# Current challenges of implementing land-use and land-cover change in climate assessments

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**Abstract.** Land-use and land-cover change (LULCC) represents one of the key drivers of global environmental change. However, the processes and drivers of anthropogenic land-use activity are still overly simplistically implemented in Dynamic Global Vegetation Models (DGVMs) and Earth System Models (ESMs), whose published results are used in major assessments of processes and impacts of global environmental change such as the reports of the Intergovernmental Panel on Climate Change (IPCC). In the absence of coupled models of climate, land use and biogeochemical cycles to explore land use – climate interactions across spatial scales, information on LULCC is currently provided as exogenous data from the land-use change modules of Integrated Assessment Models (IAMs) to ESMs and DGVMs, while data from dedicated land-use change models (LUCMs) are rarely considered. In this article, we discuss major uncertainties and existing shortcomings of current implementation strategies originating in both LULCC data-provider and LULCC data-user communities. We identify, based on literature review and the analysis of empirical and modeled LULCC data, three major challenges related to LULCC representation, which are currently not or insufficiently accounted for: (1) provision of consistent, harmonized LULCC time series spanning from historical reconstructions to future projections while accounting for uncertainties due to different land-use modeling approaches, (2) accounting for sub-grid processes and bi-directional changes (gross changes) across spatial scales and (3) the allocation strategy of LULCC at the grid cell level in ESMs and DGVMs. Based on these three challenges, we discuss the reasons that hamper the development of implementation strategies that sufficiently account for uncertainties in the land-use modeling process and conclude that both providers and users of LULCC data products often miss appropriate knowledge of the requirements and constraints of one another's models, thus leading to large discrepancies

between the representation of LULCC data and processes in both communities. We propose to focus future research on the joint development and evaluation of enhanced LULCC time series, which account for the diversity of LULCC modeling and increasingly include empirically based information about sub-grid processes and land-use transition trajectories.

5   **Keywords.** land-climate interaction, gross transitions, land-use allocation, Earth System model, global vegetation model, land-use harmonization

# 1 Introduction

Anthropogenic land-use and land-cover change (LULCC) is a key driver of altering the land surface (Ellis, 2011; Ellis et al., 2013; Turner et al., 2007) with manifold impacts on biogeochemical and biophysical processes that feedback on climate
10   (Arneth et al., 2010; Brovkin et al., 2004; Mahmood et al., 2014; McGuire et al., 2001; Sitch et al., 2005), and affect food security (Hanjra and Qureshi, 2010; Verburg et al., 2013), fresh water availability and quality (Scanlon et al., 2007) as well as biodiversity (Newbold et al., 2015). Hence, LULCC is now being increasingly included in Dynamic Global Vegetation Models (DGVMs) and Earth System Models (ESMs) to quantify historical and future climate impacts both in terms of biophysical (surface energy and water balance) and biogeochemical variables (carbon and nutrient cycles) (Le Quéré et al.,
15   2015; Luyssaert et al., 2014; Mahmood et al., 2014). For example, land-use change has been estimated to act as a strong carbon source since pre-industrial times (Houghton et al., 2012; Le Quéré et al., 2015; McGuire et al., 2001) and the land being a potential net source of greenhouse gases to the atmosphere (Tian et al., 2016). Livestock husbandry, rice cultivation, and the large-scale application of agricultural fertilizers further contributed to the increase in atmospheric $CH_4$ and $N_2O$ concentration (Davidson, 2009; Zaehle et al., 2011). Local and regional observational studies suggest impacts of LULCC on
20   biophysical surface properties, e.g. surface albedo and water exchange, eventually affecting temperature and precipitation patterns (Alkama and Cescatti, 2016; Pielke et al., 2011).

Carbon fluxes are understood quite well for some compartments of the global carbon cycle, e.g. fossil fuel combustion and the ocean sink (Le Quéré et al., 2015), but the quantification of LULCC flux suffers from high uncertainties (Ballantyne et al., 2015) due to definition issues (Pongratz et al., 2014; Stocker and Joos, 2015), the simplistic representation of LULCC in
25   models that are used to quantify these fluxes (de Noblet-Ducoudre et al., 2012; Jones et al., 2013; Pugh et al., 2015) as well as the uncertainty about LULCC history (Ellis et al., 2013; Klein Goldewijk and Verburg, 2013). Quantification of LULCC impacts on climate further depends on the diversity of modeling approaches in the land-use change modeling community (National Research Council, 2014) that serve as data provider for climate models. However, assessments also depend on the interpretation of LULCC in DGVMs and ESMs and parameterization of land-atmosphere processes in consequence of
30   LULCC (Brovkin et al., 2013; de Noblet-Ducoudre et al., 2012; Hibbard et al., 2010; Pitman et al., 2009). There is still a high uncertainty range in the representation of LULCC as provided by land-use change models (LUCMs) and Integrated Assessment Models (IAMs) (Prestele et al., 2016), as well as how this information is utilized by ESMs and DGVMs.

Currently reported uncertainties of the outputs of these models may be underestimated by not accounting for these sources of uncertainty. Current LULCC representation therefore requires improvement to narrow down the uncertainty range and increase the confidence level of climate assessments. Additionally, assessments of the global water cycle, freshwater quality, biodiversity and non-$CO_2$ greenhouse gases would benefit from an improved representation of LULCC.

5 The overall objective of this article is to identify existing shortcomings of the current LULCC representation within DGVMs and ESMs, reveal the underlying mechanisms and constraints that have hampered improved representations until now, and propose pathways to improve current representations. We review current literature (from the land-use, carbon cycle and climate modeling communities), support our arguments by analysis using satellite LULCC products and model outputs for historical, current and future periods, and identify three critical challenges which should receive more attention in future

10 research on land use – climate interactions.

## 2 Provision of a spatially explicit, continuous and consistent time series of LULCC

To distinguish the contribution of anthropogenic LULCC to radiative forcing through greenhouse gas emissions from emissions attributed to fossil fuel combustion, consistent LULCC time series covering at least the period since the industrial revolution (~1750) are required (Le Quéré et al., 2015; Shevliakova et al., 2009). Because of the long-term legacy effects of

15 LULCC on soil carbon cycle processes, spatially explicit maps of LULCC need to span continuously and consistently from historical into future times. Connecting inconsistent LULCC time series and applying them in ESMs and DGVMs to quantify the interactions and feedbacks between LULCC and climate would lead to large artificially induced changes ('jumps') in land use. Consequently, jumps e.g. in carbon and nutrient pools in the transition period would distort legacy fluxes working on decadal to centennial time scale, rendering the simulations useless for reliably determining the magnitude

20 and rate of climate impacts.

However, observational data on LULCC is not available at global scale with sufficient temporal and spatial resolution, and historical coverage. For that reason a wide variety of datasets and models, all trying to represent global land use, are utilized to produce the required LULCC time series. Modeling of LULCC is split up into historical backcasting approaches and future scenario modeling, both in turn applying a range of different modeling approaches, assumptions about drivers and the

25 spatial allocation of changes (National Research Council, 2014; Yang et al., 2014). Moreover, the different models are initialized with different data sources of land use and land cover, i.e. also the models within one community (future or historical) do not provide consistent information about the current state of land use and land cover (Figure 1). Thus, the land-use change modeling community provides a variety of independent datasets at spatially explicit or world region level either for the historical time (from present day up to 10 000 BC into the past), or for the future under different scenario

30 assumptions (from present day up to 2100), without being connected and consistent at the transition from historical backcasting to future projection and accompanied by a variety of uncertainties (Klein Goldewijk and Verburg, 2013; Prestele et al., 2016). These datasets do not agree about the amount and the spatial pattern of land affected by human activity (both

with respect to land cover and land management). Moreover, varying detail of classification systems, inconsistent definition of individual categories (e.g., forest or pasture), and individual model aggregation techniques, amplify the discrepancies among models (Alexander et al., 2016; Prestele et al., 2016).

