ELUM: A spatial modelling tool to predict soil greenhouse gas changes from land conversion to bioenergy in the UK

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Highlights

- ELUM models soil greenhouse gas balance of bioenergy land-use change in UK to 2050

- It is based on the ECOSSE model, but quick and easy to use, with added features

- It is able to support life-cycle assessments and policy making for bioenergy
- Consultation with anticipated users guided usability and functionality
- Greenhouse gas balance is highly dependent on initial land use and new energy crop

Abstract

The ELUM Software Package spatially predicts the net soil greenhouse gas balance of land-use change to grow energy crops in the UK up to 2050. It is able to support a range of analyses of bioenergy, and was developed in consultation with anticipated users. Results can be obtained according to specific interests, viewed in the graphical interface and exported for a variety of purposes. The functionality of the software is demonstrated through different case studies, which show an array of applications.

Keywords: land-use change; bioenergy; soil carbon; greenhouse gas; soil organic matter model; spatial model

Software availability

Name of software: ELUM Software Package

Developer: Mark Pogson, University of Aberdeen, University of Bolton and Liverpool John Moores University

Availability and documentation: software and user guide freely available via http://www.elum.ac.uk/

Year first available: 2016

Software required: Java, Microsoft Windows 32-bit or higher

Programming languages: Java, Python, Fortran

1. Introduction

Bioenergy is predicted to contribute 10% of primary energy demand in the UK by 2050, rising from 3% currently (DECC, 2012). Up to 3Mha of the 18Mha of agricultural land in the UK may be dedicated to biomass feedstock production (UK Bioenergy Strategy, 2012; Rowe et al., 2009; Taylor, 2008), with comparable predictions elsewhere (Mantau et al., 2010; U.S. DOE, 2006).

Bioenergy has the potential for favourable greenhouse gas (GHG) balances (Smith et al., 2015; Bringezu et al., 2009), but this depends on the effects of land-use change (LUC) to grow energy crops (Berndes et al., 2011; Guo and Gifford, 2002). The Ecosystem Land Use Modelling & Soil Carbon GHG Flux Trial (ELUM) project has quantified the GHG balance of LUC to grow energy crops in the UK through a combination of field measurements and simulation (Harris et al., 2014). As part of this, the ECOSSE model (Smith et al., 2010) has been successfully evaluated to predict soil GHG balances at site-level (Dondini et al., 2014, 2015), and applied spatially to estimate the potential effects of large-scale energy crop cultivation in the UK (Richards et al., 2016).

There is an established need for spatial modelling of a range of aspects of LUC (Celio et al., 2014; Mas, 2014) and user-friendly interfaces for environmental modelling software (Schiavina et al., 2015). Due to the predicted scope of bioenergy deployment in the UK, it is important that estimates of its impacts are available to a wide audience – especially scientists and policy makers in public and private sectors – and that users can obtain results specific to their interests rather than rely on published data for particular scenarios. Existing software is not suitable for this purpose for several reasons, including large computing requirements and highly involved operation, which may require extensive data processing and knowledge of programming code. Here we present the ELUM Software Package, an accessible spatial modelling tool which provides estimates of the net soil GHG balance of LUC to grow energy crops anywhere in the UK up to 2050 according to a range of options. The software is intended to support bioenergy value chain and life-cycle assessments of the likely consequences of different bioenergy land-use policies and practices, and was developed in consultation with anticipated users to ensure its suitability.

For clarity and simplicity, rather than presenting absolute emissions, results represent the difference between emissions following LUC and corresponding emissions had no transition occurred; results therefore show the effect of the LUC itself. Results are reported as CO_2-equivalent (CO_2e) values for net GHG, CO_2, N_2O and CH_4 emissions, and changes in soil carbon (soil C), per hectare of land and per oven-dry tonne of biomass yield.

Carbon stored in the harvested biomass is excluded from results in order to separate out the effects of LUC on the soil itself, as are all associated cultivation and harvesting emissions, such as from fertiliser production, machinery and transport. This enables results to be used for a range of purposes without imposing undue assumptions. Only direct transitions from existing land-uses are considered; indirect LUC and future transitions (Searchinger et al., 2008) are beyond the scope of ELUM.

ELUM considers LUC to grow the following first-generation crops (Kretschmer, 2011): wheat, sugar beet and oil seed rape (OSR), and the following second-generation crops (Rowe et al., 2009): short rotation forestry (SRF) Poplar, short rotation coppice (SRC) Willow, and *Miscanthus* × *giganteus* (*Miscanthus*). Conversion of land is considered from arable, grass and forest.

We describe the development and functionality of the software package before demonstrating its use in different case studies. These highlight important points to consider when interpreting results, and also show potential opportunities and risks associated with LUC to grow energy crops. However, the case studies are neither predictions of likely bioenergy deployment, nor recommendations of policies to pursue or avoid.

