Programme Area: Bioenergy

Project: ELUM

Title: Report on Findings of Effects on Land-use Change into Bioenergy Crops

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.

This report documents the key results and findings of the spatial modelling work undertaken to determine how land-use change to bioenergy crops affects soil global warming potential in the UK, for the period 2015-2050. This work is the culmination of earlier deliverables that provided data on the impacts of transitions to bioenergy crops on soil carbon (Work Package 2), greenhouse gas emissions at the network sites (Work Package 3) and the subsequent development and parameterisation of the model (Work Package 4, deliverable D4.3). The model outputs generated as part this deliverable provide the raw data for the look-up table that forms the basis of the spatial modelling tool described in deliverable D4.3.

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Some information and/or data points will have been superseded by later peer review, please refer to updated papers published via www.elum.ac.uk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: PM07.4.6

Report on the Findings of Effects on Land-Use Change (LUC) into Bioenergy Crops

REPORT

V1.5

19/11/2014

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EXECUTIVE SUMMARY

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

Deliverable D4.6:	Report on the findings i.e. Model outputs and what this uncovers in terms of effects of LUC into Bioenergy crops and subsequent crop management on soil carbon and GHG in the UK. Results to be presented as bioenergy opportunity maps, in line with future predictions of renewable energy requirements across the UK.
Acceptance Criteria:	This report will provide a detailed discussion of the findings of the meta-model - in terms of effects of LUC into Bioenergy crops and subsequent soil carbon and GHG in the UK. The report will include Bioenergy opportunity maps, in line with future predictions of renewable energy requirements across the UK. The opportunity maps will also be provided separately as high resolution images (jpeg or similar). 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).

The aim of the ELUM project has been to develop a model to predict greenhouse gas fluxes and changes in soil organic carbon content resulting from the conversion of land to bioenergy crop production. This report documents the key results and findings of the spatial modelling work undertaken to determine how land-use change to bioenergy crops affects soil global warming potential (GWP) in the UK, for the period 2015-2050. This work is the culmination of earlier deliverables that provided data on the impacts of transitions to bioenergy crops on soil C (WP2), greenhouse gas emissions at the network sites (WP3) and the subsequent development and parameterisation of the model (WP4, deliverable D4.3). The model outputs generated as part this deliverable provide the raw data for the look-up table that forms the basis of the spatial modelling tool described in deliverable D4.3.

KEY FINDINGS

- Conversion of rotational crops to *Miscanthus*, SRC and SRF and conversion of permanent grass to SRF show beneficial changes in soil GWP over a significant area.

- Conversion of permanent grass to *Miscanthus*, permanent grass to SRF and forest to SRF show small detrimental changes (0 to 50 t CO_2e ha^{-1} after 35 years) in soil GWP over a significant area (where CO_2e is carbon dioxide-equivalent).

- Conversion of permanent grass to wheat, oilseed rape and sugar beet and all conversions from forest show large detrimental changes (> 50 t CO_2e ha^{-1} after 35 years) in soil GWP over most of the simulation area, largely due to moving from uncultivated soil to regular cultivation.

- Conversion of permanent grass to SRC (willow) also shows large detrimental changes (> 50 t CO_2e ha^{-1} after 35 years) in soil GWP over most of the simulation area, largely due to poor SRC yields leading to lower carbon returns to the soil (see below)

- Impact of soil GWP is dominated by effects on soil organic carbon with the difference among *Miscanthus*, SRC and SRF largely determined by yield, since higher yields mean higher carbon returns to the soil, which increases soil organic carbon stocks relative to low yield.

- Low yields lead to SOC decline, so a target for management of perennial energy crops is to achieve the best possible yield by using the most appropriate energy crop and cultivar for the local situation, as long as this can be done without excessive nitrogen fertiliser use, which would increase nitrous oxide emissions.

- Overall, SRF (poplar) offers the greatest beneficial impact on soil GWP, in terms of both the magnitude and spatial extent of the decreases in GWP.

- The high, medium and low climate projections have an insignificant impact on modelled soil GWP.

- Some sources of uncertainty in the model results relating to natural variability in yield, climate and soils are difficult to quantify and should be considered when interpreting the results.

- The criteria for selection of bioenergy crops extends beyond direct effects on soil GWP to include GWP increases/decreases resulting from displaced food production, bio-physical factors (e.g. the energy-density of the crop) and socio-economic factors (e.g. expenditure on harvesting equipment).

Summary of methods

The ECOSSE soil carbon and nitrogen model was used to simulate the effects of land-use change from rotational cropland, permanent grassland and forest to bioenergy crops on soil organic carbon content and greenhouse gas emissions for a 35 year period running from 2015 and 2050. Three ‘null’ transitions for rotational crops, permanent grass and forest were also simulated to provide results for unchanged land-use for comparison.

The model was applied over the whole of the UK on a 1 km grid basis. Grid cells which contain inappropriate land for growing bioenergy crops were excluded from the simulations. Simulations were carried out for each of the 5 dominant soil types in each grid cell, using soil data from the Harmonized World Soil Database. Simulations were conducted using three different climate scenarios: low, medium and high emissions.

Prior to each simulation, the model is initialised based on the assumption that the soil organic carbon in the soil column is at stable equilibrium under the initial land use at the start of the simulation. Following initialisation, the main simulation is executed, which begins with land-use change from the initial land-use type to the bioenergy crop. Any soil cultivation carried out during land-use change is simulated. The model then simulates soil dynamics under the bioenergy crop. The annual plant inputs of carbon and nitrogen to the soil are calculated from the annual yield estimate for the crop (obtained from a range of yield models), using crop-specific ratios estimated from the literature.

Each perennial bioenergy crop (*Miscanthus*, SRC and SRF) is re-established after a 20-year period (the estimated productive life-span of the crop). Nitrogen fertiliser is applied annually to each crop (if appropriate) following best-practice guidelines.

For all land-use types the changes in soil organic carbon and emissions of greenhouse gases are calculated for the top metre of the soil profile (since this is the depth to which soil data is provided by the soil database). Changes in soil organic carbon and greenhouse gas emissions resulting from land-use change are calculated by subtracting the results of the appropriate null transition from the land-use change results, so that a change can be attributed solely to the land-use change. For example, to calculate the impact of land-use change from permanent grass to SRC, the results from the permanent grass null transition (i.e. grass remaining as grass), are subtracted from the permanent grass to SRC results.

The results express the area-weighted average obtained from each of the 5 dominant soil types in each grid cell. All results are reported in terms of CO_2-equivalent values (CO_2e), using IPCC 100-year GWPs.

Summary of results
Net global warming potential represents the combined effects of changes in nitrous oxide, methane and soil organic carbon, and is therefore the most comprehensive measure of bioenergy impacts. Only second-generation bioenergy crops (*Miscanthus*, SRC and SRF) showed any beneficial changes in soil GWP; all conversions to first-generation bioenergy crops (wheat, sugar-beet and oilseed rape) showed a detrimental GWP.

Of the three initial land-uses, conversion from rotational crops has the most favourable net GWP. Conversion of rotational crops to SRF, SRC and *Miscanthus* each showed a beneficial response in almost all grid cells, with mean net GWPs of -126.9, -37.8 and -76.4 t CO_2e ha^{-1} over 35 years respectively (section 3.1.4.1). In contrast, all conversions from permanent grass result in a detrimental change in net GWP in all grid cells except for SRF, which shows a small beneficial (> -21 t CO_2e ha^{-1}) change over large parts of the West Midlands, East Midlands and East Anglia (section 3.1.4.1). Transitions from forest show detrimental soil GWPs in all grid cells with mean soil GWPs of 88.7, 128.6 and 102.9 CO_2e ha^{-1} over 35 years for SRF, SRC and *Miscanthus* respectively (section 3.1.4.3). Overall, conversion of rotational crops to SRF is the most favourable conversion because it has the most beneficial net GWP over the largest area.

Conversion of land to bioenergy crops shows a large spatial and temporal variation in net GWP and its components: soil organic carbon, nitrous oxide and methane. The impact of land-use change on soil GWP depends upon the type of land-use being converted, the type of bioenergy crop planted and the geographic location. Overall, changes in soil organic carbon content have the largest impact on net GWP, followed by changes nitrous oxide and methane emissions. In general, most of the benefits to soil GWP from favourable conversions are realised in the first 15-20 years following conversion. After this time, the rate of decrease in net GWP slows as the soil carbon content approaches a new equilibrium.

Simulations using different climate scenarios reveal a general trend towards more beneficial GWPs as climate increases from low to high emissions, though the difference between scenarios is very small for all transitions (section 3.2).

References to other ELUM Reports

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

- BI1001_PM07.3.5_WP3_Bioenergy GHG and LUC v1.0
- BI1001_PM07.4.3_WP4_LUC and Crop Management Model v1.0

Full-page versions of each of the maps in this report are provided in a separate appendix:

- BI1001_PM07.4.6_WP4_Effects on LUC in Bioenergy v1.5 Appendix II

CONTENTS

1. INTRODUCTION

The modelling work of the ELUM project is divided into two main parts. The first is the development and validation of the ECOSSE soil organic carbon (SOC) and greenhouse gas (GHG) emission model, using data from ELUM field measurements as reported in deliverable report D4.3 (BI1001_PM07.4.3_WP4_LUC and Crop Management Model v1.0). The second part is to apply the updated ECOSSE model spatially in the UK, using existing datasets as inputs, thus forming the basis for the meta-model and spatial modelling tool (as detailed in D4.3).

The principal objective of the spatial modelling exercise is to estimate the effects of land-use change (LUC) into Bioenergy crops on SOC content and GHG emissions in the UK in order to identify bioenergy opportunities. Eighteen LUCs are considered:

- Rotational crops (which includes rotations consisting entirely of arable crops and also those including rotational grass) to *Miscanthus*, short rotation coppice (SRC; here represented by willow, since this is the SRC species used in commercial plantations in the UK) and short rotation forestry (SRF; here represented by poplar, since this generally shows the highest yield under UK conditions)
- Permanent grass and forest to wheat, oilseed rape (OSR), sugar beet, *Miscanthus*, SRC and SRF
- Three 'null' transitions for rotational crops, permanent grass and forest to provide results for unchanged land use as a baseline.

Conversion from rotational crops to OSR, sugar beet and wheat are not considered because the rotational crops land-use prior to transition is assumed to be the same as that following the transition, resulting in no change in GWP.

This report provides a summary of the ECOSSE model, its application at the national scale and the input data used to drive the simulations. Results from the spatial simulations carried out to determine the effects of land-use change (LUC) into bioenergy crops on SOC, GHG emissions and net GWP in the UK are presented. Net GWPs from simulations carried out using data from low, medium and high emission climate scenarios are compared to determine the impact of climate uncertainty.

Results are for the whole of the UK on a 1 km grid basis and express the area-weighted average obtained from simulations of the 5 most dominant soil types in each grid cell.

For consistency and ease of comparison, all results (i.e. CH_4, N_2O, change in SOC and net GWP) are reported in terms of CO_2-equivalent values (CO_2e), using IPCC 100-year GWPs (IPCC, 2001); net GHG is therefore referred to as net GWP throughout the report. More recent IPCC reports have provided updated GWPs from those given in the IPCC 2001 report. However, for consistency with national inventory GHG emission estimates, we have used the IPCC 2001 GWP values, following the recommended practice for national GHG inventories. Results show the cumulative total of each output variable and are relative to the value obtained if no transition had occurred (hence results show directly the effect of the transition).

2. METHODS

2.1 ECOSSE model

The ECOSSE (Estimation of Carbon in Organic Soils – Sequestration and Emissions) model simulates soil C and N dynamics in mineral and organic soils using meteorological, land use, land management and soil data, and simulates changes in SOC and soil GHG emissions. The model is able to function at the field scale or at the national scale (using only the limited data available at this scale).

ECOSSE was developed from concepts originally derived for mineral soils in the RothC model (Jenkinson & Rayner 1977, Jenkinson *et al*. 1987, Coleman & Jenkinson 1996) and SUNDIAL model (Bradbury *et al*. 1993, Smith *et al*. 1996). ECOSSE describes soil organic matter using 5 pools: inert organic matter, humus, biomass, resistant plant material and decomposable plant material. All of the major processes of C and N turnover are included in the model, but each process is simulated using only simple equations driven by readily available inputs. This enables ECOSSE to be used for national scale simulations for which only limited input data are available.

ECOSSE simulates the soil profile to a depth of up to 3 metres, dividing the soil into 5 cm layers to facilitate the accurate simulation of processes to depth. Plant C and N inputs are added monthly to the decomposable and resistant plant material pools. During the decomposition process, material is exchanged between the soil organic matter pools according to first-order rate equations, characterised by a specific rate constant for each pool. The rate constant of each pool is modified dependent on the temperature, water content, plant cover and pH of the soil (with additional modifiers dependent upon soil bulk density and inorganic N concentration in the case of anaerobic decomposition). The decomposition process results in gaseous losses of CO_2 and CH_4, with CO_2 losses dominating under aerobic conditions and CH_4 losses under anaerobic conditions. ECOSSE also simulates the oxidation of atmospheric CH_4, which, under aerobic conditions, can lead to the soil being a net consumer of CH_4.

The nitrogen (N) content of the soil follows the decomposition of the soil organic matter, with a stable C:N ratio defined for each soil organic matter pool at a given pH, and N being either mineralised or immobilised to maintain that ratio. Nitrogen is released from decomposing soil organic matter as ammonium (NH_4^+) or nitrified to nitrate (NO_3^-). C and N may be lost from the soil by the processes of leaching (NO_3^-), dissolved organic C, and dissolved organic N, denitrification to nitric oxide (NO) and nitrous oxide (N_2O), volatilisation or crop off-take. C and N may be returned to the soil by plant inputs, inorganic fertilisers, atmospheric deposition or organic amendments (e.g. manure, crop residues).

ECOSSE models the soil water content of each layer using a “tipping bucket” approach based on SUNDIAL (Smith *et al*. 1996). Water flows through the soil as ‘piston flow’, whereby water from precipitation entering the soil forces water in the soil deeper into the soil profile. Precipitation fills the uppermost soil layer with water until it reaches field capacity. Any remaining precipitation is then used to fill the next layer to field capacity.

This process is repeated until no precipitation remains or the bottom of the profile is reached. Any precipitation water remaining after filling all layers to field capacity is partitioned between drainage (water leaving the soil profile), and excess, which is used to fill layers to saturation from the bottom of the profile upwards. ECOSSE uses the observed depth of the water table, the available water at saturation and weather data to calculate the restriction to drainage (i.e. the fraction of the remaining water that becomes excess), that is required to achieve the observed water table depth. Water is also lost from the top of the profile as evapotranspiration, which is estimated using the Thornthwaite (1948) method.

2.2 Spatial application of the model

The spatial simulations of the UK are carried out on a 1 km grid basis consisting of nearly 0.25 million grid cells. Grid cells which contain inappropriate land for growing bioenergy crops were excluded from the simulations based on the UKERC 7w land-use constraints (Lovett *et al.*, 2014; see section 3.2.3.2 in report D4.3 for more details). The UKERC 7w constraints mask excludes grid cells that meet one or more of the following criteria:

- Slope ≥ 15%
- Peat (soil C ≥ 30%)
- Designated areas
- Urban areas, roads, rivers
- Parks
- Scheduled Monuments/World Heritage Sites
- Woodland (except transitions to SRF)

The simulation of each LUC is carried out for up to 5 different soil types in each grid cell to capture soil heterogeneity at the sub-grid cell level. All combinations of LUC from rotational crops, permanent grass and forest to: wheat, oilseed rape, sugar beet, *Miscanthus*, SRC and SRF were simulated, except for rotational crops to wheat, oilseed rape and sugar beet which, being types of rotational crops, were considered to be equivalent to no LUC. Three ‘null’ transitions for rotational crops, permanent grass and forest were also simulated to provide results for unchanged land-use for comparison.

The rotational crops land-use category represents land used to grow arable crops and includes all-arable rotations and rotations that include rotational or temporary grassland for part of the rotation. The permanent grass land-use category represents permanent, uncultivated grassland only, since rotational grass is not a land-use, and is part of rotational farming represented better by the rotational crops category.

Results have been obtained using three different climate scenarios (see below) for a 35-year period running from 2015 to 2050. Prior to each simulation, the model is initialised based on the assumption that the SOC in the soil column is at stable equilibrium under the initial land use at the start of the simulation (see section 2.1.1 in report D4.3).

Following initialisation, the main simulation is executed. This begins with LUC from the initial land-use type to the bioenergy crop. Any soil cultivation carried out during LUC is simulated. Since rotational cropland typically undergoes annual cultivation, the model assumes there is no additional cultivation required for the establishment of bioenergy crops. In contrast, the model simulates soil cultivation for LUC from permanent grass and forestry because these land-use types typically require ground preparation before bioenergy crops are planted. The model simulates physical fragmentation of soil organic matter resulting from cultivation by moving a proportion of the C and N in the humus pool, (which has a slow decomposition rate), to the decomposable and resistant plant material pools (which have faster decomposition rates). Redistribution of soil organic matter during cultivation is simulated by homogenising the vertical distribution of the soil organic matter pools down to the cultivation depth. The simulated cultivation depth for conversion from forest and permanent grass is 0.5 and 0.3 m respectively.

After simulation of the LUC cultivation, the model simulates soil dynamics under the bioenergy crop. The annual plant inputs of C and N to the soil are calculated from the annual yield of the crop (provided as an input to the model), using crop-specific ratios estimated from the literature.

For perennial bioenergy crops the model simulates annual yield dynamics over the lifetime of the crop to account for reduced yields during establishment and peak yield later in the crop lifecycle. Yield dynamics are modelled using the lifetime mean annual yield of the crop (as an input to the model) and five crop-specific parameters:

1. $Y_{peak\text{-}ratio}$ - ratio of peak annual yield to lifetime mean annual yield, used to calculate peak annual yield.

2. T_{peak} – time required for the crop to reach peak annual yield.

3. T_0 – time spent at initial yield, before annual yield begins to increase towards peak annual yield. Used to approximate a sigmoidal growth curve.

4. $Y_{0\text{-}frac}$ – initial yield as a fraction of lifetime mean annual yield. This parameter is calculated from the other parameters to ensure that the lifetime mean annual yield of the crop is preserved.

5. Lifetime – the lifespan of the crop.

The parameter values for each perennial crop, which are based on expert opinion, are given in Table 1.1. The simulated yield dynamics are characterised by 3 stages: a period spent at initial annual yield (SRF only), a period of linearly increasing annual yield and a period spent at peak annual yield. An example of the growth dynamics of each crop given by the parameter values in Table 1.1 is shown in Figure 1.1. The lifetime mean annual yields used as an input to the model are taken from a number of sources, which are described in section 2.3.3.

Table 1.1: Yield model parameters for *Miscanthus*, SRC and SRF. See text for an explanation of each parameter.

Crop	$Y_{peak\text{-}ratio}$	T_{peak} (years)	T_0 (years)	$Y_{0\text{-}frac}$	Lifetime (years)
Miscanthus	1.1	5	0	0.299	20
SRC	1.1	6	0	0.433	20
SRF	1.6	15	4	0.267	20

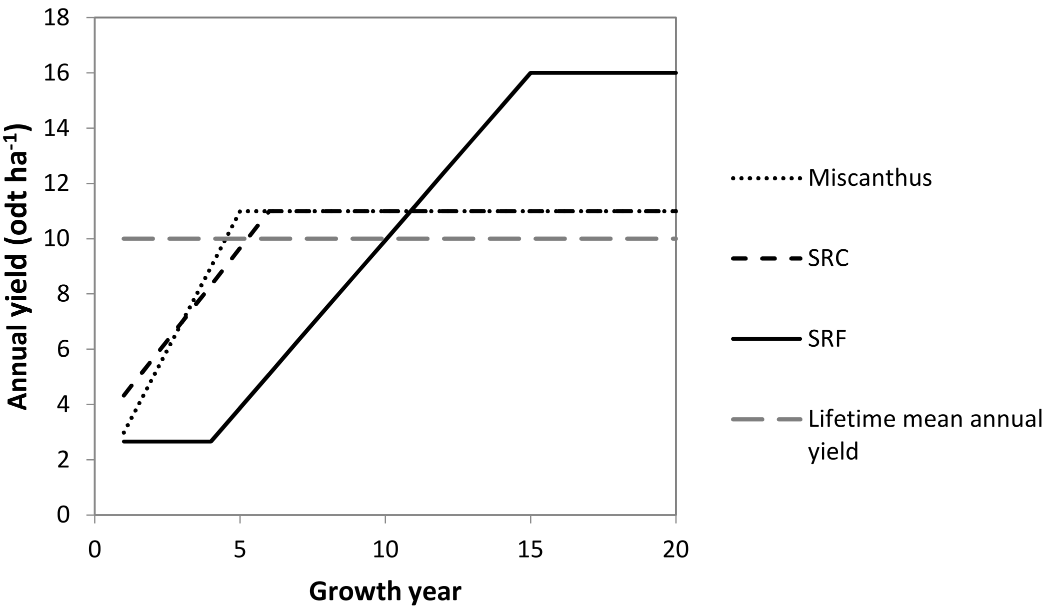


Figure 2.1: Annual yield dynamics of *Miscanthus*, SRC and SRF over the 20-year lifespan of each crop, with a lifetime mean annual yield of 10 odt ha^{-1}. Lifetime mean annual yield is represented by the dashed grey line for comparison.

