ASSESSING UNCERTAINTIES IN LAND-COVER PROJECTIONS

Based on
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 analyzed 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 modeling 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.
3.1 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 preindustrial 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; Chen and Dirmeyer 2016; Smith et al. 2016b]. 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 socioeconomic factors, such as population dynamics, wealth, diet and urbanization, 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].

Modeling at a range of spatial scales has been applied to understand the LULC response to climatic and socioeconomic drivers and to assess the potential for mitigation and adaptation to climate change [Verburg and 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 socioeconomic and climate futures. Attempts have been made to characterize the uncertainty in socioeconomic drivers through scenarios, including the IPCC’s special report on emissions scenarios (SRES) [Nakicenovic and Swart 2000], and more recently, shared socioeconomic pathways (SSPs) [O’Neill et al. 2017] in combination with representative concentration pathways (RCPs) [van Vuuren et al. 2011]. Furthermore, different modeling approaches have the potential to produce different LULC outcomes, for example due to the inclusion of alternative assumptions or in the processes represented.

Model intercomparison studies, drawing together the findings of many different modeling approaches, have previously considered aspects of LULC, for example the agricultural model intercomparison and improvement project (AgMIP) [Schmitz et al. 2014; von Lampe et al. 2014], the intersectoral impact model intercomparison project (ISI-MIP) [Nelson et al. 2014a], and the coupled model intercomparison 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 parameterization [Robinson et al. 2014; Schmitz et al. 2014]. However, there has been no previous model intercomparison 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, that is do global and regional results systematically 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 analyze uncertainties in global and European LULC, by comparing projections from a diverse range of models and scenarios. The aim was to quantify the current range of LULC projections and to better un-
nderstand 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 socioeconomic 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 intercomparisons using aligned scenarios.

Data from 18 models and 75 scenarios were considered [Table 3-1]. 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. 2011; Nishina et al. 2015) were used, with variables for the initial condition, model and scenario (climate and socioeconomic) 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 modeling [Bates et al. 2015]. 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 approach could be considered more accurate.

3.2 Materials and methods

3.2.1 Models of land use or land cover

Modeled 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 3-1 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 parameterization. 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], for example pasture is land used to grow herbaceous forage crops, either cultivated or growing wild, and therefore ranges from intensively managed grassland through to savannas 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 categorization was selected to avoid some of the definitional issues, for example between managed and unmanaged forest, and to maximize the model coverage. Urban and other natural vegetation or unmanaged areas were not analyzed.
due to the lower numbers of models able to provide these types.

Models were categorized into four types based on the overall approach: computable general equilibrium (CGE), partial equilibrium (PE), rule-based, and hybrid [Table 3-1]. CGE and PE are both economic equilibrium optimization 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 categorized as rule-based in contrast need not take an economic approach, but rather represent processes or behavioral mechanisms, for example in an agent-based model, for example Murray-Rust et al. [2014], or use empirically derived relationships, for example Engström et al. [2016]. The hybrid approach combines demands modeled using economic equilibrium models with spatial allocations using rule-based approaches [DG Brown et al. 2014].

3.2.2 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 3-1], including business as usual and scenarios with mitigation measures. No attempt was made to align the inputs between models, and consequently, the results are not based on the same set of scenarios or parameterization data. The majority of scenarios were either SSP or SRES based, but in some cases parameters were adjusted away from the scenario baseline values, for example FABLE. Alternatively, some models have conducted experiments where either the socioeconomic or climate scenario was held at present-day values, within an otherwise SSP or SRES scenario, for example 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 smaller number of similar categories (as done by Busch [2006]). Additionally, there are difficulties in mapping between SRES and SSP/RCP [van Vuuren and Carter 2014]. Consequently, scenarios were described by a series of values, with default values obtained from the SRES and SSP descriptions [Table C-1] [Nakicenovic and Swart 2000; IIASA 2015]. The aim was to characterize 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 C-2 gives the resultant characterization for all scenarios.

