Assessing uncertainties in land cover projections

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Uncertainties in land cover projections

Abstract

Understanding uncertainties in land cover projections is critical to investigating land-based climate mitigation policies, assessing the potential of climate adaptation strategies, and quantifying the impacts of land cover change on the climate system. Here we identify and quantify uncertainties in global and European land cover projections over a diverse range of model types and scenarios, extending the analysis beyond the agro-economic models included in previous comparisons. The results from 75 simulations over 18 models are analysed and show a large range in land cover area projections, with the highest variability occurring in future cropland areas. We demonstrate systematic differences in land cover areas associated with the characteristics of the modelling approach, which is at least as great as the differences attributed to the scenario variations. The results lead us to conclude that a higher degree of uncertainty exists in land use projections than currently included in climate or earth system projections. To account for land use uncertainty, it is recommended to use a diverse set of models and approaches when assessing the potential impacts of land cover change on future climate. Additionally, further work is needed to better understand the assumptions driving land use model results and reveal the causes of uncertainty in more depth, to help reduce model uncertainty and improve the projections of land cover.

1 Introduction

Land use and land cover (LULC) change plays an important role in climate change, biodiversity and the provision of ecosystem services. LULC change is believed to be responsible for a substantial proportion of total carbon dioxide (CO_2) emissions, 10-20% since 1990 (Houghton *et al.*, 2012; Le Quéré *et al.*, 2015) and approximately a third since pre-industrial times (Le Quéré *et al.*, 2015), while land-based, climate mitigation measures could contribute substantially to the abatement of future greenhouse gas emissions (Rose *et al.*, 2012). Biogeophysical (e.g. surface albedo and roughness) and biogeochemical effects are also altered by LULC change, and play an important role in changes to climate and water availability, at regional and global scales (Levis, 2010; Sterling *et al.*, 2012; Mahmood *et al.*, 2014; Smith *et al.*, 2015; Chen & Dirmeyer, 2016). Climate change also impacts LULC, both through direct effects on crops and natural vegetation and through land management and land use changes implemented as adaptation responses (Parry *et al.*, 2004; Howden *et al.*, 2007). LULC is not only influenced by climate change, but also by socio-economic factors, such as population dynamics, wealth, diet and urbanisation, which are important for determining demand for agricultural and forestry commodities (Foley *et al.*, 2011; Tilman *et al.*, 2011; Smith *et al.*, 2013; Weinzettel *et al.*, 2013).

Modelling at a range of spatial scales has been applied to understand the LULC response to climatic and socio-economic drivers, and to assess the potential for mitigation and adaptation to climate change (Verburg & Overmars, 2009; Fujimori *et al.*, 2012; Calvin *et al.*, 2013; Meiyappan *et al.*, 2014; Stehfest *et al.*, 2014; Harrison *et al.*, 2015). Uncertainty arises due to the range of potential socio-economic and climate futures. Attempts have been made to characterise the uncertainty in socio-economic drivers through scenarios, including the IPCC's special report on emissions scenarios (SRES) (IPCC, 2000), and more recently, shared socio-economic pathways (SSPs) (O'Neill *et al.*, 2015) in combination with representative concentration pathways (RCPs) (van Vuuren *et al.*, 2011). Furthermore, different modelling approaches have the potential to produce different LULC outcomes, e.g. due to the inclusion of alternative assumptions or in the processes represented.

Model inter-comparison studies, drawing together the findings of many different modelling approaches, have previously considered aspects of LULC, e.g. the agricultural model inter-comparison and improvement project (AgMIP) (Schmitz *et al.*, 2014; von Lampe *et al.*, 2014), the inter-sectoral impact model inter-comparison project (ISI-MIP) (Nelson *et al.*, 2014), and the coupled model inter-comparison project (CMIP) (Brovkin *et al.*, 2013). CMIP deals primarily with the impact of land use on climate, and AgMIP, which is closely linked to the agricultural sector of ISI-MIP, has a broad focus on various aspects of agricultural models. AgMIP compared the results from 10 global agro-economic models to 2050, demonstrating significant LULC change differences, even within the same scenario, due to differences in model assumptions and parameterisation (Robinson *et al.*, 2014; Schmitz *et al.*, 2014). However, there has been no previous model inter-comparison of LULC projections which examines uncertainty over the breadth of relevant model types. Further knowledge gaps exist in understanding the relative role of model and scenario uncertainty, as well as the influence of model spatial extent, i.e. do global and regional results systemically differ? Understanding uncertainties in LULC projections is critical to investigating the effectiveness of land-based climate mitigation policies, in assessing the potential of climate adaptation strategies, and in quantifying the impacts of land cover change on the climate system.

This study seeks to address these knowledge gaps, and identify and analyse uncertainties in global and European LULC, by comparing projections from a diverse range of models and scenarios. The aim is to quantify the current range of LULC projections and to better understand the associated sources and levels of uncertainty, including ascertaining the role of different model structure and geographic extent in projected land cover uncertainty. The study goes beyond existing comparisons in a number of ways. Firstly, it incorporates a wider range of model types, including process or rule-based models in addition to the computable-general equilibrium and partial equilibrium models evaluated in AgMIP. Secondly, it compares models from different spatial extents, including both global and regional-scale models for the European continent. Europe was chosen for this comparison because of the availability of a large number of regional models. Finally, it incorporates a broader range of socio-economic and climate scenarios. Rather than using a small set of common scenarios (Schmitz *et al.*, 2014; von Lampe *et al.*, 2014), model teams were invited to submit multiple, potentially dissimilar scenarios, which allows the potential extent of scenario space to be more fully covered. The approach also supports the inclusion of a greater diversity of scenarios and models. For example, without the requirement to implement particular scenarios, models that have been developed for different purposes, and thus have implemented different scenarios, can still be included. This allows us to achieve a fuller representation of the range of uncertainty in projected LULC change than has previously been possible in model inter-comparisons using aligned scenarios.

