SOM, each decomposing with a specific rate constant. Decomposition is sensitive to temperature, soil moisture and clay content of the soil, and so soil texture, soil pH, soil bulk density, monthly climate and land-use data are the inputs to the model (Coleman and Jenkinson, 1996; Smith et al., 1997).

All of the major processes of C and N turnover in the soil are included in the model, but each of the processes is simulated using only simple equations driven by readily available input variables, allowing it to be developed from a field-based model to a national-scale tool, without high loss of accuracy. ECOSSE differs from RothC and SUNDIAL in the addition of descriptions of a number of processes and impacts that are not important in the mineral arable soils that these models were originally developed for. More importantly, ECOSSE differs from RothC and SUNDIAL in the way that it makes full use of the limited information that is available to run models at national scale. In particular, measurements of soil C are used to interpolate the activity of the SOM and the plant inputs needed to achieve those measurements. Any data available describing soil water, plant inputs, nutrient applications and timing of management operations are used to drive the model and so better apportioning the factors determining the interpolated activity of the SOM. However, if any of this information is missing, the model can still provide accurate simulations of SOM turnover, although the impact of changes in conditions will be estimated with less accuracy due to the reduced detail of the inputs. This novel approach will be discussed further below.

In summary, during the decomposition process, material is exchanged between the SOM pools according to first order rate equations, characterised by a specific rate constant for each pool, and adjusted according to rate modifiers dependent on the temperature, moisture, crop cover and pH of the soil. Under aerobic conditions, the decomposition process results in gaseous losses of carbon dioxide (CO_2); under anaerobic conditions losses as methane (CH_4) dominate. The N content of the soil follows the decomposition of the SOM, with a stable C:N ratio defined for each pool at a given pH, and N being either mineralised or immobilised to maintain that ratio. Nitrogen is released from decomposing SOM as ammonium (NH_4^+) or nitrified to nitrate (NO_3^-). Carbon and N may be lost from the soil by the processes of leaching (NO_3^-), dissolved organic C (DOC), and dissolved organic N (DON), denitrification, volatilisation or crop off-take; or, C and N may be returned to the soil by plant inputs, inorganic fertilisers, atmospheric deposition or organic amendments (Figure 2.1). The soil is divided into

5 cm layers, so as to facilitate the accurate simulation of these processes down the soil profile. The formulation and simulation approach used for each of these processes is described in detail below.

The specific ECOSSE input requirements are:

– Climate/atmospheric data:
  - Long-term (30 years) average monthly rainfall, potential evapotranspiration (PET) and temperature
  - Monthly rainfall, temperature and potential evapotranspiration
– Soil data:
  - Initial total SOC content
  - Soil clay, silt and sand content
  - Soil bulk density
  - Soil pH
– Land-use/land-management data:
  - Land-use for each simulation year

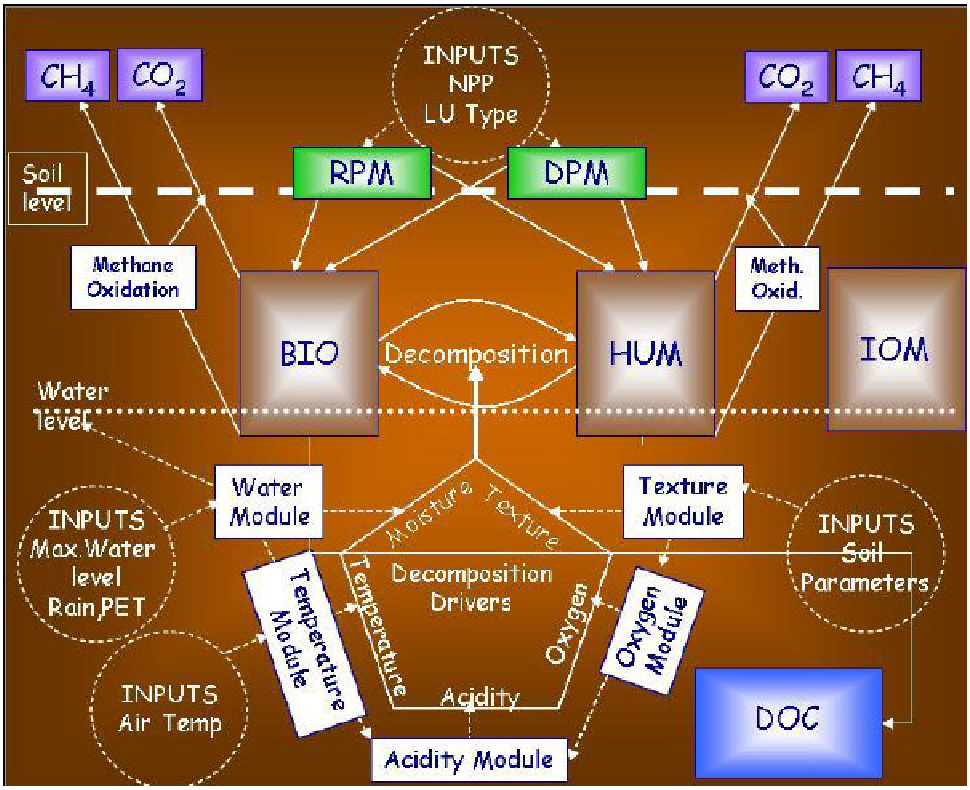


Figure 2.1: Structure of the carbon components of ECOSSE. Picture from ECOSSE User-Manual (Smith et al., 2001)..

Several modifications were made to the ECOSSE model based on the findings arising from the model evaluation carried out in the first two years of the ELUM project (see report D4.2 - PM06.4.2_Report on Existing Models and Spatial Meta-Model Test v2.0).

Model developments

- Model initialisation (spin-up)
  - More stable equilibrium
  - Applicable for all initial land uses

The initialisation (spin-up) of the model is based on the assumption that the soil column is at stable equilibrium under the initial land use at the start of the simulation. The initialisation procedure has been modified so that it uses estimated yearly plant inputs, land management practices and measured initial total soil C to estimate a soil turnover rate which would maintain this equilibrium. An iterative method is used to gain the solution of the decomposition equations to estimate an overall turnover rate. This analytical method also ascertained the relative soil carbon pool sizes. Further dynamical runs of the model are used to optimise the estimate of the turnover rate through another iterative update method to produce a stable soil C equilibrium.

- Water model
  - Improved water movement through soil layers
  - Changed the routine in daily time-steps rather than monthly, to account for dry periods

When running spatial simulations ECOSSE operates on a monthly rather than daily time-step to reduce computation time. However, running the soil water sub-model on a monthly time-step can lead to unrealistically dry soil under certain climatic conditions. To avoid this problem the soil water sub-model was modified to operate on a daily time-step whilst the rest of the model continued to operate on a monthly time-step. In order to drive the daily water model, daily mean climatic variables were calculated from the monthly climatic input data.

- Pedotransfer functions
  - Updated equations to reflect range of soil types in UK

The Harmonised World Soil Database (HWSD; FAO, IIASA, ISRIC, ISSCAS and JRC, 2009) used to initialise soil conditions in the model does not include information on the water-holding capacities of soils. In the absence of measurement data, soil water-holding capacities can be estimated using pedotransfer functions that are based on other soil properties such as bulk density, clay fraction and organic carbon content. We modified ECOSSE to use the British Soil Survey pedotransfer functions (Hutson et al, 1992) to better reflect the range of soil types in the UK.

- Crop model
  - Accounts for all required crop types for site-specific runs (in response to meteorological conditions)
  - Read in results from dedicated crop models for spatial runs under specified climates
  - Establishment and periodic re-establishment of crop

The ECOSSE crop model was parameterised for the range of bioenergy crops. The original crop model was developed specifically for annual arable crops. Therefore the model was developed to enable perennial bioenergy crops to be simulated. This work included modifications to allow establishment and periodic re-establishment of perennial bioenergy crops.

- Methane model
  - Added oxidation rate modifiers for inorganic N concentration, pH and bulk density

The methane model simulates both methane production and methane oxidation in the soil. The methane oxidation component was extended to include oxidation rate modifiers for soil inorganic N concentration, pH and bulk density in order to better account for the effects of fertiliser input and soil properties on methane consumption rates.

- Spatial driver

In order to execute the large number of simulations required, we developed an external simulation driver for ECOSSE. The driving software extracts input data from a range of data sources, compiles the data into ECOSSE input files and then runs multiple point simulations in parallel. The output from the individual point simulations is aggregated into a single set of output files representing a complete spatial simulation. By enabling the simulations to take place in parallel it is possible to fully utilise the available computing power, allowing the full suite of spatial simulations to be completed within the required time frame.

2.1.2. Data overview

A model can only be properly validated against independent data: i.e., data that was not used to develop and evaluate the model itself. The procedures of model development, involving derivation of equations, parameter fitting or other data dependent methodologies, amalgamate the effects of any processes that have not been included in the model into the description of those processes that are included. If the model is evaluated against independent data, it is likely that the effect of the missing process will be different with respect to the process it has been amalgamated into, so the model evaluation will show an error, exposing this fault. Therefore a quantitative analysis of model performance should use independent measurements for the full range of conditions in which the model is to be used, providing assessments of both association and coincidence between simulations and measured data.

Site-specific modelling is performed to evaluate and validate the process-based model ECOSSE performance to accurately simulate soil C and GHG fluxes under the following land-use transitions: arable to SRF/Willow/*Miscanthus* and grassland to SRF/Willow/*Miscanthus*. The work underpins the spatial modelling and meta-model (Figure 2.2).

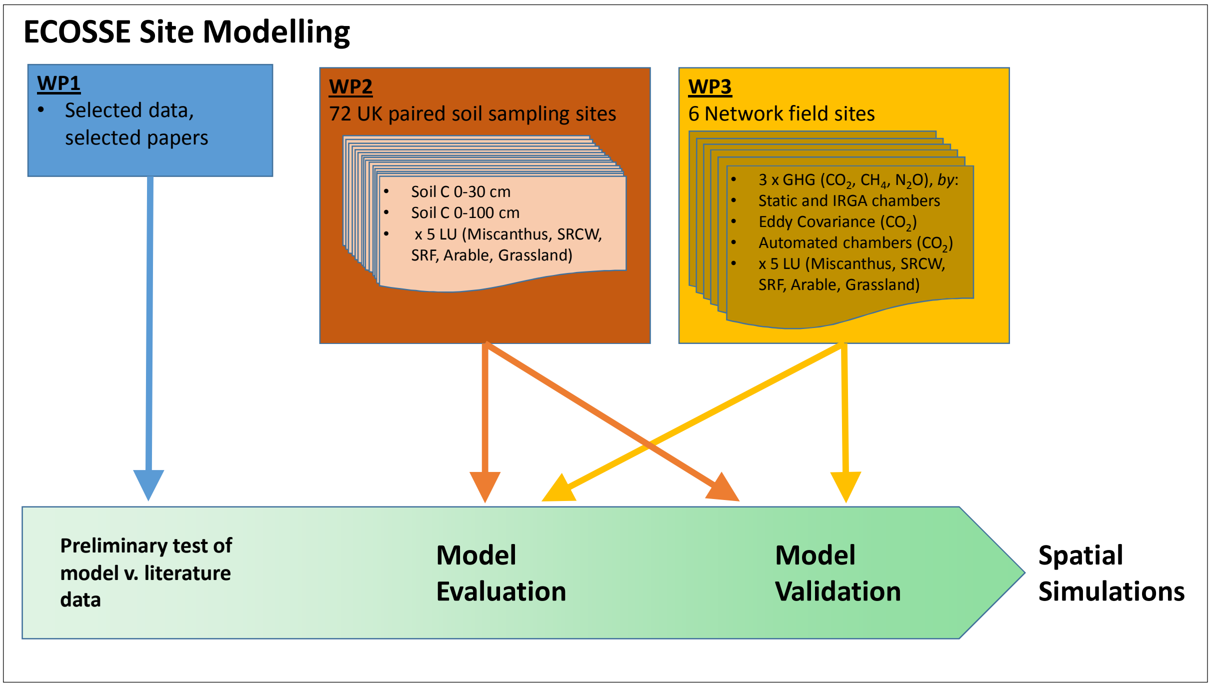


Figure 2.2: Dependences of WP1-WP3 with the WP4 tasks.

The selection criteria used to choose the sites for testing the ECOSSE model was to cover the majority of vegetation types, based on the availability of site data within the ELUM project.

The data provided by the WP2 team was used for testing soil C simulation whereas the data provided by the WP3 team was used for testing soil GHG fluxes (CO_2, N_2O and CH_4).

The WP2 sampling activity for year 2 of the ELUM project focused on transitions from conventional crop to *Miscanthus x Giganteus* (from now on referred to as *Miscanthus*) and Willow; whereas the WP2 sampling activity for year 3 focused on the distribution of the soil C through the soil profile. Therefore the ECOSSE model has been evaluated and validated:

- To simulate soil C changes after land-use changes to *Miscanthus* and Willow
- To simulate the distribution of soil C in 1 metre soil (0-10 cm soil intervals)
- To simulate the distribution of the soil C in the soil pools
- To simulate GHG fluxes under bioenergy crops (*Miscanthus*, Willow and SRF) and conventional crops (arable and grassland).

Uncertainty analysis at site level has been used to define the uncertainty ranges when applying the model at larger spatial scales. The modelled soil C obtained using site inputs have been compared to the modelled soil C obtained using the soil attributes extracted from the HWSD.

An overview of the sites and data used for the evaluation and validation of the ECOSSE model is reported below:

1) Model evaluation

- Total soil C
  - Year 2 Chronosequence site (WP2)
    - Twenty-nine sites (40 transitions: 20 transitions to *Miscanthus* and 20 transitions to Willow) – soil C measurements at 0-30 cm soil depth
- GHG fluxes
  - Network sites (WP3) – Lincolnshire (Arable, *Miscanthus*, Willow) and East Grange (grassland, SRF)
    - Chamber measurements of GHG fluxes (data available for all fields)
    - Eddy Covariance measurements of CO_2 fluxes (data available for all fields at Lincolnshire and SRF field at East Grange)
    - Chamber measurements of CO_2 fluxes on root-exclusion experiment plots (data available for *Miscanthus* field)

2) Model validation

- Total soil C
  - Year 2 Chronosequence site (WP2)
    - Twenty-nine sites (38 transitions: 20 transitions to *Miscanthus* and 18 transitions to Willow) – soil C measurements at 0-100 cm soil depth
- Distribution of total soil C in 1 metre soil
  - Year 3 Chronosequence site (WP2)
    - Seven transitions – soil C measurements at 1 metre soil depth (10 cm soil layers)
- GHG fluxes
  - Network sites (WP3) – Aberystwyth (LUC from grassland to *Miscanthus*), West Sussex (LUC from grassland to Willow) and East Grange (LUC from arable to Willow)
    - Chamber measurements of GHG fluxes (data available for all fields)
    - Eddy Covariance measurements of CO_2 fluxes (data available for *Miscanthus* at Aberystwyth and both Willow and grassland fields at West Sussex)
    - Chamber measurements of CO_2 fluxes on root-exclusion experiment plots (data available for *Miscanthus* and Willow fields)

3) Model uncertainty

- Year 2 Chronosequence site (WP2)
  - Twenty-eight sites (38 transitions: 19 transitions to *Miscanthus* and 19 transitions to Willow) – soil C measurements at 0-100 cm soil depth
  - Twenty-eight sites (38 transitions: 19 transitions to *Miscanthus* and 19 transitions to Willow) – soil attributes extracted from the Harmonized World Soil Database (HWSD)
- Year 1 Chronosequence site (WP2)
  - Ten sites (transitions to SRF) – soil texture measurements at 0-30 cm soil depth
  - Ten sites (transitions to SRF) – soil texture soil texture from Falloon soil database

Further detailed information on sample design (number of measurements, plots etc.) and site location can be found in the ELUM report D2.3 (B1001_PM06.2.3_WP2 Year 2 Chronosequence Report v1.1), report D3.2 (BI1001_PM04.3.2_WP3 Year 1 Report v1.0) and report D2.4 (BI1001_PM07.2.4_WP2_Year 3 Chronosequence Report v1.0).

2.1.3 Evaluation and validation of soil C simulations

Twenty-nine chronosequence sites across the UK comprising 40 transitions were sampled by the WP2 team (year 2 of the ELUM project), representing land-use changes from traditional land use (arable, grassland) to *Miscanthus* and Willow. All sites were selected to evaluate and validate ECOSSE using measurements of soil organic C.

The chronosequence site characteristics are described in detail in the ELUM deliverable report D2.3.

The temperature and precipitation data at each site location were extracted from the ECA&D European Climate Assessment & Dataset, and a long-term average was taken (Table A1, A2). This dataset is known as E-OBS and is publicly available (http://eca.knmi.nl/). Monthly potential evapotranspiration (PET) was estimated using the Thornthwaite equation (Thornthwaite, 1948).

Land-use history (transition length, establishment year and rotation year), management history (fertiliser applications - type and amount applied) soil organic C, soil bulk density, soil texture and soil pH were provided by WP2 (D2.3). Soil samples were taken at two soil depths (0-30 cm and 0-100 cm) using two different sampling procedures; therefore, two sets of soil characteristics were available for model simulation.

The model simulations were done in two consecutive steps:

1. Model evaluation using measured soil C, soil texture and bulk density at 0-30 cm soil depth.
2. Model validation using measured soil C, soil texture and bulk density at 0-100 cm soil depth

A further evaluation of the ECOSSE model was carried out to test the model accuracy to simulate the distribution of the total soil C to 1 metre soil depth.

Seven transitions to bioenergy crops (*Miscanthus*, Willow and SRF) were re-sampled by the WP2 team in the year 3 of the ELUM project; soil samples were collected at 1 m soil depth and divided in 10 cm depth layers (further information on the site selection and sampling procedures can be found in the ELUM deliverable report D2.4). The model simulations were performed using the reference site soil characteristics (soil C content, soil bulk density and soil pH) as inputs to the model. The model structure allows the user to specify the soil characteristics for 9 soil layers to a total depth of 3 metres. Therefore, soil inputs were given for the following soil depths: 0-10 cm, 10-20 cm, 20-30 cm, 30-40 cm, 40-50 cm, 50-60 cm, 60-70 cm, 70-80 cm, 80-100 cm. Soil texture data were not available for all soil depths; therefore we used the soil texture values measured to a depth of 30 cm as input to all soil layers. The length of the simulations was based on the time after transition to bioenergy crop. The modelled soil C at each of the soil layers were then compared to the soil C measured at the bioenergy crop.

2.1.4 Evaluation and validation of soil GHG fluxes simulations

Monthly simulations of soil CO_2, N_2O and CH_4 fluxes were evaluated against monthly chamber measurements. In addition, the soil CO_2 predicted by the ECOSSE model has been compared to the CO_2 flux measured by the Eddy Covariance towers and by chambers installed on root-exclusion plots (where applicable). The network sites (WP3) chosen for model evaluation were Lincolnshire and East Grange. At Lincolnshire, soil GHG measurements were made on arable, *Miscanthus* and Willow sites, while at East Grange a transition from grassland to SRF was sampled.

Model validation has been carried out comparing CO_2, N_2O and CH_4 flux simulations against flux chamber measurements taken at three different network sites: Aberystwyth (grassland to *Miscanthus*), West Sussex (grassland to Willow) and East Grange (arable to Willow). In addition, the soil CO_2 predicted by the ECOSSE model has been compared to the CO_2 flux measured by the Eddy Covariance towers and by chambers installed on root-exclusion plots (where applicable).

The experimental sites covered a wide range of soil characteristics and meteorological conditions (Table 2.1, 2.2), hence, providing a good representation of the variety of conditions that occur in the UK.

Further detailed information on sample and site location can be found in the ELUM deliverable report D3.2.

The input data required for ECOSSE (monthly rainfall and temperature, soil properties and land-use information) were provided by the WP3 teams and are listed below:

- Soil bulk density (0-30 cm soil depth)
- Soil %C (0-30 cm soil depth)
- Soil texture (0-30 cm soil depth)
- Land-use history:
  - Harvest Dates
  - Length of transition (age of bioenergy crop at the time of sampling)
  - Annual yield
  - Previous land use
  - Fertiliser type and amount
  - Herbicide
- Meteorological data (monthly rainfall and temperature)

Soil inputs for each network site are summarised in Table 2.2. Long-term temperature and precipitation data for the sites were extracted from the ECA&D European Climate Assessment & Dataset; monthly potential evapotranspiration (PET) was estimated using the Thornthwaite equation (Thornthwaite, 1948; Table 2.1) as shown below:

$$PE_m = 16N_m\left(\frac{10\bar{T}_m}{I}\right)^a \quad \text{mm}$$

where m is the months 1, 2, 3…12, N_m is the monthly adjustment factor related to hours of daylight, T_m is the monthly mean temperature (C), I is the heat index for the year, given by:

$$I = \sum i_m = \sum\left(\frac{\bar{T}_m}{5}\right)^{1.5} \quad \text{for m = 1…12}$$

and: a = 6.7*10-7*I3 - 7.7*10-5*I2 + 1.8*10-2*I + 0.49.

At each site, the ECOSSE model has been run for the reference field (i.e. no land-use transition) and the bioenergy crop field (i.e. following transition from the reference land cover). The reference sites have been run for the conventional crop (arable, grassland) with no land-use change and the length of the simulations has been defined by the age of the plantation. At the bioenergy sites, the model has been run for reference site (conventional crop) with land-use change to bioenergy crop; the length of the simulations was based on the time after transition to bioenergy crop. Measured soil characteristics and meteorological data have been used as inputs to drive the model (see above for input details), and the results of the simulations were compared to the GHG fluxes measured at the sites.

We expected a monthly underestimate of the soil CO_2 flux simulations because the ECOSSE model simulates heterotrophic respiration, Rh (from living micro-organisms + decomposition of old C sources i.e. sapotrophic), while the CO_2 fluxes measured at the sites represent the total CO_2 efflux from the soil profile (root autotrophic + heterotrophic respiration). In order to compare the modelled and measured Rh, we estimated the measured Rh as a proportion of the measured CO_2 flux, depending on the measurement type, vegetation type and growing season.

	Aberystwyth			East Grange			Lincoln			West Sussex		
Month	Rainfall (mm)	Temperature (C˚)	Potential evapotranspiration	Rainfall (mm)	Temperature (C˚)	Potential evapotranspiration	Rainfall (mm)	Temperature (C˚)	Potential evapotranspiration	Rainfall (mm)	Temperature (C˚)	Potential evapotranspiration
January	152.27	3.86	15.05	102.71	2.88	11.46	48.02	4.1	13.29	79.68	5.29	16.28
February	111.94	3.89	17.46	72.06	3.13	14.52	36.87	4.41	16.58	54.06	5.22	18.08
March	124.28	5.42	28.56	74.25	4.88	27.17	40.7	6.48	29.8	55.31	7.04	29.88
April	85.85	7.34	45.08	52.6	7.16	46.92	43.14	8.62	47.74	46.05	9.26	47.51
May	81.97	10.25	69.44	60.92	9.97	72.2	44.89	11.58	73.01	46.64	12.35	72.95
June	92.75	12.63	88.9	60.19	12.83	96.32	56.22	14.49	97.11	48.44	15.03	95.04
July	104.75	14.59	100.92	66.58	14.36	105.42	48.96	16.75	111.78	48.6	17.21	109.57
August	113.57	14.42	92.54	76.91	14.17	95.6	54.93	16.61	102.52	52.2	17.42	103.41
September	121.37	12.58	70.76	84.4	11.97	70.06	49.03	14.24	75.61	59.56	15.31	78.53
October	174.01	9.67	46.01	100.13	8.92	43.43	55.41	10.66	46.3	99.26	12.16	51.23
November	171.44	6.59	26.87	93.76	5.26	21.65	53.09	6.95	24.66	87.71	8.48	29.16
December	168.48	4.38	16.57	91.1	3.16	12.25	50.71	4.42	14.04	86.34	5.95	18.08

Table 2.1: Long-term climate data for the Network sites.

Soil depth (cm)	Model input data	Aberystwyth				East Grange				Lincoln		West Sussex	
		Miscanthus1	Grass1	Miscanthus2	Grass2	Grass	SRF	Arable	Willow	Arable	Miscanthus	Willow	Grass
0-15	C content (Kg/ha)	67347	34061	56046	45396	40196	33588	32335	49540	31923	36015	28926	43135
	Bulk density (g/cm^3)	0.76	0.54	0.68	0.72	1.20	1.18	1.04	1.10	1.13	1.38	1.36	0.97
	pH	5.9	5.9	5.9	5.9	6.7	6.5	6.8	6.1	6.6	7.4	6.7	6.8
	clay content (%)	6.1	38.1	4.8	6	34	34	34	34	28	28	29	29
	silt content (%)	49.3	57.8	43.2	50.3	33	33	33	33	42	42	42	42
	sand content (%)	44.6	38.4	52	43.7	33	33	33	33	30	30	29	29
15-30	C content (Kg/ha)	50180	20943	34684	32538	43011	38927	40766	57816	36334	33376	23513	24665
	Bulk density (g/cm^3)	0.8	0.49	0.74	0.82	1.52	1.53	1.38	1.38	1.41	1.49	1.48	1.52
	pH	5.8	5.8	5.8	5.9	6.8	6.6	6.9	6.1	6.8	7.4	6.8	7.0
	clay content (%)	8.3	4.2	7.0	8.8	34	34	34	34	28	28	29	29
	silt content (%)	52.9	37.3	50.2	52.8	33	33	33	33	42	42	42	42
	sand content (%)	38.8	58.5	42.8	38.4	33	33	33	33	30	30	29	29

Table 2.2: Input information for the Network sites.

Eddy covariance (EC) measures ecosystem respiration R_{eco}, which is the sum of the heterotrophic respiration (Rh; from living micro-organisms + decomposition of old C sources i.e. sapotrophic), autotrophic respiration (Ra; plant roots), and plant respiration. To estimate the Rh from the measured R_{eco}, the approach of Hardie et al. (2009), revisited by Abdalla et al. (2013), was applied as shown in the equations below.

$$CO_{2\,(\text{soil micro-organisms})} = 36\%\ R_{eco} \quad (1)$$

$$CO_{2\,(\text{catotelm})} = 10\text{-}23\%\ R_{eco} \quad (2)$$

$$Rh_{\,(\text{heterotrophic respiration})} = CO_{2\,(\text{soil micro-organisms})} + CO_{2\,(\text{catotelm})} = 46\text{-}59\%\ R_{eco} \quad (3)$$

To represent the variations in Rh throughout the year, Rh was assumed to be at the lowest value of the range (46% R_{eco}) during the summer (June-August), highest value (59% R_{eco}) during the winter (December-February) and mean value (52.5% R_{eco}) during the rest of the year (March-May and September-November).

Chamber measurements represent the total CO_2 flux from the soil as the sum of autotrophic respiration (Ra) and heterotrophic respiration (Rh). We conducted a literature review to determine the partitioning of the total respiration (Rtot) measured by the chambers under different vegetation type. Additional experiments within the ELUM project were also undertaken to directly quantify the Rh and Ra at selected network sites; where available, we used the Rh site data to validate the model performance and to estimate the Rh from the total respiration measured with the chambers (Lincolnshire – *Miscanthus*, West Sussex – Willow, Aberystwyth – *Miscanthus*). An overview of the data source and the monthly proportion of Rh for each vegetation type and at each site are shown below:

1. Lincolnshire

- Arable (Koerber et al., 2010)
    - Jan – May: Rh = 32% Rtot
    - Jun – Sept: Rh = 79% Rtot
    - Oct – Dec: Rh = 67% Rtot
- Willow (Pacaldo et al., 2013)
    - Jan – Dec: Rh = 25% Rtot
- *Miscanthus* (from direct measurements on root-exclusion plots)
    - Jan – Feb/Nov - Dec: Rh = 41% Rtot
    - Mar – Jun: Rh = 85% Rtot
    - Jul – Oct: Rh = 44% Rtot

2. West Sussex

- Grassland (Byrne & Kiely, 2006)
    - Jan – May: Rh = 60% Rtot
    - Jun – Aug: Rh = 40% Rtot
    - Sept – Dec: Rh = 60% Rtot

Where Rtot is 60% of measured CO_2 to account for plant respiration

- Willow (from direct measurements on root-exclusion plots)
    - Jan – Dec: Rh = 82% Rtot

3. Aberystwyth

- Grassland (Byrne & Kiely, 2006)
    - Jan – May: Rh = 60% Rtot
    - Jun – Aug: Rh = 40% Rtot
    - Sept – Dec: Rh = 60% Rtot

Where Rtot is 60% of measured CO_2 to account for plant respiration

- *Miscanthus* (from direct measurements on root-exclusion plots)
    - Jan – Feb/Nov - Dec: Rh = 62% Rtot
    - Mar – Oct: Rh = 36% Rtot

4. East Grange

- Arable (Koerber et al., 2010)
    - Jan – May: Rh = 32% Rtot
    - Jun – Sept: Rh = 79% Rtot
    - Oct – Dec: Rh = 67% Rtot
- Willow (Pacaldo et al., 2013)
    - Jan – Dec: Rh = 25% Rtot
- SRF (Millard et al., 2010)
    - Jan – Dec: Rh = 61% Rtot
- Grassland (Byrne & Kiely, 2006)
    - Jan – May: Rh = 60% Rtot
    - Jun – Aug: Rh = 40% Rtot
    - Sept – Dec: Rh = 60% Rtot

Where Rtot is 60% of measured CO_2 to account for plant respiration

2.1.5 Uncertainty of soil C simulation

The Harmonized World Soil Database (HWSD; FAO, IIASA, ISRIC, ISSCAS and JRC, 2009) has been used for spatial simulation of soil C and GHG fluxes (see section 2.2). We conducted a study to define the uncertainty arising when applying a large spatial dataset at site level. We therefore ran the model for the Year 2 chronosequence sites using two sets of data as inputs to the model:

1. Measured soil C, bulk density, soil texture and pH at 0-100 cm soil depth.

2. All soil characteristics from HWSD database (0-100 cm soil depth),

The soil C outputs of the two set of simulations were then compared.

