Dear Dr. Perdigão,

Thank you very much again for the time and effort spent on our manuscript.

We revised the manuscript according to the minor revisions requested.

Please find below a detailed point-to-point reply to all individual comments and a marked-up version showing all changes eventually made to the manuscript. Page/line references in our response refer to the clean version of the revised manuscript.

With kind regards,

Reinhard Prestele

Reviewer #1 (A. Di Vittorio)

The authors have done a tremendous job of revising this manuscript. It is better organized, more clear and consistent, and overall a very good paper that explains, demonstrates, and proposes advances to three major challenges of global lulcc in the context of earth system modeling. The authors responded very well to all the reviewers' comments, and I don't have any major concerns with this version. I suggest some minor clarifications/edits below, and am looking forward to seeing this paper published soon.

Response: We thank the reviewer for the positive evaluation of our revised manuscript. We addressed all comments as detailed in the point-to-point reply below.

specific suggestions/comments:

Introduction

page 3, lines 13-16: This sentence is awkward. Should there be an "and" in place of the comma between "studies" and "reviews" (two serial clauses), or is there a third serial clause associated with "…in the context…" that needs a verb? It also may be helpful to state the three challenges here.

Response: Thanks for pointing to this. We rephrased the sentences for clarity (page 3, lines 14-17).

Challenge 1

page 3, line 26: "e.g." is not needed here. If you are concerned that this implies that nothing else can 'jump,' you can try something like "Corresponding jumps in carbon and nutrient…"

Response: Agreed. We replaced '*Consequently, jumps e.g. in carbon and nutrient pools…*' by '*Corresponding jumps in carbon and nutrient pools…*' (page 3, line 27)

page 4, line 5: Figure 1 doesn't really illustrate this point (it may work better for the next sentence). More appropriate would be table of the independent data sets (refer to Table S1 and maybe add the future projections to it?).

Response: We agree that the reference was misplaced and moved it to the subsequent sentence. We additionally included a reference to the supplementary information and Table S1. (page 4, line 5 & 7).

' […] and a variety of independent datasets at spatially explicit or world region level is provided to the user community (e.g. climate modeling) (see Supplement S1 and Table S1 for the example of the historical data).'

page 4, lines 32-33: Awkward sentence. If it is 'within' the data, how is it not considered?

Response: We rephrased the sentence (page 4, lines 33-34):

'*Beyond this inarguable success, several uncertainties are to date not, or only partially, addressed in the LUH data.*'

page 5, line 20: "…amounts…"

Response: Changed accordingly (page 5, line 22).

page 6, line 2: "providing land-use data to climate models" isn't necessary here

Response: We removed '*providing land-use data to climate models*' as suggested (page 6, lines 3-4).

Challenge 2

page 7, lines 10-11: This more general definition does not make sense to me. Just because an area change is not included in a product does not mean it is a gross change. It could be that a particular category is not represented, which is different than a gross change.

Response: We agree that this statement was too vague. We added explanation to account for the case mentioned by the reviewer (i.e., if a category is not represented). It now reads (page 7, lines 11-13):

'*A more general definition would include all area changes (i.e., gains and losses of all categories represented in a product) that are not depicted in land-use change products*.'

page 8, line 6: Is there a context for this 40-year period? Is it based on current day statistics/assumptions? Is it a projection of historical baselines? Is it a future projection?

Response: We now explicitly mention that the 40-year period is based on the availability of data for this CLUMondo scenario, which simulates annual land system changes between 2000 and 2040 (page 8, lines 6-7).

'We tracked all changes between five land-use and land-cover categories (cropland, pasture, forest, urban, and bare) at the original resolution over the time period 2000 to 2040.'

Challenge 3

page 11, line 19: Is this the same simulation as above?

Response: It is indeed the same simulation. We rephrased the sentence to add this piece of information as following (page 11, line 22):

'[…] we reclassified the outputs of the same CLUMondo simulation utilized in section 3.2 […]'

page 13, lines 8-14: This seems incomplete, and the example given is likely not universal, and is not correct depending on the maps in question. First of all, there are more cases: exact match, lu ag on natural lc, lc ag on natural lu, and spatial combinations/redistributions of the latter two. It would seem that transition matrices would work best with the exact match, and would pose challenges for all other cases. But the result (in terms of which cover to convert) of applying of the matrices to the mismatched land cover in each cell would be dependent on the given transitions and land use/cover in each cell, even if using a single set of rules to apply the matrices (these rules will also have uncertainty).

Response: We agree with the reviewer. We rephrased the paragraph in a way that we still mention the issue (exact match vs. mismatched land cover/land use), but do not present a universal solution, which is indeed dependent on the background land cover, the land use data and the specific model in question (page 13, lines 11-19).

Recommendations

page 15, lines 4-5: This isn’t necessarily the case if the DGVM is designed to accommodate integrated land cover and land use dynamics.

Response: We think the reviewer has a valid point here. At the same time, there are currently hardly any (if none?) DGVMs designed to accommodate integrated land cover and land use dynamics available. Moreover, in this section we still discuss the situation where data is passed between land-use change models and TBMs, i.e. no integrated land cover/use. We thus feel the statement is correct and decided not to change.

Outlook

page 15, lines 9-17: The introduction of the ‘offline’ strategy is a bit confusing here, especially since the next sentence does not explain it, but rather asks for an integrated framework. It sounds like you refer the ‘ways forward’ as the decoupled strategy, then want to discuss ‘offline’ coupling which needs to be defined here, all leading up to full integration. Maybe the topic sentence should present this progression, then the text can walk through each in turn. Currently, the “land use, land cover and the climate system…” sentence is out of place.

Response: We rephrased the paragraph to emphasize that we indeed aimed at presenting the progression from the ‘offline’ coupling to an integrated modeling framework (page 15, lines 12ff).

We discuss the recommended improvements in the ‘offline’ coupling in section 5, acknowledging that full integration will also take some time. In section 6 we then give an outlook what should be done, in our point of view, to improve the understanding of land use – climate interactions, i.e. model integration.

page 15, line 17: I recommend the terminology of “preliminary results of the iESM.” The “first” results, based on a completed feedback coupling experiment, are still in in review.

Response: Changed as suggested (page 15, line 21).

Reviewer #2 (Anonymous)

The authors have made considerable improvements during the revision phase and the comments from my first review were addressed satisfactory. The current manuscript is now better structured and much clearer also to ‘non-specialists’ in this field. Based on my current review, I suggest minor revisions in which the comments below should be addressed before the paper could be accepted for publication.

Response: We thank the reviewer for the positive evaluation of our revised manuscript. We accommodated the additional comments raised by the reviewer as detailed in the point-to-point reply below.

General Comments:

I would like to ask the authors to make sure that it will be clear throughout the manuscript that the content of this paper is based on the authors’ opinion (e.g. with regard to the challenges and reasons for the difficulties are and how to they could be overcome).

Response: We have rephrased some additional sentences clearly indicating that the suggested ways forward are perspectives of the authors (see examples below). Moreover, during the first revision of the manuscript, we put major efforts in highlighting the 'opinion' character of the manuscript (e.g., by the extensive usage of 'could', 'should' and 'might' constructions in section 5 and section 6). However, the identified problems and underlying reasons are based on literature review and analysis and not part of the authors' opinion.

Examples:

'*Simultaneously, we suggest that the land-use and remote-sensing communities should engage to reduce uncertainties in land-use and land-cover products by: […]*' (page 14, lines 10-11)

'If not yet possible at the global scale […], we recommend the implementation of regional scale evaluation schemes using smaller scale, high accuracy remote sensing products as a starting point for later integration into global applications.' (page 14, 20-23)

'Rather than improving de-coupled data products and models on an individual basis and connecting them 'offline' through the exchange of files, we argue that land use, land cover and the climate system need to be studied in an integrated modeling framework.' (page 15, lines 13-15)

In the manuscript, many different acronyms are being used which are difficult to recall throughout the paper. As the journal is aimed at an interdisciplinary audience, I suggest that the authors add a list of acronyms to the supplementary information and mention the existence of such a list in the introduction section of the paper.

Response: We do acknowledge that the use of acronyms might be difficult for the reader (but is essential for readability) and added a list to the SI as suggested by the reviewer (SI page 1, lines 1-19). Additionally, we refer to this list at the first time, when we introduce an acronym in the introduction (page 2, line 6).

'*Anthropogenic land-use and land-cover change (LULCC; for a list of acronyms used in the paper see Supplement S0) is a key cause […]*'

I suggest using Roman numerals throughout the text to identify the three Challenges and to distinguish the challenges from section numbers. E.g. The caption for the second P3 L19 would then read '2 Challenge I: Spatial explicit …'

Response: Good point. We changed the section headers accordingly. Additionally, Roman numerals are now used when listing the challenges in the abstract (page 1, lines 28 & 30).

Instead of just saying 'for details see SI' or similar when refereeing to the Supplementary Information, please provide the section number within the SI to make it easier for the reader too find the information.

Response: We apologize that we were not consistent in referencing the supplementary material throughout the manuscript. We adjusted all references to the SI by adding the section number (e.g., page 6, line 20: *'[…] (Figure 2, background map; Supplement S2.1)'*).

Specific Comments:

P1L23-25: Please split this long sentence.

Response: Done. We split the sentence into (page 1, lines 23-26):

'*Fully coupled models of climate, land use and biogeochemical cycles to explore land use – climate interactions across spatial scales are currently not available. Instead, information on land use is provided as exogenous data from the land-use change modules of Integrated Assessment Models (IAMs) to TBMs.*'

P1L29: suggest replacing 'due to' with 'associated with'.

Response: Changed accordingly (page 1, line 29).

P1L30-31: Can you provide some more elaboration on what the 'allocation strategy' entails, as this might not be clear from the abstract.

Response: Given the brief, concise character of the abstract and to keep the balance in the abstract we see no possibility to do this. We feel the statement summarizes the issue quite well in a short, concise way and we are explaining it in detail in the paper.

P2L17: Maybe add 'effected' before 'land'

Response: We thank the reviewer for the suggestion. However, the 'potential net source of GHGs' does not only refer to land affected by change, but to 'the land' as a whole. We therefore prefer not to change this sentence.

P2L21: 'the short history', please add details what 'short' entails (e.g. since when)

Response: We added *'(~10 years; Canadell et al., 2007)'* to the sentence to add detail to *'the short history'* (page 2, line 22).

P2L21: please add examples what 'external data' are.

Response: We added '*(e.g. maps of global cropland or pasture distribution)*' to the sentence (page 2, line 23).

P2L22: '… short history …' … '…along with…' … '…led to issues that render… ' … '… uncertain'. This sentence is not clear to me; how can the points mention 'render' something 'uncertain'. Please consider rephrasing.

Response: We rephrased the sentence for clarity (page 2, lines 22-25).

'The short history […], along with the need to include external data […], have led to several issues that complicate the quantification of land-use change impacts on climate and biogeochemical cycles using TBMs.'

P2L27: Pease specify what an ''offline' coupling' entails.

Response: We specify 'offline' coupling in the subsequent sentence and now connected the sentences to make this more clear (page 2, lines 28-31). 'Offline' coupling refers to the situation, where data is passed between different types of models (IAMs/LUCMs and TBMs) without feedbacks between the different types of models.

P3L27: 'reliably determining' please consider rephrasing

Response: We rephrased the sentence (page 3, lines 27-28). It now reads:

'Corresponding jumps 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 the quantification of climate impacts'

P4L23: 'Smoothly connected'; what does this mean, is this similar to Figure1? Please elaborate.

Response: We added a reference to Figure 1 (page 4, line 27). Indeed this figure is intended to visualize the 'smooth connection' between historical and future land use time series (schematically).

P4L26 'the harmonization'; which one? LUH?

Response: We added the word 'process' to clarify (page 4, line 27). 'Harmonization' describes the process of connecting the historical and future land use data in this sentence.

P4L32-32: … 'serves as a basis to implement anthropogenic impact on … Please consider rephrasing

Response: We rephrased the sentence to improve readability (page 4, lines 33-34). It now reads:

'*The harmonization ensured for the first time consistent land-use input for climate model intercomparisons and thus facilitated the implementation of anthropogenic impact on the land in climate models.*'

P5L23: Consider rephrasing the sentence.

Response: We rephrased the sentence aiming at improved readability into (page 5, lines 24-25):

'[…], an inappropriate representation of the uncertainty about land-use history is likely to affect model outcomes regarding changes in local to regional climate.'

P6L17: Please specify what 'cropland development' is.

Response: Cropland development refers to the dynamics of future cropland expansion / abandonment. We rephrased the sentence (page 6, lines 17-18). It now reads:

'*Model comparison further revealed that while land-use change models represent the future development of cropland area more consistently, […]*'

P6L19: How were these projections derived? Please clarify where they come from (i.e. reference or refer to section in SI)

Response: We provide the reference to the projections in the subsequent sentence (Prestele et al., 2016). Additionally, we now include a reference to the section in the SI, where we describe the analysis underlying Figure 2 (page 6, lines 20-21).

P7L31: 'meaning that …?... many are' I think there is a word missing.

Response: Agreed, thanks. We added '*TBMs*' to the sentence (page 7, line 32).

P9L10: replace 'larger' with 'longer'

Response: Changed as suggested (page 9, line 11).

P10L8: Please elaborate in more detail what 'through soils' means.

Response: We rephrased the sentence and added a reference to be more specific (page 10, lines 9-11).

'[…] while cropland expanding on former grassland would have a less immediate impact on ecosystem carbon stocks due to the long time lag (years to centuries) for the resulting changes in soil carbon to be realized (Pugh et al., 2015).'

P10L29: 'They'? Who? Gibbs? Please clarify.

Response: We replaced '*They*' by '*Gibbs et al. (2010)*' (page 10, line 31).

P11L6: Please elaborate in what these products are better.

Response: We admit that 'better products' was a very vague phrasing and replaced it with the following to be more specific (page 11, lines 8-9):

'[…] though products with higher resolution (up to ~30m), more frequent temporal coverage, and increasing thematic detail are just emerging; Ban et al., 2015 […]'

P11L15: What are 'neighborhood effects'?

Response: We agree that neighborhood effects were not sufficiently defined and added a short explanation (page 11, line 18). The sentence now reads:

'[…] neighborhood effects (i.e., cropland expansion in a grid cell also depends on the availability of suitable land in the surrounding grid cells).'

P12L4: replace 'complex interplays' with 'the complex interplay'

Response: Replaced as suggested (page 12, line 8).

P13L8: move the reference at the end of the sentence.

Response: We feel that moving the reference, which explicitly refers to the translation of CCI-LC categories to PFTs and not the background vegetation map per se, would rather confuse the reader. We therefore decided not to change this sentence.

P13L10: Please check the grammar of the sentence.

Response: We checked the grammar and rephrased the sentence according to our response to comment 'page 13, lines 8-14' of reviewer #1.

P13L20: To make things even more clear, I suggest restating the three sources again.

Response: We accommodated this comment by rephrasing the first part of the sentence and splitting it into (page 13, 23- 26):

'As we have shown in section 2, three major sources of uncertainty, which include the uncertainty about land-use history, inconsistencies in present-day land-use estimates, and structural differences across IAMs and LUCMs, are poorly addressed through the almost exclusive implementation of the LUH dataset within the climate modeling community.'

P13L22: replace 'impact' with 'influence' or 'change'

Response: We replaced '*impact*' by '*influence*' (page 13, line 26).

P13L24-26: Move the last part of the sentence to the beginning.

Response: Rephrased as suggested (page 13, lines 29-31).

P14L18: Remove 'our'

Response: Removed (page 14, line 21).

P14L26-18: Split sentence.

Response: We split the sentence into (page 14, lines 30-32):

'Based on such analyses, multi-century reconstructions and projections for climate and ecosystem assessments could be enhanced for at least the satellite era. As models extend further into the past, the detailed information could be gradually replaced by model assumptions, supported by additional reference data such as historical maps and statistics.'

P15L3: Please rephrase 'have to ensure to use'

Response: We replaced '*have to*' by '*must*' to increase readability (page 15, line 6).

P15L14: please replace 'very large level of uncertainties' with a more appropriate phrase.

Response: The sentence has been rephrased into (page 15, line 18):

'[…] accumulating an increasing level of uncertainty along the modeling chain.'

Figures:
Figure1: Please provide information for the interdisciplinary audience how the spatial patterns are being distorted. Maybe with a schematic showing grid cells or discuss more explicit in the text.

Response: We agree that this statement might be confusing and thus removed it from the figure caption (page 28, line 5). As we discuss in the text (page 4, line 27), the harmonization 'tries to conserve the spatial pattern of the IAM', which however cannot fully be achieved due to the different land-use pattern in the historical and future maps (as discussed in section 2). How and to what extent a 'distortion of the spatial pattern' happens depends strongly on the IAM maps in question. To properly describe and quantify, one would need to compare the original IAM maps with the LUH maps, which we believe is outside the scope of this paper.