Data from 18 models and 75 scenarios were considered (Table 1). Statistical methods were used to augment qualitative insights from comparing between the model results. To quantify the relative importance of factors associated with the components of the variability, a multiple linear regression and analysis of variance (ANOVA) (Yip *et al.*, 2013; Nishina *et al.*, 2014) were used, with variables for the initial condition, model and scenario (climate and socio-economic) factors, and residual or unexplained variability. The robustness of the analysis and completeness of the scenario and model variables were assessed, including through the use of linear mixed effects modelling (Bates *et al.*, 2014). The analysis identifies and draws inference from the variability between the LULC projections, and separates the factors driving future LULC uncertainty between the impacts of model-related factors (model type, resolution and extent) and the scenario characteristics. It is not the intention to identify which model or scenario is more plausible, or to indicate which model or approach could be considered more accurate.

2 Materials and Methods

2.1 Models of land use or land cover

Modelled data were obtained from 18 models providing scenario results for land use or land cover areas, with either a global or European geographic extent. Research groups covering a further 5 models were approached, but did not submit data. Table 1 gives details for each of the models included in the analysis. No attempt was made to align the scenario definitions, initial conditions or other model parameterisation. The land use or cover types from each model were used to provide the areas of cropland, pasture and forest. The definition of these types was based on FAO (2015), e.g. pasture is land used to grow herbaceous forage crops, either cultivated or growing wild, and therefore ranges from intensively managed grassland through to savannahs and prairies. All models were able to provide these three types, in some cases by aggregating more detailed types, except CAPS and MAGNET that provided only cropland and pasture areas. The categorisation was selected to avoid some of the definitional issues, e.g. between managed and unmanaged forest, and to maximise the model coverage. Urban and other natural vegetation or unmanaged areas were not analysed due to the lower numbers of models able to provide these types.

Models were categorised into four types based on the overall approach; computable-general equilibrium (CGE), partial equilibrium (PE), rule-based, and hybrid (Table 1). CGE and PE are both economic equilibrium optimisation approaches, with CGE models representing the entire economy, including links between production, income generation and demand, while PE models cover only part of the economy, in this case land-based sectors (Robinson *et al.*, 2014). The models categorised as rule-based in contrast need not take an economic approach, but rather represent processes or behavioural mechanisms, e.g. in an agent-based model, e.g. Murray-Rust *et al.* (2014), or use empirically derived relationships, e.g. Engström *et al.* (2016). The hybrid approach combines demands modelled using an economic equilibrium models with spatial allocations using rule-based approaches (National Research Council, 2014).

Scenarios

Research groups submitted results for multiple scenarios, to allow both a broad range of potential land cover results to be included and the variation from different scenarios to be determined. A total of 75 scenarios were used (Table 1), including business-as-usual and scenarios with mitigation measures. No attempt was made to align the inputs between models, and consequentially the results are not based on the same set of scenarios or parameterisation data. The majority of scenarios were either SSP or SRES based, but in some cases parameters were adjusted away from the scenario baseline values, e.g. FABLE. Alternatively, some models have conducted experiments where either the socio-economic or climate scenario was held at present day values, within an otherwise SSP or SRES scenario, e.g. FARM and CLIMSAVE-IAP. A number of models did not submit any scenarios accounting for the impacts of climate change (i.e. AIM, FALAFEL, GCAM, GLOBIOM, LandSHIFT and MAgPIE). It is therefore not possible to fully describe the scenarios by mapping them onto a small number of similar categories (as done by Busch (2006)). Additionally, there are difficulties in mapping between SRES and SSP/RCP (van Vuuren & Carter, 2014). Consequently, scenarios were described by a series of values, with default values obtained from the SRES and SSP descriptions (Table S1) (IPCC, 2000; IIASA, 2015). The aim was to characterise the scenarios in a way that is consistent with the scenario and broadly represents it, rather than specify the exact inputs used. Where a parameter differs from the default, the adjusted figure was used for that scenario. Table S2 gives the resultant characterisation for all scenarios.

2.2 Processing of model results

To provide a spatially and temporally consistent dataset the model scenario results submitted were processed as follows:

Interpolation to decadal ends

Model results were analysed at decadal end years from 2010 to 2100. Ten models did not provide values for these years, and in these cases values were linearly interpolated between the closest years provided. This interpolation was done for AIM, CAPS, CLIMSAVE-IAP, EcoChange, IMAGE and MAGNET.

Extraction of global and European aggregated areas

The analysis was conducted on aggregated areas at a global and European level. The model results were processed to extract these areas, e.g. by summing gridded data. The area for Europe was taken as the EU27 member states, i.e. the current 28 member states of the European Union excluding Croatia, which joined in 2013. The EU27 states were selected, as the set of countries that could be extracted from most models without the need for further adjustments. Where gridded global data were provided, a mask was applied to extract land cover areas for the EU27 states. Regional classification of GCAM also provided EU27 areas directly. Where model outputs did not directly provide areas for the EU27 (e.g. the case of the AIM model, which produced results for the EU25 only), pro rata adjustments based on country areas were applied. The largest adjustment factor applied was an increase of 8.8% between EU25 and EU27.

Difference to FAO data at 2010

The initial land cover areas were not constrained to be equal between the models. The difference for each land cover type, model and scenario at 2010 was calculated from empirical land use data (FAOSTAT, 2015). This initial condition delta was use in the statistical analysis to determine and account for the variability in the land cover projections based on the difference in initial conditions.

2.3 Statistical analysis of model results

The aim of the statistical analysis was to identify the sources of variance in the model results. The analysis identified the variables, related to the models, scenarios and initial condition, with a multiple linear regression of the areas for each land cover type, year, and spatial extent, associated with the project land cover areas. The observed variance was then partitioned into components attributed to the selected variables in an analysis of variance approach (ANOVA), to quantify the sources of variability in the results.