2. The ELUM Software Package

2.1 Development

The ELUM Software Package is intended to be accessible to a wide range of users. The following key requirements were therefore identified from the outset, and refined throughout the development process in response to user feedback:

- Accessible: free to use, graphical user interface (GUI), low computing requirements, no installation, flexible data storage options;
- Standalone: no separate data or software requirements (except Java running on Windows), results and analysis are presented within package, comprehensive user guide;
- Immediate: results are obtained quickly and directly, default options are provided;
- Flexible: various options are provided for results, regions and data export.

Many features benefit all users, such as speed and ease of use, but others involve balancing conflicting requirements, such as the need for flexible options versus the potential for confusion and misinterpretation. These issues were resolved in a number of ways, including the provision of appropriate default options, pop-up information windows, and colour-coding and labelling of results.

Software development included extensive interaction with anticipated users, ranging from informal discussions throughout the three-year project, to an annual review process with feedback from an academic and industrial panel. This motivated several features, including options for regional selection, types of results, analysis tools and data formats (Hillier et al., 2016). It also helped in creating a help file suitable for a broad audience, which documents not only the software but also the model, results and terminology. Initial users include the Bioenergy Value Chain Model (Samsatli, 2015), for which the ability to export results in different formats and disaggregate emissions is particularly important.

2.2 Structure

The ELUM Software Package comprises two main sections: a GUI (Fig. 1), and a collection of programs and data files (Fig. 2), which are all operated from the GUI. ELUM is supplied as a stand-alone folder which does not require installation.