The HWSD soil database is based on a 30 arc-second grid, which we have aligned onto a 1 km grid for the UK, and it reports the soil attributes for the dominant soil types for each grid cell and the percentage of the grid cell that is covered by the soil types. Therefore, for each site, we ran the model using the soil characteristics of all dominant soil types at the specific location (e.g. 5 soil types = 5 model runs, Table A3). The soil C outputs of each model simulation were then averaged based on the percentage of the grid cell that is covered by each dominant soil type.

The ELUM deliverable report D4.2 (BI1001_PM06.4.2_Report on Existing Models and Spatial Meta-Model Test v2.0) reported the evaluation and validation of soil C simulations after conversion to SRF. The soil texture data for the 28 transitions to SRF (10 sites) were extracted from the "Falloon" soil database (1 km resolution). The "Falloon" database and the model define the soil texture as the relative proportions of sand (63-2000 µm), silt (2-63 µm) and clay (< 2 µm) within the soil.

Soil texture, and particularly clay content, is an important factor in ECOSSE, as the clay content of the soil impacts aerobic decomposition by altering the partitioning between CO_2 evolved and the biomass (BIO) and humus (HUM) pools formed during decomposition. In other words, the clay content is used to determine the efficiency of decomposition under non-N-limiting conditions.

Texture values to 30 cm soil depth have being determined for all 28 transitions as part of WP2 activities (see Table A4 for details) and were used to test the model sensitivity to soil texture. We performed a *local* sensitivity analysis: a simple form of sensitivity analysis which entails adjustment of model input components one-at-a-time, whilst all others remain constant and the influence of the input on the model outputs is examined. The purpose of this analysis was to determine if there is a variation in the soil C outputs when using site texture inputs instead of data extracted from a large spatial dataset (e.g. "Falloon" soil database); therefore, for each transition to SRF, we only changed the soil texture input whilst all others remain constant. The model was then re-run for each transition and the results of each SRF species sampled at the same site were averaged. The averaged soil C for each site was then compared to the soil C modelled using the "Falloon" soil texture data.

2.1.6 Statistical analysis

The model results were evaluated statistically using the approach proposed by Smith et al. (1996b, 1997).

The degree of association between simulated and measured values was determined using the correlation coefficient (R), and the significance of the correlation was assessed using the Student's t test. This tells us whether the two sets of data have the same trend, and is important if the results are to be extrapolated beyond the scope of the experiment. 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., 1996b).

Where replicates were available, the degree of coincidence between the simulated and measured values was determined using the lack of fit statistic (LOFIT) and its significance was assessed using an *F*-test (Whitmore, 1991). This tells us whether the difference in the paired values of the two data sets is significant.

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 $E < E_{95}$, then the model bias cannot be reduced using these data.

Where replicates were not available, the total error was calculated as the root mean squared error (*RMSE*). This is the average total difference between measured and simulated values. The bias in the simulations with respect to the measurements was calculated as the mean difference (*M*) (Addiscott and Whitmore, 1987).

All statistical results were considered to be statistically significant at $P<0.05$.

2.2. Spatial and Meta-model

2.2.1 Spatial simulation

Spatial runs are performed using the ECOSSE soil model. The model has previously been demonstrated to accurately simulate the range of soil types and climatic conditions present in the UK (Smith et al., 2010 a,b; Bell et al., 2010), and is able to model the range of GHG emissions required for the project.

Soil data from LandIS (for England and Wales) and equivalent data for Scotland and Northern Ireland (as described by Falloon et al., (2006)) have been collated and tested for spatial simulations. Similar forms of these data have previously been used in ECOSSE, and are therefore well established in the model. For licensing reasons, Harmonized World Soil Database (HWSD) data (FAO, 2009) will be used to obtain the final results for the meta-model.

Meteorological data have been formatted from UKCP09 Spatially Coherent Projections, using high, medium and low unperturbed decadal averages up to 2050 (Defra, 2009), which have previously been used in ECOSSE. Yield data from Miscanfor (Hastings et al., 2009), ForestGrowth SRC (Tallis et al., 2012) and ESC-CARBINE (Pyatt et al., 2001; Thompson and Matthews, 1989) models have been obtained using the same UKCP09 climate and HWSD soil data, which are used as inputs to ECOSSE (Figure 2.3). These models are used due to their validated accuracy and use of compatible data.

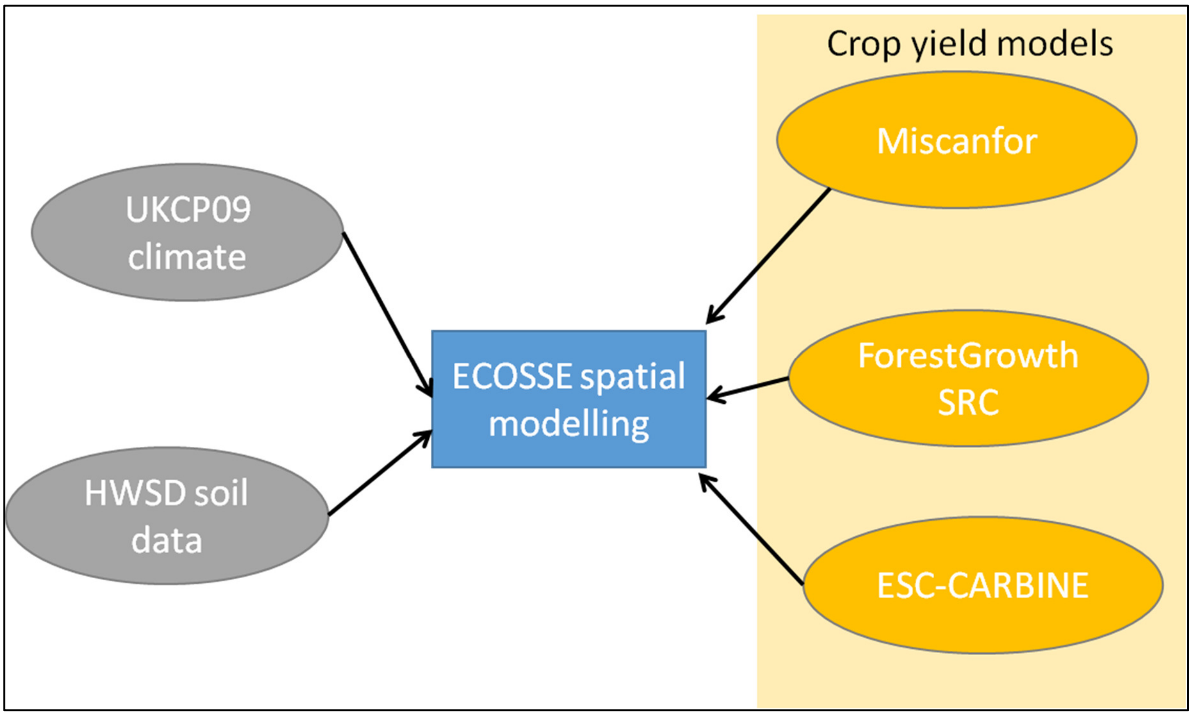


Figure 2.3: Sources of input for ECOSSE spatial simulations.

Significant computing resources are required for the spatial simulations. Using a 1 km grid, there are nearly 0.25 million grid cells in the UK, and each cell may contain up to 5 different soil types, each of which must be simulated. There are 18 land-use transitions to consider (i.e. all combinations of transitions from: arable, grass and forest, to: wheat, oil seed rape, sugar beet, short-rotation coppice, short-rotation forest and *Miscanthus*), as well as 3 'null' transitions (i.e. results for unchanged land-use, for comparison). This results in over 5 million simulations to run, neglecting multiple soil types in each grid cell. Results have been obtained using three different climate scenarios and two different soil datasets – bringing the number of simulations to around 30 million, and over 100 million when all soil types are considered. Further to this, results for different management and yield improvements have been also considered. A monthly time-step is used in the model, with daily water calculations, and the model is run for 35 years, in addition to significant spin-up iterations to reach equilibrium prior to the land-use transition.
In order to minimise the time required for simulations, work has been performed to remove redundant code within the model, as well as to optimise the control scripts which call the ECOSSE executable file and process outputs.

Details on spatial simulations can be found in the ELUM deliverable report D4.6 (PM07.4.6_WP4_Effects on LUC into Bioenergy v1.0).

2.3.2 Meta-model

Detailed process-based soil models are often difficult to use for non-specialists, have large data requirements, and may take a very long time to run (as described above). The purpose of the meta-model is to provide results more straightforwardly and faster. This is possible by either:

- Statistical regression: use results from the process-based model to identify simple statistical relationships, and thus greatly reduce the complexity of calculations
- Look-up table: store results from the process-based model in order to directly look up values

Using statistical regression means that the size of data required for the meta-model is relatively small, but results will be less accurate, particularly if several variables are involved. Conversely, using a look-up table provides more accurate results, since they are simply the results from the process-based model.

The meta-model provides results for:

- Whole UK (1 km grid) up to year 2050
- Different climates (high, medium and low climate change scenarios)
- 18 different transitions (from: arable, grass and forest, to: wheat, oil seed rape, sugar beet, short rotation coppice, short rotation forest and *Miscanthus*)
- 5 different variables (combined GHG, CO_2, CH_4, N_2O and soil C); time units discussed in Section 2.3.3)
- Different units (t /ha and t /odt (oven dry tonne))

In addition to the above requirements, the meta-model also provides results for:

- Different management practices
- Yield improvements

Each change in the above would have a multiplicative effect on the size of the look-up table, which would quickly make the look-up table prohibitively large. However, since the effect of each is expected to be relatively straightforward (compared with the combined effects of all inputs), it is likely that a good statistical regression could be obtained on results. We therefore propose to use a look-up table for the majority of the meta-model, in order to provide the most accurate results possible, while performing a statistically-derived calculation for the effects of different management and yield improvements, in order to keep the look-up table at a reasonable size while maintaining flexibility in user options.

A sensitivity analysis of the spatial results was carried out to determine the effects of variations in bioenergy crop yield and nitrogen fertiliser application rates on the output variables. Determining the sensitivity of the model outputs to these two inputs enables the uncertainty in the results related to uncertainty in the values of these two variables to be quantified and a relationship between the inputs and outputs to be obtained. The analysis was carried out on a randomly selected subset of the grid cells (approximately 1 in 200 cells) because the computing time required to explore the effects over the full simulation grid were prohibitive. Simulations for each land-use transition were run for a period of 35 years (2015 – 2050) for the low, medium and high emissions climate scenarios using the same input datasets as used for the full spatial simulations.

The following yield and fertiliser levels were used in the analysis:

- Yield: +5, +10, +20, and +50% (with +0% as the reference level)
- Fertiliser: -20, -10, +10 and +20 % application rate (with +0% as the reference level)

All output variables have been converted to t CO_2e ha^{-1}.

Further to obtaining results, the meta-model is also able to apply a land-cover mask (derived from CEH Land Cover Map 2007 (CEH, 2011)) and spatial mask for different levels of region (derived from Ordnance Survey Boundary-Line OpenData (OS, 2012)). These methods have also been implemented. The levels of region are:

- Countries (England, Northern Ireland, Scotland, Wales)
- Regions (also known as Government Office Regions (GORs), European Parliamentary Constituencies and first-level NUTS (Nomenclature of Units for Territorial Statistics) regions of the European Union)
- Counties
- Districts/boroughs/unitary regions

A framework is also in place to apply a constraints mask to exclude inappropriate land according to different criteria, based on the UKERC constraints masks.

In summary, the meta-model:

1. Obtains results from the look-up table for the selected geographical area, time period and climate
2. Adjusts results according to management and yield improvement options
3. Applies required land masks
4. Outputs the processed results in a suitable format.

While the meta-model provides access to information far quicker than the ECOSSE model (by several orders of magnitude), the size of data involved inherently means operations may take some time to complete. For small geographical areas, with only a few outputs selected, results would be expected to be obtained within a few seconds or minutes, depending on the selections and computer. However, for all possible transitions, outputs, comparisons and plots to complete for the whole UK takes around 3 hours on a good desktop computer, and the volume of data means it takes around 30 minutes to save the results following simulation (though this can be avoided by selecting an output folder beforehand, so no files need to be copied from the temporary folder). This should not be of great concern, as users need only click a single button and wait for the selected results, and users can pre-select what results they require.

2.3.3 Outputs

For consistency, all results (i.e. CO_2, CH_4, N_2O, soil C and net emissions) are reported in terms of CO_2-equivalent values, using IPCC 100-year Global Warming Potentials (IPCC, 2001). Results are given for each time-step in the selected time period. Results are for the cumulative total up to each time point, and are relative to the value obtained if no transition had occurred (hence results show directly the effect of the transition).

Results are presented as cumulative rather than annual values because:

- Time-series results clearly show the effects of the transition
- Spatial results reflect the entire time period
- There is less scope for ambiguity in results (e.g. annual results fluctuate within each time period, hence reporting a single annual result for each period may be misleading)
- Mean annual results for any period can be calculated by subtracting the initial value from the final value for the time period and dividing by the number of years (hence users who are interested in obtaining annual values can do this)

Results are output from the meta-model as csv files, with each row corresponding to a single grid cell, and each column corresponding to a time point. In order to permit results to be easily loaded into GIS and to reduce file sizes, we have devised a method to write outputs from Fortran in true csv format (i.e. with a single delimiter between values), rather than according to fixed-width columns. This reduces the speed of writing operations, but increases the flexibility of the package.

The meta-model is able to output multiple results (depending on what outputs the user selects), but to avoid duplication, the location of each grid cell is only written to a single file. Each grid cell is assigned a unique ID which is reported in each file (including the list of locations); this enables results from the ELUM package to be directly loaded into GIS software by linking the cell ID in each file. Further details of loading results into GIS are provided in Appendix V.

3. RESULTS

3.1 Evaluation and validation of ECOSSE Model

3.1.1 Soil organic carbon

The model simulations of the total C show a good fit against the measured soil C, for both reference and bioenergy crops (*Miscanthus* and Willow), at 0-30 cm soil depth (Figure 3.1, 3.2, 3,3).

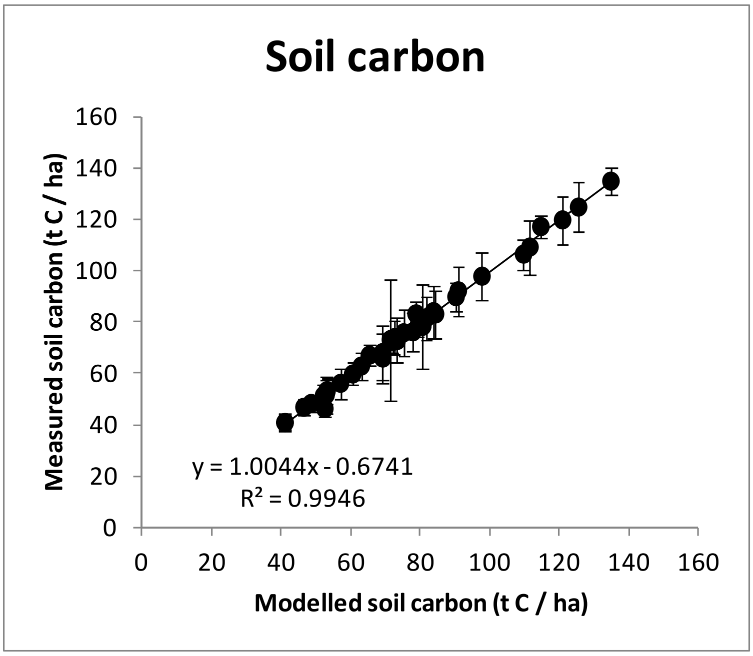


Figure 3.1: Correlation between measured and modelled soil C at the reference sites at 0-30 cm soil depth. Error bars represent 95% confidence interval of measured values.

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 provided by the WP2 study, we assumed that all the reference sites were in equilibrium condition at the time of sampling.

Figures 3.2 and 3.3 show the correlation between modelled and measured soil C at the *Miscanthus* and Willow fields, respectively, at 0-30 cm soil depth. Overall, the simulated C correlates well with the measured C (Table 3.1).

The R value of the soil C at both *Miscanthus* (R = 0.93) and Willow (R = 0.74) sites showed a significant (P < 0.05) association between simulated and measured values. The calculated value of E indicated that the simulations at both *Miscanthus* and Willow sites show no significant bias ($E < E_{95}$). Finally the *LOFIT* value showed that the model error was within (i.e. not significantly larger than) the measurement error.

At most of the *Miscanthus* sites, the simulated SOC was within the 95% confidence interval of the measured SOC (error bars in Figure 3.2). At sites 11, 16, 19 and 42 the model estimated a lower soil C content compared to the measured values (51.9 t C ha^{-1} vs. 54.6 t C ha^{-1}, 56.4 t C ha^{-1} vs. 63.6 t C ha^{-1}, 55.21 t C ha^{-1} vs. 58.9 t C ha^{-1}, 53.5 t C ha^{-1} vs. 69.4 t C ha^{-1}, respectively).

At site 42 we found the highest discrepancy between measured and modelled soil C at 30 cm soil depth (53.5 t C ha^{-1} vs. 69.4 t C ha^{-1}, respectively). At this same location a Willow site has also been sampled (site 41) and we found the same discrepancy between modelled and measured soil C. Both sites have been converted from the same arable site, therefore a possible explanation of the difference between measured and modelled values could be that the C content of the reference site was not in equilibrium condition at the time of sampling (year 2011); hence, the simulation started from a C content lower than its real value at the time of the transition to bioenergy crops (year 2006).

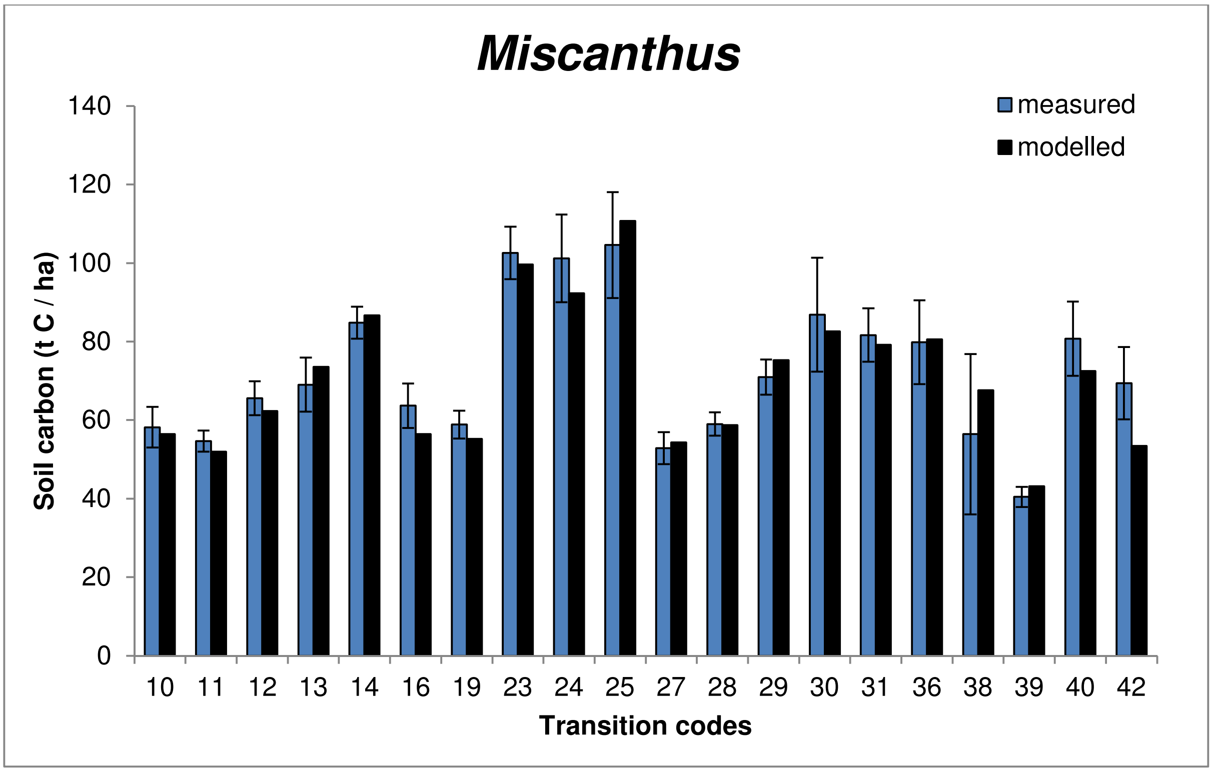


Figure 3.2: Results of modelled and measured soil C for *Miscanthus* sites (0-30 cm soil depth). Error bars represent 95% confidence interval of measured values.

	Miscanthus	Willow
R = Correlation Coeff.	0.94	0.74
t -value	11.61	4.62
t-value at (P=0.05)	2.11	2.10
Significant association?	Yes - Good	Yes - Good
E = Relative Error	1	4
E (95% Confidence Limit). = +/-	10	10
Significant bias?	No - Good	No - Good
LOFIT = Lack of Fit	10988	87948
F	0.01	0.08
F (Critical at 5%)	1.71	1.69
Significant error between simulated and measured values?	No - Good	No - Good
Number of Values	20	20

Table 3.1: Results of statistical analysis for model simulation of soil carbon at 0-30 cm depth.

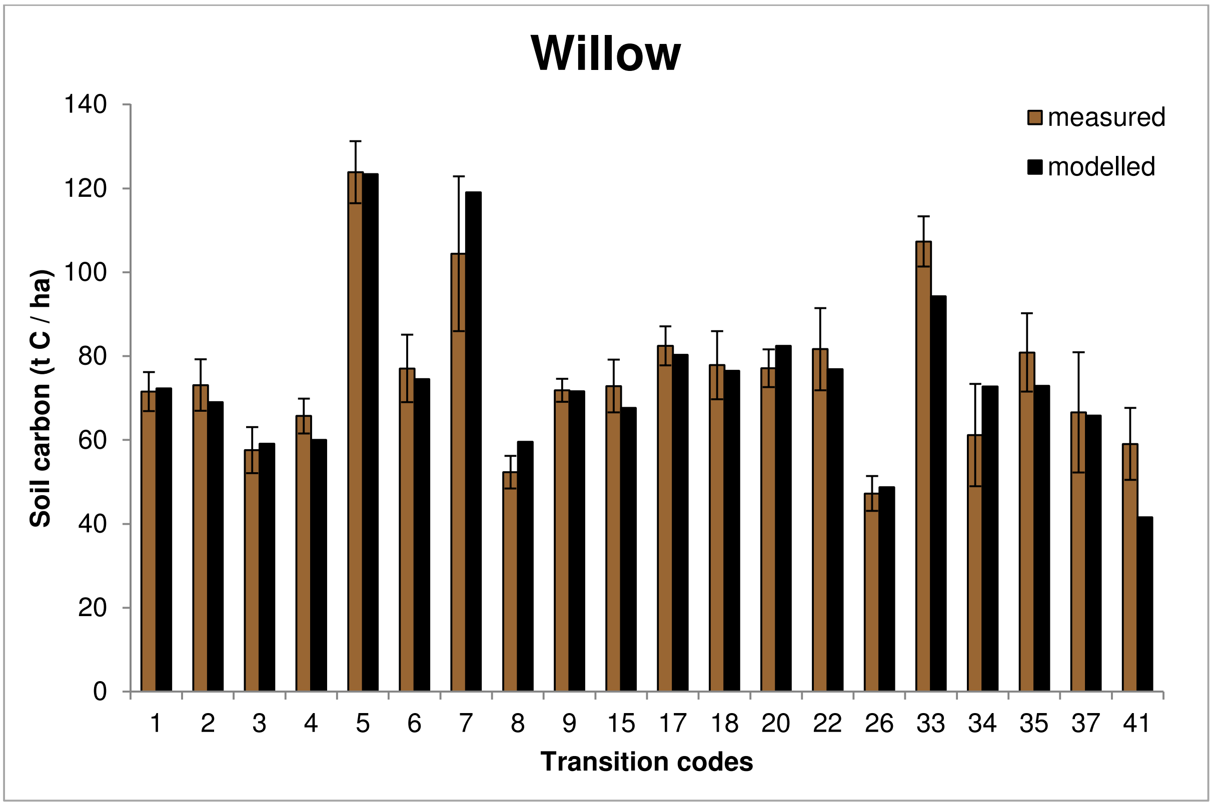


Figure 3.3: Results of modelled and measured soil C for Willow sites (0-30 cm soil depth). Error bars represent 95% confidence interval of measured values.

At most of the Willow sites, the simulated SOC was within the 95% confidence interval of the measured SOC (error bars in Figure 3.2). At sites 4, 33 and 41 the model estimated a lower soil C content compared to the measured values (60.0 t C ha^{-1} vs. 65.7 t C ha^{-1}, 94.3 t C ha^{-1} vs. 107.4 t C ha^{-1}, 41.6 t C ha-1 vs. 59.1 t C ha^{-1}, respectively) while for sites 8 and 20 the model simulated a higher accumulation of C compared to the site measurements. However, simulated SOC content showed a good fit against soil measurements at all sites (Table 3.1).

The model simulations of the total C at 0-100 cm soil depth again showed a good correlation with the measured SOC, for both *Miscanthus* (Figure 3.4) and Willow fields (Figures 3.5).

Measured soil C at site 38 has a very high error, which is due to the higher stone content in the soil cores compared to the other *Miscanthus* fields and to a lower number of soil cores collected at this site. In fact, two soil cores (instead of three) have been collected at site 38, leading to a bigger 95% confidence interval of the measured values compared to other sites. A high error in the measured soil C has also been found at two Willow sites (site 18 and 33); natural soil heterogeneity, particularly at 30-50 cm soil depth, appears to be the only explanation of such variability in soil C at these sites.

The statistics of the SOC at the 0-100 cm soil depth reflected the good model performance found for the top soil layer, with a high correlation between simulated and measured values and no significant bias for both *Miscanthus* and Willow sites (Table 3.2).

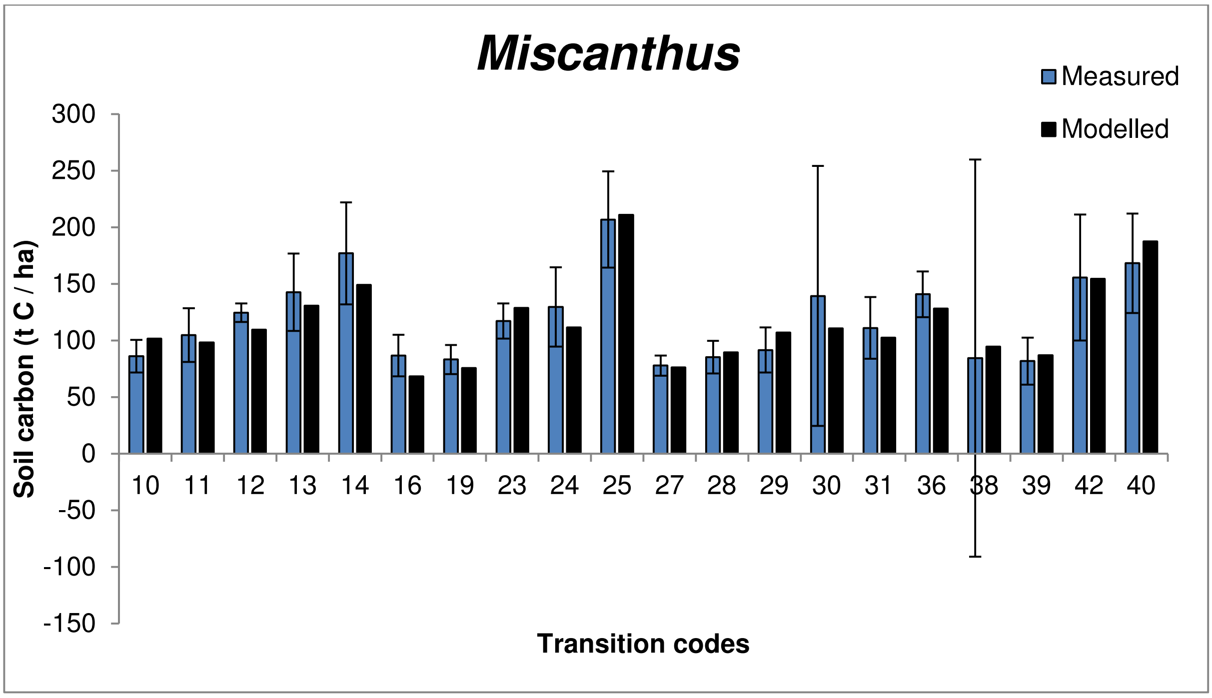


Figure 3.4: Results of modelled and measured soil C for *Miscanthus* sites (0-100 cm soil depth). Error bars represent 95% confidence interval of measured values.