The modelled area for each land cover type and year was assumed to be a multiple linear function of 10 variables (Table S3). The factors used can be classified into three groups: those associated with 1) the model, 2) the scenario, or 3) the initial conditions. The models were described by three variables: 1) model type, 2) number of cells, 3) and the model extent. The scenarios were described by five socio-economic variables and the CO_2 concentration, as a proxy to the climate scenario. The initial condition delta represents the difference between the model result and historic baseline in 2010 (FAOSTAT, 2015). The regression fitting process was conducted for the three land cover types considered at the decadal end years 2010-2100. To avoid over-fitting, and to identify the predictive variables of the modelled areas, an Akaike information criterion (AIC) approach was used (Akaike, 1973). An estimated ‘best approximating model' can be objectively selected using AIC (Burnham & Anderson, 2004). The candidate regression model was selected that minimized the AIC score, and therefore accounts for the trade-off between goodness of fit and the model complexity.

ANOVA was used on the regression model to decompose the variability of the model (Yip *et al.*, 2013; Nishina *et al.*, 2014). The Type II sum of squares values were calculated for each variable in the fitted regression model. The Type II approach has the important advantage that, unlike Type I sums of squares, they do not depend on the order in which variables are considered, and has been suggested to be suitable for use with unbalanced data (Langsrud, 2003), although Type II sum of squares are not constrained to sum to the total variance in the raw data. The interaction terms were not determined (Nishina *et al.*, 2014), and the variance associated with such interactions are incorporated within the residual.

3 Results

3.1 Variations in modelled land cover areas

The results display a wide variation for all assessed land cover types. The global and European land cover over time are shown in Figures 1 and 2, plotted both as absolute areas and scaled to match the FAOSTAT (2015) areas at 2010. Global cropland areas follow the pattern of the cone of uncertainty, with relatively small initial differences between scenarios (1290-1650 Mha, 95% interval at 2010), which diverge over time across a range of scenarios (930-2670 Mha at 2100). However, the global pasture and forest areas do not fit this pattern. They demonstrate a relatively large initial variation, which does not change substantially over time. The main reasons for these discrepancies in initial conditions are due to uncertainty in current areas, and differences in the definition of land cover (both in models and in observations). There is a lack of agreement particularly over what constitutes pasture and forest, e.g. how to categorise grazed forest land or semiarid grazing (Ramankutty *et al.*, 2008). For example models, such as GLOBIOM, only considers pasture which is used for grazing, while others (e.g. CAPS) follow the broader FAO (2015) definition. Scaling to a common starting value allows the model trends without these differences to be observed, and shows the pattern of increasing variability over time (Figures 1-ii & 2-ii). FAOSTAT (2015) data were used to display historic values, and are a commonly used source for such data at the global scale. A small number of scenarios suggest rapid changes in some types of land cover. For example, compared to the present-day, FALAFEL under SSP1 gives a reduction in global cropland of 43% by 2050, and LandSHIFT an increase of 76-107%.

The European land cover areas (Figure 2) show some of the same patterns of variations as the global areas (Figure 1), including lower initial variation for cropland than for pasture or forest. Some of the European regional models produce many of the more extreme area changes, with CLIMSAVE-IAP, CRAFTY and EcoChange all producing the highest or lowest scaled areas for multiple cover types, although most of the European regional models do not extend past 2050. CLIMSAVE-IAP has a relatively high initial value for pasture, which in the SRES A1 and B1 scenarios decreases rapidly, while forest is lower and decreases substantially in all scenarios, in contrast to the majority of other model results.

3.2 Analysing the projected land cover uncertainty

The coefficient of variation, i.e. the ratio of the standard deviation to the mean, was used to provide a comparative measure of dispersion across model runs between the global and European areas and the land cover types considered (Figures 3-i & 4-i). These figures again illustrate that the initial variation is relatively low for cropland, but increases over time. Pasture and forest areas do not exhibit this pattern with global forest area variability decreasing over time, and pasture area variability remaining relatively constant over time; both show a minimum in 2050. The coefficient of variation is generally higher at the European than the global level, particularly for pasture and forest areas.

The ANOVA results show the relative importance of different sources of variance for each land cover type and decadal end year (Figures 3-ii & 4-ii). The decomposition was based on 10 variables (Table S3) plus a residual, for the variation not captured by these variables. Higher variance fractions imply that a variable has a greater ability to explain the total variance. The initial condition delta has been calculated based on the 2010 baseline area, and therefore 100% of the fraction of variance is associated with it at that point. The faction of variance associated with the initial condition, in general, decreases over time. For global pasture and forest areas the initial condition remains the most important factor over all time periods.

There is a discontinuity in the results between 2050 and 2060 (Figures 3 & 4) because a number of model results end at 2050. A similar but less substantial effect also occurs between 2080 and 2090 for European data. These effect were removed by rerunning the analysis using only scenarios that extend to 2100 (Figures S1 & S2), but at the expense of removing approximately half (39 of 75) of the available scenarios. The model results, and therefore the analysis, do not change for the period 2060-2100 for global areas and from 2080 in the European data, as no model scenario ends during these periods. In the period prior to 2050, European and global cropland has more variance associated with socio-economic scenario variables when only using results that extend to 2100, while pasture and forest variances are largely unchanged.

3.3 Sources of variability

The variables characterising the scenarios (Table S3) have a relatively low fraction of variance for all land cover types, and particularly for the global pasture and forest projections (Figures 3-ii & 4-ii). The fraction of variance for the model characteristics was similar to, or higher than, that for the variables used to characterise the scenarios in most cases for global areas. The relatively high fraction of variance suggests that given only knowledge of the scenario, based on the scenario typologies used, one would only be able to predict a small percentage of the total variation in the results. European data overall have a greater proportion of variance associated with scenario variables, but still show a substantial fraction associated with variables used to characterise the models, indicating that models of a similar type have a level of commonality in behaviour. The coefficient of variation in Europe is higher than the global coefficient of variation, for all time points and for all land cover types. Moreover, the fraction of variance explained by the initial conditions within Europe diminishes more quickly in comparison to the global data.

The high fraction of variance for model types arises because of the substantial association found between model type and land cover area. For example, the model type coefficients in the linear regressions for cropland at 2050 and 2100 (Tables S4-S7) suggest CGE models have a lower projected cropland in 2050 and 2100 than PE models. The similarity in model behaviour may arise because similar model types are more likely to have similar implicit or explicit assumptions, or other commonalities such as the data used to derive model parameter values. Some, albeit lower, association occurred with model resolution, represented as the number of grid cells, which again may be due to model similarities. One of the research questions was to determine if model extent played a substantial role in the projected land uses. The results do not find substantial associations between land cover projections and model extent, i.e. support for systemic differences between regional and global model results for European areas were not found. The spatial hotspots of uncertainty are examined in Prestele *et al.* (2016).