The first attempt to connect the different sources of data and provide a consistent time series for climate modeling applications has been developed during the 5th phase of the Coupled Model Intercomparison Project (CMIP5) by Hurtt et al. (2011) and has recently undergone update for the upcoming CMIP6 (Lawrence et al., 2016). This dataset (*LUH*) is commonly used in modeling studies to determine LULCC – climate interactions and feedbacks. Hurtt et al. (2011) extended their Global Land Use Model (GLM, Hurtt et al. (2006)) to produce a consistent time series of LULCC for the time period 1500-2100. The LULCC projections of four IAMs were smoothly connected to the HYDE historical reconstruction of agricultural land use (Klein Goldewijk et al., 2011), applying the decadal spatial LULCC patterns from the projections to the HYDE map of 2005. This strategy tries to conserve the original patterns, rate and location of change as much as possible, and to reduce the differences between the models due to definition of land-use categories (e.g., what constitutes a forest in the individual models). To achieve the final harmonized time series and explicit transitions (i.e., information about the source and target land use between two subsequent years on a grid cell basis), the LULCC time series are used as input into the GLM model and constrained by further data on wood harvesting activities, shifting cultivation and biomass density. While this strategy ensured for the first time consistent input for climate model intercomparisons, and serves as a basis to implement anthropogenic impact on the land component in climate models, several uncertainties are not, or only poorly, considered. These uncertainties are likely to propagate into ESMs and impact the amplitude, and possibly even the sign of LULCC – climate interactions and feedbacks.

The first major uncertainty is that by considering the HYDE baseline dataset exclusively for the historical time period, the reconstruction is erroneously regarded as observational data, rather than as model output accompanied by various sources of uncertainty (Klein Goldewijk and Verburg, 2013). Alternative spatially explicit reconstructions have been proposed (Kaplan et al., 2010; Pongratz et al., 2008; Ramankutty and Foley, 1999) (see SI for additional information, Table S1), and shown to differ both in terms of the total cultivated area, but also in how this area changes spatially over time (Meiyappan and Jain, 2012). The main uncertainties relate to the scarcity of input data (i.e., mainly population estimates) for historical times, the assumption about the functional relationship between population density and land use (e.g., linear or non-linear) and the spatial allocation scheme of regional or national LULCC estimates to specific grid cell locations. Klein Goldewijk and Verburg (2013) demonstrated the uncertainties in the backcasting modeling process in detail using the example of HYDE and emphasize the difficulties to properly quantify them.

The uncertainty about LULCC history has several implications for land use – climate interactions (Brovkin et al., 2004). For instance, Meiyappan et al. (2015) found the difference in cumulative LULCC emissions among three historical reconstructions for the 21th century modeled by one DGVM to be about 18 PgC or ~11 % of the mean LULCC emission. Another study, using three commonly-used net LULCC datasets in one DGVM, revealed differences of about 20 PgC or ~9 % of the mean LULCC emission since 1750 (Bayer et al., 2016). Jain et al. (2013) further found contrasting trends in

LULCC emissions at regional scale during the past three decades, which originate in different amount and rates of LULCC in the individual regions based on the realization of historical land use. And as biophysical climate impacts of LULCC are suggested to be substantial, especially on a regional scale (Pielke et al., 2011; Pitman et al., 2009), an inappropriate representation of these uncertainties is likely to also affect the implications derived about LULCC contribution to changes in local to regional climate. Using the HYDE reconstruction exclusively thus implicitly considers high confidence about LULCC history in many large scale assessments and comparison studies (e.g., Kumar et al., 2013; Le Quéré et al., 2015; Pitman et al., 2009), which form also the basis for the development of climate change mitigation and adaptation policies (Mahmood et al., 2015).

Second, large inconsistencies exist between estimations of present-day land use and land cover. The harmonization procedure proposed by Hurtt et al. (2011) does not consider the differences between different data about the current state of land use and land cover by connecting the future projections exclusively to the HYDE end map (Figure 1). This uncertainty, however, is represented also in the starting maps of the different land-use change models providing LULCC data to climate models (Prestele et al., 2016). The differences can result in substantial deviations of the seasonal and spatial pattern of surface albedo, net radiation and partitioning of latent and sensible heat flux (Feddema et al., 2005) and affect carbon flux estimates proposed by DGVMs across spatial scales (Quaife et al., 2008). While the rising operational application of remote sensing during recent decades has opened a powerful resource to map land cover on global scale, definition issues (Sexton et al., 2015), and difficulties in the derivation of individual land-use and land-cover categories (Friedl et al., 2010), lead to a variety of global land-cover products with large differences (Ban et al., 2015; Congalton et al., 2014). Although this lack of knowledge is well recognized (Bontemps et al., 2012), progress so far is limited to the mapping of single LULCC processes such as forest dynamics (Hansen et al., 2013) or data assimilation efforts such as the Geo-Wiki project to improve the accuracy of global land cover maps (Fritz et al., 2012). While these projects are promising and certainly contribute to improved representation of current land use and land cover at global scale, a comprehensive and reliable LULCC product covering all relevant processes is still missing.

Finally, for future projections used within the IPCC-context, the land-use trajectories are provided by different IAMs, whereby each of them represents an individual scenario of the recent RCP/SSP framework (O'Neill et al., 2015; van Vuuren et al., 2011), a so-called 'marker scenario' (Popp et al., in review). Land-use change model intercomparisons, however, indicate that the uncertainty range emerging from different assumptions in the model structure and different input data substantially impacts the model results (Alexander et al., 2016; Schmitz et al., 2014). Due to the large range across model outcomes per scenario, the problems of using 'marker scenarios' from different models are evident. However, no better alternative to this approach seems to be currently available, and representing uncertainty across models is regarded valuable (Popp et al., in review). Model comparisons further revealed that while land-use change models represent cropland processes and development more consistently, the representation of pastures and forests is poor. For example, the projections for pasture areas in 2030 of 11 IAMs and LUCMs show large variations for many world regions (Figure 2, background map). These projections were based on a wide range of scenarios, and thus variation in outcomes was to be expected. However, the

variation attributed to the difference in model structure is larger than the variation due to different scenarios in most regions (Figure 2, bar plots). The main part of the variation relates to the different starting points of the models. This implies that in many cases the different LULCC time series actually do not represent different outcomes resulting primarily from different assumptions about future development of anthropogenic LULCC, but rather differences between which land-use data input is

5  used to calibrate the models and how LULCC drivers and processes are implemented in the models.

These three sources of uncertainty are poorly addressed through the almost exclusive implementation of the *LUH* dataset within the climate modeling community. A wider range of harmonized time series is therefore likely to substantially impact the outcomes of studies on LULCC – climate interactions. Yet the actual impact of alternative harmonized time series on climate impacts has never been tested. Multi land-use change model ensembles would be required to provide a better

10  estimate of the range of uncertainty for historic, current and future times across scenarios. Ideally, future models should be directly connected to different LULCC histories that are constrained by different plausible realizations of current land use and land cover. Such an approach would ensure a comprehensive coverage of the uncertainties accumulating across temporal and spatial scales prior to feeding the LULCC data into climate models and allow for testing of the climate model sensitivity to different realizations of LULCC.