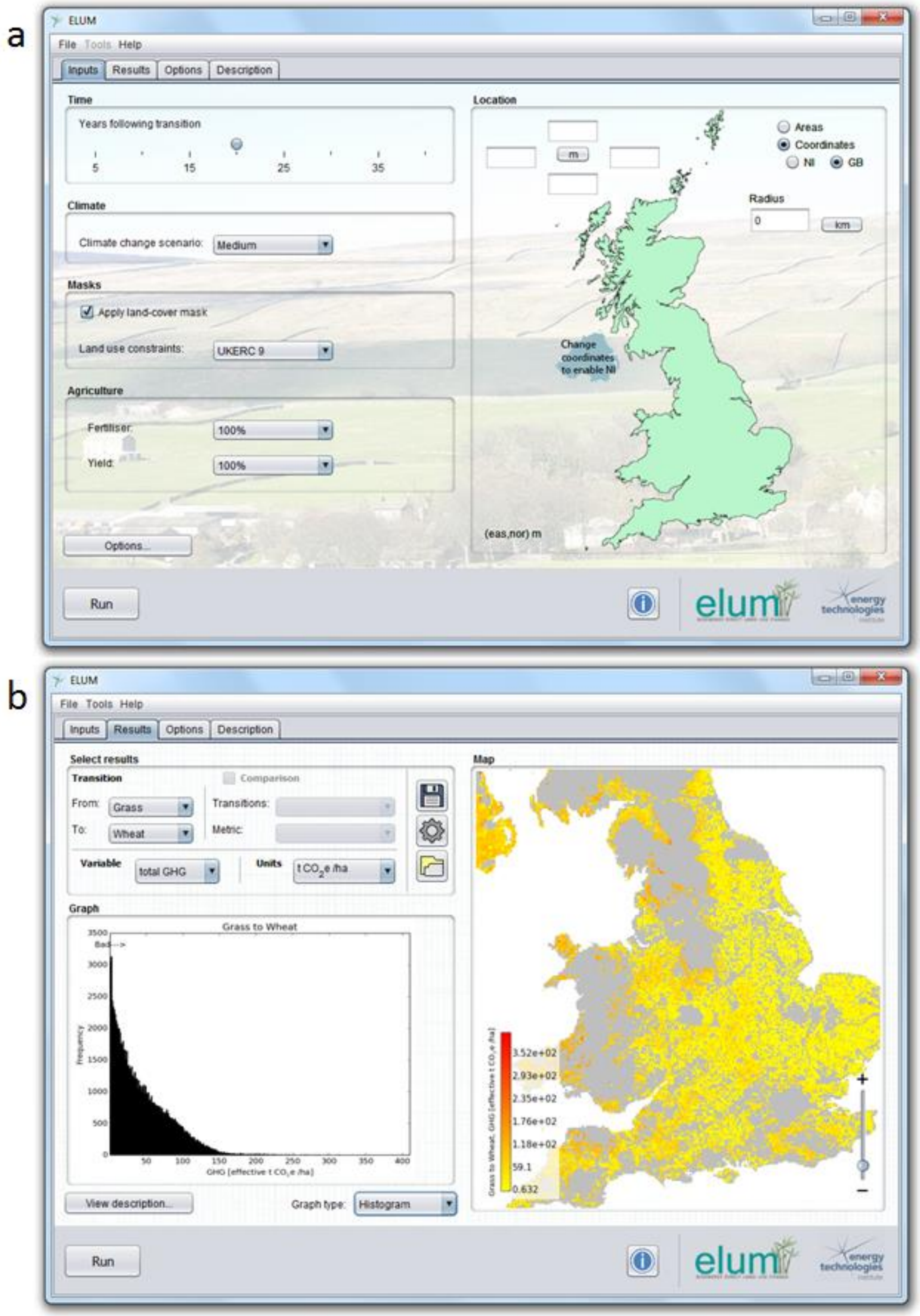

Fig. 1. ELUM graphical user interface (GUI). There are four different tabs which allow users to select from a range of options and view results; two are shown: (a) inputs, (b) results.

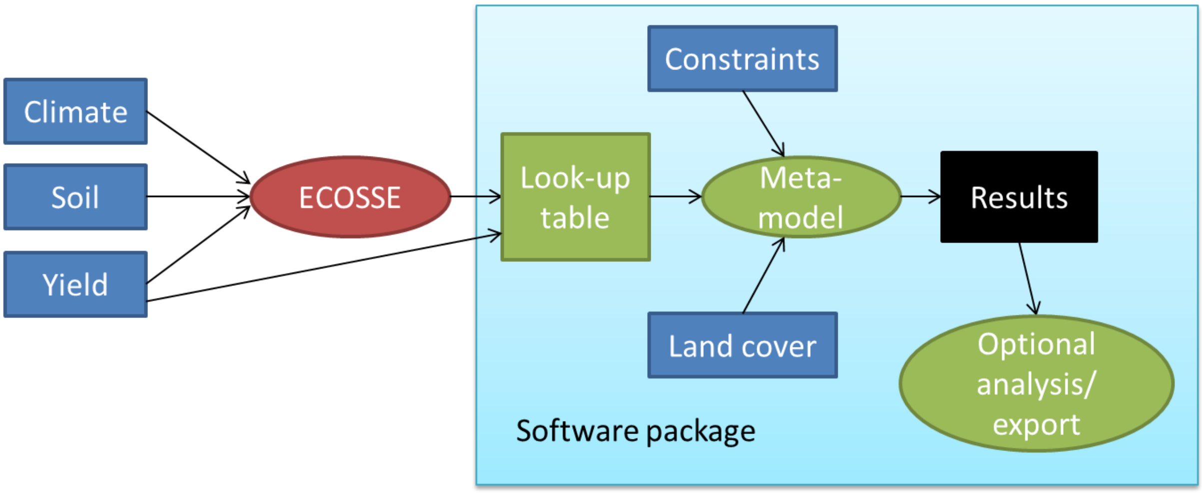

Fig. 2. ELUM Software Package organisation. Data files are shown as rectangles and programs as ovals. All features of the software package are operated from a GUI (see Fig. 1).

2.3 Underlying model

The ECOSSE model (Smith et al., 2010) underlies results in ELUM. It is not part of the software itself but has been used to obtain the results, which are stored in a look-up table (Fig. 2).

ECOSSE models soil disturbance (due to planting, harvesting or removal of crops), changes in soil carbon inputs from litter biomass (via decomposition rates), and changes in fertiliser quantity and timing. Please see Richards et al. (2016) for a full description of the ECOSSE simulations performed for ELUM, including data inputs (EUROSTAT, 2014; FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012), processing (Hastings et al., 2014; Pyatt et al., 2001; Thompson and Matthews, 1989; Lieth, 1975) and calculation of CO2-equivalent (CO2e) emissions (IPCC, 2001, 2013).

2.4 Meta-model

The meta-model is a program in the software package which accesses results from the look-up table and processes them according to user selections. The meta-model, in combination with the look-up table, is used in place of the underlying ECOSSE model to simplify operation and significantly decrease computation time.

In order to reduce the size of the look-up table, only results for default fertiliser and yield values are stored; results for a range of non-default values are estimated in the meta-model by rescaling results according to relationships obtained from linear-regression of ECOSSE results. These relationships provide very good approximations to the actual ECOSSE outputs, as described further in the user guide.

Users can select geographical areas by grid reference or by regions from a range of administrative levels. Results have a spatial resolution of 1km but are best used at regional and national scales due to inherent spatial uncertainties in the underlying data.