The residual component quantifies the variation that is not associated with any of the regression variables (Table S3), or interactions between them (e.g. between the initial condition and model type variables). Thus, if key explanatory variables are not included in the scenario or model typologies then the residual will tend to increase. To check that important variables were not overlooked, a mixed model analysis was conducted (for an overview see Bates *et al.* (2014)), a statistical technique which combines random effects and a set of explanatory variables. The mixed model used the regression variables selected by minimized AIC score as fixed effects, and random effects for the model, and socio-economic and climate scenario (Figures S7 & S8). The mixed model showed that the random effect variances associated with the model and scenarios parameters were of a similar or lower magnitude compared to the residual for global land covers. Similarly, the random effect variances for the European data were also mostly lower than the residuals, but with some exceptions, (e.g. the climate scenario variance for cropland from 2060-2080), suggesting that some unknown variables may be missing from the scenario typologies, which if included could improve the fit and reduce the residual, and potentially alter the relative importance of the existing variables. However, overall the random effects result suggests that the scenario characterisation was sufficient for the purpose of the analysis. Although alternative sets of variables could be equally valid in describing the scenarios and models, due to correlations in the model inputs and the variables selected, the mixed model results provide support for the chosen scenario and model typologies.

4 Discussion

4.1 Limitations and robustness

The inclusion of 18 models (from the 23 known suitable models), covering a wide range of modelling approaches and research institutions, provides a good representation of the diversity of the LULC modelling community. The inclusion of further models or scenarios could alter the outcome of the analysis if the sample used here is not representative of all models. Higher numbers of scenarios or models would also tend to increase the significance of the results and provide greater confidence in the conclusions. The scenarios included are dominated by SRES (IPCC, 2000) and SSP (O'Neill *et al.*, 2015) based scenarios, as much of the existing land-use modelling effort is based on these scenario frameworks, with the result that more extreme changes may fall outside the range of the land cover projections used here. Consequently, the true range of outcomes due to scenario uncertainty could be greater than represented here.

Models and scenarios may be represented by different numbers of results, meaning the dataset is defined as unbalanced. For example, the number of scenarios per model ranges from 1 to 8 (with a median of 4). As each model scenario is given equal weight, models with a larger number of scenarios have a greater impact on the outcome of the analysis. To assess the possible impact of the inequality of weighting between models, a variation of the analysis was undertaken with each model having an equal weight overall, i.e. by weighting each scenario by the reciprocal of the number of scenarios for that model. The results were only slightly different from those for which each scenario had an equal weight (Figures S3 & S4). The weighted scenario approach creates a bias towards the scenarios from models that have fewer scenarios overall, whereas the unweight approach is biased towards models with a greater number of scenarios. That both approaches result in similar outcomes suggests that the biases are small in both cases. The equal weighting approach was preferred by the authors due both to its relative simplicity, and that each scenario should be viewed as equally likely, rather than being dependant on the number of scenarios from a particular model. A variant of the analysis was also conducted with the outlying (>1.96 standard deviation from the mean in the last year of the model run) results removed. The outcome showed a greater fraction of variance associated with scenario variables for forest, at the European and global extent, and also for European pasture (Figures S5 & S6). Although some level of variation in the outcomes was noted in all of the variants (Figures S1-6), the outcomes were sufficiently consistent for the inferences drawn to remain valid and to provide a level of confidence in their robustness.

Variations in the initial areas has the potential to lead to diverging future land cover results, even from a single model. Therefore, to allow the statistical analysis to account for some commonality in projected land cover areas based on the differences in initial conditions, a variable for the difference between observed areas and model results at 2010 was included (Table S3). An alternative approach to the differences in initial condition would be to compare land cover model projections with harmonised inputs. However the initial condition variations results, in part, from differences in the land cover definitions (Ramankutty *et al.*, 2008; Verburg *et al.*, 2011), and would therefore be challenging to standardisation across a diverse range of models. The approach used here of unaligned scenarios and ANOVA provides the ability to use existing model projections and to account for the variation in initial condition, but provides a less direct comparison and requires more complex analysis, compared to using standardising inputs.

The fraction of variance associated with the initial condition variable was found to reduce over time (Figures 3 & 4), and to become relatively small by 2100 for global cropland and European pasture and cropland, but to remain the dominant variable for global pasture. To further test the impact of variations in initial conditions, the analyses were run with scenarios restricted to those within 4% and 8%, respectively, of the median model value at 2010 (Figures S9 & 10). The approach of constraining the scenarios by initial condition, reduces the number of scenarios that can be included, and in some cases insufficient scenarios met the restriction to allow the statistical methods to operate (i.e. for European pasture and forest, Figure S10). The results show that reducing the diversity in initial conditions (by constraining the scenarios included) lowers the fraction of variance associated with it, and increase the fraction found to be associated with scenario variables (Figures S9 & 10). Nonetheless, substantial variance was also associated with model variables, at least as greater as that related to the scenario variables. Therefore, as in Figures 3 & 4, uncertainty arising from model characteristics was found to be an important factor in the variability of land cover projection.

4.2 Has cropland received a disproportionate research focus?

The results show that cropland areas initially have a relatively low level of variability with a 'cone of uncertainty' increasing with time, while the same pattern is not seen in pasture and forest areas (Figures 1 & 2). These patterns of uncertainty may in part be explained by the issues around the definition of pasture and forest (Ramankutty *et al.*, 2008; Verburg *et al.*, 2011). However, it is hard to explain why uncertainty would not increase over time for all land covers. One potential explanation is that a larger proportion of future uncertainty associated with cropland has been modelled and quantified. That is to say, more of the potential for future variability in pasture and forest areas remain as epistemic uncertainty (Walker *et al.*, 2003). The fraction of variance (Figures 3-ii & 4-ii) is also supportive of the view that the uncertainty of cropland areas is more fully represented, as European and global cropland and European forest areas show a higher fraction of variance for the scenario variables, indicating that under alike scenarios the models behave, to some extent, in a similar manner.