15  Moreover, a systematic approach to reduce uncertainties and a more rigorous evaluation of approaches to project global land-use changes need to be developed. Integration of various empirical data streams into the models could lead to a better representation of current land use and land cover. Increasing computing and storage capacity facilitates access to high resolution observational data (e.g., Hansen et al., 2013; Chen et al., 2015), while different reporting schemes under international policy frameworks provide increasing amount and quality of data on national to regional scales (e.g., Kohl et

20  al., 2015). Concurrently, systematic approaches to test model results against independent data sources are required. If not yet possible at the global scale, the land-use change modeling community should start to implement evaluation schemes at regional scales using smaller scale, high accuracy remote sensing products to improve the credibility of their model outputs.

**3 Considering gross land-use changes**

Net land-use changes refer to the summed grid-cell difference between two subsequent time steps at a certain spatial and

25  temporal resolution. Gross change representations provide additional information about land-use changes on a sub-grid scale. In case of gross change, the land-use and land-cover categories are provided in a transition matrix as input to, e.g., DGVMs or ESMs, determining the amount of area that has changed from one category to another in each grid cell between two time steps. The total area in a grid cell, which has been affected by change, can be calculated by the sum of all individual changes. Gross changes have been shown to be substantially larger than net changes due to bi-directional change processes happening

30  at the same time step (Fuchs et al., 2015a; Hurtt et al., 2011) that are obscured in net change representations. For example, 20 km$^2$ cropland at $t_1$ and 40 km$^2$ at $t_2$ within a grid cell does not necessarily mean that this change resulted from clearing exactly 20 km$^2$ of forest. Equally plausible would be clearance of forest of larger spatial extent, while at the same time also a

certain amount of cropland was abandoned, resulting in the same net areal change. These sub-grid dynamics have been shown to be of importance when modeling change of carbon and nutrient stocks in response to LULCC (Bayer et al., 2016; Fuchs et al., 2015b; Stocker et al., 2014; Wilkenskjeld et al., 2014).

Providing accurate estimates of historical and future gross change is a difficult task, since gross changes vary with spatial and temporal resolution (Fuchs et al., 2015a) and the explicit identification of source and target categories (i.e., which land use is converted to another) requires to solve a large, under-determined mathematical system (Hurtt et al., 2011). Currently, the land-use change modeling community either (1) adds sub-grid information by constraining the under-determined system using a set of boundary conditions such as information on minimum transitions derived from previous modeled time series for historical and future times, wood harvest statistics and biomass density measures (Hurtt et al., 2011; Hurtt et al., 2006) or (2) derives gross/net ratios from empirical data such as historical maps or high resolution remote sensing products which can be subsequently applied to existing net representations (Fuchs et al., 2015a; Fuchs et al., 2015c). The former approach very much depends on the resolution of the original LULCC time series and their ability to represent land-use change dynamics on a sub-grid scale. For example, if the input LULCC time series reports changes at a 0.5 x 0.5 degree regular grid in a net change approach, minimum transitions are also constrained to this resolution. An example is shown in Figure 3 by re-gridding LULCC information of a dedicated high-resolution LUCM (5 arcminutes spatial resolution) to the commonly applied 0.5 x 0.5 degree grid in DGVMs. The analysis is based on a simulation tracking the changes between five land-use and land-cover categories (cropland, pasture, forest, urban, and bare) over a time period of 40 years. In the *LUH* dataset areal changes due to shifting cultivation and wood harvest (only if wood harvest demand is not met by deforestation in the minimum transitions and thus leads to additional areal changes) are assumed to be the main gross change processes resulting in distinctly higher change rates mainly in the tropics (Hurtt et al., 2011; Stocker et al., 2014). Higher gross change rates are expected to have a large impact on the carbon fluxes (Bayer et al., 2016). It is thus important that Figure 3 indicates that also in large parts of the temperate zone and high latitudes gross change processes play an important role and may be underestimated by the currently used *LUH* dataset. Figure 3 is only based on one realization of one LUCM, i.e. not necessarily representing the full extent and spatial pattern of global scale gross changes, and only depicts the loss of information while re-gridding to coarser resolutions. Thus, information below the spatial resolution of the original data is still not captured. Therefore the data-based approach has clear advantages where the required information can be obtained. Fuchs et al. (2015a) have shown that the integration of different empirical data sources capture bi-directional transitions at the sub-grid level, which are especially important for heterogeneous areas and mosaic land systems, which are typical for regions of limited resources, high population densities or a combination of both (van Asselen and Verburg, 2012).

The transition matrix provided with the *LUH* data accounts partly for gross changes, but the values are dependent on a number of assumptions and the gross change rates have not been evaluated against empirical data. For example, urban expansion is applied proportionally to the remaining land-use and land-cover categories and in the case of agricultural expansion choices in the model configuration have to be made, whether primary or secondary land is converted preferentially. These choices, however, have serious impacts on the spatio-temporal pattern of the remaining primary,

secondary and managed land, which in consequence propagate into the ESM or DGVM results (Hurtt et al., 2011). The increasing availability of remote sensing data (e.g., Chen et al., 2015; Hansen et al, 2013) opens the opportunity to evaluate the assumptions of current allocation rules. Moreover, in regions where driving factors of small-scale land-use change processes are more complex and not easy to determine due to frequent land-use changes, high-resolution empirical data can

5   provide additional information and accuracy to currently available data.

## 4 Allocation of managed land in ESMs and DGVMs

The impacts of anthropogenic activity on the land surface and consequently on the interaction between the terrestrial system and the atmosphere have long been understudied (Flato et al., 2013). Most ESMs in CMIP5 treated the land surface as a static representation of current land-use and land-cover distribution typically derived from remote sensing products (Brovkin

10   et al., 2013; de Noblet-Ducoudre et al., 2012). DGVMs, some of which are incorporated in the land surface component of ESMs, were originally designed to model potential natural vegetation as a dynamic function of monthly climatology, bioclimatic limits, soil type and the competitiveness of different wood- or grass-shaped plant functional types (PFTs) (Prentice et al., 2007). However, over the last decade, representation of human land-cover change, and also some land-use aspects have increasingly be captured, albeit with levels of complexity which vary from crops as grassland to more detailed

15   agricultural representations (Bondeau et al., 2007; Le Quéré et al., 2015; Lindeskog et al., 2013). Crop functional types (CFTs) and management options have been introduced in some models, explicitly parameterizing the phenology, biophysical and biogeochemical characteristics of major crop types, and distinguishing important management options such as irrigation, fertilizer application, occurrence of multiple cropping, or processing of crop residues (Bondeau et al., 2007; Lindeskog et al., 2013). The information about the extent and exact location of managed land is taken from external datasets provided by

20   IAMs or LUCMs. Hence, the modelers have to decide in which way the natural vegetation in a grid cell has to be reduced (in case of expansion of managed land) or increased (in case of abandonment of managed land). This has resulted in a range of different strategies (Table 1). This decision is important as it impacts the distribution of the vegetation in a grid cell, as well as the mean length of time that land has been under a particular use, with consequences for both the biogeochemical and biophysical properties. For example, new cropland expanding on forest would lead to a large and relatively rapid loss of

25   ecosystem carbon due to deforestation, while cropland expanding on former grassland would have a less immediate, and probably smaller, impact on ecosystem carbon stocks. Likewise, the albedo and partitioning of energy differs strongly between forest and grassland land covers. The implementation of this decision affects the assessment of carbon and nutrient budgets over long time periods and possibly also the robust determination of LULCC impact on regional temperature and precipitation patterns that respond to changes in biophysical forcing at the land surface (de Noblet-Ducoudre et al., 2012).