Two different spatial masks can be applied by the meta-model. UK land-cover data are obtained from CEH Land Cover Map 2007 (Morton et al., 2011), which rescale results according to the initial land-cover in each grid cell. By applying the land-cover mask, spatial per-hectare results show the combination of emissions and available land (i.e. the effective emissions per hectare spread across each whole grid cell); thus summed time-series results reflect the total available land for the initial land-use of each transition. By removing the land-cover mask, results represent emissions on productive land without accounting for how much land is available; this allows users to separate out the effects of LUC and land availability, or post-process results to apply different land-cover masks. In contrast, land constraints data are obtained from Lovett et al. (2014), which are used to exclude entire grid cells deemed inappropriate to grow energy crops for environmental or practical reasons; users can select from different levels of constraints, with a minimum level imposed on all results, as described in the user guide.

Results are displayed within the GUI as spatial maps, time-series graphs and frequency histograms, as explored in the case studies below. Results are saved as comma-separated value (csv) files, which can be opened in spreadsheet applications or imported into a geographical information system (GIS); users are therefore able to post-process results according to their interests. Results can also be exported as Ascii Grid and kml files.

3. Case studies

We present three case studies to demonstrate the functionality of ELUM. Details of how to operate the software are included in the user guide. All examples assume medium climate change (UK Climate Projections, 2009), using yield predictions based on standard fertiliser application (Defra, 2010), the highest level of land-use constraints (Lovett et al., 2014) and exploiting current practice and technology; these assumptions can all be changed by users according to their interests.

Positive values indicate emissions to the atmosphere, except for soil C where positive values indicate removals from the atmosphere. The presented results are taken directly from the software outputs, which can be viewed interactively in the GUI (Fig. 1b).

3.1 Comparison of second-generation crops in Norfolk

This case study demonstrates regional selection, comparison tools, and the effects of initial land-use. Results are obtained for transitions to grow second-generation crops in Norfolk, (Fig. 3). The land-cover mask is not applied (see Section 2.4). Fig. 3a shows that transitions from arable to SRF in Norfolk cause a mean reduction in soil GHG emissions over the following 35 years, with average emissions around 3.5t CO_2e /ha/y lower than if the land remained under arable cropping. Conversely, transitioning from forest to SRF causes a mean increase in soil GHG emissions (primarily due to initial soil disturbance), but this levels out after around 15 years (Fig. 3b). This illustrates the important effect of not only which energy crop is grown, but also the previous land-use (St Clair et al., 2008).