Figure2: due to the different values of the Initial variations it is impossible to properly compare the values shown in the right bar plots for different regions. To make the bar plots comparable I suggest adding the % in the categories or normalising the values shown on the right by the initial value before generating the bar plots on the right.

Response: We improved the caption for clarity (page 29, lines 2ff), but do not think that adding % labels to the bar plot would increase the readability of the figure. The purpose of the figure is to highlight the broad patterns of the variation (as discussed in section 2.3; page 6, lines 17-27), rather than comparing discrete values of individual regions.

The reviewer is absolutely correct that the initial variation varies across the regions, as well as the total variation does. Thus, we use relative values to compare the contribution of different variance components across regions. The purpose of the right bar plots is mainly to visualize the distribution of model, scenario and residual components in regions where their summed contribution is small (e.g., Canada, USA, Australia,…). They are comparable across regions in a way that they represent the % of the components model, scenario and residual on the part of variation that is not explained by the initial variation.

Figure 3: add to caption that this is based on singe model.

Response: We accommodated this comment by adding *'[…] one realization of a single LUCM (CLUMondo; FAO 3 demand scenario)'* to the caption (page 30, lines 2-3).

Figure 4: To make the values of the individual bars comparable, I suggest showing annual averages instead of sums over periods of different length.

Response: The reviewer has a valid point that the time periods of NLCD and CORINE differ in their length. However, we think the suggested changes would be misleading. We present the sum of changes (in terms of area) only to indicate that the total agricultural expansion is different across products and time periods where change products are available. At the same time, we present the relative contribution of the sources to these total agricultural expansion, which we also use for 'comparison' in the text (page 10, lines 18 ff). Showing annual averages would add detail to the data, we actually cannot obtain from CORINE and NLCD. Moreover, such a processing would not change the relative contribution of the individual sources (since we do not have annual information), which we refer to in our analysis.

Supplementary Information Section

P5L14: Please add reference to the 'Akaike information criterion'.

Response: We added the following reference (SI page 6, line 14):

Akaike, H.: Information theory and an extension of the maximum likelihood principle, in Second International Symposium on Information Theory, edited by B. N. Petrov and B. F. Csaki, pp. 267–281, Budapest., 1973.

P7L16: Please add correct Reference.

Response: Figure S1 depicts the workflow described in this paragraph. We thus believe it is the correct reference. Additionally, we added Figure 3 as a reference, which presents the final product of the analysis in the main text of the paper (SI page 8, line 16).

P15L1, P26Tabel3 and P18FigureS3: The category 'unvegetated fist' is not shown in Figure 5 and Figure S4. Please either add this category to the Figures or give detailed reasons why this is not shown

Response: The reviewer is absolutely correct, that we did not include the 'unvegetated first' category in Figures 5 and S4. Thanks for pointing to the missing explanation. We added explanation accordingly to the figure captions (page 34, line 5; SI page 23, line 5). The reason for not including it into the figure is that the share of this category is negligible small (< 0.1 %) and would thus not add any useful information.

P18FigureS3: Please use same colours for the classifications as in Figure 5 and Figure S4.

Response: We changed the colors accordingly (SI page 19).

Current challenges of implementing anthropogenic land-use and land-cover change in models contributing to climate change 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 Terrestrial Biosphere Models (TBMs). The published results of these models 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 f~~Fully coupled models of climate, land use and biogeochemical cycles to explore land use – climate interactions across spatial scales are currently not available.~~,~~ Instead, information on land use is ~~currently~~ provided as exogenous data from the land-use change modules of Integrated Assessment Models (IAMs) to TBMs. In this article, we discuss, based on literature review and illustrative analysis of empirical and modeled LULCC data, three major challenges of this current LULCC representation and their implications for land use – climate interaction studies: (I~~1~~) provision of consistent, harmonized, land-use time series spanning from historical reconstructions to future projections while accounting for uncertainties associated with~~due to~~ different land-use modeling approaches, (II~~2~~) accounting for sub-grid processes and bi-directional changes (gross changes) across spatial scales and (III~~3~~) the allocation strategy of independent land-use data at the grid cell level in TBMs. We discuss the reasons that hamper the development of improved land-use representation that sufficiently accounts for uncertainties in the land-use modeling process. We propose that LULCC data-provider and –user communities should engage in 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, to

improve the representation of land use in TBMs. Moreover, we suggest to concentrate on the development of integrated modeling frameworks that may provide further understanding of possible land-climate-society feedbacks.

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; for a list of acronyms used in the paper see Supplement S0) is a key cause of alterations in the land surface (Ellis, 2011; Ellis et al., 2013; Turner et al., 2007), with manifold impacts on biogeochemical and biophysical processes that influence climate (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 Terrestrial Biosphere Models (TBMs), including Dynamic Global Vegetation Models (DGVMs) and Land Surface Models (LSMs) (Fisher et al., 2014), 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., 2015; Luyssaert et al., 2014; Mahmood et al., 2014). For example, LULCC 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). 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), turning the land to a potential net source of greenhouse gases to the atmosphere (Tian et al., 2016). Local and regional observational studies suggest impacts of LULCC on biophysical surface properties, e.g. surface albedo and water exchange, eventually affecting temperature and precipitation patterns (Alkama and Cescatti, 2016; Pielke et al., 2011).

TBMs have been originally designed to study the interactions between natural ecosystems, biogeochemical cycles and the atmosphere. The short history of implementing land-use change in TBMs (~10 years; Canadell et al., 2007), along with the need to include external data (e.g., maps of global cropland or pasture distribution) to represent land-use change, have led to several issues that complicate ~~render~~ the quantification of land-use change impacts on climate and biogeochemical cycles using TBMs~~uncertain~~. For example, carbon fluxes related to land-use change that increase the atmospheric concentration of greenhouse gases are the largest source of uncertainty in the global carbon budget (Ballantyne et al., 2015; Le Quéré et al., 2015). Similarly, biophysical impacts of land-use change on climate are not yet sufficiently understood and quantified (Pielke et al., 2011). The lack of process understanding and reliable quantification of impacts can be attributed to a separated history of land-use research and land-cover research and the current ‘offline’ coupling of different models, where~~.~~ ~~Mostly,~~ external land-use information from Integrated Assessment Models (IAMs) or dedicated land-use change models (LUCMs) is imposed on the natural vegetation scheme of TBMs. This current land-use representation is, amongst others, sensitive to the definition of individual land-use categories (e.g., what exactly defines a ‘pasture’), inconsistencies in the definition of the land-use carbon flux (Pongratz et al., 2014; Stocker and Joos, 2015), the implementation and parameterization of land use in TBMs (Brovkin et al., 2013; de Noblet-Ducoudré et al., 2012; Di Vittorio et al., 2014; Hibbard et al., 2010; Jones et al., 2013; Pitman et al., 2009; Pugh et al., 2015), the structural differences across IAMs and LUCMs (Alexander et al., 2016; Prestele et al., 2016; Schmitz et al., 2014), and the uncertainty about land-use history (Ellis et al., 2013; Klein Goldewijk and Verburg, 2013; Meiyappan and Jain, 2012).

Currently reported uncertainties of the outputs of land use – climate interaction studies may be underestimated by insufficiently accounting for the aforementioned sources of uncertainty. The current land-use representation therefore requires improvement to narrow down the uncertainty range in reported results of land use – climate studies and eventually increase the confidence level of climate change assessments. Assessments of the global water cycle, freshwater quality, biodiversity and non-CO_2 greenhouse gases would also benefit from an improved land-use representation.

The overall objective of this article is to review three important challenges faced in connecting models to assess land use – climate interactions and feedbacks, discuss the underlying mechanisms and constraints that have hampered improved representations until now, and propose pathways to improve the land-use representation. We review recent literature from the land use, land cover, carbon cycle and climate modeling communities and support our arguments by illustrative analysis of satellite land-cover products and outputs of the land-use change model CLUMondo (Van Asselen and Verburg, 2013). Each of the following sections presents one of the three challenges we identify to be crucial in future land use – climate interaction studies and~~,~~ reviews the issue and its implications for the results of modeling studies, based on previously published literature and in the context of the widely applied Land Use Harmonization (LUH) dataset published by Hurtt et al. (2011). In section 5 we propose pathways to improve the current LULCC representation for each of the challenges and conclude with an outlook on future research priorities.

2 Challenge I~~1~~: Spatially explicit, continuous and consistent time series of land-use change

2.1 Background and emergence

Current TBMs require consistent, continuous and spatially explicit time series of land-use change, covering at least the period since the industrial revolution (~1750) to disentangle the contributions of land use and fossil fuel combustion to carbon cycling and radiative forcing (Le Quéré et al., 2015; Shevliakova et al., 2009). Without time series of at least this length, important legacy fluxes will be missed in the calculations. The application of discontinuous land-use change time series in TBMs to quantify the interactions and feedbacks between land use and climate would lead to large artificially induced changes (‘jumps’) in land use. Corresponding jumps ~~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 and rate~~ quantification of climate impacts.

However, observational data on LULCC is not available at global scale with the required temporal and spatial resolution, consistency, and historical coverage (Verburg et al., 2011). Instead, models are utilized to represent global land use and produce the required land-use change time series. Land-use modeling is typically split up into historical backcasting approaches and future scenario modeling. Both forward and backward looking models apply a range of different modeling approaches, assumptions about drivers and the spatial allocation of land-use changes (National Research Council, 2014; Yang et al., 2014), and are often initialized with different representations of present-day land use (Prestele et al., 2016). Thus, even the models within one community (future or historical) do not provide consistent information on land use and land-use change over time, and a variety of independent datasets at spatially explicit or world region level is provided to the user community (e.g. climate modeling) (see Supplement S1 and Table S1 for the example of the historical data~~Figure 1~~). These historical and future datasets are not connected and consistent in the transition period and entail a variety of uncertainties (Klein Goldewijk and Verburg, 2013) (Figure 1). In consequence, these datasets disagree about the amount and the spatial pattern of land affected by human activity. 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).

2.2 Current approach to provide consistent data: The Land Use Harmonization (LUH)

Large efforts have been undertaken to connect the different sources of land-use data and provide ~~-~~consistent time series for climate modeling applications during the 5th phase of the Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012) by the Land Use Harmonization project (Hurtt et al., 2011). The resulting dataset (hereafter referred to as LUH data) is commonly used in modeling studies dealing with land use – climate interactions and feedbacks. It has recently been updated for the upcoming 6th Phase of the Coupled Model Intercomparison Project (CMIP6; Eyring et al., 2016; Lawrence et al., 2016) and data for the historical period have been published (hereafter referred to as LUH2). Due to the lack of comprehensive documentation of the updated version at the time this paper was written and as, to our best knowledge, the points we demonstrate using LUH will be still valid with the new product, we primarily refer to the CMIP5 version in the remainder of this paper.

Hurtt et al. (2011) extended their Global Land Use Model (GLM; Hurtt et al., 2006) to produce a consistent time series of land-use states (= fraction of each land-use category in a grid cell) and transitions (= changes between land-use categories in a grid cell) for the time period 1500-2100. The cropland, pasture and wood harvest projections of four IAMs were smoothly connected to the History Database of the Global Environment (HYDE) historical reconstruction of agricultural land use (Klein Goldewijk et al., 2011) and historical wood harvest estimates by applying the~~. The~~ decadal spatial patterns from the projections ~~were applied~~ to the HYDE map of 2005 (Figure 1). This~~e~~ harmonization process 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 cropland, pasture and wood harvest. To achieve the final harmonized time series and explicit transitions, the pre-processed land-use time series are used as input into the GLM model and constrained by further data and assumptions about the occurrence of shifting cultivation, the spatial pattern of wood harvest, priority of the source of agricultural land and biomass density (Hurtt et al., 2011). The harmonization ensured for the first time consistent land-use input for climate model intercomparisons~~,~~ and thus facilitated the ~~serves as a basis to~~ implementation of anthropogenic impact on the land ~~component~~ in climate models. Beyond this inarguable success, several uncertainties ~~aspects remain within the LUH data that~~ are to date ~~are~~ not, or only partially, addressed in the LUH data~~considered~~. In the following section we discuss the main uncertainties and how they may propagate into TBMs, impacting the amplitude, and possibly even the sign of land-use interactions and feedbacks.

2.3 Open issues in the LUH data and their implications for climate change assessments

The first major uncertainty of the LUH data evolves from the exclusive consideration of the HYDE baseline dataset for the historical period. The HYDE reconstruction is erroneously regarded as observational data, rather than as model output accompanied by various sources of uncertainty (Klein Goldewijk and Verburg, 2013). Importantly, the LUH2 data will additionally include the HYDE low and high estimates of land use for the historical period (Lawrence et al., 2016). However, alternative spatially explicit reconstructions have been proposed (Kaplan et al., 2010; Pongratz et al., 2008; Ramankutty and Foley, 1999) (see Supplement S1 and Table S1 for additional information on these reconstructions), and shown to differ substantially both in terms of the total cultivated area and spatial pattern over time (Meiyappan and Jain, 2012). These differences originate in the scarcity of historical 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 allocation scheme used to distribute regional or national estimates of agricultural land to specific grid cell locations (Klein Goldewijk and Verburg, 2013).

The uncertainty about land-use history has several implications for land use – climate interactions (Brovkin et al., 2004). For instance, Meiyappan et al. (2015) found the difference in cumulative land-use emissions among three historical reconstructions for the 21th century modeled by one TBM to be about 18 PgC or ~11 % of the mean land-use emission. Another study, using three commonly-used net land-use datasets in one TBM, revealed differences of about 20 PgC or ~9 % of the mean land-use emission since 1750 (Bayer et al., 2017~~in press~~). Jain et al. (2013) further found contrasting trends in land-use emissions at regional scale during the past three decades, which originate in different amounts and rates of land-use change in different realizations of historical land use. Further, as biophysical climate impacts of land use are known to be substantial, especially on a regional scale (Alkama and Cescatti, 2016; Pielke et al., 2011; Pitman et al., 2009), an inappropriate representation of the uncertainty about land-use history ~~range of historical land-use change~~ is likely to affect model outcomes ~~the implications derived~~ regarding ~~land-use contribution to~~ changes in local to regional climate. Using the HYDE reconstruction exclusively implies high confidence about land-use history in many large scale assessments and comparison studies (Kumar et al., 2013; Le Quéré et al., 2015; Pitman et al., 2009), which is in fact lacking. As a result, important uncertainties are being excluded from climate change mitigation and adaptation policies developed based on these studies (Mahmood et al., 2015).

Second, large inconsistencies exist between estimates of present-day land use. The LUH approach does not consider the differences between different data regarding the current state of land use as it connects the future projections exclusively to the HYDE end map (Figure 1~~Figure 1~~). The present-day starting maps of historical reconstructions and future projections are based on maps derived from the integration of remotely sensed land-cover maps and (sub-)national statistics of land use (e.g., Erb et al., 2007; Fritz et al., 2015; Klein Goldewijk et al., 2011; Ramankutty et al., 2008). The land-cover maps in turn disagree about extent and spatial pattern of agricultural land (Congalton et al., 2014; Fritz et al., 2011) due to both inconsistent definitions of individual land-use and land-cover categories (e.g., Sexton et al., 2015) and difficulties in identifying them from the spectral response (Friedl et al., 2010). These differences propagate into the starting maps of the various land-use change models~~ providing land-use data to climate models~~, including the IAMs providing data for the LUH (Prestele et al., 2016). Removing these 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 TBMs across spatial scales (Quaife et al., 2008).

Finally, the future projections used in the LUH are provided by different IAMs, whereby each of them represents an individual scenario of the four representative concentration pathways (RCP) in CMIP5 or the five shared socioeconomic pathways (SSP) in CMIP6 (O'Neill et al., 2015; van Vuuren et al., 2011). These are referred to as 'marker scenarios' in case of the SSPs. A 'marker scenario' entails the implementation of a SSP by one IAM that was elected to represent the characteristics of the qualitative SSP storyline best, while additional implementations of the same SSP in other IAMs are 'non-marker scenarios' (Popp et al., 2016; Riahi et al., 2016). Alternative RCP or SSP implementations were not considered in LUH. Land-use change model intercomparisons and sensitivity studies, however, indicate that the uncertainty range emerging from different assumptions in the models, input data, and spatial configuration substantially impacts the model results (Alexander et al., 2016; Di Vittorio 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 valuable (Popp et al., 2016). Model comparisons further revealed that while land-use change models represent the future development of cropland area~~processes and development~~ more consistently, the representation of pastures and forests (if modeled) is poor. For example, the projections of 11 IAMs and LUCMs show large variations in pasture areas in 2030 for many world regions (Figure 2~~Figure 2~~, background map; Supplement S2.1). These projections were based on a wide range of scenarios, and thus variation in outcomes was to be expected (Prestele et al., 2016). The variation attributed to the difference in model structure exceeds the variation due to different scenarios in most regions (Figure 2~~Figure 2~~, bar plots), while the main part of the variation relates to the different starting points of the models, i.e. deviation from FAO pasture areas in the year 2010. This implies that in many cases the different land-use projections actually do not represent different outcomes resulting from different scenario assumptions, but rather differences between land-use data input used to calibrate the models and the implementation of drivers and processes in the models. Consequently, differences in future climate impacts of land use are likely also affected by the structural differences across land-use change models.