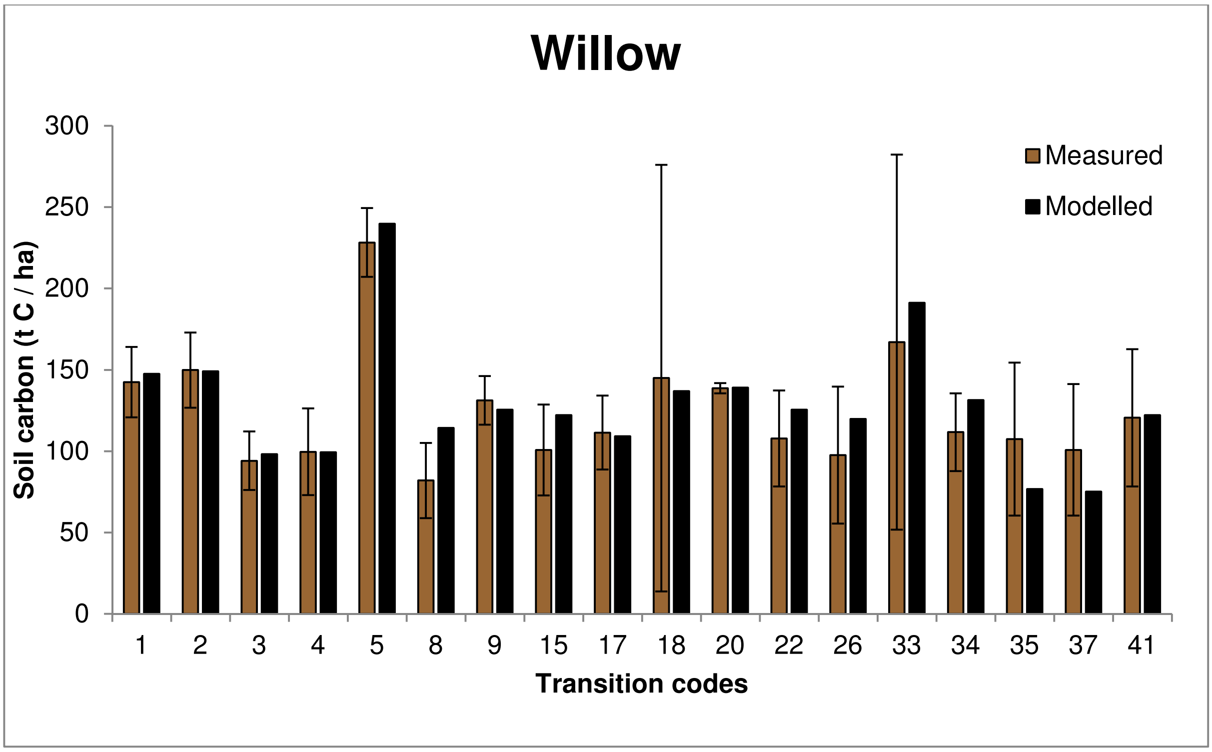


Figure 3.5: Results of modelled and measured soil C for Willow sites (0-100 cm soil depth). Error bars represent 95% confidence interval of measured values.

	Miscanthus	*Willow*
R = Correlation Coeff.	0.93	0.90
t -value	10.24	8.15
t-value at (P=0.05)	2.11	2.13
Significant association?	Yes - Good	Yes - Good
E = Relative Error	3	-3
E (95% Confidence Limit). = +/-	92	87
Significant bias?	No - Good	No - Good
LOFIT = Lack of Fit	10816	14298
F	0.00	0.00
F (Critical at 5%)	1.71	1.77
Significant error between simulated and measured values?	No - Good	No - Good
Number of Values	20	18

Table 3.2: Results of statistical analysis for model simulation of soil carbon at 0-100 cm depth.

The change in soil C (ΔC) has been calculated as the difference between the soil C at the bioenergy sites and the soil C at the reference. These results are important as they directly show the effect of the land-use transition itself, which is how results are presented in the meta-model. At 0-30 cm soil depth, the modelled transitions from conventional crops (arable and grassland) to *Miscanthus* lead to a ΔC that was within the 95% confidence intervals of the measured values (Figure 3.6). Site 42 was the only site where the ΔC was not accurately simulated by the model. At Site 42, the land-use change from arable to *Miscanthus* has led to a small increase in soil C (1.1 t C ha^{-1}) after 8 years; whereas, the results of the model simulations at Site 42 showed a decrease in soil C (16.5 t C ha^{-1}) after 8 years of land-use change from arable to *Miscanthus*.

The modelled transition from conventional crops (arable and grassland) to Willow at 0-30 cm soil depth also correlates well with the measured values, with the modelled ΔC within the 95% confidence intervals of the measured values at all sites (Figure 3.7).

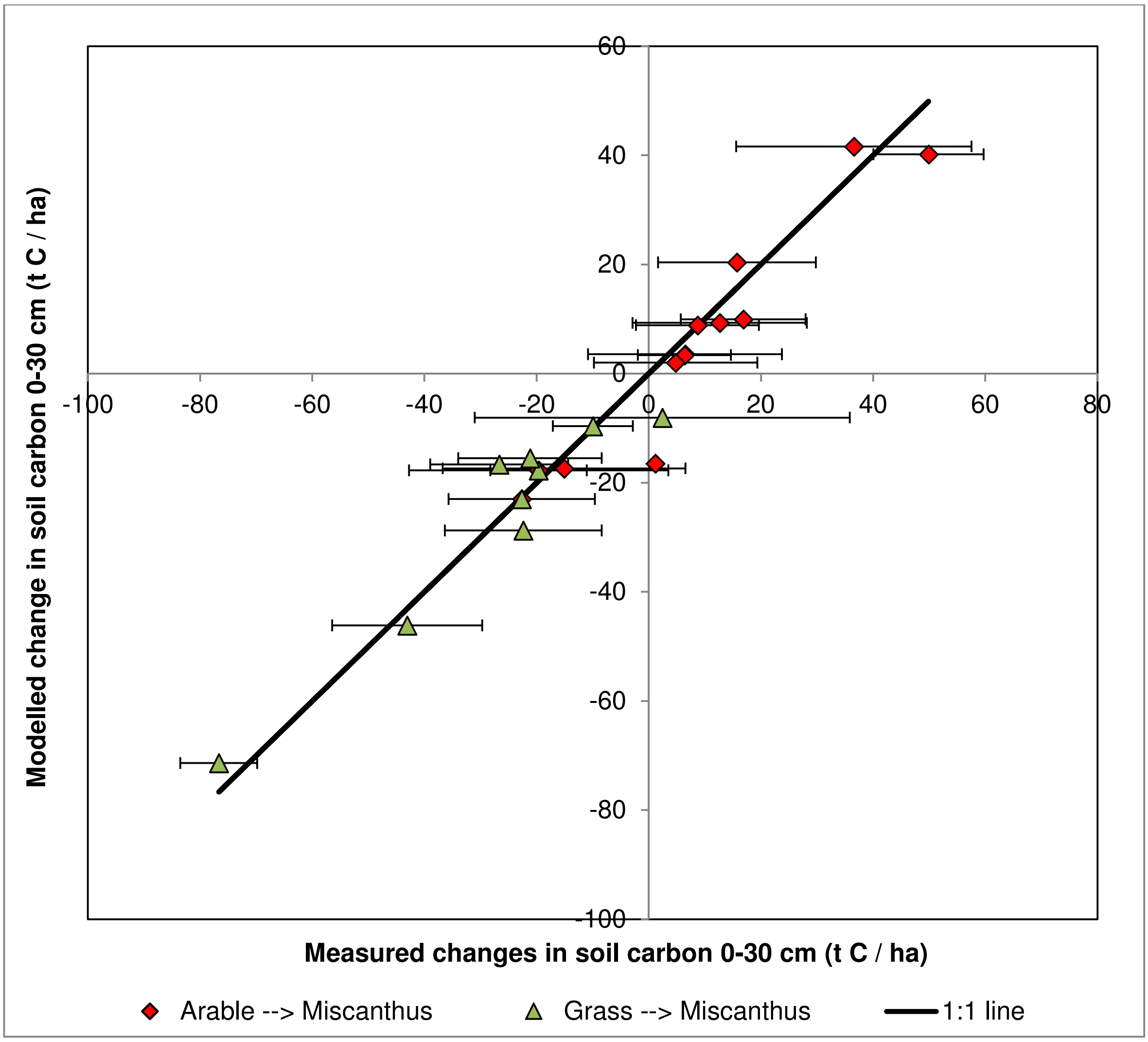


Figure 3.6: Measured and modelled ΔC after transition to *Miscanthus* at 0-30 cm soil depth. Error bars represent 95% confidence interval of measured values.

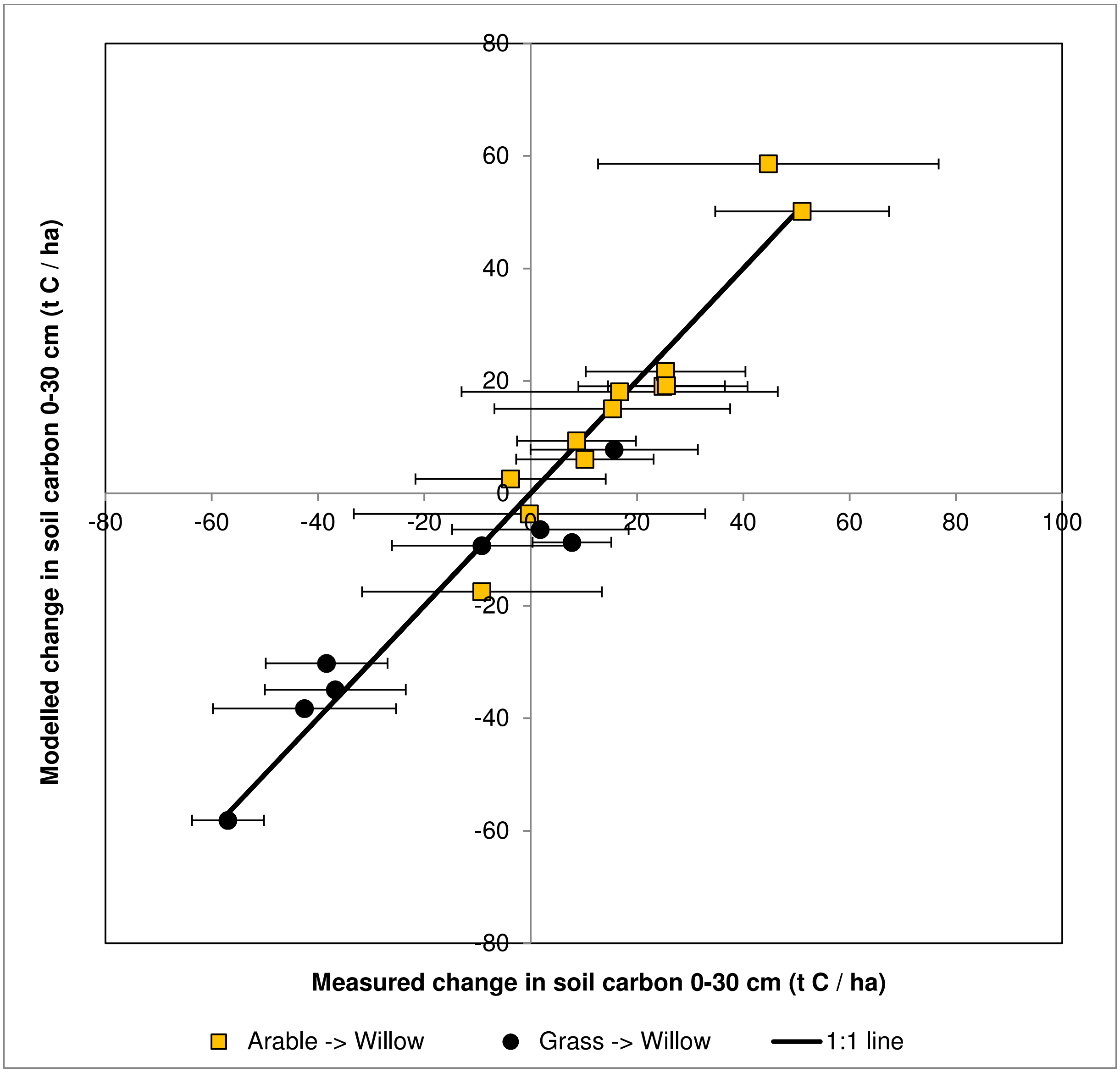


Figure 3.7: Measured and modelled ΔC after transition to Willow at 0-30 cm soil depth. Error bars represent 95% confidence interval of measured values.

Overall, at 0-100 cm, the ΔC simulated by the model is well correlated to the measured soil C changes, for both transitions to *Miscanthus* (Figure 3.8) and Willow (Figure 3.9). All the ΔC simulated by the model is within the 95% confidence intervals of the measured values.

The simulated changes in soil C are well associated with the measured values, with a correlation coefficient for *Miscanthus* of 0.97 and 0.84, at 0-30 cm and 0-100 cm soil depth respectively, and of 0.97 and 0.91 at 0-30 cm and 0-100 cm soil depth respectively, for Willow. 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 *Miscanthus* and to Willow (Table 3.3).

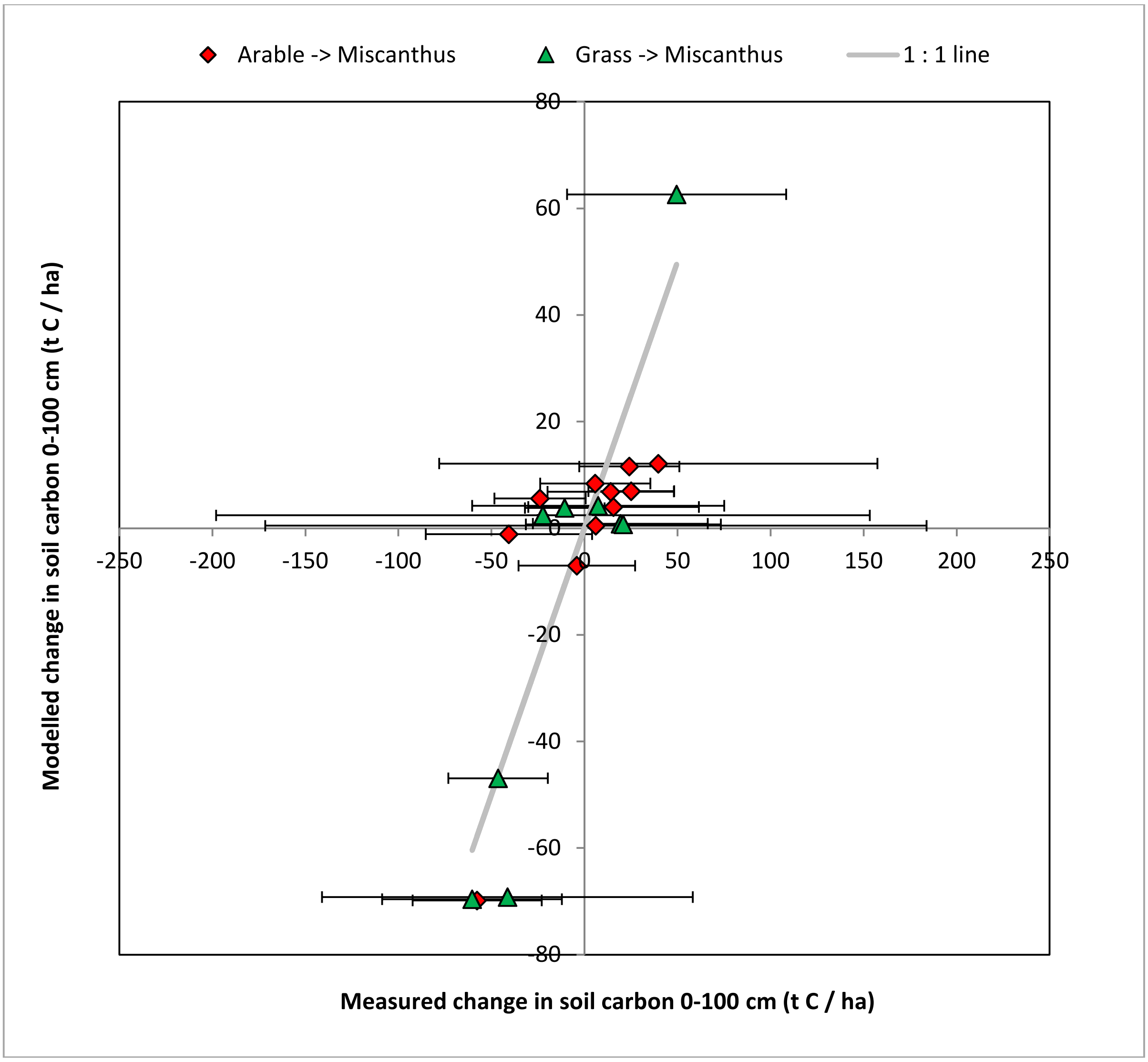


Figure 3.8: Measured and modelled ΔC after transition to *Miscanthus* at 0-100 cm soil depth. Error bars represent 95% confidence interval of measured values.

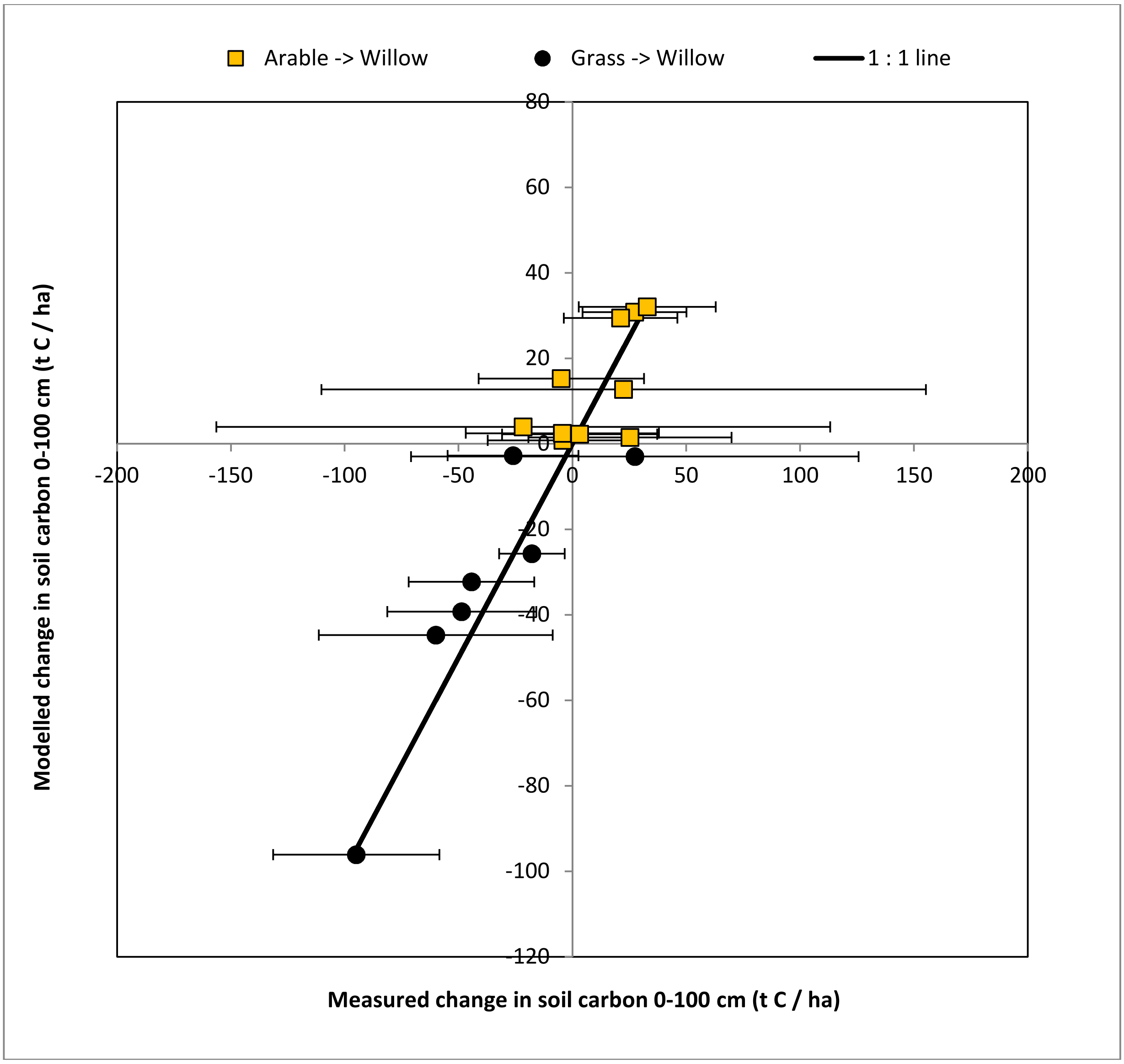


Figure 3.9: Measured and modelled ΔC after transition to Willow at 0-100 cm soil depth. Error bars represent 95% confidence interval of measured values.

	Miscanthus		Willow	
	0-30 cm	0-100 cm	0-30 cm	0-100 cm
R = Correlation Coeff.	0.97	0.84	0.97	0.91
t -value	18.32	6.52	16.99	8.69
t-value at (P=0.05)	2.10	2.10	2.10	2.12
Significant association?	Yes - Good	Yes - Good	Yes - Good	Yes - Good
E = Relative Error	-53	-134	114	37
E (95% Confidence Limit). = +/-	-253	-962	657	-222
Significant bias?	No - Good	No - Good	No - Good	No - Good
LOFIT = Lack of Fit	9875	59949	9806	34882
F	0.03	0.20	0.04	0.11
F (Critical at 5%)	1.69	1.70	1.69	1.75
Significant error between simulated and measured values?	No - Good	No - Good	No - Good	No - Good
Number of Values	20	20	20	20

Table 3.3: Results of statistical analysis for model simulation of ΔC at 0-30 cm and 0-100 cm depths for transition to *Miscanthus* and Willow.

3.1.2 Distribution of soil organic carbon in the soil profile

The distribution of soil C has been measured at nine sites in UK, representing transitions from arable to Willow (Site 2 and Site 3), grassland to Willow (Site 35), arable to *Miscanthus* (Sites 27 and Site 36), grassland to *Miscanthus* (Site 28) and grassland to SRF (Site 8).

Overall, the model simulations of the total C show a good fit against the measured soil C, for both reference (Figure 3.10) and bioenergy fields (Figure 3.11, 3.12 and 3.13), with a correlation coefficient, *R*, between 0.92 and 0.99 for the bioenergy sites (Table 3.4). At all bioenergy sites, the statistical analysis showed no model bias ($E < E_{95}$) and a good coincidence ($F < F$ *(critical at 5%))* between modelled and measured soil C.

Despite the good statistical correlation between the overall modelled and measured soil C, we found a lower coincidence between modelled and measured values under *Miscanthus* and Willow at specific soil depths (Figure 3.11, 3.12). In particular, at site 28, representing a transition from grassland to *Miscanthus*, the modelled soil C in the top three layers (0-30 cm soil depth) was higher than the measured values (Figure 3.11). Both model and measurements reported a reduction of C after changing the land-use from grassland to *Miscanthus*, but the magnitude of such decrease in soil C content at the top 30 cm soil depth was higher in the measured values (45.4 t C ha^{-1}) compared to the modelled soil C (39.7 t C ha^{-1}). The same lack of coincidence was also found under Willow at site 3 (transition from arable to Willow) but just at 20-30 cm soil layer (Figure 3.12). Whereas at site 35, a transition from grassland to Willow, the model underestimated the soil C at 0-10 cm and 10-20 cm soil layers compared to the measured values (Figure 3.12).

Despite the reduction in correlation between model and measured values at some depths, the model follows the same trend as the measured values at all sites highlighting the ability of the model to simulate soil C with a high degree of accuracy and in great detail.

	Willow			*Miscanthus*			SRF
Site codes	**2**	**3**	**35**	**27**	**28**	**36**	**8**
R = Correlation Coeff.	0.96	0.92	0.97	0.96	0.98	0.99	0.97
t -value	8.70	6.13	10.93	8.52	14.21	17.23	10.79
t-value at (P=0.05)	2.36	2.36	2.36	2.36	2.36	2.36	2.36
Significant association?	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good
E = Relative Error	1	-14	15	-11	-41	8	-12
E (95% Confidence Limit).	16	31	19	23	12	15	52
Significant bias?	No - Good	No - Good	No - Good	No - Good	Yes - Bad	No - Good	No - Good
LOFIT = Lack of Fit	422	923	1658	243	3866	387	855
F	0.02	0.10	0.12	0.04	0.38	0.02	0.04
F (Critical at 5%)	2.19	2.19	2.19	2.19	2.19	2.19	2.19
Significant error between simulated and measured values?	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good
Number of Values	9	9	9	9	9	9	9

Table 3.4: Results of statistical analysis for model simulation of C distribution in 1 metre soil profile. Transition to *Miscanthus*, Willow and SRF.

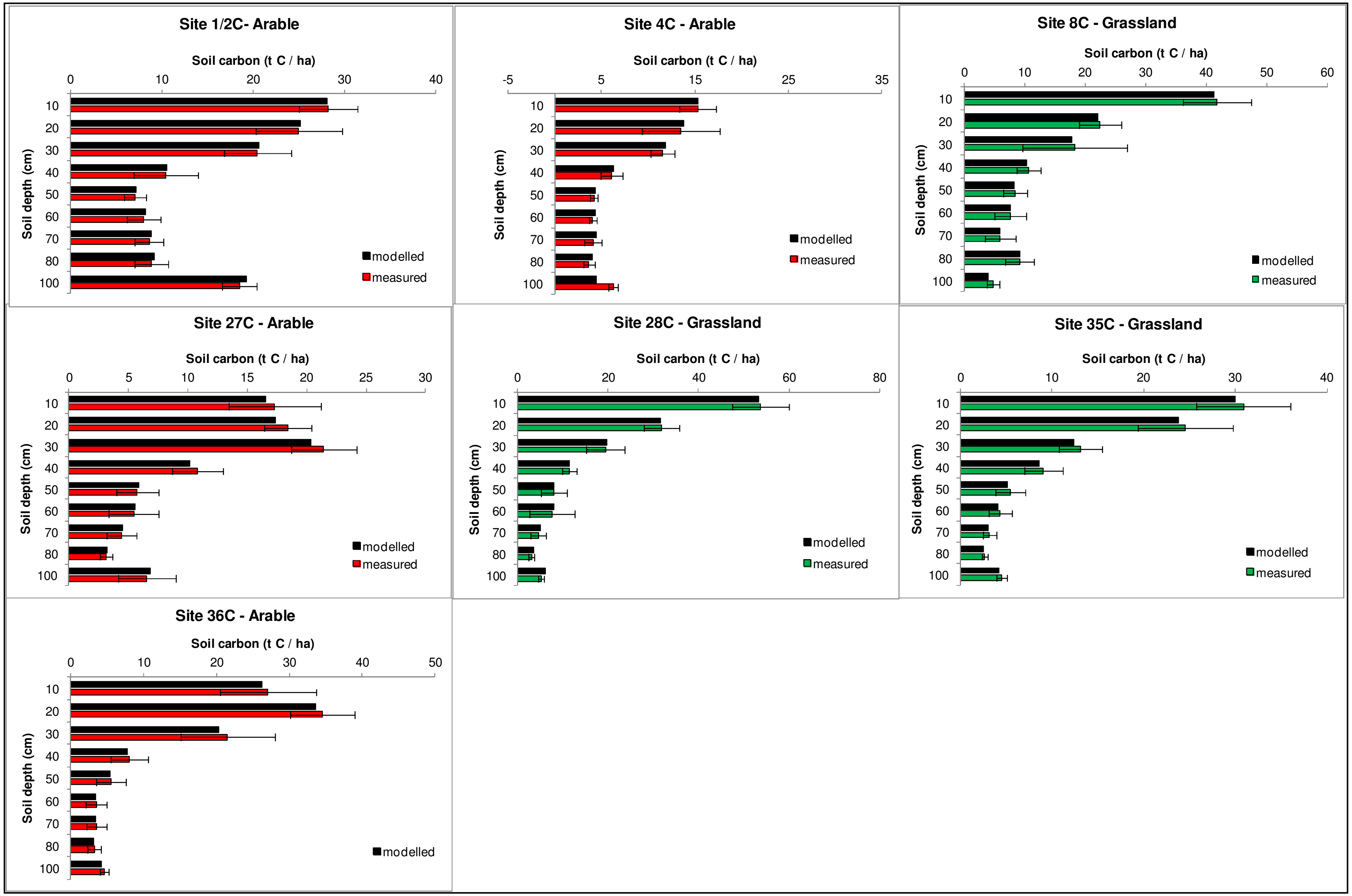


Figure 3.10: Measured and modelled soil C at 9 soil depths and for 9 conventional fields. Error bars represent 95% confidence interval of measured values.