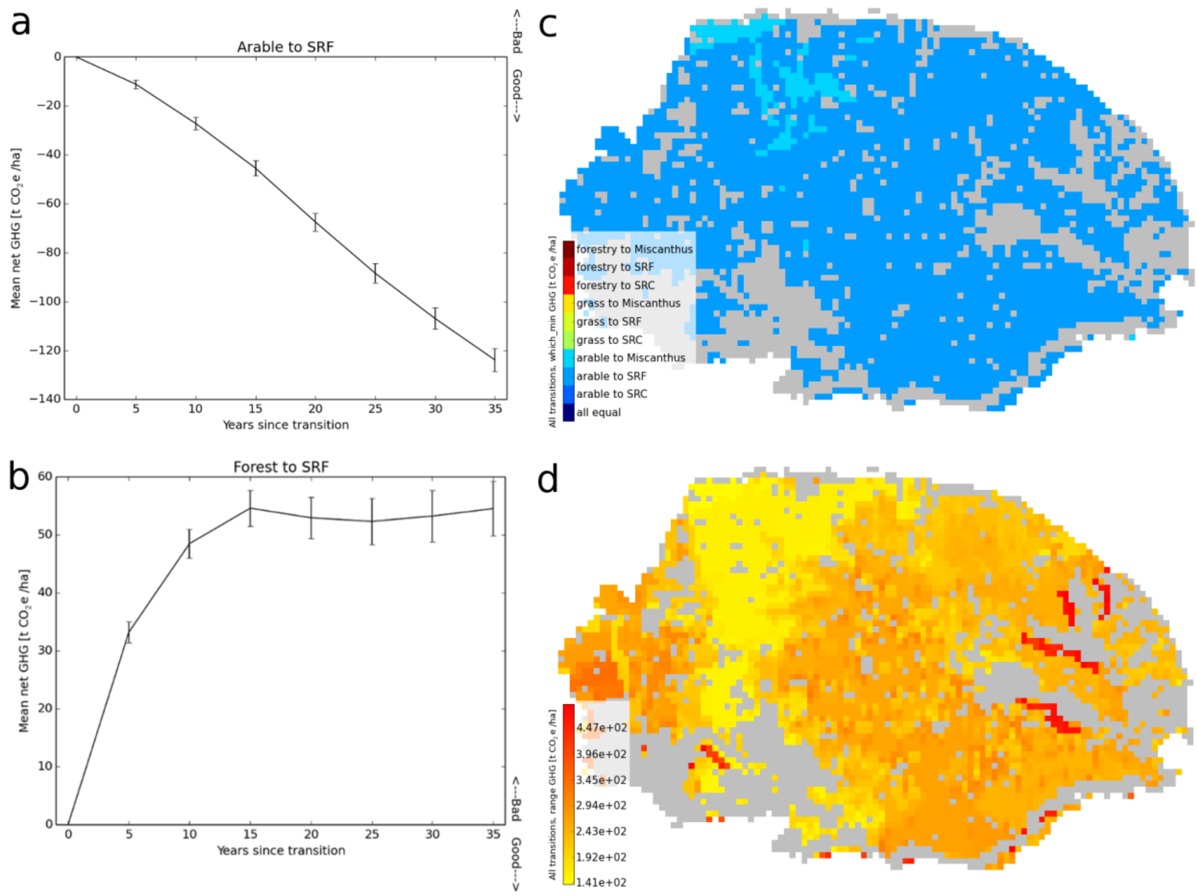

Fig 3. Transitions to grow second-generation crops in Norfolk, 2015-2050. (a) arable to SRF mean emissions, (b) forest to SRF mean emissions, (c) transitions which cause the lowest cumulative emissions, (d) difference between the highest and lowest emissions for different transitions. No land-cover mask is applied. Grey areas on the maps show excluded areas, either due to zero yield or land-use constraints. Error bars show 95% confidence intervals obtained from comparisons with field studies (see user guide and Discussion).

Second-generation crop transitions are compared in Fig. 3c, showing that transitions from arable to SRF cause the lowest emissions almost everywhere, with the exception of some small areas in the north-west where it is arable to *Miscanthus*, based on predicted yields. Fig. 3d shows the difference between the highest and lowest emissions spatially for all the transitions; it demonstrates the wide range of effects, which could vary by up to ~450t CO_2e /ha in the considered time period and region.

3.2 Soil C changes within 50km of Oxford

This case study demonstrates spatial selection, disaggregation of emissions, and the effects of the land-use mask and units. Results are compared for soil C changes following LUC within 50km of Oxford 2015- 2030 (Fig. 4). The land-cover mask is applied. Slightly over half of transitions from arable to SRC result in a net sequestration of soil C (Fig. 4a,b). However, plotting emissions per oven-dry tonne of yield (Fig. 4b), rather than per hectare (Fig. 4a) changes the shape of the distribution. Both are correct; the distributions simply reflect the different measures being used.