A potential interpretation consistent with the results is that cropland and European land covers have received greater research focus, leading to lower variance in initial areas, greater consistency between models, and a higher degree of uncertainty represented in the projections. For example, many LULC models derive forest area change from changes in agricultural area, and do not consider factors such as demand for forest products or non-market ecosystem services (Schmitz *et al.*, 2014). Other reasons may also potentially explain these features of the results, e.g. related to fewer definitional or measurement issues for cropland and within Europe (Ramankutty *et al.*, 2008). However, if relative research focus between land cover types plays a part, such an asymmetry would be hard to justify as forests cover 31% of the global land surface, and pasture 26%, but cropland only 11% (FAOSTAT, 2015). The focus on cropland may be due to the importance of food production, as crops provide 90% of the global calories consumed by human (Kastner *et al.*, 2012). But, in the context of climate the biophysical and biogeochemical effects for all land covers are of importance (Levis, 2010), and cropland accounts for a minority of land cover change over the past 50 years, with pasture accounting for 60% of the expansion in agricultural land, in part due to dietary shifts (Alexander *et al.*, 2015). Furthermore, if other land covers have received less attention in the models, then cropland areas may inadequately account for the interactions between demands for other uses such as timber production or other ecosystem services.

4.3 Implications from land cover projections uncertainty

The results suggest that there are systematic differences in future land cover areas based on the modelling approach (as described above), as well as uncertainty that was not associated with the model or scenario characteristics used here (i.e. the residuals in Figures 3 & 4). Although the results suggest that model typology has an influence on land cover projections, they cannot identify the specific assumption or parameterisation that gives rise to this behaviour (discussed further below as an area for further research). CGE cropland projections are lower than from PE models (Tables S4-S7) potentially due to the interactions between the agricultural sector and the rest of the economy. This has been shown to give rise to smaller price increases in CGE compared to PE results (von Lampe *et al.*, 2014), which could create a lower agricultural supply response and lower cropland areas, as seen here.

Reducing uncertainties in land covers projections is desirable, to provide greater clarity of response to scenarios characteristics. However, to determine which model or model type is 'better' for a specific purpose, or to obtain a set of modelling assumptions that could be considered definitively accurate is problematic. Such a determination would require choosing between alternative model assumptions and the resultant model behaviour, based on some criteria. Although evaluation using historic time series of land cover might appear to offer a potential for such criteria, practical and theoretical issues arise. Firstly, there are limited historic time series of land cover data that can be used as references, and they are themselves an outputs of other models and therefore subject to a range of uncertainties (Goldewijk, 2001; Pontius *et al.*, 2008; Hurtt *et al.*, 2011). Secondly, even the ability to reproduce historic land use change does not ensure that future conditions will be adequately represented. Finally, given limited series of historic data, these data may have been implicitly or explicitly used to calibrate and tune the model, therefore greatly diminishing any inference that can be drawn from their reproduction. The situation contrasts with the modelling of some other systems (e.g. weather forecasting) where models can be repeatedly confronted with previously unseen data, to allow a measure of model efficacy to be determined.

Standardisation of initialisation data and definitions could also be used to reduce the spread of future LULC projections. However, there is uncertainty inherent in the initial conditions data, and similarly there is no unique and objectively accurate definition of land cover types. The goal of the land use modelling community should be to capture the range of uncertainty, including that in initial conditions, as opposed to attempting to standardise on a single set. Up to now, there have been efforts to 'harmonise' land use, e.g. (Hurtt *et al.*, 2011), rather than expose the differences and assess this uncertainty. Standardisation may achieve the aim of greater consistency of results, but in doing so provide false certainty in land cover projections. This does not mean that inaccurate data should be used, but that appropriate consideration and representation of uncertainty in the initial state should be included.

Further research is needed to assessed the plausibility of model assumptions, and attempt to identify the modelling approaches that are more appropriate for certain conditions. Such an approach could potentially identify model improvements, as well as convergence on LULC definitions and initial condition data, to over-time support a reduction in model uncertainty. The assessment of the validity of assumptions is however challenging, and must be based on regional level empirical data and expert knowledge, without a global dataset against which to validate. Also, the importance of individual assumptions for the model behaviour is often unclear due to the complexity of these models (Pindyck, 2015). Sensitivity analysis to testing model behaviour needs to be conducted in order to understand the role of assumptions and parameters, both individually and in combination. A full exploration of the parameter space requires systematic methods, such as a Monte Carlo method, rather than a one-at-a-time sensitivity analysis (Saltelli & Hombres, 2010; Butler *et al.*, 2014), as well as experiments to understanding the role of modelling assumptions. Despite these difficulties, such work is needed to better understand the key assumptions driving land use model results, and to compare them between models, in an attempt to reduce model uncertainty and to improve the projections of land cover. In the meantime, using a wide range of land use models to account for model uncertainty is important to account for the revealed uncertainties within assessments. Accounting for uncertainties in the coupled LULC and earth system need to be considered, due to the feedback effects that may dampen or amplify responses. Therefore, LULC and earth system models also need to be studied in a way that allows the uncertainty of the coupled system to be assessed.

4.4 Land cover uncertainty in earth system models

Although further research will help to identify, understand and where appropriate update models to address the sources of these model differences, uncertainty in future LULC is likely to remain, and possibly even increase, as more processes are represented and scenario and parameter uncertainty is more fully captured. For example, 6 of the 18 models did not submit any scenarios that included the impact of climate change, supporting the view that work remains to fully evaluate future LULC uncertainty. Nonetheless, this study clearly demonstrates that the current levels of uncertainty in projected LULC are substantial, which has implications not only for the assessment of future climate change, but also for the success of land-based mitigation and adaptation options. The level of uncertainty in future LULC demonstrated here may not be fully explored within the current representations of many earth system model projections (Rounsevell *et al.*, 2014). In an analogous situation, regarding model uncertainty in climate projections within the IPCC process, results from multiple earth system models developed at different modelling centres are used to capture model uncertainty (Solomon *et al.*, 2007). Given the present status of LULC models, if restricted model types are used to explore uncertainty, perhaps due to the specific purpose or research question under consideration, then a lower uncertainty in outcomes may result, which should be taken into account. However, where possible, it would be preferable to include a diverse set of models and approaches to more fully quantify model uncertainty and to ensure that outcomes from particular models or approaches do not dominate.