3 Challenge II~~2~~: Considering gross land-use changes

3.1 Background and emergence

Typically, net land-use changes are applied in TBMs. Net land-use changes refer to the summed grid-cell difference in land-use categories between two subsequent time steps at a certain spatial and temporal resolution. Gross change representations provide additional information about land-use changes on a sub-grid scale. The total area in a grid cell, which has been affected by change, can be calculated by the sum of all individual changes (i.e., area gains and area losses). Gross changes have been shown to be substantially larger than net changes due to bi-directional change processes happening 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 time t_1 and 40 km^2 at time 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.

'Gross changes' are not consistently defined across communities. Commonly, shifting cultivation (mostly occurring in parts of the tropics nowadays), and cropland-grassland dynamics (i.e., the bi-directional process of cropland expansion and abandonment) are referred to as gross changes (Fuchs et al., 2015a; Hurtt et al., 2011). Moreover, in the carbon cycle and climate modeling communities, wood harvest (in addition to forest cleared for agricultural land) is sometimes included in gross changes (Hurtt et al., 2011; Stocker et al., 2014; Wilkenskjeld et al., 2014). A more general definition would include all area changes (i.e., gains and losses across all categories represented in a product) that are not depicted in ~~current~~ land-use change products (Fuchs et al., 2015a). The larger the averaging unit (be it in terms of grid cell or time), the greater the discrepancy between gross and net changes becomes. Re-gridding of high-resolution (e.g., 5 arc minutes) land-use information to the TBM grid (~0.5 degree) thus entails additional loss of information on land-use transitions unless gross changes are considered.

These sub-grid dynamics have been shown to be of importance when modeling change of carbon and nutrient stocks in response to land-use change in recent TBM studies (Bayer et al., 2017~~in press~~; Fuchs et al., 2015b; Stocker et al., 2014; Wilkenskjeld et al., 2014). For example, Bayer et al. (2017~~in press~~) found the global cumulative land-use carbon emission to be ~33 % higher over the time period 1700-2014. Stocker et al. (2014) likewise report increased carbon emissions in recent decades and for all RCPs when accounting for shifting cultivation and wood harvest. Similarly, Wilkenskjeld et al. (2014) found a 60 % increase in the annual land-use emission for the historical period (1850-2005) and a range of 16-34 % increase for future scenarios, when accounting for gross changes. Recently, Arneth et al. (2017) demonstrated uniformly larger historical land-use change carbon emissions across a range of TBMs when shifting cultivation and wood harvest were included, which has implications for understanding of the terrestrial carbon budget as well as for estimates of future carbon mitigation potential in regrowing forest.

Except for such sensitivity studies, gross changes have hardly been considered so far in land use – climate interaction studies (a notable exception being Shevliakova et al., 2013), mainly due to two reasons. First, gross change estimates have not been available until recently. Deriving estimates of historical and future gross change is a difficult task, since gross changes vary with spatial and temporal scale (Fuchs et al., 2015a), i.e. they are dependent on the scale of the underlying net change product used for modeling and to what extent gross change processes are included in the individual land-use change models. Second, the implementation of bi-directional changes below the native model grid often entails substantial technical modification to TBM structure, meaning that many TBMs are currently not ready to include information on gross changes or only started recently to include it.

3.2 Example: Gross changes due to re-gridding in the CLUMondo model

To illustrate the amount of land-use and land-cover changes that might be missed in net representations, we conducted an analysis based on the output of a dedicated high-resolution LUCM (CLUMondo; 5 arc minutes spatial resolution; Eitelberg et al., 2016; Van Asselen and Verburg, 2013). We tracked all changes between five land-use and land-cover categories (cropland, pasture, forest, urban, and bare) at the original resolution over the~~a~~ time period ~~of 40 years~~2000 to 2040. Aggregating to ca. 0.5 degree resolution allowed to differentiate the gross area from the net area affected by change (see Supplement S2.2 for methodological details). The results, shown in Figure 3, indicate that gross changes are substantially higher than net changes all over the globe, including the temperate zone and high latitudes. It has to be noted that Figure 3~~Figure 3~~ is only based on one realization of a single LUCM, i.e. not necessarily representing the full extent and spatial pattern of global scale gross changes. The analysis only depicts the loss of information while re-gridding from 5 arc minutes to 0.5 degree resolution. Thus, bi-directional changes below the spatial resolution of the original data are~~is~~ still not captured.

3.3 Current approaches to provide gross change information: LUH and analysis of empirical data

To provide estimates of gross change, the land-use change modeling community currently follows two different approaches. First, Hurtt et al. (2011), within the framework of LUH, propose a matrix that provides explicit transitions between cropland, pasture, urban, and natural vegetation. Sub-grid scale information is added to net transitions (that are derived from historical or projected land-use data and referred to as 'minimum transitions') through assumptions about the extent of shifting cultivation practices and the spatial pattern of wood harvest. In each grid cell, where shifting cultivation appears according to a map of Butler (1980), an average land abandonment rate is added to each transition from and to agricultural land. In LUH2 an updated shifting cultivation estimate based on the analysis of Landsat imagery will be included and replace the aforementioned simple assumption (Lawrence et al., 2016). Wood harvest is regarded as gross change, if the wood harvest demand from statistics (historical) or IAMs (future) is not met by deforestation for agricultural land in the net transitions or the GLM model is run in a configuration where deforestation for agricultural land is not counted towards wood harvest demand.

The second approach derives gross/net ratios and a transition matrix directly from empirical data such as historical maps or high-resolution remote sensing products. These ratios can be subsequently applied to existing historical or future net representations to provide estimates of additional area affected by change (Fuchs et al., 2015a).

3.4 Open issues in the current approaches

The LUH gross transitions account for some aspects of gross changes. However, the values are dependent on what one includes in the definition of gross changes and are based on overly simplistic assumptions. Most of the gross transitions appear in parts of the tropics, where shifting cultivation is assumed to be an important agricultural practice (Bayer et al., 2017~~in press~~; their Figure S1). Gross changes outside of these areas are mainly related to wood harvest, i.e. the (additional) area deforested to meet external wood harvest demands. Although these are regarded as gross changes in some literature (e.g., Hurtt et al., 2011; Stocker et al., 2014), we argue that wood harvest not leading to an actual areal change of land-cover (e.g., forest to cropland) should be rather referred to as land management than gross change. Excluding wood harvest from the LUH data restricts the occurrence of gross changes to the areas of shifting cultivation. However, our analysis of CLUMondo output (Figure 3), along with the European analysis of Fuchs et al. (2015a), suggests substantial amounts of gross changes (below the 0.5 degree LUH grid) also in the temperate zone and the high latitudes. Consequently, the LUH approach heavily depends on the resolution of the original land-use data (provided by IAMs or historical reconstructions) and their ability to represent land-use change dynamics on a sub-grid scale.

The data-based approach avoids the process uncertainty which hinders high-resolution model projections of land use, but is limited to the time period where empirical data through remote sensing is available. Additional sources such as historical land-use and land-cover maps and statistics (Fuchs et al., 2015c) may contribute to cover ~~larger~~ longer time periods, although with limited spatio-temporal resolution and spatial coverage, and an associated increase in uncertainty. It is thus difficult to develop multi-century reconstructions or future scenarios including gross changes using data-based approaches, since the derived gross/net ratios are only valid for periods of data coverage and are expected to change over time (Fuchs et al., 2015a).

4 Challenge III~~3~~: Allocation of managed land in TBMs

4.1 Background and emergence

The LSMs in most Earth System Models (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 et al., 2013; de Noblet-Ducoudré 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). Thus, the early TBMs were not able to sufficiently account for anthropogenic activity on the land surface and consequently the impact of land use on climate and biogeochemical cycles (Flato et al., 2013). However, over the last decade, representation of human land-cover change, and also some land management aspects, have increasingly been added to these models, albeit with levels of complexity which vary from crops as grassland to more detailed 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). However, since TBMs do not include representations of human activity as a driver of changes on the land surface, information about the extent and exact location of managed land is required from external data sources such as IAMs or LUCMs.

IAMs and LUCMs usually provide land-cover information (e.g., forest, grassland, shrubland) along with land-use information (e.g., cropland and pasture). However, as modeling changes in natural vegetation type is one of the primary functions of many TBMs, only land-use information has been used in the LUH (Hurtt et al., 2011). Hence, TBM 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, which we show as an illustration in Table 1~~Table 1~~ for a non-exhaustive list of models. The decision is important as it impacts the distribution of the natural 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 (Reick et al., 2013). For example, new cropland expanding on forest would lead to a large and relatively rapid loss of ecosystem carbon due to deforestation, while cropland expanding on former grassland would have a less immediate impact on ecosystem carbon stocks due to the long time lag (years to centuries) for the resulting changes in soil carbon to be realized (Pugh et al., 2015). ~~through soils.~~ Likewise, the albedo and partitioning of energy differs strongly between forest and grassland land covers (Mahmood et al., 2014; Pielke et al., 2011). In the following sections we illustrate, based on literature review and analysis of empirical and modeled data, that the previously described simple allocation algorithms, applied globally, within TBMs do not account well for the spatio-temporal variation of land-use and land-cover change.

4.2 Spatial heterogeneity of cropland transitions – empirical evidence

Table 2~~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) shrubland systems to be the main source of expanding agricultural land, followed by low productivity grasslands and forests (Figure 4~~Figure 4~~a). 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 4~~Figure 4~~b). 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 show, 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. 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., 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. Gibbs et al. (2010)~~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. Grasslands have been detected as the main source of agricultural land in Northern China, e.g., by Li (2008), Liu et al. (2009) and Zuo et al. (2014), while in the Yangtze River basin woodlands contribute most (Wu et al., 2008) (Table 2~~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 agricultural change dynamics varies across world regions and a single global algorithm to replace natural vegetation by managed land in TBMs is likely to be overly simplistic.

4.3 Example: Spatial heterogeneity of cropland transitions in the CLUMondo model

As it is not possible to compare the land-use allocation strategies of TBMs with historical change data at global scale due to the lack of accurate global land-use and land-cover products (though ~~better~~ products with higher resolution (up to ~30m), more frequent temporal coverage, and increasing thematic detail are just emerging; Ban et al., 2015), we additionally tested to what extent cropland expansion simulated by the land-use change model CLUMondo (Eitelberg et al., 2016; Van Asselen and Verburg, 2013) represents one or more of the simplified algorithms currently considered in TBMs (Table 1~~Table 1~~).

CLUMondo models the spatial distribution of land systems over time, instead of land use and land cover directly. Land systems are amongst others characterized by a mosaic of land use and land cover within each grid cell. The land systems are allocated to the grid in each time step 'based on local suitability, spatial restrictions, and the competition between land systems driven by demands for different goods and services' (Eitelberg et al., 2016; Van Asselen and Verburg, 2013). Thus, the determination of the source land use or land cover upon cropland expansion can be interpreted as a complex algorithm taking into account external demands, the land-use distribution of the previous time step, local suitability in a grid cell and neighborhood effects (i.e., cropland expansion in a grid cell also depends on the availability of suitable land in the surrounding grid cells). This strategy differs from the one in TBMs in a way that not one simple rule is applied to each grid cell equally, but accounts for the spatial heterogeneity of drivers of land-use change.

In order to compare the sources of cropland expansion in CLUMondo to the globally applied rules in TBMs, we reclassified the outputs of the same~~a~~ CLUMondo simulation utilized in section 3.2 (FAO3D; Eitelberg et al.; 2016) according to their dominant land-use or land-cover type to derive transitions (Table S6) and classified the changes within each ca. 0.5 x 0.5 degree grid cell as either grassland first, forest first, proportional, or a complex reduction pattern (Table 3; Figure S2-3 and additional explanation in Supplement S2.4). Additionally, a grid cell was labeled 'undefined', if grassland or forest was not available in the source map.

Figure 5~~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 of cropland expansion in a detailed land-use change model. The majority of grid cells with substantial cropland expansion (> 10 % of grid cell area) where we could detect an algorithm (i.e., the grid cell was not classified 'undefined') show a complex reduction pattern of the remaining land-use and land-cover categories, i.e., any algorithm applied to these grid cells in a TBM could be seen as equally good or bad. The remaining grid cells account only for 24-27 % globally. 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.

4.4 Current approach to provide allocation information: the transition matrix

In CMIP5, most ESMs implemented a proportional reduction of natural vegetation rather arbitrarily due to reasons of simplicity or internal model constraints; others converted grassland preferentially and/or treated croplands differently from pastures upon transformation (de Noblet-Ducoudré et al., 2012). However, none of them depicts the complex interplay~~s~~ of biophysical and socioeconomic parameters leading to a heterogeneous spatial pattern of land-use change within the coarse grid-resolution used in ESMs. As we have shown in the previous sections, empirical evidence and land-use change models suggest that this complexity is poorly represented by simplistic, globally applied, algorithms. The efforts of LUH thus included the provision of a transition matrix, i.e. the explicit identification of source and target categories between agricultural land and natural vegetation at the grid cell level. For each annual time step, the exact fraction of a grid cell that has changed from one land-use category to another is determined, thus providing the option to replace the simple allocation options by detailed information about land-use transitions within each grid cell (Hurtt et al., 2011).

4.5 Open issues of transition matrices

The provision of transition matrices, however, generally brings up a sequence of additional challenges, which we illustrate using the example of LUH in the following. First, the decision which land-cover type should be replaced upon cropland or pasture expansion (or introduced in case of abandonment) is in fact only shifted from the TBM community to the IAM/LUCM community and the accuracy of the transitions are heavily dependent on the sophistication (i.e., knowledge about and depiction of land-use change drivers and processes at the grid scale) of the land-use allocation algorithm in the original model providing the land-use data. Many current models simulate land-use changes on a world-region level and downscale these aggregated results to the required grid cell level (Hasegawa et al., 2016; Schmitz et al., 2014). In the LUH approach these downscaled data are used to derive the minimum transitions between agricultural land use and natural vegetation. Additional assumptions are made to allocate changes in land-use states to explicit transitions, not accounting for the spatial and temporal heterogeneity of the multiple drivers of land-use change. For example, urban expansion is applied proportionally to cropland, pasture and (secondary) natural vegetation. Upon transitions between natural vegetation and agricultural land, choices in the model configuration have to be made, whether primary or secondary land is converted preferentially. These choices are similar to the grassland or forest first reduction algorithms applied in TBMs.

Moreover, due to the lack of empirical long-term, high-accuracy land-use and land-cover change information and the inconsistencies between agricultural land-use data and land-cover information from satellites, global IAMs and LUCMs are rarely evaluated against independent data (Verburg et al., 2015). It is thus not clear yet to what extent the spatial land-use patterns simulated by these models and provided to LUH represent a good estimate of real past and future land-use changes. In consequence, transitions derived from these modeled time series are necessarily uncertain.

Hence, it is evident that more and improved empirical information on land-use transitions is required to improve land-use change modeling, and to estimate the natural systems at risk under agricultural expansion. However, the specific problem of allocating new agricultural land in DGVMs and LSMs 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 LSMs coupled to 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 and differences in historical reconstructions (as discussed in section 2), fractions of agricultural land on a grid-scale are subject to~~necessarily show~~ differences between the background map and the external land-use dataset. Consequently, the PFT composition outside the prescribed agricultural land can represent either the real heterogeneity in natural vegetation, or represent 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 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 Recommendations for improving the current LULCC representation across models

5.1 Tackling uncertainties in the harmonization

The Land Use Harmonization (Hurtt et al., 2011) has allowed to include anthropogenic impacts on the land surface for the first time in the CMIP5 climate change assessments. As we have shown in section 2, three major sources of uncertainty, which include the uncertainty about land-use history, inconsistencies in present-day land-use estimates, and structural differences across IAMs and LUCMs, are poorly addressed through the almost exclusive implementation of the LUH dataset within the climate modeling community. A~~and a~~ wider range of harmonized time series is therefore likely to substantially ~~impact~~ influence the outcomes of studies on land use - climate interactions. The actual impact of alternative harmonized time series on carbon cycle (and other ecosystem processes) and climate has never been tested, mainly due to the lack of alternative provision of such products. One would need a multi-model ensemble design t~~T~~o properly account for and disentangle the individual contribution of different historical reconstructions, the multitude of present-day land-use products and varying future land-use change modeling approaches.~~, one would need a multi model ensemble design.~~ Different future scenario models would need to be connected to different instances of historical reconstructions, both constrained by different plausible realizations (i.e., based on previously published, peer-reviewed approaches) 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 land-use data into climate models and allow for testing climate model sensitivity to different realizations of land-cover and land-use information.

