Dear Dr. Perdigão,

Thank you very much for the time and effort spent on our manuscript and the open discussion, as well as the provision of additional helpful comments how to improve our manuscript.

We revised the manuscript as detailed in the response to the reviewers during the open discussion including

- A revision of the title to *Current challenges of implementing anthropogenic land-use and land-cover change in models contributing to climate change assessments*,
- Clarification of the structure (including subsections) and providing additional guidance about the framing of the manuscript in the introduction and throughout the individual sections,
- A clearer distinction between sections 3 (*Challenge 2: Considering gross land-use changes*) and 4 (*Challenge 3: Allocation of managed land in TBMs*),
- A separate recommendation section (*Recommendations for improving the current LULCC representation across models*) that summarizes the 'ways forward' we propose to the individual challenges,
- An outlook section (*Outlook: towards model integration across disciplines*) that discusses model integration as a long-term goal
- Additional discussion and justification on controversial statements in the original manuscript where possible (e.g., on the gross change challenge)

Please find below a short summary of major changes to the manuscript and how they relate to the major concerns raised by the referees, followed by 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

General Response

First of all we would like to thank the three reviewers for their time and effort they spent to review our manuscript. The detailed and constructive comments certainly helped us to improve the manuscript.

The first two reviewers are supportive of the paper, acknowledge its importance and we were able to revise the manuscript in such a way that all comments and requests are met. The comments of reviewer #3 have a different nature. We were able to address the more specific comments of reviewer #3, but disagree with the overall comment of this reviewer on lack of relevance of the paper.

Reviewer #1 suggests a reframing of the manuscript from our 'three challenges' and paying more attention to the distinction between land use and land cover or their separate research history, respectively. These are valid points which helped us to improve the manuscript. We resolved this by more clearly describing the framing of the paper. For example, there was room for misinterpretation of the structure in the original manuscript: while we intended to present one important challenge ('main issue') per section, the reviewer identifies the three main challenges already in section 2 (*Provision of spatially explicit, continuous and consistent time series of LULCC*) and thus the other two sections seem to be disconnected. We therefore included a guiding paragraph at the end of the introduction to clarify our underlying structure as following:

'Each of the following sections presents one of the three challenges we identify to be crucial in future land use – climate interaction research, 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.'

Reviewer #2 comments broadly concentrate around hiddenness of the 'ways forward' in the individual sections. We addressed this in the revised version following the reviewer's suggestions and included sub-headings, re-organized the (sub-)sections towards a common structure and moved the 'ways forward' to a separate section and also slightly expanded on these.

Reviewer #3 concludes that we do not provide 'new insights, synthesis or analysis' and suggests a reframing of our manuscript towards the 'development of new diagnostics for evaluation of global LULCC reconstructions or models'. We do not share this view. The current manuscript is a review, supported by data (e.g., CORINE and NLCD land cover data in section 4) and new analysis (e.g., allocation of managed land as shown by CLUMondo in section 4) of the most dominant issues related to land use and climate modeling. The manuscript brings together, to our knowledge for the first time, prominent challenges in land use – climate interaction studies. This view is shared by the other reviewers. The purpose of the paper is to review the current problems and progress, and identifying possible ways forward for the community. We do agree with the reviewer's assessment that identifying more conclusively the ways forward to overcome existing stumbling blocks adds to the value of the manuscript and revised the paper to strengthen that aspect.

For a detailed list of how we addressed the individual reviewer's comments and improved the manuscript, please see our following responses inline in blue.

Reviewer #1 (A. Di Vittorio)

The authors examine current practices of providing LULCC data and simulating LULCC effects on the earth system in global models and identify 3 main issues related to reliable provision and use of LULCC data. They then move on to the limitations in data for gross land use/cover transitions, and finally discuss land conversion assumptions in modeling as a source of uncertainty. They also make 3 suggestions on how to improve the provision and use of LULCC data.

I appreciate this paper and am pleased that it discusses relatively overlooked, yet very important, issues regarding LULCC and global modeling. I generally agree with the assessment, but think that the paper needs some reorganization and some additional discussion to fully and clearly make its case. The main issues requiring attention are summarized here, with specific comments/suggestions following:

Response: We thank the reviewer for the kind words and the appreciation of our work. We are pleased that the reviewer generally agrees with our assessment. We revised the paper to provide a more clear structure as we feel the current framing provided some misunderstanding: we did not aim to first identify the three main issues and then 'move on to limitations in data for gross land use/cover transitions, and finally discuss land conversion assumptions in modeling', but the three main issues are intended to be the three sections following the introduction, namely (1) *Provision of continuous and consistent LULCC time series*, (2) *Consideration of gross land-use change*, and (3) *Allocation of managed land in TBMs*. We refer to this and explain more in the responses to following comments.

1) The paper needs a consistent framing and argument. The three main issues are different between the abstract, text and conclusion. It appears (see abstract lines 28-34 and page 3 lines 5-10) that the point is to show that the 3 main issues are indeed main issues, based on literature, an example, and discussion of two underlying factors (1) gross transitions and 2) land use change to land cover change translation), and provide suggestions for moving forward. But the main issues are not referred to in the later sections, and these two aspects are not introduced up front so that they can be discussed in the context of the main issues. And the suggestions are not related to the issues.

Response: Based on the assumptions the reviewer made regarding the three main issues and the underlying factors, we entirely agree that there is a lack of consistency and disconnection throughout the manuscript. We added a paragraph at the end of the introduction that clarifies the structure (page 3, lines 13-19; please see the general response). We removed the confusing sentences that give the impression that we present the 'main issues' in the first section (after the introduction) and discussing 'underlying factors' subsequently. The revised manuscript ensures that each section (2, 3, 4) treats one of the challenges outlined in the abstract and picked up in the recommendation section individually, connected by the overarching topic of 'open issues in land use – climate interaction studies'.

In conjunction with the changes outlined later on in this document regarding structure requested by reviewer #2, we believe that we have addressed the concern raised.

2) It isn't clear that lack of information on gross transitions is a fundamental factor for the 3 main issues. While there is a lot of uncertainty in estimating gross transitions, and there is need to improve related data, this seems more like an example of a more fundamental driver. One thing that cuts through the three issues and incorporates gross transitions is data quality. In fact, that is largely what issue 2 in the text describes. And ultimately issue 3 as well (initial, present-day data sets for future projections). Maybe there are only two main issues (single historical product with no uncertainty and uncharacterized/large model uncertainty in future land projections) and two underlying factors (data quality and independent land use

and land cover implementation). Then the underlying factors provide guidance for the two communities to work together to address the two issues as they apply to both the human and dgv/es models.

Response: We rephrased the section in such a way that we no longer present the lack of information on gross transitions as a fundamental factor for other issues/challenges. We strengthened our view that gross transitions are a challenge in itself, since these additional changes are hardly considered in climate models, but may have a substantial impact, e.g. on the resulting carbon signal. Indeed, it closely links to both of the other challenges, to the harmonization (section 2) in terms of data quality and to the allocation (section 4) in terms of how the DGVMs/ESMs are able to implement the transitions. However, the reframing suggested by the reviewer would have made the gross transitions to one out of several 'data quality' issues, which we feel is not appropriate. The topic of gross transitions goes beyond data quality issues due to their scale dependency, i.e. even if we would be able to reduce uncertainties due to technical restrictions (e.g., in remote sensing products) or model assumptions, sub-grid processes would need to be addressed separately. Similarly, the suggested reframing would exclude the uncertainty from present-day land-use (and land-cover) products which different land-use model intercomparison exercises have identified as an important source of variation across land-use models (Alexander et al., 2016; Schmitz et al., 2014). We however agree that challenge 1 (*Provision of consistent time series*) is mainly related to data quality, which we emphasized in the revised version of the manuscript.

3) The underlying factor of the traditional separation of land use research from land cover research is not addressed until section 4, even though it cuts through the main issues and there is also a main point in the conclusion that land use modeling needs to be integrated with land cover/ecosystem modeling. And one of the suggestions calls for specific land use to land cover conversion information in place of just land use information. You also use land cover products for figure 5, which are not necessarily consistent with agricultural land use data. Furthermore, this separation is not explicitly discussed, with LULCC being a whole throughout the text, even when discussing how each land model has to make land cover conversion assumptions to accommodate independent land use data. You mainly focus on the land cover conversion uncertainty, but the separation of land use and land cover is the underlying source. There is some additional literature addressing this specific issue that would be useful to the authors. I would also be happy to discuss this further with the authors, as I am trying to finish a manuscript looking at how land cover conversion uncertainty affects carbon and climate projections. Look me up if you are coming to AGU in San Francisco this year.

Response: The reviewer has a valid point that we did not carefully separate between land use and land cover throughout the manuscript and especially in section 4. We checked again and changed accordingly by spelling out land use and/or land cover where applicable. As mentioned later on in the response to reviewer #2, we additionally clarified the structure such that a recommendation section focuses on the short term improvements (i.e., how to tackle the individual issues within the current offline coupling of models) and an outlook section discusses the model integration. We do not necessarily agree that the separation of land use from land cover research 'cuts through the main issues', but it rather applies to our issue 3 (*Allocation of managed land in TBMs*). In addition to this, we discuss the issues arising in the data used for the current coupling in section 2. We clarified this in a revised manuscript as outlined in the response to the reviewers first general comment.

Specific comments and suggestions:

Abstract

page 1, lines 31-32: this subgrid and gross transition is not on page 5 as a main source of uncertainty. The second main source in the text is inconsistencies of present day data. You do later discuss transitions, and make a statement in the conclusion, however.

Response: See response to this reviewers main comments.

page 2, lines 1-2: I think I know who you mean (providers and users), but it is unclear who is included in the "joint development and evaluation" here.

Response: Thanks for pointing to that. We rephrased this sentence to clarify as following (page 1, lines 32-35):

'We propose that LULCC data-provider and –user communities should engage in the joint development and evaluation of enhanced LULCC time series, […]'

page 2, line 12: What do you include as a DGVM here? Some consider any model having vegetation growth in response to environmental conditions as a DGVM. For others a DGVM specifically includes prognostic biogeography (i.e., the extent of vegetation types change according to environmental conditions) and/or successional vegetation processes (e.g., stages of forest stand growth following a forest clearing disturbance).

Response: We agree with the reviewer that the DGVM terminology is misleading in our manuscript. We replaced it with the term *'terrestrial biosphere model (TBM)',* which covers models with both static and dynamic vegetation. Additionally, we added a short explanation that makes clear that this term is meant to be inclusive of a range of modeling approaches (page 2, lines 10-12), as basically any terrestrial biosphere model that is able to include land use from an external data set will face the challenges discussed in our manuscript. As models with dynamic vegetation can substantially differ from land surface models coupled to ESMs in the exact implementation of external data, we differentiate between DGVMs and ESMs in our section 4.

page 2, line 26: you should also cite: Meiyappan and Jain, 2012. Three distinct global estimates of historical land-cover change and land-use conversions for over 200 years, Frontiers in Earth Science, 6(2):122-139 (I noticed you cite it later).

Response: Good point. We included the reference (page 3, line 3).

page 2, lines 29-30: you should also cite: Di Vittorio et al., 2014. From land use to land cover: restoring the afforestation signal in a coupled integrated assessment-earth system model and the implications for CMIP5 RCP simulations, Biogeosciences, 11, 6435-6450.

Response: We apologize that we have not been aware of this work during the preparation of the manuscript. We included the reference (page 2, line 32).

Provision of LULCC

page 4, lines 11-13: The CMIP5 product harmonizes only land use, and as such the land cover (forest, grass, etc.) and how it is altered by land use is determined independently by the DGVMs/ESMs, and can be dramatically different between models for a given scenario (in fact, prescribed scenarios can be substantially altered in ESMs by this, see Di Vittorio paper listed above). The CMIP6 product is also including forest cover in the harmonization, both for the historical period (with reference to satellite data) and for the IAM scenarios (which actually project all land cover).

Response: We agree that the term LULCC is not appropriate in this context. We improved this paragraph by exchanging the term 'LULCC' by 'land use'. Furthermore, we replaced the sentence

'This strategy tries to conserve the original patterns, rate and location of change as much as possible, and to reduce the differences between the models due to definition of land-use categories (e.g., what constitutes a forest).'

by

'The harmonization 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 inconsistent definitions of cropland, pasture and wood harvest.' (page 4, lines 26-28)

page 4, lines 14-15: Only land use is input to and output from GLM for CMIP5, and forest cover is included for CMIP6.

Response: We revised as mentioned in the response to the previous comment.

page 5, line 12: It isn't clear here that you have shifted away from the harmonization group of models to a more general group providing present-day lulc data for future projections.

Response: It is not really a shift from the harmonization group of models to a more general group, but we are not aware of work that has compared the differences in the starting maps of the IAMs contributing to the CMIP5 harmonization only. The cited Prestele et al. (2016) paper indeed includes additional (non-IA) models, but still three out of four models that provide data to the CMIP5 harmonization. These do not agree about initial areas as well. We clarified as following (page 6, lines 1-2):

'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.'

pages 5-6, lines 24-5: Two points here: 1) In the IPCC context, only land use was used, with forest cover coming into play for CMIP6, even though the IAMs project land types for the entire terrestrial surface. This introduces uncertainty beyond just the model structure/assumptions and different input data (see the Di Vittorio paper listed above). 2) The starting point of lulcc determination isn't just about which land-use input data or how processes are implemented. The spatial configuration of these data and the model are key factors in determining model outcomes. And each model has a unique spatial configuration. Gridded models/data do not necessarily resolve this spatial issue because regional values are often just resampled to the grid. See: Di Vittorio et al, 2016. What are the effects of Agro-Ecological Zones and land use region boundaries on land resource projection using the Global Change Assessment Model, Environmental Modelling and Software, 85:246-265

Response:

1) We agree with the reviewer about the missing land cover information being a major constraint in the CMIP5 LUH product and expanded the discussion about the missing land cover information in CMIP5 LUH in the section *Allocation of managed land in TBMs* (page 9, lines 31 ff.). We do not think that the discussion about uncertainty emerging from the fact, that only land use is provided to DGVMs/ESMs and they utilize different implementation schemes on their background land cover, would fit in section 2 where we discuss the uncertainties arising during land-use modeling and the harmonization.

2) We agree that the spatial configuration of the individual models even increases the uncertainty range and appreciate the reference to the Di Vittorio et al. (2016) paper. We included this additional uncertainty issue by rephrasing page 6, lines 11-14 to:

'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).'

page 6, line 2: How were the variables normalized? Could the dominance of initial pasture area be due to it just being the largest difference in relation to the other variables? Also, it would be more clear if you were specific in the text and the caption in describing that the "starting point" and "initial" are the pasture area in relation to fao in 2010, and that "model" is actually model type and presumably the spatial resolution/configuration.

Response: We included a clear mentioning how the data were processed in the supplementary material (Supplement S2.1) and improved the caption of Figure 2 as suggested. The areas are indeed in absolute terms, which indeed makes it likely to have larger deviations, if regression coefficients were interpreted directly. However, in the text we describe the relative contribution of each group of variables in the regression model (initial, model, scenario and residual; Table S2) to the total variation in pasture areas. The relative contribution is derived by dividing the sum of squares related to groups by the total sum of squares obtained from an ANOVA (type II sum of squares, i.e. not dependent in which variables are considered in the model; see Alexander et al., 2016) applied to the regression results. These are not affected by the larger difference in the initial deviation.

page 6, lines 6-14: I completely agree! While recent feedback on LUMIP has prompted the provision of LU-forest uncertainty along with the CMIP6 LUH product, it still falls short of the comprehensive approach discussed here.

Response: We thank the reviewer and also appreciate initial consideration of uncertainty along with LULCC data provided to LUMIP, e.g. that additional high and low estimates of historical land use will be included (Lawrence et al., 2016). However, we think a more ambitious approach should be taken into consideration for future MIPs.

page 6, lines 15-22: The separation of land use and land cover is a critical factor omitted from this discussion. While land use and land cover are often said in the same breath and the LULC(C) acronym is widely used, in nearly all cases people are referring to either land use or land cover. Research is clearly split along these lines, and land use data are remarkably inconsistent with land cover data. Land use and land cover need to be studied together, as an integrated process, in order to reduce LULCC uncertainties and inconsistencies between these two groups of data.

Response: We agree with the reviewer that there is a large discrepancy between land use and land cover research and data products and that this will be an important challenge to overcome in future by integrating the research lines. In fact, model integration is one of the key points of our conclusions. We highlighted this point more clearly in the revised manuscript by rephrasing our three conclusion points in section 5 (*Recommendations for improving the current LULCC representation across models*) and additionally discuss the model integration in section 6 (*Outlook: towards model integration across* disciplines).