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6 References

Akaike H (1973) Information theory and an extension of the maximum likelihood principle. In: *Second International Symposium on Information Theory* (eds Petrov BN, Csaki BF), pp. 267–281. Academiai Kiado, Budapest.

Alexander P, Rounsevell MDA, Dislich C, Dodson JR, Engström K, Moran D (2015) Drivers for global agricultural land use change: The nexus of diet, population, yield and bioenergy. *Global Environmental Change*, **35**, 138–147.

van Asselen S, Verburg PH (2013) Land cover change or land-use intensification: simulating land system change with a global-scale land change model. *Global change biology*, **19**, 3648–67.

Baranzelli C, Jacobs-crisioni C, Batista F, Castillo CP, Barbosa A, Torres JA, Lavalle C (2014) *The Reference scenario in the LUISA platform – Updated configuration 2014 Towards a Common Baseline Scenario for EC Impact Assessment procedures*. Luxembourg Publications Office of the European Union.

Bates D, Mächler M, Bolker BM, Walker SC (2014) Fitting linear mixed-effects models using lme4. *ArXIV e-print; in press, Journal of Statistical Software*.

Brovkin V, Boysen L, Arora VK et al. (2013) Effect of Anthropogenic Land-Use and Land-Cover Changes on Climate and Land Carbon Storage in CMIP5 Projections for the Twenty-First Century. *Journal of Climate*, **26**, 6859–6881.

Burnham KP, Anderson DR (2004) Multimodel Inference: Understanding AIC and BIC in Model Selection. *Sociological Methods & Research*, **33**, 261–304.

Busch G (2006) Future European agricultural landscapes—What can we learn from existing quantitative land use scenario studies? *Agriculture, Ecosystems & Environment*, **114**, 121–140.

Butler MP, Reed PM, Fisher-vanden K, Keller K, Wagener T (2014) Environmental Modelling & Software Identifying parametric controls and dependencies in integrated assessment models using global sensitivity analysis. *Environmental Modelling and Software*, **59**, 10–29.

Calvin K, Wise M, Clarke L, Edmonds J, Kyle P, Luckow P, Thomson A (2013) Implications of simultaneously mitigating and adapting to climate change: Initial experiments using GCAM. *Climatic Change*, **117**, 545–560.

Chen L, Dirmeyer PA (2016) Adapting observationally based metrics of biogeophysical feedbacks from land cover/land use change to climate modeling. *Environmental Research Letters*, **11**, 034002.

Dendoncker N, Bogaert P, Rounsevell M (2006) A statistical method to downscale aggregated land use data and scenarios. *Journal of Land Use Science*, **1**, 63–82.

Engström K, Rounsevell MDA, Murray-Rust D et al. (2016) Applying Occam's Razor to global agricultural land use change. *Environmental Modelling & Software*, **75**, 212–229.

FAOSTAT (2015) *Resources/Land (2015-12-16)*. Food and Agriculture Organization of the United Nations, Rome, Italy.

Foley JA, Ramankutty N, Brauman KA et al. (2011) Solutions for a cultivated planet. *Nature*, **478**, 337–42.

Fujimori S, Masui T, Matsuoka Y (2012) AIM/CGE [basic] manual Discussion paper series (Vol. 2012-01). *Center for Social and Environmental Systems*.

Goldewijk KK (2001) Estimating global land use change over the past 300 years: The HYDE Database. *Global Biogeochemical Cycles*, **15**, 417.

Harrison PA, Holman IP, Berry PM (2015) Assessing cross-sectoral climate change impacts, vulnerability and adaptation: an introduction to the CLIMSAVE project. *Climatic Change*, **128**, 153–167.

Havlík P, Valin H, Herrero M, Obersteiner M, Schmid E, Rufino MC (2014) Climate change mitigation through livestock system transitions. *Proceedings of the National Academy of Sciences*, **111**, 3709–3714.

Houghton R a., House JI, Pongratz J et al. (2012) Carbon emissions from land use and land-cover change. *Biogeosciences*, **9**, 5125–5142.

Howden SM, Soussana J-F, Tubiello FN, Chhetri N, Dunlop M, Meinke H (2007) Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences*, **104**, 19691–19696.

Hurtt GC, Chini LP, Frolking S et al. (2011) Harmonization of land-use scenarios for the period 1500-2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands. *Climatic Change*, **109**, 117–161.

IIASA (2015) *SSP Database (version 0.93)*. International Institute for Applied Systems Analysis, Laxenburg, Austria.

IPCC (2000) *Special report on emissions scenarios: a special report of working group III of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge, UK.

Kastner T, Rivas MJI, Koch W, Nonhebel S (2012) Global changes in diets and the consequences for land requirements for food. *Proceedings of the National Academy of Sciences of the United States of America*, **109**, 6868–6872.

von Lampe M, Willenbockel D, Ahammad H et al. (2014) Why do global long-term scenarios for agriculture differ? An overview of the AgMIP Global Economic Model Intercomparison. *Agricultural Economics*, **45**, 3–20.

Langsrud Ø (2003) ANOVA for unbalanced data: Use Type II instead of Type III sums of squares. *Statistics and Computing*, **13**, 163–167.

Levis S (2010) Modeling vegetation and land use in models of the Earth System. *Wiley Interdisciplinary Reviews: Climate Change*, **1**, 840–856.

Mahmood R, Pielke RA, Hubbard KG et al. (2014) Land cover changes and their biogeophysical effects on climate. **953**, 929–953.

van Meijl H, van Rheenen T, Tabeau a., Eickhout B (2006) The impact of different policy environments on agricultural land use in Europe. *Agriculture, Ecosystems & Environment*, **114**, 21–38.