The annual yield dynamics of perennial crops typically follow a sigmoidal curve. Here, we employed a simple linear-based approach to yield modelling to maintain model parsimony. *Miscanthus* and SRC establish quickly and do not have a very pronounced sigmoidal growth curve. Therefore, the linear increase during establishment will only result in a small error in the timing of plant inputs to the soil (and subsequent effects on the timing of changes in SOC and GHG emission). For SRF, which has a longer establishment time and a more pronounced sigmoidal growth curve, we introduced an additional flat growth phase at the start of establishment to better approximate the sigmoidal curve and minimise the error in the timing of plant inputs.

Each perennial bioenergy crop is re-established after a 20-year period (the estimated productive lifespan of the crop). It is assumed that re-establishment does not involve further cultivation. This assumption has been made because perennial bioenergy crops can be re-established with only shallow soil disturbance or very localised soil disturbance. *Miscanthus* crops can be re-established by herbicide application of the existing crop followed by direct drilling of rhizomes. Ploughing of *Miscanthus* can be avoided by exposing the rhizomes on top of the soil so that they dehydrate and die (Caslin *et al*, 2011). SRC can be removed by application of herbicide followed by mulching of the stools (using a bush-hogger), into the top 5-10 cm of the soil (Defra, 2004) and SRF may be re-established by planting between previous stumps (McKay, 2011). The impacts of soil disturbance during re-establishment of perennial bioenergy crops are poorly understood and require further research (Grogan and Matthews, 2002). However, since the re-establishment of these crops can be made with only shallow soil disturbance (the top 5-10 cm), or very localised disturbance (e.g. direct drilling of *Miscanthus* and replanting SRF between stumps), we expect the impacts on SOC to be small. Fertiliser is applied to *Miscanthus* and SRC at an annual rate of 30 and 60 kg N ha^{-1} respectively, following recommended practice (Caslin *et al*, 2011a; Defra, 2010). Fertiliser is applied to SRF at a rate of 45 kg N ha^{-1}. No fertiliser is applied to *Miscanthus*, SRC and SRF during the first 2 years after planting, again following best-practice guidelines (Caslin *et al*, 2011a; Defra, 2010).

Forest is assumed to be unfertilised. Rotational crops, permanent grass, wheat, oilseed rape and sugar beet are assumed to be fertilised at a rate equal to the annual crop N demand. Crop N demand is a function of plant yield and the C:N ratio of the plant. Modelled crop N demand is high for wheat because it has a low C:N ratio and a relatively high yield. In contrast, modelled N demand for permanent grass is significantly lower because it has a higher C:N ratio.

For all land-use types the changes in SOC and emissions of GHGs are calculated for the top metre of the soil profile. Only the top metre is considered because this is the depth to which soil parameters are provided by the HWSD soil database (see section 2.2.1). Changes in SOC, CH_4 and N_2O resulting from LUC are calculated by subtracting the results of the appropriate null transition from the LUC results, so that a change can be attributed solely to the LUC. For example, to calculate the impact of LUC from permanent grass to SRC, the results from the permanent grass null transition (i.e. grass remaining as grass), are subtracted from the permanent grass to SRC results. Each grid cell value in the model output represents the area-weighted mean of the simulations carried out for each soil type in the grid cell.

2.2.1 Soil data

The Harmonised World Soil Database (HWSD) version 1.2 was used to provide initial soil conditions in the model (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). The HWSD provides soil data to a depth of 1 metre at a resolution of 30 arc seconds (approximately 1 km), for the dominant soil types in each grid cell.

The soil properties used from this database to drive ECOSSE were: organic C content, bulk density, pH, and sand, silt and clay faction. The HWSD does not include information on the water-holding capacities of soils so these were estimated using British Soil Survey pedotransfer functions (Hutson and Cass, 1992), which performed well in evaluations (Donatelli *et al*, 1996; Givi *et al*, 2004).

The HWSD also provides the percentage of grid cell area covered by each soil type. The percentage cover is applied to the ECOSSE results for each dominant soil type in each grid cell to produce area-weighted grid cell mean responses.

2.3.2 Climate data

ECOSSE requires precipitation and air temperature data which are used to drive the soil water model and to determine temperature-based rate modifiers of various soil processes. The meteorological driving data has been taken from the UKCP09 Spatially Coherent Projections (Murphy *et al*, 2009). UKCP09 provides average monthly temperature and precipitation in a 25 km grid for overlapping 30-year periods centred upon decades ranging from the 2020s to the 2080s, for high, medium and low emissions scenarios.

2.3.3 Yield data

ECOSSE requires yield data for each land-use type in order to estimate the monthly plant inputs to the soil. Yield data for the bioenergy crops have been obtained from a range of sources of varying spatial resolution.

Defra yield statistics from 2000 to 2008 were used to establish baseline yield values for wheat, oilseed rape and sugar beet. Baseline yields (yields at the start of the simulation period) for wheat and oilseed rape were calculated for each NUTS (Nomenclature of Territorial Units for Statistics) level 1 region (12 regions for the UK). Defra only provide national average yield values for sugar beet so the calculated baseline yield is restricted to a single national value in this case. The baseline yield values for the rotational crop land-use category follow those of wheat.

Yield estimates for wheat, oilseed rape and sugar beet under different climate scenarios were obtained by adjusting the baseline yields using the Miami model (Lieth, 1975). Miami is an empirical net primary production (NPP) model that estimates annual net primary production from mean annual temperature and annual precipitation. The Miami estimate of net primary production was calculated for each decade in each grid cell using the same UKCP09 climate data that was used for the ECOSSE simulations. The percentage change in net primary production relative to the baseline Miami net primary production was applied to the baseline yield data to adjust the yield for each climate scenario. Yield estimates for permanent grass and forest are obtained using net primary production estimates from Miami, which are then linearly rescaled according to observed peak yields (Living Countryside, 2013) to reflect differences in grass and forest productivity.

Lifetime mean annual yield estimates for *Miscanthus*, SRC and SRF were obtained from simulations using the models Miscanfor (Hastings *et al*., 2009), ForestGrowth SRC (Tallis *et al*., 2012) and ESC-CARBINE (Pyatt *et al*., 2001; Thompson and

Matthews, 1989) respectively. The yield predictions have been obtained using the same UKCP09 climate and HWSD soil data used as inputs to ECOSSE. These models are used due to their validated accuracy and use of compatible data. The lifetime mean annual yields are provided for each decade because the UKCP09 climate data provides long-term average climate values centred on each decade (see section 2.3.2). As an ECOSSE simulation progresses, the annual yield for each year of the simulation is calculated from the lifetime mean annual yield (as described in section 2.2) for the current decade. Therefore, if the lifetime mean annual yield changes between decades, this is reflected by a change in the annual yield calculated within the model.

SRC is represented here by willow. The yield modelling study of Hastings et al (2013) found that SRC poplar outperformed SRC willow in all regions within Great Britain. However, willow is the SRC species used in commercial plantations in the UK, with a breeding and propagation program in Rothamsted and several European Union countries. SRC poplar currently has a much lower commercial status than SRC willow. This may in part be due to SRC poplar being a less practical crop for farmers because it produces thicker stems that are not easy to harvest, whereas willow produces thinner stems that can be harvested with a modified forage harvester. We therefore believe that willow, despite lower yields, is likely to remain the dominant commercial SRC species.

SRF is represented here by poplar, since Hastings *et al* (2013) found that poplar outperformed all other SRF species included in the study except for sitka spruce in the Scottish Highlands and Pennines (areas which are mostly within the UKERC constraints mask). The other SRF species included in the study are: aspen (*Populus tremula* L.), black alder (*Alnus glutinosa* L.), European ash (*Fraxinus excelsior* L.), sitka spruce (*Picea sitchensis* [Nong.] Carr.) and silver birch (*Betula pendula* Roth). The lifetime mean annual yields of SRF poplar across Great Britain were at least double those of other species. With no clear commercial benefits of selecting other SRF species over poplar, we assume the strong commercial incentive offered by the much higher yields will mean that poplar will be the dominant SRF species in the UK.

3. RESULTS

This section describes and illustrates the findings from the spatial simulations. Interpretation of the findings, including explanations for each section of results, is covered in the Discussion (section 4).

3.1 Land-use change

The effects of LUC to bioenergy crops shown in this section are obtained from simulations carried out using the medium climate scenario. All results refer to the period 2015 - 2050 unless otherwise stated. The effects of each climate scenario are described in section 3.2 of this report. The maps relating to change in SOC and net GWP are divided into 3 categories, each with a specific colour scale: beneficial responses (green, change in SOC greater than 0 t CO_2e ha^{-1}), small detrimental responses (amber, change in SOC between 0 and -50 t CO_2e ha^{-1}) and larger detrimental responses (red, change in SOC less than -50 t CO_2e ha^{-1}). The maps relating to CH_4 and N_2O are divided into just 2 categories: beneficial (green) and detrimental (red) in order to maintain brevity and because these variables influence net GWP less than changes in SOC. Larger (full-page) versions of all maps are available in a separate appendix: BI1001_PM07.4.6_WP4_Effects on LUC in Bioenergy Appendix II v1.5.

3.1.1 Effects on soil organic carbon

The mean, minimum and maximum changes in SOC from 2015 to 2050 following LUC from rotational crops, permanent grass and forest are shown in Tables 3.1, 3.2 and 3.3 respectively.

Table 3.1: Mean, minimum and maximum cumulative change in SOC (t CO_2e ha^{-1}) from 2015-2050 following conversion from rotational crops to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	n/a	n/a	n/a	55.4	18.7	102.9
Min	n/a	n/a	n/a	-0.7	-27.4	9.9
Max	n/a	n/a	n/a	121.8	114.4	205.4

Table 3.2: Mean, minimum and maximum cumulative change in SOC (t CO_2e ha^{-1}) from 2015-2050 following conversion from permanent grass to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	-85.4	-119.9	-118.6	-44.7	-70.0	-24.3
Min	-220.6	-283.5	-282.5	-147.8	-186.3	-147.1
Max	-37.8	-65.3	-64.2	1.7	-33.0	30.2

Table 3.3: Mean, minimum and maximum cumulative change in SOC (t CO_2e ha^{-1}) from 2015-2050 following conversion from forest to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	-117.9	-149.7	-148.5	-78.2	-102.0	-64.0
Min	-321.5	-369.0	-365.4	-216.8	-251.8	-219.1
Max	-56.8	-81.6	-80.6	-31.0	-56.6	-4.6

Grid cells with a larger detrimental, small detrimental and beneficial change in SOC are shown in Figures 3.1, 3.2 and 3.3 respectively. These maps (together with the results presented in Tables 3.1 to 3.3) show that whilst there is a strong spatial variation in SOC response for each LUC, the initial land-use type is the most significant determinant of SOC response, with transitions from rotational crops being broadly beneficial and transitions from permanent grass and forest being broadly detrimental. In general, the change in SOC resulting from conversion from forest is more detrimental than from grass.

3.1.1.1 Conversion of rotational crops

Conversion of rotational crops to *Miscanthus*, SRC and SRF generally result in a beneficial change in SOC, with conversion of rotational crops to SRF showing a beneficial change in every simulated grid cell. Rotational crops to SRF shows the largest mean accumulation of SOC, nearly double that of rotational crops to *Miscanthus*, which has the next highest mean accumulation of SOC.

Conversion from rotational crops to *Miscanthus* and SRC shows some areas with a small detrimental change in SOC, though for *Miscanthus* this is restricted to a very small number of grid cells in East Anglia which have only a very small detrimental change in SOC and is therefore of minor concern. No conversions from rotational crops show a large detrimental change in SOC. All other LUCs show a mean (detrimental) loss of SOC. LUCs from permanent grass and forest to wheat, OSR and sugar beet show the largest mean SOC losses.

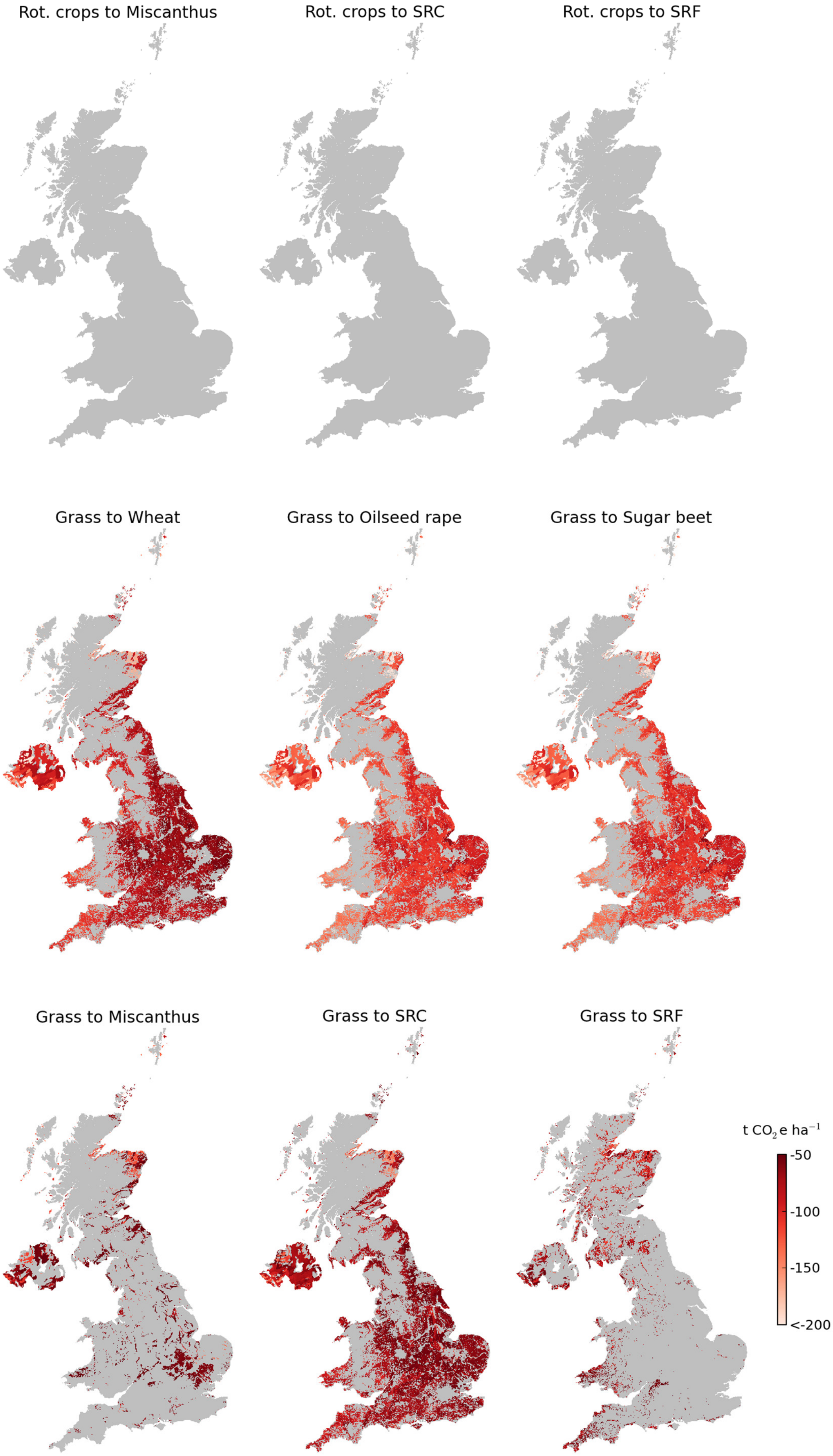
3.1.1.2 Conversion of permanent grass

All conversions from permanent grass show a mean detrimental change in SOC, with conversions to wheat, OSR and sugar beet showing the most detrimental changes. However, conversions from permanent grass to *Miscanthus* and SRF show a beneficial SOC response in some grid cells. For *Miscanthus* this beneficial response is restricted to a small number of grid cells in southern England, whereas for SRF the beneficial response is widespread over central and eastern England.

Conversions from permanent grass to wheat, OSR and sugar beet are dominated by large detrimental changes in SOC. Of these conversions, only wheat has areas that fall into the small detrimental change category, and these are confined to a small number of grid cells occurring predominantly in East Anglia and East Midlands.

3.1.1.3 Conversion of forest

As with conversions from permanent grass, all conversions from forest show a mean detrimental change in SOC, with conversions to wheat, OSR and sugar beet showing the most detrimental changes. Moreover, none of the transitions from forest show a beneficial change in SOC anywhere in the simulated area. A small detrimental change in SOC occurs for two of the bioenergy crops: SRF (over most of the simulated area) and *Miscanthus* (confined mainly to two areas located in southern and north-east England). All other transitions from forest (wheat, OSR, sugar beet and SRC) show a large detrimental change in SOC throughout the simulation area.



Not to be disclosed other than in line with the terms of the Technology Contract.