Considering gross land use changes

How does this relate to the three issues in the previous section? Is this really a major driver of the 3 issues, or something along for the ride? It is clearly present in issues 1 and 2 (although the present day isn't discussed, only past and future), while its absence in IAM projection may be the relevant link (as the transitions are determined by a single independent model, which is part of issue 1)

Response: See earlier responses. We clarified in the text that we do not argue that missing gross transition representation is a major driver of the uncertainty in land-use data sets used for the harmonized time series. Separate from the uncertainties discussed in the previous section we argue that gross transitions are an issue that have not got enough attention throughout the communities apart from shifting cultivation in the tropics.

page 7, lines 21-23: Just a note: You are well aware that gross transition information is highly uncertain, and current work suggests that the CMIP5 LUH data product may actually overestimate gross transitions in the tropical regions.

Response: Indeed, gross transition information is uncertain, especially if it is provided by models that have multiple other sources of uncertainty (as discussed in section 2) or simple assumptions about the spatial distribution of shifting cultivation have to be made (as in the CMIP5 harmonization). For this reason, we call for additional work on this topic, based on empirical data, such as the updated shifting cultivation estimate for the CMIP6 LUH product (which the reviewer probably refers to here) or the recent work by Fuchs et al.

page 7, line 32: there are no land cover categories in CMIP5 LUH, only primary and secondary land. wood harvest is associated with forest or non-forest, but this land cover designation is based on a threshold of a potential biomass model, rather than more commonly used land cover or potential vegetation data sets.

Response: We removed 'land-cover' from the sentence, as it is indeed misleading along with the CMIP5 LUH data. We additionally moved the discussion about the derivation of explicit transitions to section 4 to distinguish between gross changes and explicit transitions. The sentence now reads (page 12, line 24-25):

'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.'

Moreover, even if forest/non-forest land cover is provided for CMIP6, the decision how to derive the transitions (e.g., forest to crop or non-forest to crop) has to be made? We thus believe our main argument in this paragraph about the simplistic assumptions to derive transitions remain unaffected.

page 8, line 14: "…increasingly been captured…"

Response: Corrected accordingly.

Allocation of managed land in ESMs and DGVMs

Ah, finally! This aspect of separate land use and land cover information/modeling is a factor in all 3 of your main sources of uncertainty, and as such needs to be mentioned up front and related to these uncertainty sources.

Response: See the general response, previous responses and the response to reviewer #2 how we clarified the structure in the revised manuscript to address this comment. In short, section 2 now focuses on the uncertainties within the land-use and land-cover data provider community ('data quality') and its implications for climate assessments upon coupling to DGVMs/ESMs. Section 3 picks up an important, but so far hardly considered challenge (gross changes), while section 4 discusses the issues arising when using external land-use data in DGVMs/ESMs, including the underlying source of the separated land-use and land-cover research lines.

page 8, lines 27-28: and scenarios and over relatively short time periods (see Di Vittorio et al 2014)

Response: We rephrased this paragraph. It now reads (page 10, lines 4-9):

'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 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).'

page 9, lines 26-27: this is consistent with land cover being studied separately from land use, and your examples also relate to your second main source of uncertainty.

Response: The reviewer is correct that the overview of these studies also show that there is a mix of approaches in studying current land-use and land-cover changes that necessarily leads to some kind of uncertainty. However, this statement was intended to emphasize that we did not conduct a systematic review, but rather use the studies as an illustration to support our argument that the change pattern is spatially heterogeneous.

pages 9-10, lines 30-12: glad you did this! But what determines the source of land use in CLUMondo? It is important to clearly state how this model differs in this selection versus those that use the methods by which you classify the changes. Generally, more info is needed regarding how the different classified algorithms are defined, in relation to how they are implemented in dgvms/esms. The reader should be able to understand what is going on without digging through the supplemental material. Maybe a table of the definitions?

Response: We included some more detail in the main text (page 11, line 10 onwards; see below) and added a table with the definitions (Table 3). In the original manuscript we aimed to keep methodological descriptions as short as possible, as we apply the analysis mainly for illustrative purposes.

'CLUMondo models the spatial distribution of land systems over time, instead of land use and land cover directly. Land systems are among 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 the 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. 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 a CLUMondo simulation (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).'

page 10, lines 5-8: what about the undefined category, which is the dominant category according to the figures (not the complex)? what does it stand for? are you grouping this with the complex category?

Response: Good point. We seem to have missed the undefined category somewhere on the line and added this piece of information to the text (page 11, line 22; see below), including a table that explains the individual categories (Table 3). In principle, undefined means that it was not possible to detect on of the algorithms (forest first, grassland first, etc.). We are not grouping it with the complex category, as this category basically entails the opposite: all major land-cover types have been available, but there is no priority which one is reduced upon cropland expansion.

'Additionally, a grid cell was labeled 'undefined', if grassland or forest was not available in the source map.'

page 10, line 16: the IAM community has been projecting land use AND land cover for some time, although not necessarily gross transitions.

Response: Agreed. But it is about gross transitions and transition matrices here and as IAMs/LUCMs provide the transition matrices, they need to derive the exact source category somehow as well. How will this be done? As the reviewer mentioned earlier, there are not many IAMs which actually project land use and land cover at a regular grid scale, but instead resample/downscale aggregated results. Thus, it very much depends on the sophistication of the allocation procedure, how 'accurate' the derived transition matrices will be. Additionally, these downscaled maps are usually not evaluated against observational data. Thus, by using transition matrices (and the ability of DGVMs/ESMs to incorporate them), the issue would be solved for ESMs/DGVMs, but did not disappear and requires further research. We now elaborate in more detail on this issue in section 4.5 (*Open issues of transition matrices*).

Conclusions and recommendations

page 11, lines 17-20: this is an important point, but it hasn't been clearly demonstrated in the text, largely because the paper generally refers to LULCC as a whole.

Response: We resolved this issue by applying the revisions mentioned in our previous responses and the response to reviewer #2, i.e. refining land-use and land-cover terminology and reorganization of the sections. Additionally, we moved the discussion about model integration into section 6 (*Outlook: towards model integration across* disciplines) thus separating it from the more short-term recommendations.

page 11, lines 20-23: while not an individual, agent-based behavioral model, GCAM has been integrated with CESM as the iESM, implementing two-way feedbacks between the human and environmental systems, particularly for terrestrial systems and the effects on land projection. See the oft-noted paper above, which runs the iESM, and: Collins et al, 2015, The integrated Earth system model version 1: formulation and functionality. Geoscientific model development, 8, :2203-2219. There should also be a paper coming out soon on a complete experiment using the iESM to examine the effects of the feedbacks.

Response: We accommodated this comment in section 6 (*Outlook: towards model integration across disciplines*; page 15, lines 15-20):

‘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 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.’

page 12, lines 1-19: It isn’t clear how these suggestions relate to your three proposed primary issues with LULCC (which should also be restated in this conclusion – 1) uncertainty in lulcc data products is lacking due to not enough different products generated, 2) present-day lulc data are inconsistent and thus contain high uncertainty, and 3) uncertainty in lulcc projections is largely driven by initial data uncertainty over other model-specific sources). Issues 2 and 3 appear to mainly consist of data quality issues. Also note that your second main source on page 5 does not refer to gross or subgrid transitions at all, just to inconsistencies in present day data. Please make your conclusions/suggestions more consistent with the theme of the paper.

Response: See previous responses. The main challenges are meant to be (1) *Provision of a spatially explicit, continuous and consistent time series of land-use change*, (2) *Considering gross land-use changes* and (3) *Allocation of managed land in TBMs.* Related to these challenges we suggest to (1) Develop enhanced harmonized time series including uncertainty, (2) supplement the time series with estimations of gross transitions and (3) the development of transition matrices based on sophisticated land-use models and empirical data. We now explicitly mention them in the abstract, discuss each of them in one section (2-4) of the manuscript and propose ‘ways forward’ in section 5 (*Recommendations for improving the current LULCC representation across models*) for each challenge.

Supplemental material

Figure S1 seems a lot more complicate with more steps than described in the text, which makes more sense.

Response: Please see response to comment pages 9-10, lines 30-12.

Reviewer #2 (Anonymous)

The authors discuss in their manuscript the major uncertainties and shortcomings associated with the implementation of land-use and land-cover changes (LULCC) in climate change assessments. Additionally, three major challenges are identified and the reasons for them are discussed.

General Comment: Generally, I think this paper raises some important issues related to implementation of LULCC in the modelling community. Raising awareness to this issues with the help of an extended literature review will be beneficial in tacking this problems.

Response: We thank the reviewer for the kind words and the overall positive evaluation of our manuscript.

However, I think the manuscript would benefit from not only raising awareness of the issues and the reasons behind it but also providing a 'way forward'. This is sometimes done in the individual sections but I think the suggestions get lost in the wealth of information presented in the manuscript. I therefore suggest adding a separate recommendation section in which the authors clearly state in short and precise form what could/should be done to overcome the challenges and which part of the community they see in a better position to take the lead (if possible), instead of having the conclusions and recommendations combined in one section.

Response: Indeed, the manuscript intends to provide guidance for the involved communities (i.e., IAM, LUCM, DGVM, ESM, remote sensing) on the 'ways forward' based on the different challenges identified. We aimed to do this by discussing each of the challenges within one section and bringing them together in the conclusion section with additional recommendations. However, we see that this could be done better with an improved guidance for the reader throughout the manuscript. We think that the reviewer makes useful suggestions how to reorganize the manuscript in a way that the intended structure becomes clearer. We therefore decided to follow these suggestions and improved the manuscript by:

- Streamlining the discussion within the individual sections into 'description of the challenge and underlying reasons', 'examples', 'current solutions' and 'shortcomings of current solutions'
- Adding subheadings accordingly. For example, section 2 (*Challenge 1: Spatially explicit, continuous and consistent time series of land-use change*) has been re-structured into the following sub-sections:
    - *2.1 Background and emergence*
    - *2.2 Current approach to provide consistent data: The Land Use Harmonization (LUH)*
    - *2.3 Open issues in the LUH data and their implications for climate change assessments*
- Moving the recommendations from the individual sections to section 5 (*Recommendations for improving the current LULCC representation across models*), whereas each sub-section deals with one of the challenges identified in sections 2-4 and, including an indication which part of the community we think is in charge of taking the lead

We feel that this reorganization of the structure helped to simultaneously clarify the main concerns of reviewer #1.

The abstract and P3L5-10 ('overall objectives) do not match. Please make sure that these points are consistent throughout the document.

Response: We checked for consistency throughout the document, rephrased the particular part of the abstract (page 1, lines 26 ff.) and added a paragraph giving guidance on the structure of the manuscript according to the response to reviewer #1 (page 3, lines 13 ff.).

This brings me to my general comment; The paper covers a lot of material but very often the structure of the document gets lot. I therefore suggest the authors to go through the document and make sure that the reader can follow the train of thought easily. This could be achieved for example by adding subheading to the sections and having similar structure within each of the sub-sections. This also applies to the Supplements which should also convey a clear structure within the sub-sections.

Response: We clarified the structure as outlined in the response to the reviewer's previous comments. Additionally, we clarified the structure of the supplementary material, which now provides additional information in line with the structure of the main text. To improve guidance throughout the supplements, we added a reference to the section/figure/table that the particular supplement refers to in the main text

Specific Comments: In the title of the manuscript it should become clear that the document is about 'anthropogenic' land-use and land cover changes and that the assessments are with regard to 'climate change'. I therefore suggest revising the title.

Response: We added 'anthropogenic' to the title and exchanged 'climate assessments' by 'climate change assessments' to be unambiguous. We revised the title (in addition to the changes suggested by reviewer #3) into

'Current challenges of implementing anthropogenic land-use and land-cover change in models contributing to climate change assessments'

P1L20-23: Suggested to split sentence

Response: We split the sentence into (page 1, lines 21-23):

'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).'

P2L22-26: I think this is an interdisciplinary journal, it would be beneficial for readers outside of the community, if examples of the uncertainties could be given (e.g. it might not be clear to the readers what 'definition issues' are (see also P5L 16)).

Response: We agree that the 'definition issues' were not sufficiently explained in the text. We thus added an explanation and examples. The paragraph reads now (in line with changes according to main comment 1), reviewer #1 (page 2, lines 23 ff.):

'[…] 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). […] 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-Ducoudre 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 et al., 2012).'

Accordingly page 5, lines 33 ff.:

'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).

P3L1: which 'sources'? Please specify

Response: The sources are listed in the previous paragraph. We added a reference to make this unambiguous (page 3, lines 4-5).

'Currently reported uncertainties of the outputs of land use – climate interaction studies may be underestimated by insufficiently accounting for the aforementioned sources of uncertainty.'

P3L27-31 Please be more specific and elaborate on the dataset

Response: Unfortunately, there is not a single dataset we could elaborate on here and we rephrased the paragraph to emphasize the variety of datasets provided from the various land-use change models (page 3, lines 32 ff.). We argue that the diversity of models produce a tremendous amount of data, which is not necessarily consistent and comparable due to the underlying reasons listed in the preceding paragraph (i.e., two independent land-use change modeling communities (historical, future), different data sources, varying assumptions and drivers in the models.)

P4L6&L9: What does 'LUH' and 'HYDE' stand for?

Response: The reviewer is absolutely correct that we missed to spell out the acronyms. We included the full terms in the revised manuscript (LUH: page 4, line 11; HYDE: page 4, line 24).

P5L18: 'large differences' in which variable?

Response: We refer to global land-cover products in this sentence, i.e. the variable is land cover or the individual classes (such as forest, grassland, etc.), respectively. We will rephrase to remove ambiguity. See the response to comment P2L22-26.

P5L23: what are the 'all relevant processes' to the authors? Elaborate. What is still missing.

Response: This is indeed a reasonable comment and the elaboration on this question would probably easily fill another publication, which we think is out of the scope of our manuscript. The paragraph the comment refers to has been removed due to the re-structuring of the manuscript. However, we addressed this comment by including discussion about separated history of land-use and land-cover research in section 4 and the model integration in section 6.

P5L26: It is not clear what a 'marker scenario' entails.

Response: We added a clarifying sentence and additional references in this paragraph (page 6, lines 8-11):

'A 'marker scenario' entails the implementation of a SSP scenario 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 scenario (Popp et al., 2016; Riahi et al., 2016)'.

P5L33: 'large variations' in which variable?

Response: The variable is 'pasture areas'. We rephrased the sentence accordingly to make this clear (page 6, lines 18-19).

'For example, the projections of 11 IAMs and LUCMs show large variations in pasture areas in 2030 for many world regions (Figure 2, background map).'

P6L5: The differences in output arising from different models the input and calibration etc. is not only an issue in the assessment of LULCC but generally applies to all models…Maybe if you look at other modelling communities and how they quantify these uncertainties.

Response: We entirely agree that these issues are not unique to the LULCC modeling community. However, it is not the purpose of the paper to describe detailed methods/metrics of how the uncertainties could be quantified. But in section 5 (*Recommendations for improving current LULCC representation across models*), we outline what would conceptually be needed to (1) quantify the uncertainty range and (2) provide suggestions how it could be reduced.

We argue that little attention has been paid to the evaluation of land use models and the quantification of the uncertainty in their projections. This leads to a situation where often model and input data related differences dominate the scenario related uncertainties. We acknowledge that there are activities starting towards quantifying the uncertainties related to model assumptions (Riahi et al., 2016). However, two main issues are not resolved yet: (1) the 'marker' implementation of SSPS are intended to be used for climate change assessments without providing an error/uncertainty range due to different model interpretations, which would allow to quantify the uncertainty propagation into the final assessments and (2) all 'marker scenarios' are interpreted by a very similar kind of models (IAMs), which – especially when it comes to the spatial pattern of LULCC projections (= input to DGVMs/ESMs) – largely differ from alternative realizations of land-use allocation models (Prestele et al., 2016).

P 6L11: the problem is how to define 'plausible' realisations.

Response: It is indeed a difficult task. However, there are different products available for global land cover only (e.g., the ESA-CCI product, the MODIS product) or integrated with land-use statistics (e.g., Fritz et al., 2015; Klein Goldewijk et al., 2011; Ramankutty et al., 2008), which show substantial variations in the extent and especially the spatial pattern of land-use distribution. To elect one of these to the 'best' might be difficult due to technical and analytical constraints. Nonetheless, we would assume them to be 'plausible' since they are based on sound science (either remote sensing directly and/or remote sensing and statistics) and we added this deliberation to the manuscript in section 5 (page 13, lines 24-28).

'To 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.'

P7L 2: Elaborate why sub-grid dynamics 'have been shown important'

Response: We added a few examples summarizing the results in the referenced publications (page 7, lines 15-24):

'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., in press; Fuchs et al., 2015b; Stocker et al., 2014; Wilkenskjeld et al., 2014). For example, Bayer et al. (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.'

P7L6: what are 'under-determined mathematical systems' in this context?

Response: We removed this expression in the revised manuscript. Instead, we are now describing in section 3.3 (*Current approaches to provide gross change information: LUH and analysis of empirical data*) in more detail how the approach of Hurtt et al. (2011) works.

P7L8: what are 'minimum-transitions' in this context?