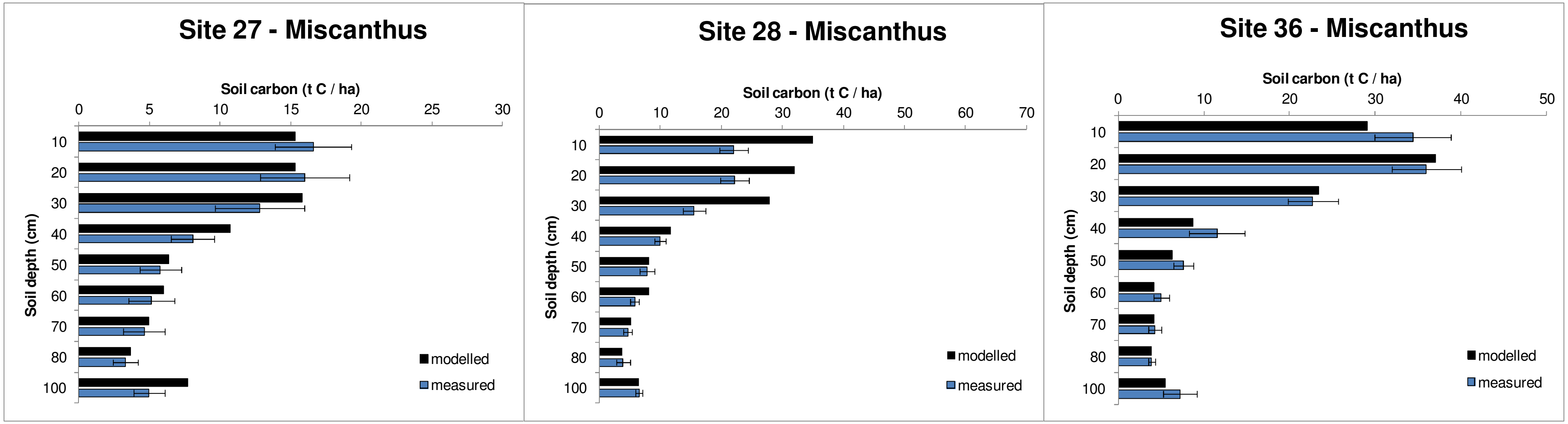


Figure 3.11: Measured and modelled soil C at 9 soil depths and for three *Miscanthus* fields. Error bars represent 95% confidence interval of measured values.

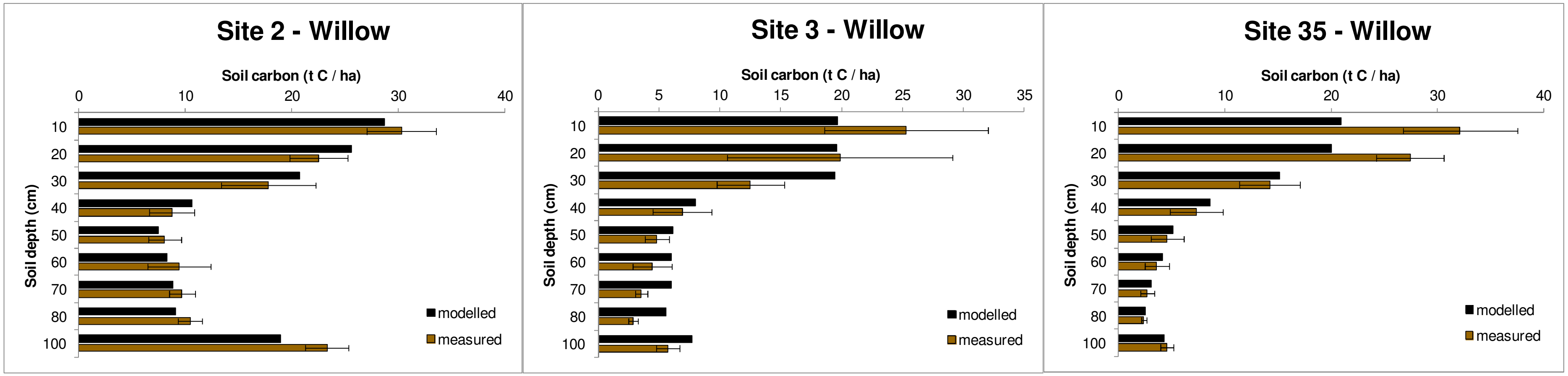


Figure 3.12: Measured and modelled soil C at 9 soil depths and for three Willow fields. Error bars represent 95% confidence interval of measured values.

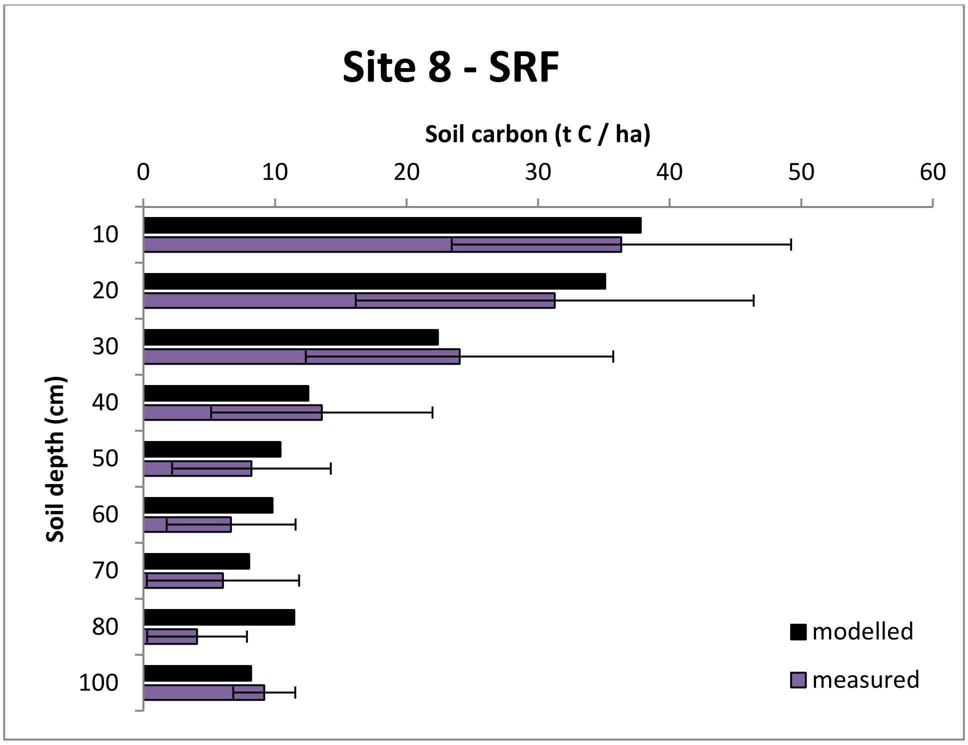


Figure 3.12a: Measured and modelled soil C at 9 soil depths for an SRF field. Error bars represent 95% confidence interval of measured values.

3.1.3 Soil CO_2, N_2O and CH_4 Fluxes

The validation and evaluation of the ECOSSE model to simulate soil GHG fluxes has been previously done using one year of flux data (2012), measured using chamber techniques (D4.2 - PM06.4.2_Report on Existing Models and Spatial Meta-model Test). Several modifications were made to the ECOSSE model (see section 2.1.1) and the improved ECOSSE version has been used to validate and evaluate the model using two years of chamber data for all network sites (2012 and 2013 data), together with the EC data and chamber measurements taken at root-exclusion plots (see Section 2.1.2. for data overview).
The ECOSSE model simulates heterotrophic respiration, Rh, while the CO_2 fluxes measured at the sites represent the total CO_2 efflux from the soil profile (autotrophic + heterotrophic respiration). We therefore estimated the measured Rh as a proportion of the measured total CO_2 flux, as described in Section 2.1.4, and compared to the modelled Rh.

The results of the comparison between measured and modelled Rh over the *Miscanthus* field at the Lincolnshire site are presented in figure 3.13. At this field, three datasets of CO_2 measurements were provided by the WP3 team: chamber (IRGA), EC and chamber measurements on root/litter exclusion plots (NRL). The CO_2 measured at the NRL plots is directly comparable to the modelled CO_2, while the Rh from IRGA and EC had been estimated from the total respiration.

The modelled CO_2 flux follows the same seasonal pattern of all measurements, with a statistically significant association between modelled and measured CO_2 at the NRL plots (R = 0.44) and EC measured CO_2 (R = 0.54), as well as no significant error between modelled and all measured values, and no bias in the model (Table 3.5). The Rh estimated from the IRGA measurements is the only set of data that does not correlate well with the modelled outputs (R = 0.26).

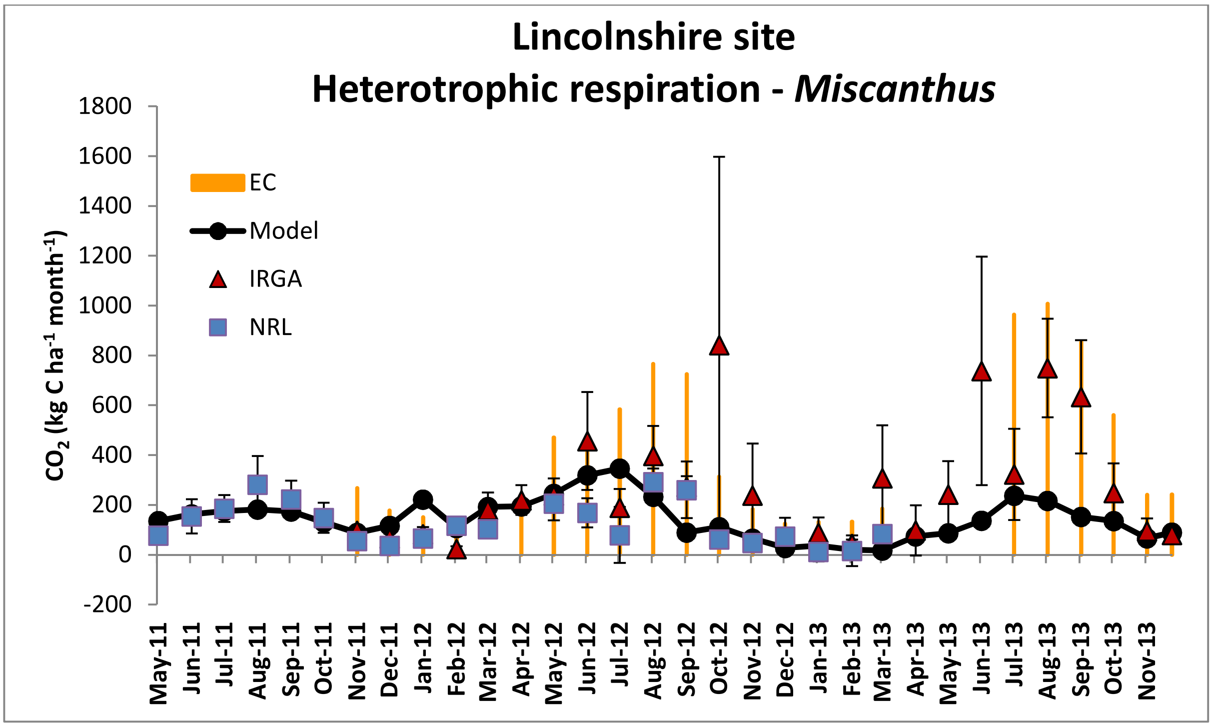


Figure 3.13: Soil heterotrophic respiration over the measured period; data from Lincolnshire site. Heterotrophic respiration estimated from three datasets: EC = eddy covariance, IRGA = static chamber, NRL = chamber measurements from root/litter exclusion plots. Error bars represent 95% confidence interval of measured values.

At the Willow and arable fields, the model has been validated against the IRGA and EC datasets (Figure 3.14 and 3.15). Overall the modelled CO_2 correlates well with the measured values at both sites and for both datasets, with the exception of the Rh estimated from the EC at the arable site (Table 3.5). It is important to note that at the arable site the EC was installed in April 2012 and less data are therefore available (13 months) compared to the other fields.

CO_2							
	Miscanthus			Willow		Arable	
	IRGA	EC	NRL	IRGA	EC	IRGA	EC
R = Correlation Coeff.	0.26	0.54	0.44	0.44	0.70	0.75	0.50
t-value	1.29	2.88	2.18	2.32	4.32	5.31	1.91
t-value at (P=0.05)	2.07	2.09	2.09	2.07	2.09	2.07	2.20
Significant association?	No - Bad	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	No - Bad
E = Relative Error	48	N/A	-16	-5	N/A	34	N/A
E (95% Confidence Limit).	46	N/A	60	35	N/A	40	N/A
Significant bias?	Yes - Bad	N/A	No - Good	No - Good	N/A	No - Good	N/A
LOFIT = Lack of Fit	13683479	N/A	9556	2200231	N/A	11892230	N/A
F	0.20	N/A	0.06	0.13	N/A	0.12	N/A
F (Critical at 5%)	1.60	N/A	1.65	1.60	N/A	1.62	N/A
Significant error between simulated and measured values?	No - Good	N/A	No - Good	No - Good	N/A	No - Good	N/A
Number of Values	25	22	22	25	21	24	13

Table 3.5: Results of statistical analysis of model simulation of CO_2 fluxes. Data from Lincolnshire site. EC = eddy covariance, IRGA = static chamber, NRL = chamber measurements from root/litter exclusion plots.

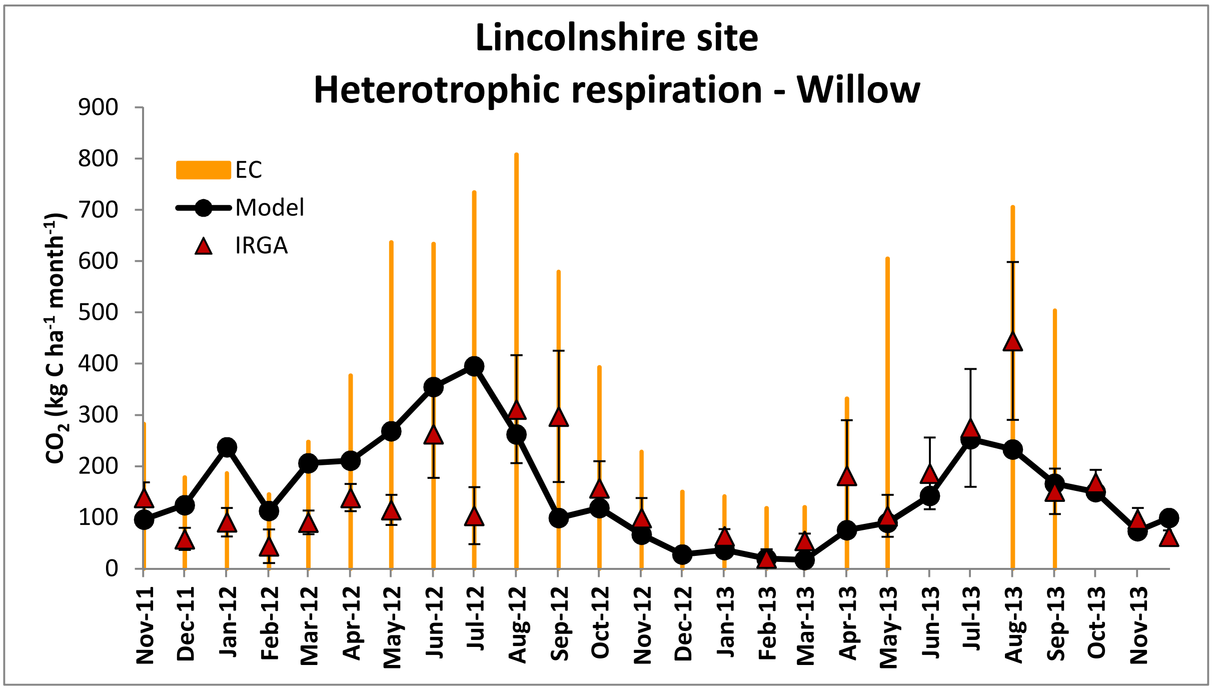


Figure 3.14: Soil heterotrophic respiration over the measured period; data from Lincolnshire site. Heterotrophic respiration estimated from three dataset: EC = eddy covariance, IRGA = static chamber, NRL = chamber measurements from root/litter exclusion plots. Error bars represent 95% confidence interval of measured values.

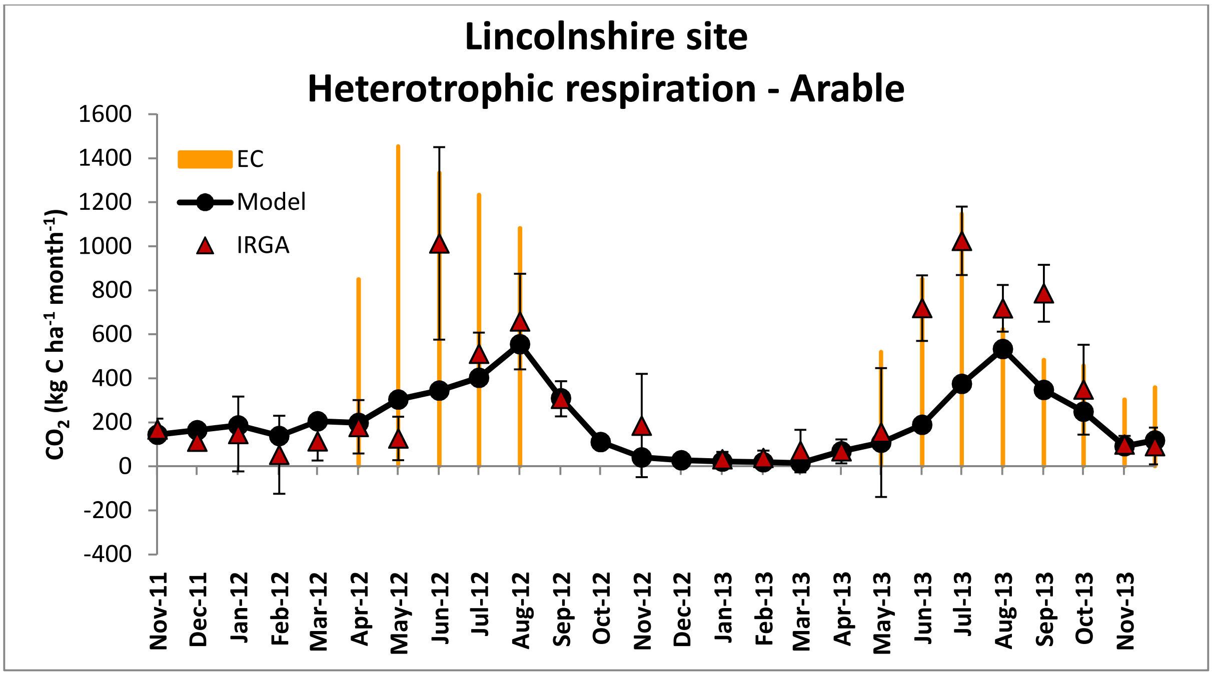


Figure 3.15: Soil heterotrophic respiration over the measured period; data from Lincolnshire site. Heterotrophic respiration estimated from three dataset: EC = eddy covariance, IRGA = static chamber, NRL = chamber measurements from root/litter exclusion plots. Error bars represent 95% confidence interval of measured values.

Model performance to simulate soil CO_2 fluxes under SRF and grassland has been validated against data collected at the East Grange site (Figure 3.16 and 3.17). The modelled outputs follow the same pattern of the measured values and the statistical analysis show good correlation with both IRGA and EC datasets for both SRF and grassland. Moreover, we found no statistically significant error between modelled and measured values as well as no bias in the model (Table 3.6).

Under grassland, the heterotrophic respiration derived from the IRGA measurements during the summer period of 2012 was lower than the modelled values (Figure 3.17). This lack of correlation underlines the difficulties in measuring soil respiration under grassland, due to the occlusion of vegetation within the chamber. When deriving heterotrophic respiration from grassland, we accounted that 60% of the measured CO_2 is plant respiration, as reported by Byrne & Kiely (2006). At this particular site, the grass was cut just before the start of the measurement period, therefore in 2012 little vegetation was present in the field, resulting in a lower estimation of the heterotrophic respiration compared to the modelled values.

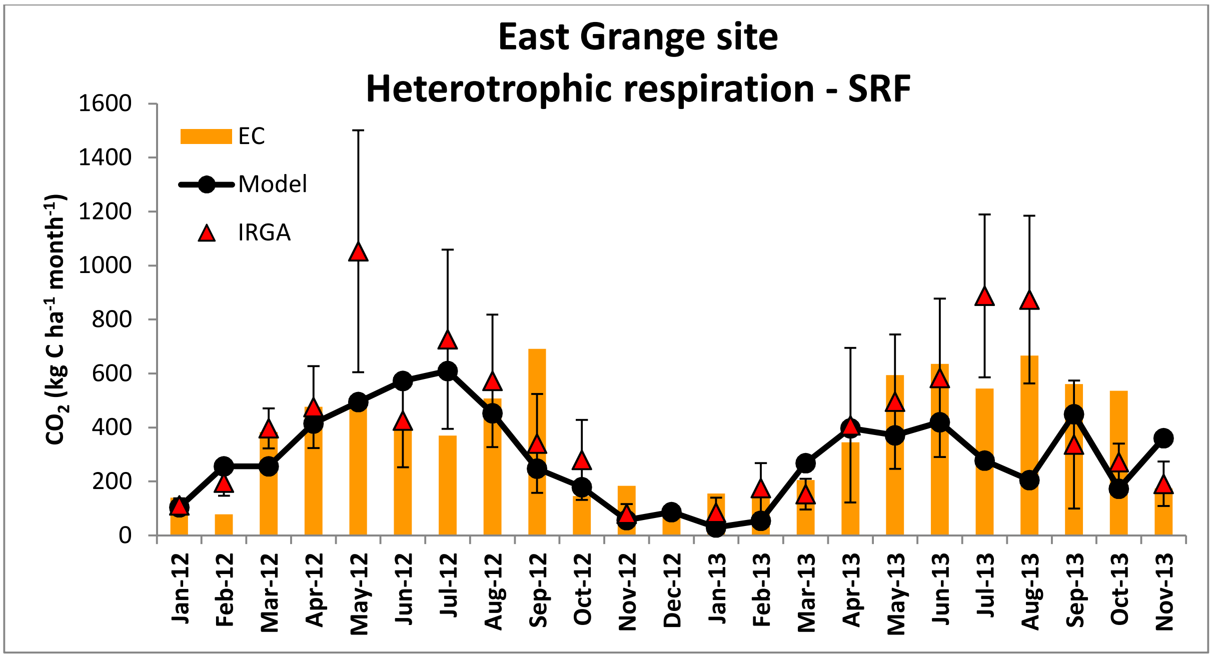


Figure 3.16: Soil heterotrophic respiration over the measured period; data from East Grange site. Heterotrophic respiration estimated from three dataset: EC = eddy covariance, IRGA = static chamber. Error bars represent 95% confidence interval of measured values.

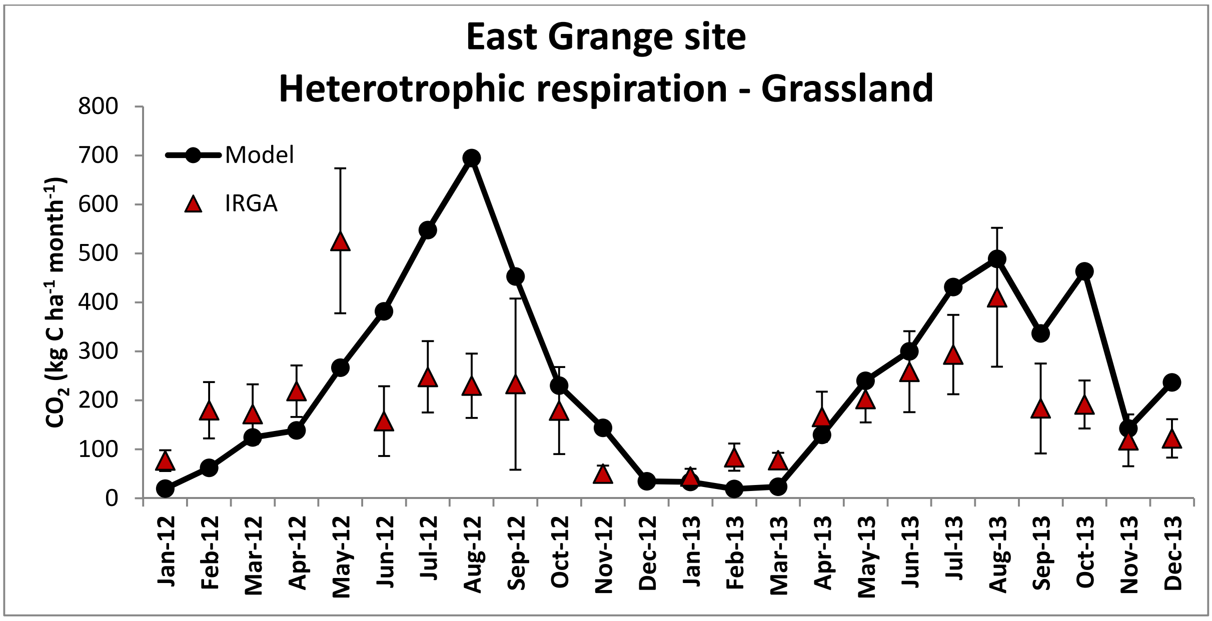


Figure 3.17: Soil heterotrophic respiration over the measured period; data from East Grange site. Heterotrophic respiration estimated from one dataset: IRGA = static chamber. Error bars represent 95% confidence interval of measured values.

	SRF		Grassland
	IRGA	EC	IRGA
R = Correlation Coeff.	0.54	0.68	0.54
t - value	2.98	2.91	2.98
t-value at (P=0.05)	2.08	2.23	2.08
Significant association?	Yes - Good	Yes - Good	Yes - Good
E = Relative Error	40.63	N/A	-34
E (95% Confidence Limit).	44.24	N/A	36
Significant bias?	No - Good	N/A	No - Good
LOFIT = Lack of Fit	52490	N/A	52490
F	0.24	N/A	0.24
F (Critical at 5%)	1.63	N/A	1.63
Significant error between simulated and measured values?	No - Good	N/A	No - Good
Number of Values	23	12	23

Table 3.6: Results of statistical analysis of model simulation of CO_2 fluxes. Data from East Grange site. EC = eddy covariance, IRGA = static chamber.

The results of the correlation between modelled and measured soil N_2O and CH_4 fluxes are shown in Figure 3.18 and 3.19, respectively. Both N_2O and CH_4 are very small fluxes and the model outputs are within the errors of the measurements, for both GHG and at all fields. The statistical results for N_2O and CH_4 fluxes are summarised in Table 3.7.

The high variability of the measured N_2O and CH_4 fluxes leads to a statistically significant error between simulated and measured values. However, the lack of model bias underlines the ability of the model to adequately describe the physical processes. Therefore, the validation of the model to simulate N_2O and CH_4 fluxes have been carried out without any further modifications to the model itself.