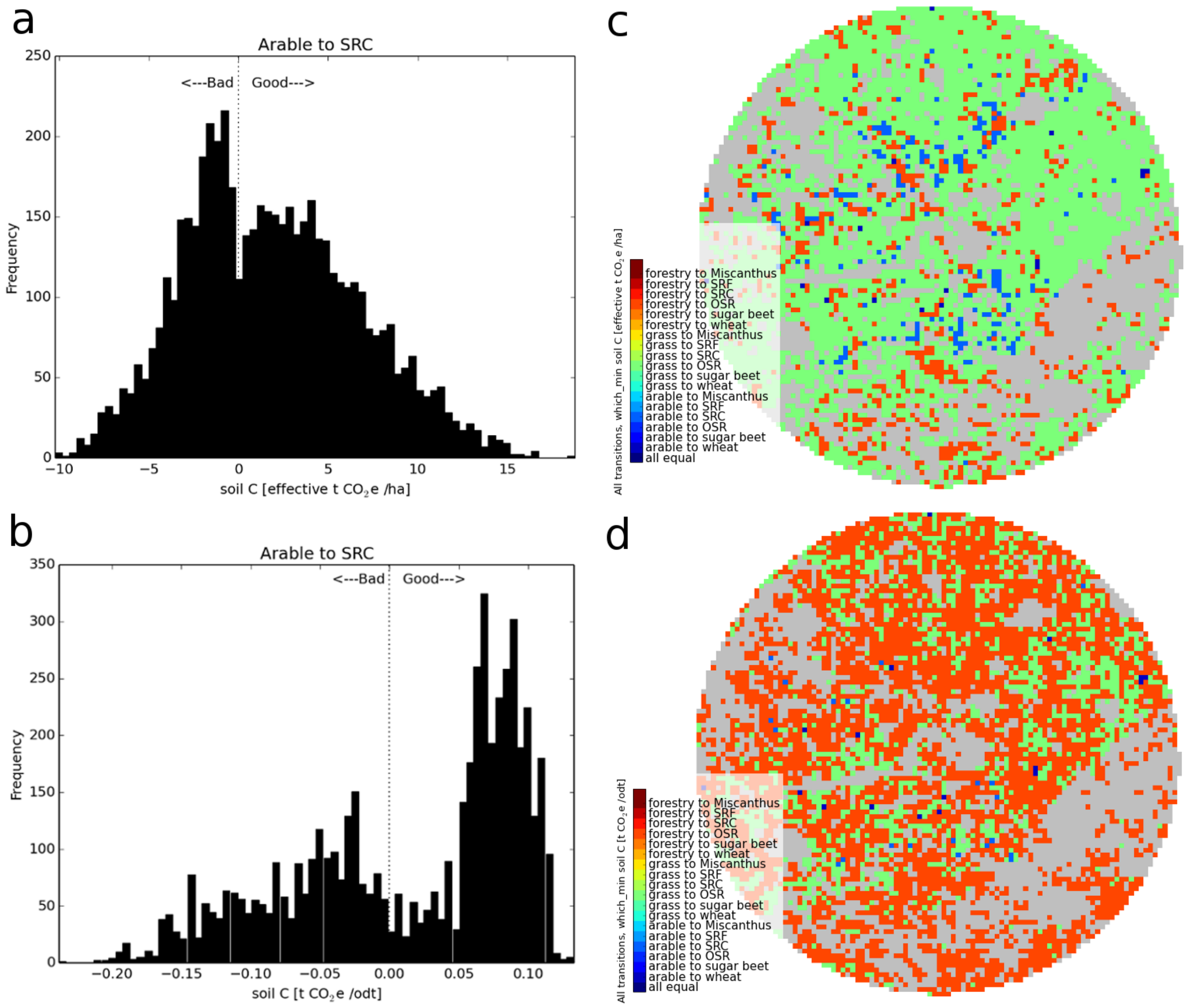

Fig. 4. Soil C changes within 50km of Oxford, 2015-2030. (a) arable to SRC soil C changes per hectare, (b) as (a) but per oven-dry tonne of yield, (c) transitions which cause the greatest loss or smallest gain of soil C per hectare, (d) as (c) but per oven-dry tonne of yield. Results are rescaled according to a land-cover mask.

Converting permanent grassland to OSR causes the greatest loss of soil C in most areas (Fig. 4c). However, the role of the land-cover mask is important; not only does the transition itself cause a loss of soil C, but there is also a relatively large area of permanent grassland present, and it is this combination which causes the greatest loss of soil C compared to other transitions. In contrast, transitions from forestry to OSR generally cause the greatest loss of soil C per oven-dry tonne of biomass produced (Fig. 4d); hence this transition in fact causes greater soil C losses, but less forest land exists in the area considered. This could also be shown by obtaining results per hectare without the land-cover mask (results not shown – but see Case Study 1). However, it is important to note the effect of the land-cover mask here: if a grid cell contains no forest land, for example, but does contain another land-cover, then a transition from something other than forest would be shown to cause the greatest loss of soil C in that grid cell, even if a transition from forest would have caused an even greater loss had forest land existed in that cell. These are not flaws of the method, rather points to consider when performing spatial analysis, depending on the units and spatial masks used, which would be determined by the particular interests of users.

3.3 UK-wide transitions from permanent grassland

This case study demonstrates reversals of emission trends, and the potential effects of large-scale LUC. UK-wide results are obtained for transitions from permanent grassland (hereafter just grassland) to wheat and SRF (Fig. 5). Rotational grassland (less than 5 years old) is excluded; this is classed as arable land in ELUM as the grass usage occurs as part of a rotation (see Discussion). The land-cover mask is applied; this assumes that all grassland is available for conversion, which is of course unrealistic, but please see Sections 2.4 and 3.2 for further discussion.