Response: Minimum transitions entail the changes between LULC categories only accounting for one-directional changes and derived from previously modeled net change time series. We added this explanation to the text (page 8, lines 17-18).

P7L21-23: Rephrase sentence

Response: We moved the statement to section 3.4 (*Open issues in the current approaches*) and rephrased to (page 9, lines 3-5):

'[…]. 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.'

P10: rephrase 'allocation issue' do you mean the shifts between the communities and their perceived responsibilities

Response: 'Allocation issue' actually refers to the decision which land-cover type is replaced upon cropland and pasture expansion in the model. We moved the statement to section 4.5 (*Open issues of transition matrices*) and rephrased to (page 12, lines 14-16):

'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 […].'

P10 Maybe you would like to add to your decision that 'satellite data' is also not 'directly measured data' but also goes through a mathematical conversion process.

Response: That is indeed a good point and we added a sentence that explicitly mentions that satellite data is not directly measured data, too (page 14, lines 16-17; see below). We think compared to the modeled LULCC data, satellite data entails a much more 'directly measured' component in most cases and can contribute to the evaluation of land-use change models.

'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.'

P11L24: Can you elaborate what 'improved communication' should entail in an ideal case. Additionally, I think it is not only the 'understanding' but first the 'awareness' of different assumptions and constrains needs to be achieved and before one can understand and tackle the problems.

Response: We believe improved communication eventually entails engaging in model integration as outlined in section 6 (*Outlook: towards model integration across disciplines*). Simultaneously the individual challenges discussed in the manuscript need to be resolved through joint engagement across the communities in the individual tasks (see recommendations now in section 5). Indeed, raising awareness of different assumptions and constraints is a first step and a major objective of the manuscript. By reorganizing the manuscript as described in our previous responses, we clarified this in the revised version, including recommendations which part of the community could most likely take the lead.

Figures: P24: add a 'log' label to the legend and add colour areas without change in grey to make the light yellow areas better stand out.

Response: We added the grey background. We did not include a log label, since the legend labels are given in km².

Supplement SP2L7: can you provide more details on the updated version, i.e. reference

Response: We added reference as far as possible (SI page 2, line 8).

The updated version is based on Ramankutty et al. (2008) for the static map of cropland distribution. 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 recently been removed.

SP5: Can you comment on the uncertainties associated with the CORINE data

Response: We added a short paragraph of uncertainties related to the CORINE data (SI page 9, lines 23 ff.). We do not think that it would add important information to the manuscript, if we elaborate comprehensively on the uncertainty in the CORINE data. We actually only use the change product for illustration in terms of cropland transition trajectories. These aggregated results are probably not heavily affected by uncertainty in the CORINE data.

SP6L8: Can you elaborate on what the 'thematic accuracy' entails.

Response: 'Thematic accuracy' entails the capability of CORINE land cover maps to represent the 'true' land-cover class as compared to an independent validation data set (EEA, 2006). We added an explanatory sentence and the reference in the respective section of the supplementary material (SI page 9, lines 30-32).

Reviewer #3 (Anonymous)

The manuscript by Prestele et al., "Current challenges of implementing land-use and land-cover change in climate assessments", provides an overview of recent publications on interactions among land-use, carbon cycling, and different aspects of climate. First, the manuscript aims "…to identify existing shortcomings of the current LULCC representations within DGVMs and ESMs, reveal the underlying mechanisms and constraints that have hampered improved representations until now, and propose pathways to improve current representations" (page 3, lines 5-7). Second, based on the literature review, the manuscript attributes the lack of progress in including LULCC into climate assessments, to 1) the failure to account for uncertainty in reconstruction and future scenarios of gridded LULCC; 2) resolving sib-grid changes in land-use activities (e.g. gross transitions); 3) allocation of primary lands to managed lands in DGVMs and ESMs. Manuscript reviews a number of studies and discusses a wide range of limitations, specifically in CMIP5 historical reconstruction and future scenario. It has interesting discussion of how to use remote sensing data in improving treatment of LULCC processes in scenario development and its implementation into DGVMs and ESMs.

Response: The reviewer presents a good summary of the objectives of our manuscript. We thank the reviewer for the time spent on our manuscript and we appreciate the positive evaluation of our discussion about implementing remote sensing data in land – climate interaction studies.

For some of the following comments we sometimes split the original comments of the reviewer to address individual points.

However, the title is not appropriate because climate assessments such as IPCC do not implement LULCC – IPCC assessments review literature. CMIPs are not part of the IPCC, although their model simulations provide input to IPCC.

Response: The reviewer has a valid point here. Our current title is misleading, although we did not intend to equate the CMIP simulations with the IPCC assessment. We thus changed the title in addition to the changes suggested by reviewer #2 into:

'Current challenges of implementing anthropogenic land-use and land-cover change in models contributing to climate change assessments'

The manuscript has four major shortcomings: 1) While the manuscript reviews and synthesizes a number of recent studies on the development of scenarios of LULCC and of LULCC for climate and carbon cycling, it does not actually provide new insights or synthesis of LULCC implementation in ESMs and DGVMs. The manuscript provides a discussion of how the CMIP5 scenario was constructed and its limitations, but does not discuss differences in land use components of different ESMs or DGVMs. Or how they implemented the CMIP5 LULCC scenario. Table 1 gives 4 examples: 3 DGVMs (2 of which are variants of LPJ model) and a new HadGEM2-Jules ESM. There is no comprehensive analysis of CMIP5 ESMs or TRENDY DGVMs used in the AR5 in respect to LULCC. Thus, the manuscript's first goal is not supported by new insights beyond those previously published in literature.

Response: The reviewer raises a valid point that the wording of our main objectives leaves room for interpretation which requires clarification. It is not the purpose of the manuscript to focus on the technical details of land modules and/or LULCC implementation of ESMs/DGVMs. This has been done in related publications (e.g., De Noblet-Ducoudré et al., 2012) as the reviewer states correctly. Instead, we provide a synthesis of issues arising along the chain of activities regarding land-use in climate change assessments (remote sensing, modeling, scenario development, implementation in DGVMs/ESMs). For that purpose we review the literature and identify the three challenges that comprise our three main sections. For each challenge, we show why it is a challenge, what implications this challenge can have for carbon cycling and climate assessments, and discuss limitations in the current approach to overcome this particular challenge.

In this way, the manuscript provides important guidance to the communities involved, as we bring together the individual points for the first time, including recommendations for potential ways forward. In fact, Table 1 should be regarded as an illustration to support our argument rather than a comprehensive analysis. We clarified this by extending the wording in reference to Table 1 (page 10, line 3):

'This has resulted in a range of different strategies, which we show as an illustration in Table 1 for a non-exhaustive list of models.'

We feel accommodating changes as outlined in the response to the other two reviewers will better clarify the value of our manuscript.

Additionally, please note: We intentionally did not submit a 'research article' but a 'short communication' type of manuscript, since it is intended as a guidance or perspective for future research, rather than new fundamental research.

2) The manuscript claims that the limited characterization of uncertainty in CMIP5 and CMIP6 LU reconstructions and scenarios is responsible for the lack of progress on LULCC in climate assessments. There is no reason to believe that's true. CMIP is designed to compare climate models and ESMs under a common set of forcings and capture model structural uncertainty. CMIPs never claimed to capture all uncertainty due to input forcing. It's a well-established practice in climate MIPs to provide a standard scenario for all forcings – greenhouse gases, short-lived species, solar, constants, volcanoes and LULCC, particularly over historical periods. Such GCM or ESM simulations are extremely computationally expensive. Permutation of alternative forcings datasets is not likely something that many climate centers will be able to engage and afford. The idea of multiple LULCC reconstructions advocated by the paper for CMIPs is not practical. If some modeling group/center wants to explore uncertainty due to LULCC, there is more than one scenario that is available even from the GLM model: Hurtt et al. (2006) included both scenarios based on SAGE and HYDE datasets. Hurtt et al. 2011 examines different assumptions in the GLM model.

Response: We do not seek to claim that 'the limited characterization of uncertainty in LU reconstructions and scenarios is responsible for lack of progress on LULCC in climate assessments' in our manuscript. We argue that the current characterization of uncertainty is insufficient and errors unaccounted for propagate into climate assessments. For example, LUMIP (contributing to the goals of CMIP6) aims to answer the scientific question '*What are the global and regional effects of land-use and land-cover change on climate and biogeochemical cycling (past-future)?*' (Lawrence et al., 2016), which we think can only be done if there is a sufficient quantification of uncertainty in the land-use forcing data set in place as well. We now present the uncertainty in the land-use forcing as a source of uncertainty in the current coupling in section

5 (*Recommendations for improving the current coupling strategies*) and propose pathways how to reduce this uncertainty.

We agree with the point that CMIP is designed to compare climate models instead of forcing data sets, but it is similarly true that CMIP – due to its highly structured design – acts as a prototype for activities outside of CMIP and its forcing datasets (and as such the LUH) are widely used as a standard outside of CMIP, too. Please note, we do not restrict our arguments to the CMIP comparisons, but use it as an example at several places in the manuscript due to its high impact and pioneer role in the community.

We added at several locations in the revised manuscript that we do not restrict our arguments to CMIP and use LUH as an example (e.g., page 3, line 16; page 12, lines 14-15). In our view a 'well-established' practice is not necessarily the same as 'best practice'. The fact that climate modeling centers cannot (or in some cases do not prioritize to) explore uncertainty in LULCC does not necessarily imply that it should not be done at all. If not practical in such a comprehensive way as proposed in section 5 of the revised manuscript, then the communities need to come up with alternative strategies to tackle these uncertainties, e.g. determining a limited set of simulations that appears to significantly affect climate and carbon cycling using less computationally expensive DGVMs or offline land surface models (see our conclusion section). We now include this discussion explicitly in section 5 (page 14, lines 1-6):

'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.'

Harmonization to a common input for climate models is a major first step to have LULCC included in the climate simulations; in a next step the communities need to find a way to systematically approach the related uncertainties. Here our recommendations and conclusions could provide guidance on how to move forward and we rephrased them to be more specific (see sections 5 and 6).

The main bottleneck for improving LULCC characterization in the CMIP is poor representation of LULCC processes in GCMs and ESMs. Most CMIP5 ESMs or TRENDY DGVMs can't use the information available in CMIP5 or CMIP6 historical reconstructions or future scenarios. For example, most of the CMIP5 models use only information about land use fractions, and not gross transitions provided by the Hurtt et al. (2011) data set. With the exception of very few models, ESMs do not represent shifting cultivation or wood harvesting.

Response: We agree that one of the major issues in land use – climate interaction studies is the 'poor representation' of LULCC in GCMs and ESMs. In fact, we identify it as one of the main issues in our manuscript as well (section 4) and emphasized it additionally following the suggestions of reviewer #1 and #2. Given the low certainty in inputs of additional products such as wood harvest and shifting cultivation (Erb et al., 2016; Hurtt et al., 2011), inclusion of the processes in ESMs is not necessarily the only bottleneck. Simultaneously, we do not agree that a 'main bottleneck' (e.g., the poor representation) justifies neglecting other important issues (such as the uncertainty in LU modeling and the gross transitions) we raise in the manuscript. Instead, the LU modeling community should clearly communicate these issues as well and take the lead on improving the products (see section 5).

Another unsupported assumption in the manuscript is that, by making additional ESMs or GCMs with alternative representations of LULCC history, one would get a better handle on the uncertainty in climate feedback of LULCC. It's not necessarily true: most studies with and without LULCC typically find a small difference in global climate and small regions with statistically distinguishable differences in climate characteristics. One would need a large ensemble of such simulations to find differences between the biogeophysical effects of alternative LULCC reconstructions and scenarios, unless they are really different as in future scenarios. Biogeophysical differences should be more pronounced, but the problem is that CMIP5 or even CMIP6 ESMs are incapable of representing major LU processes such as shifting cultivation, wood or crop harvesting..

Response: Regarding biogeochemical effects it has been shown that alternative reconstructions make a large difference to carbon emissions (e.g., Bayer et al., in press; Meiyappan et al., 2015). From these findings we derive that alternative reconstructions are 'likely to substantially impact' LULCC – climate interactions and propose to determine a limited set of contrasting simulations (using DGVMs, offline LSMs) that could be tested in ESMs (see section 5). For example, the work of Kaplan et al. (2011) and Fuchs et al. (2013) has shown that historical reconstructions can substantially differ from HYDE, thus we think it is an important scientific question how alternative reconstructions could affect the climate signal. Additionally, the uptake of a high/low estimate of historical land use in LUMIP (Lawrence et al., 2016) after feedback from the community (see the open discussion of the LUMIP paper, Lawrence et al. (2016), in *Geoscientific Model Development*), indicates that the uncertainty in LU products is indeed an important issue that needs to be further explored.

3) The manuscript questions assumptions in CMIP5 Hurtt et al. 2011 reconstruction and future scenario. The Hurtt et al. (2011) effort, for the first time, harmonized historical reconstruction with the 4 Representative Concentration pathways (RCP) scenario and took into account gross transitions between different LU types in both tropics and extra-tropics. The authors are mistaken in their assumption that no-shifting cultivation in the extra-tropics implies no gross-transitions in the extra-tropics; for example, non-zero transitions between pastures to crops and crops to pastures. Furthermore, for CMIP6 (Lawrence et al. 2016), there will be a focus and additional LUH reconstructions available, as well as more details about the relationship between land cover and land use categories. I think a lot of criticism of the CMIP5 LULCC reconstruction and scenario is valid but the authors are overlooking improvements in the new reconstruction for CMIP6, which is publicly available now on the CMIP6 website.

Response: We acknowledge the effort of the Hurtt et al. (2011) harmonization activity and its contribution to enhance LULCC representation in land use – climate interaction studies. But, as the reviewer states later on, there are also limitations in the CMIP5 product. We do not assume that gross transitions can only appear in the tropics due to shifting cultivation (page 8, lines 16 ff.), but argue that due to the resolution of the minimum transitions, gross transitions, especially in the temperate zone and the high latitudes, might be missed (page 9, lines 3 ff.).

In terms of CMIP6 and the LUH2 product, we do not overlook the improvements, but explicitly mention the update and now included a specific mentioning why we refer to the CMIP5 product throughout the manuscript (page 4, lines 15-20):

'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.'

We admit that it is extremely difficult at the moment to follow the improvements compared to the LUH CMIP5 product, since documentation of the new products is restricted to a rather generic description (Lawrence et al., 2016) and thus we might miss some details. We are aware that the new historical product is publicly available, but the final dataset does not allow to trace back how the individual processes were implemented. To our best knowledge – apart from the indisputable improvements between the two products (e.g., additional focus on land management, improved shifting cultivation estimate) – some of our main criticisms (e.g., gross transitions in the extra-tropics, derivation of LU transitions) will be untouched even with the new product.

While it's possible to construct more detailed scenarios for recent periods with satellite coverage or for specific countries (e.g., Table 2 in the manuscript), particularly in the Northern Hemisphere, it is difficult if not impossible to develop multi-century reconstructions on a global scale with consistent sets of assumptions. Making simple assumptions in ESM is not an unreasonable approach for global, multi-century analyses. Assuming transitions based on the satellite era for the entire CMIP-style experiments may be problematic, as well, for pre-industrial or future periods.

Response: We agree that making simple assumptions is a reasonable approach to get started with the land-use implementation in DGVMs/ESMs and that the satellite era might not be representative for multi-century analysis as well. We included this thought in section 3.4 (*Open issues in the current approaches*; page 9, lines 8-13):

'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 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).'

However, at least for this era the model assumptions should be carefully evaluated. Based on sufficient transition information for present-day, these assumptions could be, e.g., gradually replaced over time (backward and forward) based on scenario assumptions or regional characteristics (e.g., Fuchs et al., 2015). Sensitivity analysis could provide additional insights how individual decisions affect the land-use pattern, even over long time periods. In such a way the models would account for spatio-temporal variability in land-use transitions.

4) The rationale for including analysis from the CLUMondo model is not clear – it demonstrates how spatio-temporal variations could be different within the grid. It does not show that such patterns will affect climate or carbon cycling. Besides the CLU-Mondo analysis, there is now new analysis in this manuscript. So, there are no new insights/analysis, just a synthesis of other studies, which are already partially covered by the authors in related publications (e.g., Alexander et al. 2016, Bayer et al, 2016, Prestele et al. 2016).

Response: We added a sentence to our objectives, which explicitly mentions the illustrative purpose of the CLUMondo analysis (page 3, lines 11-13).

'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).'

Specifically, the rationale for including CLUMondo analysis is to show that a simple allocation algorithm (such as forest will be cleared upon cropland expansion) applied globally might not sufficiently account for the spatio-temporal heterogeneity in the change patterns. Previous publications have shown that these decisions can affect regional climate and carbon cycling (e.g., de Noblet-Ducoudre, 2012), and thus our analysis should be taken as an illustration that further research is required on how these decisions affect the ESM results. We emphasized the illustrative purpose of the CLUMondo analysis by moving it to a separated sub-section (4.3, *Example: Spatial heterogeneity of cropland transitions in the CLUMondo model*).