Meiyappan P, Dalton M, O'Neill BC, Jain AK (2014) Spatial modeling of agricultural land use change at global scale. *Ecological Modelling*, **291**, 152–174.

Murray-Rust D, Brown C, van Vliet J, Alam SJ, Robinson DT, Verburg PH, Rounsevell M (2014) Combining agent functional types, capitals and services to model land use dynamics. *Environmental Modelling and Software*, **59**, 187–201.

National Research Council (2014) *Advancing Land Change Modeling: Opportunities and Research Requirements*. The National Academy Press, Washington, DC, USA, 142 pp.

Nelson GC, Valin H, Sands RD et al. (2014) Climate change effects on agriculture: economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences of the United States of America*, **111**, 3274–9.

Nishina K, Ito A, Falloon P et al. (2014) Decomposing uncertainties in the future terrestrial carbon budget associated with emission scenario, climate projection, and ecosystem simulation using the ISI-MIP result. *Earth System Dynamics Discussions*, **5**, 1197–1219.

O'Neill BC, Kriegler E, Ebi KL et al. (2015) The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*.

Parry ML, Rosenzweig C, Iglesias a., Livermore M, Fischer G (2004) Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Global Environmental Change*, **14**, 53–67.

Pindyck RS (2015) *The Use and Misuse of Models for Climate Policy*. National Bureau of Economic Research, Cambridge, MA, USA.

Pontius RG, Boersma W, Castella JC et al. (2008) Comparing the input, output, and validation maps for several models of land change. *Annals of Regional Science*, **42**, 11–37.

Popp A, Humpenoeder F, Weindl I et al. (2014) Land-use protection for climate change mitigation. *Nature Climate Change*, **4**, 2–5.

Powell T (2015) *Closing loops to rebalance the global carbon cycle: Biomass flows modelling of global agricultural carbon fluxes*.

Prestele R, Alexander P, Rounsevell M et al. (2016) Hotspots of uncertainty in land use and land cover change projections: a global scale model comparison. *Global Change Biology*.

Le Quéré C, Moriarty R, Andrew RM, Peters GP, Ciais P, Friedlingstein P, Jones SD (2015) Global carbon budget 2014. 47–85.

Ramankutty N, Evan AT, Monfreda C, Foley J a. (2008) Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, **22**, 1–19.

Robinson S, van Meijl H, Willenbockel D et al. (2014) Comparing supply-side specifications in models of global agriculture and the food system. *Agricultural Economics (United Kingdom)*, **45**, 21–35.

Rose SK, Ahammad H, Eickhout B et al. (2012) Land-based mitigation in climate stabilization. *Energy Economics*, **34**, 365–380.

Rounsevell MDA, Arneth A, Alexander P et al. (2014) Towards decision-based global land use models for improved understanding of the Earth system. *Earth System Dynamics*, **5**, 117–137.

Saltelli A, Hombres BD (2010) Sensitivity analysis didn ' t help . A practitioner ' s critique of the Stern review. **20**, 298–302.

Sands RD, Jones CA, Marshall E (2014) *Global Drivers of Agricultural Demand and Supply. ERR-174*. Economic Research Service, U.S. Department of Agriculture.

Schaldach R, Alcamo J, Koch J, Kölking C, Lapola DM, Schüngel J, Priess J a. (2011) An integrated approach to modelling land-use change on continental and global scales. *Environmental Modelling & Software*, **26**, 1041–1051.

Schmitz C, van Meijl H, Kyle P et al. (2014) Land-use change trajectories up to 2050: insights from a global agro-economic model comparison. *Agricultural Economics*, **45**, 69–84.

Smith P, Haberl H, Popp A et al. (2013) How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? *Global change biology*, **19**, 2285–302.

Smith P, House JI, Bustamante M et al. (2015) Global change pressures on soils from land use and management. *Global Change Biology*, 1008–1028.

Solomon S, Qin D, Manning M et al. (2007) Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press*.

Stehfest E, van Vuuren D, Kram T et al. (2014) *Integrated Assessment of Global Environmental Change with IMAGE 3.0. Model description and policy applications*. PBL Netherlands Environmental Assessment Agency. The Hague, Netherlands.

Steinbuks J, Hertel TW (2014) Confronting the Food-Energy-Environment Trilemma : Global Land Use in the Long Run. *Environmental and Resource Economics*, 1–26.

Sterling SM, Ducharne A, Polcher J (2012) The impact of global land-cover change on the terrestrial water cycle. *Nature Climate Change*, **3**, 385–390.

Tilman D, Balzer C, Hill J, Befort BL (2011) Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, **108**, 20260–4.

Verburg PH, Overmars KP (2009) Combining top-down and bottom-up dynamics in land use modeling: Exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. *Landscape Ecology*, **24**, 1167–1181.

Verburg PH, Neumann K, Nol L (2011) Challenges in using land use and land cover data for global change studies. *Global Change Biology*, **17**, 974–989.

van Vuuren DP, Carter TR (2014) Climate and socio-economic scenarios for climate change research and assessment: Reconciling the new with the old. *Climatic Change*, **122**, 415–429.

van Vuuren DP, Edmonds J, Kainuma M et al. (2011) The representative concentration pathways: An overview. *Climatic Change*, **109**, 5–31.

Walker WE, Harremoës P, Rotmans J, van der Sluijs JP, van Asselt MB a., Janssen P, Krayer von Krauss MP (2003) Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support. *Integrated Assessment*, **4**, 5–17.

Weinzettel J, Hertwich EG, Peters GP, Steen-Olsen K, Galli A (2013) Affluence drives the global displacement of land use. *Global Environmental Change*, **23**, 433–438.

Yip S, Ferro CAT, Stephenson DB (2013) A simple, coherent framework for partitioning uncertainty in climate predictions. *Journal of Climate*, **24**.