30   In CMIP5, most ESMs implemented a proportional reduction rather arbitrarily due to reasons of simplicity or internal model constraints; others convert grassland preferentially or further treat cropland and pasture differently (de Noblet-Ducoudre et al., 2012). However, the spatial pattern and transition trajectories of LULCC are complex interplays of biophysical and

socioeconomic parameters, which are not properly represented by these simplistic, globally applied, algorithms. Moreover, the question on which type of natural land (grassland or forest) new agricultural land should be allocated, is not only an empirical question, but also largely depends on the currently available data sources and model types.

Identifying transition trajectories from empirical data is still difficult to achieve globally (though better products are just

5 emerging, Ban et al., 2015), but to some extent possible at regional to continental scale. Table 2 summarizes dominant sources of cropland expansion for several world regions and demonstrates the heterogeneity in the spatial pattern of expanding agriculture. For Europe, the CORINE land cover product (Bossard et al., 2000) indicates over two consecutive time periods (1990-2000, 2000-2006) shrub vegetation associations to be the main source of expanding agricultural land (45 % and 39 %, respectively), followed by low productivity grasslands accounting for 22 % and 13 %, and forests (14 %

10 and 17 %) (Figure 4a). In contrast, over a similar time period, the NLCD (Homer et al., 2015) for the USA shows low productivity grasslands as the dominant source of new croplands, while pastures are predominantly converted from forest or shrubland systems and grasslands only account for around 20 % of new pastures (Figure 4b). A large-scale study by Graesser et al. (2015) covering Latin America and based on the interpretation of MODIS images for the time period 2001-2013, identified the dominant trajectory of forests being first converted to pastures and subsequently to cropland. They also show,

15 however, varying patterns on national and ecoregion scale. This regional variation is also emphasized by Ferreira et al. (2015), who describe a satellite-based transition matrix as input for a modeling study for different states in Brazil. However, they do not distinguish non-forest natural vegetation such as the Cerrado systems, which might be another important source for agricultural land (Grecchi et al., 2014). A study conducted by Gibbs et al. (2010) investigating agricultural expansion in the tropics in the 1980s and 1990s based on data from Food and Agriculture Organization of the United Nations (2000) (i.e.,

20 areas with less than 10 % forest cover are not considered) concludes that more than 80 % of new agricultural land originates from intact or degraded forests. They further found large variability in agricultural sources across seven major tropical regions, e.g., substantially higher conversions from shrublands and woodlands to agricultural land in South America and East Africa. Further large-scale remote sensing studies are available from Northern China and the Yangtze River basin. Grasslands have been detected as the main source of agricultural land in Northern China, e.g., by Li (2008), Liu et al. (2009)

25 and Zuo et al. (2014), while in the Yangtze River basin woodlands contribute most (Wu et al., 2008) (Table 2). All the mentioned studies indeed combine different approaches to derive changes, cover different time periods and are not representative of current agricultural change hotspots (Lepers et al., 2005). However, this kind of aggregated analysis already indicates that the spatial pattern of change dynamics is varying and a single global algorithm to replace natural vegetation by managed land in ESMs is likely to be overly simplistic.

30 As it is not possible to compare the algorithms with historical change data at global scale due to the lack of global LULCC products with sufficient accuracy, we additionally tested to what extent changes simulated by the land-use change model CLUMondo (Eitelberg et al., 2016; Van Asselen and Verburg, 2013) represent one or more of the simplified algorithms currently considered in ESMs (Table 1). We therefore classified the changes in the simulated data within each ca. 0.5 x 0.5

degree grid cell as either grassland first, forest first, proportional, i.e., reduction as a proportion of the fractional coverage of each PFT within the grid cell, or a complex reduction pattern (see SI for methodological details, Table S6, Figure S2-3).

Figure 5 shows the results of this analysis for decadal time steps between 2000 and 2040. Based on the CLUMondo data it is clear that a single simple algorithm does not account for the temporal and spatial heterogeneity in the process of taking land into use in a more detailed land-use change model. The majority of grid cells with substantial cropland expansion (> 10 % of grid cell area) show a complex reduction pattern of the remaining land-use and land-cover categories, i.e., any algorithm applied to these grid cells could be seen as equally good or bad. The remaining grid cells, where our method detected one of the algorithms account only for 24-27 % on a global scale. Moreover, the spatial distribution of grid cells that are classified to the same algorithm is very heterogeneous and changing over time. It has to be noted that this analysis builds on only one realization of one LUCM and results may differ if using another data source in terms of overall cropland expansion and the exact grid cell location of changes. However, the analysis does not aim at identifying the exact location of a particular algorithm, but rather emphasizing the heterogeneous pattern of cropland expansion.

According to the patterns simulated by CLUMondo, simple algorithms applied globally thus do not account well for the spatio-temporal variation of LULCC. An alternative would be transition matrices that include explicit information about the source of expanding agricultural land at the grid cell scale. Providing such transition matrices, however, shifts the allocation issue from the DGVM/ESM community to the IAM/LUCM community and would still lack the empirical justification and evaluation against observational data for most applications. For example, in the current harmonization approach (Hurtt et al., 2011) transitions are derived using simple rules without accounting for the spatial and temporal heterogeneity of the multiple drivers of LULCC, e.g., by assigning urbanization proportionally to the other categories and putting cropland or pasture preferentially on primary or secondary land. Thus, much more work has to be done on understanding the processes driving land-use change in different land systems and providing empirical justification for allocation algorithms across different scales in land-use change models. Exploring the large collections of high-resolution satellite imagery with global coverage, e.g., the Landsat archive (30 m spatial resolution) or the European Sentinel mission (10-60 m spatial resolution) may offer opportunities to continuously improve and evaluate land-use change models in future. Nevertheless, current products lack the required accuracy. Limitations and uncertainties in modeled LULCC time series thus have to be clearly communicated by the data providers and taken into account by the data users.

Although it is evident that more empirical information on land-use transitions is required to improve land-use change modelling, and to estimate the natural systems at risk under agricultural expansion, the specific problem of allocating new agricultural land in DGVMs and ESMs also has a strong model and data-structure component. In many DGVMs, the grass and forest PFTs on non-agricultural land in a grid cell are mostly not considered different systems, but are part of one complex vegetation structure, thus not representing spatial-horizontal heterogeneity. Therefore, when agriculture expands into such natural systems, all natural PFTs need to be reduced proportionally. If handled otherwise (i.e., when removing a specific PFT preferentially), the vegetation dynamics would slowly converge again towards the initial PFT mix (if all boundary conditions like climate and soil properties remain unchanged).