As mentioned in previous responses, the manuscript does not aim to present comprehensive new analysis, but rather use illustrative analysis using the CLUMondo model to support our arguments. In doing so, we provide a synthesis of currently untackled, or insufficiently tackled, challenges at the interface of land-use and climate modeling, and try to present guidance for the communities involved.

I think the most interesting part of the paper is the section on remotely sensed data (high and low resolution) in development of new diagnostics for evaluation of global LULCC reconstructions or models. Perhaps the authors can re-frame their analysis and demonstrate how such data can be used to improve or evaluate reconstructions (e.g. the one in CMIP6) or to create new diagnostics to evaluate ESMs and DGVMS.

Response: In our view, our manuscript brings together three major challenges/issues at the interface of land-use and climate modeling, which can serve as a guidance on the 'ways forward' to the communities involved – we therefore do not share the opinion that the remotely-sensed data should be the chief focus of the paper. Certainly there is also a need to develop new diagnostics as mentioned by the reviewer, but this is beyond the scope of this current paper. However, the reviewer raises a fair point and we added this need to section 5 (*Recommendations for improving the current LULCC representation across models*) of the revised manuscript.

'Simultaneously, 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) […]'

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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 ~~Dynamic Global Vegetation~~Terrestrial Biosphere Models (~~DGVMs) and Earth System Models (ESMs), whose~~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 fully coupled models of climate, land use and biogeochemical cycles to explore land use – climate interactions across spatial scales, information on ~~LULCC~~land use is currently provided as exogenous data from the land-use change modules of Integrated Assessment Models (IAMs) to ~~ESMs and DGVMs, while data from dedicated land-use change models (LUCMs) are rarely considered.~~TBMs. In this article, we discuss ~~major uncertainties and existing shortcomings of current implementation strategies originating in both LULCC data-provider and LULCC data-user communities. We identify~~, based on literature review and ~~the~~illustrative analysis of empirical and modeled LULCC data, three major challenges ~~related to~~ of this current LULCC representation~~, which are currently not or insufficiently accounted~~ and their implications for land use – climate interaction studies: (1) provision of consistent, harmonized ~~LULCC~~, land-use time series spanning from historical reconstructions to future projections while accounting for uncertainties due to different land-use modeling approaches, (2) accounting for sub-grid processes and bi-directional changes (gross changes) across spatial scales and (3) the allocation strategy of ~~LULCC~~ independent land-use data at the grid cell level in ~~ESMs and DGVMs. Based on these three challenges, we~~TBMs. We discuss the reasons that hamper the development of

~~implementation strategies~~ improved land-use representation that sufficiently ~~account~~accounts for uncertainties in the land-use modeling process ~~and conclude~~. We propose that ~~both providers and users of LULCC data products often miss appropriate knowledge of the requirements and constraints of one another's models, thus leading to large discrepancies between the representation of~~ LULCC data-provider and ~~processes in both~~ user communities~~. We propose to focus future research on~~ 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) is a key ~~driver~~cause of ~~altering~~alterations in the land surface (Ellis, 2011; Ellis et al., 2013; Turner et al., 2007), with manifold impacts on biogeochemical and biophysical processes that ~~feedback on~~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 ~~Earth System Models (ESMs)~~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, ~~land-use change~~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) ~~and the land being a potential net source of greenhouse gases to the atmosphere (Tian et al., 2016).~~. Livestock husbandry, rice cultivation, and the large-scale application of agricultural fertilizers further contributed to the increase in atmospheric CH_4 and N_2O concentration (Davidson, 2009; Zaehle et al., 2011)~~.~~, 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). ~~Carbon fluxes are understood quite well for some compartments of the global carbon cycle, e.g. fossil fuel combustion and the ocean sink~~ 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, along with the need to include external data to represent land-use change, have led to several issues that render the quantification of land-use change impacts on climate and biogeochemical cycles 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)~~, but the quantification of LULCC flux suffers from high uncertainties (Ballantyne et al., 2015) due to definition issues~~. 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. 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 ~~simplistic representation~~implementation and parameterization of ~~LULCC~~land use in ~~models that are used to quantify these fluxes~~TBMs (Brovkin et al., 2013; de Noblet-~~Ducoudre~~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)~~ as well as the uncertainty about LULCC history~~, the structural differences across IAMs and LUCMs (~~Ellis~~Alexander et al., ~~2013; Klein Goldewijk and Verburg, 2013~~2016; Prestele et al., 2016; Schmitz et al., 2014)~~. Quantification of LULCC impacts on climate further depends on~~, and the ~~diversity of modeling approaches in the land-use change modeling community (National Research Council, 2014) that serve as data provider for climate models. However, assessments also depend on the interpretation of LULCC in DGVMs and ESMs and parameterization of land-atmosphere processes in consequence of LULCC (Brovkin et al., 2013; de Noblet-Ducoudre et al., 2012; Hibbard et al., 2010; Pitman et al., 2009). There is still a high~~ uncertainty ~~range in the representation of LULCC as provided by land-use change models (LUCMs) and Integrated Assessment Models (IAMs)~~ about land-use history ~~(Prestele et al., 2016)~~(Ellis et al., 2013; Klein Goldewijk and Verburg, 2013; Meiyappan and Jain, 2012)~~, as well as how this information is utilized by ESMs and DGVMs.~~ .

Currently reported uncertainties of the outputs of ~~these models~~land use – climate interaction studies may be underestimated by ~~not~~insufficiently accounting for ~~these~~the aforementioned sources of uncertainty. ~~Current LULCC~~The current land-use representation therefore requires improvement to narrow down the uncertainty range ~~and~~in reported results of land use – climate studies and eventually increase the confidence level of climate change assessments. ~~Additionally, 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~~ of LULCC~~.

The overall objective of this article is to ~~identify existing shortcomings of the current LULCC representation within DGVMs and ESMs, reveal~~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 ~~current representations.~~the land-use representation. We review ~~current~~recent literature ~~(~~from the land~~-~~ use, land cover, carbon cycle and climate modeling communities~~)~~, and support our arguments by illustrative analysis ~~using~~of satellite ~~LULCC~~land-cover products and ~~model~~ outputs ~~for historical, current and~~ 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 ~~periods, and identify three critical challenges which should receive more attention in~~ land use – climate interaction studies, 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 ~~on land use – climate interactions.~~priorities.

~~2 Provision of a spatially~~2 Challenge 1: Spatially explicit, continuous and consistent time series of ~~LULCC~~land-use change

~~To distinguish the contribution of anthropogenic LULCC to radiative forcing through greenhouse gas emissions from emissions attributed to fossil fuel combustion,~~

2.1 Background and emergence

Current TBMs require consistent ~~LULCC~~, continuous and spatially explicit time series of land-use change, covering at least the period since the industrial revolution (~1750) ~~are required~~ 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). ~~Because of the long-term legacy effects of LULCC on soil carbon cycle processes, spatially explicit maps of LULCC need to span continuously and consistently from historical into future times. Connecting inconsistent LULCC~~Without time series ~~and applying them~~of at least this length, important legacy fluxes will be missed in ~~ESMs and DGVMs~~the calculations. The application of discontinuous land-use change time series in TBMs to quantify the interactions and feedbacks between ~~LULCC~~land use and climate would lead to large artificially induced changes (‘jumps’) in land use. Consequently, jumps e.g. in carbon and nutrient pools in the transition period would distort legacy fluxes working on decadal to centennial time scale, rendering the simulations useless for reliably determining the magnitude and rate of climate impacts.

However, observational data on LULCC is not available at global scale with ~~sufficient~~the required temporal and spatial resolution, consistency, and historical coverage~~. For that reason a wide variety of datasets and~~ (Verburg et al., 2011). Instead, models~~, all trying~~ are utilized to represent global land use~~, are utilized to~~ and produce the required ~~LULCC~~land-use change time series. ~~Modeling of LULCC is~~Land-use modeling is typically split up into historical backcasting approaches and future scenario modeling~~, both in turn applying~~. 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)~~. Moreover, the different models~~ and are often initialized with different ~~data sources~~representations of present-day land use ~~and land cover, i.e. also~~(Prestele et al., 2016). Thus, even the models within one community (future or historical) do not provide consistent information ~~about the current state of~~on land use and land~~ cover (Figure 1). Thus, the land~~-use change ~~modeling community provides~~over time, and a variety of independent datasets at spatially explicit or world region level ~~either for the~~ is provided to the user community (e.g. climate modeling) (Figure 1). These historical ~~time (from present day up to 10 000 BC into the past), or for the~~ and future ~~under different scenario assumptions (from present day up to 2100), without being~~ datasets are not connected and consistent ~~at~~in the transition ~~from historical backcasting to future projection and accompanied~~

~~by~~period and entail a variety of uncertainties (Klein Goldewijk and Verburg, 2013~~; Prestele et al., 2016~~). ~~These~~In consequence, these datasets ~~do not agree~~disagree about the amount and the spatial pattern of land affected by human activity~~ (both with respect to land cover and land management).~~. Moreover, varying detail of classification systems, inconsistent definition of individual categories (e.g., forest or pasture), and individual model aggregation techniques, amplify the discrepancies among models (Alexander et al., 2016; Prestele et al., 2016).

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

~~*The* first attempt~~Large efforts have been undertaken to connect the different sources of land-use data and provide ~~a~~ consistent time series for climate modeling applications ~~has been developed~~ during the 5^{th} phase of the Coupled Model Intercomparison Project (CMIP5~~)~~; Taylor et al., 2012) by the Land Use Harmonization project (Hurtt et al~~. (~~., 2011)~~ and has recently undergone update for the upcoming CMIP6 (Lawrence et al., 2016). This~~. The resulting dataset (~~*LUH*)~~hereafter referred to as LUH data) is commonly used in modeling studies ~~to determine LULCC~~ dealing with land use – climate interactions and feedbacks. It has recently been updated for the upcoming 6^{th} Phase of the Coupled Model Intercomparison Project (CMIP6; ~~Hurtt~~Eyring et al~~. (2011)~~., 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 ~~LULCC~~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 ~~LULCC~~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)~~, applying the~~ and historical wood harvest estimates. The decadal spatial ~~LULCC~~ patterns from the projections were applied to the HYDE map of 2005. ~~This strategy~~The harmonization tries to conserve the original patterns, rate and location of change as much as possible, and to reduce the differences between the models due to definition of ~~land-use categories (e.g., what constitutes a forest in the individual models).~~cropland, pasture and wood harvest. To achieve the final harmonized time series and explicit transitions~~ (i.e., information about the source and target land use between two subsequent years on a grid cell basis), the LULCC~~, the pre-processed land-use time series are used as input into the GLM model and constrained by further data ~~on wood harvesting activities,~~and assumptions about the occurrence of shifting cultivation, the spatial pattern of wood harvest, priority of the source of agricultural land and biomass density~~. While this strategy~~ (Hurtt et al., 2011). The harmonization ensured for the first time consistent land-use input for climate model intercomparisons, and serves as a basis to implement anthropogenic impact on the land component in climate models. Beyond this inarguable success, several ~~uncertainties~~ aspects remain within the LUH data that to date are not, or only ~~poorly~~partially, considered. ~~These~~In the following section we discuss the main uncertainties ~~are likely to~~and how they may propagate into

~~ESMs and impact~~TBMs, impacting the amplitude, and possibly even the sign of ~~LULCC – climate~~land-use interactions and feedbacks.

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

The first major uncertainty ~~is that by considering~~of the LUH data evolves from the exclusive consideration of the HYDE baseline dataset ~~exclusively~~ for the historical ~~time~~ period~~, the~~. 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). ~~Alternative~~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 ~~SI~~Supplement S1 and Table S1 for additional information~~, Table S1~~ on these reconstructions), and shown to differ substantially both in terms of the total cultivated area~~, but also in how this area changes spatially~~ and spatial pattern over time (Meiyappan and Jain, 2012). ~~The main uncertainties relate to~~ 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 ~~spatial~~ allocation scheme ~~of~~ used to distribute regional or national ~~LULCC~~ estimates of agricultural land to specific grid cell locations~~.~~ (Klein Goldewijk and Verburg ~~(~~, 2013)~~ demonstrated the uncertainties in the backcasting modeling process in detail using the example of HYDE and emphasize the difficulties to properly quantify them.~~.

The uncertainty about ~~LULCC~~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 ~~LULCC~~land-use emissions among three historical reconstructions for the 21th century modeled by one ~~DGVM~~TBM to be about 18 PgC or ~11 % of the mean ~~LULCC~~land-use emission. Another study, using three commonly-used net ~~LULCC~~land-use datasets in one ~~DGVM~~TBM, revealed differences of about 20 PgC or ~9 % of the mean ~~LULCC~~land-use emission since 1750 ~~(Bayer et al., 2016).~~(Bayer et al., in press). Jain et al. (2013) further found contrasting trends in ~~LULCC~~land-use emissions at regional scale during the past three decades, which originate in different amount and rates of ~~LULCC in the individual regions based on the realization~~land-use change in different realizations of historical land use. ~~And~~Further, as biophysical climate impacts of ~~LULCC~~land use are ~~suggested~~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 ~~these uncertainties~~ the range of historical land-use change is likely to ~~also~~ affect the implications derived ~~about LULCC~~regarding land-use contribution to changes in local to regional climate. Using the HYDE reconstruction exclusively ~~thus implicitly considers~~implies high confidence about ~~LULCC~~land-use history in many large scale assessments and comparison studies (~~e.g.,~~ Kumar et al., 2013; Le Quéré et al., 2015; Pitman et al., 2009)~~, which form also the basis for the development of~~ , 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 ~~estimations~~estimates of present-day land use~~ and land cover.~~. The ~~harmonization procedure proposed by Hurtt et al. (2011)~~LUH approach does not consider the differences between different data

~~about~~regarding the current state of land use ~~and land cover by connecting~~as it connects the future projections exclusively to the HYDE end map (Figure 1~~Figure 1~~). ~~This uncertainty, however, is represented also in the~~ The present-day starting maps of ~~the different~~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~~-use change models providing LULCC data to climate models~~cover maps in turn disagree about extent and spatial pattern of agricultural land (~~Prestele~~Congalton et al., ~~2016~~2014; Fritz et al., 2011)~~. The differences can result in substantial deviations of the seasonal and spatial pattern of surface albedo, net radiation and partitioning of latent and sensible heat flux (Feddema et al., 2005) and affect carbon flux estimates proposed by DGVMs across spatial scales~~ 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 (~~Quaife~~Friedl et al., ~~2008~~2010)~~. While the rising operational application of remote sensing during recent decades has opened a powerful resource to map land cover on global scale, definition issues (Sexton et al., 2015), and difficulties in the derivation of individual land-use and land-cover categories~~. 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 (~~Friedl~~Feddema et al., ~~2010~~2005)~~, lead to a variety of global land-cover products with large differences~~ and affect carbon flux estimates proposed by TBMs across spatial scales (~~Ban~~Quaife et al., ~~2015; Congalton et al., 2014~~2008)~~. Although this lack of knowledge is well recognized (Bontemps et al., 2012), progress so far is limited to the mapping of single LULCC processes such as forest dynamics (Hansen et al., 2013) or data assimilation efforts such as the Geo-Wiki project to improve the accuracy of global land cover maps (Fritz et al., 2012). While these projects are promising and certainly contribute to improved representation of current land use and land cover at global scale, a comprehensive and reliable LULCC product covering all relevant processes is still missing.~~.

Finally, ~~for~~the future projections used ~~within the IPCC-context, the land-use trajectories~~in the LUH are provided by different IAMs, whereby each of them represents an individual scenario of the ~~recent RCP/SSP framework~~ 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)~~, a so-called~~. These are referred to as 'marker scenarios' in case of the SSPs. A 'marker scenario' ~~(Popp et al., in review).~~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 ~~model structure and different~~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 ~~regarded valuable (Popp et al., in~~

~~review).~~valuable (Popp et al., 2016). Model comparisons further revealed that while land-use change models represent cropland processes and development more consistently, the representation of pastures and forests (if modeled) is poor. For example, the projections ~~for pasture areas in 2030~~ of 11 IAMs and LUCMs show large variations in pasture areas in 2030 for many world regions (Figure 2~~Figure 2~~, background map). These projections were based on a wide range of scenarios, and thus variation in outcomes was to be expected~~. However, the~~ (Prestele et al., 2016). The variation attributed to the difference in model structure ~~is larger than~~exceeds the variation due to different scenarios in most regions (Figure 2~~Figure 2~~, bar plots~~). The~~), 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 ~~LULCC time series~~land-use projections actually do not represent different outcomes resulting ~~primarily~~ from different scenario assumptions~~ about future development of anthropogenic LULCC~~, but rather differences between ~~which~~ land-use data input ~~is~~ used to calibrate the models and ~~how LULCC~~ the implementation of drivers and processes in the models. Consequently, differences in future climate impacts of land use are ~~implemented in the~~likely also affected by the structural differences across land-use change models.