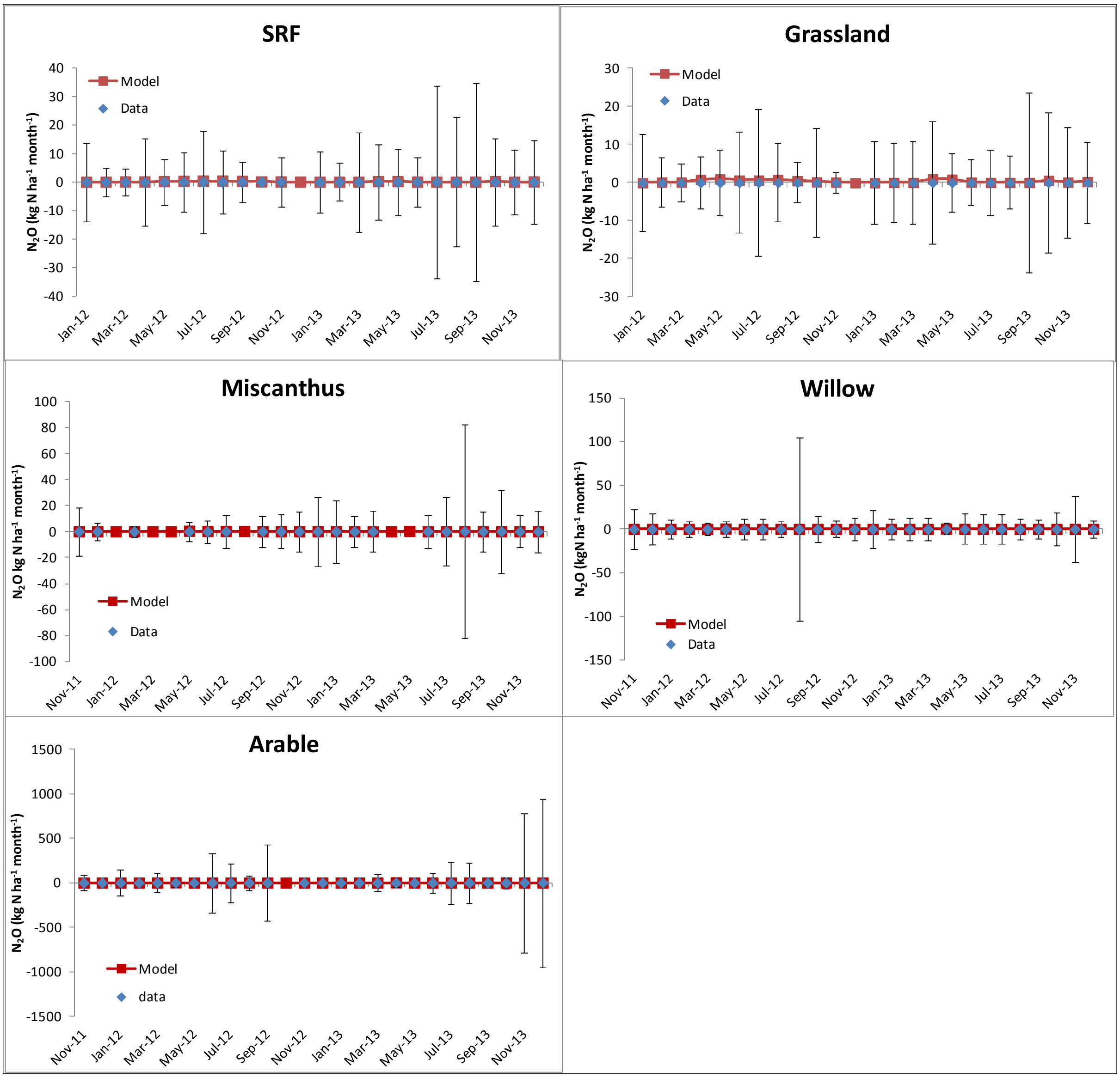


Figure 3.18: Soil N2O fluxes over the measured period. Data for *Miscanthus*, arable and Willow are from Lincolnshire site, data for SRF and grassland are from East Grange sites.

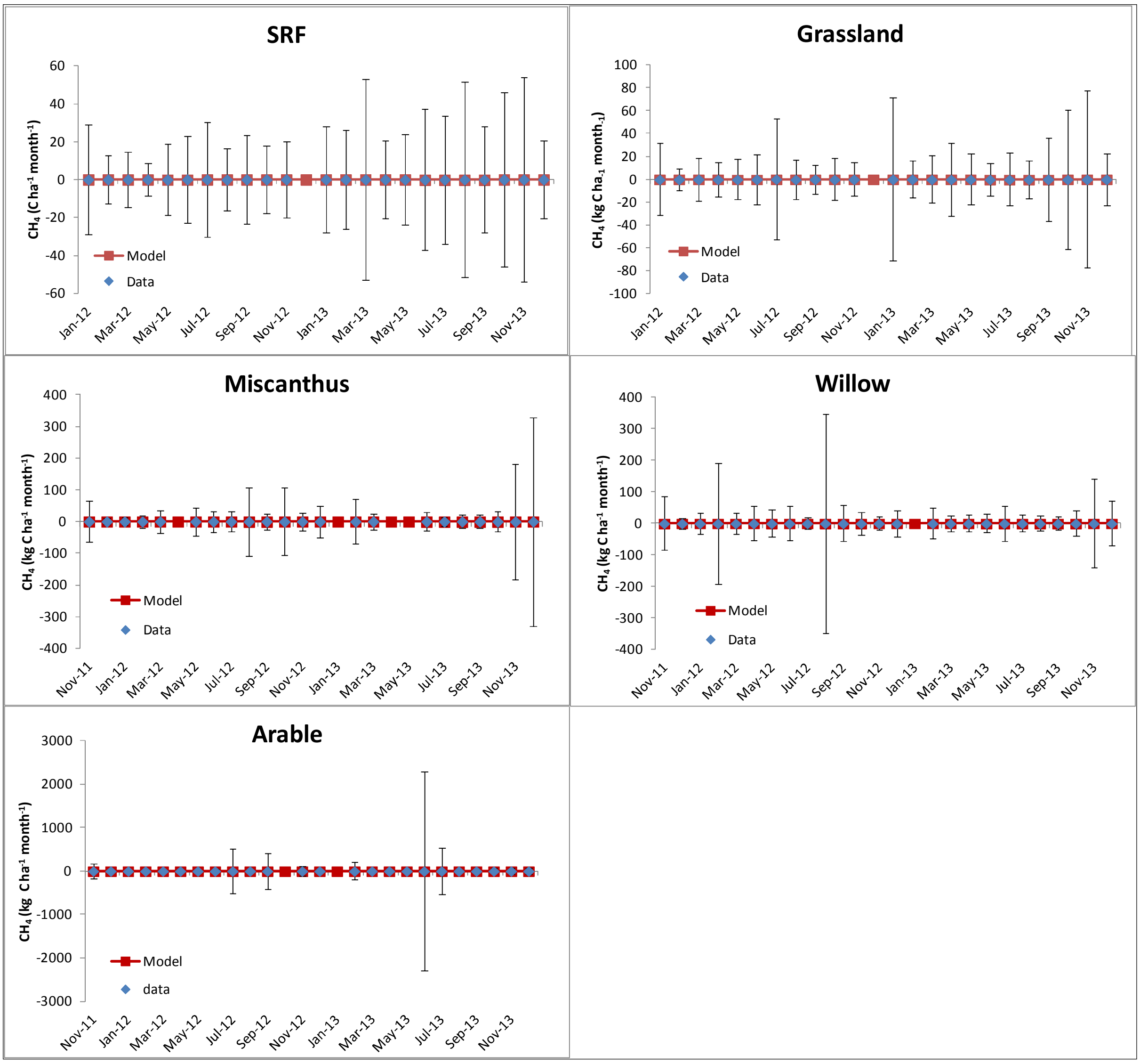


Figure 3.19: Soil CH_4 fluxes over the measured period. Data for *Miscanthus*, arable and Willow are from Lincolnshire site, data for SRF and grassland are from East Grange sites.

	N_2O					CH_4				
	Miscanthus	Willow	Arable	SRF	Grassland	Miscanthus	Willow	Arable	SRF	Grassland
R = Correlation Coeff.	-0.15	-0.13	-0.20	0.19	-0.12	0.28	0.18	-0.29	0.53	0.41
t - value	0.64	0.66	0.97	0.86	0.56	1.28	0.88	1.44	2.68	1.91
t-value at (P=0.05)	2.10	2.06	2.07	2.08	2.08	2.09	2.07	2.07	2.10	2.10
Significant association?	No - Bad	No - Bad	No - Bad	No - Bad	No - Bad	No - Bad	No - Bad	No - Bad	Yes - Good	No - Bad
E = Relative Error	-369	-1109	24	-830	-2365	1666	-902	400	-235	-340
E (95% Confidence Limit).	154060	256382	80869	99	75	768774	-542191	662151	-206423	-260916
Significant bias?	No - Good	No - Good	No - Good	Yes - Bad	Yes - Bad	No - Good	No - Good	No - Good	No - Good	No - Good
LOFIT = Lack of Fit	2	5	38	6	46	6	6	24	1	1
F	3.34	54.66	0.43	40.75	312.92	3.61	6.50	0.66	2.38	4.09
F (Critical at 5%)	1.69	1.59	1.60	1.63	1.63	1.65	1.60	1.62	1.63	1.63
Significant error between simulated and measured values?	Yes - Bad	Yes - Bad	No - Good	Yes - Bad	Yes - Bad	Yes - Bad	Yes - Bad	No - Good	Yes - Bad	Yes - Bad
Number of Values	20	26	25	23	23	22	25	24	23	23

Table 3.7: Results of statistical analysis of model simulation of N_2O and CH_4 fluxes. Data for *Miscanthus*, arable and Willow are from Lincolnshire site, data for SRF and grassland are from East Grange site.

The results of the model evaluation underline the ability of the ECOSSE model to accurately describe soil processes (e.g. seasonal patterns of fluxes) on monthly time-steps; therefore, to independently evaluate the ECOSSE model, all remaining network sites (Aberystwyth, West Sussex and East Grange) were simulated using the ECOSSE version used for the model evaluation and the results of all GHG fluxes compared to the flux measurements.

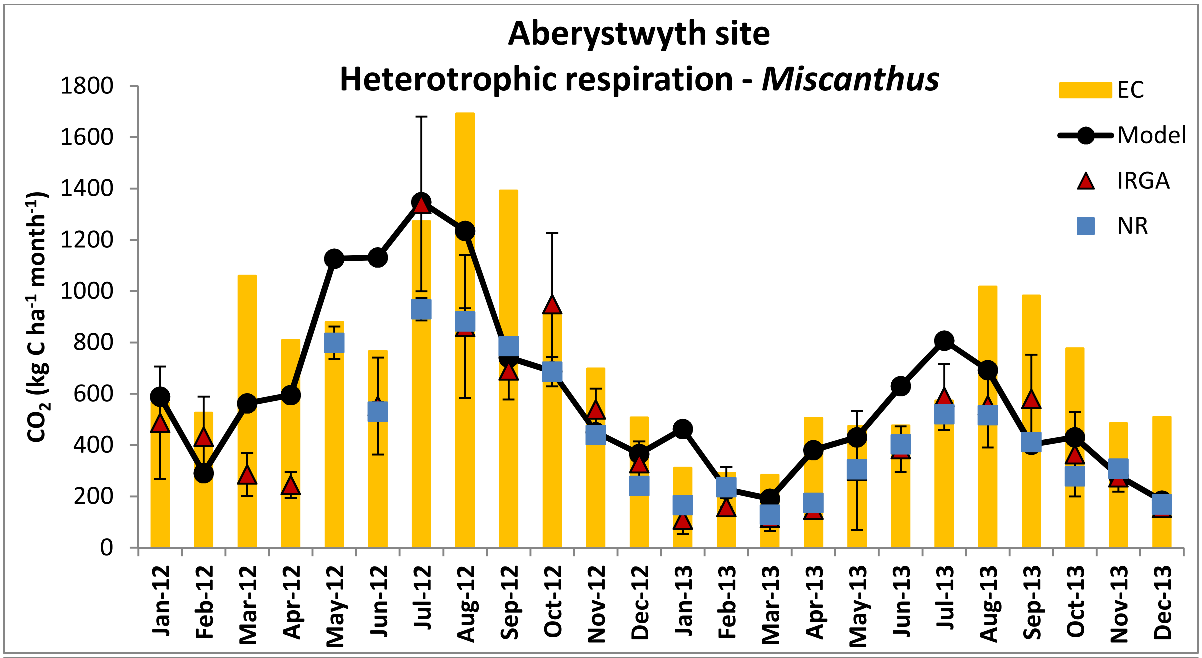
Overall, the simulated CO_2 follows the same pattern as the measured values at all sites (Figures 3.20-3.23). The statistics highlighted a good correlation and no significant error between modelled and measured values as well as no model bias (Table 3.8), with the exception of the IRGA measurements taken in the grassland field at the Aberystwyth site. At this field, technical problems were reported with the exclusion of leaves from the chamber prior to gas sampling. Therefore we believe that the cause of the bias is due to the inclusion of plant respiration in the gas samples and not a model malfunction.

Under grassland, the heterotrophic respiration derived from the IRGA measurements does not always show a good correlation with the modelled values, particularly during the summer months (Figures 3.17 and 3.21). This lack of correlation is mainly due to the difficulties in monitoring soil respiration under grassland, due to the occlusion of vegetation within the chamber. When deriving heterotrophic respiration from grassland, we estimated that 60% of the measured CO_2 can be attributed to plant respiration, as reported by Byrne & Kiely (2006), but this crude estimate doesn't always reflect the field conditions. For an accurate quantification of the proportion of the CO_2 derived from the plant occluded in the chambers, field experiments should be conducted to explicitly quantify the plant respiration and its biomass.

The independent evaluation of the model to simulate N_2O and CH_4 fluxes shows no error between simulated and measured values and no significant bias in the model (Table 3.9). However, no correlation between measured and modelled values has been found for the majority of the sites. The lack of significant association between modelled and measured CH_4 and N_2O fluxes is due to the very low values of both fluxes; if the measured values do not show any seasonal trend it is almost impossible to have a significant correlation with the model outputs. Therefore we expected such low correlation, which does not represent a failure in the model as it is always within the error of the measurements.

The ECOSSE model is a soil model which simulates soil heterotrophic respiration. Here we compared the model results against three different sources of data, two of them (IRGA and EC) producing results on total soil respirations (autotrophic + heterotrophic respiration). The CO_2 measured at the root-exclusion plots is directly comparable to the modelled CO_2, providing the best dataset for model validation. Overall, the results of the model validation and evaluation underline the ability of the model to simulate soil CO_2 fluxes adequately.

Fluxes of CH_4 and N_2O were shown to be close to negligible across all land-uses and represent an extremely small proportion of the total GHG balance (as reported in the ELUM deliverable report D3.3). This flux has been modelled adequately on a monthly time-step and no improvements can be made to the model with the available flux data.



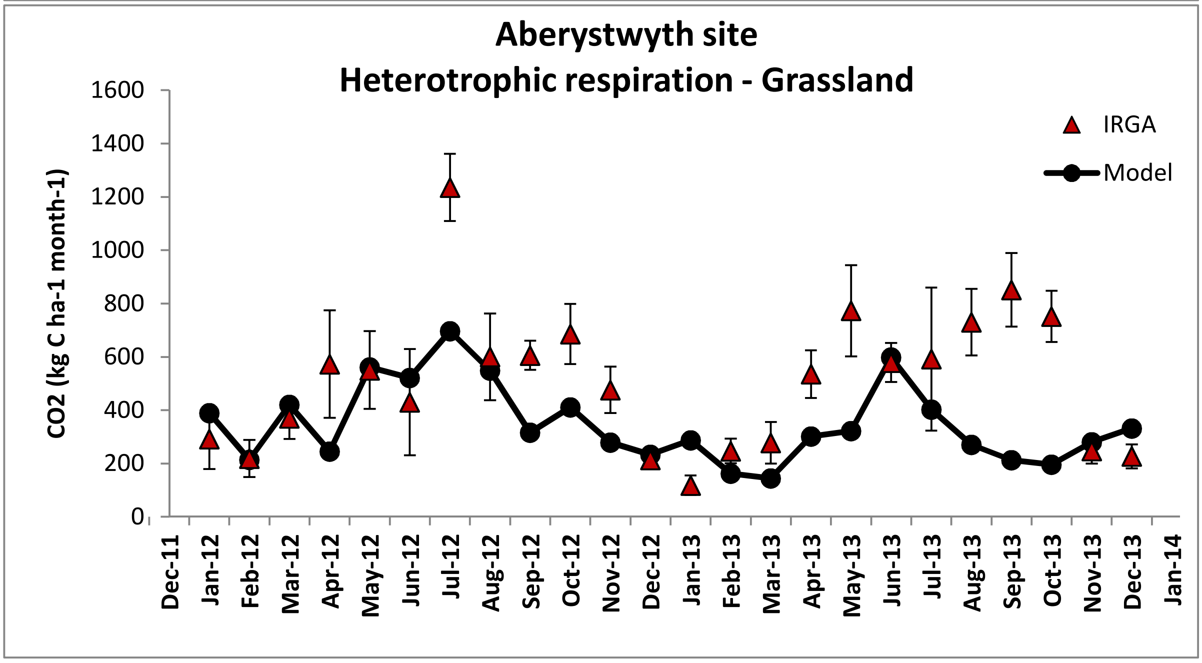


Figure 3.20: Soil heterotrophic respiration over the measured period; data from Aberystwyth site. Heterotrophic respiration estimated from three datasets: EC = eddy covariance, IRGA = static chamber, NR = chamber measurements from root-exclusion plots. Error bars represent 95% confidence interval of measured values.

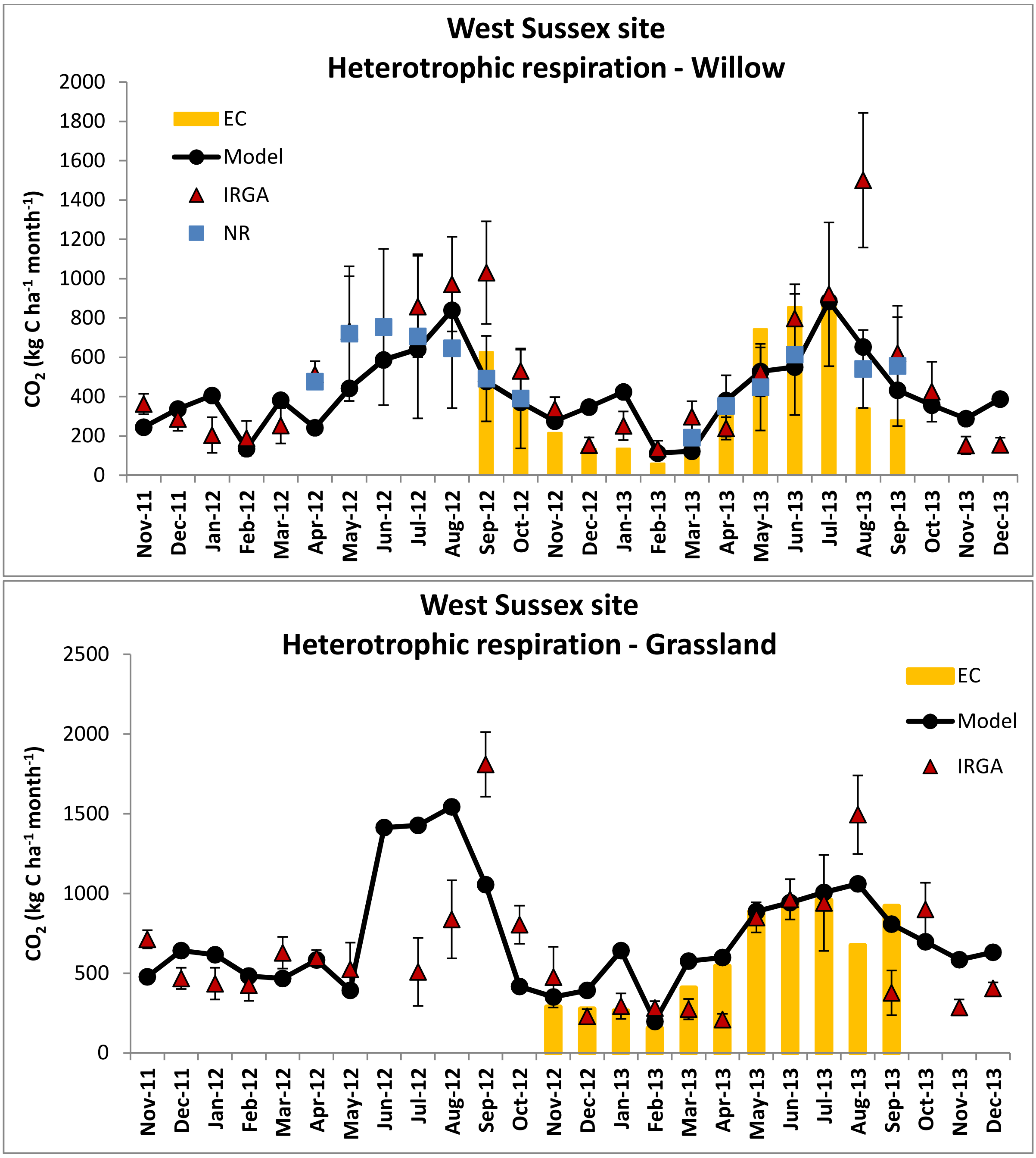
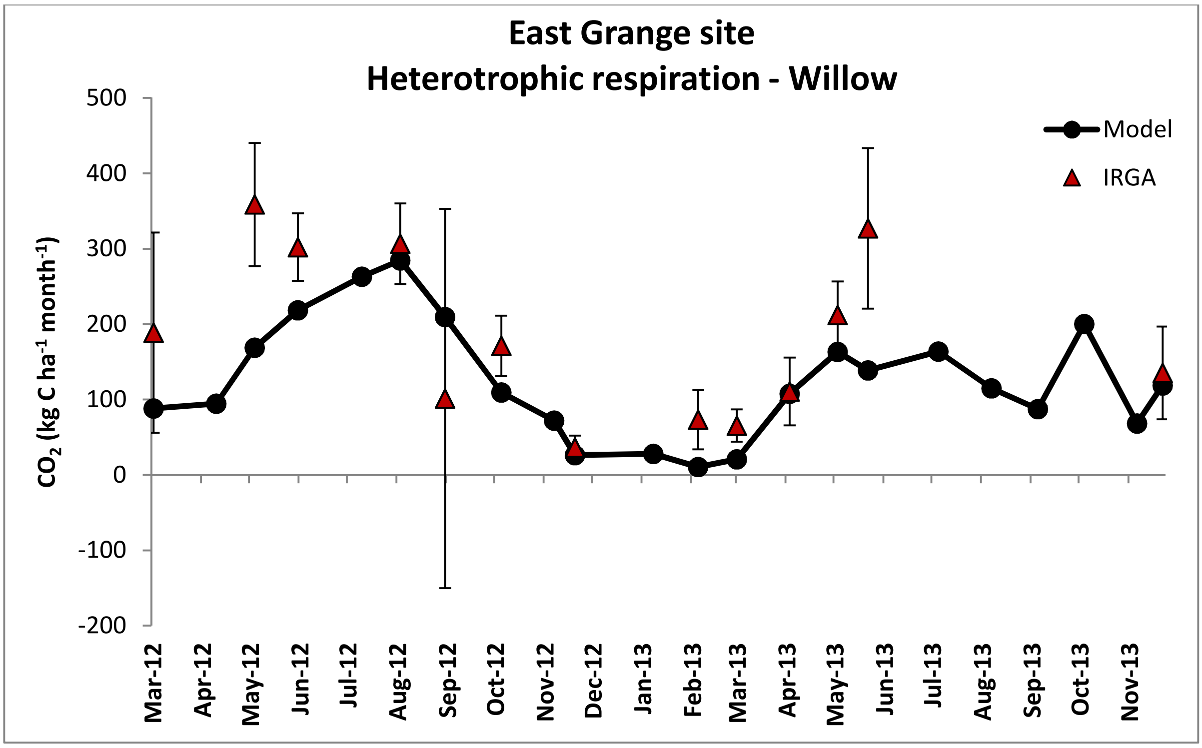


Figure 3.21: Soil heterotrophic respiration over the measured period; data from West Sussex site. Heterotrophic respiration estimated from three datasets: EC = eddy covariance, IRGA = static chamber, NR = chamber measurements from root-exclusion plots. Error bars represent 95% confidence interval of measured values.



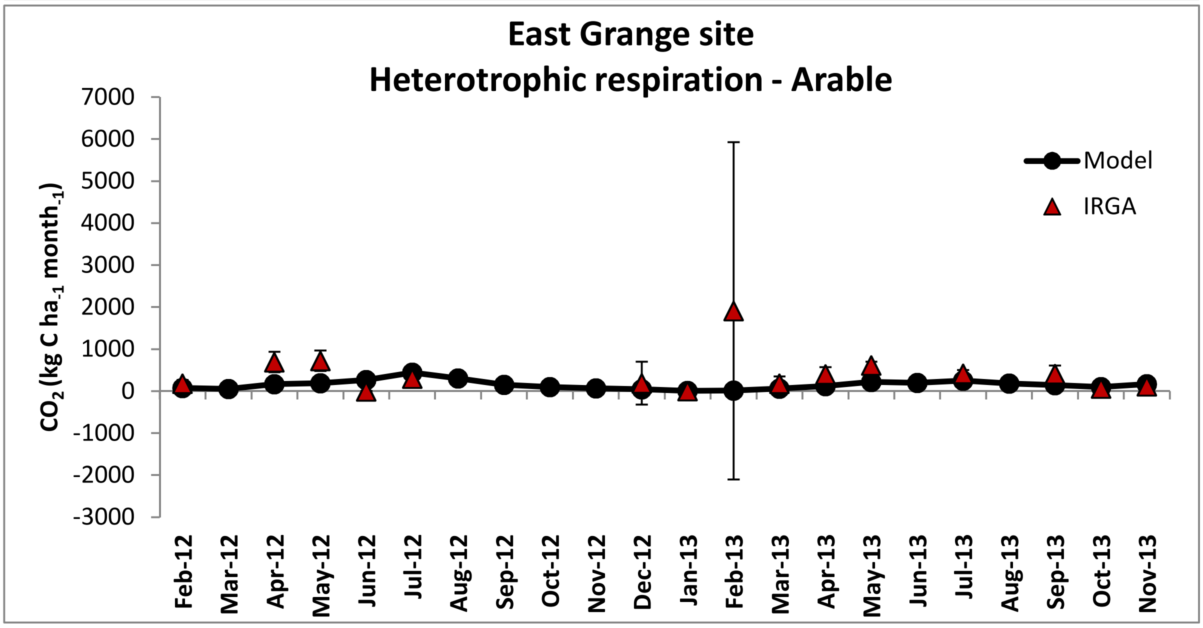


Figure 3.22: Soil heterotrophic respiration over the measured period; data from East Grange site. Heterotrophic respiration estimated from one dataset: IRGA = static chamber. Error bars represent 95% confidence interval of measured values.

CO_2											
	Aberystwyth				**West Sussex**					**East Grange**	
	Miscanthus			Grassland	Willow			Grassland		Willow	Arable
	IRGA	EC	NR	IRGA	IRGA	EC	NR	IRGA	EC	IRGA	IRGA
R = Correlation Coeff.	0.80	0.70	0.83	0.53	0.74	0.77	0.75	0.51	0.98	0.70	-0.10
t-value	6.10	4.65	6.10	2.91	5.25	3.99	3.34	2.85	16.72	3.28	0.35
t-value at (P=0.05)	2.08	2.07	2.11	2.07	2.07	2.20	2.20	2.07	2.26	2.20	2.18
Significant association?	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	Yes - Good	No - Bad
E = Relative Error	-30	N/A	-23	77	18	N/A	-2	-11	N/A	30	6764%
E (95% Confidence Limit).	30	N/A	162	20	28	N/A	4	21	N/A	40	6774%
Significant bias?	No - Good	N/A	No - Good	Yes - Bad	No - Good	N/A	No - Good	No - Good	N/A	No - Good	No - Good
LOFIT = Lack of Fit	92471	N/A	37068	3867022	13161257	N/A	6277	239423	N/A	9067	36643916%
F	0.07	N/A	0.02	0.26	0.07	N/A	0.00	0.08	N/A	0.14	53%
F (Critical at 5%)	1.63	N/A	1.71	1.62	1.60	N/A	1.92	1.60	N/A	1.92	187%
Significant error between simulated and measured values?	No - Good	N/A	No - Good	No - Good	No - Good	N/A	No - Good	No - Good	N/A	No - Good	No - Good
Number of Values	23	24	19	24	25	13	13	25	11	13	14

Table 3.8: Results of statistical analysis of model simulation of CO_2 fluxes. Data from Aberystwyth, West Sussex and East Grange sites. EC = eddy covariance, IRGA = static chamber, NR = chamber measurements from root/litter exclusion plots.

	N_2O						CH_4					
	Aberystwyth		**West Sussex**		**East Grange**		**Aberystwyth**		**West Sussex**		**East Grange**	
	Miscanthus	Grassland	Willow	Grassland	Willow	Arable	*Miscanthus*	Grassland	Willow	Grassland	Willow	Arable
R = Correlation Coeff.	0.34	0.06	-0.02	0.25	0.12	0.61	0.31	0.51	0.18	0.27	0.53	0.05
t – value	1.72	0.30	0.08	1.24	0.48	3.25	1.52	2.81	0.91	1.40	2.51	0.20
t-value at (P=0.05)	2.07	2.07	2.06	2.06	2.12	2.10	2.07	2.07	2.06	2.06	2.12	2.10
Significant association?	No - Bad	No - Bad	No - Bad	No - Bad	No - Bad	Yes - Good	No - Bad	Yes - Good	No - Bad	No - Bad	Yes - Good	No - Bad
E = Relative Error	92	-36	28	-80	-613	7	67	-7	269	-19	-492	-69
E (95% Confidence Limit).	97	87	118	105	210	73	245	369	302	273	1291	241
Significant bias?	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good
LOFIT = Lack of Fit	193	29	0	4	3	29	1728	320	5	5	1	2
F	0.37	0.68	0.37	0.62	22.62	0.25	0.33	0.34	0.61	0.30	0.53	0.76
F (Critical at 5%)	1.63	1.62	1.59	1.59	1.74	1.69	1.62	1.62	1.59	1.59	1.74	1.69
Significant error between simulated and measured values?	No - Good	No - Good	No - Good	No - Good	Yes - Bad	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good	No - Good
Number of Values	24	24	26	26	18	20	24	24	26	26	18	20

Table 3.9 Results of statistical analysis of model simulation of N_2O and CH_4 fluxes. Data from Aberystwyth, West Sussex and East Grange sites.