3.2.3 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 analyzed 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 performed 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, for example by summing gridded data. The area for Europe was taken as the EU27 member states, that is 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
Table 3-1. 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.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Key publication</th>
<th>Spatial resolution data (model, if different)</th>
<th>Spatial extent*</th>
<th>Temporal resolution data (model, if different)</th>
<th>Model type (classification)</th>
<th>Scenario descriptions (number of scenarios)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAPS</td>
<td>Meiyappan et al. [2014]</td>
<td>0.5 × 0.5 degree grid</td>
<td>Global</td>
<td>2005, 2030, 2050, and 2100</td>
<td>Allocation model using demand from CGE or PE model (Hybrid)</td>
<td>SSP3, SSP5, RCP4.5, and RCP8.5; each under estimated model parameters from historical data from Ramankutty et al. [2008] and Klein Goldewijk et al. [2011]. (8) SRES A1, A2, B1, and B2; each under current baseline and the socioeconomic factors for the SRES scenario†. (8)</td>
</tr>
<tr>
<td>CLIMSAVE-IAP</td>
<td>Harrison et al. [2015]</td>
<td>10 × 10 arcminute grid</td>
<td>Europe (EU27+2)</td>
<td>2010 and 2050</td>
<td>Rule-based</td>
<td>FAO 4 Demand, Carbon, Potential Protected Area. (3)</td>
</tr>
<tr>
<td>CRAFTY</td>
<td>Murray-Rust et al. [2014]</td>
<td>1 × 1 km grid</td>
<td>Europe (EU27)</td>
<td>2010-2040; decadal (annual)</td>
<td>Agent-based model (Rule-based)</td>
<td>SRES A1, A2, B1, and B2. (4)</td>
</tr>
<tr>
<td>DynaCLUE</td>
<td>Verburg and Overmars [2009]</td>
<td>1 × 1 km grid</td>
<td>Europe (EU27)</td>
<td>2000-2040; decadal (annual)</td>
<td>Allocation model using demand from CGE or PE model (Hybrid)</td>
<td>Three core socioeconomic scenarios: growth and globalization, BAU, and sustainable development; Three shock scenarios: climate, energy price, and pandemic shocks. (6)</td>
</tr>
<tr>
<td>EcoChange</td>
<td>Dendoncker et al. [2006]</td>
<td>250 × 250 m grid</td>
<td>Europe (EU27+2)</td>
<td>2010, 2020, 2050, 2080</td>
<td>Rule-based</td>
<td></td>
</tr>
<tr>
<td>Model name</td>
<td>Key publication</td>
<td>Spatial resolution data (model, if different)</td>
<td>Spatial extent*</td>
<td>Temporal resolution data (model, if different)</td>
<td>Model type (classification)</td>
<td>Scenario descriptions (number of scenarios)</td>
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</tr>
<tr>
<td>FABLE</td>
<td>Steinbaks and Hertel [2016]</td>
<td>Global</td>
<td>Global</td>
<td>2005-2105; annual</td>
<td>PE</td>
<td>Baseline consistent with SRES A1B and RCP2.6, with other scenarios adjusting population, climate to RCP8.5, oil prices, economic growth and more stringent GHG emission regulations. (6)</td>
</tr>
<tr>
<td>FARM</td>
<td>Sands et al. [2014]</td>
<td>13 regions</td>
<td>Global</td>
<td>2005-2050; five year steps</td>
<td>CGE</td>
<td>SSP1, SSP2, and SSP3; each under the current climate and climate scenario RCP4.5, RCP6.0, and RCP8.5, respectively†. (6)</td>
</tr>
<tr>
<td>GCAM</td>
<td>Calvin et al. [2013]</td>
<td>32 regions</td>
<td>Global</td>
<td>2010-2100; decadal</td>
<td>PE</td>
<td>SSP1, SSP2, SSP3, SSP4, and SSP5. (5)</td>
</tr>
<tr>
<td>GLOBIOM</td>
<td>Havlik et al. [2014]</td>
<td>5 x 5 arcminute grid</td>
<td>Global</td>
<td>2010, 2030, 2050, and 2100 (annual)</td>
<td>PE</td>
<td>SSP1, SSP2, and SSP3. (3)</td>
</tr>
<tr>
<td>IMAGE</td>
<td>Stehfest et al. [2014]</td>
<td>0.5 x 0.5 degree grid (5 x 5 arcminute grid)</td>
<td>Global</td>
<td>2005-2100; five year steps</td>
<td>Allocation model using demand from CGE model (Hybrid)</td>
<td>SSP2 reference and high bioenergy demand scenario under RCP2.6. (2)</td>
</tr>
<tr>
<td>LandSHIFT</td>
<td>Schaldach et al. [2011]</td>
<td>5 x 5 arcminute grid</td>
<td>Global</td>
<td>2005-2100; five year steps</td>
<td>Rule-based</td>
<td>Fuel and heat scenarios, with both BAU and regulation assumptions for each. (4)</td>
</tr>
<tr>
<td>LUISA</td>
<td>Baranzelli et al. [2014]</td>
<td>100 x 100 m grid</td>
<td>Europe (EU28)</td>
<td>2010-2050; decadal (annual)</td>
<td>Cellular automata and statistical model (Rule-based)</td>
<td>Reference scenario. (1)</td>
</tr>
<tr>
<td>MAgPie</td>
<td>Popp et al. [2014a]</td>
<td>0.5 x 0.5 degree grid</td>
<td>Global</td>
<td>1995-2100; five year steps</td>
<td>PE</td>
<td>Scenarios based on SSP2, with and without bioenergy CCS. (2)</td>
</tr>
<tr>
<td>PLUM</td>
<td>Engström et al. [2016]</td>
<td>157 countries</td>
<td>Global</td>
<td>1990-2100; annual</td>
<td>Rule-based</td>
<td>SRES A1, A2, B1, and B2. (4)</td>
</tr>
</tbody>
</table>