~~These three sources of uncertainty are poorly addressed through the almost exclusive implementation of the *LUH* dataset within the climate modeling community. A wider range of harmonized time series is therefore likely to substantially impact the outcomes of studies on LULCC – climate interactions. Yet the actual impact of alternative harmonized time series on climate impacts has never been tested. Multi land-use change model ensembles would be required to provide a better estimate of the range of uncertainty for historic, current and future times across scenarios. Ideally, future models should be directly connected to different LULCC histories that are constrained by different plausible realizations of current land use and land cover. Such an approach would ensure a comprehensive coverage of the uncertainties accumulating across temporal and spatial scales prior to feeding the LULCC data into climate models and allow for testing of the climate model sensitivity to different realizations of LULCC.~~

~~Moreover, a systematic approach to reduce uncertainties and a more rigorous evaluation of approaches to project global land-use changes need to be developed. Integration of various empirical data streams into the models could lead to a better representation of current land use and land cover. Increasing computing and storage capacity facilitates access to high resolution observational data (e.g., Hansen et al., 2013; Chen et al., 2015), while different reporting schemes under international policy frameworks provide increasing amount and quality of data on national to regional scales (e.g., Kohl et al., 2015). Concurrently, systematic approaches to test model results against independent data sources are required. If not yet possible at the global scale, the land-use change modeling community should start to implement evaluation schemes at regional scales using smaller scale, high accuracy remote sensing products to improve the credibility of their model outputs.~~

~~3~~3 Challenge 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. ~~In case of gross change, the land-use and land-cover categories are provided in a transition matrix as input to, e.g., DGVMs or ESMs, determining the amount of area that has changed from one category to another in each grid cell between two time steps.~~ The total area in a grid cell, which has been affected by change, can be calculated by the sum of all individual changes~~.~~ (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 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 ~~LULCC~~ land-use change in recent TBM studies (Bayer et al., ~~2016~~in press; Fuchs et al., 2015b; Stocker et al., 2014; Wilkenskjeld et al., 2014)~~.~~. For example, Bayer et al. (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.

~~Providing accurate estimates of historical and future gross change is a difficult task, since gross changes vary with spatial and temporal resolution (Fuchs et al., 2015a) and the explicit identification of source and target categories (i.e., which land use is converted to another) requires to solve a large, under-determined mathematical system~~ 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 (~~Hurtt~~Fuchs et al., ~~2011~~2015a)~~. Currently, the land-use change modeling community either (1) adds sub-grid information by constraining the under-determined system using a set of boundary conditions such as information on minimum transitions derived from previous modeled time series for historical and future times, wood harvest statistics and biomass density measures~~, 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 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; ~~(Hurtt~~Eitelberg et al., ~~2011; Hurtt et al., 2006)~~2016; Van Asselen and Verburg, 2013~~ or (2) derives gross/net ratios from empirical data such as historical maps or high resolution remote sensing products which can be subsequently applied to existing net representations (Fuchs et al., 2015a; Fuchs et al., 2015c). The former approach very much depends on the resolution of the original LULCC time series and their ability to represent land-use change dynamics on a sub-grid scale. For example, if the input LULCC time series reports changes at a 0.5 x 0.5 degree regular grid in a net change approach, minimum transitions are also constrained to this resolution. An example is shown in Figure 3 by re-gridding LULCC information of a dedicated high-resolution LUCM (5 arcminutes spatial resolution) to the commonly applied 0.5 x 0.5 degree grid in DGVMs. The analysis is based on a simulation tracking the changes between five land-use and land-cover categories (cropland, pasture, forest, urban, and bare) over a time period of 40 years. In the *LUH* dataset areal changes due to shifting cultivation and wood harvest (only if wood harvest demand is not met by deforestation in the minimum transitions and thus leads to additional areal changes) are assumed to be the main gross change processes resulting in distinctly higher change rates mainly in the tropics (Hurtt et al., 2011; Stocker et al., 2014). Higher gross change rates are expected to have a large impact on the carbon fluxes (Bayer et al., 2016). It is thus important that Figure 3 indicates that also in large parts of the temperate zone and high latitudes gross change processes play an important role and may be underestimated by the currently used *LUH* dataset. Figure 3 is only based on one realization of one LUCM, i.e. not necessarily representing the full extent and spatial pattern of global scale gross changes, and only depicts the loss of information while re-gridding to coarser resolutions. Thus, information below the spatial resolution of the original data is still not captured. Therefore the data-based approach has clear advantages where the required information can be obtained. ~~). We tracked all changes between five land-use and land-cover categories (cropland, pasture, forest, urban, and bare) at the original resolution over a time period of 40 years. 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 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 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., 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 ~~Fuchs~~(e.g., Hurtt et al~~.~~ ~~(2015a~~., 2011; Stocker et al., 2014)~~ have shown that the integration of different empirical data sources capture bi-directional transitions at the sub-grid level, which are especially important for heterogeneous areas and mosaic land systems, which are typical for regions of limited resources, high population densities or a combination of both .~~, 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 ~~(van Asselen and Verburg, 2012)~~Fuchs et al. (2015a)~~.~~

~~The transition matrix provided with the *LUH* data accounts partly for gross changes, but the values are dependent on a number of assumptions and the gross change rates have not been evaluated against empirical data. For example, urban expansion is applied proportionally to the remaining land-use and land-cover categories and in the case of agricultural expansion choices in the model configuration have to be made, whether primary or secondary land is converted preferentially. These choices, however, have serious impacts on the spatio-temporal pattern of the remaining primary, secondary and managed land, which in consequence propagate into the ESM or DGVM results .~~, 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 (~~Hurtt~~Fuchs et al., ~~2011~~2015c) may contribute to cover larger 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).~~.~~ ~~The increasing availability of remote sensing data (e.g., Chen et al., 2015; Hansen et al, 2013) opens the opportunity to evaluate the assumptions of current allocation rules. Moreover, in regions where driving factors of small-scale land-use change processes are more complex and not easy to determine due to frequent land-use changes, high-resolution empirical data can provide additional information and accuracy to currently available data.~~

4

4 Challenge 3: Allocation of managed land in TBMs

4.1 Background and emergence

~~ESMs and DGVMs~~

~~The impacts of anthropogenic activity on the land surface and consequently on the interaction between the terrestrial system and the atmosphere have long been understudied (Flato et al., 2013). Most ESMs~~) 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-~~Ducoudre~~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). ~~However, over the last decade, representation of human land-cover change, and also some land-use aspects have increasingly be captured~~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). ~~The~~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 ~~taken~~required from external ~~datasets provided by~~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, ~~the~~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). This~~ 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~~, and probably smaller,~~ impact on ecosystem carbon stocks through soils. Likewise, the albedo and partitioning of energy differs strongly between forest and grassland land covers~~. The implementation of this decision affects the assessment of carbon and nutrient budgets over long time periods and possibly also the robust determination of LULCC impact on regional temperature and precipitation patterns that respond to changes in biophysical forcing at the land surface~~ (~~de Noblet-Ducoudre~~Mahmood et al., ~~2012~~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.

~~In CMIP5, most ESMs implemented a proportional reduction rather arbitrarily due to reasons of simplicity or internal model constraints; others convert grassland preferentially or further treat cropland and pasture differently (de Noblet-Ducoudre et al., 2012). However, the spatial pattern and transition trajectories of LULCC are complex interplays of biophysical and socioeconomic parameters, which are not properly represented by these simplistic, globally applied, algorithms. Moreover, the question on which type of natural land (grassland or forest) new agricultural land should be allocated, is not only an empirical question, but also largely depends on the currently available data sources and model types.~~

~~Identifying transition trajectories from empirical data is still difficult to achieve globally (though better products are just emerging, Ban et al., 2015), but to some extent possible at regional to continental scale.~~

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)~~(Bossard et al., 2000) indicates over two consecutive time periods (1990-2000, 2000-2006) ~~shrub vegetation associations~~shrubland systems to be the main source of expanding agricultural land~~ (45 % and 39 %, respectively),~~, followed by low productivity grasslands ~~accounting for 22 % and 13 %,~~ and forests ~~(14 % and 17 %)~~ (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~~ also~~ 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. ~~However, they~~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)~~(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. They further found large variability in agricultural sources across seven major tropical regions, e.g., substantially higher conversions from shrublands and woodlands to agricultural land in South America and East Africa. ~~Further large-scale remote sensing studies are available from Northern China and the Yangtze River basin.~~ Grasslands have been detected as the main source of agricultural land in Northern China, e.g., by Li (2008), Liu et al. (2009) 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 ~~is varying~~varies across world regions and a single global algorithm to replace natural vegetation by managed land in ~~ESMs~~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 ~~algorithms~~land-use allocation strategies of TBMs with historical change data at global scale due to the lack of accurate global ~~LULCC~~land-use and land-cover products ~~with sufficient accuracy,~~(though better products are just emerging; Ban et al., 2015), we additionally tested to what extent ~~changes~~cropland expansion simulated by the land-use change model CLUMondo (Eitelberg et al., 2016; Van Asselen and Verburg, 2013) ~~represent~~represents one or more of the simplified algorithms currently considered in ~~ESMs~~TBMs (Table 1~~Table 1~~). ~~We therefore~~

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. 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 a CLUMondo simulation (FAO3D; Eitelberg et al.; 2016) according to their dominant land-use or land-cover type to derive transitions (Table S6) and classified the changes ~~in the simulated data~~ within each ca. 0.5 x 0.5 degree grid cell as either grassland first, forest first, proportional, ~~i.e., reduction as a proportion of the fractional coverage of each PFT within the grid cell, or~~ or a complex reduction pattern (~~see SI for methodological details,~~ Table ~~S6,~~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 ~~in the process~~ of ~~taking land into use~~cropland expansion in a~~ more~~ 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~~, where our method detected one of the algorithms~~ account only for 24-27 % ~~on a global scale~~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.

~~According to the patterns simulated by CLUMondo, simple algorithms applied globally thus do not account well for the spatio-temporal variation of LULCC. An alternative would be transition matrices that include explicit information about the source of expanding agricultural land at the grid cell scale. Providing such transition matrices, however, shifts the allocation issue from the DGVM/ESM community to the IAM/LUCM community and would still lack the empirical justification and evaluation against observational data for most applications. For example, in the current harmonization approach~~

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 (~~Hurtt~~de Noblet-Ducoudré et al., ~~2011~~2012)~~ transitions are derived using simple rules without accounting for the spatial and temporal heterogeneity of the multiple drivers of LULCC, e.g., by assigning urbanization proportionally to the other categories and putting cropland or pasture preferentially on primary or secondary land. Thus, much more work has to be done on understanding the processes driving land-use change in different land systems and providing empirical justification for allocation algorithms across different scales in land-use change models. Exploring the large collections of high-resolution satellite imagery with global coverage, e.g., the Landsat archive (30 m spatial resolution) or the European Sentinel mission (10-60 m spatial resolution) may offer opportunities to continuously improve and evaluate land-use change models in future. Nevertheless, current products lack the required accuracy. Limitations and uncertainties in modeled LULCC time series thus have to be clearly communicated by the data providers and taken into account by the data users.~~

~~Although~~. However, none of them depicts complex interplays 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 ~~modelling~~modeling, and to estimate the natural systems at risk under agricultural expansion. However, the specific problem of allocating new agricultural land in DGVMs and ~~ESMs~~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 ~~land surface modules in~~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)~~(ESA, 2014), and a translation to PFTs, e.g., ~~Poulter et al. (2011)~~Poulter et al. (2011), as background vegetation map on which agricultural land is imposed. Due to inaccuracies in global remote sensing land~~-~~-cover products ~~(Congalton et al., 2014) and the previously mentioned~~and differences in historical reconstructions~~,~~ (as discussed in section 2), fractions of agricultural land on a grid-scale necessarily show difference between the background map and the external land-use dataset. Consequently, the PFT composition outside the prescribed agricultural land can represent either real heterogeneity in natural vegetation, or a mix of natural and anthropogenic land cover due to differences in the datasets. In the first case, empirical data or transition matrices would help to make the right allocation decision, in the second case, rather the woody PFTs should be converted, while the grass PFTs that represent uncertainty in agricultural land-use products should remain unchanged. However, these cases are difficult to distinguish and empirically justified transition matrices, together with more accurate present-day land-cover products, would provide a useful tool for reducing uncertainties due to allocation decisions in ESMs.

5 ~~Conclusion and recommendations~~ Recommendations for improving the current LULCC representation across models

~~In this article we identify three major shortcomings of LULCC representations at the interface of land-use change modeling and ESMs/DGVMs. Both communities have developed sophisticated models during the past decades, with different priorities leading to a situation where mainly IAMs act as data provider for ESMs and DGVMs with regard to the research on land use – climate interactions. However, to improve the representation of complex interactions and feedbacks between the land system and the climate system, further coupling and integrating of these different types of models would be required on the long term, where anthropogenic activity on the land system is considered as an integral part of the models instead of an external boundary condition. A fully integrated coupling of behavioral land system models and terrestrial biosphere models may provide further~~

~~understanding of possible land-climate-society feedbacks (Arneth et al., 2014; Verburg et al., 2015), since the current coupling strategy rarely accounts for the complexity of human-environmental relationships and feedbacks (Rounsevell et al., 2014).~~ ~~In the meantime, improved communication between the communities and understanding the assumptions and constraints in the models of each other is crucial to properly account for uncertainties and error propagation into the interpretation of final results. Currently, the variety (and accompanied uncertainty) in land-use change modeling is poorly represented in the widely and often exclusively used *LUH* dataset as we have shown in this article. The land system, however, is suggested to have great capacity in terms of climate mitigation and adaptation and will therefore play an important role in the development of future climate policies. However, to be able to realistically quantify these potentials based on models, the current LULCC representation is likely to be not sufficient. We thus propose several pathways, how current LULCC representation and consequently the quantification of land use – climate interactions and feedbacks can be improved and call for:~~

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

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

~~Development of~~

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 are poorly addressed through the almost exclusive implementation of the LUH dataset within the climate modeling community and a wider range of harmonized time series is therefore likely to substantially impact 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. To 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, 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 limitations discussed in our section 2, regional scale evaluation schemes using smaller scale, high accuracy remote sensing products 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 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 ~~rather than simple, globally applied, allocation rules. Moreover, DGVMs and ESMs~~, which account for the spatio-temporal heterogeneity of land-use change drivers is essential.

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

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, rather than improving de-coupled data products and models on an individual basis, an advancement of the ‘offline’ coupling strategy would also be required. 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 is overly limited, accumulating a very large level of uncertainties 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 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).

~~(3)~~

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Table 1: Examples of allocation rules at grid cell level to implement agricultural land in different ~~DGVMs and ESMs.~~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 reporting main sources of agricultural expansion or allow for land cover change detection~~.~~

Region	Temporal coverage	Main source of new cropland	Main source of new pasture	Reference
Europe	1990-2000 / 2000-2006	Shrubland / Shrubland*		~~Bossard et al. (2000)~~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. 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'.