The high computational demands of complex ESMs probably do not allow for multiple runs including all the uncertainties in land-use forcing. However, to derive robust results from climate model intercomparisons, a sufficient quantification of uncertainty in the land-use forcing dataset is urgently required. If this proves impractical through ESM simulations, we recommend to utilize less computational expensive models such as DGVMs and offline LSMs to assess the full range of uncertainty and determine a limited set of simulations, which appears to significantly affect biogeochemical cycles and climate. These can be subsequently used to test the uncertainty range in ESMs.

Simultaneously, we suggest that the land-use and remote-sensing communities should engage to reduce uncertainties in land-use and land-cover products by:

(1) Developing diagnostics for the evaluation of land-use reconstructions based on satellite data and additional proxy data such as pollen reconstructions (Gaillard et al., 2010) or archeological evidence of early land use (Kaplan et al., 2016).

(2) Developing systematic approaches to evaluate results of land-use change models against independent data sources, utilizing the full range of high-resolution satellite data (e.g., the Landsat archive and the European Sentinel satellites), reference data obtained from (sub-)national reporting schemes under international policy frameworks (e.g., Kohl et al., 2015) and innovative methods such as volunteered geographic information and crowd-sourcing (Fritz et al., 2012). Although satellite data is also not directly measured empirical data, but goes through a mathematical conversion process prior to a final land-cover product, it can improve representations of present-day land cover. If not yet possible at the global scale due to the limitations discussed in ~~our~~ section 2, we recommend the implementation of regional

scale evaluation schemes using smaller scale, high accuracy remote sensing products as a~~may be a good~~ starting point for later integration into global applications.

5.2 Gross change representations

The full extent of gross changes is still not well understood (see section 3). Thus, the land-use community should explore high-resolution remote-sensing imagery regarding their ability to derive gross change estimates and improve understanding of sub-grid dynamics which are not yet captured by their models. 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, should receive special attention. Based on such analyses, multi-century reconstructions and projections for climate and ecosystem assessments could be enhanced for at least the satellite era.~~,~~ ~~while a~~As models extend further into the past, the detailed information could be gradually replaced by model assumptions, supported by additional reference data such as historical maps and statistics.

5.3 Transition matrix from empirical data

Explicit information of land-use transitions instead of annual land-use states is essential for questions regarding carbon and nutrient cycling. We argue that simple, globally applied, assumptions about these transitions or the shift of the responsibility from TBMs to land-use models may not solve the problem (section 4). Thus, the development of dedicated transition matrices increasingly based on empirical data (as soon as new products emerge) and sophisticated land-use change allocation models, which account for the spatio-temporal heterogeneity of land-use change drivers is essential.

Simultaneously, TBMs must ~~have to~~ ensure to use the full detail of information provided by the implementation of explicit transition information in their land modules. Due to internal model structure proportional reduction of PFTs need to be applied in models with internally simulated dynamic vegetation. However, we recommend the utilization of explicit transition information ~~should be used~~ to further evaluate discrepancies between the potential natural vegetation scheme and LULCC data provided by LUCMs and IAMs.

6 Outlook: towards model integration across disciplines

The 'ways forward' listed in the previous section will only be the first stage of a process towards improved LULCC representation in climate change assessments. ~~For questions regarding the impact of anthropogenic land-use activity on climate, r~~Rather than improving de-coupled data products and models on an individual basis~~,~~ and connecting them 'offline' through the exchange of files, we argue that ~~advancement of the 'offline' coupling strategy would also be required. L~~land use, land cover and the climate system need to be studied in an integrated modeling framework. As we have shown in this paper, most of the challenges and related uncertainties originate in the disparate disciplinary treatment of the individual aspects. Although sophisticated models have been developed during the past decades within each community, the current 'offline' coupling seems~~is~~ overly limited, accumulating an ~~very large~~increasing level of uncertainty~~ies~~ along~~in~~ the modeling chain.

Integration of these different types of models, where anthropogenic activity on the land system is considered as an integral part of ESMs, instead of an external boundary condition, might help to reduce these uncertainties, although it will certainly further complicate the interpretation of model responses. For example, Di Vittorio et al. (2014) report preliminary~~first~~ results of the iESM (Collins et al., 2015), an advanced coupling of an IAM and an ESM, implementing two-way feedbacks between the human and environmental systems, and show how this improved coupling can increase the accuracy of information exchange between the individual model components. In the long term, additionally including behavioral land system models (e.g., agent-based approaches) in the coupling, may provide further understanding of possible land-climate-society feedbacks (Arneth et al., 2014; Verburg et al., 2015), since the current modeling chain rarely accounts for the complexity of human-environmental relationships and feedbacks (Rounsevell et al., 2014).

Acknowledgements

The research in this paper has been supported by the European Research Council under the European Union's Seventh Framework Programme project LUC4C (Grant No. 603542), ERC grant GLOLAND (No. 311819) and BiodivERsA project TALE (No. 832.14.006) funded by the Dutch National Science Foundation (NWO). This research contributes to the Global Land Project (www.globallandproject.org). This is paper number 26 of the Birmingham Institute of Forest Research.

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Table 1: Examples of allocation rules at grid cell level to implement agricultural land in different TBMs

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 thatreport~~ing~~ 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

Table 3: Definition of classified algorithms in the CLUMondo exercise (section 4.3). CLUMondo data were preprocessed as described in the text and Supplement S2.4. Each ca. 0.5 x 0.5 degree grid cell was assigned a label according to the distribution of changes seen in the higher resolution (5 arc minute) CLUMondo data. Land types according to the reclassification of CLUMondo land systems shown in Table S6; mosaics refer to a mixture of vegetation within a grid cell (e.g. forest and grassland).

Label	Within a 0.5 x 0.5 degree grid cell…
UNDEFINED	…*forest* or *grassland* were not available for conversion to cropland.*
UNVEGETATED FIRST	…*urban* or *bare* were converted to cropland, although vegetation was available.
FOREST FIRST	...*forest* was predominantly converted to cropland, although *grassland* and *mosaics* were available.
GRASSLAND FIRST	…*grassland* was predominantly converted to cropland, although *forest* and *mosaics* were available.
PROPORTIONAL	(1) …*mosaics* were predominantly converted to cropland, although *forest* and *grassland* were available
	(2) …*forest* and *grassland* were converted proportionally to cropland.
COMPLEX	...*forest, grassland*, and *mosaics* were simultaneously converted without a preference to one of the classes or proportional reduction.

* If one of the two classes is not available for conversion, either of the preferential algorithms (unvegetated, forest or grassland first) could be correct, but not executed because of the lack of the source that should be converted ‘first’.

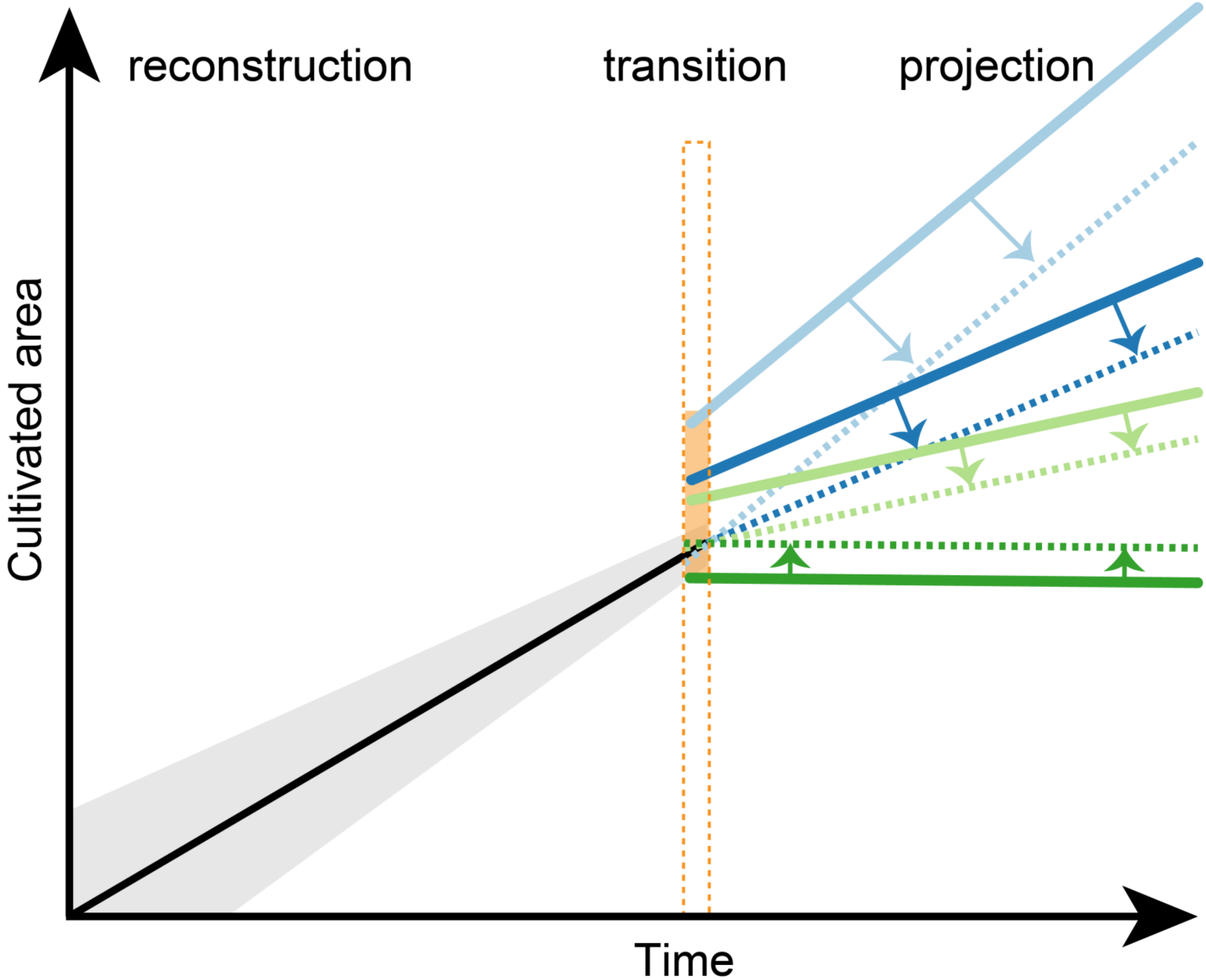


Figure 1: Simplified scheme of the harmonization process. Future projections from different models (solid colored lines) are smoothly connected (dashed colored lines) to the HYDE historical reconstruction (black line; grey shading represents the uncertainty range of LULCC history). Uncertainty about extent and pattern of current land use and land cover (orange shading) is removed~~,~~ and 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).~~

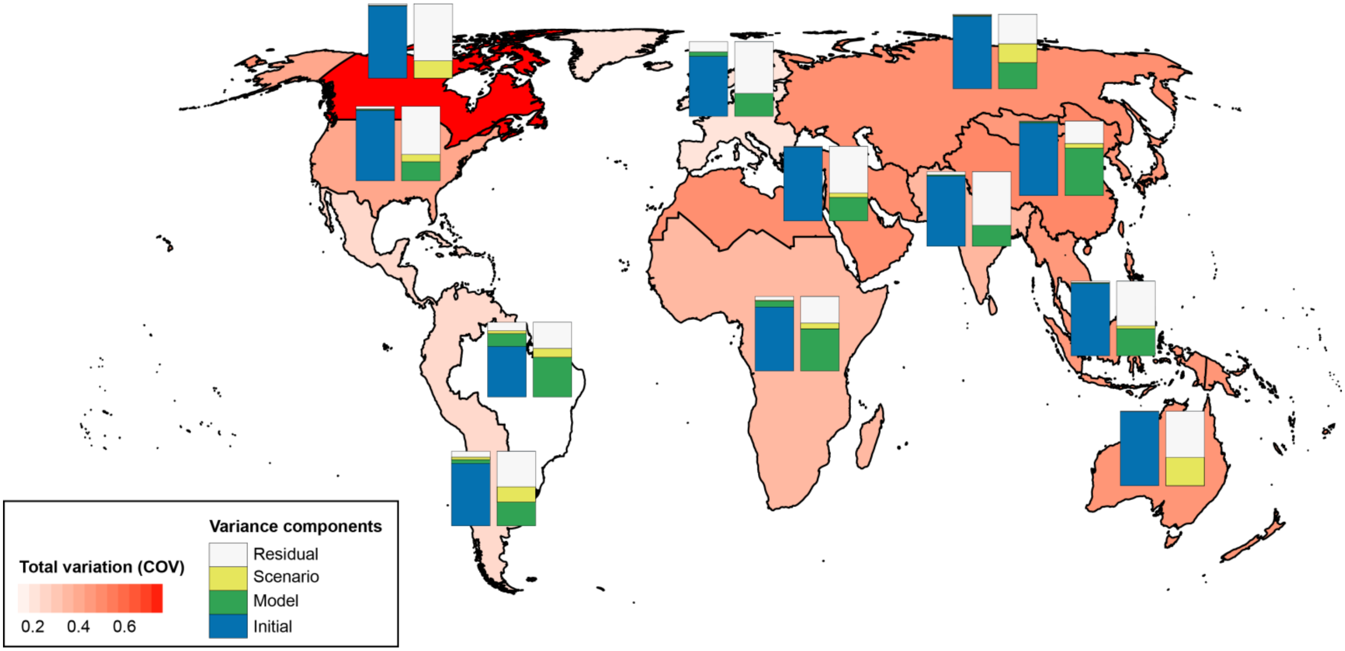


Figure 2: Variation (expressed as coefficients of variation) of pasture projections for 12 world regions in 2030 (shading of the background map). The left bar plots show the relative contribution (in %) ~~and relative attribution of total variation to~~ of initial variation (pasture area in relation to values reported by FAOSTAT (2015) for the year 2010), model related variation (model type and spatial configuration) and scenario ~~parameters~~ related variation to the total variation in a region~~(bar plots)~~. ~~Left bar plot per region including initial variation,~~ The right bar plots show the relative contribution (in %) of variance components to the part of total variation that cannot be attributed to initial variation. ~~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 Supplement S2.1 (Table S2) and in Alexander et al. (2016).

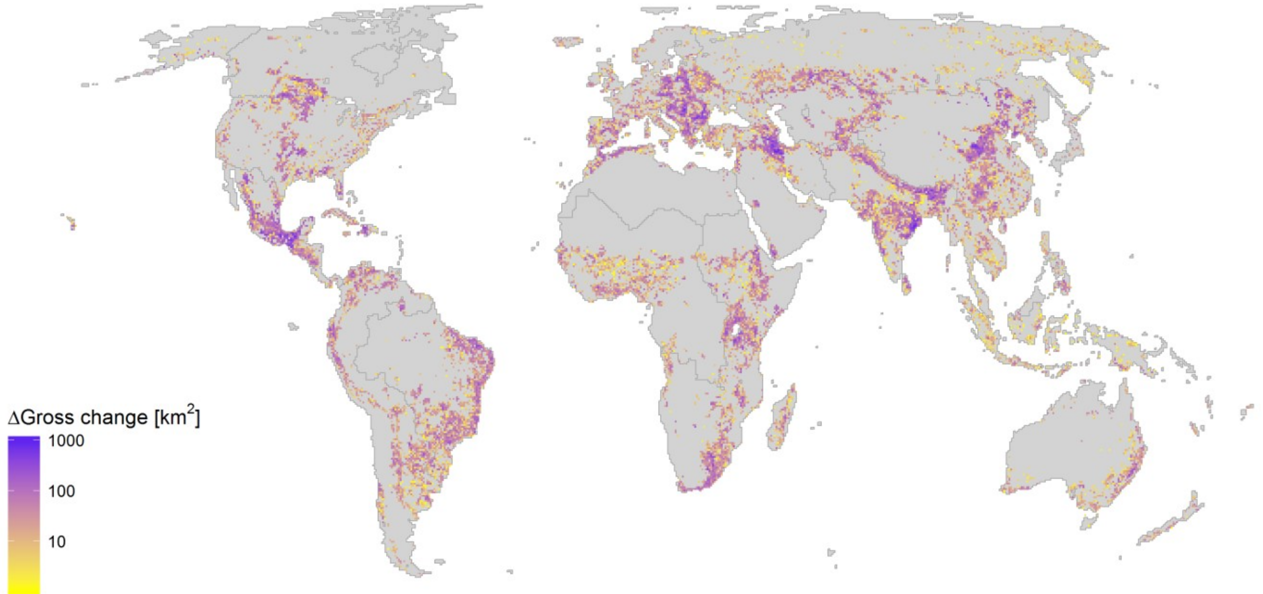


Figure 3: Difference between gross versus net area affected by change at grid cell level (ca. 0.5 x 0.5 degree) as shown by one realization of a single LUCM ~~the (~~(CLUMondo; ~~model (~~FAO 3 demand scenario). Areas affected by net or gross change have been accumulated over a 40 year simulation period (2000-2040). 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 (Supplement S2.2; Figure S1). 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.