3.1.5 Uncertainty and sensitivity analysis of the process-based model to simulate soil carbon

HWSD data are tested here as they will be used in the spatial ECOSSE simulations as the basis of results used in the meta-model. In the spatial simulations, ECOSSE simulates all soil types (up to a maximum of 5) in each grid cell. We replicate this method here for the forty chronosequence sites sampled in year 2 of the ELUM project from WP2; the attributes of these soils are reported in Table A3. Since we are unable to specify exactly the soil type in the database which corresponds to the soil at the experimental sites, the land-use change simulations to the bioenergy crops (*Miscanthus* and Willow) have been run using the soil attributes of all the dominant soil types as inputs to the model. The soil C outputs of each model simulation were then averaged based on the percentage of the grid cell that is covered by each dominant soil type and compared to the measured soil C at the chronosequence sites (Figure 3.23). This test is important to understand the uncertainty in spatial results, where a single value is obtained for each grid cell (which is averaged over the dominant soils). Overall, the model underestimates the soil C, but the correlation coefficient (*R*) value show a significant association ($P < 0.05$) between simulated and measured values ($R = 0.79$). Moreover, the relative error, *E*, and the lack of fit, LOFIT, suggest that there is no bias in the difference between simulated and measured values (Table 3.10).

Due to the nature of the HWSD data, where the locations of soils within each grid cell are unknown, it is not possible to define which HWSD soil type corresponds to a given field site, or whether the soil type of the field site is within the dominant soils reported in the dataset. However, the good correlation between modelled and measured values, together with the lack of model bias suggests a good match between the HWSD and field soils.

R = Correlation Coeff.	0.79
t-value	7.21
t-value at (P=0.05)	2.04
Significant association?	Yes - Good
E = Relative Error	0
E (95% Confidence Limit).	106
Significant bias?	No - Good
LOFIT = Lack of Fit	69205
F	0.00
F (Critical at 5%)	1.50
Significant error between simulated and measured values?	No - Good
Number of Values	40

Table 3.10: Results of statistical analysis of model simulation of soil carbon at 0-100 cm depth using inputs from HWSD database.

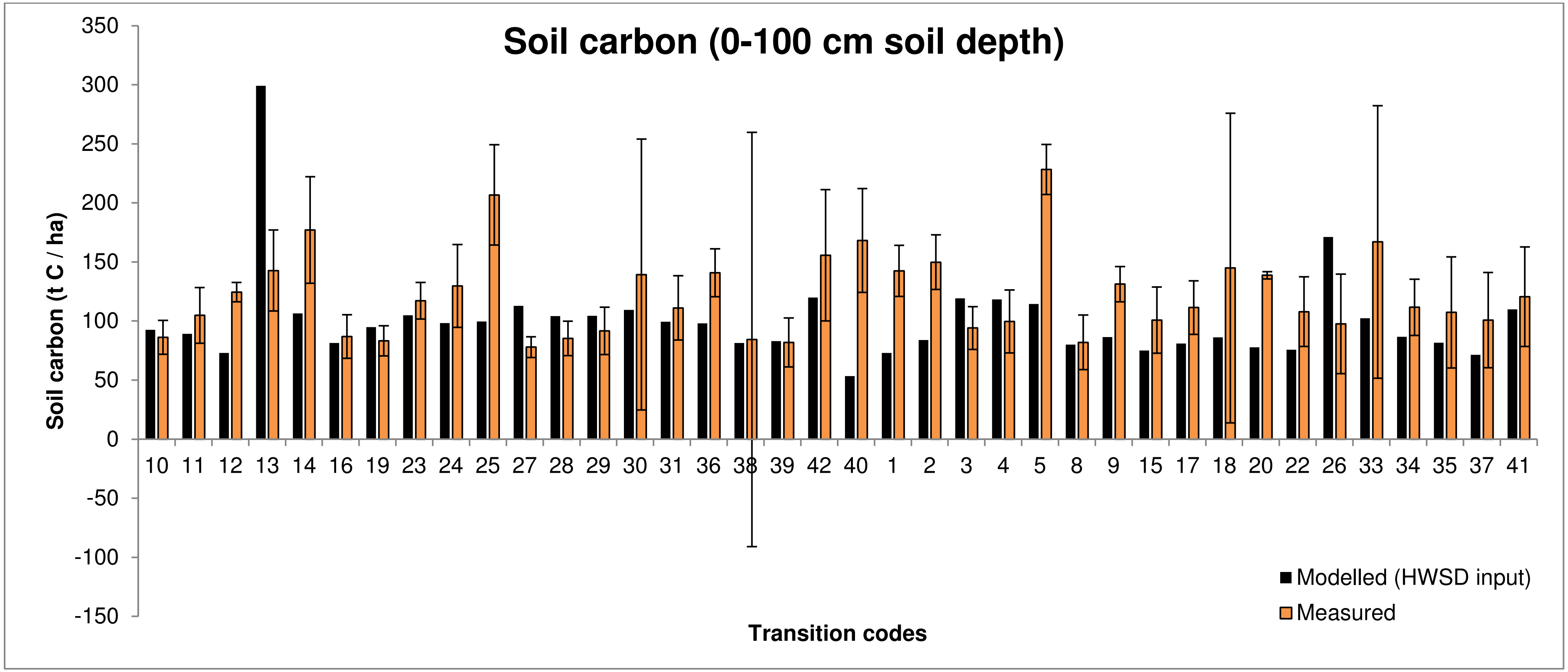


Figure 3.23: Comparison between modelled soil carbon using HWSD soil database (HWSD input) as inputs to the model and the site measurements (Measured).

The ELUM deliverable report D4.2 reported the evaluation and validation of soil C simulations after conversion to SRF. The soil texture of the 28 transitions to SRF (10 sites) was the only soil characteristic extracted from the "Falloon" soil database (Fallon et al., 2006) as direct measurements were not available. Texture values for the field sites have been determined as part of WP2 activities and were used to test the model sensitivity to soil texture. The result of the *local* sensitivity analysis indicated that there is no significant variation in the soil C outputs when using site-texture inputs instead of data extracted from a large spatial dataset, as the "Falloon" soil database (Figure 3.24).

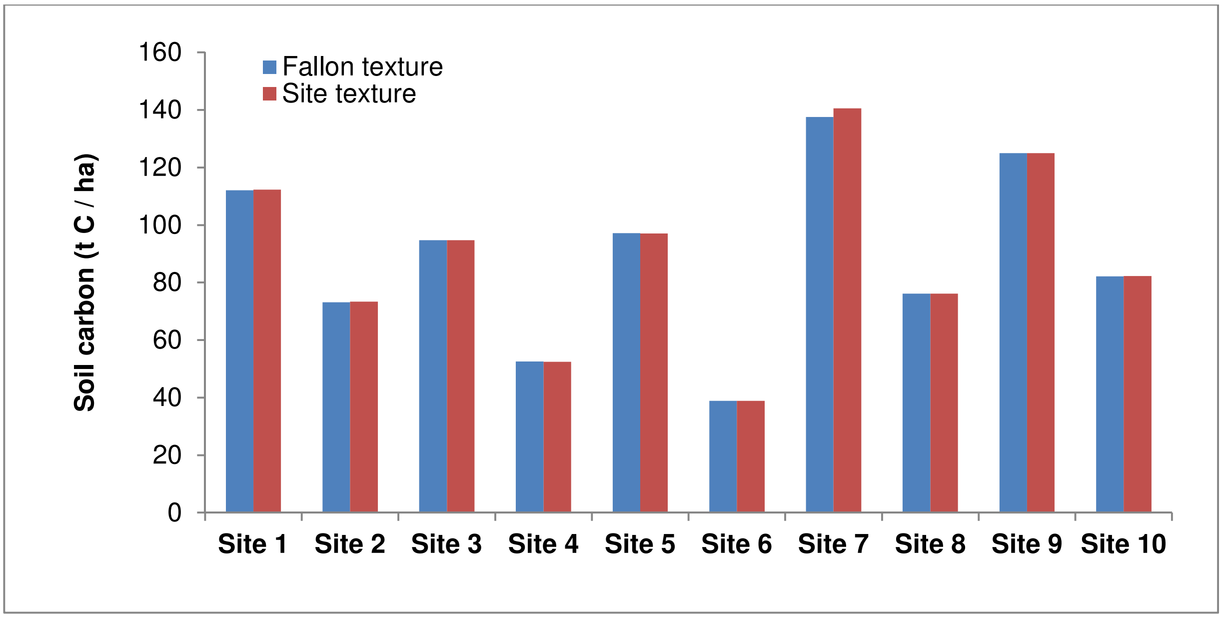
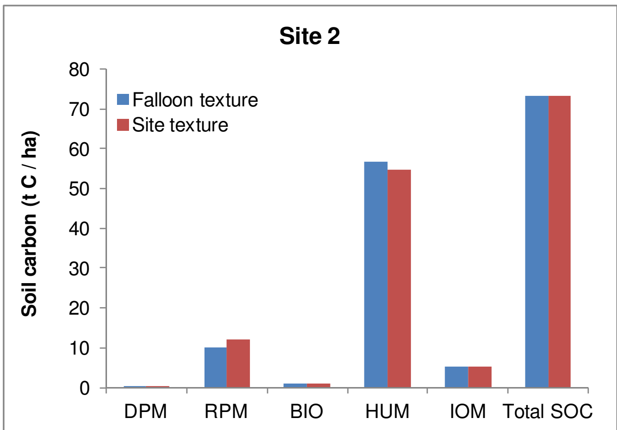


Figure 3.24: Comparison between modelled soil carbon using "Fallon" soil texture as inputs to the model and the site measurements. All other soil inputs to the model are from direct measurements.

However, we found a variation in the distribution of the soil C in the soil pools, in particular in the resistant plant material pool (RPM) and the humus pool (HUM), as shown for two test sites in Figure 3.25.



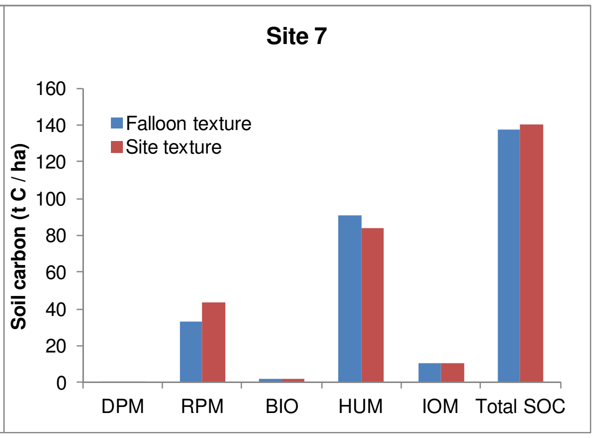


Figure 3.25: Comparison between modelled soil carbon pools and total soil carbon using "Fallon" soil texture as inputs to the model and the site measurements. All other soil inputs to the model are from direct measurements taken at Site 2 and 7.

In the model, the clay percentage influences the decomposition rate and the C distribution in the soil pools. A higher clay content will result in a lower C content in the RPM (slow turnover decomposition rate constant of $3yr^{-1}$) and a higher C content in the HUM (fast turnover, decomposition rate constant of $0.02yr^{-1}$). In other words, the clay content is used to determine the efficiency of decomposition under non-nitrogen-limiting conditions.

3.2 Spatial Model

3.2.1 Model descriptions

3.2.1.1 Underlying model

Results are based on the ECOSSE model (see section 2.1.1 for details), which has been extensively validated, including against field measurements across the UK for biomass crops (Dondini et al., 2014).

ECOSSE uses soil data inputs for:

- Soil texture
- Soil C
- Bulk density
- pH

and monthly meteorological data inputs for:

- Temperature
- Precipitation

The model is initialised to equilibrium conditions at year zero, when the land-use transition then occurs.

Transitions:

- Arable to wheat, sugar beet and OSR assume no transition (that is, the arable crop prior to transition is assumed to be the same as following the transition).
- Arable to other crops assumes the arable is wheat.
- Wheat is winter wheat.
- *Miscanthus* is *Miscanthus x Giganteus*.
- SRF is Poplar due to its observed higher yields than other species.
- SRC is Willow due to its more widespread use as SRC than Poplar, and thinner stems making it more suited to regular harvesting.

Management assumptions:

- Fertiliser is applied according to Defra guidelines for each crop (Defra, 2010).

3.2.1.2 Yield models

Yields for conventional crops are estimated using a method based on the Miami model (Lieth, 1975), with yields adjusted linearly according to observed peak yields for each crop type (Living Countryside, 2013). Yields for SRF, SRC and *Miscanthus* are input to ECOSSE using simulated yields obtained by the models ESC-CARBINE (Pyatt et al., 2001; Thompson and Matthews, 1989), ForestGrowth-SRC (Tallis et al., 2013) and MiscanFor (Hastings et al., 2009) respectively; these yields are all obtained using the same soil and climate data as ECOSSE. The results from these yield models are also present in the look-up table.

3.2.1.3 Meta-model

Results from ECOSSE are stored in a look-up table within the ELUM software package, which are processed according to user inputs; this combination of look-up table and processing is referred to as the 'meta-model', and ECOSSE is referred to as the 'underlying model'. The meta-model is used instead of the ECOSSE model in order to simplify operation and to decrease computing time significantly.

The majority of results from the meta-model are directly obtained from the ECOSSE model look-up table, subject to processing to convert units and apply masks. However, results for non-default fertiliser and yield improvement options are adjusted by equations obtained by statistical regression of ECOSSE; this is necessary because the look-up table would be too large if all ECOSSE results were stored for all the possible options.

Benefits of the look-up table approach for the meta-model:

- Results are as reliable as possible, since results from the underlying model are directly reported (except for non-default fertiliser and yield improvement)
- Comparatively fast to use
- Future modifications are relatively straightforward, since results for different transitions, climates and regions, for example, can be obtained from the underlying model and used to create a new look-up table, without further modelling work to approximate the results of the underlying model

Limitations of the meta-model:

- The data storage space for the meta-model is comparatively large
- Results are restricted to those considered by the underlying model (although use of regression equations for non-default options works around this)

3.2.1.4 Regression equations

Results for non-default fertiliser and yield improvements are not stored in the look-up table for reasons of storage space. In order to obtain results for different fertiliser and yield improvement options, results in the look-up table are adjusted by equations obtained by statistical regression of ECOSSE results for different fertiliser and yield values. A statistical analysis of a random spatial sample of ECOSSE results in the UK was obtained for a range of fertiliser and yield changes. These were used to obtain a relationship between the percentage change in the independent variables and the resultant percentage change in each emission.

3.2.2 Look-up table

3.2.2.1 Description

Results from ECOSSE are stored in the look-up table for each:

- Grid cell
- Time step
- Climate projection
- Output variable (e.g. Soil C)

Results are stored as t CO_2e /ha values; in order to calculate t CO_2e /odt values, the oven dry yields for each crop are also stored in the look up table, for each:

- Grid cell
- Time step
- Climate projection

Yields are stored as odt/ha values; hence emission values in the look-up table are divided by yield values in the look-up table to obtain t CO_2e /odt values.

Data in the look-up table can easily be opened in a GIS. Results are cumulative up to each time point; to obtain average values for any time period, simply subtract the value at the start of the time period from the value at the end of the time period, and divide by the length of the time period.

3.2.2.2 Directory structure

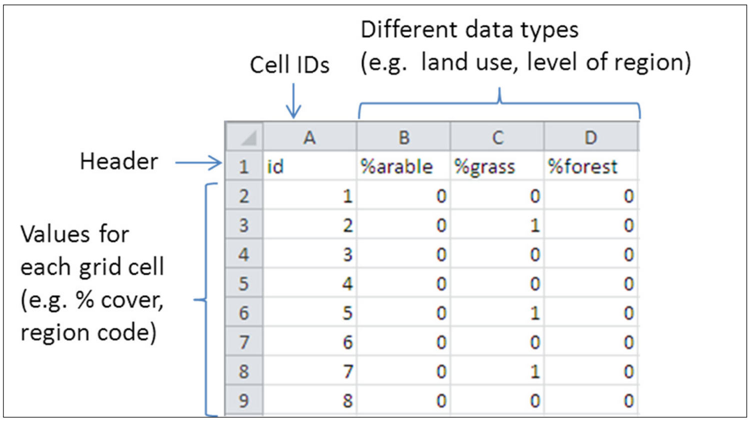
The look-up table is divided into several files and subfolders for convenience. The structure is similar to the ELUM results folder layout, including the use of a single grid file and separate files for each variable. Differences include the presence of separate folders for different climate projections, as well as separate yield folders.

The directory structure of the look-up table is:

- Grid (grid.csv)
- Land-cover (lcm.csv)
- Constraints mask (cons.csv)
- Regions map (reg.csv)
- ID raster (id.txt)
- 🗀 Low climate change (low)
    - 🗀 Yields (yield)
        - Wheat (LUe1.csv)
        - Sugar beet (LUe2.csv)
        - OSR (LUe3.csv)
        - SRC (LUe4.csv)
        - SRF (LUe5.csv)
        - Miscanthus (LUe6.csv)
    - 🗀 From arable (LUs1)
        - 🗀 To wheat (LUe1)
            - GHG (var1.csv)
            - CO_2 (var2.csv)
            - CH_4 (var3.csv)
            - N_2O (var4.csv)
            - Soil C (var5.csv)
        - 🗀 To Sugar beet (LUe2)
            - …
    - 🗀 From grass (LUs2)
        - 🗀 …
    - 🗀 …
- 🗀 Medium climate change (med)
    - 🗀 …
- 🗀 …

3.2.2.3 File formats

The format of the grid file and result file for each variable (or yield) is the same as for ELUM results. Masks for land-cover, constraints and boundaries all follow a similar layout (see Figure 3.26).



	A	B	C	D
1	id	%arable	%grass	%forest
2	1	0	0	0
3	2	0	1	0
4	3	0	0	0
5	4	0	0	0
6	5	0	1	0
7	6	0	0	0
8	7	0	1	0
9	8	0	0	0

Figure 3.26: Example of the mask file

3.2.3 Masks

3.2.3.1 Existing land-cover

If the existing land-cover mask is applied, then per-hectare results in each grid cell are rescaled according to the fractional area of each existing land-cover. For example, for transitions from grass, results are adjusted for each grid cell to reflect the amount of grassland available. This gives the effective emissions per unit area for the whole grid cell. Total values in the time series results therefore represent expected values of all available land if any given type were converted.

If users remove the land-cover mask, t CO_2e /ha values apply only to land which is converted (so values are unaffected by the available land area), but summed values assume whole grid cells are used, and therefore overstate actual totals.

Users can apply their own land-cover masks by post-processing outputs in a GIS. Any land-cover mask can be applied, but users are responsible for applying appropriate masks (i.e. applying masks which represent the initial land-uses assumed in the results).

3.2.3.2 Constraints

Results are excluded for grid cells which contain inappropriate land for growing bioenergy crops, based on data from UKERC.

For Great Britain (GB), the constraints are:

Exclusions	**UKERC 7w**	**UKERC 7**	**UKERC 9w**	**UKERC 9**
Slope ≥ 15%	●	●	●	●
Peat (soil C ≥ 30%)	●	●	●	●
Designated areas	●	●	●	●
Urban areas, roads, rivers	●	●	●	●
Parks	●	●	●	●
Scheduled Monuments/World Heritage Sites	●	●	●	●
Woodland (except transitions to SRF)	●	●	●	●
Woodland (all transitions)		●		●
Naturalness score ≥ 75%			●	●
Naturalness score ≥ 65% inside national parks/areas of outstanding natural beauty			●	●

For Northern Ireland (NI), only grid cells which contain peat are excluded due to lack of data coverage for further constraints. Peat is defined for NI as grid cells with a dominant soil which contains at least 30% soil C in the top 30 cm layer.

The UKERC 7w constraints are the lowest level of mask permitted; this mask is implicit to results in the look-up table and cannot be removed. This prevents results being obtained for land conversion which is not only inappropriate, but also not sufficiently well-studied to be properly modelled (this is why use of woodland is permitted in UKERC 7w and UKERC 9w exclusion masks for SRF, but is excluded for SRC). For all crops other than SRF, use of UKERC 7w and UKERC 9w exclusion masks is automatically changed to 7 and 9 respectively.

3.2.4 Uncertainty

Uncertainty in national scale simulations has two components, uncertainty due to errors in the model and uncertainty due to the reduced detail and precision in data available at national scale.

Firstly, at national scale the uncertainty in simulations is likely to be greater than at field scale due to the reduced detail of the inputs. For example in croplands, detailed management factors such as sowing date and timing of fertiliser applications cannot usually be specified when the resolution of the simulations is larger than the size of the management unit.

Uncertainty in national scale simulations is also greater than at field scale due to the reduced precision of the input data. For example, the C content of the soil in a 5 ha field can be precisely measured and the error in the measurement defined using replicates, whereas at the national scale the soil C content for grid cells is estimated from typical or averaged soil C values for the major soil types identified in the cell (e.g. Batjes 2009). Additional uncertainty may arise from unrecorded land use. Further uncertainty is introduced by large grid cell sizes and predicted meteorological data.

The following graphs show the effect of the variation of yield and fertiliser applications on N_2O emissions and soil C at 0-100 cm soil depth.

The results are based on the average amount of change over all sensitivity sites. The graphs presented are based on medium climate results, since the patterns with either low or high climate scenarios simply following the same patterns.

Figure 3.27 shows the effect of different fertiliser applications on total N_2O fluxes after conversion from arable after a period of 35 years. The results show that changing fertiliser levels has a low impact on the N_2O fluxes following LUC to *Miscanthus* and a higher impact following LUC to SRF.

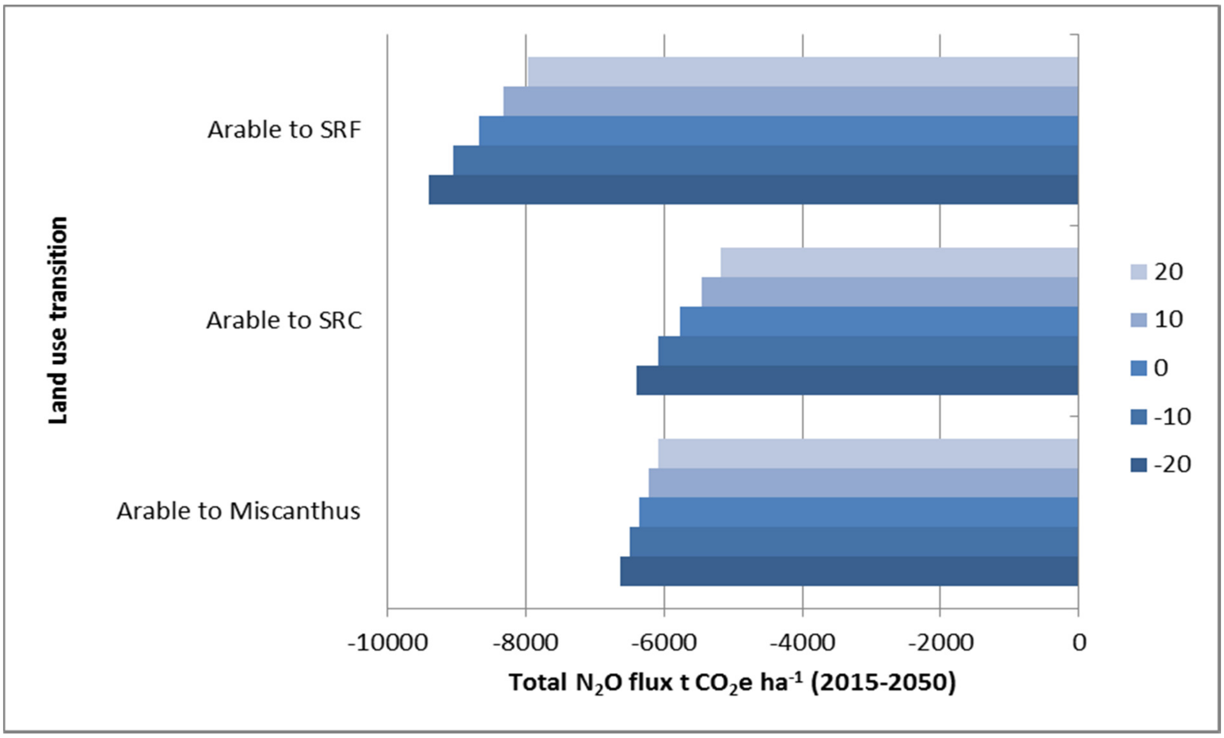


Figure 3.27: Total N_2O flux between 2015 and 2050 for land-use transitions from arable to SRF, SRC and *Miscanthus* for five fertiliser levels.

Figure 3.28 shows the effect of different fertiliser applications on total N_2O fluxes after conversion from forest and over a period of 35 years. The results show that the land-use change to *Miscanthus* and to Oil Seed Rape show a relatively small sensitivity of the N_2O fluxes to changes in fertiliser levels. The N_2O fluxes arising after conversion to arable (wheat) show the highest sensitivity to fertiliser applications.

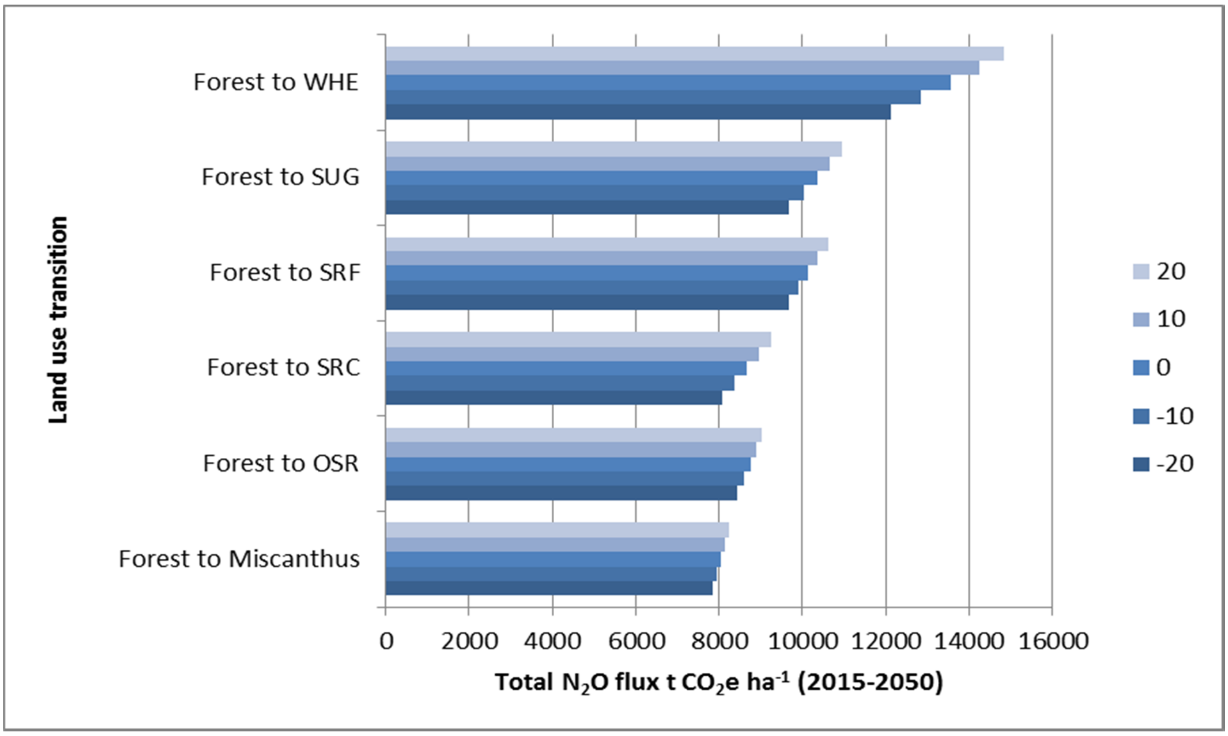


Figure 3.28: Total N_2O fluxes between 2015 and 2050 for five fertiliser levels and land-use transitions from forest to Wheat (WHE), Sugar Beet (SUG), SRF, SRC, Oils Seed Rape (OSR) and *Miscanthus*.