For land surface modules in ESMs, the situation is slightly more complex. Most ESMs (if not incorporating dynamic vegetation through a DGVM) are using a remote sensing product such as the ESA CCI-LC (ESA, 2014), and a translation to PFTs, e.g., Poulter et al. (2011), as background vegetation map on which agricultural land is imposed. Due to inaccuracies in global remote sensing land cover products (Congalton et al., 2014) and the previously mentioned differences in historical

5  reconstructions, fractions of agricultural land on a grid-scale necessarily show difference between the background map and the external land-use dataset. Consequently, the PFT composition outside the prescribed agricultural land can represent either real heterogeneity in natural vegetation, or a mix of natural and anthropogenic land cover due to differences in the datasets. In the first case, empirical data or transition matrices would help to make the right allocation decision, in the second case, rather the woody PFTs should be converted, while the grass PFTs that represent uncertainty in agricultural land-use

10  products should remain unchanged. However, these cases are difficult to distinguish and empirically justified transition matrices, together with more accurate present-day land-cover products, would provide a useful tool for reducing uncertainties due to allocation decisions in ESMs.

# 5 Conclusion and recommendations

In this article we identify three major shortcomings of LULCC representations at the interface of land-use change modeling

15  and ESMs/DGVMs. Both communities have developed sophisticated models during the past decades, with different priorities leading to a situation where mainly IAMs act as data provider for ESMs and DGVMs with regard to the research on land use – climate interactions. However, to improve the representation of complex interactions and feedbacks between the land system and the climate system, further coupling and integrating of these different types of models would be required on the long term, where anthropogenic activity on the land system is considered as an integral part of the models instead of

20  an external boundary condition. A fully integrated coupling of behavioral land system models and terrestrial biosphere models may provide further understanding of possible land-climate-society feedbacks (Arneth et al., 2014; Verburg et al., 2015), since the current coupling strategy rarely accounts for the complexity of human-environmental relationships and feedbacks (Rounsevell et al., 2014).

In the meantime, improved communication between the communities and understanding the assumptions and constraints in

25  the models of each other is crucial to properly account for uncertainties and error propagation into the interpretation of final results. Currently, the variety (and accompanied uncertainty) in land-use change modeling is poorly represented in the widely and often exclusively used *LUH* dataset as we have shown in this article. The land system, however, is suggested to have great capacity in terms of climate mitigation and adaptation and will therefore play an important role in the development of future climate policies. However, to be able to realistically quantify these potentials based on models, the

30  current LULCC representation is likely to be not sufficient. We thus propose several pathways, how current LULCC representation and consequently the quantification of land use – climate interactions and feedbacks can be improved and call for:

(1) Development of enhanced harmonized LULCC time series which incorporate the uncertainty range about current understanding of LULCC for historical, current, and future time periods (e.g., through plausible and documented error bands considering different modeling approaches and land cover products), rather than ignoring these differences through a single realization and application of one harmonized time series in land use – climate studies. Although running fully coupled ESMs with multiple instances of LULCC representations might be too expensive in terms of computing time and capacity, simpler DGVMs and offline land surface models could be used to identify the minimum LULCC accuracy required within which bounds uncertainty in LULCC does not significantly affect biogeochemical cycles and climate.

(2) Inclusion of gross change processes in LULCC time series beyond shifting cultivation in the tropics, considering as much sub-grid processes as possible (i.e., bi-directional changes below model resolution) based on the integration of empirical data as well as sufficient tracking of changes when re-gridding LUCM and IAM net change representations to DGVM or ESM resolution.

(3) Development of dedicated transition matrices increasingly based on empirical data (as soon as new products emerge) and sophisticated land-use change allocation models rather than simple, globally applied, allocation rules. Moreover, DGVMs and ESMs have to ensure to use the full detail of information provided by the implementation of gross change algorithms in their models. Due to internal model structure most DGVMs need to apply proportional reduction of PFTs in case of expanding agricultural land. However, explicit transition information should be used to further evaluate discrepancies between the potential natural vegetation scheme and LULCC data provided by LUCMs and IAMs.

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**Table 1: Examples of allocation rules at grid cell level to implement agricultural land in different DGVMs and ESMs.**

| Model | Land use /cover types | Allocation strategy | Reference |
|---|---|---|---|
| LPJ-GUESS | natural, cropland, pasture | proportional reduction | Lindeskog et al. (2013) |
| HadGEM2-JULES | natural (tree, shrub, grass) cropland, pasture | grassland first | Clark et al. (2011) |
| ORCHIDEE | natural (tree, grass), cropland, pasture | proportional reduction | Krinner et al. (2005) |
| LPJ-mL | natural (tree, grass), cropland, pasture | proportional reduction | Bondeau et al. (2007) |

**Table 2: Case studies and continental scale remote sensing studies reporting main sources of agricultural expansion or allow for land cover change detection.**

| Region | Temporal coverage | Main source of new cropland | Main source of new pasture | Reference |
|---|---|---|---|---|
| Europe | 1990-2000 / 2000-2006 | | Shrubland / Shrubland* | Bossard et al. (2000) |
| USA | 2001-2006 / 2006-2011 | Grassland / Grassland | Shrubland / Forest | Homer et al. (2015) |
| Latin America | 2001-2013 | Pasture | Forest | Graesser et al. (2015) |
| Northern China | 1989-1999 / 1999-2003 | Grassland / Grassland | - | Li (2008) |
| | 1986-2000 | Grassland | - | Liu et al. (2009) |
| | 1995-2010 | Grassland | - | Zuo et al. (2014) |
| Yangtze River Basin | 1980-2000 | Woodland | - | Wu et al. (2008) |
| Brazil | 1994-2002 | Forest | Forest | Ferreira et al. (2015) |
| Tropics | 1980-2000 | | Forest* | Gibbs et al. (2010) |