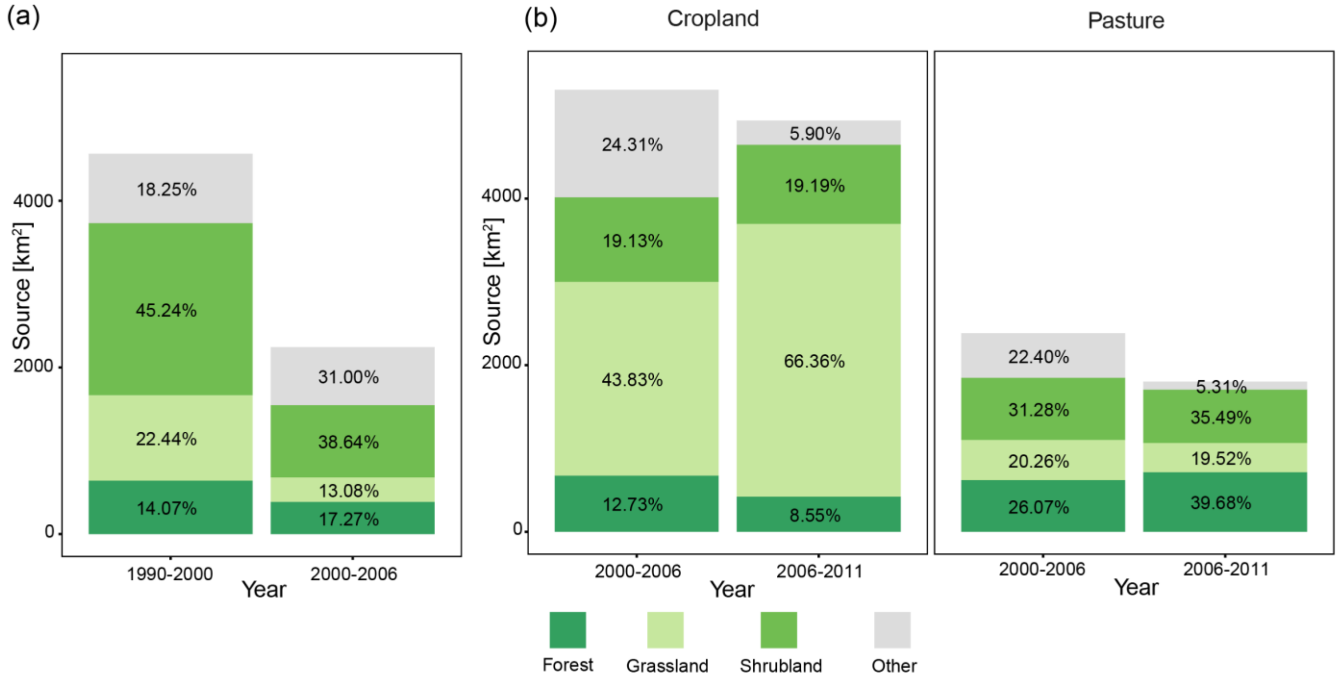
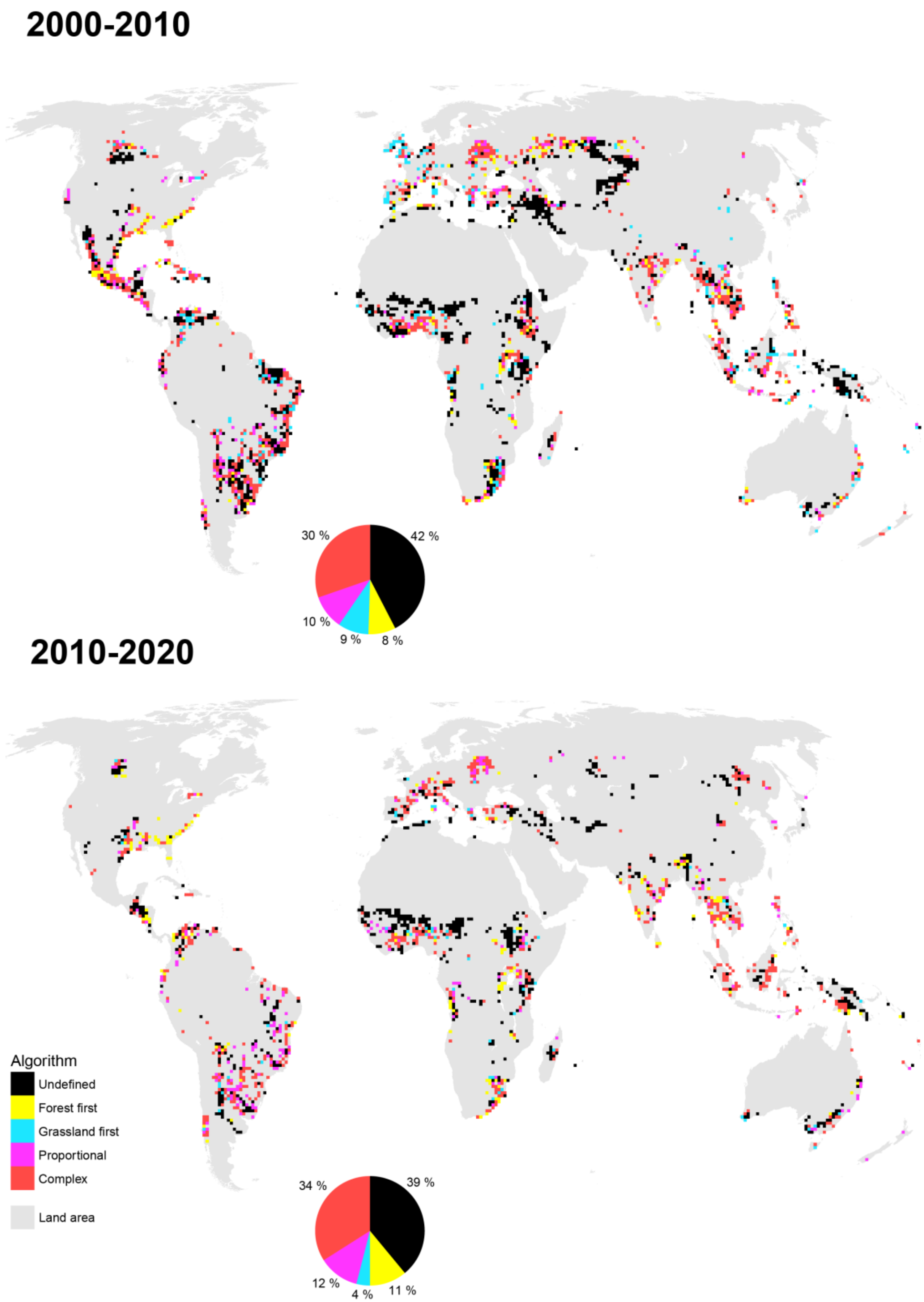
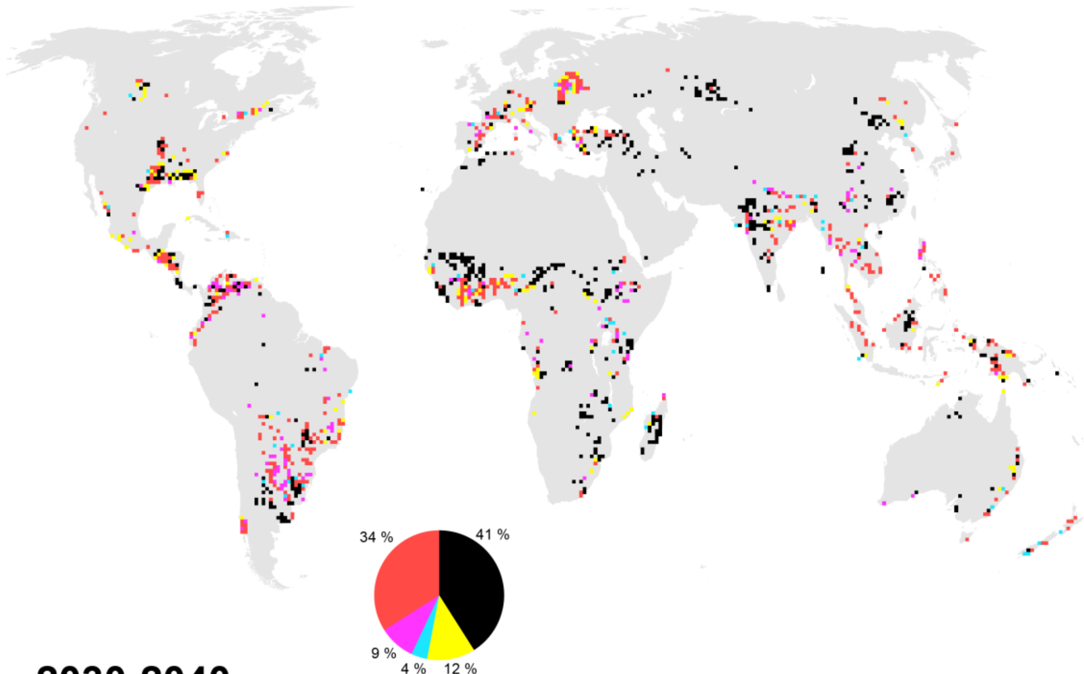


Figure 4: Sources of agricultural land (cropland and pasture combined) for two time periods in Europe based on the CORINE land cover data (a) and sources of cropland and pasture for two time periods in the USA based on the NLCD land cover data (b) (Supplement S2.3, Table S3). Changes between different agricultural classes are not considered as expansion of agricultural land. Aggregation of CORINE and NLCD legends to forest, grassland and shrubland according to Tables S4-5. Other includes urban land, wetlands, water and bare land.


2000-2010
30 %
42 %
10 %
9 %
8 %
2010-2020
Algorithm
Undefined
Forest first
Grassland first
Proportional
Complex
Land area
34 %
39 %
12 %
4 %
11 %

2020-2030



2030-2040

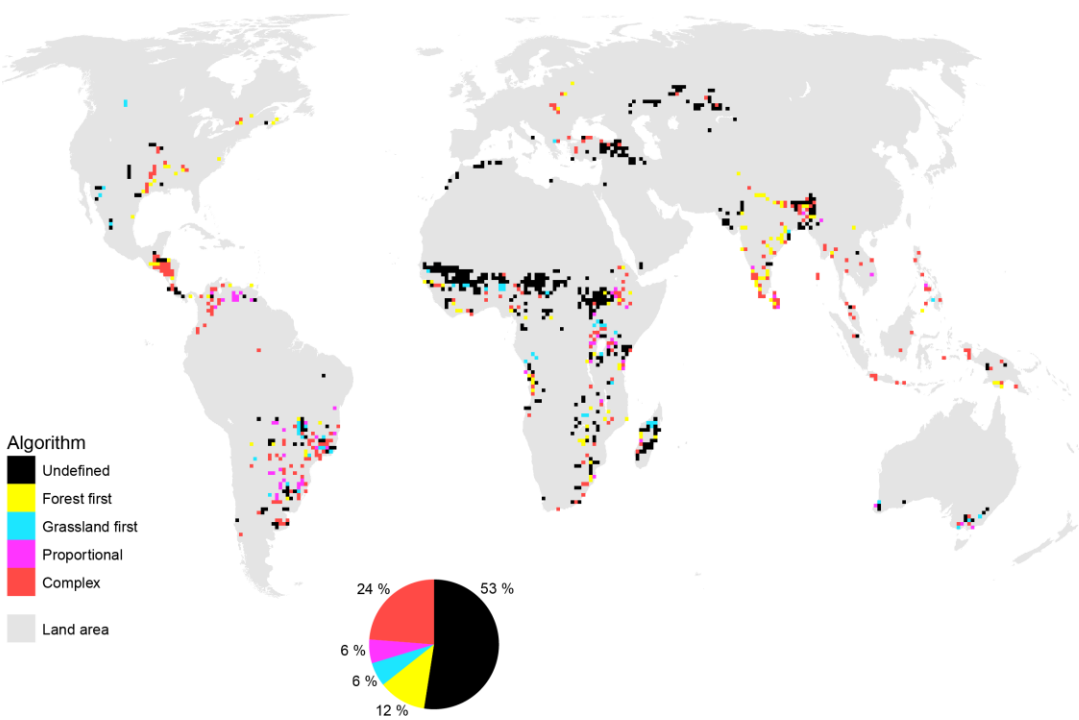


Figure 5: Transitions from natural vegetation to cropland as shown by the CLUMondo model (FAO 3 demand scenario) from 2000 to 2040 in decadal time steps. Colored grid cells represent areas with at least 10 % of cropland expansion within a ca. 0.5 x 0.5 degree grid cell. Grid cells are classified to forest first (yellow), grassland first (cyan), proportional (magenta) and complex (red) reduction algorithm as described in the text (for details see Supplement S2.4~~SI~~). Black grid cells denote areas where the validity of none algorithm could be detected. Grid cells classified to unvegetated first (Table 3) are not shown due to very small contribution (< 0.1 %). 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).

Supplementary Information

S0 List of acronyms

CFT	Crop Functional Type
CMIP5 / CMIP6	Coupled Model Intercomparison Project Phase 5 / 6
DGVM	Dynamic Global Vegetation Model
ESM	Earth System Model
FAO	Food and Agricultural Organization of the United Nations
GLM	Global Land-use Model (Hurtt et al., 2006)
HYDE	History Database of the Global Environment (Klein Goldewijk et al., 2011)
IAM	Integrated Assessment Model
IPCC	Intergovernmental Panel on Climate Change
LSM	Land Surface Model
LUCM	Land-Use Change Model
LUH	Land Use Harmonization (Hurtt et al., 2011)
LULCC	Land-Use and Land-Cover Change
PFT	Plant Functional Type
RCP	Representative Concentration Pathway
SSP	Shared Socioeconomic Pathway
TBM	Terrestrial Biosphere Model

S1 Overview of historical land use reconstructions

Several approaches have been published within the last two decades to reconstruct the history of human utilization of land to meet their needs of food, fiber and space for settlement on a global scale. Depending on the objective of the particular study they cover different time periods, spatial resolutions and methods of reconstruction (Table S1~~Table S1~~). In the following paragraphs we summarize the methodologies of four spatially explicit historical reconstructions. For details, please see the original publications.

HYDE

The History Database of the Global Environment (HYDE) was originally developed by Klein Goldewijk (2001), covering spatially explicit historical population estimates and land-use patterns for the past 300 years at 0.5° resolution. Several updates and extensions led to version HYDE 3.1, which was used for the Land Use Harmonization (LUH) in CMIP5 (Klein Goldewijk et al. (2011); this is the version we refer to here and in the article). Recently there has been a update to version HYDE 3.2, which now covers a time period from 10 000 BC to 2015 AD at 5 arcminute spatial resolution and includes further agricultural management layers (such as irrigation) (Klein Goldewijk, 2016).

The underlying principle of the HYDE reconstruction is the relationship between human population and agricultural activity expressed in a per capita use of cropland and pasture area, leading to a spatial dependency of land-use activities to human settlements. Klein Goldewijk et al. (2010) first derived time series of population numbers from a vast number of sources on a subnational or national scale (depending on data availability, e.g. McEvedy and Jones (1978), Livi Bacci (2007) and Maddison (2001); see Klein Goldewijk (2001) and Klein Goldewijk et al. (2011) for details) and translated them to population density maps using patterns from Landscan (2006) for recent time and a combination of suitability maps for historic time. For the period 1961-2000, the per capita use of cropland and pasture was calculated from FAO statistics on country or subnational level. Prior to 1961 the per capita land use numbers were dynamically estimated country by country following Ruddiman and Ellis (2009) and adjusted accounting for low population numbers (= higher per capita land use), but also limitations in technology and a maximum area of land that can be cultivated by a subsistence farmer (= lower per capita land use). Using the per capita usage of cropland and pasture to estimate cropland and pasture total areas on a (sub-)national level for every time step, spatial allocation of the total areas to the 5 arcminute grid was implemented using two sets of weighing maps: On the one side, present distribution of cropland and pasture was derived by integrating FAO statistics and additional subnational statistics for the USA and China with two satellite derived land cover products representative for recent time (DISCover version 2, Loveland et al. (2000); GLC2000, Bartholome and Belward (2005)). The weighing map for historical time, on the other side, was constructed by combining the earlier described population density maps and different biophysical suitability parameters, namely soil quality, distance to rivers, steepness of terrain and thresholds for annual mean temperature. Both maps were subsequently used to allocate (sub-) national totals of agricultural areas to specific grid cells, while the influence of the historic map gradually increases when going further into the past.