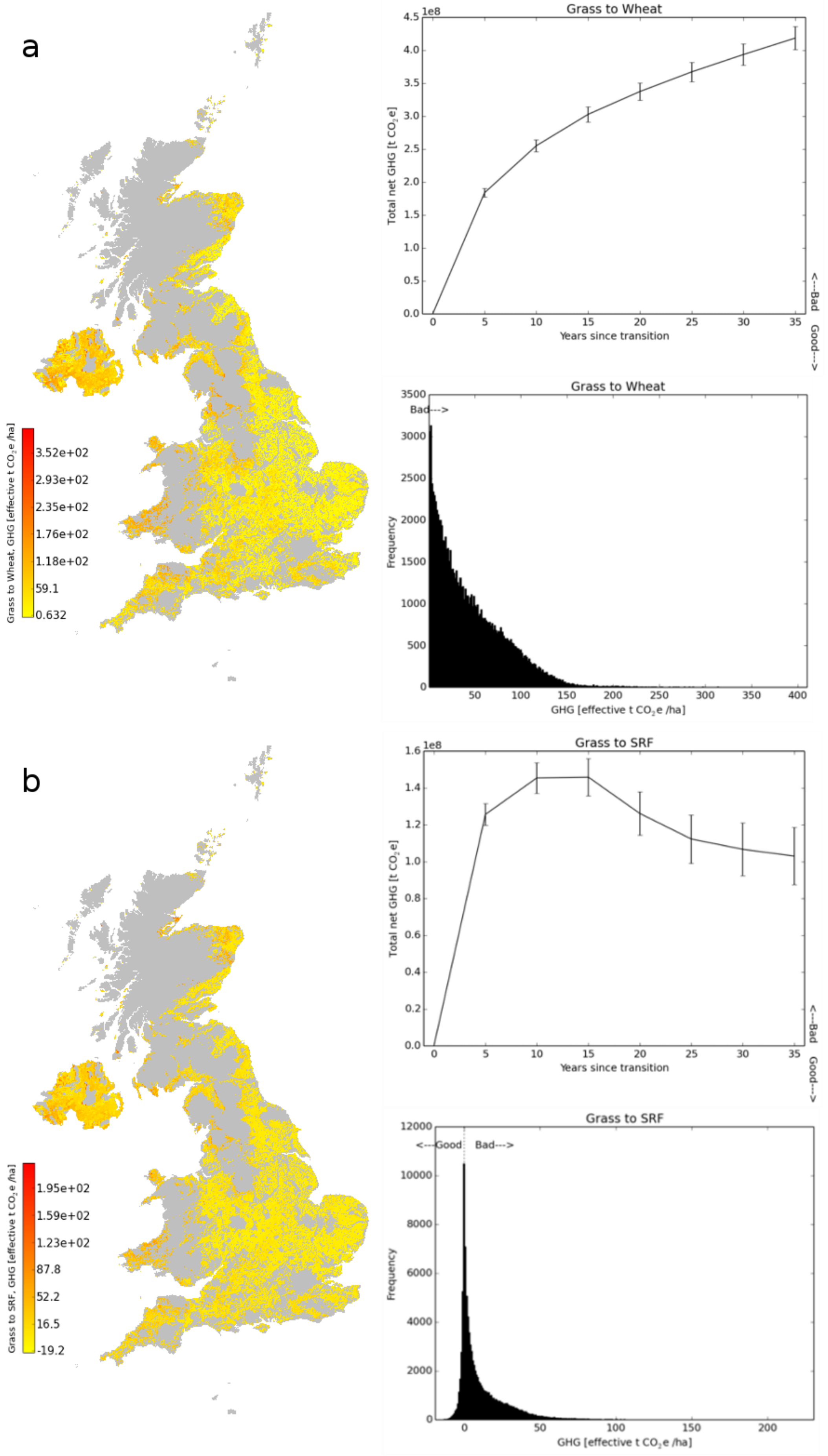
a
Grass to Wheat, GHG [effective t CO2e /ha]
3.52e+02
2.93e+02
2.35e+02
1.76e+02
1.18e+02
59.1
0.632
Grass to Wheat
1e8
Total net GHG [t CO2e]
Years since transition
<---Bad
Good--->
Grass to Wheat
Bad--->
Frequency
GHG [effective t CO2e /ha]
b
Grass to SRF, GHG [effective t CO2e /ha]
1.95e+02
1.59e+02
1.23e+02
87.8
52.2
16.5
-19.2
Grass to SRF
1e8
Total net GHG [t CO2e]
Years since transition
<---Bad
Good--->
Grass to SRF
<---Good
Bad--->
Frequency
GHG [effective t CO2e /ha]

Fig. 5. UK-wide transitions from grassland, 2015-2050. (a) transition to wheat, (b) transition to SRF. Maps show cumulative net GHG emissions per hectare in 2050; graphs show cumulative net emissions versus time; histograms show frequencies of cumulative emissions in 2050. Results are rescaled according to a land-cover mask.

Transitions from grass to wheat and SRF both cause large soil GHG emissions. If all grassland in the UK (almost 3.3Mha, excluding inappropriate or protected areas) is converted to grow wheat in 2015, it releases over 400Mt CO_2e from the soil to the atmosphere by 2050, when emissions are still increasing (Fig. 5a, time-series graph). Converting all grassland to SRF releases over 140Mt CO_2e from 2015 to 2030, which is reduced to 100Mt CO_2e by 2050 (a reversal of emission trends; Fig. 5b, time-series graph) due to diminishing effects of the initial soil disturbance and higher plant litter inputs to the soil than under the initial land-use.