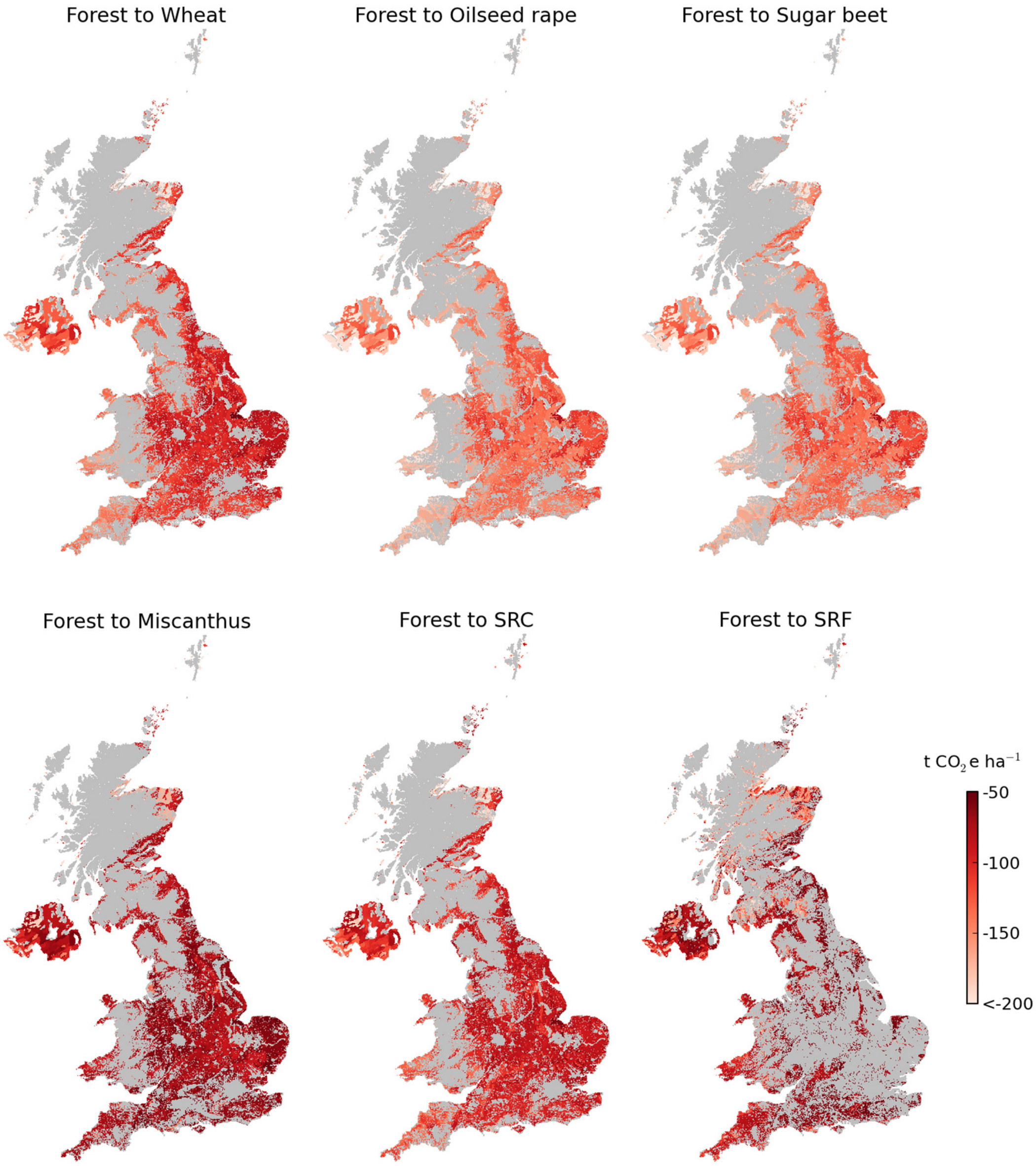
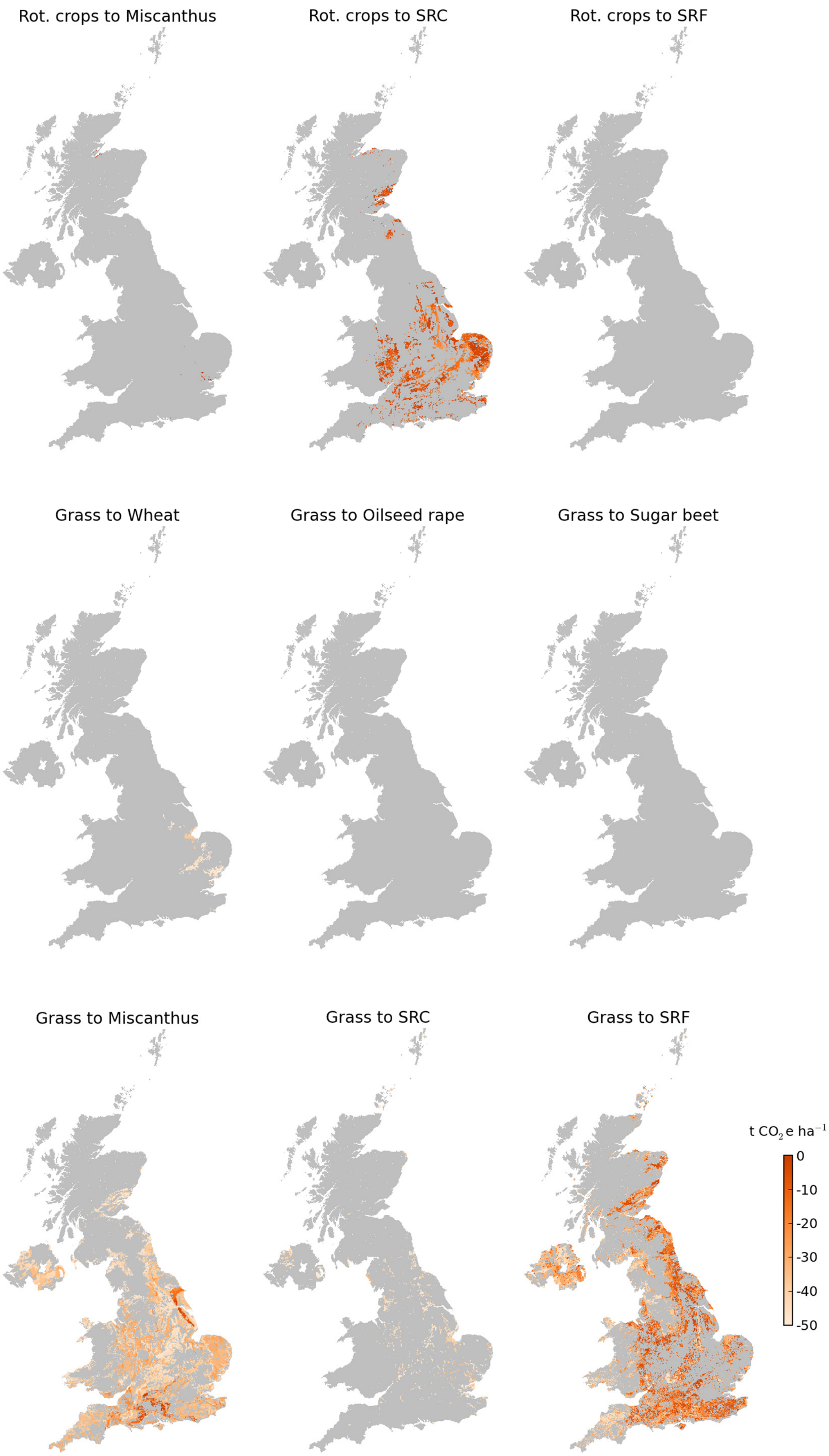


Figure 3.1: Maps showing grid cells with a large negative (detrimental) change in SOC (less than -50 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in SOC. Grey represents excluded areas and areas that do not have a large negative change in SOC.



Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
0
-10
-20
-30
-40
-50

Figure 3.2: Maps showing grid cells with a small negative (detrimental) change in SOC (between 0 and -50 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in SOC. Grey represents excluded areas and areas that do not have a small negative change in SOC.

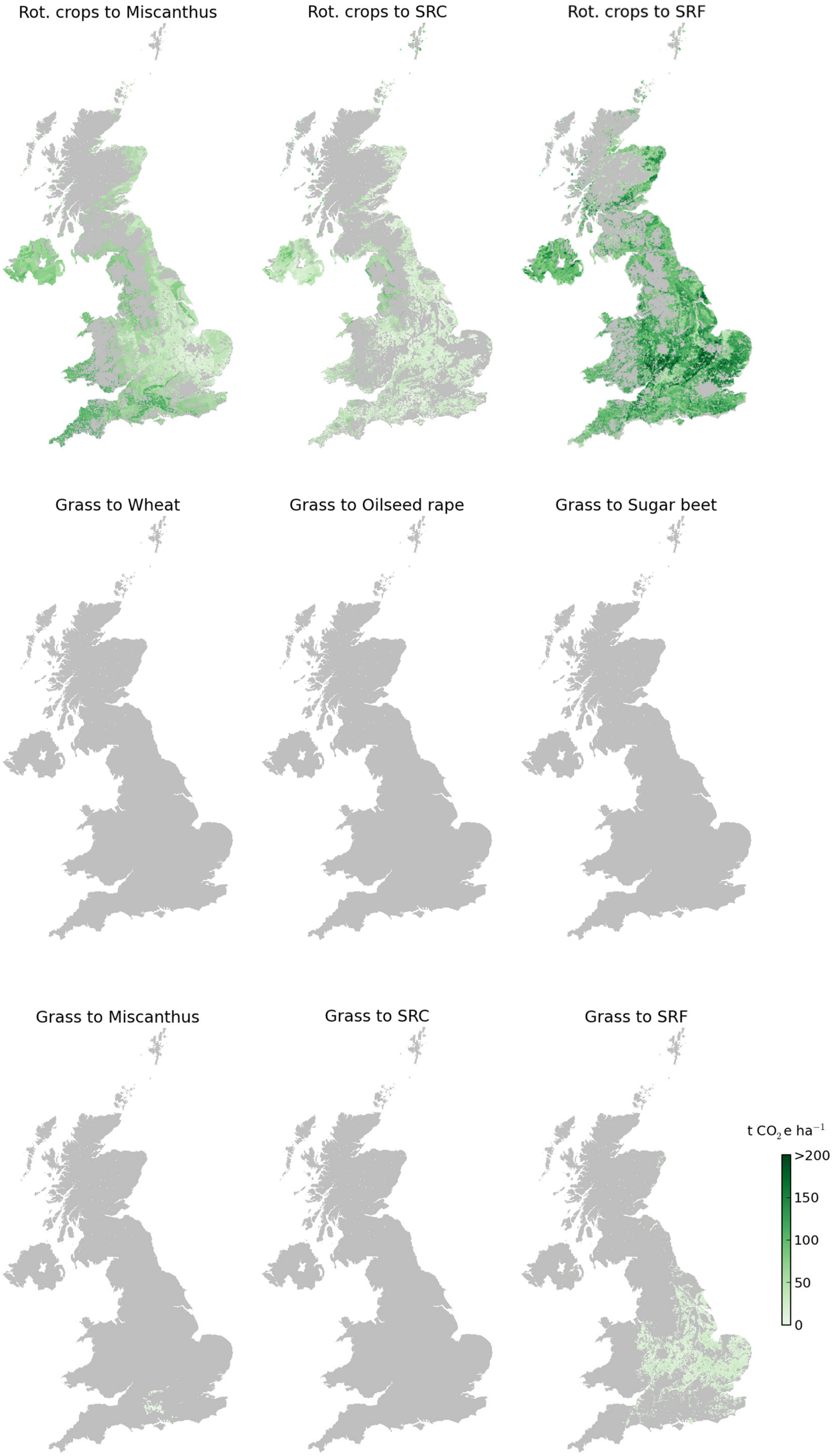

Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
>200
150
100
50
0

Figure 3.3: Maps showing grid cells with a positive (beneficial) change in SOC (more than 0 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in SOC. Grey represents excluded areas and areas that do not have a positive (beneficial) change in SOC.

3.1.1.4 Temporal dynamics

The mean cumulative change in SOC over time for each transition is shown in Figure 3.4. Conversion from rotational crops to *Miscanthus* and SRF show the most rapid increases in SOC, with both crops showing an approximately equal increase in SOC after the first 10 years. After 10 years, however, SRF begins to accumulate SOC more rapidly than *Miscanthus*. Rotational crops to SRC shows little change in SOC after 5 years, then begins to gradually increase.

All other LUCs show rapid SOC loss during the first 5 years following conversion. The rapid SOC loss during this period is due to the simulated cultivation event that occurs when converting permanent grass and forest to a bioenergy crop (see section 2.2).

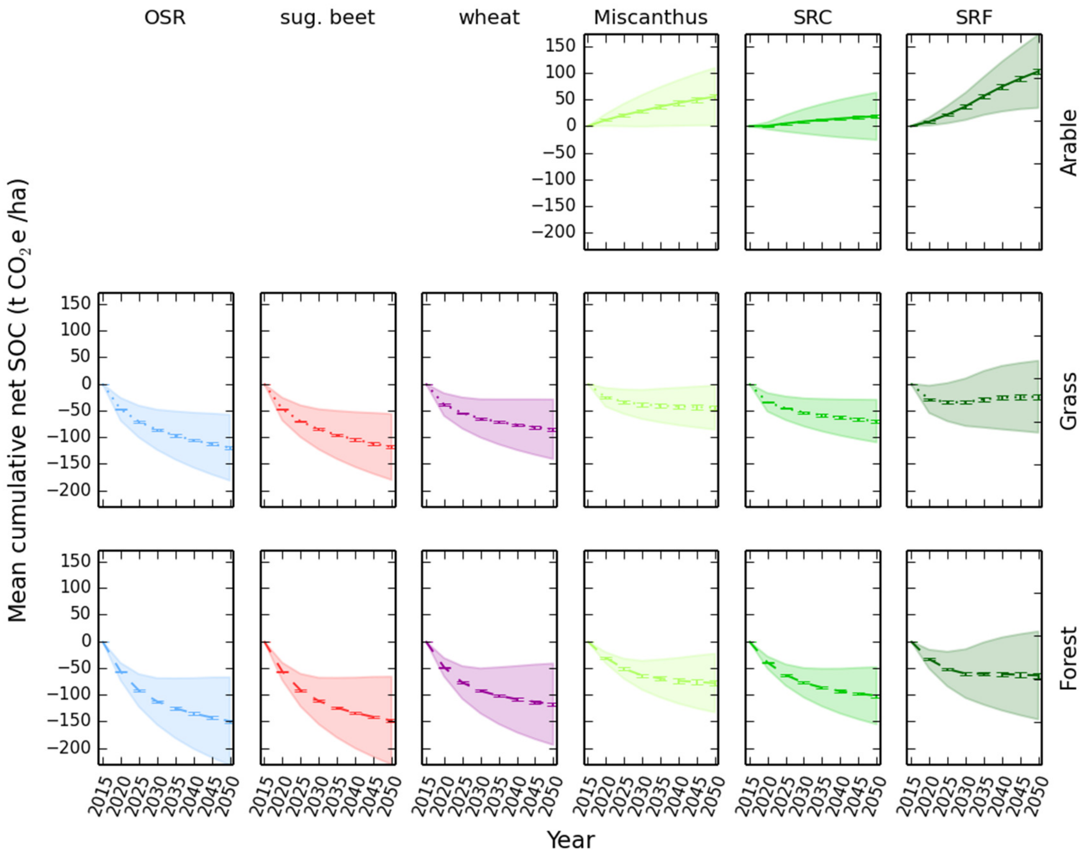


Figure 3.4: Time series of mean cumulative change in soil organic carbon (SOC) resulting from land-use change to bioenergy crops in 2015 under the medium emissions climate scenario. Shaded areas show the 95% confidence interval of the distribution of modelled results from the simulations across the UK. Error bars show the model error based on the comparison of modelled and measured SOC from the site-level modelling study.

After five years, some LUCs begin to show a significant decrease in the rate of SOC loss, with permanent grass to SRF beginning to show an accumulation of SOC approximately 15 years after LUC. Thirty-five years after LUC, permanent grass and forest to *Miscanthus* and forest to SRF are, on average, approaching a new equilibrium (or near-equilibrium) SOC level, in which plant C inputs to the soil approximately equal C losses from the soil.

3.1.2 Effects on N_2O fluxes

The mean, minimum and maximum changes in N_2O flux from 2015 to 2050 following LUC from rotational crops, permanent grass and forest are shown in Tables 3.4, 3.5 and 3.6, respectively. Comparison of these results with those of changes in SOC in Tables 3.1, 3.2 and 3.3 show that, overall, mean changes in N_2O emissions have a much smaller impact than mean changes in SOC.

Table 3.4: Mean, minimum and maximum cumulative change in N_2O flux (t CO_2e ha^{-1}) from 2015-2050 following conversion from rotational crops to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	n/a	n/a	n/a	-21.0	-19.0	-24.0
Min	n/a	n/a	n/a	-33.6	-30.8	-37.3
Max	n/a	n/a	n/a	-13.2	-12.5	-15.8

Table 3.5: Mean, minimum and maximum cumulative change in N_2O flux (t CO_2e ha^{-1}) from 2015-2050 following conversion from permanent grass to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	35.9	10.9	20.5	8.8	10.5	8.6
Min	23.6	-0.6	10.3	0.2	1.6	-2.1
Max	74.8	54.3	62.1	43.9	49.2	44.2

Table 3.6: Mean, minimum and maximum cumulative change in N_2O flux (t CO_2e ha^{-1}) from 2015-2050 following conversion from forest to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	52.4	27.3	36.9	24.7	26.6	24.7
Min	39.0	16.8	25.4	13.6	17.9	16.5
Max	88.0	56.4	66.5	42.9	47.7	42.3

The spatial distribution of detrimental and beneficial change in N_2O emissions are shown in Figures 3.5 and 3.6 respectively. These maps show that there is less spatial variation in N_2O emissions than for changes in SOC. Where changes in N_2O are beneficial (Figure 3.6), the effect is more pronounced on the west side of the UK than on the east. Within the permanent grass and forest land-use categories, conversion to wheat results in the most detrimental change in N_2O emissions, followed by sugar beet.

Mean changes resulting from conversion to OSR, *Miscanthus*, SRC and SRF are all fairly similar.

3.1.2.1 Conversion of rotational crops

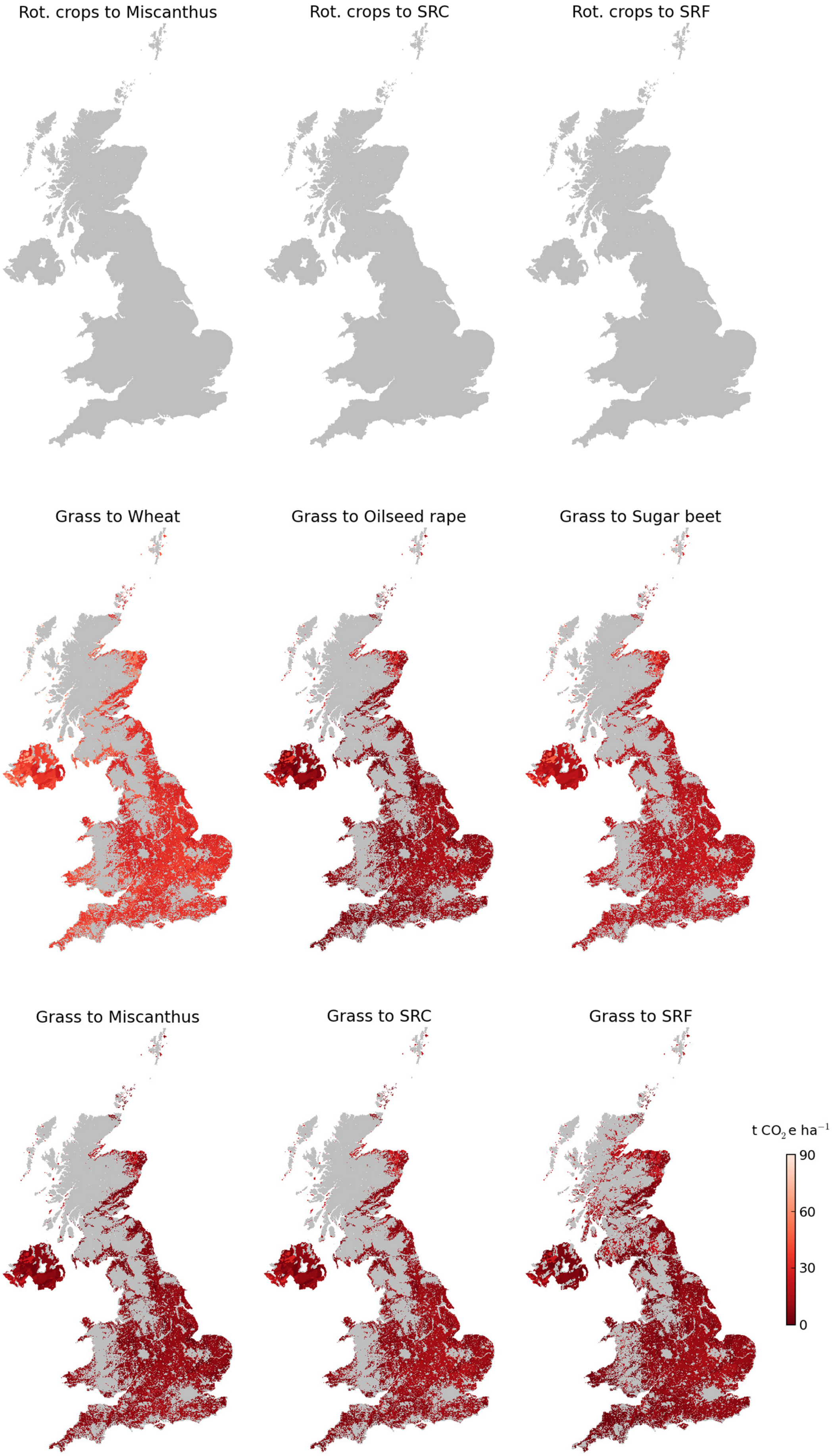
Conversion of rotational crops to *Miscanthus*, SRC and SRF results in a negative (beneficial) change in N_2O emissions in every grid cell. The largest beneficial changes occur under SRF, followed by *Miscanthus* and then SRC, though the mean changes are all fairly similar (within 5 t CO_2e ha^{-1} of each other).

3.1.2.2 Conversion of permanent grass

Conversion of permanent grass to bioenergy crops generally shows a small mean (detrimental) increase in N_2O emissions (typically less than 21 t CO_2e ha^{-1}), although the change following conversion to wheat is significantly higher than for other bioenergy crops (35.9 t CO_2e ha^{-1}). Conversions from permanent grass to wheat, sugar beet, *Miscanthus* and SRC show a detrimental change in N_2O emissions in every simulated grid cell. SRF predominantly shows a detrimental change in N_2O emissions except in a few small areas in the South West and North West of England, where very small (> -3 t CO_2e ha^{-1}) beneficial reductions in N_2O emissions occur. Similarly, OSR shows very small (> -1 t CO_2e ha^{-1}) beneficial changes in N_2O emissions in two very small areas in South Wales and the North West of England.

3.1.2.3 Conversion of forest

Conversion from forest always (in every grid cell) results in a detrimental change in N_2O emissions. The mean change in N_2O emission for each bioenergy crop is always larger for conversion from forest than from permanent grass.


Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
90
60
30
0

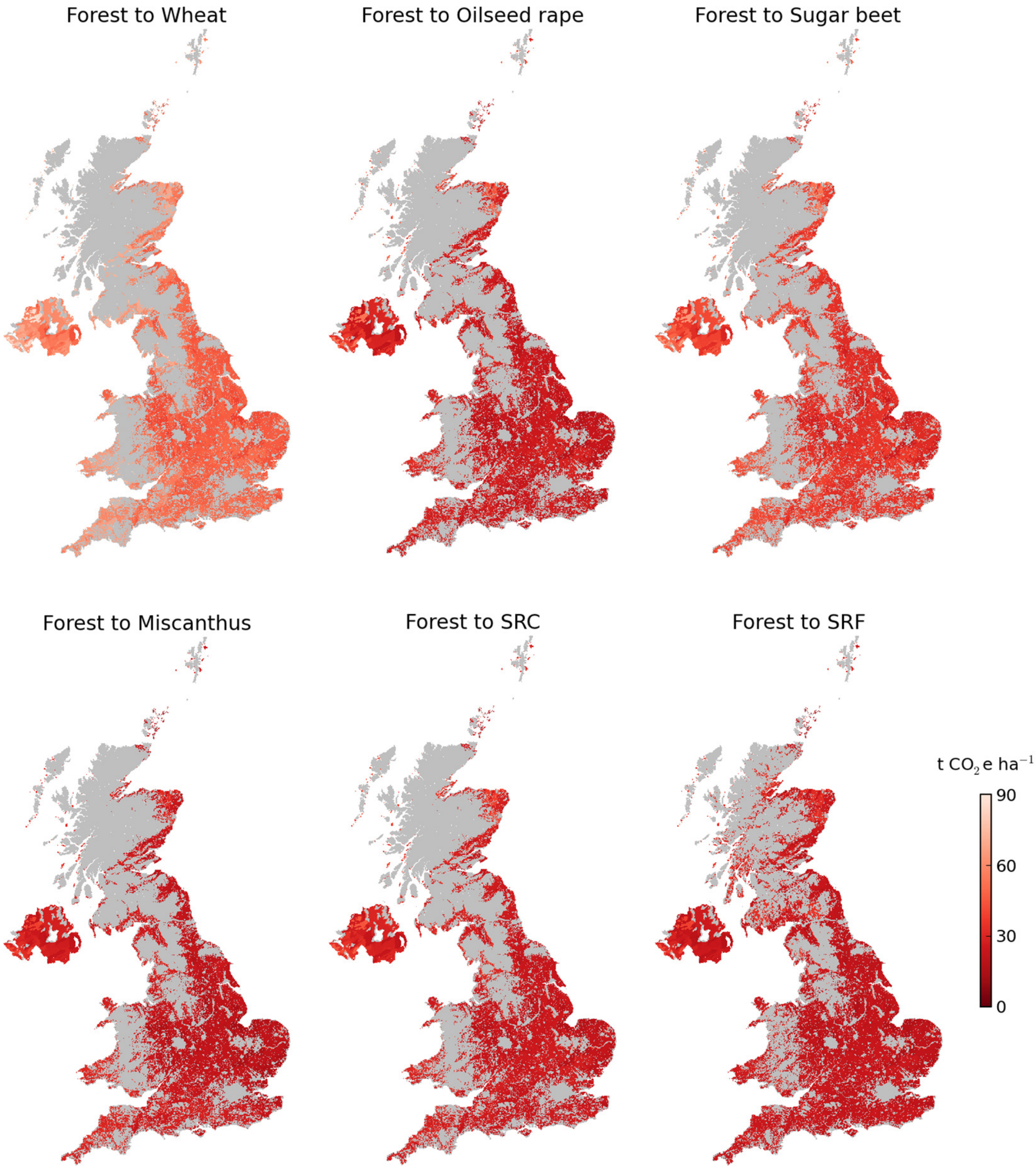
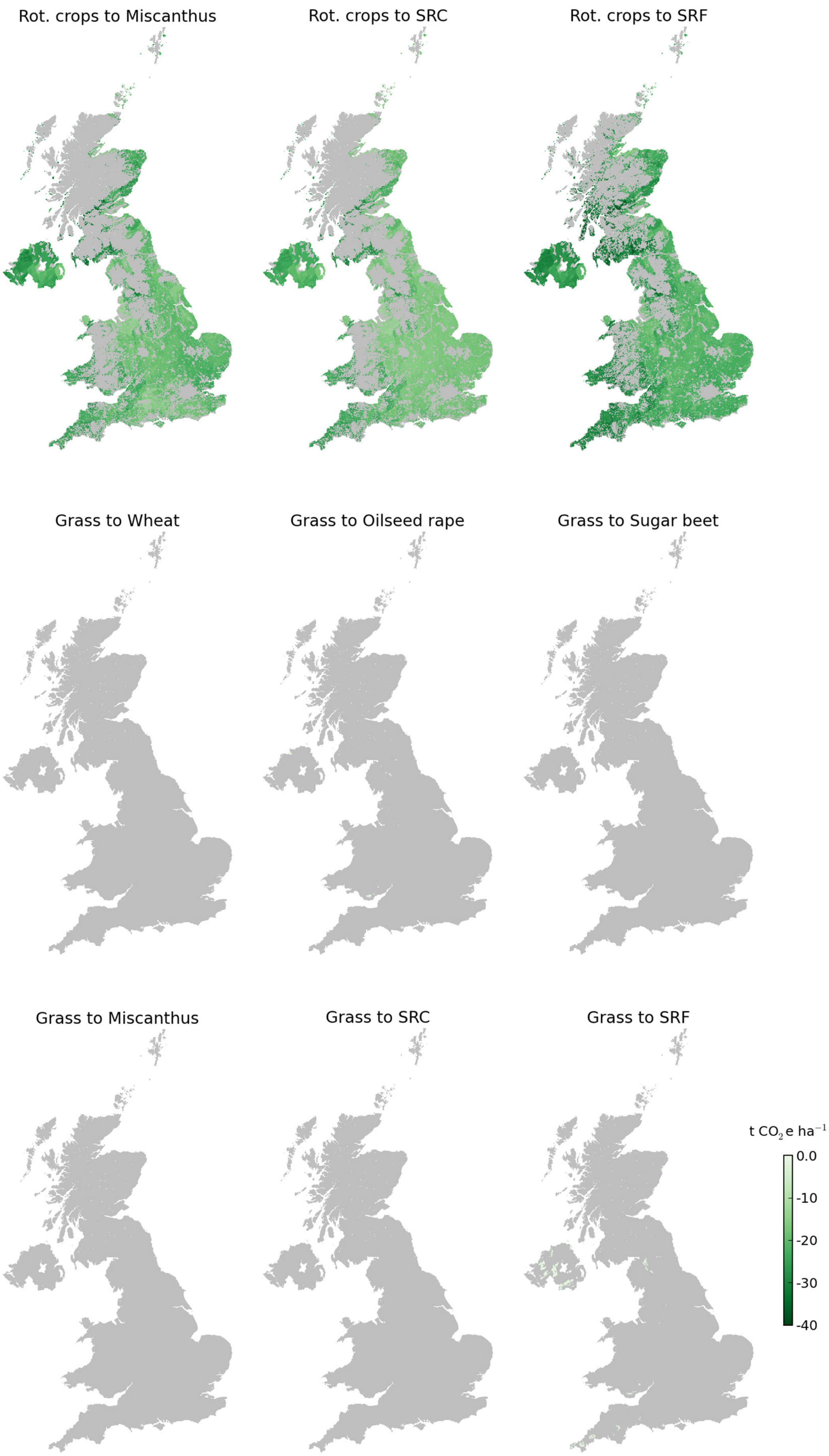


Figure 3.5: Maps showing grid cells with a positive (detrimental) change in N_2O emissions (t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in N_2O emissions. Grey represents excluded areas and areas that do not have a positive (detrimental) change in N_2O emissions.



Not to be disclosed other than in line with the terms of the Technology Contract.

Figure 3.6: Maps showing grid cells with a negative (beneficial) change in N_2O emissions (t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in N_2O emissions. Grey represents excluded areas and areas that do not have a negative (beneficial) change in N_2O emissions.

3.1.2.4 Temporal dynamics

The change in mean cumulative N_2O flux over time for each land-use transition is shown in Figure 3.7. Conversions from rotational crops to *Miscanthus*, SRC and SRF show a fairly linear decrease in cumulative N_2O flux over the 35-year simulation period. In contrast, all conversions from permanent grass and forest show a rapid increase 5 years after LUC. After the first 5 years, the N_2O responses begin to diverge: transitions from permanent grass to *Miscanthus*, SRC and SRF start to gradually decrease, while permanent grass to sugar beet levels off and the remaining transitions continue to have a steady, approximately linear increase in N_2O flux.

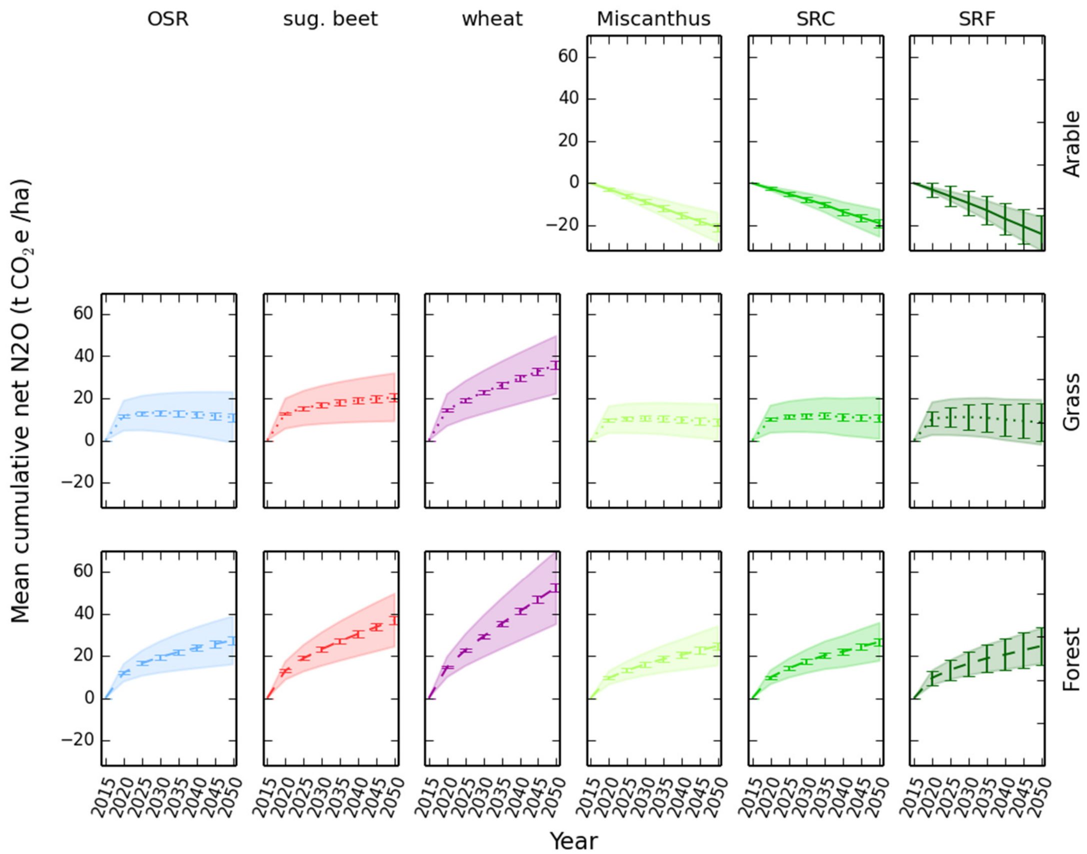


Figure 3.7: Time series of mean cumulative N_2O flux resulting from land-use change to bioenergy crops in 2015 under the medium emissions climate scenario. Shaded areas show the 95% confidence interval of the distribution of modelled results from the simulations across the UK. Error bars show the model error based on the comparison of modelled and measured N_2O from the site-level modelling study.

3.1.3 Effects on CH_4 fluxes

The mean, minimum and maximum changes in CH_4 flux from 2015 to 2050 following LUC from rotational crops, permanent grass and forest are shown in Tables 3.7, 3.8 and 3.9 respectively. Comparison of these results with changes in SOC and N_2O (see Tables 3.1, 3.2 and 3.3 and Tables 3.4, 3.5 and 3.6 respectively) show that, overall, mean changes in CH_4 emissions are approximately 2 to 4 orders of magnitude smaller than those of SOC and N_2O. Even the largest beneficial change (-1.1 t CO_2e ha^{-1}) and largest detrimental change (1.78 t CO_2e ha^{-1}) in CH_4 flux are very small in comparison to changes in SOC and N_2O. Therefore, changes in CH_4 emissions resulting from LUC can be considered to have an insignificant impact on net GWP. The spatial distribution of detrimental and beneficial change in CH_4 emissions are shown in Figures 3.8 and 3.9 respectively. These maps are primarily included for the sake of completeness since the difference between the detrimental and beneficial responses are so small, they can, for all intents and purposes, be considered zero.

Table 3.7: Mean, minimum and maximum cumulative change in CH_4 flux (t CO_2e ha^{-1}) from 2015-2050 following conversion from rotational crops to bioenergy crops under the medium climate scenario.

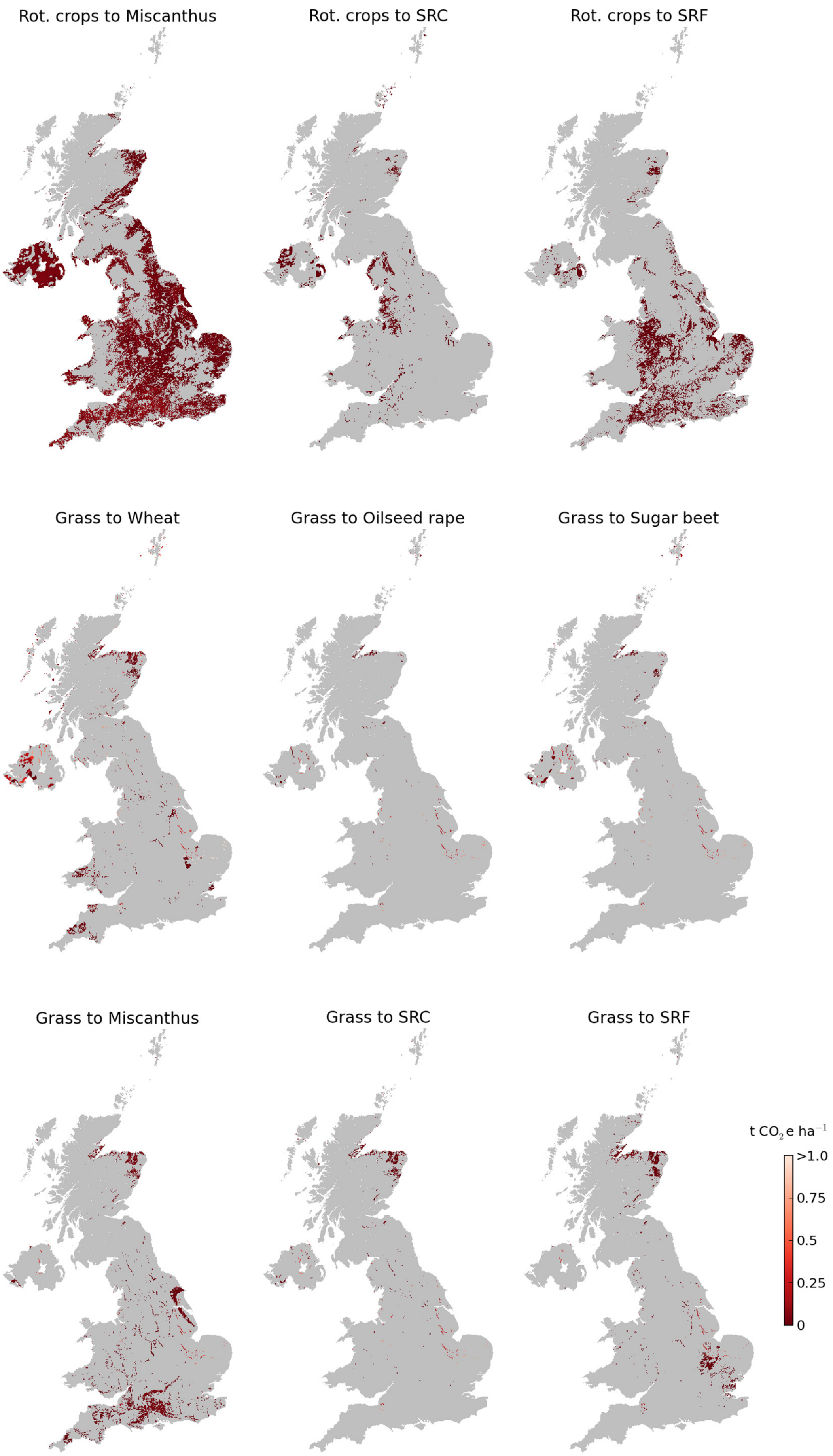
	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	n/a	n/a	n/a	0.02	-0.03	-0.04
Min	n/a	n/a	n/a	-1.10	-1.03	-1.22
Max	n/a	n/a	n/a	0.10	0.03	0.02

Table 3.8: Mean, minimum and maximum cumulative change in CH_4 flux (t CO_2e ha^{-1}) from 2015-2050 following conversion from permanent grass to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	-0.04	-0.11	-0.11	-0.02	-0.07	-0.05
Min	-0.12	-0.19	-0.19	-0.11	-0.14	-0.14
Max	1.02	0.56	0.68	0.43	0.69	0.37

Table 3.9: Mean, minimum and maximum cumulative change in CH_4 flux (t CO_2e ha^{-1}) from 2015-2050 following conversion from forest to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	-0.02	-0.09	-0.09	0.00	-0.05	-0.02
Min	-0.10	-0.18	-0.18	-0.06	-0.13	-0.13
Max	1.78	0.74	0.89	0.48	0.81	0.5


Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
>1.0
0.75
0.5
0.25
0

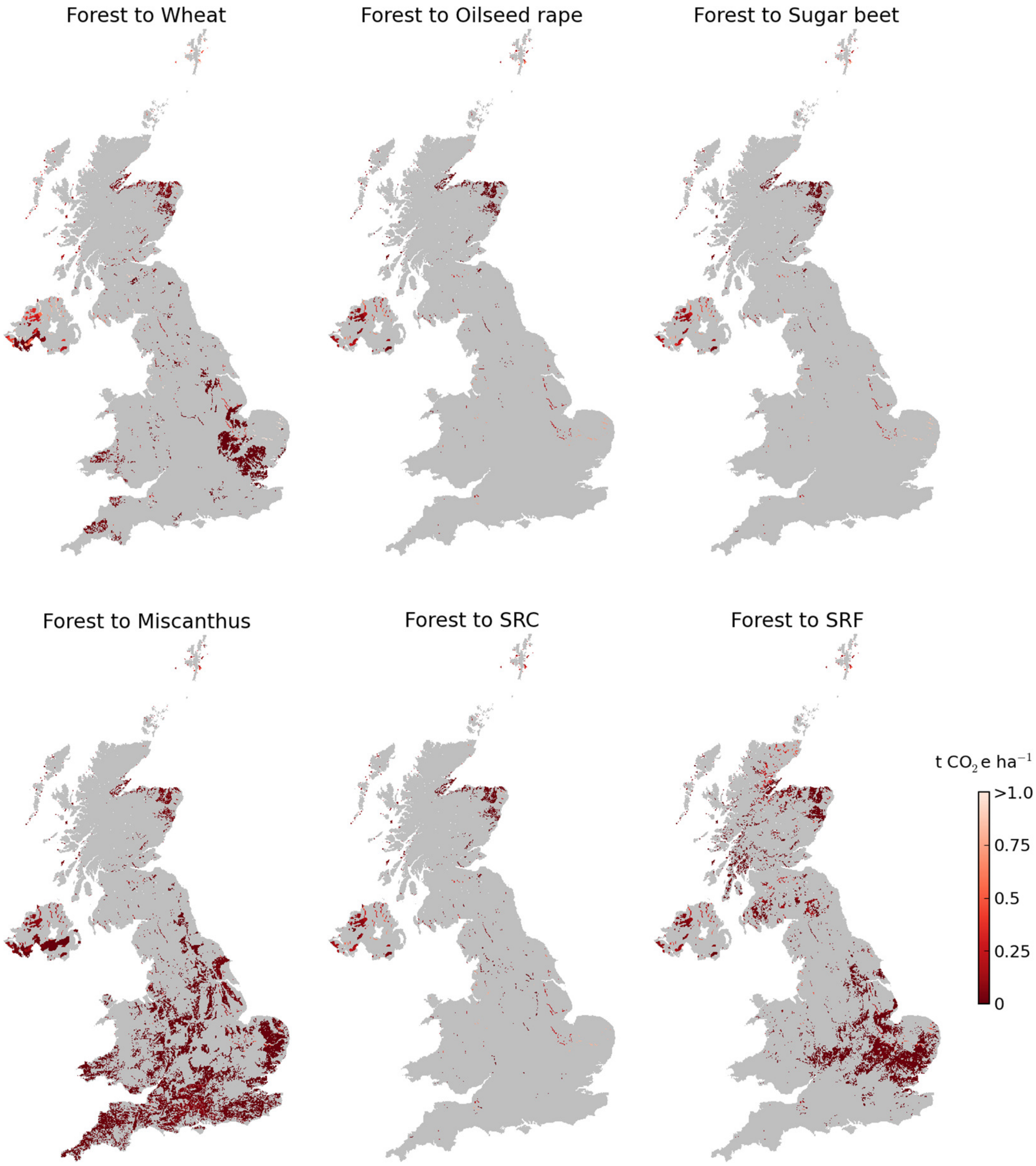
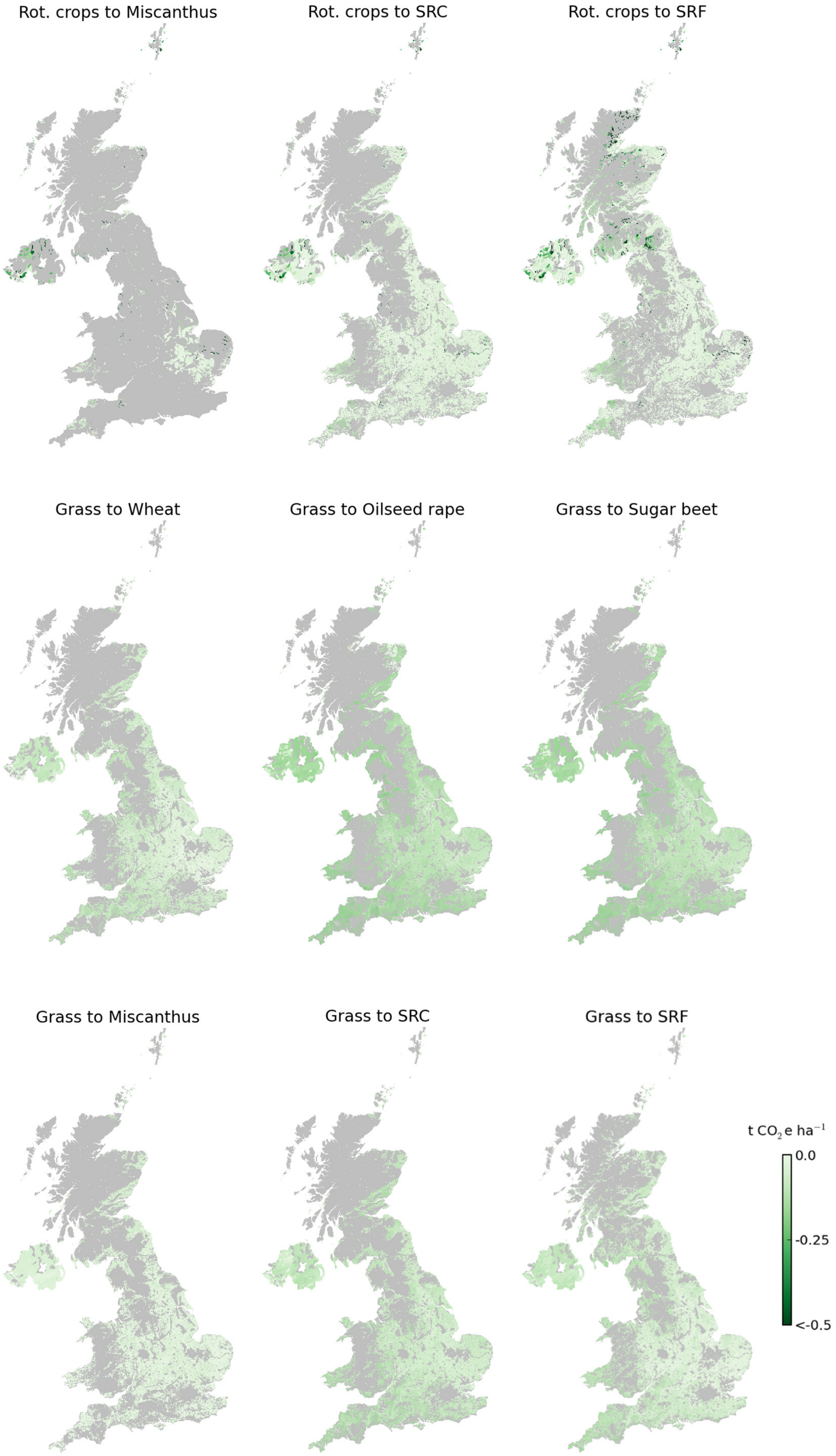


Figure 3.8: Maps showing grid cells with a positive (detrimental) change in CH_4 emissions (t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in CH_4 emissions. Grey represents excluded areas and areas that do not have a positive (detrimental) change in CH_4 emissions.


Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
0.0
-0.25
<-0.5

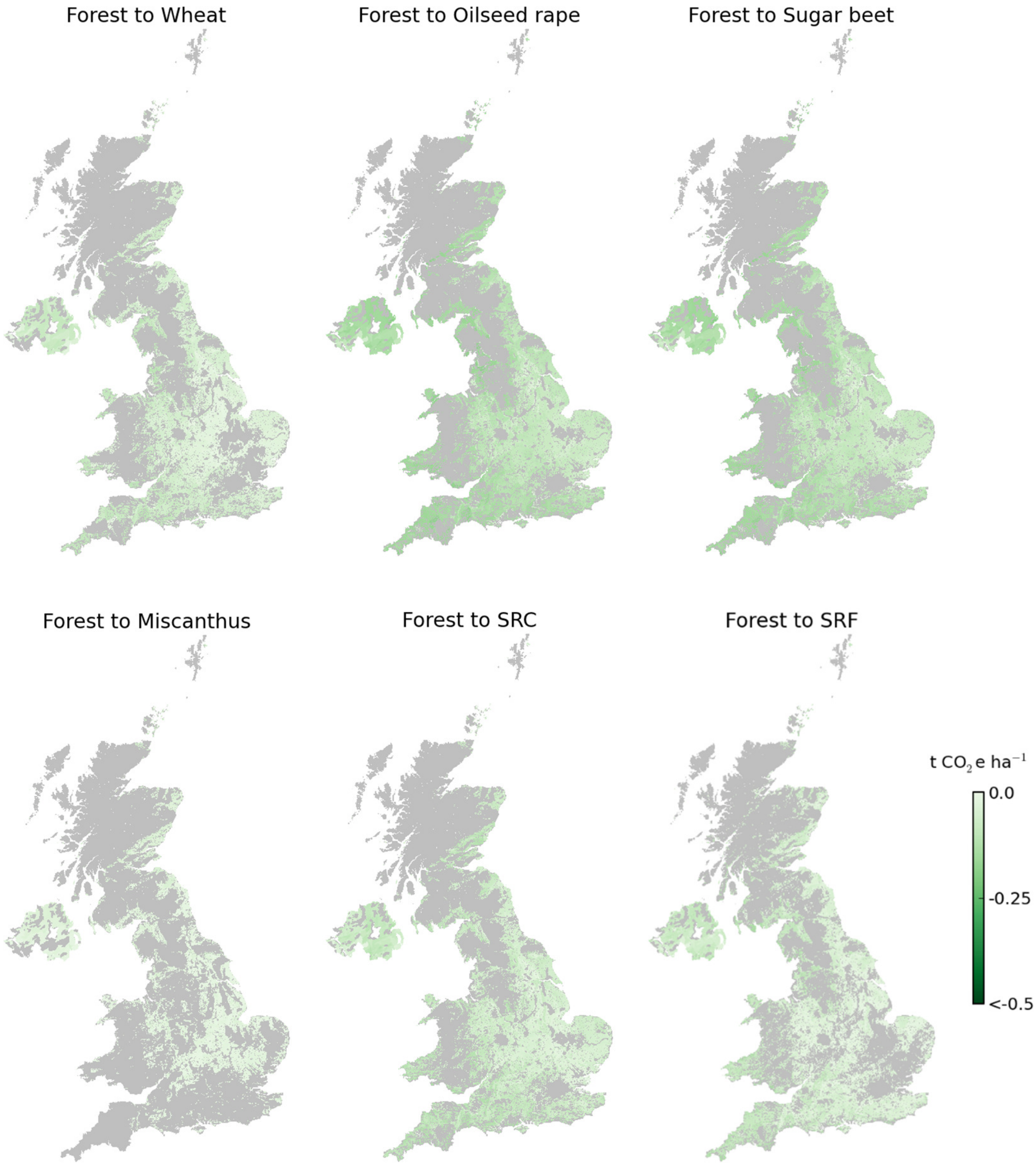


Figure 3.9: Maps showing grid cells with a negative (beneficial) change in CH_4 emissions (t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of change in CH_4 emissions. Grey represents excluded areas and areas that do not have a negative (beneficial) change in CH_4 emissions.

3.1.4 Effects on net global warming potential

Net GWP represents the combined GWPs resulting from changes in N_2O, CH_4 and SOC (expressed as CO_2e), and is therefore the best measure of bioenergy opportunity. Net GWP is calculated as the sum of changes in N_2O and CH_4 emissions, minus the change in SOC (where a positive change in SOC represents a beneficial accumulation of C). A positive net GWP is detrimental and a negative net GWP is beneficial, discounting all other factors.

The mean, minimum and maximum changes in net GWP from 2015 to 2050 following LUC from rotational crops, permanent grass and forest are shown in Tables 3.10, 3.11 and 3.12 respectively. Grid cells with a large detrimental, small detrimental and beneficial net GWP over the simulation period 2015 to 2050 are shown in figures 3.10, 3.11 and 3.12 respectively.

Table 3.10: Mean, minimum and maximum cumulative change in net GWP (t CO_2e ha^{-1}) from 2015-2050 following conversion from rotational crops to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	n/a	n/a	n/a	-76.4	-37.8	-126.9
Min	n/a	n/a	n/a	-146.1	-138.4	-230.2
Max	n/a	n/a	n/a	-20.7	9.4	-34.8

Table 3.11: Mean, minimum and maximum cumulative change in net GWP (t CO_2e ha^{-1}) from 2015-2050 following conversion from permanent grass to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	121.3	130.7	139.0	53.5	80.5	32.9
Min	64.5	69.6	77.1	11.3	39.2	-21.2
Max	300.4	332.7	341.9	185.6	236.8	172.6

Table 3.12: Mean, minimum and maximum cumulative change in net GWP (t CO_2e ha^{-1}) from 2015-2050 following conversion from forest to bioenergy crops under the medium climate scenario.

	Wheat	OSR	Sugar beet	*Miscanthus*	SRC	SRF
Mean	170.3	176.9	185.3	102.9	128.6	88.7
Min	96.1	98.3	105.9	58.4	75.1	23.5
Max	405.9	431.0	437.3	255.0	300.1	258.9

3.1.4.1 Conversion of rotational crops

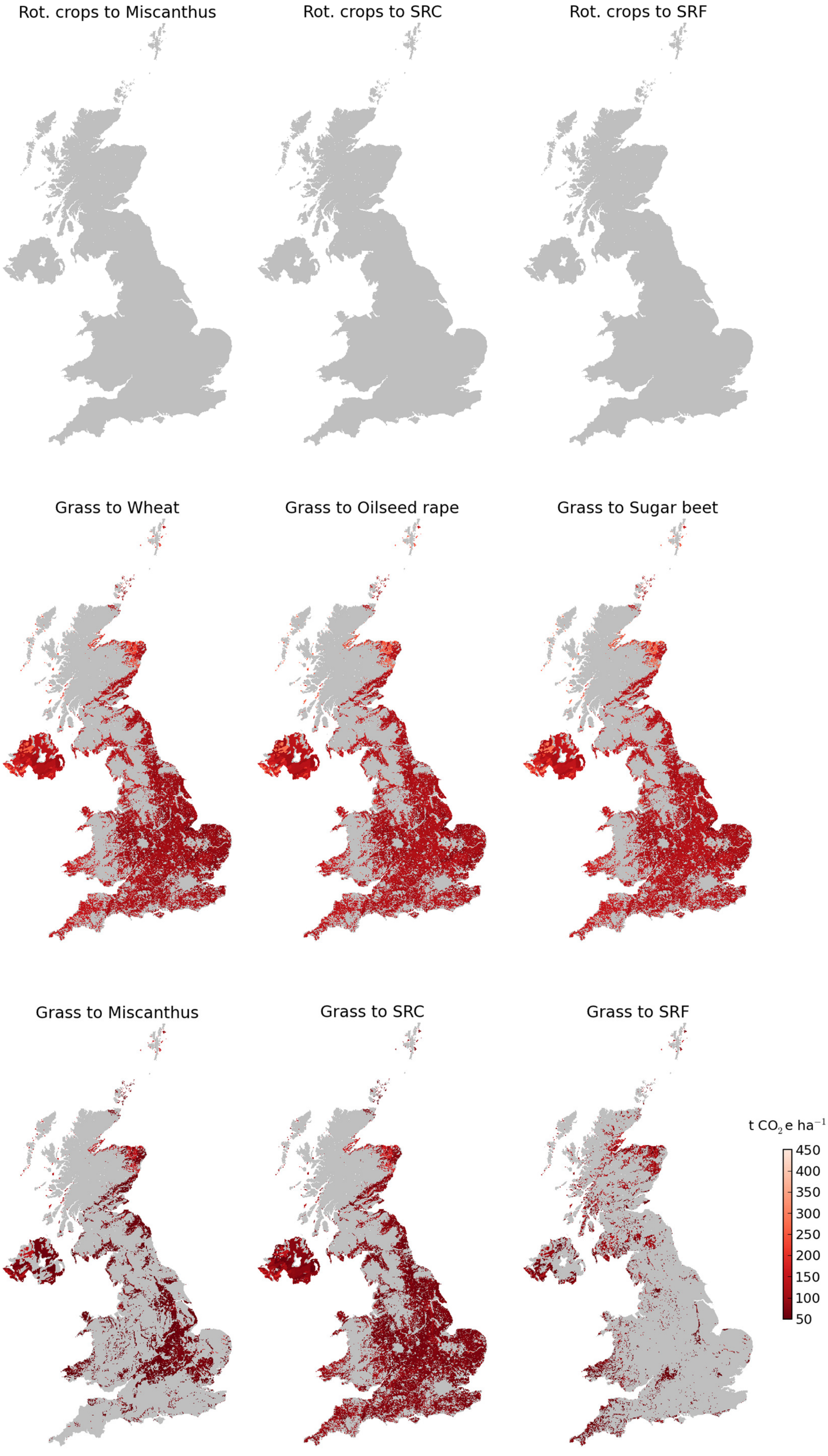
Of the three initial land-uses, conversion from rotational crops presents the most favourable bioenergy opportunities in terms of net GWP. Conversion from rotational crops to *Miscanthus* and SRF shows a beneficial net GWP in all simulated grid cells. Conversion from rotational crops to SRC is beneficial in most of the simulated grid cells, but does show a small detrimental net GWP in a small number of grid cells in the east of England. Overall, in terms of net GWP, conversion to SRF offers the best bioenergy opportunity because it has the most beneficial net GWP over the largest area (Figure 3.12). However, in some areas, most notably in parts of South West England, southern England, south and west Wales, and in a narrow band north and south of the Humber), *Miscanthus* presents an equal or slightly better bioenergy opportunity than SRF. In contrast, SRC does not show a more beneficial net GWP than SRF or *Miscanthus* in any areas of significant size. Moreover, SRC shows a very small detrimental net GWP in small areas within England. None of the conversions from rotational crops show a large detrimental change in net GWP.

3.1.4.2 Conversion of permanent grass

In general, permanent grass provides less favourable opportunities for bioenergy (in terms of net GWP arising from biomass production) than rotational cropland. All conversions from permanent grass result in either a small or large detrimental change in net GWP in all grid cells except for SRF, which shows a small beneficial (> -21 t CO_2e ha^{-1}) change over large parts of the West Midlands, East Midlands and East Anglia (Figure 3.12). *Miscanthus* and SRF show a small detrimental net GWP over large parts of the simulated area (Figure 3.11). For SRF, many of the grid cells that fall into the small detrimental category are at the least detrimental end of the category with a net GWP less than 15 t CO_2e ha^{-1}. In contrast, most of the SRC cells in the small detrimental category lie at the high end of the category (> 30 t CO_2e ha^{-1}), except for 2 significant areas: an area in southern England and the narrow band north and south of the Humber. SRC shows a small detrimental change in net GWP in only a very few grid cells. Wheat, OSR and sugar beet show a large detrimental net GWP in all simulated grid cells.

3.1.4.3 Conversion of forest

Overall, forest provides the least favourable opportunities for bioenergy (in terms of net GWP arising from LUC to biomass production). None of the transitions from forest show a beneficial decrease in net GWP in any grid cells (Figure 3.12). SRF is the only transition from forest with grid cells in the small detrimental category (cells with a net GWP between 0 and 50 t CO_2e ha^{-1}, Figure 3.11), with all cells having a net GWP greater than 23 t CO_2e ha^{-1}. These cells occur mainly in the West Midlands, East Midlands and East Anglia. All grid cells for transitions to wheat, OSR, sugar beet, *Miscanthus* and SRC fall into the large detrimental net GWP category (cells with a net GWP > 50 t CO_2e ha^{-1}).



Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
450
400
350
300
250
200
150
100
50

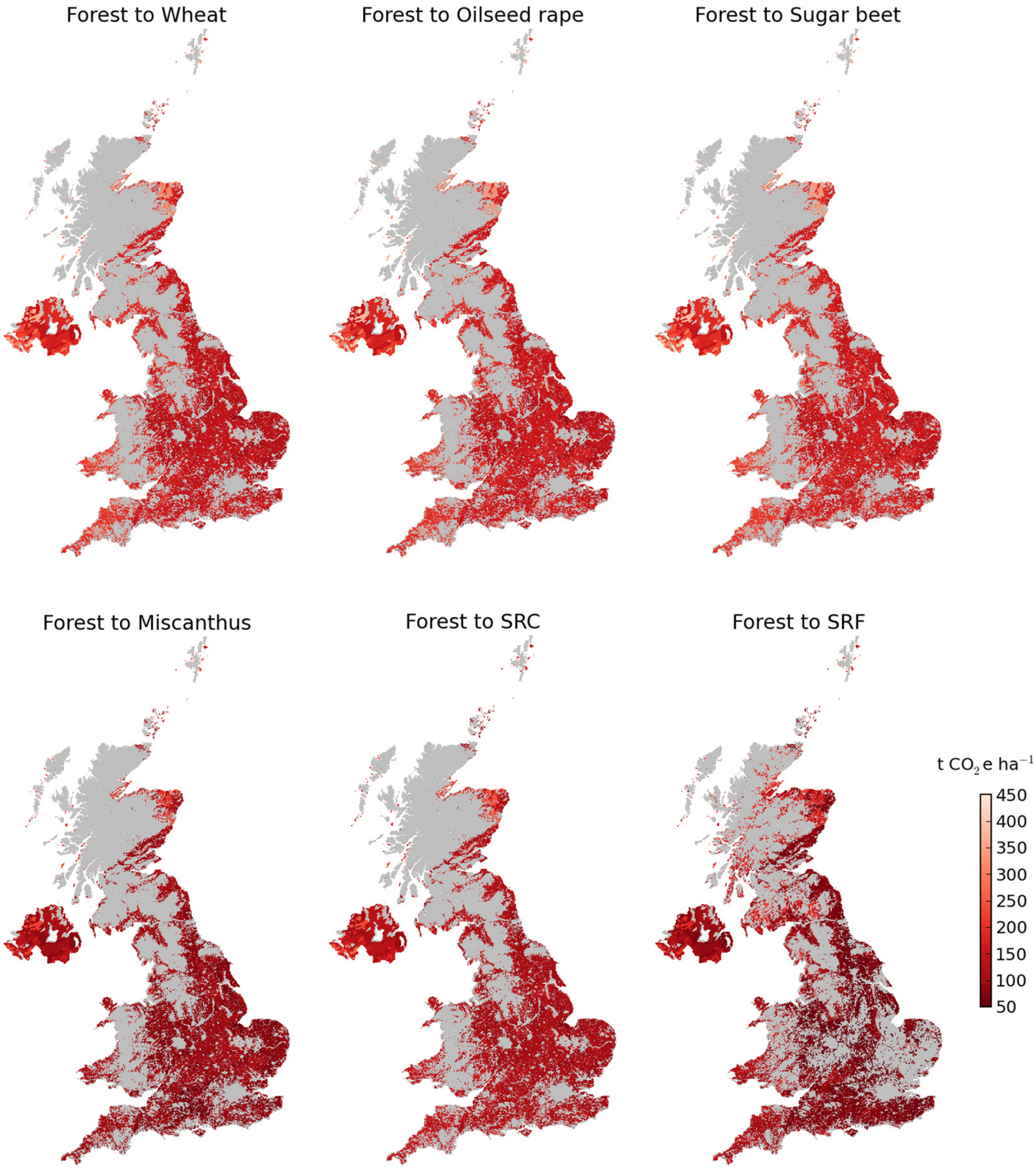


Figure 3.10: Maps showing grid cells with a large positive (detrimental) net GWP (greater than 50 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of net GWP. Grey represents excluded areas and areas that do not have a large positive net GWP.


Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
50
40
30
20
10
0

Figure 3.11: Maps showing grid cells with a small positive (detrimental) net GWP (between 0 and 50 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of net GWP. Grey represents excluded areas and areas that do not have a small positive net GWP.

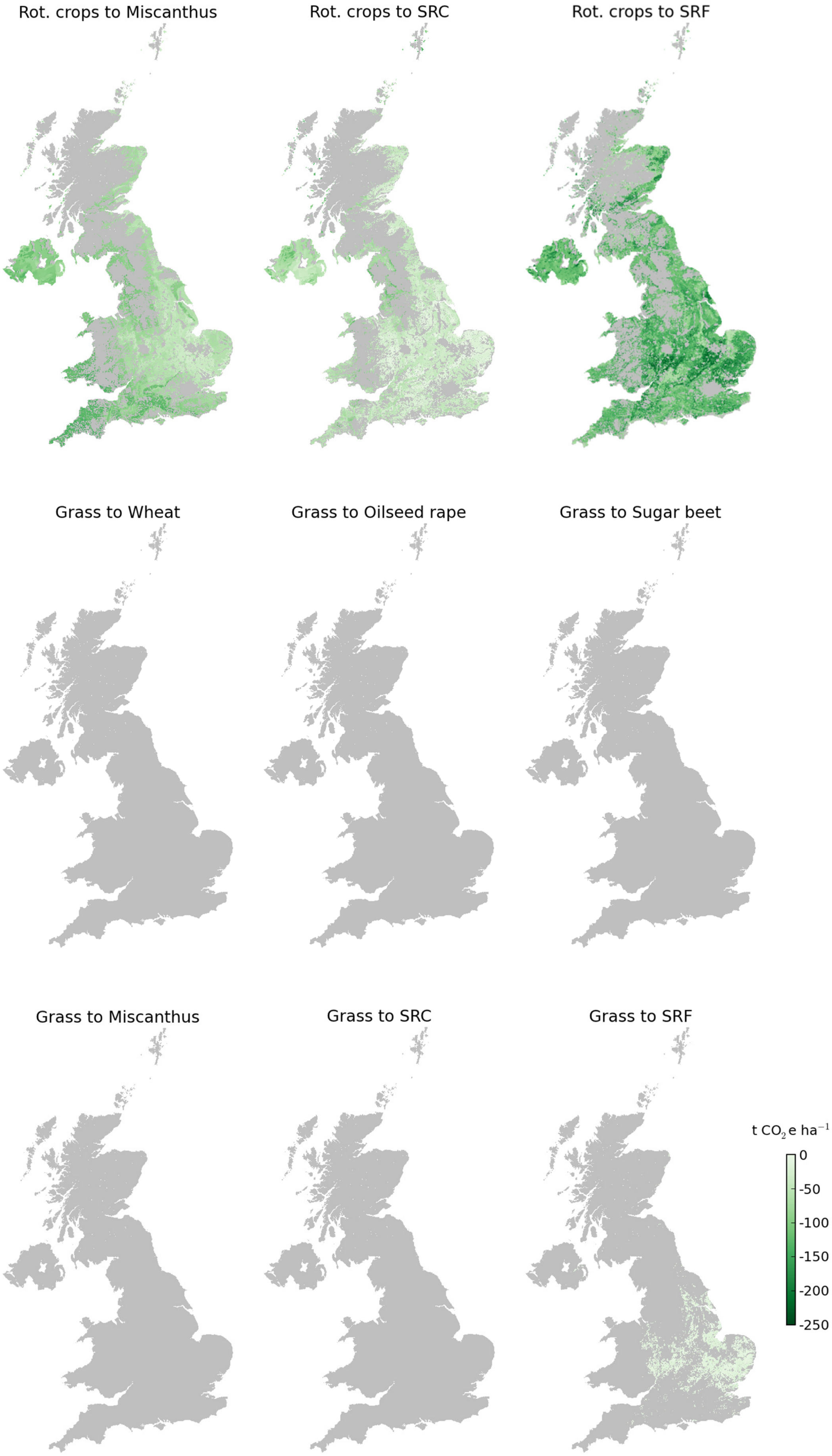

Rot. crops to Miscanthus
Rot. crops to SRC
Rot. crops to SRF
Grass to Wheat
Grass to Oilseed rape
Grass to Sugar beet
Grass to Miscanthus
Grass to SRC
Grass to SRF
t CO_2e ha^{-1}
0
-50
-100
-150
-200
-250

Figure 3.12: Maps showing grid cells with a negative (beneficial) net GWP (less than 0 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops, permanent grass and forest to bioenergy crops under the medium climate scenario. The legend shows the colour code of net GWP. Grey represents excluded areas and areas that do have a negative (beneficial) net GWP.

3.1.4.4 Temporal dynamics

The changes in mean cumulative net GWP over time for each land-use transition are shown in Figure 3.13. Conversion from rotational crops to *Miscanthus*, SRC and SRF show a decrease in net GWP over the 35-year simulation period, although there is little change in net GWP during the first 5 years following conversion of rotational crops to SRC.

In contrast, all conversions from permanent grass and forest show a rapid increase in net GWP 5 years after LUC. After the first 5 years, the net GWP of most LUCs continues to increase at a slower, more or less linear rate. However, in 2030 (15 years after conversion), the net GWP of permanent grass to SRF begins to decrease.

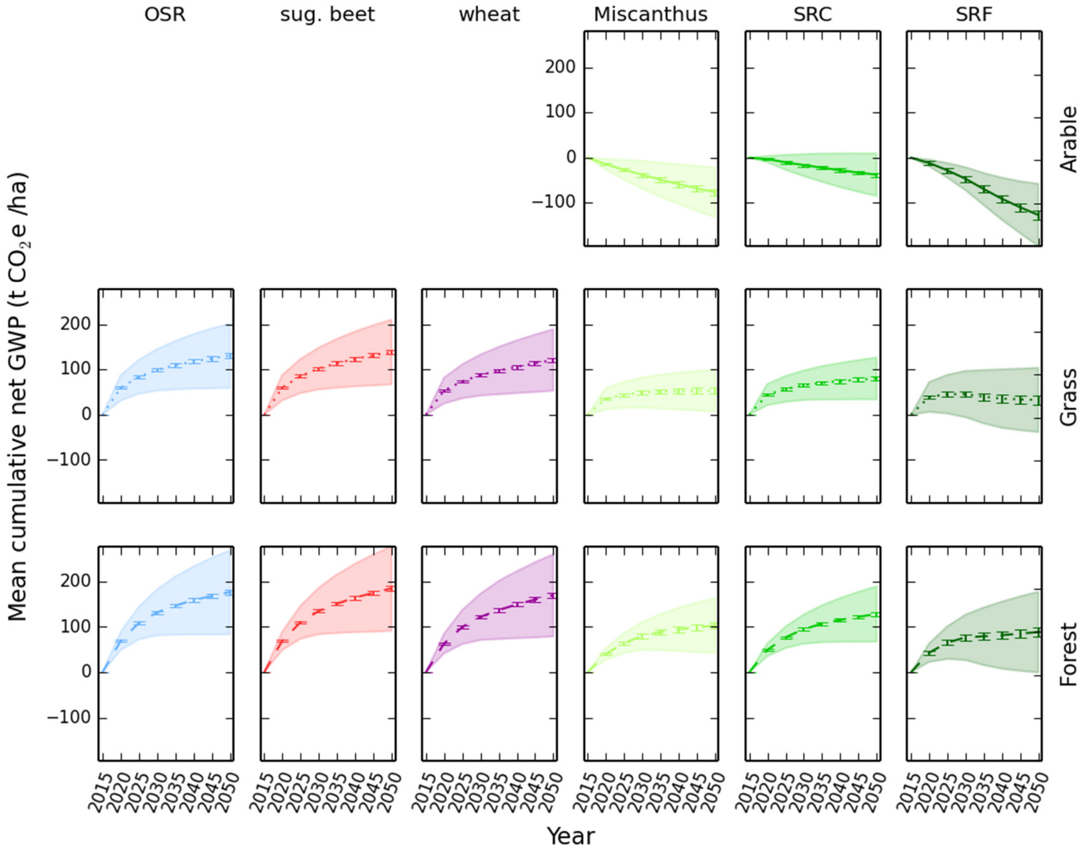


Figure 3.13: Time series of mean cumulative net GWP resulting from land-use change to bioenergy crops in 2015 under the medium emissions climate scenario. Shaded areas show the 95% confidence interval of the distribution of modelled results from the simulations across the UK. Error bars show the estimated error based on the comparison of modelled and measured net GWP from the site-level modelling study.

These results show that the relative bioenergy opportunity of each transition can be dependent upon the time frame over which the changes in net GWP are evaluated. Whilst most of the relative opportunity offered by most transitions remains similar over the 35-year simulation period, the relative opportunity offered by some transitions changes over time.

For example, in 2050 (35 years after conversion), rotational crops to SRF, on average, offers the biggest reduction in net GWP. However, in 2025 (10 years after conversion), both rotational crops to SRF and to *Miscanthus* show more or less equal reductions in net GWP. Similarly, the change in net GWP of permanent grass to SRF and permanent grass *Miscanthus*, and of forest to SRF and forest to *Miscanthus* begin to diverge after 2025-2030.

3.2 Effects of climate scenario

Figure 3.14 shows the effects on change in net GWP of the low and high emissions scenarios relative to the medium emissions scenario. For most transitions, a low emissions scenario results in a small detrimental change in net GWP and the high emissions scenario results in a small beneficial change in net GWP. The exceptions to this pattern are conversions from permanent grass and forest to wheat which show the opposite response: a beneficial change under the low emissions scenario and a detrimental change under the high emissions scenario. For all conversions, the difference attributable to climate scenario is very small in comparison to the effects of LUC, being within +/- 2 t CO_2e ha^{-1}.

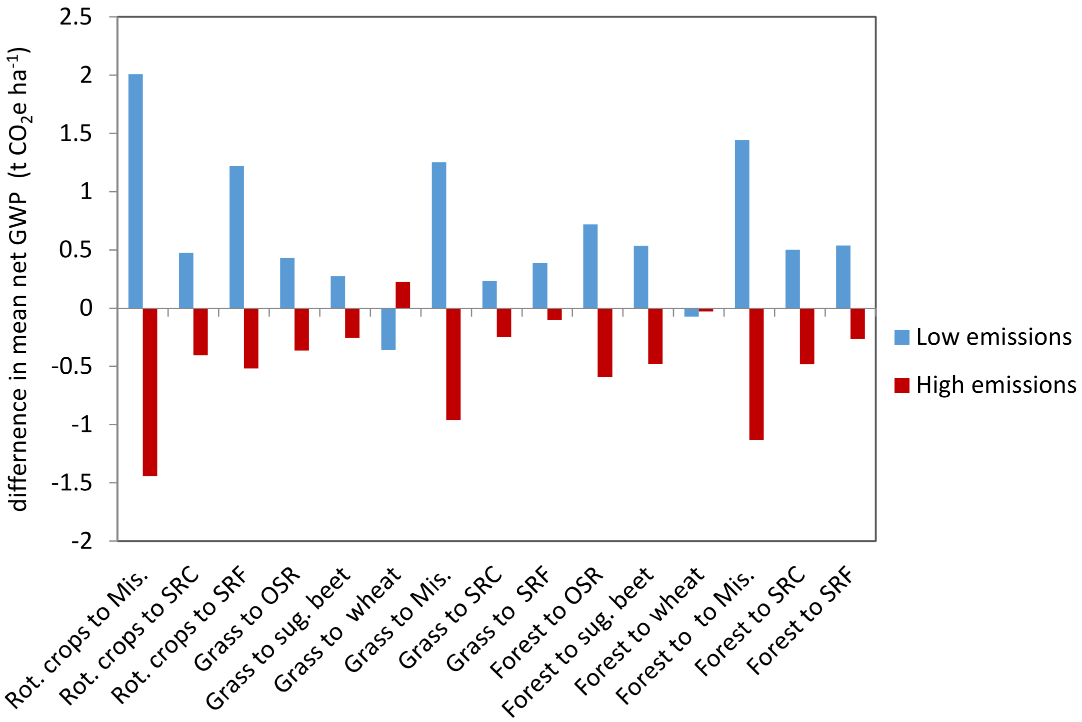


Figure 3.14: Difference in mean cumulative change in net global warming potential (GWP) for 2015-2050 of each land-use transition for the low and high emission UKCP09 climate scenarios relative to the medium emissions scenario.

Conversions to *Miscanthus* show the largest changes due to climate scenario. The example of rotational crops to *Miscanthus* (Figure 3.15) shows that the beneficial changes in net GWP are marked with a larger difference between grid cells than between climate scenarios.

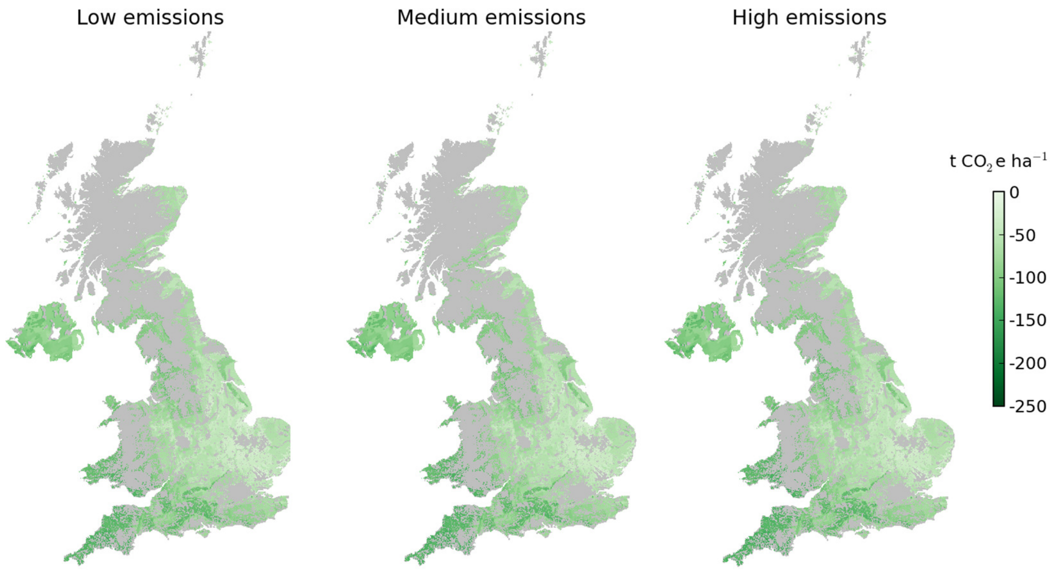


Figure 3.15: Impact of UKCP09 climate emissions scenarios on the area of negative (beneficial) net GWP (less than 0 t CO_2e ha^{-1}) for the period 2015 to 2050, following conversion from rotational crops to *Miscanthus*. The legend shows the colour code of net GWP. Grey represents excluded areas and areas that do have a negative (beneficial) net GWP.

3.3 Bioenergy yields

ECOSSE uses bioenergy yield predictions as inputs to the model (see section 2.3.3). A selection of yield results is presented here for comparison with emission outputs. Long term trends in the modelled bioenergy yields under the medium climate scenario are shown in Figure 3.16. The difference between modelled annual yields in the 2020s and 2050s for wheat, OSR, sugar beet and SRC are small (0.5 to 4%); in contrast, the differences for *Miscanthus* and SRF (poplar) are relatively large (ca. 10%).

Figure 3.17 shows the spatial distribution of modelled annual yields for each bioenergy crop in the 2030s. The 2030s was chosen because this decade is the mid-point of the simulation period and therefore best represents the mean annual yields for the whole simulation period. There is very little spatial variation in the wheat, OSR and sugar beet because: a) the baseline yields are obtained from coarse-scale Defra statistics (see section 2.3.3) and b) there is little regional variation in OSR yields. The highest *Miscanthus* yields occur in the south west of the UK, and in two bands in south England and north/south of the Humber. The highest SRC (willow) yields occur in parts of West Wales, North West England and the Highlands of Scotland. Most of the highest yielding areas of SRC fall in the area unsuitable for bioenergy crop production and are therefore excluded from the simulations. SRF shows high yields over most of the UK, except in large parts of Scotland (which are largely excluded from the simulations).

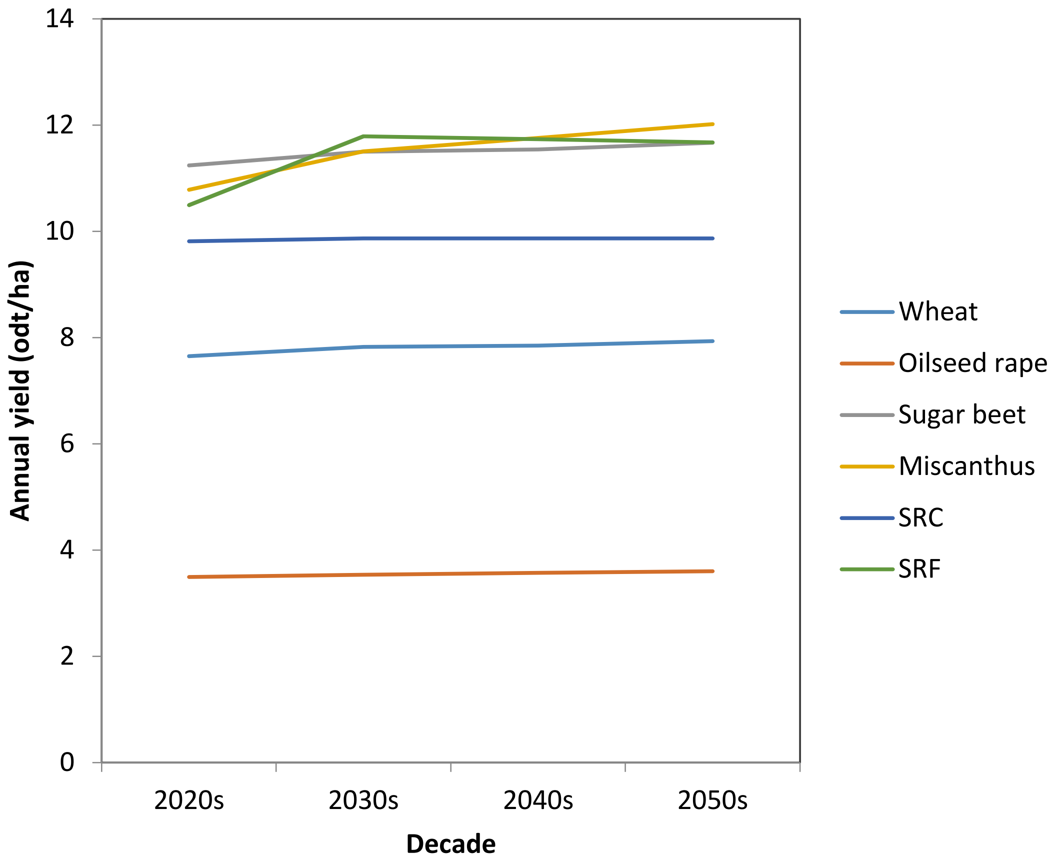


Figure 3.16: Trends in the modelled UK mean annual yield of bioenergy crops (odt ha^{-1}, where odt is oven dry tonnes) under the UKCP09 medium climate scenario, from the 2020s to the 2050s. Miscanthus, SRC and SRF yields were obtained from simulations using the models Miscanfor, ForestGrowth SRC and ESC-CARBINE. Defra yield statistics from 2000 to 2008 were used to establish baseline yield values for wheat, oilseed rape and sugar beet, which were then adjusted for future climate using the MIAMI model.