* source refers to all new agricultural land, i.e. cropland and pasture combined

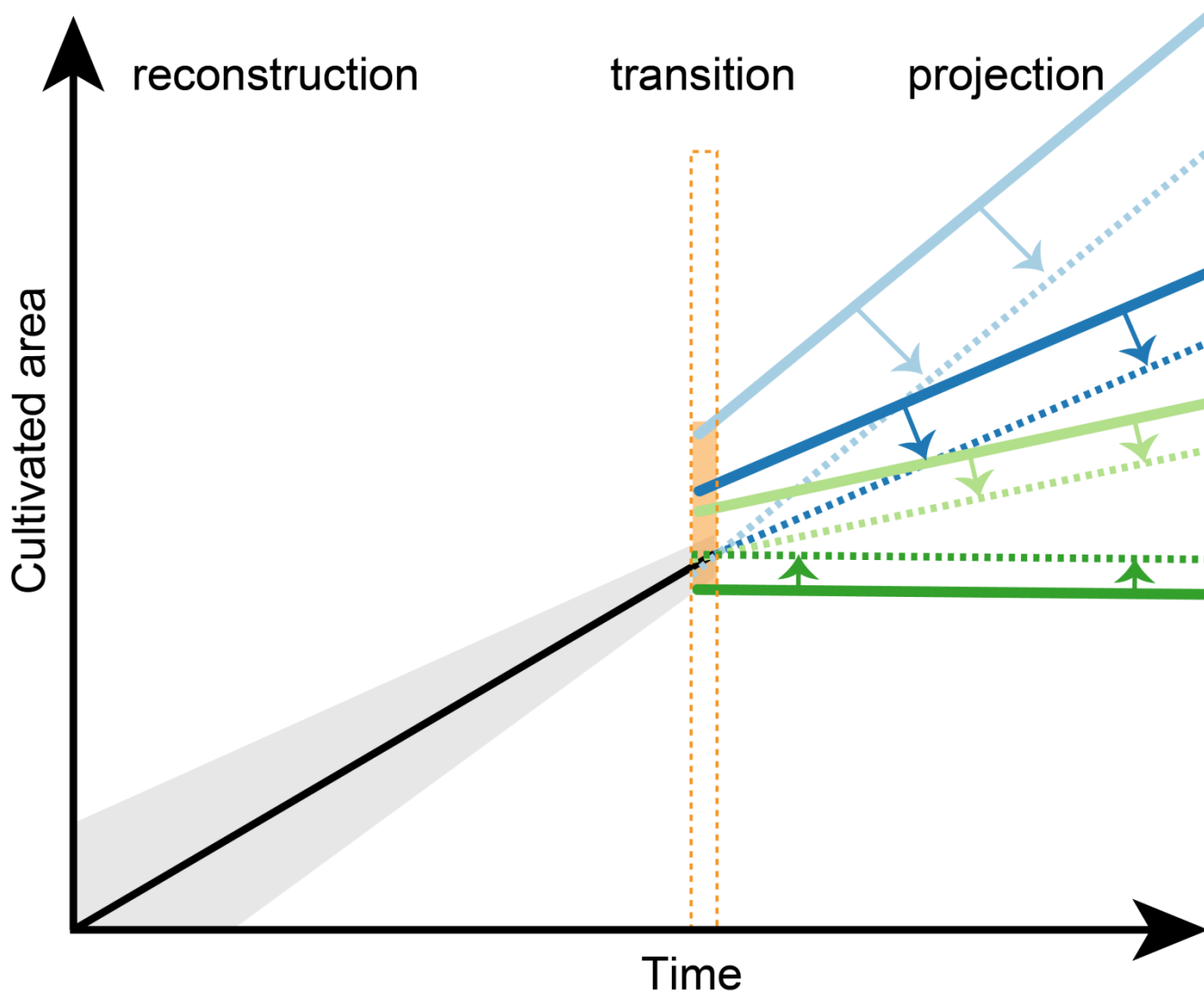



**Figure 1: Simplified scheme of the harmonization process. Future projections from different models (solid colored lines) are smoothly connected (dashed colored lines) to the HYDE historical reconstruction (black line; grey shading represents the uncertainty range of LULCC history). Uncertainty about extent and pattern of current land use and land cover (orange shading) is removed, the total areas of cultivated land projected by the different models are changed and the spatial patterns of change are likely to be distorted (not shown).**

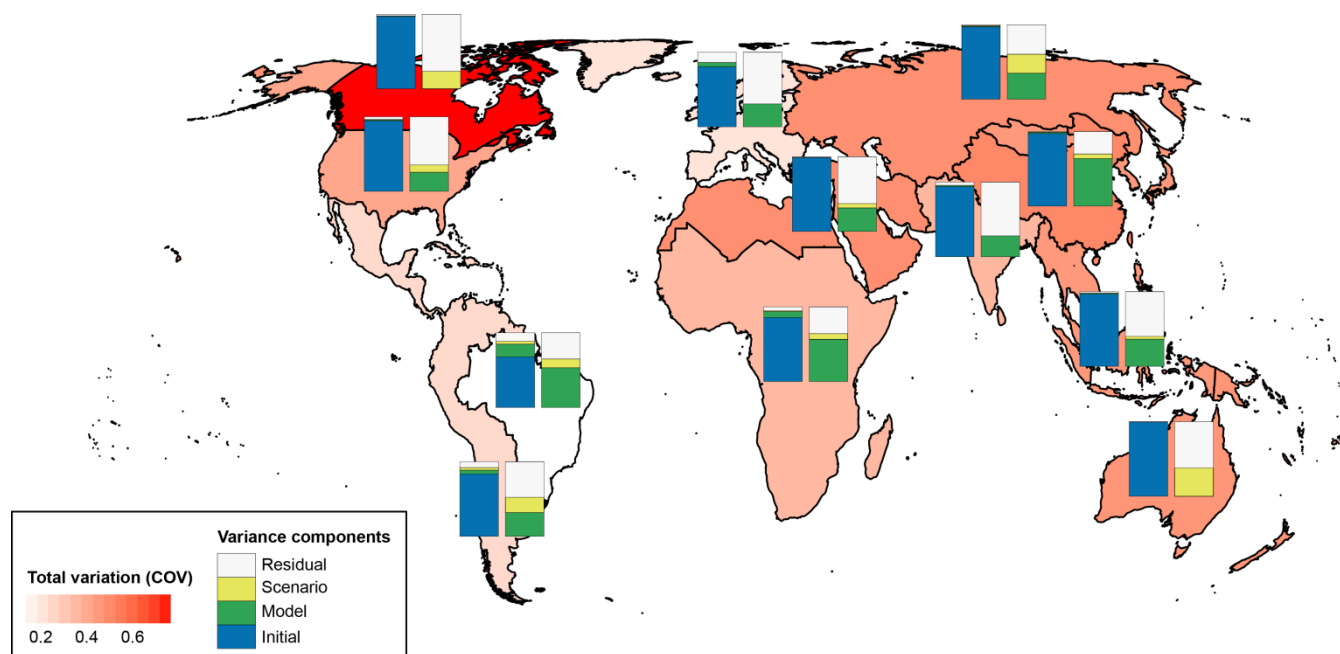



**Figure 2: Variation (expressed as coefficients of variation) of pasture projections for 12 world regions in 2030 (shading of the background map) and relative attribution of total variation to initial, model and scenario parameters (bar plots). Left bar plot per region including initial variation, right bar plot per region excluding initial variation. The figure is based on 11 regional and spatially explicit land-use change models as described in Prestele et al. (2016). Methodological details can be found in the SI (Table S2) and in Alexander et al. (2016).**

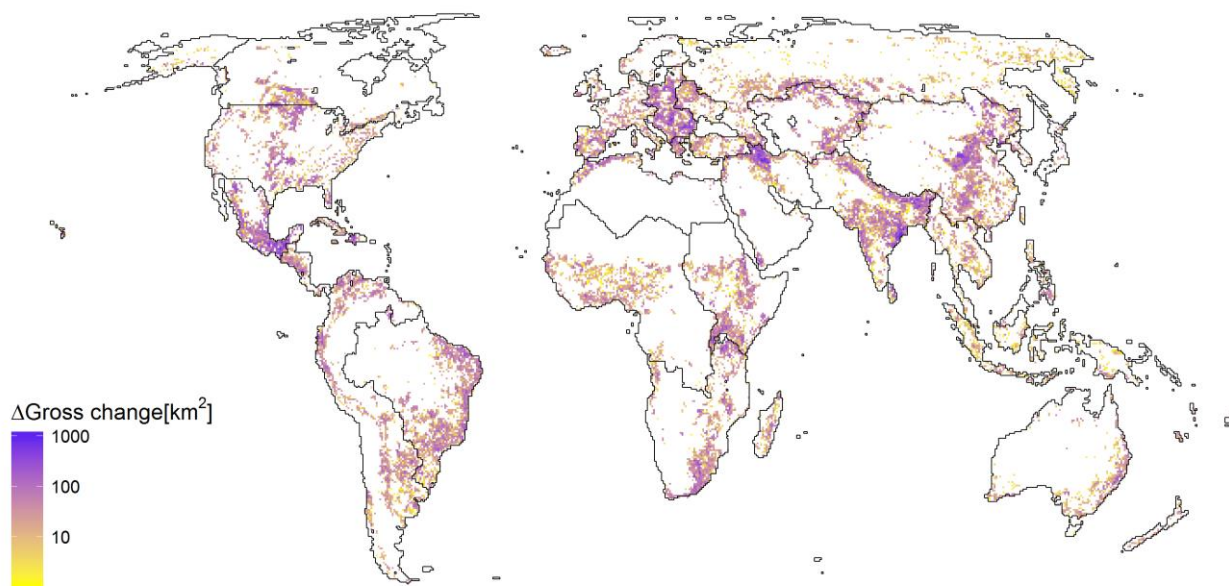



**Figure 3: Difference between gross versus net area affected by change at grid cell level (ca. 0.5 x 0.5 degree) as shown by the CLUMondo model (FAO 3 demand scenario). Areas affected by net or gross change have been accumulated over a 40 year simulation period. Net changes are calculated at ca. 0.5 x 0.5 degree resolution, while gross changes also account for bi-directional changes at the 5 arcminute native CLUMondo resolution. More intense colors indicate a larger difference between the area changed under a net and a gross change view at ca. 0.5 x 0.5 degree grid level. Note the logarithmic scale.**