Ramankutty and Foley (1999)

Ramankutty and Foley (1999) apply a hindcast modeling technique to derive spatial patterns of cropland on a global scale for the period 1700-1992. The original reconstruction did not inlcude pasture areas. A revised and updated version[1] covers the years up to 2007 both for cropland and pasture at 5 arcminute spatial resolution. The starting point for the reconstruction is

[1] The updated version is based on the global cropland and pasture maps published in Ramankutty et al. (2008) and the methodology described in Ramankutty et al. (1999). There was, however, no additional publication related to the updated dataset. The dataset was available from http://www.geog.mcgill.ca/nramankutty/Datasets/Datasets.html, but the webpage has been recently removed.

represented by the integration of satellite derived land cover products (DISCover in original data set (Loveland and Belward, 1997); BU-MODIS (Friedl et al., 2002) and GLC2000 (Bartholome and Belward) 2005 in the updated version) and FAO statistics. The national and subnational totals of cropland and pasture were calibrated to the spatial distribution of cropland and pasture areas in the earth observation product applying a linear fitting approach. This resulted in a global 5 arcminute resolution cropland and pasture map for the year 2000, representing the spatial distribution of cropland and pasture areas (Ramankutty et al., 2008). In a second step, a comprehensive data base of historical agricultural areas on (sub-)national level was compiled from different sources. FAO statistics were used for the time period from 1961 to the end point. Prior to 1961 the data base first accounts for census data. Whenever census data were not available, cropland conversion rates of Houghton and Hackler (1995) were applied to the cropland map of Richards (1990) for 1980 with some regional adjustments to avoid unrealistic agricultural areas in particular regions. The spatial allocation of the cropland areas is implemented by applying a simple hindcast model, which preserves the cropland pattern of the start map within each unit of the inventory data base for the whole time period to 1700. For that a change factor between two subsequent years is calculated from the inventory database, dividing the cropland area in the target year by the cropland area in the starting year, which is thereafter applied to each grid cell within a unit.

Pongratz et al. (2008)

Pongratz et al. (2008) extended the reconstruction of Ramankutty and Foley (1999) back to 800 AD and presented the first consistent and spatially explicit cropland and pasture reconstruction for pre-industrial times at the date of publication. For the period 1700-1992 the cropland time series is, apart from smaller regional adjustments and updates, the same than the Ramankutty and Foley (1999) data. Since they further had not published their pasture time series at that point, Pongratz et al. (2008) combined the pasture map for 1992 with change rates taken from the HYDE data base to extend it back to 1700. Unlike the pattern maintaining approach applied by Ramankutty and Foley (1999), pasture was spatially distributed around existing cropland while maintaining the pattern of total agricultural area rather than the individual shares of cropland and pasture to allow also for cropland expansion into pasture areas.

Based on this two time series covering the years 1700-1992, an extrapolation to 800 AD was applied on (sub)-national level, while using population data from McEvedy and Jones (1978) as a proxy for land-use change. Similar to HYDE, the simple measure of per capita usage of crop and pasture area was assumed to be the best approximation. However, in this case, per capita use was calculated from the 1700 maps and held constant for the whole period prior to 1700. Spatial distribution of agricultural areas was assumed to represent the patterns of 1700 for the period 800 to 1700. Besides, changes in agricultural patterns, e.g. following the European colonization in North and South America, were especially accounted for by altering the patterns in particular regions. Both time series were aggregated to a 0.5° resolution.

KK10

Kaplan et al. (2010) introduce a non-linear relationship between population numbers and area of forest clearance to calculate total areas affected by human land-use change. The basic assumption of this approach is a decreasing per capita land use over time due to intensification of already converted areas rather than expand land use to new areas when population densities increase. With the objective to build an empirical, non-linear model, population time series for the period 6050 BC to AD 1850 were compiled first. Data from McEvedy and Jones (1978) were utilized for the period 1000 BC to AD 1850 with some regional adjustments and subsequently extended back to 6050 BC by a modelling approach (Global Land USE and Technological Evolution Simulator (GLUES, see Lemmen (2009) and Wirtz and Lemmen (2003) for details). Population density was normalized to cultivatable land to prevent the model extending cropland areas into unsuitable land. A sigmoidal log-linear model was fitted to a set of empirical data from various European countries to derive a relationship between forest cover and population density accounting also for different stages of technological development over time (Kaplan et al., 2009). Concurrently, Kaplan et al. (2010) integrated different climatic and biophysical variables to indices of suitability for cropland and pasture on a 5 arcminute grid following a method of Ramankutty et al. (2002). Combining the regional level estimates of historical forest cover with the suitability datasets led to a spatially explicit representation of area affected by land-use change over time. The integration was done by allocating cropland to high quality and suitable areas first, followed by pasture. As the forest cover – population relationship originally was derived for Europe, it has been adjusted for tropical and boreal regions in the global approach by including a threshold of net primary production, where productivity of agricultural lands is higher and therefore demand for new land lower.

Table S1: Summary of historical LULCC reconstructions

Reference	Spatial resolution	Temporal coverage and resolution	Input data	Allocation
KK10, Kaplan et al. (2010)	5 x 5 arcminute	6050 BC to AD 1850, annual	population estimates, land suitability maps	based on non-linear population density – forest clearance relationship, high quality land cleared first
HYDE 3.1, Klein Goldewijk et al. (2011)	5 x 5 arcminute	10 000 BC to AD 2005, variable resolution	population estimates, FAO statistics, satellite derived products	dynamic per capita use of cropland and pasture; combination of weighing maps derived from satellite products, population and environmental parameters
Pongratz et al. (2008)	0.5 x 0.5 degree	AD 800 – AD 1992	adjusted Ramankutty and Foley (1999), HYDE 2.0, population data	constant per capita use of cropland & pasture prior to 1700, constant spatial pattern of agriculture prior to 1700
Ramankutty and Foley (1999)	5 x 5 arcminute	AD 1700 – AD 1992; update AD 1700 – 2007	census data and estimates of agricultural area, FAO statistics, satellite derived products	hindcast model, preserving agricultural pattern of 1992 within aggregated units

S2 Data and Methods

Several data and methods have been used to support our arguments in the manuscript and create the related tables and figures. To ensure readability we decided to provide methodological details in the Supplementary Information rather than in the main text of the manuscript. In the following we provide an overview of the data used, details of the data processing and how analysis was conducted. In each section heading we indicate the relation to the main text and the figures and tables that were derived from individual steps of analysis.

S2.1 Attribution of uncertainty in land use change projections (Section 2; Figure 2)

Multiple linear regression analysis followed by an ANOVA was used to decompose the variability of 43 projections of regional pasture areas for the year 2030 simulated by 11 global scale IAMs and LUCMs (Alexander et al., 2016; Prestele et al., 2016). Every individual projection has been parameterized according to 9 variables (Table S2~~Table S2~~) that characterize the model structure (model type classification, model resolution), the scenario (socioeconomic and climate scenario variables) and the initial condition (deviation of absolute pasture area from value reported by FAOSTAT (2015) in the year 2010) prior to the regression analysis. The modeled pasture area in 2030 was assumed to be a function of these 9 variables. To balance performance and complexity of the resulting regression model, variables were rejected using the Akaike information criterion (Akaike, 1973). Subsequently an ANOVA was conducted on the regression results to identify relative contribution of the variables to the total variation in the regression model of the 2030 pasture areas. The type II[2] sum of squares were calculated for each variable and divided by the total sum of squares. Subsequently, the relative contributions of the individual variables were summarized according to the grouping in Table S2. The residual term thus covers all variation that could not be explained by these 9 variables.

[2] Type II sum of squares have been used since they are not dependent on the order in which the variables are considered in the model, which has been shown suitable for unbalanced data as in our analysis (Langsrud, 2003). See Alexander et al. (2016) for details.

Table S2: Overview of variables used in the regression analysis and ANOVA (table adopted and modified according to Prestele et al. (2016))

Variable	Data type	Group
Initial condition delta	Continuous (deviation of model areas from FAO areas in 2010 (FAOSTAT, 2015)	Initial
Model type	Categorical (CGE, PE, Rule-based, Hybrid)	Model
Number of model cells (log)	Continuous	Model
CO_2 concentration 2100	Continuous	Scenario
Population 2100	Continuous	Scenario
GDP growth rate to 2100	Continuous	Scenario
Inequality ratio 2100	Continuous	Scenario
Technology change	Discrete (0=None, 1=Slow, 2=Medium, 3=Rapid)	Scenario
International trade	Discrete (1=Constrained, 2=Moderate, 3=High)	Scenario

S2.2 Derivation of gross vs. net changes due to re-gridding from a CLUMondo simulation (Section 3; Figure 3)

To identify the difference between net and gross changes due to re-gridding of high-resolution modeled land-use change information, we utilized data from a simulation of the CLUMondo model (Van Asselen and Verburg, 2013) based on the FAO 3 demand scenario (Eitelberg et al., 2016). These data are available at a 9.25 x 9.25 km regular grid (~5 arcminute) in an equal area projection and are based on the land system classification described in van Asselen and Verburg (2012). Land systems are characterized by land-cover composition, livestock numbers and land-use intensity. Each grid cell can thus be expressed as a mosaic of five LULC types (cropland, grassland, forest, urban, and bare) which varies with the world region. Upon a change from one land system to another, these characteristics also change.

We used the fractions of these five LULC types to track areal changes per grid cell at the original 9.25 x 9.25 km resolution over the whole simulation period (2000-2040). The total area changed at this resolution (sum of gains and losses for each LULC type) was assumed to be the gross changes in our analysis. In a second step, we aggregated the maps to ca. 0.5 x 0.5 degree and calculated the changes between two time steps. Due to bi-directional changes at the higher resolution (which offset each other) the total area affected by change at 0.5 x 0.5 degree resolution is usually smaller. The areal changes at 0.5 x 0.5 degree resolution were assumed to be the net changes in our analysis. By adding up the net changes and gross changes across all five LULC types and over the whole simulation period, we identified the amount of actually changed area that would be missed in a net change representation at 0.5 x 0.5 degree for this simulation (**Error! Reference source not found.**; Figure 3).

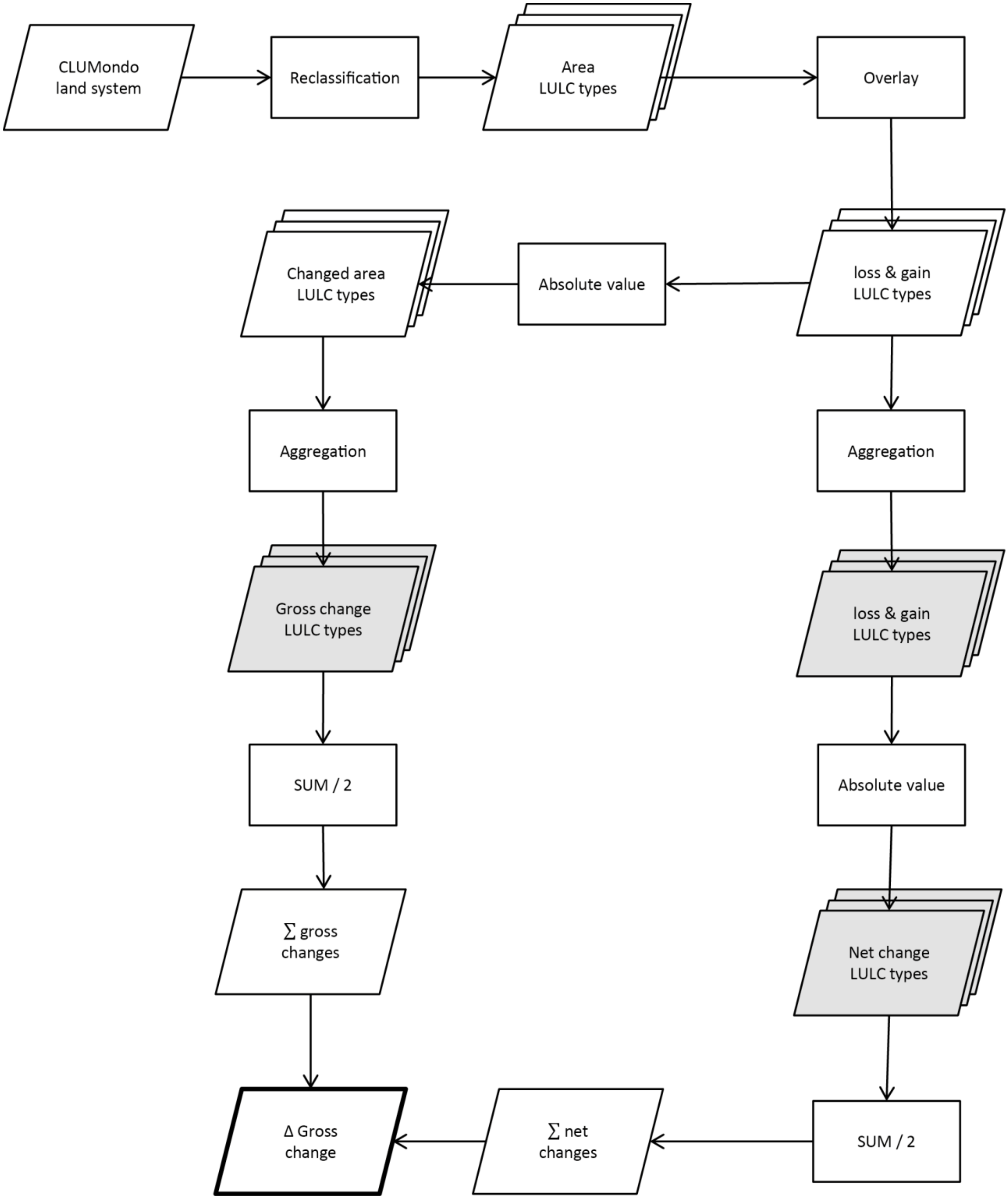


Figure S1: Preprocessing workflow of CLUMondo output for gross change analysis. Rectangles represent processing steps, parallelograms represent data. Grey shaded items emphasize aggregated data at ca. 0.5 x 0.5 degree resolution.

S2.3 Analysis of remote sensing products (Section 4; Figure 4; Table 2)

To derive dominant sources of cropland expansion from remote sensing products, we analyzed high resolution LULCC data from Europe (CORINE, 100 m spatial resolution) and North America (NLCD, 30 m spatial resolution) (Table S3~~Table S3~~). We downloaded CORINE data from http://land.copernicus.eu/pan-european/corine-land-cover. NLCD data were obtained through http://www.mrlc.gov/.

S2.3.1 Data: CORINE

CORINE was produced by computer assisted visual interpretation of satellite images processed on a country-by-country basis and subsequently merged to a comprehensive European database (EEA, 2007). It covers the years 1990, 2000, 2006 and most recently 2012 with different number of participating countries leading to different overlapping areas between the years. The land-cover classification was derived from different sensors dependent on the final year of the product (1990: Landsat-4/5 TM single date, 2000: Landsat-7 ETM single date; 2006: SPOT-4 and/or IRS P6 LISS III dual date; 2012: IRS P6 LISS III and RapidEye dual date). CORINE is provided at a spatial resolution of 100 m and 250 m in raster data format as well as in vector format. The minimum mapping unit is 25 ha. Besides the products for the years mentioned above, special LULCC products have been produced and are currently available for the periods 1990 to 2000 and 2000 to 2006. For the change products an enhanced minimum mapping unit of 5 ha was applied. The change products have been used for derivation of agricultural transitions in our analysis, thus covering all changes to agricultural areas larger than 5 ha between start and end year. All CORINE products are accompanied by a three level land-use and land-cover nomenclature varying in detail across the levels (Table S4). The first level only provides very general classes (e.g. artificial surfaces; agricultural areas; forests; etc.). The second level distinguishes 15 different categories and the highest detail is given by the 44 classes at level 3. For our analysis we used a merger of the different levels, as e.g. forests and shrubland could be only differentiated at level 2, while natural grassland could be only identified at level 3 (Table S4~~Table S4~~). See Bossard et al. (2000) for a detailed description of the legend and distinction of individual classes. Although CORINE provides a consistent framework of European land cover mapping, uncertainties in the final products are necessarily apparent. For example, the country-by-country processing of data can introduce uncertainty due to different treatment of the individual legend items during visual interpretation of the satellite imagery. However, clearly defined mapping guidelines aim to minimize these effects (Bossard et al., 2000). Moreover, the minimum mapping unit of 5 ha (in case of the change product that was used in our analysis) ignores changes on smaller areas. Thus, additional uncertainty can be introduced in areas where less changes appear. The thematic accuracy of the 2000 to 2006 change product is indicated with larger than 85%, while the accuracy for the 1990 to 2000 change product has not been assessed (see http://land.copernicus.eu/pan-european/corine-land-cover). Thematic accuracy entails the capability of CORINE land cover maps to represent the 'true' land-cover class as compared to an independent validation dataset (EEA, 2006). Although these uncertainties may propagate into our analysis of cropland transition trajectories (Table 2, Figure 4), we do not expect them to substantially change the order of source LULCC categories at the aggregated European scale.