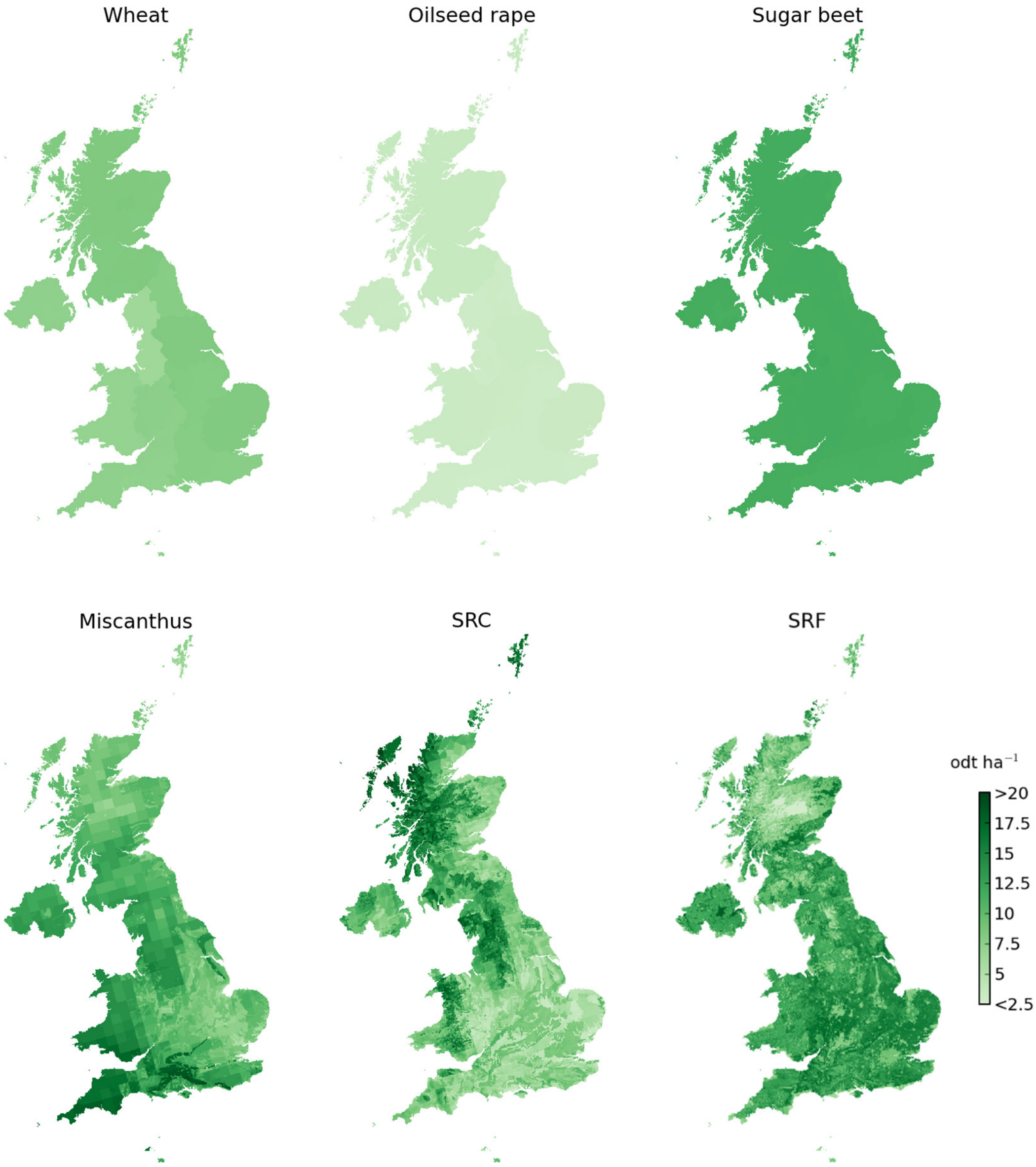


Figure 3.17: Spatial distribution of modelled annual yield of bioenergy crops as odt ha^{-1} (where odt is oven dry tonnes) in the 2030s under the UKCP09 medium emissions climate scenario. Miscanthus, SRC and SRF yields were obtained from simulations using the models Miscanfor, ForestGrowth SRC and ESC-CARBINE. Defra yield statistics from 2000 to 2008 were used to establish baseline yield values for wheat, oilseed rape and sugar beet, which were then adjusted for future climate using the MIAMI model.

4. DISCUSSION

The change in soil GWP resulting from the conversion of rotational cropland, permanent grass and forest to bioenergy crops in the UK has been modelled from 2015 to 2050 for three different climate scenarios.

4.1 Effects of land-use change

Conversion of land to bioenergy crops shows a large spatial and temporal variation in net GWP and its components: SOC, N_2O and CH_4. The impact of LUC on soil GWP depends upon the type of land-use being converted, the type of bioenergy crop planted and the geographic location. Overall, changes in SOC have the largest impact on net GWP, followed by N_2O and then CH_4.

4.1.1 Changes in soil organic carbon

Results for 2015 to 2050 show that both the initial and target land-use type have a very large impact on mean change in SOC (Figure 3.4). Conversion of rotational crops to *Miscanthus*, SRC and SRF and conversion of permanent grass to SRF are the only LUCs that lead to extensive beneficial changes in SOC. In contrast, all conversions from permanent grass to non-SRF bioenergy crops and all conversions from forest lead to mostly detrimental changes in SOC.

These findings are broadly in-line with those of empirical studies. Guo and Gifford's (2002) review of data from 74 LUC publications shows that conversion from arable land to plantation forest, secondary forest and pasture leads to significant increases in SOC, whereas conversion of forest and pasture to crop leads to large decreases. Murty *et al.* (2002) and Wei *et al.* (2014) also report significant decreases in SOC following conversion of forest to cultivated agricultural land. The timescale of SOC losses in these studies are similar to those in our study, with most of the SOC loss occurring in the first 10-20 years after conversion. After this period, rates of SOC loss slow down as the SOC approaches a new equilibrium.

4.1.1.1 Cultivation

Since rotational cropland typically undergoes frequent cultivation, the model assumes that no additional cultivation is required for the establishment of bioenergy crops. In contrast, the model simulates soil cultivation for conversion of permanent grass and forestry because these land-uses typically require ground preparation before bioenergy crops are planted. Cultivation of relatively undisturbed soil, such as soil under permanent grass and forest, usually has a large detrimental impact on SOC (Guo and Gifford, 2002). Cultivation physically fragments and redistributes soil organic matter, accelerating its decomposition, leading to a large release of CO_2 and subsequent decrease in SOC (Grandy and Robertson, 2006). The model captures this loss of SOC by simulating cultivation as described in section 2.2. This cultivation is responsible for the large detrimental change in SOC following LUC from permanent grass and forest (Figure 3.4).

4.1.1.2 Plant inputs

If LUC leads to an increase in plant C inputs to the soil, the SOC content will gradually increase over time until a new equilibrium SOC content is reached (assuming all other factors remain equal). In ECOSSE, the quantity of new plant material entering the soil organic matter pools is determined by the amount of plant biomass (calculated from yield), minus the proportion of biomass that is removed during harvest.

Across the simulation area, SRF, *Miscanthus* and sugar beet are the highest yielding bioenergy crops, with UK mean annual yields of 10-12 odt ha^{-1}. Based on reported harvest index values (Table 4.1), the model assumes that 75% of sugar beet biomass is removed during harvest, compared with 64% for *Miscanthus* and 60% for SRF. The low harvest index (relative to sugar beet) and high yields mean that SRF and *Miscanthus* have, on average, higher plant inputs to the soil than other bioenergy crops.

Table 4.1: Harvest index parameter values of bioenergy crops. Note that the wheat harvest index includes the harvest of both grain and straw.

Crop	Harvest index	Source
Miscanthus	0.64	Zhuang *et al* (2013)
Oilseed-rape	0.35	Kjellström and Kirchmann (1994), Dreccer *et al* (2000), HGCA (2014)
SRC	0.6	Caslin *et al* (2011b)
SRF	0.6	No data available so assumed to be the same as SRC
Sugar beet	0.75	Tsialtas and Karadimos (2003), Oritz *et al* (2012)
Wheat	0.77	White and Wilson (2006), Stoddart and Watts (2012)

Conversion to bioenergy crops can also lead to a change in the quality of plant inputs to the soil. Plant residues from perennial woody plants such as *Miscanthus*, SRC and SRF, are typically slower to decompose than residues from annual crops such as wheat, OSR and sugar beet (due in part to the residues having a higher C:N ratio). Slower decomposition rates reduce the rate of SOC loss. In the model, differences in crop residue decomposition rates are simulated through differential allocation of plant residues to two soil carbon pools: the decomposable plant matter pool and resistant plant matter pool. The decomposable plant matter (DPM) pool has a faster decomposition rate than the resistant plant matter (RPM) pool. To reflect the slower decomposition rates, residues from *Miscanthus*, SRC and SRF have a higher RPM:DPM ratio than residues from wheat, OSR and sugar beet.

The difference in quantity and quality of plant inputs is the principal reason behind the different SOC responses shown by each bioenergy crop type. Since the quantity of plant inputs is partially based on yield, the spatial pattern of change in SOC broadly reflects the spatial pattern of yield. This is particularly apparent with *Miscanthus*, which shows a distinct area of high yield (as estimated by the MISCANFOR model) in southern England and north and south of the Humber estuary (Figure 3.17), with a corresponding high increase in SOC in these areas following conversion from rotational crops (Figure 3.3). The high yields in these two areas are due to the prevalence of chalky soils with high soil water holding capacities, which the MISCANFOR model predicts are favourable for the growth of *Miscanthus* (Astley Hastings, personal communication, 2013). Since SOC change is largely determined by yield, (with higher yields giving higher carbon returns to the soil than lower yields), low yields can lead to a decline in SOC. The relatively detrimental impact of the permanent grass to SRC transition is largely driven by low predicted yields of SRC willow (see Figure 3.17). A target for management of perennial energy crops is, therefore, to achieve the best possible yield by selecting the most appropriate energy crop and cultivar for the local situation, as long as this can be done without excessive N fertiliser use, which would lead to increased nitrous oxide emissions (see section 4.1.2).

4.1.2 Changes in N_2O emissions

Beneficial changes in N_2O emissions following conversion of rotational crops to *Miscanthus*, SRC and SRF occur because of reductions in N fertiliser inputs (see section 2.2). In ECOSSE, reduced N fertiliser inputs lead to decreased N_2O emissions because: a) the denitrification rate slows as the nitrate concentration in the soil decreases and b) the proportion of denitrified N emitted as N_2O decreases as nitrate concentration in the soil decreases. In contrast to conversions from rotational crops, conversion of forest to wheat shows the greatest increase in N_2O because it involves a transition from a land-use that receives no fertiliser to a crop that receives a large amount of fertiliser (due to wheat's high N demand, see section 2.2).

The maps showing beneficial changes in N_2O emissions following conversion from rotational crops (Figure 3.6), show larger reductions in N_2O emissions in the west of the UK than the east. This is probably due to higher precipitation rates in the west leading to higher soil water contents. In the model, higher soil water content leads to two contrasting effects on N_2O emissions: firstly, the denitrification rate increases exponentially as the soil water content increases and secondly, the proportion of denitrified N emitted as N_2O decreases linearly as soil water content increases. The exponential increase in the first process outweighs the linear decrease of the second process, leading to a simulated net increase in N_2O emissions as soil water content increases. This response reflects empirical evidence for N_2O emissions increasing as soil water content increases (e.g. Schindlbacher *et al.*, 2004; Luo *et al.*, 2013). The greater reductions in N_2O following conversion from rotational crops in the west of the country are, therefore, likely due to higher precipitation rates leading to higher soil water contents and in turn, higher N_2O emissions. Reductions in N fertiliser inputs in high precipitation grid cells will therefore lead to greater beneficial reductions in N_2O emissions.

The initial conversion of forest to pasture and cropland (Smith and Conen, 2004) and permanent grass to bioenergy crops (Gelfand *et al.*, 2011; Nikièma *et al.*, 2012, Palmer *et al.*, 2013) causes a large initial N_2O emission. Our results show a large emission of

N_2O in the first 5 years after conversion from permanent grass and forest to all bioenergy crops (Figure 3.7). This arises due to the simulation of cultivation during LUC from permanent grass and forest as described in section 2.2.

After 5 years, the modelled rates of change in N_2O emissions decline. The large initial rates of N_2O emissions arise for similar reasons to the large SOC decreases that follow certain conversions: initial cultivation of land during LUC physically fragments and redistributes soil organic matter, accelerating its decomposition, releasing inorganic N that is used by denitrifying soil microbes leading to N_2O release (Grandy and Robertson, 2006). The subsequent slowing down of increases in N_2O emissions occurs as the rapidly decomposing soil organic matter resulting from cultivation becomes depleted and the N_2O emissions move toward the background rate.

In our results, changes in N_2O emissions following conversions from permanent grass to OSR, Miscanthus, SRC and SRF start to level off and decrease after approximately 5 years (Figure 3.7). This occurs because the modelled N fertiliser inputs to OSR, Miscanthus, SRC and SRF are lower than for permanent grass (see section 2.2).

4.1.3 Changes in CH_4 emissions

The simulated CH_4 fluxes are very small for all land-use transitions throughout the simulation area. Owing to the absence of data for water table depth, we assumed that all soils in the simulations are freely drained, with no water table. This assumption could result in some uncertainty in the simulated CH_4 fluxes because CH_4 emissions are much higher from saturated than unsaturated soils (Segers, 1998). In the UK, observed CH_4 fluxes are much higher on organic soils (which are typically poorly-drained in their natural state) than on mineral soils, and are the main source of soil CH_4 emissions (Levy *et al.*, 2012). Highly organic soils (and therefore the greatest sources of CH_4) have been excluded from the simulations (see section 3.2.3.2 of D4.3).

Moreover, even if significant areas of poorly-drained land with high CH_4 emissions are present within the simulated area, large changes in those CH_4 emission rates resulting from conversion to bioenergy crops are only likely to occur if the land is drained for bioenergy crops. We are not aware of any planned or actual drainage of extensive areas of land for bioenergy crops. Drainage is unlikely to take place on soils currently under rotational crops because the land will already have been drained (if it was necessary). Also, SRC willow and poplar are suitable for planting on soils with a shallow water table (1-2 m deep), with willow able to cope with water-logging, making it suitable for planting in areas with a high water table or areas prone to flooding (Hall, 2003). SRC therefore provides a bioenergy option that is unlikely to require the drainage of water-logged land.

For the reasons described above, we believe that the uncertainty in the CH_4 emissions associated with the assumption of a freely-draining soil is relatively small and that the simulated CH_4 fluxes are representative of the land suitable for bioenergy conversion. However, if extensive areas of water-logged land were to be drained for the establishment of bioenergy crops, it would be useful to explore the impacts on CH_4 fluxes (and changes in SOC and N_2O emissions) in more detail.

4.1.4 Temporal dynamics

The time series of mean changes in net GWP shows that the opportunities for conversion to bioenergy crops to reduce GWP in the shorter term are different from those over the longer term (the full 35-year simulation period), discussed above.

For the first 10 years after conversion (2015 to 2025), rotational crops to SRF and rotational crops to *Miscanthus* show a very similar change in net GWP. However, after 10-15 years, the change in net GWP of SRF begins to decrease at a faster rate than *Miscanthus*. This temporal pattern arises because SRF, following establishment, takes longer to achieve peak annual yield (and corresponding peak C input to the soil), than *Miscanthus* (see section 2.2). A similar change in the rate of change in net GWP occurs for SRF ~15 years after conversion from permanent grass (visible as shift to decreasing net GWP), and forest (visible as a sudden levelling off of net GWP).

For the same reason, SRC shows only a very small reduction in net GWP during the first 5 years, because in the model, this is the length of time it takes to reach peak yield. After 5 years, peak yield is reached, leading to increased inputs of C to the soil and therefore resulting in an increase in the rate of SOC accumulation.

The beneficial effects on GWP following conversion of permanent grass to SRF in parts of England are perhaps the most surprising result, given that land-use changes from permanent grass generally lead to an observed loss of SOC (see section 4.3 for a discussion of permanent and rotational grass). When permanent grass is converted to SRF, the model predicts a large initial loss of SOC due to cultivation (Figure 3.4). However, as SRF establishes and annual yield increases, the annual C inputs to the soil become large enough, on average, to halt the loss of SOC (after 10 years). Once peak annual yield is reached (after 15 years), the annual soil C inputs are large enough to outweigh losses as CO_2, leading to an accumulation of SOC.

In areas where the forecast SRF yields are highest (the West Midlands, East Midlands and East Anglia), the plant inputs of C to the soil are large enough to offset the total loss of SOC resulting from cultivation of the permanent grass, leading to a net beneficial GWP within 35 years.

4.2 Effects of climate scenario

The simulations reveal a general trend towards more beneficial GWPs as climate increases from low to high emissions, though the difference between scenarios was very small for all transitions. Changes in SOC (the main component of net GWP) due to changes in climate mainly arise through temperature and soil moisture effects on soil C turnover rates and changes in plant C inputs to the soil through climatic effects on plant growth (Smith *et al*, 2007).

The reported changes in net GWP for each conversion are relative to no conversion taking place. Therefore, differences in net GWP between climate scenarios can only arise if the climate scenario affects the bioenergy conversion and null conversion differently. Since the modelled soil processes in the bioenergy and null conversion simulations will respond equally to changes in climate, simulated differences in net GWP between climate scenarios must arise through modelled climatic impacts upon yield (and corresponding plant inputs to the soil). This is borne out by the observation that the GWP of conversions to *Miscanthus* showed the greatest sensitivity to climate scenario (Figure 3.14) and *Miscanthus* yield also showed the greatest increase in response to changes in climate (Figure 3.16).

The differences between modelled yield values under different climate scenarios are very small compared to the differences in yield between initial land-use types and bioenergy crop species, so the climate scenarios have a relatively small impact upon net GWP.

4.2 Effects of soil

The ECOSSE model requires input data for several soil properties: initial SOC content, pH, bulk density and clay content. These properties influence a range of processes within the model.

SOC content influences the amount of C lost as CO_2 during decomposition. All other factors being equal, soils with high organic carbon content will produce proportionally higher CO_2 emissions than a soil with low organic carbon content. We therefore expect soils with high organic carbon content to show greater sensitivity to changes in SOC resulting from LUC (e.g. due to cultivation). However, whilst the absolute loss of C due to cultivation is expected to be higher in soils with high organic carbon content, the relative loss of C may be lower if the clay content is higher (see below).

SOC content increases as the clay content increases (Burke *et al*, 1989). This increase occurs because clay particles strongly adhere to organic matter slowing down the decomposition process, and because clay forms aggregates that physically protect SOC from microbial decomposition (Rice, 2002). In ECOSSE, the effects of clay content on soil organic matter decomposition is modelled by altering the proportion of C released as CO_2 during decomposition (i.e. the efficiency of decomposition). As clay content increases, a smaller proportion of decomposed C is lost as CO_2 (i.e. the efficiency of decomposition increases), and a greater proportion is retained in the biomass and humus soil organic matter pools. Therefore, when clay-rich soils are cultivated during LUC, (causing a large proportion of SOC to be moved from soil organic matter pools with a faster turnover rate to soil organic matter pools with a slower turnover rate), we would expect the modelled relative SOC losses to be lower than for soils with low clay content. This behaviour is in agreement with empirical evidence (Burke *et al*, 1990).

A significant effect of soil pH on the rate of decomposition has been observed in many studies (e.g. Hall *et al*, 1998; Andersson and Nilsson; 2001). In ECOSSE, the pH rate modifier for aerobic decomposition decreases linearly as pH drops below 4.5. For pH values greater than 4.5, the rate modifier is set to 1 (i.e. has no effect upon the decomposition rate). Soils with a pH of less than 4.5 are typically highly organic. We therefore expect variations in pH between soil types to have very little impact on the model outputs because highly organic soils have been excluded from the simulation area.

In ECOSSE, bulk density affects the rate of CH_4 oxidation (i.e. consumption of CH_4). Empirical evidence shows that soils with a low bulk density tend to have higher rates of methane oxidation (Borken and Brumme, 1997) because low bulk density soils are more permeable, allowing atmospheric methane and oxygen to diffuse more freely into the soil (Dörr *et al*, 1993). Variation in bulk density in the simulated soils is very unlikely to have a significant effect on the results because: a) peat soils, which have a much lower bulk density (and therefore much higher potential oxidation rates than mineral soils), have been excluded from the simulation; b) the simulated soil CH_4 production rates are very low so it is not possible for oxidation of CH_4 to significantly affect the net GWP.