If all grassland is converted to grow either wheat or SRF, mean annual emissions over the period 2015-2050 are approximately 11Mt CO_2e /y or 3Mt CO_2e /y respectively (relative to no transition occurring). These values are obtained by averaging the cumulative emissions at 2050 over the time period; for comparison, net GHG emissions in the UK were around 570Mt CO_2e /y in 2013 (DECC, 2015), hence these transitions would represent an increase in UK GHG emissions of approximately 2% and 0.5% respectively. Although complete conversion of grassland is unrealistic, the results highlight the potentially large GHG emissions caused by certain large-scale land-use transitions to grow energy crops, or indeed to grow food crops (as shown by the transition to wheat). Some other transitions, particularly from forest, are observed to cause even greater soil GHG emissions, while others, e.g. from arable land to any second-generation crop, tend to reduce GHG emissions, as shown in the case studies above (Richards et al., 2016).

There is clear spatial variation in GHG emissions in Fig. 5 due to spatial heterogeneity in meteorological conditions, soil types and land-cover; it is particularly the latter which makes the spatial distribution in both maps so similar. From the frequency histograms, it is clear that transitions from grass to wheat increase soil GHG emissions in all cases, although the frequency peaks towards zero emissions. However, for transitions from grass to SRF, a small number of grid cells exist where net GHG emissions up to 2050 are unaffected or even slightly reduced by the transition, thus showing some opportunities to convert grassland without net GHG emissions within the considered time scale.

4. Discussion

The above results demonstrate some possible uses of the ELUM Software Package. While ELUM is user-friendly, the presented examples highlight that care must be taken when interpreting results, in part due to the nature of spatial data, particularly regarding different units and spatial masks.

The case studies are intended to demonstrate the functionality of the software, and are not predictions of bioenergy deployment, but it is evident from the results that different land-use transitions may cause considerably different emissions. Both initial and new land-uses have an important effect, as do the geographical location and time period. Transitions from grassland to SRF are generally observed to cause net GHG emissions, albeit small, relative to no LUC occurring (Fig. 5b). Conversely, arable to SRF transitions in Norfolk cause net GHG sequestration (Fig. 3a). Although the areas differ, this highlights the important distinction between grassland (which is defined to include only permanent grass) and rotational grassland (which is represented by arable land-use in ELUM); the difference between these two initial land-uses has a major effect on emissions. Particular care must therefore be taken with the term grassland in order to distinguish between permanent and rotational (Richards et al., 2016).

All land is assumed to be at equilibrium prior to transitions occurring. The validity of this assumption will vary, but model evaluation against field sites of various ages of establishment demonstrates good agreement with experiments (Dondini et al., 2014, 2015). Error bars on the time series graphs are calculated from these comparisons with field data (Richards et al., 2016). Errors exclude future uncertainties of any kind, e.g. climate and farming practices, but users may select from a number of options for these (see below).

All results in the software package are for transitions occurring in 2015, as determined by the climate data; however, due to the uncertainty in climate predictions (which are decadal averages from the central decade of a moving 30 year average; UK Climate Projections, 2009), the transition may be assumed to be within ±10 years. The use of average monthly meteorological conditions means that cumulative yields may be slightly overestimated in ELUM since extreme weather events, which tend to have a detrimental effect on yields, are not explicitly represented (Hastings et al., 2009). However, likely agronomic improvements are not considered either, which may counterbalance this to some extent (see below). Users may choose from different future climates, but little difference is found for any of the model outputs (Richards et al., 2016). This does not provide any information about climate uncertainty, simply that the range of different climates considered has only a minor effect on results to 2050.

The effects of different fertiliser applications and yields can be estimated using ELUM, but are not presented here for reasons of space. In order to isolate parameters, fertiliser is assumed not to affect yields in the range considered, so increasing fertiliser causes increases in GHG emissions, but users also have the option to increase yields, so are able to link this with fertiliser. Higher crop yields are assumed to produce corresponding increases in plant litter inputs to the soil, and therefore increase soil C sequestration.

Results are available up to 2050; additional results up to 2055 are obtained by extrapolation and included for use in a related project. Most transitions do not reach a new GHG equilibrium within this time scale, but given sufficient time, and a relatively stable climate and farming practice, this would eventually occur. Some transitions show a reversal in trends over the time period considered (e.g. Fig. 5b – permanent grassland to SRF). In the long term this may be significant, but it is not possible to make predictions beyond the time scales considered due to the range of uncertainties involved, and it does not affect most transitions.

By consulting with users throughout software development – including initial identification of users and their needs, frequent discussions with users to refine and extend functionality, and a regular review process – the ELUM Software Package makes available spatial predictions of GHG emissions from bioenergy LUC to a wide audience. Due to the number of options available, the examples presented here represent only a small fraction of possible outputs, but the aim of ELUM is for others to use it according to their particular interests.

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