S2.3.2 Data: NLCD

The National Land Cover Database (NLCD) is a high resolution (30 m) land-cover product for the USA. This Landsat derived product has been provided for the years 1992, 2001, 2006 and 2011 at the latest. For our analysis the 2001, 2006 and 2011 products have been considered, as they are provided in a harmonized collection with special change products. The NLCD dataset is classified according to a 16-class land-cover classification for the United States, developed in the 1970s by Anderson et al. (1976). The classification system distinguishes two agricultural classes, *(81) Pasture/Hay* and *(82) Cultivated Crops* (Table S5~~Table S5~~). Stehman et al. (2003) report an accuracy level of 55.7 % for the 1992 dataset. Accuracy assessment is not yet available for the 2011 data, but as 2001 and 2006 data showed significantly improved accuracy levels (78.7 % and 78.0 %, Wickham et al. (2010) and Wickham et al. (2013)) a similar (or even better) quality can be assumed for the 2011 data.

Table S3: Summary of land-cover products used for our analysis

Product	Temporal coverage	Spatial resolution / Coverage	Legend	Sensor	Classification
CORINE	1990, 2000, 2006, (2012)	100m / Europe	44 classes, 3 hierarchical levels	Landsat-4/5 TM, Landsat-7 ETM, SPOT-4, IRS P6 LISS III, RapidEye	change product, supervised, expert knowledge
NLCD	(1992), 2001, 2006, 2011	30m / USA	16 classes	Landsat	change product, spectral and knowledge based change detection

S2.3.3 Change detection

We used the dedicated change products for our analysis, which hold information about source and target classes upon land-use change. Areas of agricultural expansion were identified by every pixel that has an agricultural label (based on the inherent legend) at time t2, but not at time t1. We calculated the total expansion of agricultural areas by the difference of pixels which were assigned an agricultural label at time t2 and time t1. Subsequently, combining the areas of cropland expansion with the map of time t 1 resulted in a map of sources of agricultural area. The source maps were classified and summarized considering the underlying original legend into grassland, forest, mixed grassland/forest and unvegetated land origin (Table S4~~Table S4~~, Table S5~~Table S5~~).

Table S4: CORINE land-cover legend (Bossard et al., 2000) and aggregation applied in our analysis

Level 1	Level 2	Level 3	Aggregation

(1)	Artificial surfaces	(11) Urban fabric; (12) Industrial, commercial and transport units; (13) Mine, dump and construction sites; (14) Artificial, non-agricultural vegetated areas	(111) Continuous urban fabric; (112) Discountinuous urban fabric; (121) Industrial and commercial units; (122) Road and rail networks and associated land; (123) Port areas; (124) Airports; (131) Mineral extraction sites; (132) Dump sites; (133) Construction sites; (141) Green urban areas; (142) Sport and leisure facilities	Other
(2)	Agricultural areas	(21) Arable land; (22) Permanent crops; (23) Pastures; (24) Hegerogeneous agricultural areass	(211) Non-irrigated arable land; (212) Permanently irrigated land; (213) Rice fields; (221) Vineyards; (222) Fruit trees and berry plantations; (223) Olive groves; (231) Pastures; (241) Annual cropas associated with permanent crops; (242) Complex cultivation patterns; (243) Land principally occupied by agriculture, with significant areas of natural vegetation; (244) Agro-forestry areas	Agricultural areas
(3)	Forest and semi natural areas	(31) Forests; (32) Scrub and/or herbaceous vegetation associations; (33) Open spaces with little or no vegetation	(311) Broad-leaved forest; (312) Coniferous forest; (313) Mixed forest; (321) Natural grasslands; (322) Moors and heathland; (323) Sclerophyllous vegetation; (324) Transitional woodland-shrub; (331) Beaches, dunes, sands; (332) Bare rocks; (333) Sparsely vegetate areas; (334) Burnt areas; (335) Glaciers and perpetual snow	(311)-(313) Forest (321) Grassland (322)-(324) Shrubland (331)-(335) Other
(4)	Wetlands	(41) Inland wetlands; (42) Maritime wetlands	(411) Inland marshes; (412) Peat bogs; (421) Salt marshes; (422) Salines; (423) Intertidal flats	Other
(5)	Water bodies	(51) Inland waters; (52) Marine waters	(511) Water courses; (512) Water bodies; (521) Coastal lagoons; (522) Estuaries; (523) Sea and ocean	Other

Table S5: National Land Cover Database (NLCD) classification system according to Anderson et al. (1976) and aggregation applied in our analysis

Value	Label	Description	Aggregation
11	Open Water	All areas of open water, generally with less than 25 % cover or vegetation or soil	Other
12	Perennial Ice/Snow	All areas characterized by a perennial cover of ice and/or snow, generally greater than 25 % of total cover	Other
21	Developed, Open Space	Includes areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20 % of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes	Other
22	Developed, Low Intensity	Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20-49 % of total cover. These areas most commonly include single-family housing units.	Other
23	Developed, Medium Intensity	Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50-79 % of the total cover. These areas most commonly include single-family housing units.	Other
24	Developed, High Intensity	Includes highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80-100 % of the total cover.	Other
31	Barren Land (Rock/Sand/Clay)	Barren areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15 % of total cover.	Other
41	Deciduous Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20 % of total vegetation cover. More than 75 % of the tree species shed foliage simultaneously in response to seasonal change.	Forest
42	Evergreen Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20 % of total vegetation cover. More than 75 % of the tree species maintain their leaves all year. Canopy is never without green foliage.	Forest
43	Mixed Forest	Areas dominated by trees generally greater than 5 meters tall, and greater than 20 % of total vegetation cover. Neither deciduous nor evergreen species are greater than 75 % of total tree cover.	Forest
52	Shrub/Scrub	Areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20 % of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.	Shrubland
71	Grassland/Herbaceous	Areas dominated by grammanoid or herbaceous vegetation, generally greater than 80 % of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.	Grassland
81	Pasture/Hay	Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20 % of total vegetation.	Pasture
82	Cultivated Crops	Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as	Cropland

		orchards and vineyards. Crop vegetation accounts for greater than 20 % of total vegetation. This class also includes all land being actively tilled.	
90	Woody Wetlands	Areas where forest or shrub land vegetation accounts for greater than 20 % of vegetative cover and the soil or substrate is periodically saturated with or covered with water.	Other
95	Emergent Herbaceous Wetlands	Areas where perennial herbaceous vegetation accounts for greater than 80 % of vegetative cover and the soil or substrate is periodically saturated with or covered with water.	Other

S2.4 CLUMondo land-use change priority analysis (Section 4; Figure 5)

The CLUMondo data originate from a simulation based on the FAO 3 demand scenario (Eitelberg et al., 2016) and cover the time period from 2000 to 2040 with annual temporal resolution. Data are available at a 9.25 x 9.25 km regular grid (~5 arcminute) in an equal area projection and are based on the land system classification system described in van Asselen and Verburg (2012) (Table S6~~Table S6~~). In order to detect a particular algorithm, which is valid within a ca. 0.5 x 0.5 degree grid cell, the model output required several steps of preprocessing (Figure S2~~Figure S2~~):

- Aggregation of the CLUMondo land systems legend and reclassification of each map following the PFT scheme of DGVMs to cropland, grassland, forest and mosaics of them. We also kept the bare and artificial classes, since they would have confused the other classes otherwise (Table S6~~Table S6~~).
- Identification of grid cells with cropland expansion by overlaying maps of two subsequent time steps. Cropland expansion was identified as changes from any other class to the reclassified cropland class or changes from any other classes except than the reclassified cropland class to the reclassified mosaic cropland classes.
- Tracking of change trajectories, i.e. identification of classes that contributed to cropland expansion. The cropland expansion from the last step was used as a mask to keep only grid cells where cropland actually expanded between two time steps. This step yielded the information, which LULC type was converted to cropland (= 'contributing source').
- Aggregation to ca. 0.5 x 0.5 degree grid. This step yielded the proportion of new cropland that originates in a particular LULC type within each ca. 0.5 x 0.5 degree grid cell.
- Tracking how much of the original LULC type at t1 within a ca. 0.5 x 0.5 degree grid cell was converted to cropland in t2 (= 'available source').
- Division of 'contribution source' by 'available source'. By applying this step we could distinguish grid cells which did not contain a particular LULC type at t1 (division not defined) from grid cells where a particular LULC type was available, but not converted to cropland (division result equals 0).

As a result of the preprocessing we obtained maps, where each grid cell contained the fraction of the original LULC type at t1 that was converted to cropland in t2. Subsequently we searched across these maps for priority algorithms of LULCC within ca. 0.5 x 0.5 degree grid cells for decadal time steps following a set of rules (Figure S3~~Figure S3~~). A grid cell was classified as

- UNDEFINED, if either forest or grassland were not available at t1. For these cells a classification was not possible, since it is not clear which source class was converted with higher priority. For example, if the grid cell only contains grassland at time t1, grassland is logically converted to cropland. However, a forest first algorithm would be also true for this grid cell (and just not executed, because there was no forest to convert). The mosaic class was excluded here, since even it is not available all algorithms could be detected with the following rules.

- UNVEGETATED FIRST, if urban or bare classes in a grid cell were converted completely, while at the same time all other sources were available, but not or only partially converted. Additionally, grid cells where urban or bare classes were partially converted, while at the same time all other sources were available, but not converted.
- FOREST FIRST, if more than 90% of the available forest in a grid cell was converted to cropland, while at the same time grassland was available, but less than 90% of it was converted. Additionally, grid cells where less than 90% of the available forest was converted, while at the same time grassland or mosaic classes were available, but not converted.
- GRASSLAND FIRST, if more than 90% of the available grassland in a grid cell was converted to cropland, while at the same time forest was available, but less than 90% of it was converted. Additionally, grid cells where less than 90% of the available grassland was converted, while at the same time forest or mosaic classes were available, but not converted.
- PROPORTIONAL, if the mosaic class was converted, while at the same time grassland and forest were available, but not converted. Additionally, grid cells where the ratio of converted grassland and forest was between 0.5 and 1.5 were considered as an indicator for proportional reduction.
- COMPLEX, if at least forest and grassland were available as a source, but neither a preferential conversion nor a proportional conversion could be detected.

Table S6: CLUMondo land system classification and reclassification to broader LULC types

LS code	Land system name	Reclassification
0	Cropland; extensive with few livestock	Cropland
1	Cropland; extensive with bovines, goats & sheep	Cropland
2	Cropland; medium intensive with few livestock	Cropland
3	Cropland; medium intensive with bovines, goats & sheep	Cropland
4	Cropland; intensive with few livestock	Cropland
5	Cropland; intensive with bovines, goats & sheep	Cropland
6	Mosaic cropland and grassland with bovines, goats & sheep	Mosaic cropland/grassland
7	Mosaic cropland (extensive) and grassland with few livestock	Mosaic cropland/grassland
8	Mosaic cropland (medium intensive) and grassland with few livestock	Mosaic cropland/grassland
9	Mosaic cropland (intensive) and grassland with few livestock	Mosaic cropland/grassland
10	Mosaic cropland (extensive) and forest with few livestock	Mosaic cropland/forest
11	Mosaic cropland (medium intensive) and forest with few livestock	Mosaic cropland/forest
12	Mosaic cropland (intensive) and forest with few livestock	Mosaic cropland/forest
13	Dense forest	Forest
14	Open forest with few livestock	Forest
15	Mosaic grassland and forest	Mosaic grassland/forest
16	Mosaic grassland and bare	Grassland
17	Natural grassland	Grassland
18	Grassland with few livestock	Grassland
19	Grassland with bovines, goats and sheep	Grassland
20	Bare	Bare
21	Bare with few livestock	Bare
22	Peri-urban & villages	Urban
23	Urban	Urban

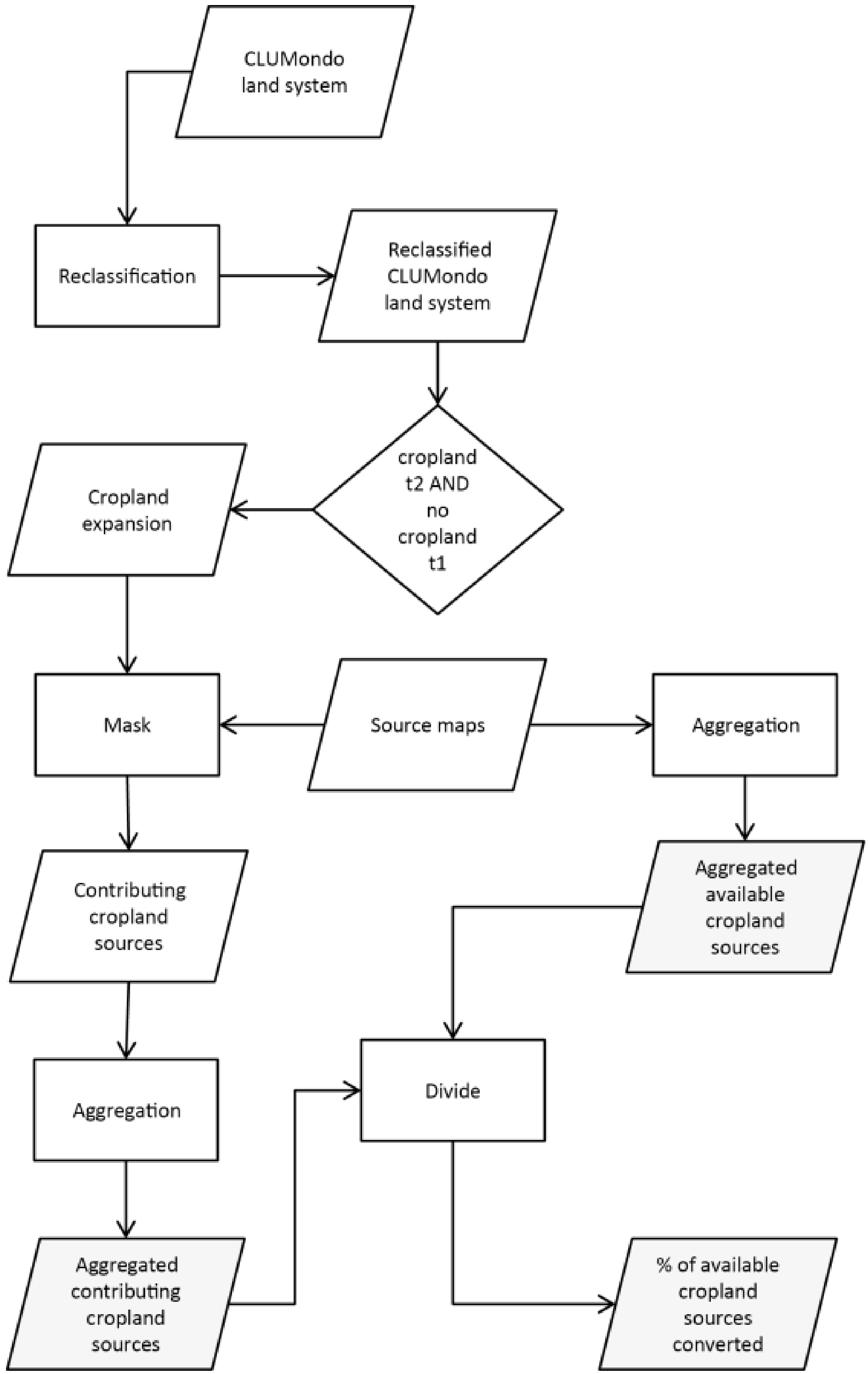
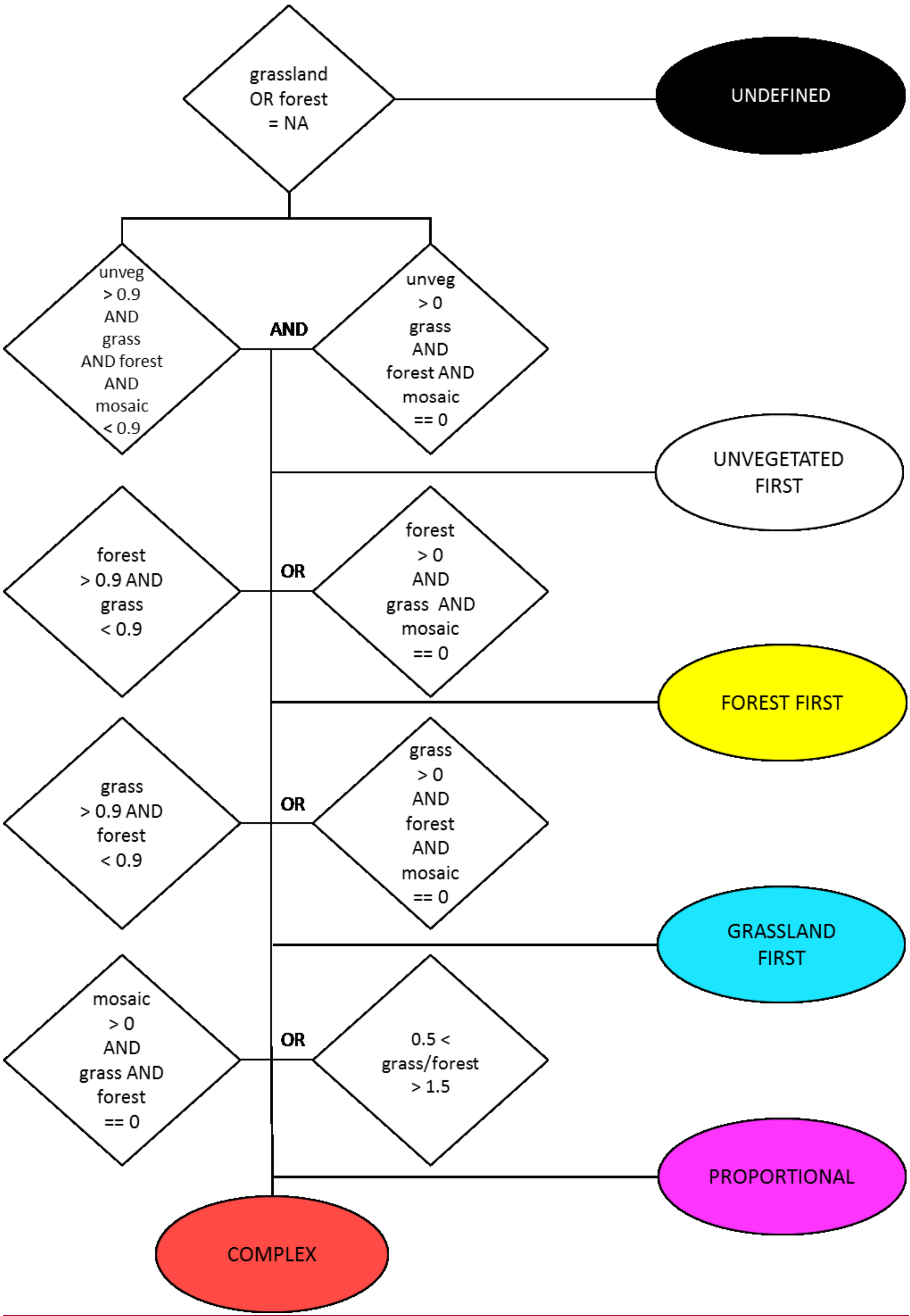