Figure 3.29 shows the effect of different fertiliser applications on total N_2O fluxes after conversion from grass and over a period of 35 years. As previously reported, the total N_2O flux is lower under *Miscanthus* and higher under wheat, with the N_2O flux under *Miscanthus* almost three times lower than under an arable crop. Also, the sensitivity of N_2O to different fertiliser levels is higher under wheat compared to *Miscanthus*. The remaining transitions again lie between the extremes and follow the same patterns.

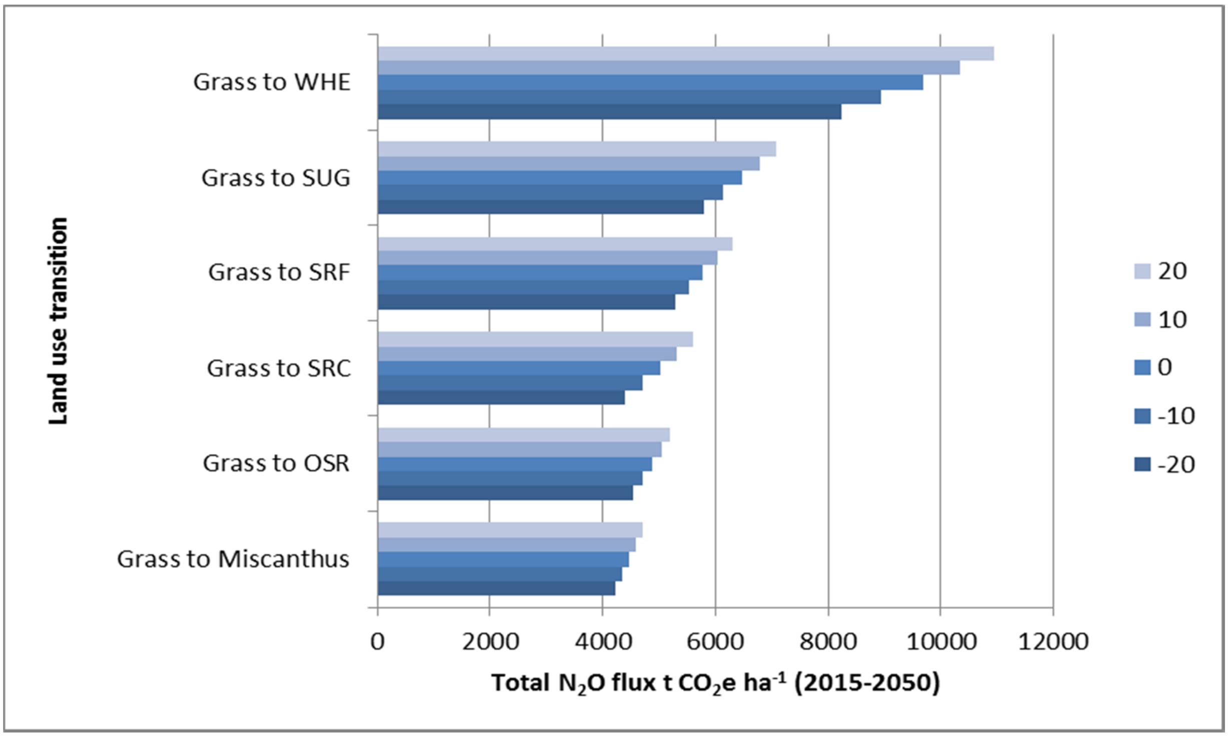


Figure 3.29: Total N_2O fluxes between 2015 and 2050 for five fertiliser levels and land use transition from grassland to Wheat (WHE), Sugar Beet (SUG), SRF, SRC, Oils Seed Rape (OSR) and *Miscanthus*.

Figures 3.30-3.32 show the change in SOC 35 years after conversion to bioenergy crops. Overall an increase of yield of 20% and 50% from the baseline values lead to a significant increase in SOC. This is particularly evident for transition to SRF and *Miscanthus*, whereas there is very little change in SOC after an increase of yield in the transitions to sugar beet (SUG) and OSR.

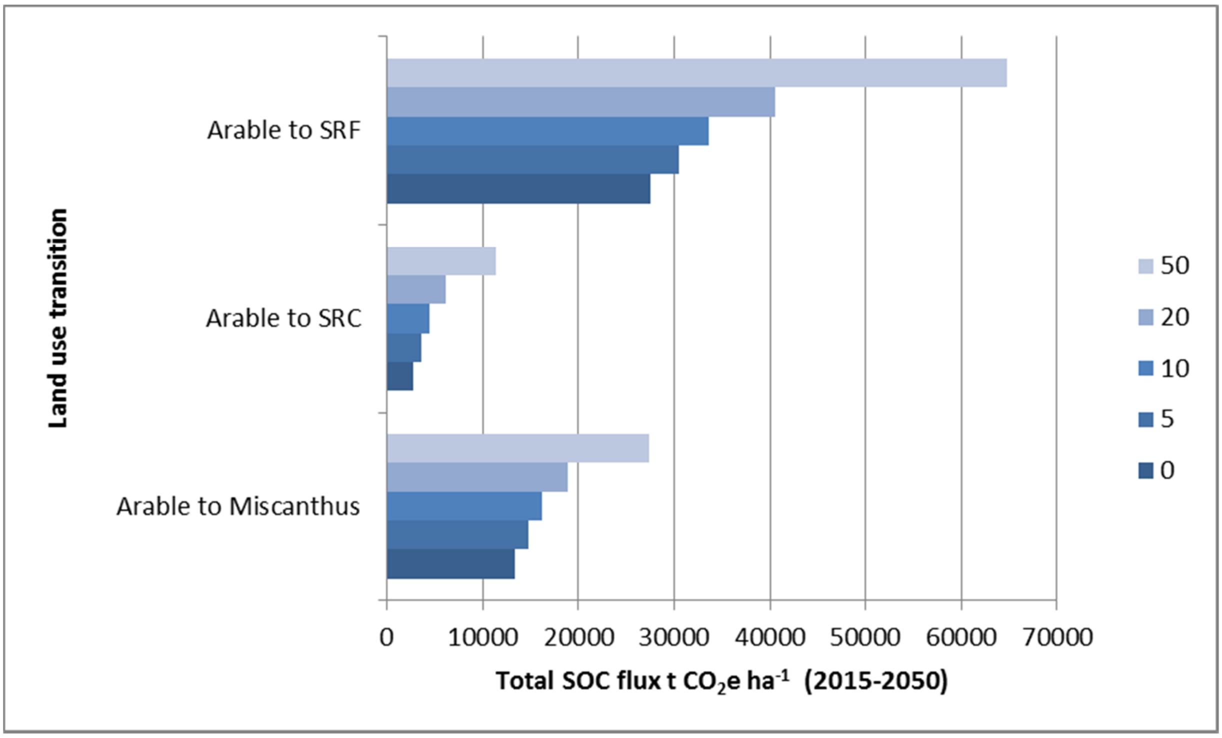


Figure 3.30: Total soil C between 2015 and 2050 for five yield levels and land-use transitions from arable to SRF, SRC and *Miscanthus*.

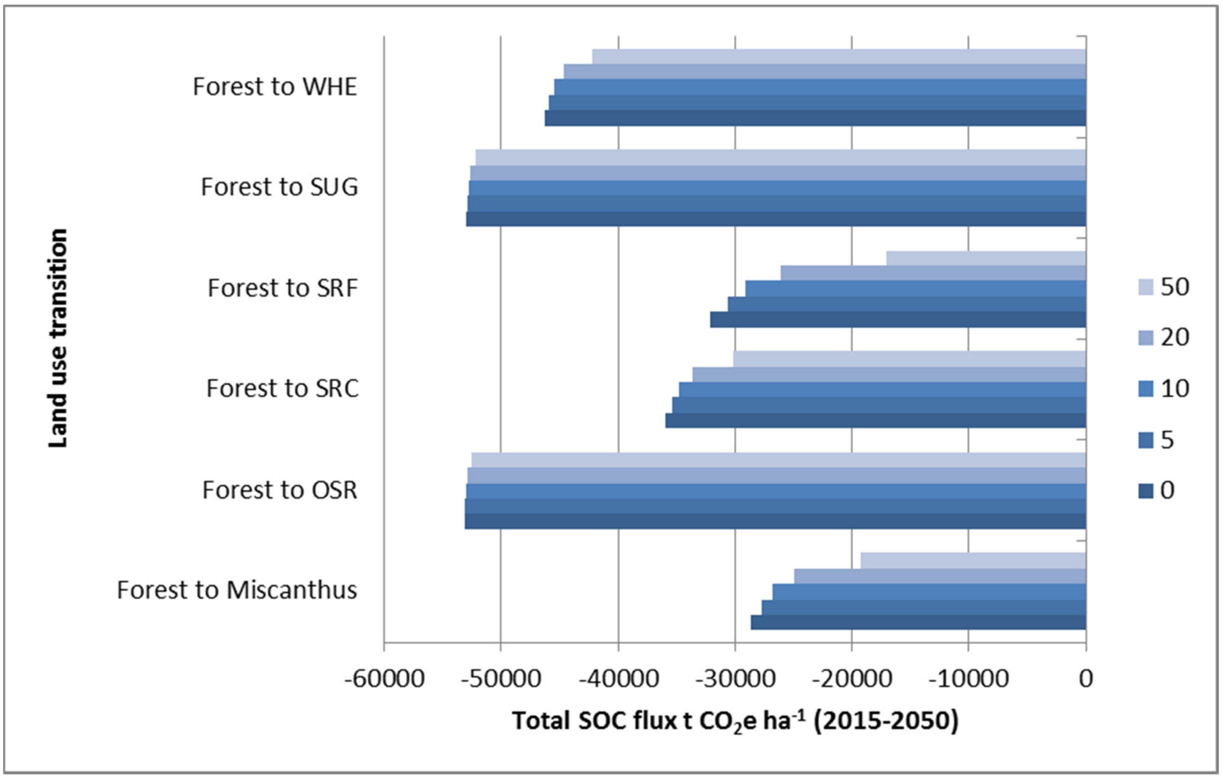


Figure 3.31: Total soil C between 2015 and 2050 for five yield levels and land-use transitions from forest to Wheat (WHE), Sugar Beet (SUG), SRF, SRC, Oil Seed Rape (OSR) and *Miscanthus*.

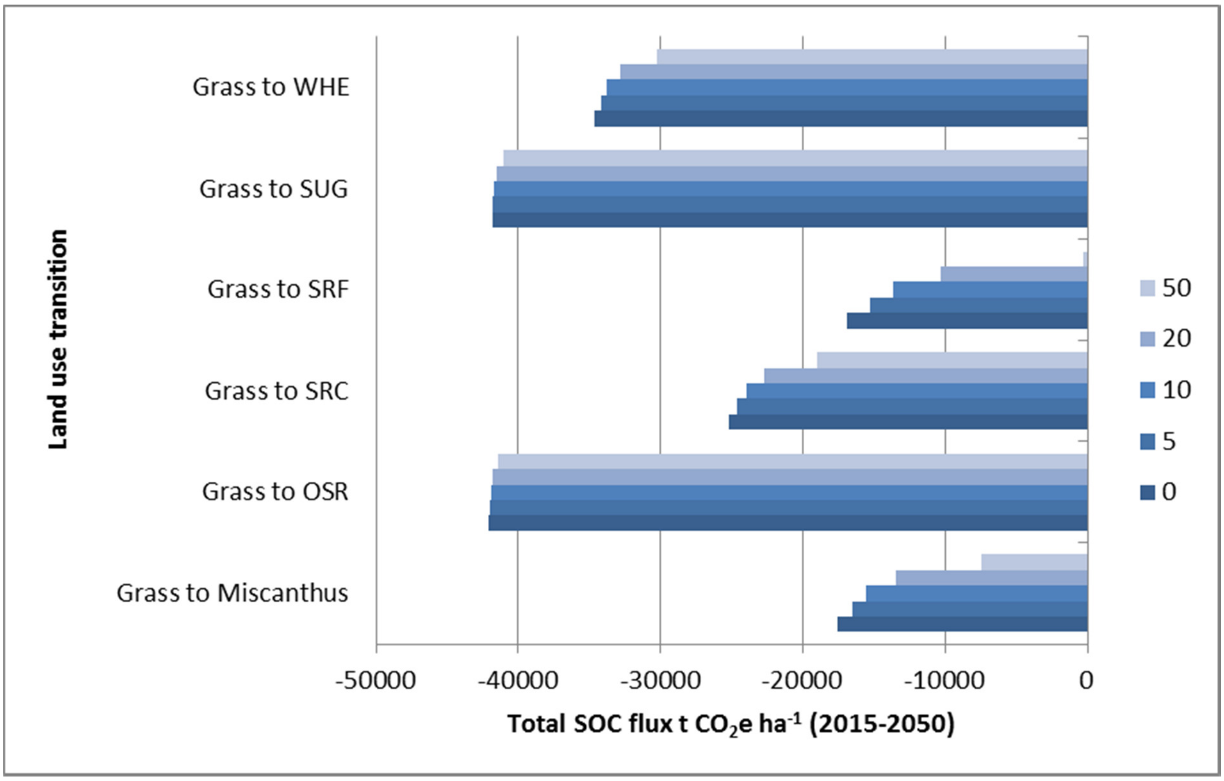


Figure 3.32: Total soil C between 2015 and 2050 for five yield levels and land-use transitions from grassland to Wheat (WHE), Sugar Beet (SUG), SRF, SRC, Oil Seed Rape (OSR) and *Miscanthus*.

3.3 Data

3.3.1 Global Warming Potentials

Values from IPCC inventory 100-year global warming potentials (IPCC, 2001).

ELUM emission	ECOSSE output	Molecular to atomic mass ratio	IPCC Factor to obtain CO_2 equivalent
CO_2	C	11/3	1
CH_4	C	4/3	23
N_2O	N	11/7	296
Soil C	C	11/3	1

3.3.2 Soil data

Soil data from the Harmonized World Soil Database (HWSD) version 1.2 (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012) were used as inputs to the ECOSSE model to obtain the results in the look-up table.

Separate data for the top- and sub-soil (0-30 cm and 30-100 cm respectively) were used for:

- Soil C
- Sand, silt and clay percentages
- Bulk density
- pH

HWSD data is on a 30 arc-second grid. Data for the UK was extracted using ArcMap and exported as Ascii grid files. These were aligned to a 1 km grid, with coordinates projected from longitude-latitude to the British/Irish National Grid by methods described by Ordnance Survey.

3.3.3 Meteorological data

Meteorological data were obtained from UKCP09 spatially coherent projections and used as inputs to the ECOSSE model to obtain the results in the look-up table. The 25 km rotated-pole grid (based on longitude-latitude) was aligned to the same 1 km grid as the soil data, with coordinates projected to the British/Irish National Grid by methods described by Ordnance Survey. Results for unperturbed scenarios were used (scenario 1 of the HADCM3 model).

UKCP09 data are provided for the central decade of a moving 30-year average (e.g. 2040s data represent the mean predicted climate for 2030-2050). Data are provided from the 2020s (i.e. no data for the 2010s decade are given). In order to obtain results from 2015, the 2020s data were used in the model for 2015-2030; for each subsequent decade, the model used the corresponding data for the decade. This method was used instead of obtaining alternative climate data for the 2010s in order to avoid any artificial sudden change in climate at 2020. For similar reasons, climate data for the 2020s was also used to spin-up the ECOSSE model to equilibrium prior to the land-use transition.

3.3.4 Land-cover data

Land-cover categories were taken from CEH LCM2007 on a 1 km grid.

ELUM category	Corresponding CEH categories
Arable	Arable and Horticulture
Grass	Improved Grassland
Forest	Forest

3.3.5 Boundary data

Shapefiles were obtained from OS OpenData Boundary-Line GB. These shapefiles were processed in ArcMap to provide a 1 km raster for each level of region.

ELUM category	Corresponding OS Boundary-Line shapefile layer
Countries	Inferred from European Region layer
Regions	European Region layer
Counties	Obtained from data within District Borough Unitary Region layer
Districts	District Borough Unitary Region layer

3.3.6 Constraints data

Data were obtained from UKERC for GB (Lovett et al., 2014). Data were converted from a 100 m grid to a 1 km grid using ArcGIS; the binary value of each 1 km cell was determined according to the mode of the binary 100 m grid cells it contained. The woodland category was separated from the rest of the constraints in order to permit simulation of conversion of woodland to SRF. Due to lack of data coverage for NI, constraints were based on soil C using HWSD soil data.

ELUM category	Corresponding UKERC category
UKERC 7w	Constraints 7b, but with woodland permitted for SRF
UKERC 7	Constraints 7b
UKERC 9w	Constraints 9b, but with woodland permitted for SRF
UKERC 9	Constraints 9b

4. DISCUSSION

4.1 Site-specific Modelling

The simulations of soil C after land-use change to Willow and *Miscanthus* show that the model accurately predicts the soil C under bioenergy crops (Figure 3.2-3.5). The statistics of the soil C at both 0-30 cm and 0-100 cm soil depths highlight the absence of significant error between simulated and measured values as well as the absence of significant bias in the model. As for the bioenergy fields, the soil C at the reference fields 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.

The modelled change in soil C after conversion to Willow and *Miscanthus*, correlates well with the measured change in soil C at both 0-30 cm and 0-100 cm soil depths (Figure 3.7-3.9). On average, at both soil depths, the land-use change from arable seems to increase the C in the soil, whereas the conversion from grassland has the opposite effect.

A further test on the model performance to simulate soil C has been carried out comparing the modelled soil C at 9 soil depths against soil C measurements.

Despite the good statistical correlation between the overall modelled and measured soil C, we found a lower coincidence between modelled and measured values under *Miscanthus* and Willow at the top 30 cm soil depths (Figure 3.11, 3.12). At site 28, representing a transition from grassland to *Miscanthus*, the modelled soil C in the top three layers (0-30 cm soil depth) was higher than the measured values (Figure 3.11). One possible reason for the discrepancy between measured and modelled soil C could be attributed to the very high C content measured at the reference grassland site. In fact, at 0-30 cm depths, the measured C content was 104.7 t C ha^{-1}, a very high value compared to other grassland sites sampled for this project. The C content measured at the reference site has been used to start the simulation of the transition, assuming that the site was in equilibrium condition at the time of sampling (year 2013), leading to a depletion in C content lower than the measured values.

Whereas at site 35, a transition from grassland to Willow, the model underestimated the soil C at 0-10 cm and 10-20 cm soil layers compared to the measured values (Figure 3.12). For this site we don't have specific information about the average yearly yields of the crops; therefore a low estimation of the plant input to the soil throughout the simulation period could have led an underestimate of the soil C at the top soil layers.

Overall, the modelling work carried out for this project confirmed a good association of the modelled and measured soil C at 1m depth. All together, these results confirm the good performance of the ECOSSE model in simulating soil C for different vegetation types (i.e. arable, grassland, Willow and *Miscanthus*) and using different data sources as input to the model.

The improvements made to the ECOSSE model result in more accurate simulations of the soil CO_2 fluxes under bioenergy crops (*Miscanthus*, Willow and SRF) as well as conventional crops.

Soil CO_2 emissions under *Miscanthus* have been quantified at two sites (Lincolnshire and Aberystwyth) using three different sampling methods. No model bias and no significant error between measured and modelled values have been found at both sites and for all sampling methods; at both sites, we also found a high correlation between measured and modelled sites, except for the IRGA values at Lincolnshire site. The lack of correlation at this site is mainly due to difference between modelled and IRGA measurements in the year 2013. In April 2013 the soil was harrowed to break up the rhizomes for improved yield, so the system was out of balance; the farmer also applied waste wood product, which leads to high CO_2 emissions undetected by the model (May-August 2013 in Figure 3.14).

Soil CO_2 emissions under Willow and SRF plantation have also been quantified using three different sampling methods. At all sites the model simulations correlates well with all types of measurements, showing no error between measured and modelled values as well as no bias in the model. This is a remarkable result which underlines the good quality of the data provided for the model evaluation and validation, as well as the good model performance to simulate soil CO_2 fluxes from Willow and SRF.

The model has also been tested against CO_2 fluxes measured under conventional crops. At two of the grassland sites (West Sussex and East Grange), the measured CO_2 fluxes correlate well with the modelled values and the statistical analysis shows no error between measured and modelled values, as well no bias in the model. However, at the Aberystwyth site we found a model bias which could be explained by the high amount of leaves enclosed in the chambers used for collecting the flux samples. Even if the estimate of the heterotrophic respiration under grassland accounts for the plant respiration, we believe that the method of estimating heterotrophic CO_2 from IRGA at this site is inadequate but the model is still simulating the soil processes accurately.

The analysis of the soil CO_2 fluxes from the arable fields reveals good model performances at both the Lincolnshire and East Grange sites. At the latter site no correlation between modelled and measured IRGA values was found. Once again, this is mainly due to the type of source data (single data point to represent monthly CO_2 fluxes); another explanation could also be the discontinuity of the IRGA measurements taken at this site (see Figure 3.19). The latter hypothesis is strengthened by the CO_2 results of the arable field at the Lincolnshire site. In fact, the IRGA measurements at the Lincolnshire site have been taken over a 2-year period and the statistical analysis shows a good correlation against the model output. Therefore, we conclude that the low correlation at the East Grange arable field is due to the quality and quantity of the measurements and that the model accurately describes the CO_2 emissions from the arable crop.

Low correlations between measurements and model simulations arose just when comparing model outputs against the IRGA dataset; this is mainly due to the nature of the measurements (single data point representing total monthly CO_2 flux), an aspect not related to the soil processes described in the model. In fact, if continuous flux measurements or direct measurements of heterotrophic respiration are compared against the model outputs, the model accurately simulates soil CO_2 fluxes. We therefore conclude that given the very limited input data used to run the model, the simulations are remarkably robust. Moreover, the overall results arising from the interaction between measurements and modelling suggest using continuous measurements on soil heterotrophic respiration (like automatic chambers installed on root-exclusion plots) for model validation.

The developments made to the model improved the simulations of the N_2O and CH_4 fluxes, resulting in no significant model bias. However, at all sites, the correlation coefficient between simulated and measured values of N_2O and CH_4 fluxes is low. We expected such low correlation as a result of the nature of the measurements and it doesn't represent a failure of the model. In fact, the measured N_2O and CH_4 fluxes are pooled from sample point data containing outliers and extreme variation between sample points in each site, which results in a high standard error of the measured values. But the N_2O and CH_4 flux simulations are within the 95% confidence interval of the measured values, suggesting that the lack of correlation between modelled and measured values is mainly due to the high variation in the measured fluxes, so the model should not be changed as a result of these measurements. It is also important to highlight that the N_2O and CH_4 fluxes are very small fluxes and represent an extremely small portion of the total GHG balance (as reported in deliverable report D3.3).

The work presented in the current report reinforces previous studies on the ability of ECOSSE to simulate soil C and test its accuracy to simulate changes in soil C and GHG fluxes after land-use change to bioenergy crops. The validation of this process-based model is robust and reinforces the accuracy of the spatial simulation for the all UK.

4.1 Model uncertainty

HWSD data have been tested here as they are used in the spatial ECOSSE simulations as the basis of results used in the meta-model. In the spatial simulations, ECOSSE simulates all soil types (up to a maximum of 5) in each grid cell. We replicate this method here for the year 2 chronosequence sites. Due to the nature of the HWSD data, where the locations of soils within each grid cell are unknown, it is not possible to define which HWSD soil type corresponds to a given field site, or whether the soil type of the field site is within the dominant soils reported in the dataset. However, the statistical analysis shows a high correlation between modelled and measured soil C ($R = 0.79$, Table 3.10) and no significant error between measured and modelled values, which suggests a good match between the HWSD and field soils. We therefore conclude that the HWSD dataset provides a reliable source of soil input to run the model spatially for the UK.

The result of the *local* sensitivity analysis on soil texture indicated that there is no variation in the soil C outputs when using site texture inputs instead of data extracted from a large spatial dataset, as the “Falloon” soil database (Figure 3.21). However, we found a variation in the distribution of the soil C in the soil pools, in particular in the resistant plant material pool (RPM) and the humus pool (HUM). In the model, the clay content is used to determine the efficiency of decomposition, influencing the decomposition rate and the C distribution in the soil pools. High clay content will result in a lower C content in the RPM (slow turnover) and a higher C content in the HUM (fast turnover). In the long-term this will cause a decrease of the total soil C content.

A large number of factors affect the amount of nitrogen fertiliser applied to a crop including the soil nitrogen status, expected crop N demand, weather, soil texture, regulations (e.g. in Nitrogen Vulnerable Zones) and economic factors (e.g. cost of fertiliser).

To quantify this uncertainty we conducted a sensitivity analysis to explore the impacts of a +/- 20% variation to the default N fertiliser application rate in a sample of the grid cells. Transitions to wheat were most sensitive to a proportional change in N fertiliser inputs: a 20% increase in N fertiliser led to a mean increase in N_2O emissions of about 5 t CO_2e ha^{-1} after 35 years (i.e. in 2050); and a 20% decrease reduced N_2O emissions by about 5.5 t CO_2e ha^{-1}. Other transitions showed mean deviations in N_2O emissions within +/- 2.5 t CO_2e ha^{-1}. The results of this analysis show that overall the change in fertiliser level has a small impact on the modelled N_2O emissions. Therefore we do not expect uncertainty around N fertilisation rates to be a source of large uncertainty in the modelling outcomes.

Climate variability and changes in the frequency and severity of extreme events can have significant, non-linear impacts on crop yields because crops exhibit threshold responses to stress factors (Porter and Semenov, 2005; Trnka et al, 2014). Therefore, the lack of short-term climate variation in the UKCP09 climate projections presents a potentially large source of uncertainty in the predicted yields and, subsequently, the bioenergy GWPs. Further uncertainty arises because the crop yield projections are derived from several different sources which vary in spatial resolution, and, in the case of modelled values, the level of sophistication of the model.

The sensitivity of mean change in SOC to increases in yield is greatest for SRF, *Miscanthus* and SRC, while wheat, sugar beet and OSR are much less sensitive. This pattern arises because SRF, *Miscanthus* and SRC are the highest yielding bioenergy crops, so a proportional increase in their yield equates to a larger absolute increase compared to the same proportional increase applied to a lower yielding crop. This, combined with yield being the most influential driver of change in SOC (see section 3.1 in deliverable report D4.6), is responsible for the observed sensitivity. In general, increases in yield of 50% are insufficient to alter the qualitative impact of land-use transitions from grass and forest to bioenergy crops on SOC, with the exception of grass to SRF. Here, a 50% increase in SRF yield is sufficient to transform a negative change in mean SOC to approximately no change in mean SOC.

Although changes in estimated yields would certainly affect the total area of land favourable for conversion to bioenergy crops, the findings of the uncertainty on yield suggest that the broad conclusions inferred from the modelling results would remain the same.

Insufficient data exist to identify spatial variation in model uncertainty. Uncertainty is therefore assumed uniform, and calculated from comparison of model results against field measurements. This provides the following guide for uncertainties, as a 95% confidence interval:

Wheat, sugar beet, OSR

Output	Uncertainty (t CO_2e /ha)
CO_2	0.5
CH_4	0.5
N_2O	0.3
Soil C	0.5
Net GHG	0.9

SRC

Output	Uncertainty (t CO_2e /ha)
CO_2	0.8
CH_4	0.3
N_2O	0.3
Soil C	0.8
Net GHG	1.2

SRF

Output	Uncertainty (t CO_2e /ha)
CO_2	0.5
CH_4	0.2
N_2O	0.3
Soil C	0.5
Net GHG	0.8

Miscanthus

Output	Uncertainty (t CO_2e /ha)
CO_2	0.8
CH_4	0.3
N_2O	1.5
Soil C	0.8
Net GHG	1.7

Even though this is the most reliable method to estimate spatial uncertainty, it does leave room for potential error. Due to the reduced detail of the inputs, the uncertainty in simulations at the national scale is likely to be greater than at the field scale. One way to improve the uncertainties around the modelled spatial results would be to adapt a C accounting method developed by the Intergovernmental Panel on Climate Change (IPCC) and work with a number of probability density functions in order to get a quantitative estimate of temporal uncertainty (Ogle et al., 2003).

4.2 Meta-model

This WP4 report provides detailed description of meta-model methodology, design, assumptions and limitations. Spatial results for the meta-model are presented in the ELUM deliverable report D4.6 (PM07.4.6_WP4_Effects on LUC into Bioenergy v1.0).

The meta-model has been formulated by use of a look-up table. This provides a quick and accurate method of obtaining results directly from the ECOSSE model, without any additional uncertainty. For non-standard fertiliser and yield improvements, the meta-model applies an equation to adjust results, based on linear regression of a sample of ECOSSE results.

The meta-model is accessed from a graphical user interface (GUI) which allows users to readily select from a number of options, apply a number of spatial masks, run the model and view results. A software package has been built around the meta-model, which performs a range of analyses of the results, including summations of emissions and comparisons of different transitions.