* 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.
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 [FAO 2015]. This initial condition delta was used in the statistical analysis to determine and account for the variability in the land-cover projections based on the difference in initial conditions.

### 3.2.4 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 projected land-cover areas. The observed variance was then partitioned into components attributed to the selected variables in an analysis of variance approach, to quantify the sources of variability in the results.

The modeled area for each land-cover type and year was assumed to be a multiple linear function of 10 variables [Table C-3]. The factors used can be classified into three groups: those associated with (i) the model, (ii) the scenario, or (iii) the initial conditions. The models were described by three variables: (i) model type, (ii) number of cells, and (iii) the model extent. The scenarios were described by five socioeconomic 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 [FAO 2015]. The regression fitting process was conducted for the three land-cover types considered at the decadal end years 2010–2100. To avoid overfitting, and to identify the predictive variables of the modeled areas, an Akaike information criterion (AIC) approach was used [Akaike 1973]. An estimated ‘best approximating model’ can be objectively selected using AIC [Burnham and 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 2013], 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 is incorporated within the residual.

### 3.3 Results

#### 3.3.1 Variations in modeled 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 3-1 and 3-2, plotted both as absolute areas and scaled to match the FAO [2015] areas at 2010. Global cropland areas follow the pattern of the cone of uncertainty, with relatively small initial differences between the 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, for example how to categorize grazed forest land or semiarid grazing [Ramankutty et al., 2008]. For example, models such as GLOBIOM only consider 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 3-1ii and 3-2ii]. FAO [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%.

Figure 3-1. Global modeled 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 to 2011 [FAO 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 area at 2010 and then applying the same scaling for all time points of that type, model, and scenario. See Table 3-1 for model and scenario information.
The European land-cover areas [Figure 3-2] show some of the same patterns of variations as the global areas [Figure 3-1], 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.

![Figure 3-2. European land cover for 16 models over a total of 64 scenarios based on the EU27 member states. Legend and format consistent with Figure 3-1. The historical time series starts at 1993, as earlier data for the states formally part of the USSR were not available [FAO 2015].](image_url)

### 3.3.2 Analyzing the projected land-cover uncertainty

The coefficient of variation, that is 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 3-3i and 3-4i]. 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 3-3ii and 3-4ii]. The decomposition was
based on 10 variables [Table C-3] 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 fraction 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 3-3 and 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 effects were removed by rerunning the analysis using only scenarios that extend to 2100 [Figures C-1 and C-2], 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 socioeconomic scenario variables when only using results that extend to 2100, while pasture and forest variances are largely unchanged.