Figure S2: Preprocessing workflow of CLUMondo output for land-use change priority analysis. Rectangles represent processing steps, parallelograms represent data. Grey shaded items emphasize aggregated data at ca. 0.5 x 0.5 degree resolution.


grassland
OR forest
= NA
UNDEFINED
unveg
> 0.9
AND
grass
AND forest
AND
mosaic
< 0.9
AND
unveg
> 0
grass
AND
forest AND
mosaic
== 0
UNVEGETATED
FIRST
forest
> 0.9 AND
grass
< 0.9
OR
forest
> 0
AND
grass AND
mosaic
== 0
FOREST FIRST
grass
> 0.9 AND
forest
< 0.9
OR
grass
> 0
AND
forest
AND
mosaic
== 0
GRASSLAND
FIRST
mosaic
> 0
AND
grass AND
forest
== 0
OR
0.5 <
grass/forest
> 1.5
PROPORTIONAL
COMPLEX

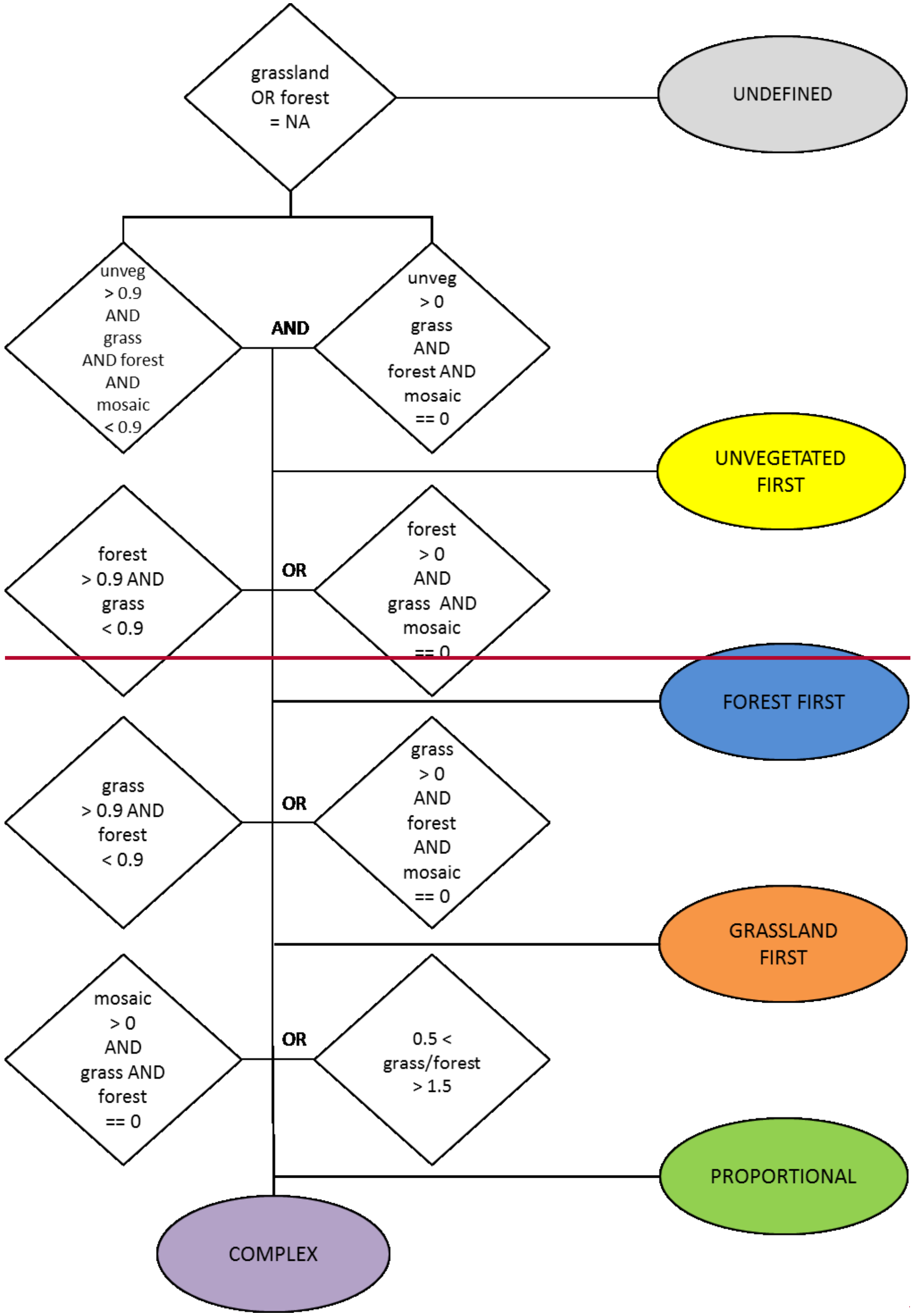
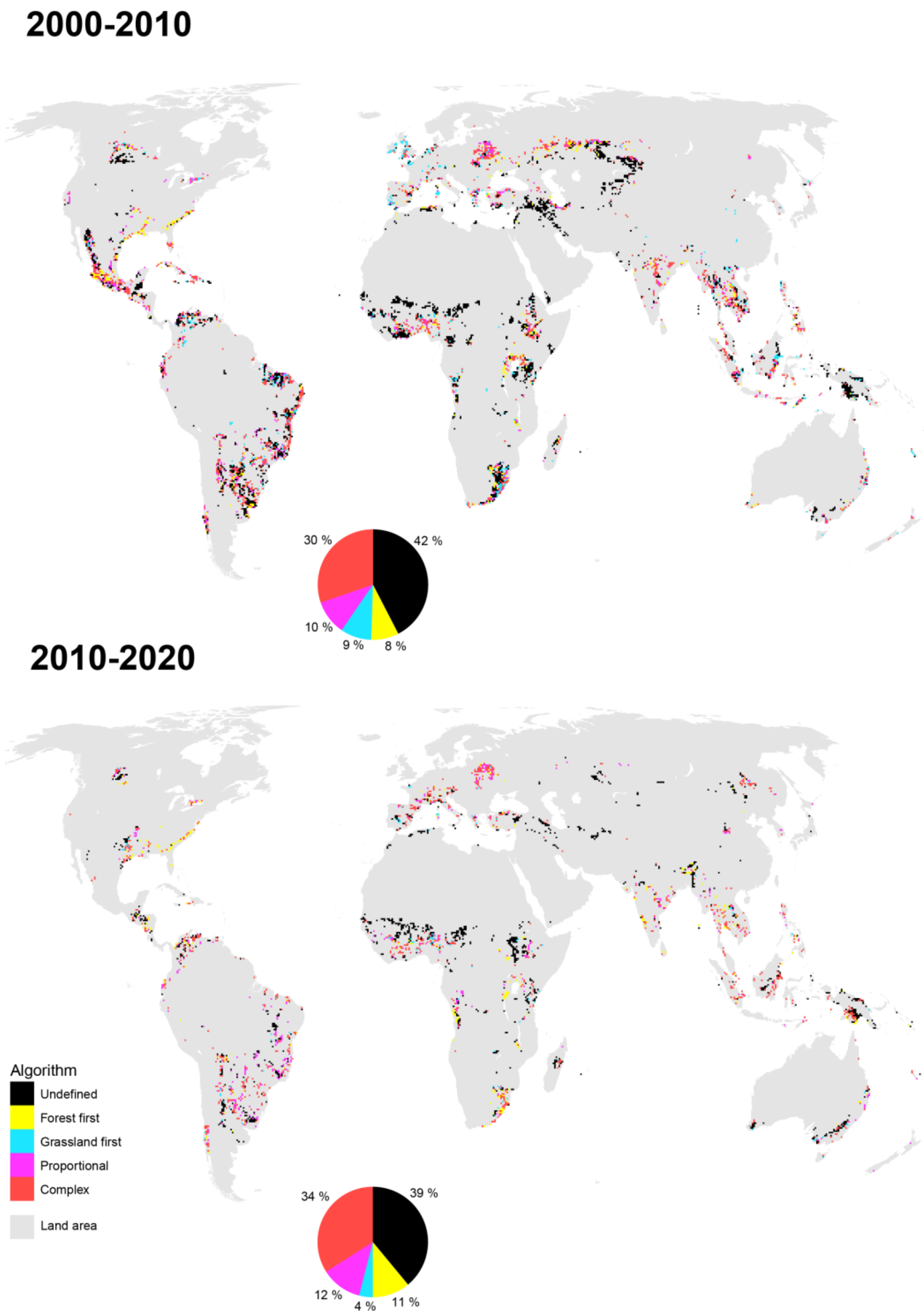
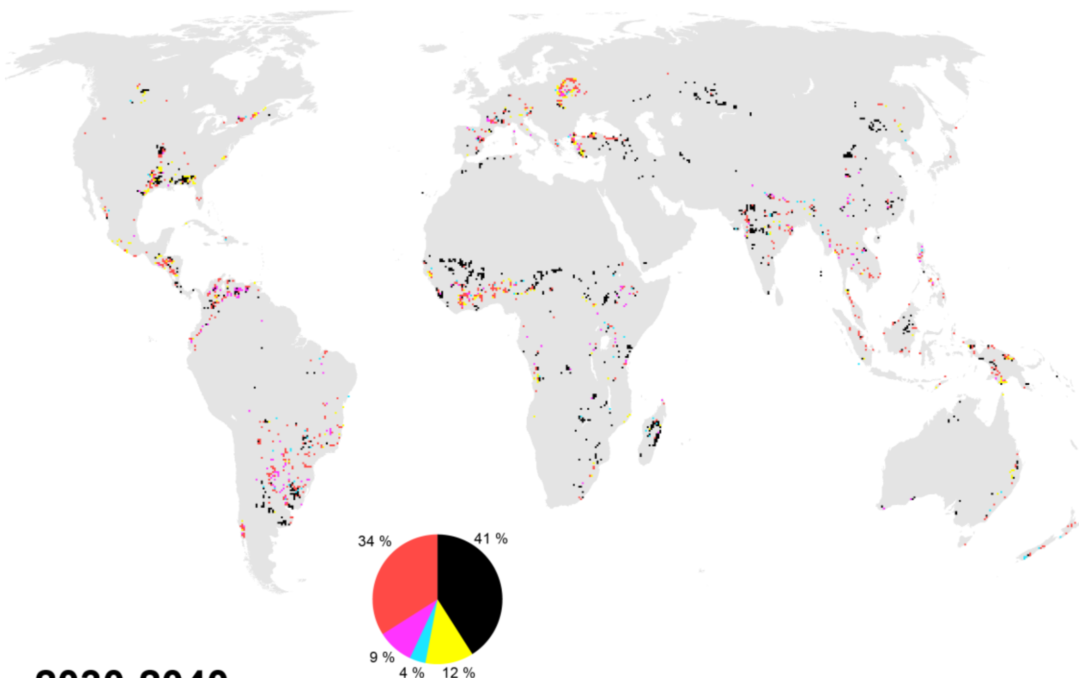


Figure S3: Classification rules applied to each ca. 0.5 x 0.5 degree grid cell to identify a predominant reduction of a particular source LULC type.

S3 Additional Results



2020-2030



2030-2040

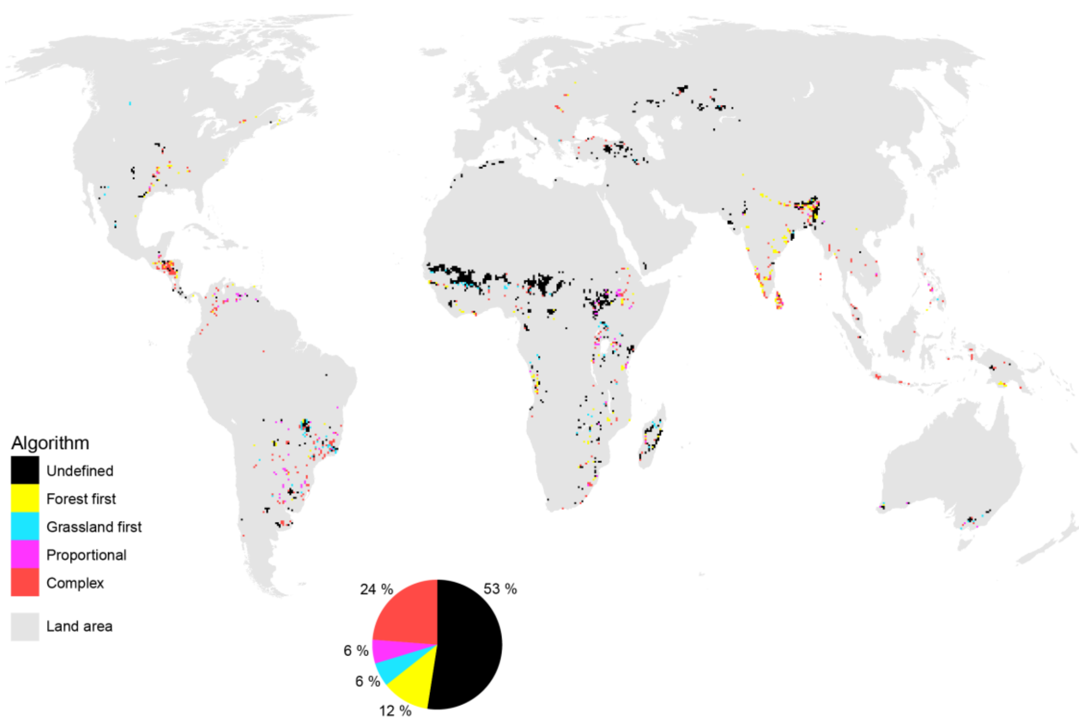


Figure S4: Transitions from natural vegetation to cropland as shown by the CLUMondo model (FAO 3 demand scenario) from 2000 to 2040 in decadal time steps. Colored grid cells represent areas with at least 10 % of cropland expansion within a ca. 0.5 x 0.5 degree grid cell. Grid cells are classified to forest first (yellow), grassland first (cyan), proportional (magenta) and complex reduction (red) algorithm as described in the text (for details see Supplement S2.4~~SI~~). Black grid cells denote areas where the validity of none algorithm could be detected. Grid cells classified to unvegetated first (Table 3) are not shown due to very small contribution (< 0.1 %).

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