4.3 Rotational grass

The permanent grass land-use type used in these simulations represents permanent, uncultivated grassland. Grassland however, may also be temporary, used in rotation with arable crops, and in these circumstances can be regarded as a crop within an arable rotation. Permanent grassland is the most abundant type of grassland in the UK, covering 5.3 million ha in 2010, compared to 1.1 million ha of temporary (mostly rotational) grassland (Khan *et al*, 2011) at any one time. Rotational grassland in any given year would be categorised as arable crops in different years, so the 1.1 million ha in any year represents a snapshot of the area of rotational grass. As such, rotational grass is not a land-use, it is simply one component of rotational farming, which includes all-arable rotations as well as grass-arable rotations. Rotational grassland is usually represented as a crop within a rotation in most existing soil organic matter models, and in ECOSSE is assumed to be a subset of arable rotational land. Permanent grassland represents a separate land-use transition as this land is only used for grass/livestock production. Rotational grass (by definition) occurs on the same land as is used for growing arable crops, so bioenergy conversion on rotational grass is equivalent to removal of land used for arable production. Rotational grassland can therefore be simulated in ECOSSE in the same way as arable-only rotations, though a slightly higher initial soil carbon content could be justified (see below).

It is expected that rotational grassland would behave in a similar way to arable land in terms of GWP response to LUC to bioenergy crops because: a) it undergoes frequent cultivation and b) it typically receives more fertiliser than permanent grassland. This expectation is supported by empirical evidence. Long-term experiments at the Woburn Research Station (run by Rothamsted Research) in the UK found that conversion of continuous arable to rotational grassland (in this case either a 3-year grass or grass-clover ley followed by two arable crops in a 5-year cycle), resulted in only a 10-15% increase in SOC after 60 years (Johnston *et al*, 2009). In contrast, the conversion of arable land to permanent grassland at the Rothamsted Research Station resulted in a doubling of organic matter (indicated by total nitrogen), in 50 years (Johnston *et al*, 2009). The small observed increase in SOC under rotational grassland suggests that the response of rotational grassland to LUC would fall between that of arable and permanent grass, but will be close to the all-arable rotations represented by our rotational crops category.

4.4 Uncertainty

The modelled GWPs are associated with a number of uncertainties. 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 compared to data available at the field scale. Uncertainty due to errors in the model has been estimated as part of the site-specific modelling exercise reported in D4.3 (BI1001_PM07.4.3_WP4_LUC). Here, we focus on uncertainties arising from the use of national-scale data.

4.4.1 Spatial and temporal resolution

The spatial and temporal resolutions of the driving data sets are given in Table 4.2. 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. For example, in croplands, detailed management factors such as sowing date and timing and rate of fertiliser applications cannot usually be specified when the resolution of the simulations is larger than the size of the management unit. The resolution of the simulation here was a 1 km^2 grid cell, whereas the size of a management unit might be a 5 ha (0.05 km^2) field, so there will be many different values for the management factors within each 1 km^2 cell. For example, the rate of N fertiliser application to grassland varies considerably according to the clover concentration in the grass sward, livestock stocking density and soil nitrogen status (Defra, 2010).

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).

Table 4.2: Spatial and temporal resolution of driving datasets used in the spatial simulations.

Input data	Spatial resolution	Temporal resolution
Harmonised World Soil Database	30 arc seconds (approx. 1km grid cells)	N/A
UKCP09 climate projections	25 km grid cells	30-year averages
Crop yield	NUTS 1 regional averages for wheat, and oilseed rape, national average for sugar beet; 1 km grid cells for *Miscanthus*, SRC and SRF, 25 km grid cells for permanent grass and forest	Annual

The uncertainty due to the reduced detail and precision of data available at the national scale can be quantified by evaluating the model at field scale, but using input drivers that are available at national scale.

4.4.2 Soil

The uncertainty associated with the use of national-scale soil data was quantified by simulating the 40 chronosequence sites from WP2, using measured soil parameters and soil parameters obtained from the Harmonised World Soil Database (HWSD). This work is described in report D4.3 (BI1001_PM07.4.3_WP4_LUC) and the results of the statistical analysis of simulations using the HWSD inputs are given below in Table 4.3. Across the 40 field sites there was a good correlation between modelled and measured SOC (0-100 cm depth), when using the measured soil parameters (r=0.92), and when using the HWSD parameters (r=0.79). In both cases there was no significant model error and no significant model bias.

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 HWSD. Despite this, there was a good correlation between modelled and measured values and a lack of model bias when using HWSD parameters as inputs. This suggests that uncertainty in model results arising from the use of HWSD data is fairly small.

Table 4.3: Results of statistical analysis of model simulation of soil carbon at 0-100 cm depth using inputs from the Harmonised World Soil Database (HWSD).

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

A similar evaluation of national scale uncertainty using ECOSSE and National Soils Inventory of Scotland soil data to simulate SOC at 60 resampled field sites in Scotland was carried out by Smith *et al.* (2010). The study found a very strong correlation between modelled and measured SOC (r=0.97). The correlation was higher in the Smith *et al* (2010) study than the current study (r=0.97 versus r=0.79). Smith *et al* (2010) obtained a higher correlation probably because the soil type at each field site could be matched to the corresponding soil type in the national soil database they used, whereas this was not possible in the current study.

4.4.2 Climate

Modelling future greenhouse gas fluxes requires projections of future climate which are subject to 3 main causes of uncertainty: natural climate variability, modelling uncertainty, and uncertainty in future emissions of greenhouse gases and other substances (Murphy *et al.*, 2009). To quantify the uncertainty associated with future emissions of greenhouse gas emissions we carried out simulations using the UK Climate Projections (UKCP09) based on low, medium and high emissions scenarios (section 3.2). These scenarios account for a range of assumptions regarding technological and economic growth.

Modelling uncertainty arises due to imperfect understanding and representation of Earth-system processes in climate models. To help account for this source of uncertainty, the UKCP09 climate projections have been produced using an ensemble of 11 variants of the HadRM3 climate model. In principle, an estimate of the impact of climate modelling uncertainty on bioenergy GWPs could have been undertaken by executing simulations using all 11 ensemble members, across all 3 emissions scenarios. However, limitations in computing power meant that simulations were restricted to a single (default) ensemble member for each emission scenario. Given the low sensitivity of GWPs to different emission scenarios we expect the sensitivity related to choice of ensemble member to also be small and, therefore, only a small source of uncertainty.

The UKCP09 climate projections used in this study, (to drive the yield models and ECOSSE), provide average monthly temperature and precipitation for overlapping 30-year periods centred upon decades ranging from the 2020s to the 2080s. Long-term averages such as these mask shorter-term climate variation which can encompass extreme events (e.g. drought).

4.4.3 Yield

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.

None of the yield models used in this study explicitly account for the effects of atmospheric N deposition on productivity. Within the simulated area of the UK, N deposition typically adds between 10 and 30 kg N ha^{-1} yr^{-1} (Fowler *et al*, 2004). However, we do not expect this level of N input to significantly affect the ECOSSE model outcomes for two reasons. Firstly, the yield models have been calibrated using UK field measurements of crops subjected to atmospheric N deposition, so the effects of N deposition are to some extent implicitly captured by the models. Secondly, farmers may adjust the rates of N fertiliser applied to crops according to the N deposition rate (Jones *et al*, 2014). For example, UK wheat farmers are advised to increase their Soil Nitrogen Supply index by 20 kg N ha^{-1} to allow for N deposition and the Defra Fertiliser Manual (Defra, 2010) factors in atmospheric N deposition (HGCA, 2009). Therefore, in fertilised cropping systems the effects of N deposition may be largely mitigated by adaptation of fertiliser practices.

Levels of atmospheric N deposition in the UK are currently in decline due to reduced N emissions (Jones *et al*, 2014), which could lead to reduced crop productivity. However, it is expected that fertiliser and other crop management practices will adjust to compensate for this reduction, and so maintain the yields predicted by the models.

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. For example, the wheat and oilseed rape yields are based on Defra average yield statistics for 12 regions in the UK (the NUTS level 1 regions), whereas sugar beet yields are based on a single national average yield value. Future wheat, oilseed rape and sugar beet yields are obtained by modifying the baseline yield observations with a simple, empirical model, Miami (Leith, 1975), whereas *Miscanthus* yield projections are obtained using a more complex, process-based model, MISCANFOR (Hastings *et al*, 2009).

The crop yield projections are based on models that are parameterised and calibrated for existing cultivars and current management practices. However, crop breeding and improvements in management practices will likely lead to increases in crop yield over time (other factors remaining equal). In addition, the yield models do not consider the impact of pests and disease.

These sources of uncertainty in yield forecasts are difficult to quantify, either due to lack of data (e.g. changes in the frequency of extreme climate events), or because they are inherently uncertain (e.g. impacts of future crop breeding). However, because these sources of uncertainty could significantly affect the GWP estimates we elected to test the sensitivity of the bioenergy GWPs to changes in yields (see section 3.2.4 in report D4.3, BI1001_PM07.4.3_WP4_LUC). The main findings from this sensitivity analysis are:

- For conversions from permanent grass and forest, yield increases of up to 50% were not sufficient to change a mean detrimental change in SOC to a mean beneficial change in SOC.
- Yield increases of up to 50% of any given bioenergy crop were generally insufficient to alter the crop's ranking in terms of changes in SOC, even when the yields of all other bioenergy crops were left unchanged.
- SRF and *Miscanthus* showed the greatest sensitivity to proportional changes in yield because they have the highest yields within the simulated area.

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

4.4.4 Fertiliser

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). For grassland, additional factors may include the percentage of clover in the grass sward and stocking density. Many of these factors vary at a finer scale than the 1 km resolution of the simulations and are not described in any spatially-defined databases. Therefore, the model makes assumptions about the amount of N fertiliser applied (see section 2.2), which presents a source of uncertainty for the modelled changes in N_2O emissions.

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. The results of this analysis are reported in BI1001_PM07.4.3_WP4_LUC and Crop Management Model v1.0 and are summarised below.

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 shifts in N_2O emissions resulting from a +/- 20% change in N fertiliser rates are modest, leading to a less than 5% change in the mean net GWP of each transition. Therefore, we do not expect uncertainty around N fertilisation rates to be a source of large uncertainty in the modelling outcomes.

4.5 Future research

The findings of this report clearly suggest that future work should target second-generation bioenergy crops (*Miscanthus*, SRC and SRF), since these offer a much more favourable soil GWP than first-generation bioenergy crops (wheat, sugar beet and oilseed rape).

Whilst the type of land-use transition was the most important factor affecting soil GWP, crop yield was found to be the most influential factor within each type of transition. However, a number of limitations of the yield data constrain the spatial accuracy of the soil GWP predictions and should be the focus of future research.

Firstly, Defra yield data for wheat (also used for the baseline rotational crop yield), sugar beet and oilseed rape are spatially coarse, being available only at regional level, and only cover a short time span. The development of high-resolution spatial datasets of bioenergy crop yield would greatly improve the spatial accuracy of soil GWP predictions.

Development of yield models is often hampered by lack of detailed soil and plant data from which to formulate process descriptions and evaluate the model. For example, only 11 UK experimental sites with sufficient data to validate the MISCANFOR model were available (Hastings *et al*, 2009). Future research should place an emphasis on detailed, long-term measurements of crop and soil attributes (yield, litter inputs, C and N contents of plant components and soil etc.), over the full life-cycle of the crop. Such data is required for the development of more robust process-based models.

Models of future crop yield vary in the factors they take into account. For example, (e.g. effects of elevated atmospheric CO_2 concentration), their level of sophistication and degree to which they have been calibrated for UK conditions. Moreover, where multiple models exist for a given crop, the yield estimates may differ considerably. For example, MISCANFOR (Hastings *et al*, 2009) predicts the highest *Miscanthus* yields to be in the south-west of England whereas the empirical model of Richter *et al* (2008) predicts relatively low yields in the south-west. Further work on model evaluation and model comparison is required to resolve these differences and reduce the uncertainty in model estimates. In the short-term, the uncertainty associated with choice of model could be quantified by modelling soil GWP using yield forecasts produced from an ensemble of yield models for each crop.

Overall, the reliability and spatial accuracy of future soil GWP modelling would benefit greatly from improvements in bioenergy yield modelling (or direct modelling of crop inputs of C to the soil).

Finally, little is known about the impact of bioenergy crop re-establishment on soil carbon. Different re-establishment techniques involve different amounts of soil disturbance, which could lead to enhanced soil organic matter decomposition rates. Soil disturbance from re-establishment could have a significant effect on long-term C sequestration, with a proportion of the C sequestered during the previous planting cycle being lost again as CO_2 to the atmosphere (Grogan and Matthews, 2002). Research into the practicality of a range of potential re-establishment techniques and their impacts on soil C dynamics should be a high priority.

5 CONCLUSIONS

The spatial modelling framework described here identifies the potential impacts of bioenergy production on soil GWP within the UK. The modelling results have identified that the following land-use transitions can lead to a beneficial decrease in soil GWP: rotational crops to *Miscanthus*, SRC and SRF, and grass to SRF. There is a large degree of variation in GWP amongst these conversions due to differences in initial land-use type, differences in bioenergy crop species, and spatially varying climatic and soil factors. This finding suggests that a bioenergy species mix, optimised to spatially variable climatic and soil conditions is required to maximise beneficial effects upon GWP.

Whilst the sources of uncertainty described in section 4.4 are numerous and often difficult to quantify, the modelling framework and GWPs reported here can assist in identifying the most appropriate land-uses, bioenergy species and areas for conversion to bioenergy crops. However, the limitations imposed by the sources of uncertainty must be considered when the results are interpreted.

In particular, given the coarse spatial resolution of some of the input data used to drive the model, we advise that the results are more reliable if interpreted at a spatial scale larger than the 1 km resolution of the model outputs. The results of an individual 1 km grid cell should not be interpreted in isolation and used to develop bioenergy strategy within that grid cell. At the 1 km scale, sub grid-cell heterogeneity in soil types, soil water status, land management practices and other factors not fully captured by the input data and model, could have a significant impact on the local soil GWP response to bioenergy crops. The model outputs are therefore best used to inform bioenergy strategy at a coarser-scale (e.g. regional scale).

Overall, this study finds that SRF offers the greatest beneficial impact on soil GWP, in terms of both magnitude and spatial extent of the resulting decreases in GWP. SRF is also the only bioenergy crop to provide potentially beneficial impacts on GWP on permanent grassland. The beneficial effects following conversion of permanent grass to SRF are perhaps surprising, given that land-use changes from permanent grass generally lead to an observed loss of SOC. It should be noted however, that the beneficial GWPs under the permanent grass to SRF transition are small, in both magnitude and spatial extent, in comparison to the beneficial GWPs resulting from conversion of rotational crops to *Miscanthus*, SRC and SRF.

The potential reductions in GWP under SRF are tempered by the observation that much of the area providing the most beneficial impacts on GWP occurs in the East Midlands and East Anglia, which lies within the grain belt. This area is less attractive for bioenergy crops because it would entail significant displacement of food production.

Miscanthus provides significant beneficial changes in net GWP in the South West of England and South West Wales, where high yields (and corresponding increases in SOC) combine with significant reductions in N_2O emissions. These regions complement the beneficial regions of SRF.

SRC offers fewer opportunities than SRF and *Miscanthus*, both in terms of the magnitude and spatial extent of its beneficial impacts on GWP, with the best locations being restricted to relatively small areas within North West England and Northern Ireland.

The criterion for selection of bioenergy crops extends beyond soil GWP to include bio-physical factors (e.g. the energy-density of the crop) and socio-economic factors (e.g. displacement of food production and required expenditure on harvesting equipment). The modelling approach used here provides spatially defined soil GWP information that may be used within a framework designed to explore bioenergy opportunities over a wider range of criteria, whilst recognising that consideration of wider ecosystem services may also come in to play in selecting opportunities for bioenergy development.

6. KEY FINDINGS

The spatial distribution of soil global warming potential has been considered in the UK for land-use conversions from rotational crops, permanent grass and forest to wheat, sugar beet, oilseed rape, *Miscanthus*, SRC and SRF in the UK, with conversions taking place in 2015 and results obtained up to 2050 for three climate emissions scenarios.

Key findings from this work are:

- Conversion of rotational crops to *Miscanthus*, SRC and SRF and conversion of permanent grass to SRF show beneficial changes in soil GWP over a significant area.
- Conversion of permanent grass to *Miscanthus*, permanent grass to SRF and forest to SRF show small detrimental changes (0 to 50 t CO_2e ha^{-1} after 35 years) in soil GWP over a significant area.
- Conversion of permanent grass to wheat, oilseed rape and sugar beet and all conversions from forest show large detrimental changes (> 50 t CO_2e ha^{-1} after 35 years) in soil GWP over most of the simulation area, largely due to moving from uncultivated soil to regular cultivation.
- Conversion of permanent grass to SRC (willow) also shows large detrimental changes (> 50 t CO_2e ha^{-1} after 35 years) in soil GWP over most of the simulation area, largely due to poor SRC yields leading to lower carbon returns to the soil (see below).
- Impact of soil GWP is dominated by effects on soil organic carbon with the difference among *Miscanthus*, SRC and SRF largely determined by yield, since higher yields mean higher carbon returns to the soil, which increases soil organic carbon stocks relative to low yield.
- Low yields lead to SOC decline, so a target for management of perennial energy crops is to achieve the best possible yield by using the most appropriate energy crop and cultivar for the local situation, as long as this can be done without excessive N fertiliser use, which would increase nitrous oxide emissions.
- Overall, SRF (poplar) offers the best bioenergy opportunities (in terms of changes in soil GWP), due both to the magnitude and spatial extent of its beneficial impacts on soil GWP.
- The high, medium and low climate projections have an insignificant impact on modelled soil GWP.
- Some sources of uncertainty in the model results relating to natural variability in yield, climate and soils are difficult to quantify and should be considered when interpreting the results.

- The criteria for selection of bioenergy crops extends beyond direct effects on soil GWP to include GWP increases/decreases resulting from displaced food production, bio-physical factors (e.g. the energy-density of the crop) and socio-economic factors (e.g. expenditure on harvesting equipment).

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APPENDIX I – GLOSSARY

AGB	Above-Ground Biomass
ASCII	American Standard Code for Information Interchange
BD	Bulk Density
BIO	Biomass
C	Carbon
CEH	Centre for Ecology & Hydrology
CH_4	Methane
CN	Carbon Nitrogen
CO_2	Carbon Dioxide
CO_2-C	Carbon Dioxide as Carbon
csv	Comma Separated Value
DOC	Dissolved Organic Carbon
DPM	Decomposable Plant Material
E	Relative Error
EC	Eddy Covariance
ECA&D	European Climate Assessment & Dataset
ECOSSE	Model to Estimate Carbon in Organic Soils – Sequestration & Emissions
ELS	Entry Level Stewardship
ELUM	Ecosystem Land Use Modelling
FR	Forrest Research
FRS	Functional Requirements Specification
GC	Gas Chromatograph
GHG	GreenHouse Gas
GIS	Graphic Information System
GOR	Government Office Regions
GPP	Gross Primary Productivity
GUI	Graphical User Interface
GWP	Global Warming Potential
ha	hectare
HUM	Humus
HWSD	Harmonized World Soil Database
IOM	Inert Organic Matter
IPCC	Intergovernmental Panel on Climate Change
IRGA	Infra-Red Gas Analyser (chamber measurements)
K	Potassium
LCA	Life Cycle Analysis
LOFIT	Lack Of Fit
LRF	Long Rotation Forestry
LUC	Land-Use Change
M	Mean Difference
N	Nitrogen
N_2O	Nitrous Oxide
NEE	Net Ecosystem Exchange
NERC	Natural Environment Research Council

NH_4^+	Ammonium
NO_3^-	Nitrate
NPP	Net Primary Production
NRL	no root/litter plots
NUTS	Nomenclature of Territorial Units for Statistics
odt	Oven Dry Tonne
OSR	Oil Seed Rape
P	Phosphorus
PET	Potential EvapoTranspiration
PM	Payment Milestone
PTF	PedoTransfer Functions
QC	Quality Control
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
SO_3	Sulphur Trioxide
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SRC	Short Rotation Coppice
SRF	Short Rotation Forestry
std err	Standard Error
SUG	Sugar Beet
TER	Total Ecosystem Respiration
UK	United Kingdom
UKCP09	UK Spatially Coherent Projections
UKERC	UK Energy Research Centre
WHE	Wheat
WP	Work Package