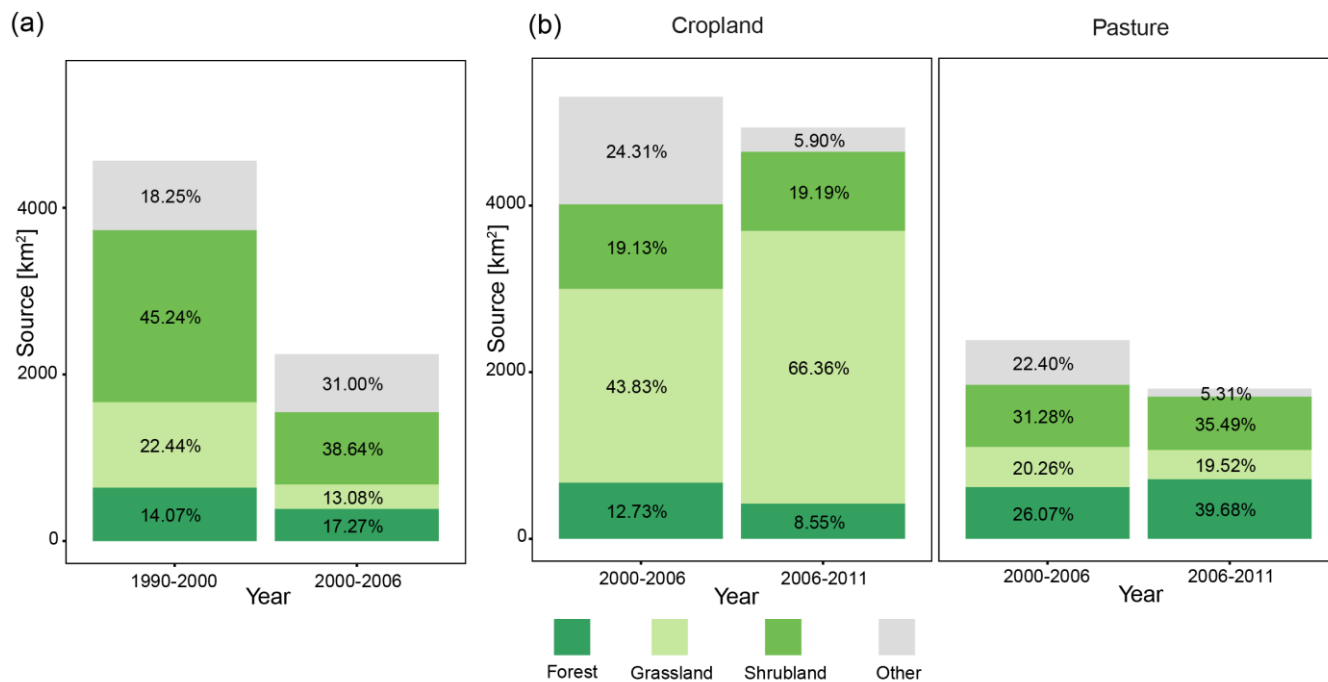
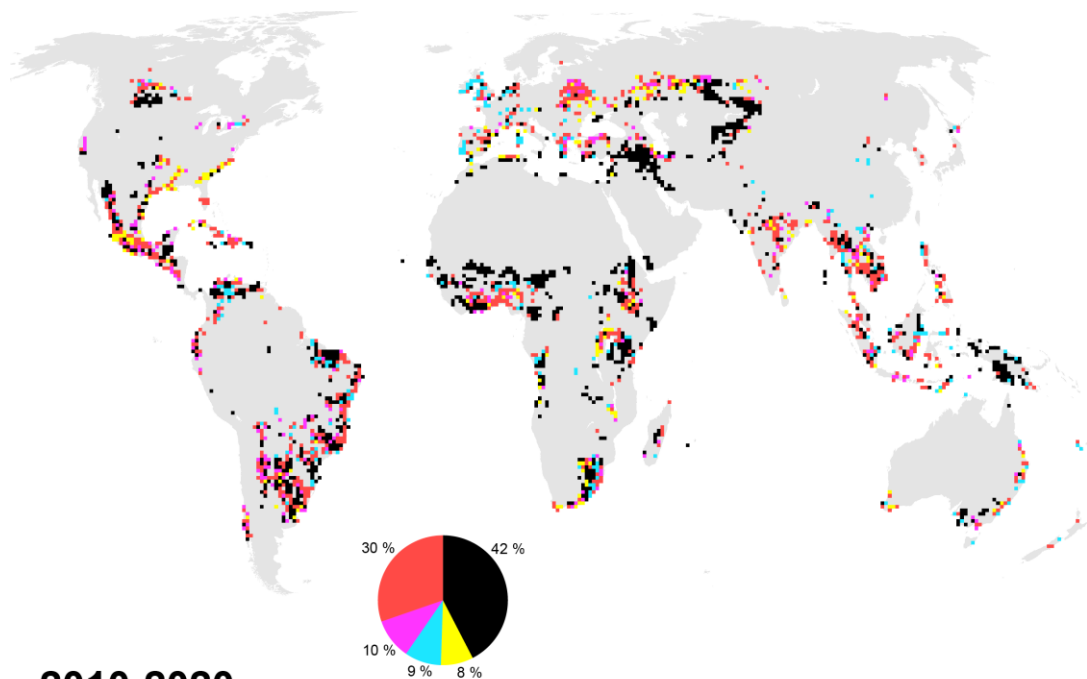
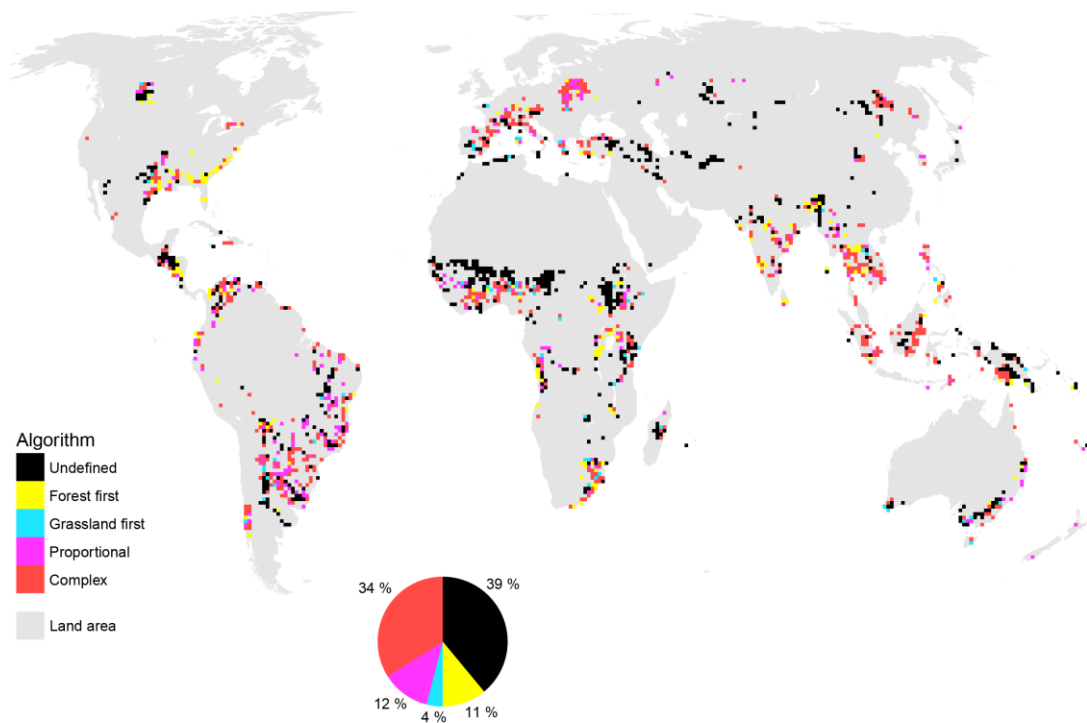
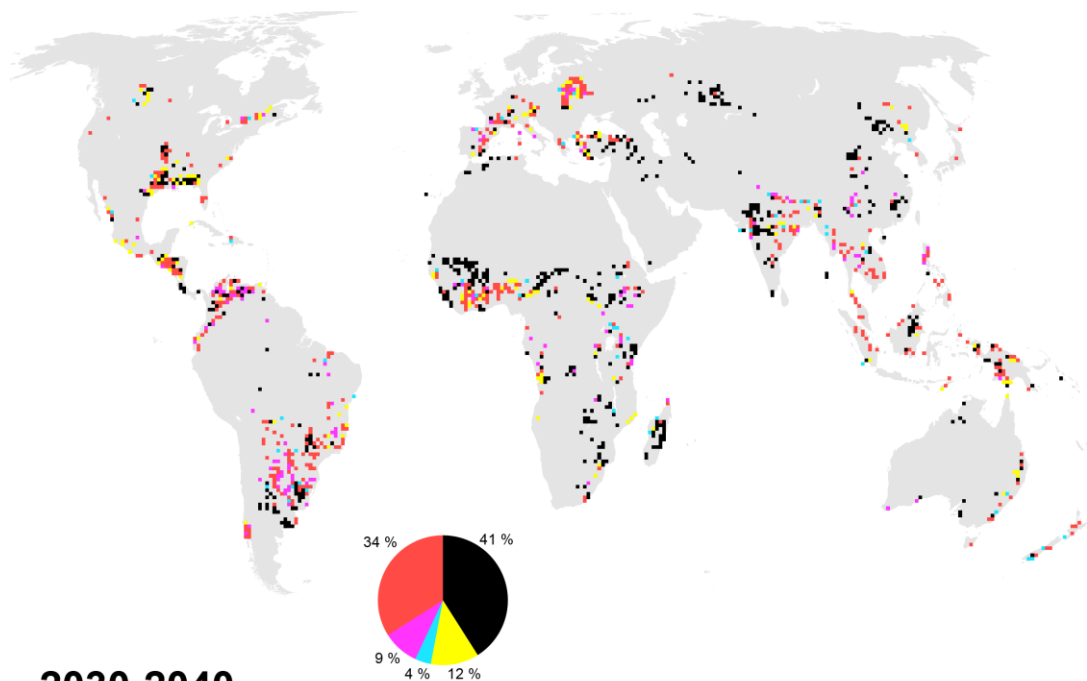