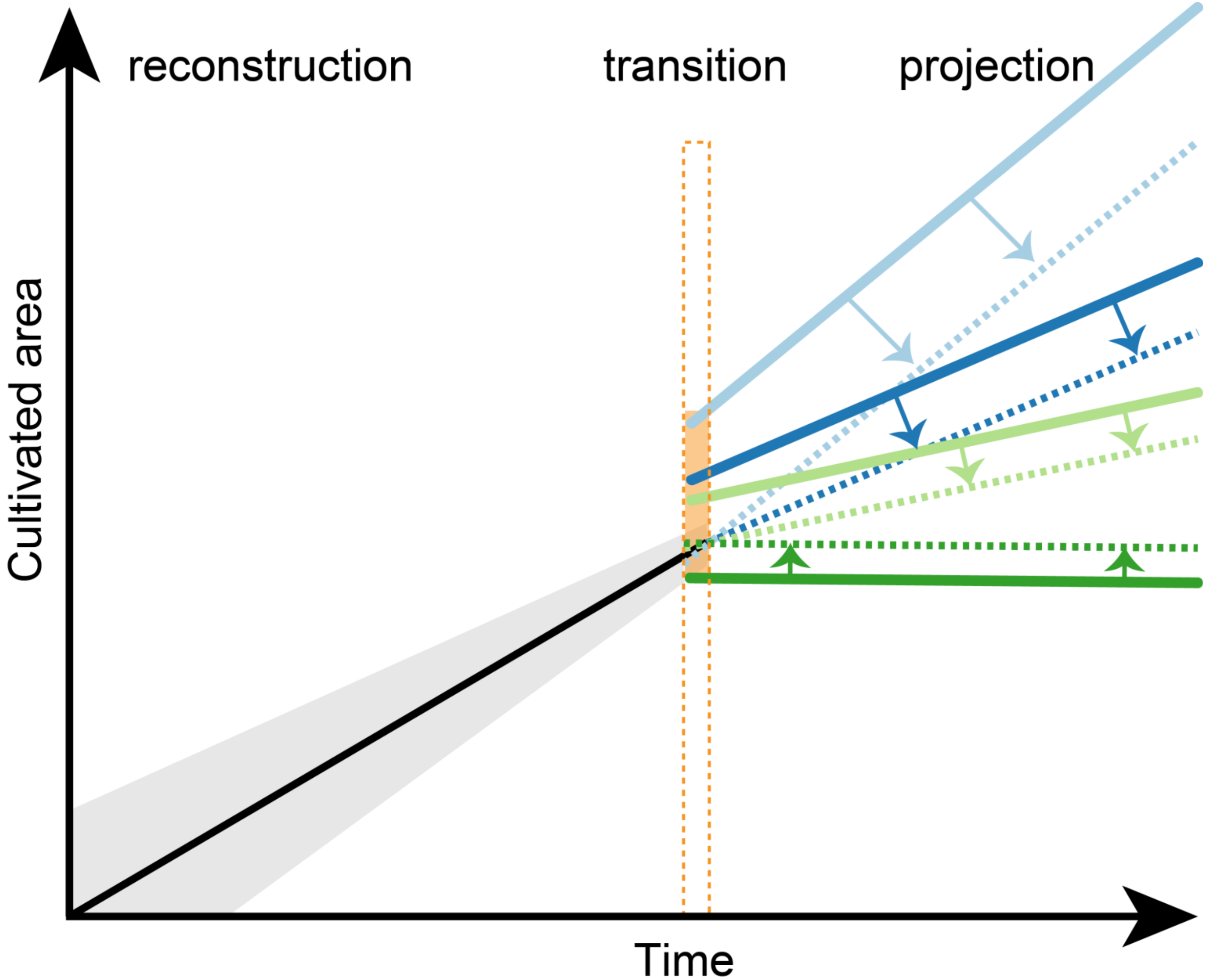


Figure 1: Simplified scheme of the harmonization process. Future projections from different models (solid colored lines) are smoothly connected (dashed colored lines) to the HYDE historical reconstruction (black line; grey shading represents the uncertainty range of LULCC history). Uncertainty about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

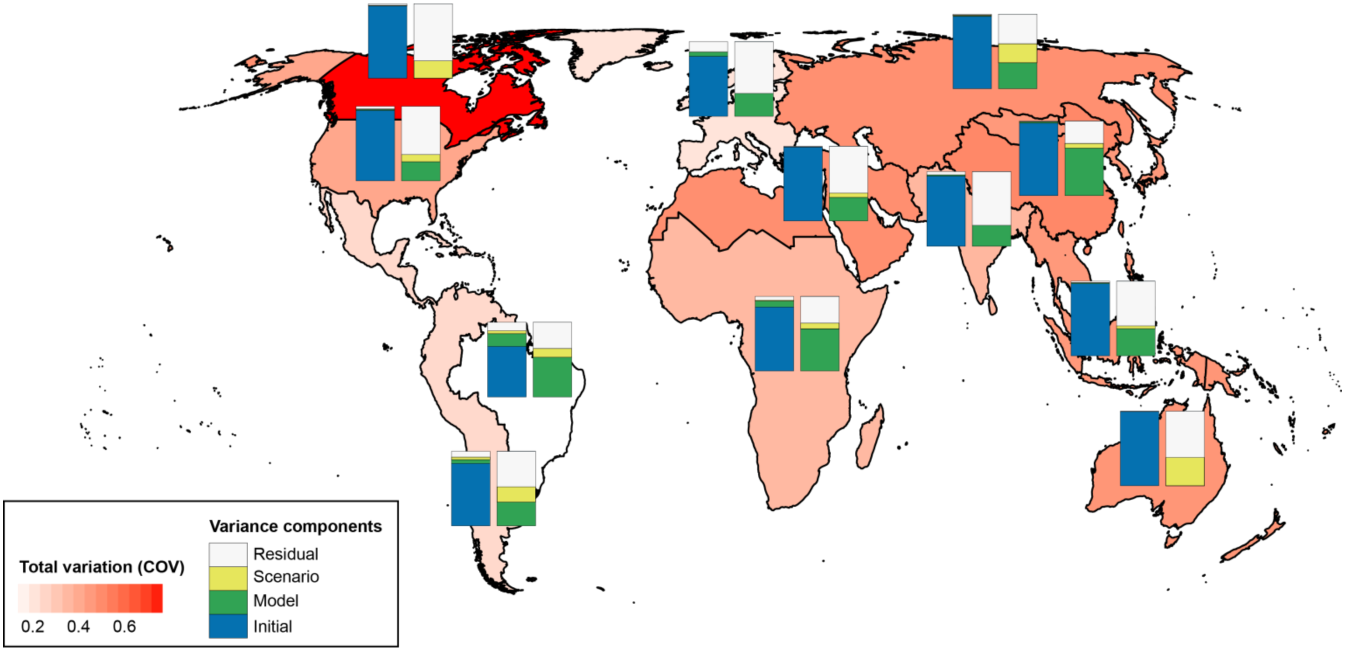


Figure 2: Variation (expressed as coefficients of variation) of pasture projections for 12 world regions in 2030 (shading of the background map) and relative attribution of total variation to initial~~, model~~ (pasture area in relation to values reported by FAOSTAT (2015) for the year 2010), model (model type and spatial configuration) and scenario parameters (bar plots). Left bar plot per region including initial variation, right bar plot per region excluding initial variation. The figure is based on 11 regional and spatially explicit land-use change models as described in Prestele et al. (2016). Methodological details can be found in ~~the SI~~Supplement S2.1 (Table S2) and in Alexander et al. (2016).

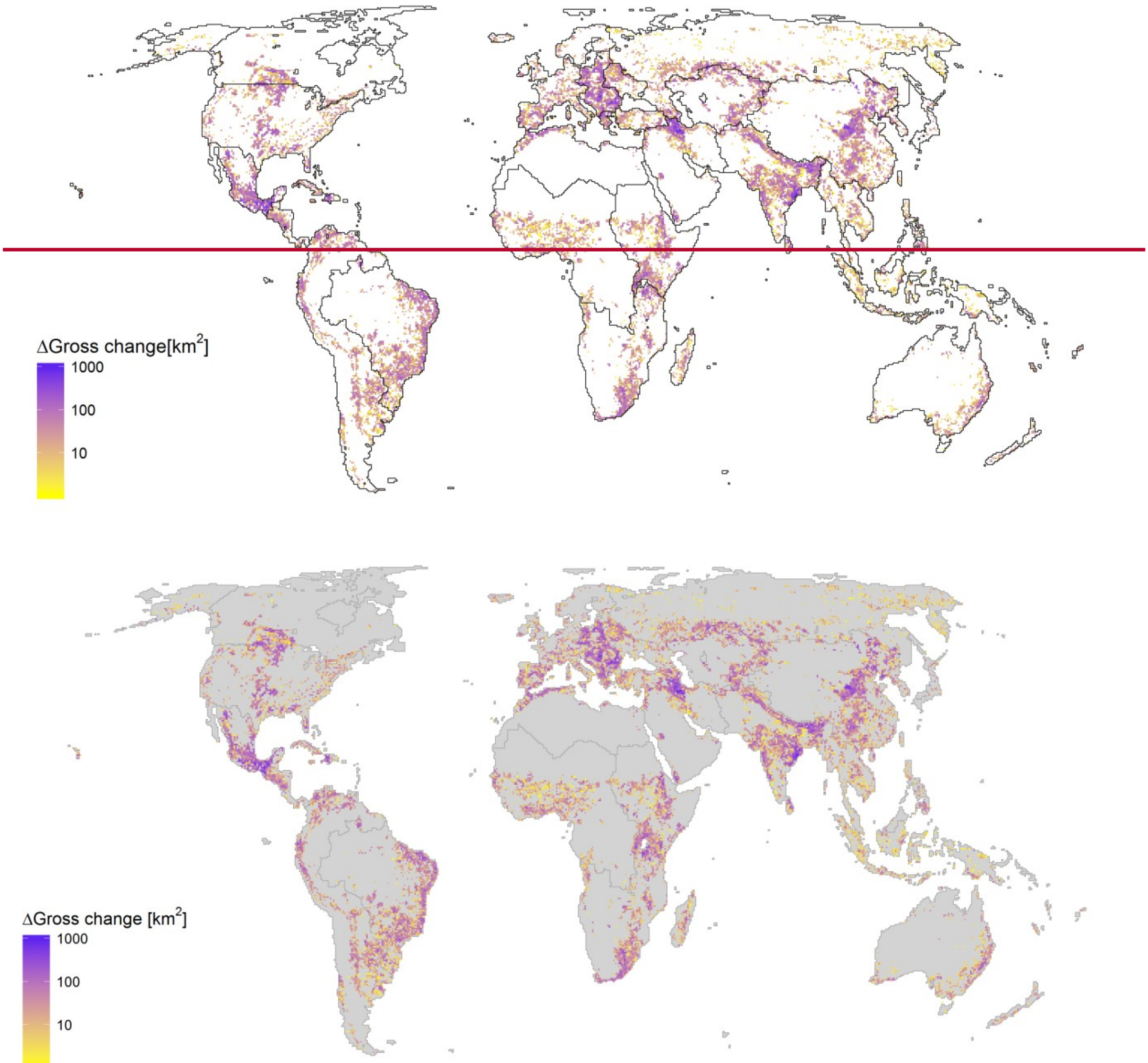


Figure 3: Difference between gross versus net area affected by change at grid cell level (ca. 0.5 x 0.5 degree) as shown by the CLUMondo model (FAO 3 demand scenario). Areas affected by net or gross change have been accumulated over a 40 year simulation period. Net changes are calculated at ca. 0.5 x 0.5 degree resolution, while gross changes also account for bi-directional changes at the 5 arcminute native CLUMondo resolution~~.~~ (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.

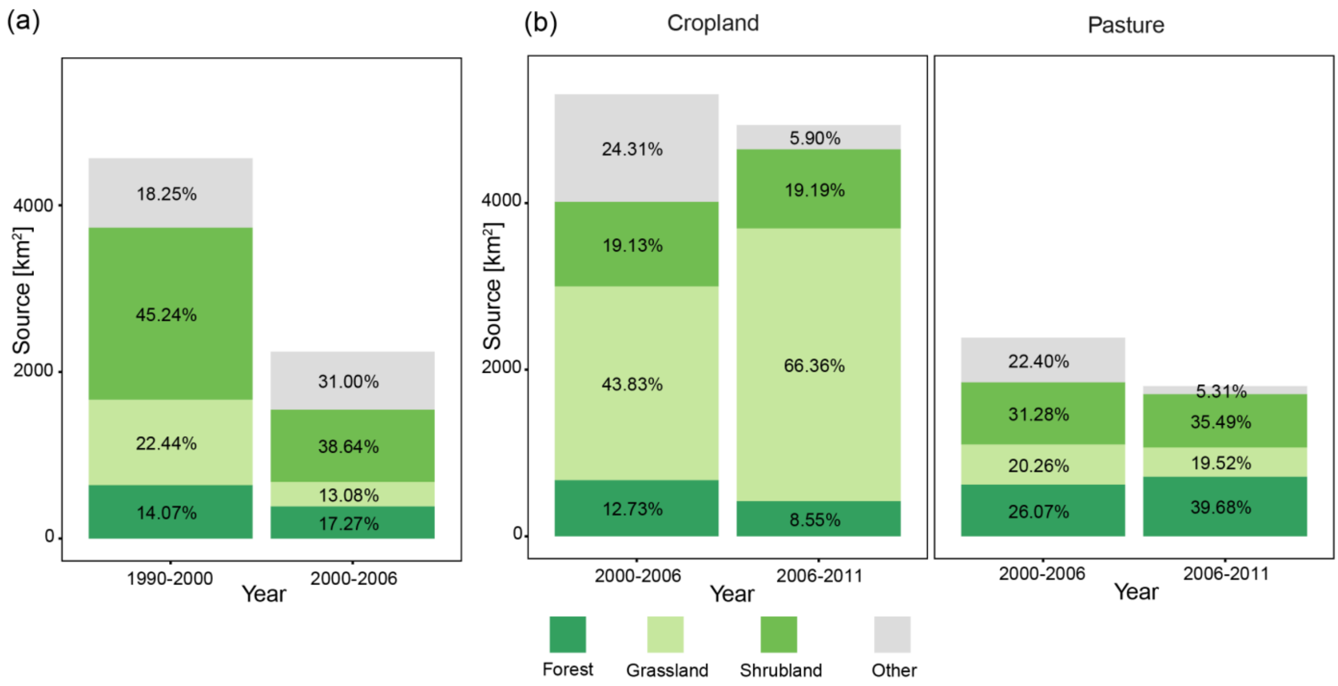
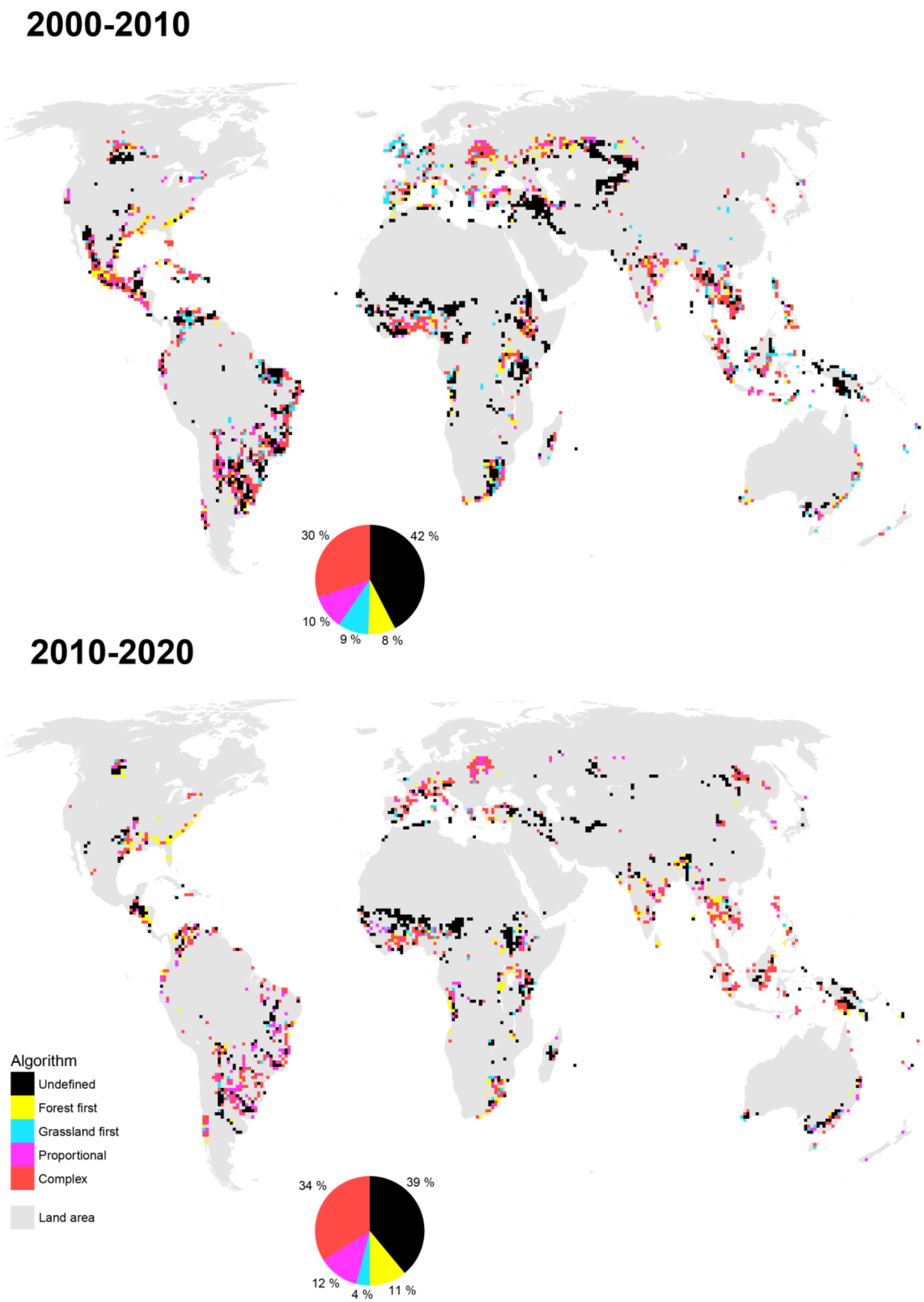
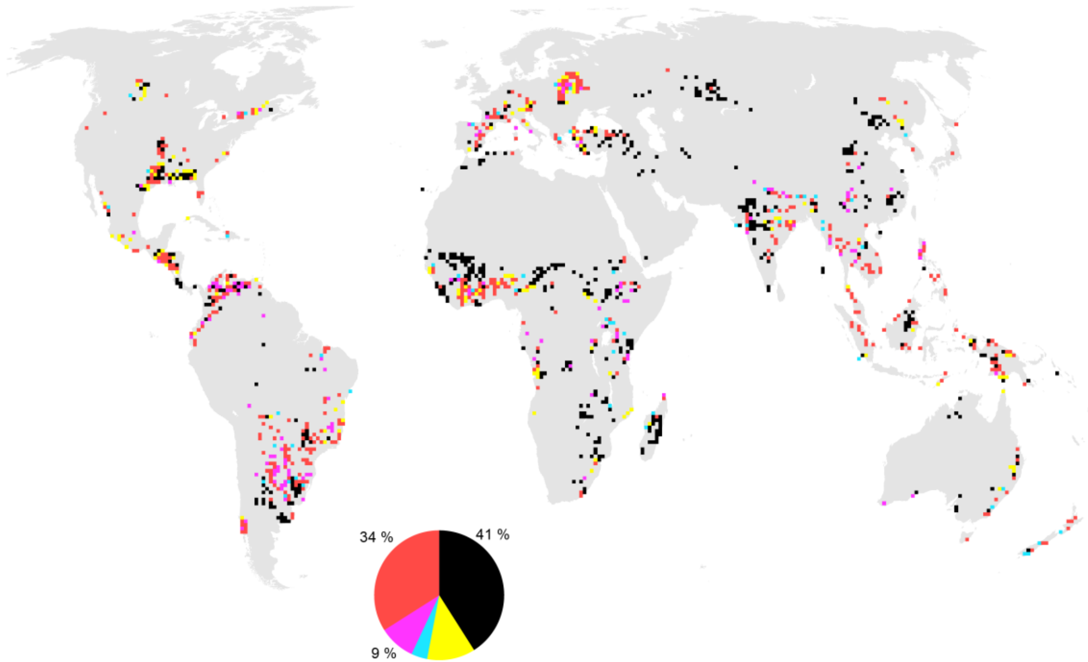