3.3.3 Sources of variability

The variables characterizing the scenarios [Table C-3] have a relatively low fraction of variance for all land-cover types, and particularly for the global pasture and forest projections [Figures 3-3ii and 3-4ii]. The fraction of variance for the model characteristics was similar to, or higher than, that for the variables used to characterize 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 characterize the models, indicating that models of a similar type have a level of commonality in behavior. 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 with 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 C-4 to C-7] suggest CGE models have a lower projected cropland in 2050 and 2100 than PE models. The similarity in model behavior 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 whether 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, that is 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] [Chapter 4].

The residual component quantifies the variation that is not associated with any of the regression variables [Table C-3], 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
Figure 3-3. 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 C-1 and C-2 [Appendix C2] show the results from an alternative analysis using only model results that extend to 2100.

Figure 3-4. Total coefficient of variation (i) and relative importance of different variance components (ii) for European (EU27) land-cover areas between 2010 and 2100. Legend and format consistent with Figure 3-3.
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. [2015]), 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 socioeconomic and climate scenario [Figures C-7 and C-8]. The mixed model showed that the random-effect variances associated with the model and scenario 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 to 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 characterization 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.

3.4 Discussion

3.4.1 Limitations and robustness

The inclusion of 18 models (from the 23 known suitable models), covering a wide range of modeling approaches and research institutions, provides a good representation of the diversity of the LULC modeling 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 [Nakicenovic and Swart 2000]- and SSP [O’Neill et al. 2017]-based scenarios, as much of the existing land-use modeling 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, that is 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 C-3 and C-4]. The weighted scenario approach creates 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 suggest 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 dependent 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 C-5 and C-6]. Although some level of variation in the outcomes was noted in all of the variants [Figures C-1 to C-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 have 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 C-3]. An alternative approach to the differences in initial condition would be to compare land-cover model projections with harmonized inputs. However, the initial condition variations result, in part, from differences in the land-cover definitions [Ramankutty et al. 2008; Verburg et al. 2011a] and would therefore be challenging to standardization 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 standardizing inputs.

The fraction of variance associated with the initial condition variable was found to reduce over time [Figures 3-3 and 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 C-9 and C-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 C-10]. The results show that reducing the diversity in initial conditions (by constraining the scenarios included) lowers the fraction of variance associated with it, and increases the fraction found to be associated with scenario variables [Figures C-9 and C-10]. Nonetheless, substantial variance was also associated with model variables, at least as great as that related to the scenario variables. Therefore, as in Figures 3-3 and 3-4, uncertainty arising from model characteristics was found to be an important factor in the variability of land-cover projections.

3.4.2 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 3-1 and 3-2]. 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. 2011a]. 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 modeled 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 3-3ii and 3-4ii] 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 variable, 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 nonmarket ecosystem services [Schmitz et al. 2014]. Other reasons may also potentially explain these features of the results, for example 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% [FAO 2015]. The focus on cropland may be due to the importance of food production, as crops provide 90% of the global calories consumed by humans [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.

3.4.3 Implications from land-cover projections uncertainty

The results suggest that there are systematic differences in future land-cover areas based on the modeling 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 3-3 and 3-4). Although the results suggest that model typology has an influence on land-cover projections, they cannot identify the specific assumption or parameterization that gives rise to this behavior (discussed further below as an area of further research). CGE cropland projections are lower than from PE models [Tables C-4 to C-7] 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-cover projections is desirable, to provide greater clarity of response to scenario characteristics. However, to determine which model or model type is ‘better’ for a specific purpose, or to obtain a set of modeling assumptions that could be considered definitively accurate is problematic. Such a determination would require choosing between alternative model assumptions and the resultant model behavior, 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 output of other models and therefore subject to a range of uncertainties [Klein Goldewijk et al. 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 modeling 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.
Standardization of initialization 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 modeling community should be to capture the range of uncertainty, including that in initial conditions, as opposed to attempting to standardize on a single set. Up to now, there have been efforts to ‘harmonize’ land use, for example Hurtt et al. [2011], rather than expose the differences and assess this uncertainty. Standardization 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 assess the plausibility of model assumptions, and attempt to identify the modeling 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 behavior is often unclear due to the complexity of these models [Pindyck 2015]. Sensitivity analysis to testing model behavior 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 and Hombres 2010; PB Butler et al. 2014], as well as experiments to understanding the role of modeling 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 needs to be considered, due to 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.

3.4.4 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 representation 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 modeling centers 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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