5. KEY FINDINGS

The conclusions and lessons learned arising from the WP4 work are summarised below, with references to the main body of the report:

- This review identifies that the ECOSSE model is extremely accurate to predict soil C after land-use change (LUC) from arable/grassland to Willow (R = 0.90), *Miscanthus* (R = 0.93) and short-rotation forest (R = 0.87; PM06.4.2), to a soil depth of 1 metre. (Section 3.1, p27).
- Soil CO_2 emissions from bioenergy and conventional crops have been measured using three different techniques, all showing a good correlation with the modelled values, with an averaged correlation coefficient of 0.6 across sites and measurement types (n = 22). Continuous measurements on root-exclusion plots appear to be the most comprehensive dataset to test model performance in simulating soil CO_2 fluxes. (Section 3.1, p27).
- The ECOSSE model is also capable of simulating small GHG fluxes such as N_2O and CH_4 fluxes under conventional and bioenergy crops. High variability in the measured non-CO_2 fluxes led to a low correlation between measured and modelled values (correlation coefficient for N_2O and CH_4 fluxes range between 0.05 - 0.61 and 0.18 - 0.53, respectively) but the model outputs were within experimental error, resulting in no error in the description of the simulated processes. (Section 3.1, p27).
- The design for the meta-model is outlined. It is primarily a look-up table, in order to provide the most accurate results possible. In fact, the benefits of the look-up table approach for the meta-model are that the results of the ECOSSE model are directly reported in the look-up table, it is comparatively fast to use and that future modifications are relatively straightforward, since results for different transitions, climates and regions, for example, can be obtained from the ECOSSE model and used to create a new look-up table, without further modelling work to approximate the results of the ECOSSE model. The only limitations of the look-up table approach are that the data storage space for the meta-model is comparatively large and the results are restricted to those considered by the model (Section 3.2, p58).
- A sensitivity analysis of the spatial results was carried out to determine the effects of variations in bioenergy crop yield and nitrogen fertiliser application rates on the output variables. In general, increases in yield of 50% are insufficient to alter the qualitative impact of land-use transitions from grassland and forest to bioenergy crops on soil C, with the exception of grassland to SRF (Section 3.2 p64).
- The uncertainties around the use of a large soil database for spatial simulations have been quantified and found to be minimal (R = 0.79); we therefore concluded that the harmonized world soil database (HWSD), used for the spatial simulations, provides a reliable source of soil input to run the model for the whole UK (Section 4.1, p73).
- Insufficient data exist to identify spatial variation in model uncertainty. Uncertainty is therefore assumed uniform, calculated from comparison of model results against field measurements (ranging between 0.3 and 1.7 t CO_2e / ha) and reported in the ELUM software package as error bars in the time series (Section 4.1, p73).

Acknowledgements

Thanks to Ed Jones and Astley Hastings (University of Aberdeen) for developments to the ECOSSE model and for providing modelled crop yield data.

The International Institute for Applied Systems Analysis for the use of the Harmonized World Soil Database during the course of this work (HWSD; FAO, IIASA, ISRIC, ISSCAS and JRC, 2009).

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APPENDIX I – CHRONOSEQUENCE SITES ANCILLARY DATA

	Temperature (degC)																		
Site Code	**1,2**	**3,4,5**	**6,7**	**8**	**9,10**	**11**	**12**	**13**	**14**	**15**	**16**	**17,18**	**19**	**20,21,22**	**23**	**24**	**25**	**26**	**27,28**
January	3.9	4.0	2.3	5.0	4.2	3.5	3.5	4.0	4.1	4.0	4.4	4.2	4.1	4.0	3.4	3.9	5.0	4.7	5.0
February	4.2	4.2	2.6	4.9	4.3	3.9	3.9	4.2	4.2	4.2	4.5	4.3	4.2	4.1	3.2	3.9	5.0	4.7	5.0
March	6.1	6.3	4.1	6.7	6.4	5.7	5.7	6.3	6.2	6.2	6.5	6.3	6.2	6.0	4.7	5.4	6.7	6.3	6.6
April	8.2	8.3	6.3	8.8	8.5	7.7	7.7	8.3	8.1	8.3	8.6	8.4	8.3	8.1	6.5	7.3	8.6	8.1	8.5
May	11.2	11.4	9.4	12.1	11.8	10.7	10.7	11.4	11.3	11.6	11.8	11.7	11.6	11.3	9.5	10.3	11.8	11.4	11.6
June	14.1	14.4	12.0	14.9	14.8	13.5	13.5	14.4	14.2	14.6	14.8	14.6	14.5	14.1	12.0	12.6	14.6	14.2	14.4
July	16.3	16.5	14.0	17.0	17.0	15.7	15.7	16.6	16.4	16.8	17.1	16.8	16.8	16.4	13.9	14.6	16.7	16.3	16.5
August	16.2	16.4	13.6	17.0	16.9	15.6	15.6	16.5	16.5	16.7	16.9	16.6	16.6	16.1	13.8	14.4	16.6	16.2	16.4
September	13.8	14.0	11.3	14.8	14.3	13.3	13.3	14.1	14.3	14.1	14.3	14.1	14.0	13.7	11.9	12.6	14.3	13.9	14.2
October	10.4	10.5	8.3	11.7	10.7	10.0	10.0	10.6	10.8	10.6	10.8	10.7	10.5	10.3	9.1	9.7	11.2	10.9	11.1
November	6.7	6.7	5.0	8.0	6.9	6.3	6.3	6.8	7.0	6.8	7.1	7.0	6.9	6.7	6.1	6.6	7.7	7.4	7.7
December	4.4	4.5	2.8	5.7	4.7	4.1	4.1	4.5	4.7	4.5	4.9	4.7	4.6	4.5	4.0	4.4	5.5	5.3	5.6

Table A1: Long-term monthly temperature

Table A1 continued

	Temperature (degC)									
Site Code	**29**	**30,31**	**32,33**	**34**	**35**	**37**	**38**	**39**	**40**	**41**
January	5.6	6.3	3.0	3.3	5.9	3.2	3.9	3.9	3.9	4.1
February	5.4	6.1	3.4	3.7	5.7	3.6	4.0	4.0	4.1	4.4
March	6.6	7.3	5.1	5.3	6.9	5.3	6.0	6.0	6.2	6.5
April	8.0	8.8	7.2	7.4	8.5	7.4	8.1	8.1	8.3	8.6
May	10.8	11.6	10.0	10.2	11.2	10.4	11.3	11.3	11.5	11.6
June	13.4	14.1	12.8	12.9	13.6	13.0	14.1	14.1	14.4	14.5
July	15.4	16.0	14.6	14.7	15.5	15.0	16.2	16.2	16.6	16.8
August	15.5	16.2	14.4	14.6	15.7	14.6	16.0	16.0	16.6	16.6
September	13.7	14.4	12.0	12.3	14.1	12.3	13.6	13.6	14.1	14.2
October	11.1	11.8	8.9	9.2	11.6	9.3	10.2	10.2	10.5	10.7
November	8.2	8.9	5.5	5.8	8.7	5.8	6.6	6.6	6.7	7.0
December	6.3	7.0	3.4	3.6	6.7	3.6	4.3	4.3	4.4	4.4

	Rainfall (mm/month)																		
Site Code	**1,2**	**3,4,5**	**6,7**	**8**	**9,10**	**11**	**12**	**13**	**14**	**15**	**16**	**17,18**	**19**	**20,21,22**	**23**	**24**	**25**	**26**	**27,28**	**29**
January	52	49	139	80	56	57	57	48	51	63	58	64	63	65	128	152	78	84	85	116
February	40	38	99	53	42	41	41	37	37	45	42	45	46	48	95	112	57	63	63	89
March	43	41	101	55	45	45	45	41	41	48	46	50	51	51	94	124	56	62	62	79
April	45	46	68	47	47	48	48	45	40	49	45	46	48	53	77	86	50	51	53	64
May	44	45	69	45	50	45	45	45	43	52	52	53	55	53	69	82	51	51	54	61
June	57	57	73	49	52	59	59	54	49	52	51	51	53	58	72	93	55	56	58	64
July	50	47	84	43	44	52	52	49	47	44	43	47	50	53	74	105	53	50	57	67
August	57	53	95	51	54	60	60	55	54	56	55	55	58	62	88	114	62	56	67	75
September	50	48	101	61	52	52	52	47	47	54	52	54	57	59	103	121	62	62	68	80
October	54	52	135	86	62	57	57	52	54	66	62	65	65	66	133	174	80	82	89	110
November	54	51	136	86	62	58	58	52	55	68	64	66	64	65	144	171	78	86	87	121
December	57	53	138	82	59	60	60	53	52	64	63	67	67	67	141	168	83	92	89	118

Table A2: Long-term monthly rainfall

Table A2 continued

	Rainfall (mm/month)								
Site Code	**30,31**	**32,33**	**34**	**35**	**37**	**38**	**39**	**40**	**41**
January	111	107	86	90	104	63	63	50	48
February	85	74	60	65	77	47	47	38	37
March	75	77	63	65	79	50	50	41	41
April	60	51	45	53	56	53	53	44	43
May	57	58	53	52	61	53	53	47	45
June	60	63	60	56	67	58	58	53	56
July	61	67	63	56	74	53	53	48	49
August	69	74	67	70	80	62	62	54	55
September	75	82	71	69	83	59	59	50	49
October	103	102	87	103	105	67	67	53	55
November	114	96	78	108	103	65	65	54	53
December	112	95	77	95	104	67	67	52	51

	Site code	1,2				3,4,5				6,7				
		HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD4	HWSD5
0-30cm	C content (Kg/ha)	46875	41580	23256	35088	35088	41895	39516	330960	23550	31500	91560	79236	17160
	BD (g/cm^3)	1.25	1.4	1.36	1.36	1.36	1.33	1.48	0.28	1.57	1.5	1.4	1.24	1.43
	pH	5.8	5.8	6.3	7.2	7.2	4.8	6.4	5.6	6	6.9	4.4	7.5	6.5
	clay (%)	51	19	9	21	21	20	10	32	5	9	4	19	10
	silt (%)	32	44	13	40	40	33	14	33	6	14	9	44	8
	sand (%)	17	37	78	39	39	47	76	35	89	77	87	37	82
30-100cm	C content (Kg/ha)	42525	32480	32550	36974	36974	39893	68880	484596	32550	42000	41223		26376
	BD (g/cm^3)	1.35	1.6	1.55	1.39	1.39	1.39	1.64	0.18	1.55	1.5	1.51	1.51	1.57
	pH	6	5.9	6.4	7.5	7.5	4.9	6.7	5.8	5.9	7.3	5	999	6.5
	clay (%)	52	31	23	21	21	20	26	25	5	17	4	999	17
	silt (%)	29	38	13	38	38	29	14	23	6	16	8	999	8
	sand (%)	19	31	64	41	41	51	60	52	89	67	88	999	75
	sft	2	2	2	2	2	2	2	1	2	2	2	3	2
	share	60	20	10	10	60	20	15	5	50	25	10	5	5

Table A3: HWSD soil attributes for the YR1 CSQ sites. Share = percentage of the grid cell that is covered by the soil type. sft is a code number: 1 for organic soils, 2 for mineral soils, 3 for mineral soils up to 30cm, 4 for mineral soils up to 10cm, 5 for mineral soils with no bulk density data, 6 for mineral soils missing all data. 999 is a null value.

Table A3 continued

	Site code	**8**						**9,10**				**11**			
		HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 5	HWSD 6	HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 1	HWSD 2	HWSD 3	HWSD 4
0-30cm	C content (Kg/ha)	38097	31746	41100	79236	42900	48960	46875	41580	55413	31746	46875	41580	23256	35088
	BD (g/cm^3)	1.53	1.43	1.37	1.24	1.43	1.36	1.25	1.4	1.31	1.43	1.25	1.4	1.36	1.36
	pH	6.3	6.5	6.6	7.5	4.9	5.4	5.8	5.8	5.6	6.5	5.8	5.8	6.3	7.2
	clay (%)	24	22	22	19	24	11	51	19	49	22	51	19	9	21
	silt (%)	28	37	36	44	24	54	32	44	32	37	32	44	13	40
	sand (%)	48	41	42	37	52	35	17	37	19	41	17	37	78	39
30-100cm	C content (Kg/ha)	42280	38052	36001		42140	28175	42525	32480	46648	38052	42525	32480	32550	36974
	BD (g/cm^3)	1.51	1.51	1.39	1.51	1.4	1.61	1.35	1.6	1.36	1.51	1.35	1.6	1.55	1.39
	pH	6.4	6.7	7	999	4.9	5.3	6	5.9	5.7	6.7	6	5.9	6.4	7.5
	clay (%)	34	29	25	999	36	20	52	31	51	29	52	31	23	21
	silt (%)	25	34	34	999	21	43	29	38	31	34	29	38	13	38
	sand (%)	41	37	41	999	43	37	19	31	18	37	19	31	64	41
	sft	2	2	2	3	2	2	2	2	2	2	2	2	2	2
	share	60	15	10	5	5	5	40	30	15	15	60	20	10	10

Table A3 continued

	Site code	12					13			14			
		HWSD1	HWSD2	HWSD3	HWSD4	HWSD5	HWSD1	HWSD2	HWSD3	HWSD1	HWSD2	HWSD3	HWSD4
0-30cm	C content (Kg/ha)	31500	41100	31290	31746	79236	63360	330960	25020	55413	47160	41697	44928
	BD (g/cm^3)	1.5	1.37	1.49	1.43	1.24	1.28	0.28	1.39	1.31	1.31	1.23	1.28
	pH	6.9	6.6	5.1	6.5	7.5	6.6	5.6	8	5.6	6.5	7.5	6.7
	clay (%)	9	22	10	22	19	22	32	18	49	47	54	48
	silt (%)	14	36	15	37	44	39	33	48	32	22	24	29
	sand (%)	77	42	75	41	37	39	35	34	19	31	22	23
30-100cm	C content (Kg/ha)	42000	36001	28350	38052		65205	484596	39480	46648	53690	32256	54810
	BD (g/cm^3)	1.5	1.39	1.5	1.51	1.51	1.35	0.18	1.41	1.36	1.3	1.28	1.35
	pH	7.3	7	5	6.7	999	7.2	5.8	8.1	5.7	7.4	8.2	7
	clay (%)	17	25	15	29	999	28	25	18	51	53	44	45
	silt (%)	16	34	17	34	999	35	23	46	31	20	22	29
	sand (%)	67	41	68	37	999	37	52	36	18	27	34	26
	sft	2	2	2	2	3	2	1	2	2	2	2	2
	share	30	30	20	15	5	65	25	10	60	15	15	10

Table A3 continued

	Site code	15				16				17,18			
		HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD4
0-30cm	C content (Kg/ha)	31746	41580	38097	41100	79236	41100	31746	30825	46875	41580	55413	31746
	BD (g/cm^3)	1.43	1.4	1.53	1.37	1.24	1.37	1.43	1.37	1.25	1.4	1.31	1.43
	pH	6.5	5.8	6.3	6.6	7.5	6.6	6.5	8	5.8	5.8	5.6	6.5
	clay (%)	22	19	24	22	19	22	22	21	51	19	49	22
	silt (%)	37	44	28	36	44	36	37	35	32	44	32	37
	sand (%)	41	37	48	42	37	42	41	44	17	37	19	41
30-100cm	C content (Kg/ha)	38052	32480	42280	36001		36001	38052	49350	42525	32480	46648	38052
	BD (g/cm^3)	1.51	1.6	1.51	1.39	1.51	1.39	1.51	1.5	1.35	1.6	1.36	1.51
	pH	6.7	5.9	6.4	7	999	7	6.7	8.1	6	5.9	5.7	6.7
	clay (%)	29	31	34	25	999	25	29	25	52	31	51	29
	silt (%)	34	38	25	34	999	34	34	35	29	38	31	34
	sand (%)	37	31	41	41	999	41	37	40	19	31	18	37
	sft	2	2	2	2	3	2	2	2	2	2	2	2
	share	50	20	15	15	50	25	20	5	40	30	15	15

Table A3 continued

	Site code	19				20,21,22				23				
		HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD4	HWSD5
0-30cm	C content (Kg/ha)	46875	41580	55413	31746	31746	41580	31500	45339	56550	41100	42300	56550	45630
	BD (g/cm^3)	1.25	1.4	1.31	1.43	1.43	1.4	1.5	1.27	1.3	1.37	1.41	1.3	1.3
	pH	5.8	5.8	5.6	6.5	6.5	5.8	6.9	6.2	5.1	6.6	6.4	5.1	5.1
	clay (%)	51	19	49	22	22	19	9	49	20	22	19	20	21
	silt (%)	32	44	32	37	37	44	14	32	38	36	36	38	39
	sand (%)	17	37	19	41	41	37	77	19	42	42	45	42	40
30-100cm	C content (Kg/ha)	42525	32480	46648	38052	38052	32480	42000	53515	47600	36001	52640	47600	38080
	BD (g/cm^3)	1.35	1.6	1.36	1.51	1.51	1.6	1.5	1.39	1.36	1.39	1.6	1.36	1.36
	pH	6	5.9	5.7	6.7	6.7	5.9	7.3	6.8	5.2	7	6.7	5.2	5.3
	clay (%)	52	31	51	29	29	31	17	47	20	25	27	20	25
	silt (%)	29	38	31	34	34	38	16	32	35	34	34	35	34
	sand (%)	19	31	18	37	37	31	67	21	45	41	39	45	41
	sft	2	2	2	2	2	2	2	2	2	2	2	2	2
	share	40	30	15	15	65	20	10	5	40	20	15	15	10

Table A3 continued

	Site code	24					25					26			
		HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 5	HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 5	HWSD 1	HWSD 2	HWSD 3	HWSD 4
0-30cm	C content (Kg/ha)	56550	41100	42300	56550	45630	55413	41697	44928	46875	41580	77421	39516	91560	41580
	BD (g/cm^3)	1.3	1.37	1.41	1.3	1.3	1.31	1.23	1.28	1.25	1.4	1.31	1.48	1.4	1.4
	pH	5.1	6.6	6.4	5.1	5.1	5.6	7.5	6.7	5.8	5.8	4.4	6.4	4.4	5.8
	clay (%)	20	22	19	20	21	49	54	48	51	19	4	10	4	19
	silt (%)	38	36	36	38	39	32	24	29	32	44	10	14	9	44
	sand (%)	42	42	45	42	40	19	22	23	17	37	86	76	87	37
30-100cm	C content (Kg/ha)	47600	36001	52640	47600	38080	46648	32256	54810	42525	32480	98098	68880	41223	32480
	BD (g/cm^3)	1.36	1.39	1.6	1.36	1.36	1.36	1.28	1.35	1.35	1.6	1.54	1.64	1.51	1.6
	pH	5.2	7	6.7	5.2	5.3	5.7	8.2	7	6	5.9	4.9	6.7	5	5.9
	clay (%)	20	25	27	20	25	51	44	45	52	31	5	26	4	31
	silt (%)	35	34	34	35	34	31	22	29	29	38	10	14	8	38
	sand (%)	45	41	39	45	41	18	34	26	19	31	85	60	88	31
	sft	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	share	40	20	15	15	10	40	30	10	10	10	60	20	15	5

Table A3 continued

	Site code	27,28					29					30,31				
		HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 5	HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 5	HWSD 1	HWSD 2	HWSD 3	HWSD 4	HWSD 5
0-30cm	C content (Kg/ha)	56550	41100	42300	56550	45630	56550	41100	42300	56550	45630	56550	41100	42300	56550	45630
	BD (g/cm^3)	1.3	1.37	1.41	1.3	1.3	1.3	1.37	1.41	1.3	1.3	1.3	1.37	1.41	1.3	1.3
	pH	5.1	6.6	6.4	5.1	5.1	5.1	6.6	6.4	5.1	5.1	5.1	6.6	6.4	5.1	5.1
	clay (%)	20	22	19	20	21	20	22	19	20	21	20	22	19	20	21
	silt (%)	38	36	36	38	39	38	36	36	38	39	38	36	36	38	39
	sand (%)	42	42	45	42	40	42	42	45	42	40	42	42	45	42	40
30-100cm	C content (Kg/ha)	47600	36001	52640	47600	38080	47600	36001	52640	47600	38080	47600	36001	52640	47600	38080
	BD (g/cm^3)	1.36	1.39	1.6	1.36	1.36	1.36	1.39	1.6	1.36	1.36	1.36	1.39	1.6	1.36	1.36
	pH	5.2	7	6.7	5.2	5.3	5.2	7	6.7	5.2	5.3	5.2	7	6.7	5.2	5.3
	clay (%)	20	25	27	20	25	20	25	27	20	25	20	25	27	20	25
	silt (%)	35	34	34	35	34	35	34	34	35	34	35	34	34	35	34
	sand (%)	45	41	39	45	41	45	41	39	45	41	45	41	39	45	41
	sft	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	share	40	20	15	15	10	40	20	15	15	10	40	20	15	15	10

Table A3 continued

	Site code	**32,33**				**34**			**35,36**				
		HWSD1	HWSD2	HWSD3	HWSD4	HWSD1	HWSD2	HWSD3	HWSD1	HWSD2	HWSD3	HWSD4	HWSD5
0-30cm	C content (Kg/ha)	56550	42300	45630	91560	31500	42300	43335	41100	55413	44928	79236	30825
	BD (g/cm^3)	1.3	1.41	1.3	1.4	1.5	1.41	1.35	1.37	1.31	1.28	1.24	1.37
	pH	5.1	6.4	5.1	4.4	6.9	6.4	6.2	6.6	5.6	6.7	7.5	8
	clay (%)	20	19	21	4	9	19	23	22	49	48	19	21
	silt (%)	38	36	39	9	14	36	40	36	32	29	44	35
	sand (%)	42	45	40	87	77	45	37	42	19	23	37	44
30-100cm	C content (Kg/ha)	47600	52640	38080	41223	42000	52640	38850	36001	46648	54810		49350
	BD (g/cm^3)	1.36	1.6	1.36	1.51	1.5	1.6	1.5	1.39	1.36	1.35	1.51	1.5
	pH	5.2	6.7	5.3	5	7.3	6.7	6.6	7	5.7	7	999	8.1
	clay (%)	20	27	25	4	17	27	28	25	51	45	999	25
	silt (%)	35	34	34	8	16	34	36	34	31	29	999	35
	sand (%)	45	39	41	88	67	39	36	41	18	26	999	40
	sft	2	2	2	2	2	2	2	2	2	2	3	2
	share	50	20	20	10	40	40	20	60	20	10	5	5

Table A3 continued

	Site code	37				38				39				40				
		HWS D1	HWS D2	HWS D3	HWS D4	HWS D1	HWS D2	HWS D3	HWS D4	HWS D1	HWS D2	HWS D3	HWS D4	HWS D1	HWS D2	HWS D3	HWS D4	HWS D5
0-30cm	C content (Kg/ha)	41580	31746	23256	45339	41580	31746	23256	45339	41580	31746	23256	45339	55413	41697	44928	46875	41580
	BD (g/cm^3)	1.4	1.43	1.36	1.27	1.4	1.43	1.36	1.27	1.4	1.43	1.36	1.27	1.31	1.23	1.28	1.25	1.4
	pH	5.8	6.5	6.3	6.2	5.8	6.5	6.3	6.2	5.8	6.5	6.3	6.2	5.6	7.5	6.7	5.8	5.8
	clay (%)	19	22	9	49	19	22	9	49	19	22	9	49	49	54	48	51	19
	silt (%)	44	37	13	32	44	37	13	32	44	37	13	32	32	24	29	32	44
	sand (%)	37	41	78	19	37	41	78	19	37	41	78	19	19	22	23	17	37
30-100cm	C content (Kg/ha)	32480	38052	32550	53515	32480	38052	32550	53515	32480	38052	32550	53515	46648	32256	54810	42525	32480
	BD (g/cm^3)	1.6	1.51	1.55	1.39	1.6	1.51	1.55	1.39	1.6	1.51	1.55	1.39	1.36	1.28	1.35	1.35	1.6
	pH	5.9	6.7	6.4	6.8	5.9	6.7	6.4	6.8	5.9	6.7	6.4	6.8	5.7	8.2	7	6	5.9
	clay (%)	31	29	23	47	31	29	23	47	31	29	23	47	51	44	45	52	31
	silt (%)	38	34	13	32	38	34	13	32	38	34	13	32	31	22	29	29	38
	sand (%)	31	37	64	21	31	37	64	21	31	37	64	21	18	34	26	19	31
	sft	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	share					60	20	15	5	60	20	15	5	40	30	10	10	10

Site code	Transitions	Clay (%) 0-15 cm	Silt (%) 0-15 cm	Sand (%) 0-15 cm	Clay (%) 15-30 cm	Silt (%) 15-30 cm	Sand (%) 15-30 cm
1	Arable	5	36	60	4	36	60
	SRF	4	40	55	5	34	60
2	Pasture	9	72	19	9	78	12
	SRF	7	78	15	11	72	18
3	Rough Pasture	2	42	56	5	45	50
	SRF	3	41	56	5	44	50
4	Rough Pasture	2	31	67	4	25	71
	SRF	2	27	71	3	22	75
5	Rough Pasture	3	42	56	6	38	59
	SRF	2	40	58	2	38	60
6	Pasture	1	21	78	1	16	83
	SRF	0	17	83	0	14	86
7	Rough Pasture	5	58	37	4	59	37
	SRF	4	52	44	7	49	45
8	Pasture	3	49	48	4	45	52
	SRF	4	51	45	5	48	47
9	Pasture	4	52	44	4	55	41
	SRF	4	64	32	5	64	31
10	Pasture	3	54	43	5	49	46
	SRF	3	53	44	4	51	46

Table A4: Measured soil texture for the YR1 CSQ sites.

APPENDIX II – FERTILISER REQUIREMENTS

Crop	Offtake kg N /t	Fertiliser kg N /ha/application	Years between application	Timing	Establishment	Assumed yield t/ha/y
Miscanthus	6	84	1	Late May	No N in 1st 2 yrs	14
Willow	3	90	3	Not specified	No N in 1st 3 yrs	10
Wheat*		160	1	40kg/ha March, 120kg/ha late April		
Sugar beet*		80	1	Spring		
Oilseed rape*		50	1	Spring		

<u>Data from Defra Fertiliser Manual (RB209), 8th Edition, 2010</u>

* Data for SNS index 3, medium soil (as Defined by Defra)

<u>Inferred C:N ratio</u>

Crop	C/N	Notes
Miscanthus	94	N content: 6kg N /t (Defra), 5kg N /t (Beale and Long (1997) Biomass and Bioenergy 12, 419-428), 2kg N /t (Strullu et al., Field Crops Research 121, 381-3) C content: 47% (Harvey J (2007) A versatile solution? Growing Miscanthus for bioenergy. Renewable Energy World, 10, 86–93) Therefore assume 47%C, 0.5%N
Willow	188	From Defra off-take data, assume double Miscanthus value
Wheat	25	Average from whole plant (Hicks PA (1928), Distribution of Carbon/Nitrogen ratio in the various organs of the wheat plant at different periods of its life history, New Phytologist 27, 108-116)
Sugar beet	50	Assume same yield as wheat, and use ratio of Defra application data to rescale
Oilseed rape	80	As above

APPENDIX III – GLOSSARY

ASCII	American Standard Code for Information Interchange
BD	Bulk Density
AGB	Above-Ground Biomass
BD	Bulk Density
BIO	Biomass
C	Carbon
CEH	Centre for Ecology & Hydrology
CH_4	Methane
CN	Carbon Nitrogen
CO_2	Carbon Dioxide
csv	Comma Separated Value
DOC	Dissolved Organic Carbon
DPM	Decomposable Plant Material
E	Relative Error
EC	Eddy Covariance
ECA&D	European Climate Assessment & Dataset
ELUM	Ecosystem Land Use Modelling
ECOSSE	Model to Estimate Carbon in Organic Soils – Sequestration and Emissions
FRS	Functional Requirements Specification
GHG	GreenHouse Gas
GIS	Graphic Information System
GOR	Government Office Regions
GUI	Graphical User Interface
GWP	Global Warming Potential
HUM	Humus
HWSD	Harmonized World Soil Database

IOM	Inert Organic Matter
IRGA	Infra-Red Gas Analyser (chamber measurements)
LOFIT	Lack Of Fit
LRF	Long Rotation Forestry
LUC	Land-Use Change
M	Mean Difference
N	Nitrogen
NRL	no root/litter plots
NPP	Net Primary Production
N_2O	Nitrous Oxide
NH_4^+	Ammonium
NO_3^-	Nitrate
odt	Oven Dry Tonne
OSR	Oil Seed Rape
PET	Potential EvapoTranspiration
PM	Payment Milestone
PTF	PedoTransfer Functions
R	Correlation coefficient
Ra	Autotrophic Respiration
Rh	Heterotrophic Respiration
RMS	Root Mean Squared Deviation
RPM	Resistant Plant Material
sd	Standard Deviation
SGR	Stage Gate Review
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SRC	Short Rotation Coppice
SRF	Short Rotation Forestry

SUG	Sugar Beet
UK	United Kingdom
UKERC	UK Energy Research Centre
UKCP09	UK Spatially Coherent Projections
WHE	Wheat
WP	Work Package