Figure captions

Figure 1. Global modelled land cover areas for cropland (a), pasture (b), and forest (c), from 13 models and a total of 54 scenarios. A historical dataset from 1961-2011 (FAOSTAT, 2015) *is shown as solid black lines, and the 95% interval of model results as grey shading. The absolute areas are shown in i) and the areas scaled to match the historical data in 2010 are shown in ii). The scaled data were determined by rebasing all results to FAO areas at 2010, and then applying the same scaling for all time points of that type, model and scenario. See Table 1 for model and scenario information.*

Figure 2. European land cover for 16 models over a total of 64 scenarios based on the EU27 member states. Legend and format consistent with Figure 1. The historical time series starts at 1993, as earlier data for the states formally part of the USSR were not available (FAOSTAT, 2015).

Figure 3. Coefficient of variation (i) and relative importance of different variance components (ii) for global land cover areas between 2010 and 2100. The shaded area between 2050 and 2060 indicates that between these points the set of model results substantially change after 2050. In (ii) variance due to model characteristics is shown in different shades of green and due to scenario characteristics in different shades of red. Figures S1 and S2 show the results from an alternative analysis using only model result that extend to 2100.

Figure 4. Total coefficient of variation (a) and relative importance of different variance components (b) for European (EU27), format as per Figure 3.

Tables

Table 1. Summary of models and scenarios data included in the analysis of land cover results. Models are classified into four types; computable-general equilibrium (CGE), partial equilibrium (PE), rule-based, and hybrid. The hybrid model type combines demand from economic equilibrium models with rule-based spatial disaggregation.

Model name	**Key Publication**	**Spatial resolution data (model, if different)**	**Spatial extent**[+]	**Temporal resolution data (model, if different)**	**Model type (classification)**	**Scenario descriptions (number of scenarios)**
AIM/CGE	Fujimori *et al.* (2012)	17 regions	Global	2005, 2010, 2030, 2050 and 2100 (annual)	CGE	SSP1, SSP2 and SSP3. (3)
CAPS	Meiyappan *et al.* (2014)	0.5 x 0.5 degree grid	Global	2005, 2030, 2050 and 2100	Allocation model using demand from CGE or PE model (Hybrid)	SSP3, SSP5, RCP 4.5 and RCP 8.5, each under estimated model parameters from historical data from Ramankutty et al.(Ramankutty *et al.*, 2008) and HYDE(Goldewijk, 2001). (8)
CLIMSAVE-IAP	Harrison *et al.* (2015)	10 x 10 arc-minute grid	Europe (EU27+2)	2010 and 2050	Rule-based	SRES A1, A2, B1 and B2, each under current baseline and the socio-economic factors for the SRES scenario*. (8)
CLUMondo	van Asselen & Verburg (2013)	9,25 x 9,25 km grid	Global	2000 - 2040; decadal (yearly)	Allocation model using demand from CGE or PE model (Hybrid)	FAO 4Demand, Carbon, Potential Protected Area. (3)
CRAFTY	Murray-Rust *et al.* (2014)	1 x 1 km grid	Europe (EU27)	2010 - 2040; decadal (yearly)	Agent-based model (Rule-based)	SRES A1 and B1. (2)
DynaCLUE	Verburg & Overmars (2009)	1 x 1 km grid	Europe (EU27)	2000-2040; decadal	Allocation model using demand from CGE or PE model (Hybrid)	SRES A1, A2, B1 and B2. (4)
EcoChange	Dendoncker *et al.* (2006)	250 x 250m grid	Europe (EU25+2)	2010, 2020, 2050, 2080	Rule-based	Three core socio-economic scenarios, growth and globalisation, BAU, and sustainable development, and three shock scenarios, climate, energy price and pandemic shocks. (6)
FABLE	Steinbuks & Hertel (2014)	Global	Global	2005-2105; annual	PE	Baseline consistent with SRES A1B and RCP 2.6, with other scenarios adjusting population, climate to RCP 8.5, oil prices, economic growth, and more stringent GHG emission regulations (6)
FALAFEL	Powell (2015)	Global	Global	2000 - 2050; decadal	Rule-based	SSP1, SSP2, SSP3, SSP4 and SSP5. (5)
FARM	Sands *et al.* (2014)	13 regions	Global	2005 - 2050; five year steps	CGE	SSP1, SSP2 and SSP3, each under the current climate and climate scenario RCP 4.5, RCP 6.0 and RCP 8.5, respectively*. (6)
GCAM	Calvin *et al.* (2013)	32 regions	Global	2010 - 2100; decadal	PE	SSP1, SSP2, SSP3, SSP4 and SSP5. (5)
GLOBIOM	Havlík *et al.* (2014)	5 x 5 arc-minute grid	Global	2010 - 2100; decadal	PE	SSP1, SSP2, SSP3 (3)
IMAGE	Stehfest *et al.* (2014)	0.5 x 0.5 degree grid (5 x 5 arc-minute)	Global	2010, 2030, 2050 and 2100 (annual)	Allocation model using demand from CGE model (Hybrid)	SSP2 reference and high bio-energy demand scenario under RCP 2.6. (2)
LandSHIFT	Schaldach *et al.* (2011)	5 x 5 arc-minute grid	Global	2005-2050; five year steps	Rule-based	Fuel and heat scenarios, with both BAU and regulation assumptions for each. (4)
LUISA	Baranzelli *et al.* (2014)	100 x 100m grid	Europe (EU28)	2010 - 2050; decadal (annual)	Cellular-automata and statistical model (Rule-based)	Reference scenario. (1)

MAGNET	van Meijl *et al.* (2006)	26 regions	Global	2007, 2010, 2020, 2030, 2050 and 2100	CGE	SSP1, SSP2 and SSP3. (3)
MAgPIE	Popp *et al.* (2014)	0.5 x 0.5 degree grid	Global	1995-2100, five year steps	PE	Scenarios based on SSP2, with and without bioenergy CCS. (2)
PLUM	Engström *et al.* (2016)	157 countries	Global	1990-2100; annual	Rule-based	SRES A1, A2, B1 and B2 (4)

Notes:
[+] EU27 is current 28 European Union member states (EU28) less Croatia. EU25 additionally excludes Romania and Bulgaria. EU25+2 & EU27+2 includes Norway and Switzerland to EU25 and EU27, respectively.
* CLIMSAVE-IAP and FARM provided results for multiple climate models under otherwise the same scenario; the mean figure for each scenario/model combination was used.