Figure 4: Sources of agricultural land (cropland and pasture combined) for two time periods in Europe based on the CORINE land cover data (a) and sources of cropland and pasture for two time periods in the USA based on the NLCD land cover data (b~~).~~) (Supplement S2.3, Table S3). Changes between different 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

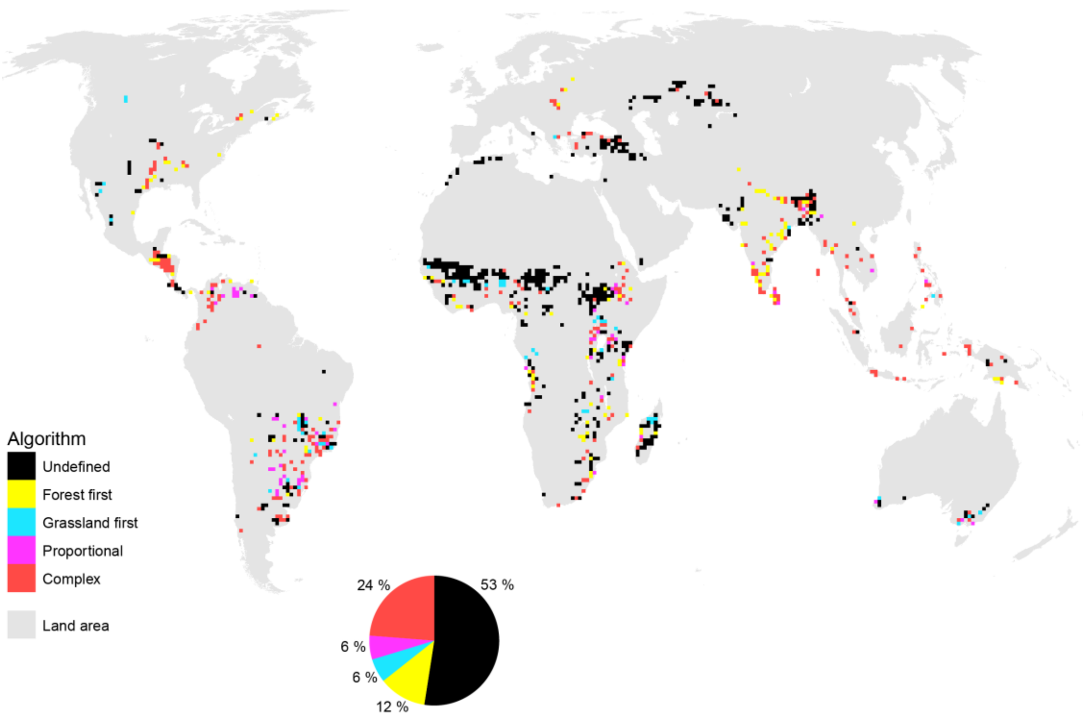


Figure 5~~:~~ Transitions from natural vegetation to cropland as shown by the CLUMondo model (FAO 3 demand scenario) from 2000 to 2040 in decadal time steps. Colored grid cells represent areas with at least 10 % of cropland expansion within a ca. 0.5 x 0.5 degree grid cell. Grid cells are classified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

Supplementary Information

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). In the following paragraphs we summarize the methodologies of four spatially explicit historical reconstructions. For details, please see the original publications.

~~S1.1~~

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 ~~data~~) 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.

~~S1.2~~

Ramankutty and Foley (1999)

Ramankutty and Foley (1999) apply a hindcast modeling technique to derive ~~global scale~~ spatial patterns of cropland on a global scale for the period 1700-1992. The original reconstruction did not ~~include~~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 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.

~~S1.3~~ *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

[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.

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 ~~these~~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.

~~S1.4~~

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 ~~the expansion of~~expand land use ~~into~~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 ~~scenario~~individual projection has been parameterized according to 9 variables (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. 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	~~Association~~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 ().

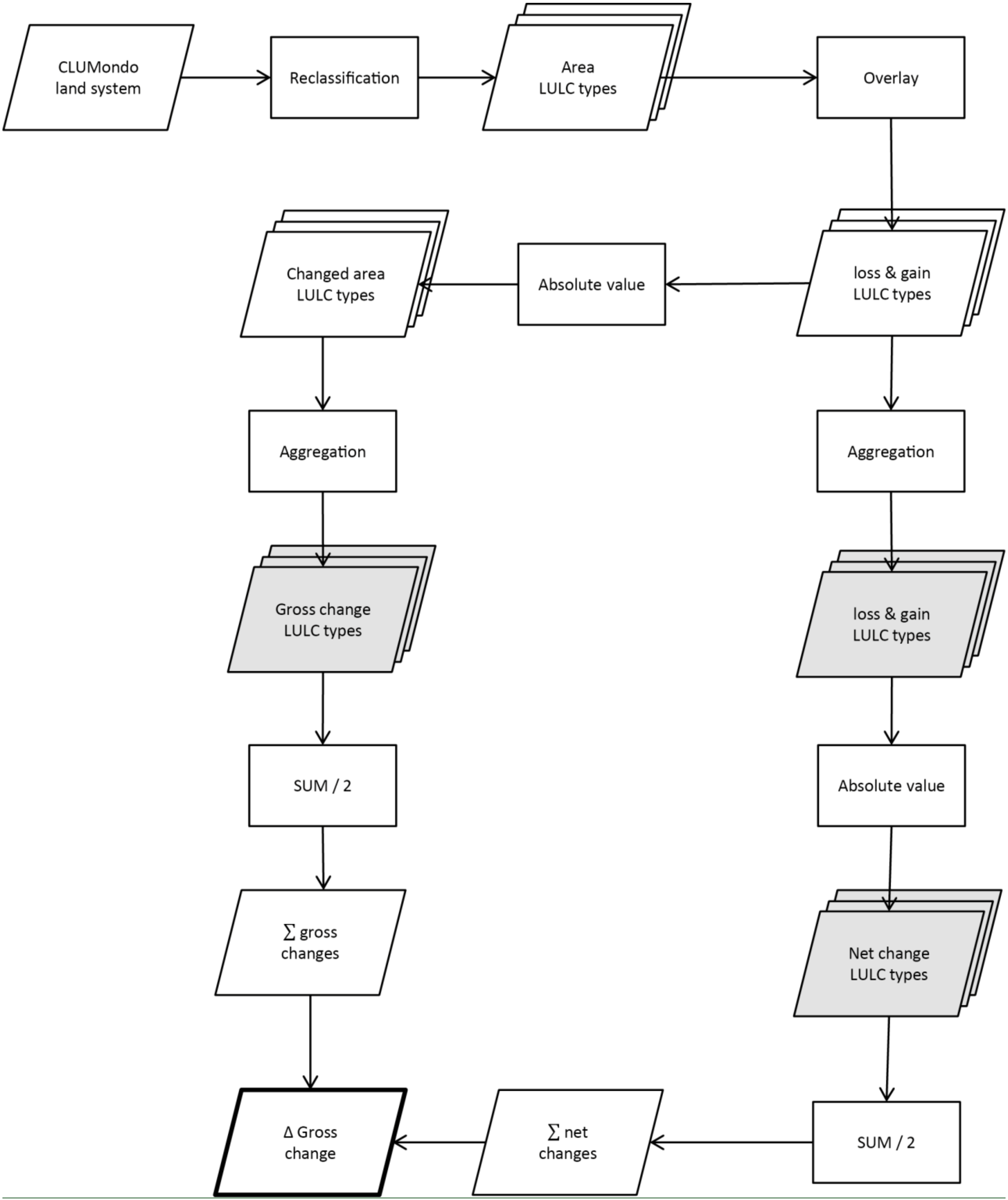


Figure S1: Preprocessing workflow of CLUMondo output for gross change analysis. Rectangles represent processing steps, parallelograms represent data. Grey shaded items emphasize aggregated data at ca. 0.5 x 0.5 degree resolution.

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). We downloaded CORINE data from http://land.copernicus.eu/pan-european/corine-land-cover. NLCD data were obtained through http://www.mrlc.gov/.

S2.~~2~~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 ~~low productivity grasslands~~natural grassland could be only identified at level 3 (Table S4). See Bossard et al. (2000) for a detailed description of the legend and distinction of individual classes. ~~Thematic accuracy of both products is indicated with larger than 85% (http://land.copernicus.eu/pan-european/corine-land-cover).~~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~~.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 ~~LULCC~~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). 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.~~2~~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~~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 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

~~S2.3 Derivation of gross vs. net changes due to re-gridding from a CLUMondo simulation~~

~~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), whose exact fractions vary 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 (Figure S1) .~~

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

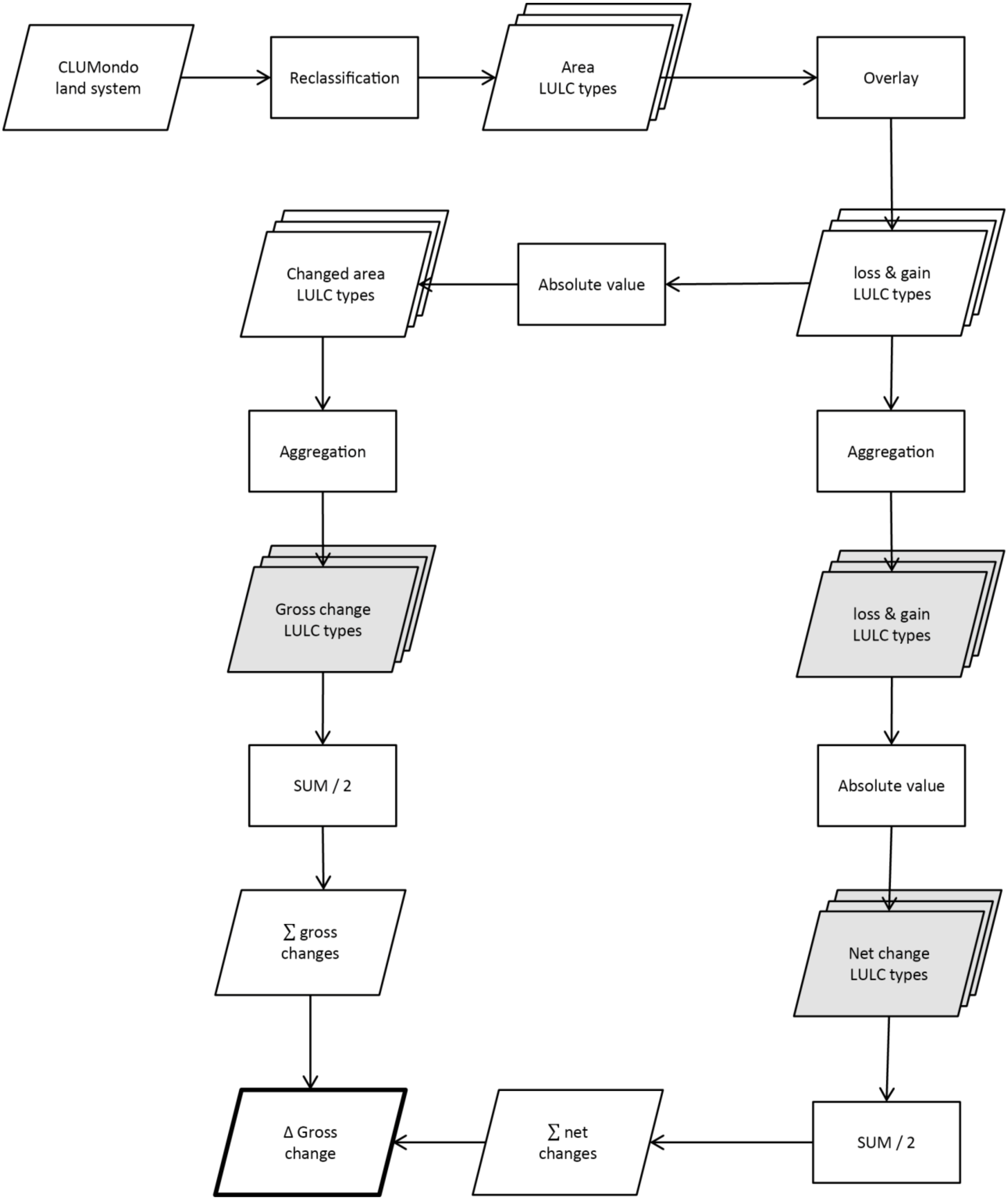
The CLUMondo data originate from a simulation based on the FAO 3 demand scenario (Eitelberg et al., 2016) and cover the time period from 2000 to 2040 with annual temporal resolution. Data are available at a 9.25 x 9.25 km regular grid (~5 arcminute) in an equal area projection and are based on the land system classification system described in van Asselen and Verburg (2012) (Table S6). 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):

- 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).
- 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). 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.