**Figure 4: Sources of agricultural land (cropland and pasture combined) for two time periods in Europe based on the CORINE land cover data (a) and sources of cropland and pasture for two time periods in the USA based on the NLCD land cover data (b). Changes between different agricultural classes are not considered as expansion of agricultural land. Other includes urban land, wetlands, water and bare land.**

**2020-2030**

**2030-2040**

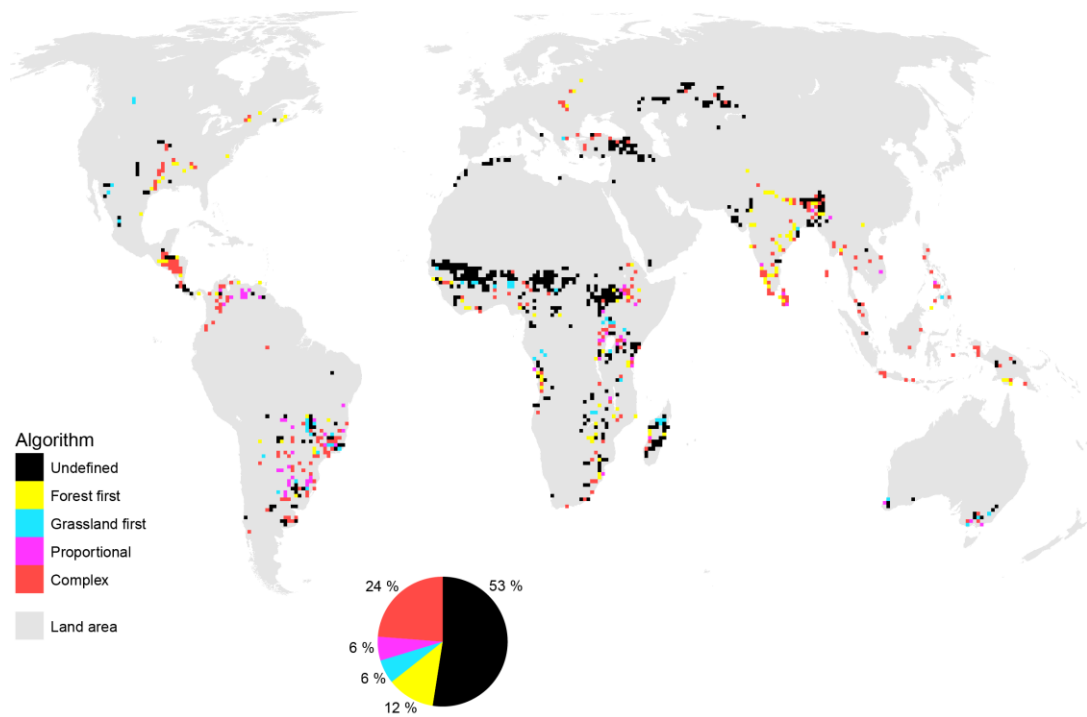



**Figure 5: Transitions from natural vegetation to cropland as shown by the CLUMondo model (FAO 3 demand scenario) from 2000 to 2040 in decadal time steps. Colored grid cells represent areas with at least 10 % of cropland expansion within a ca. 0.5 x 0.5 degree grid cell. Grid cells are classified to forest first (yellow), grassland first (cyan), proportional (magenta) and complex reduction (red) algorithm as described in the text (for details see SI). Black grid cells denote areas where the validity of none algorithm could be detected. Grid cells in this figure have been aggregated to ca. 1.0 x 1.0 degree following a majority resampling for reasons of readability. A high resolution version of the maps including the full detail of the classification results can be found in the supplementary material (Figure S4).**