~~**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.**~~

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

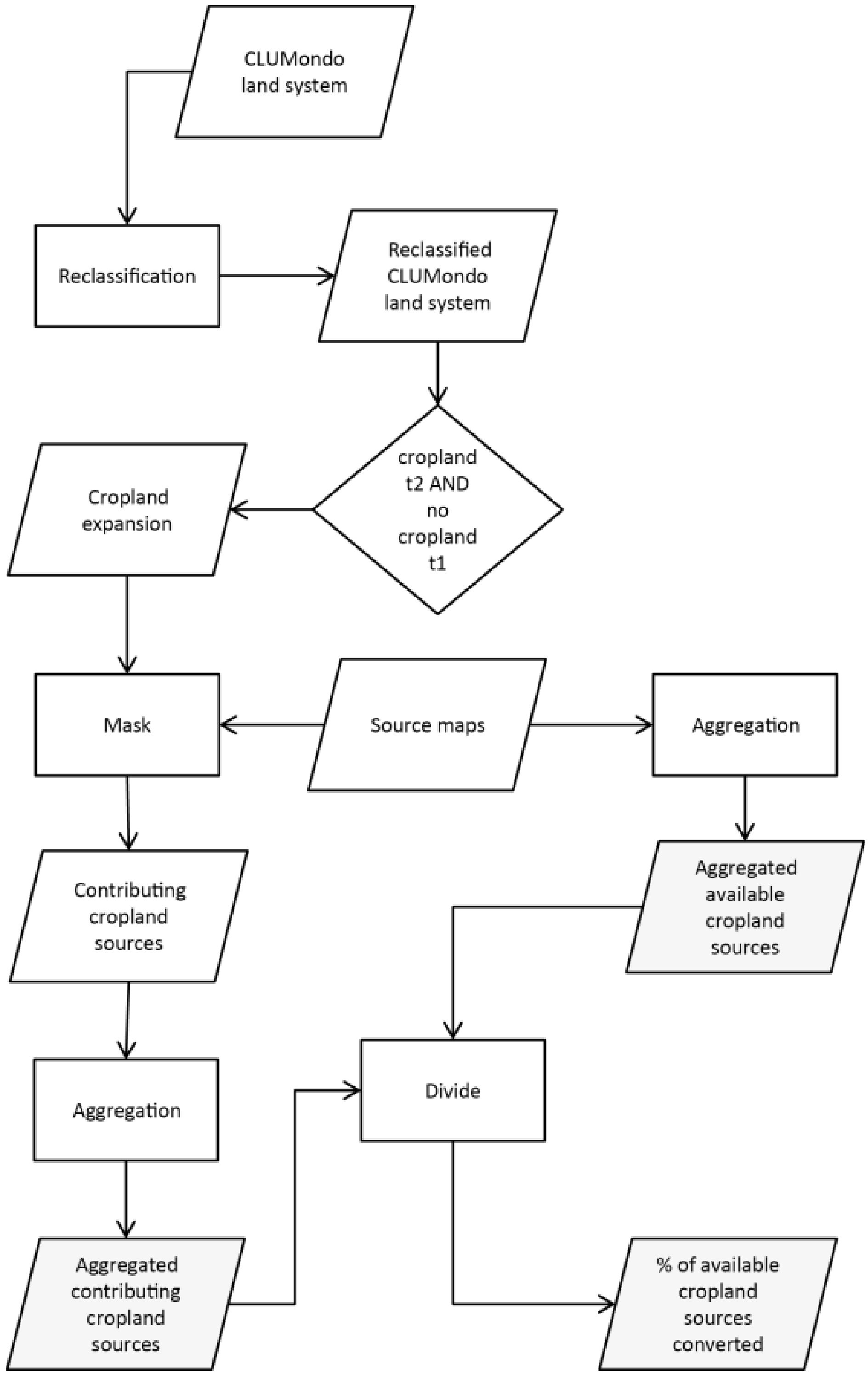
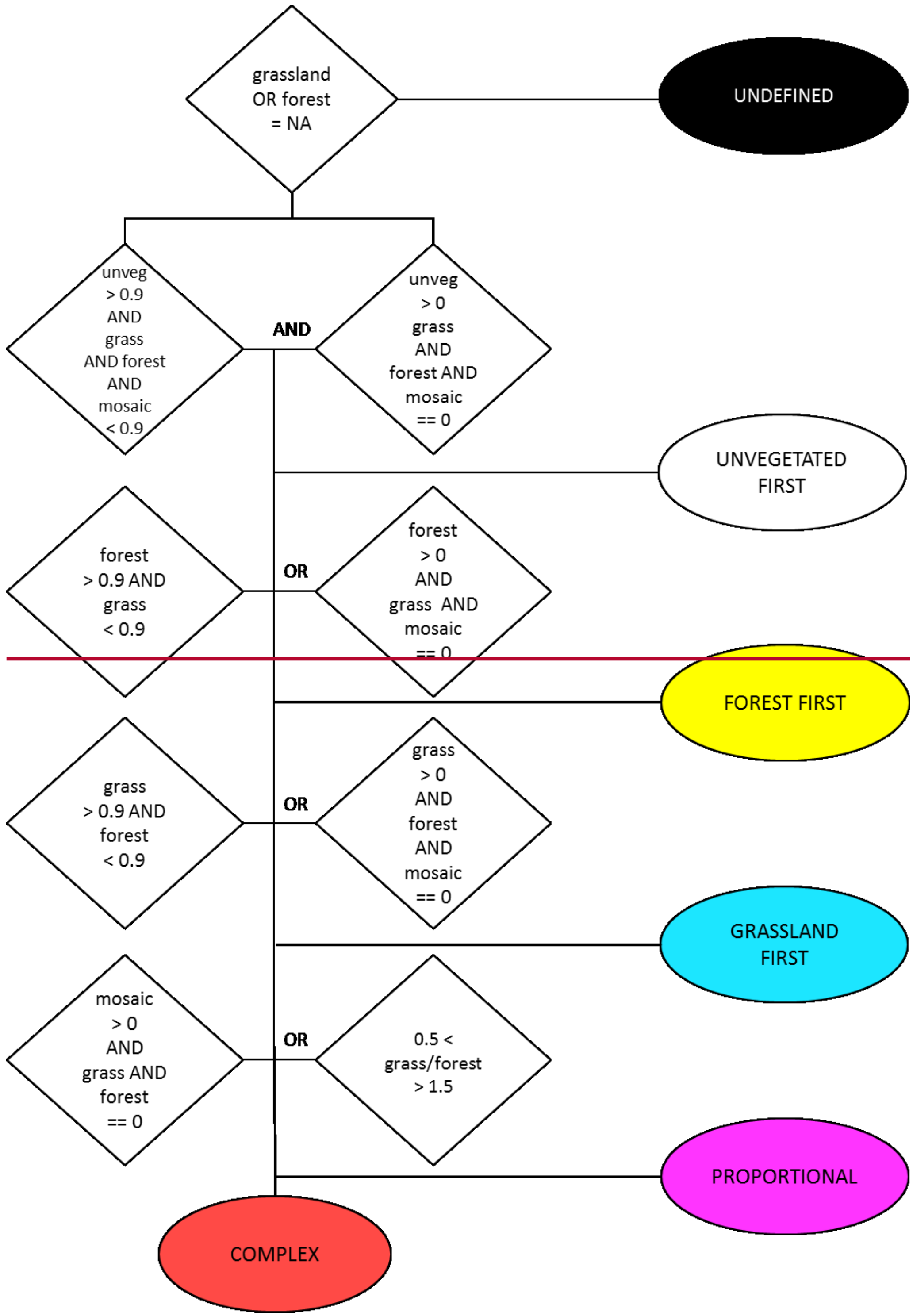


Figure S2: Preprocessing workflow of CLUMondo output for land-use change priority analysis. Rectangles represent processing steps, parallelograms represent data. Grey shaded items emphasize aggregated data at ca. 0.5 x 0.5 degree resolution.


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

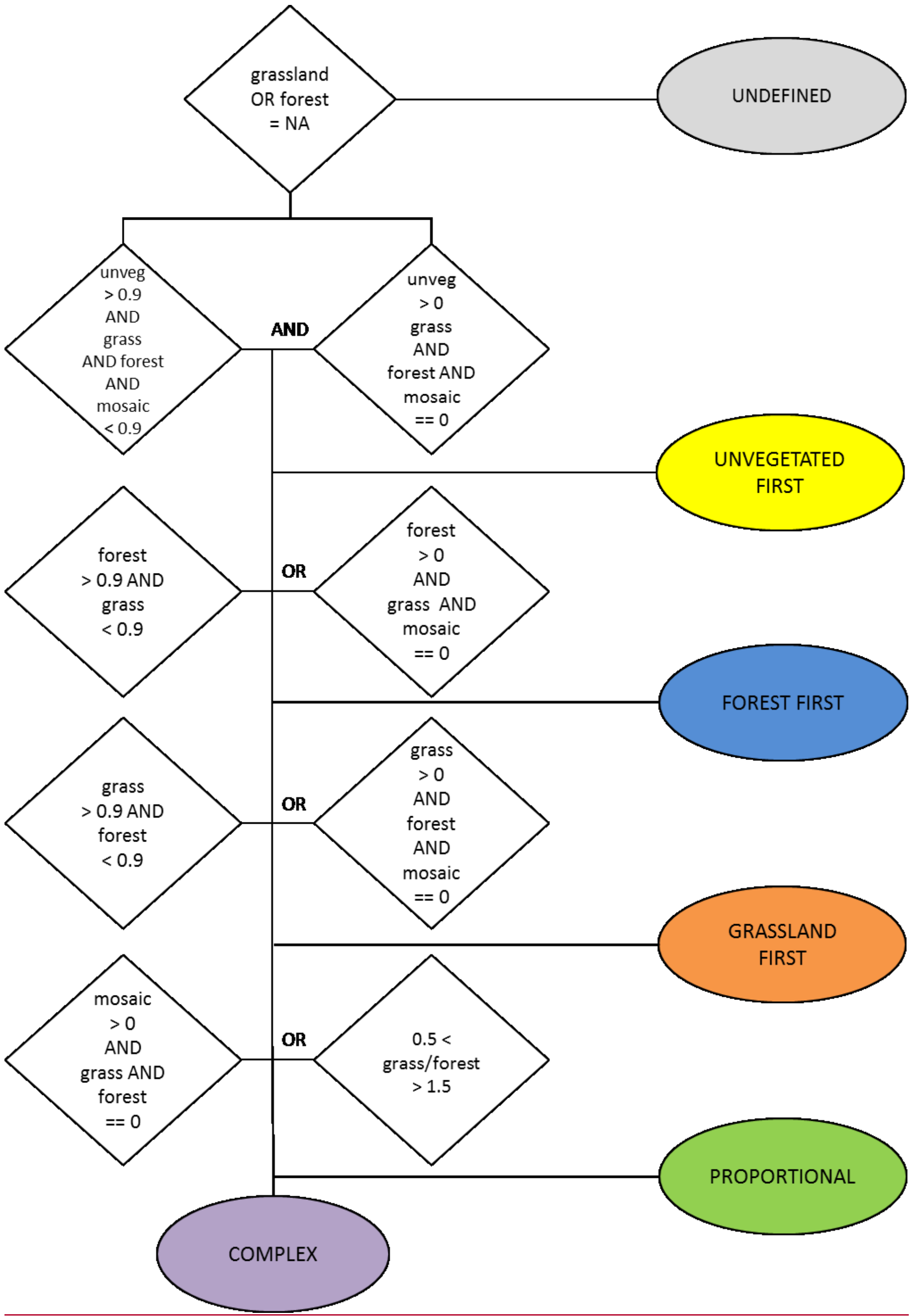
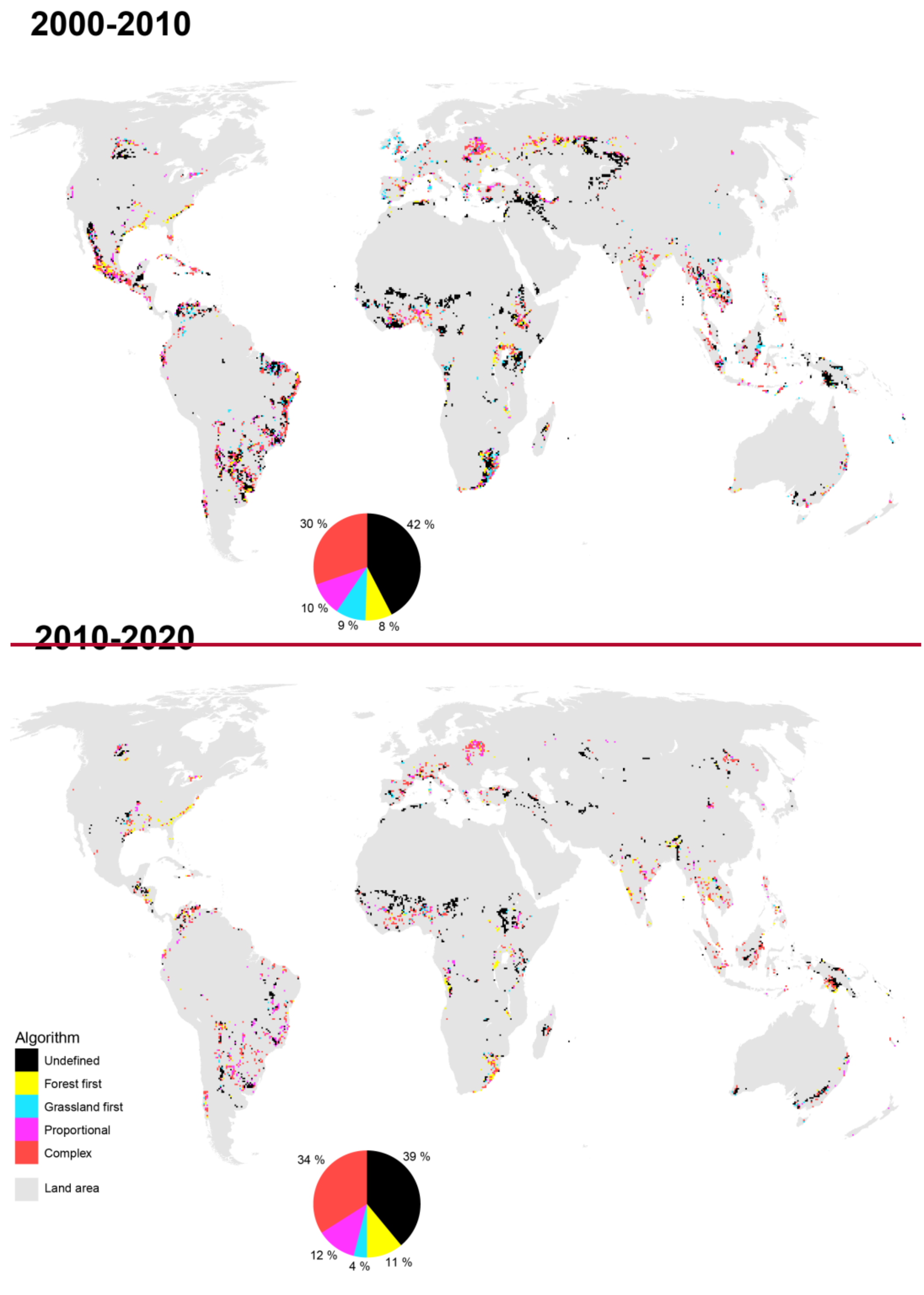
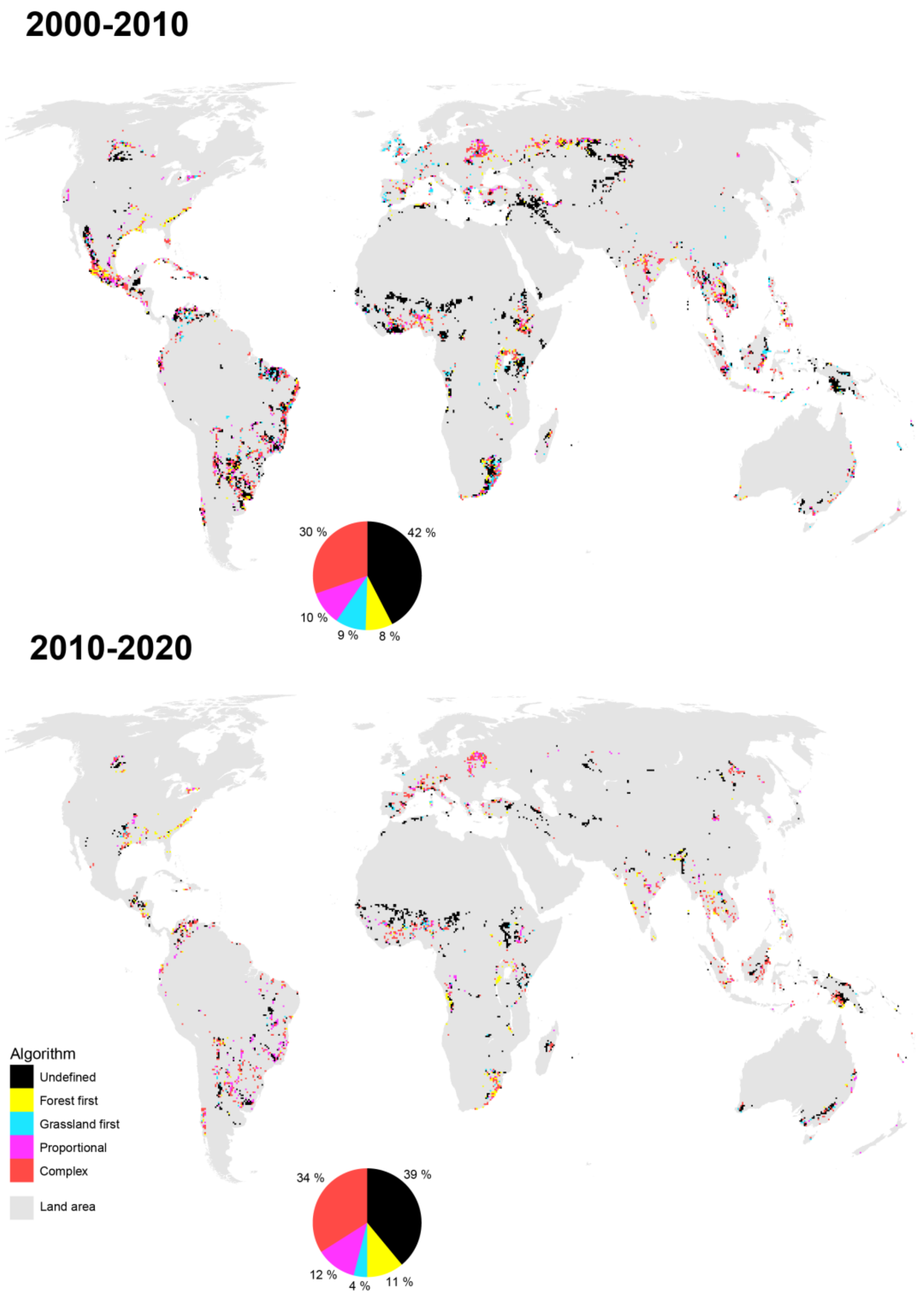


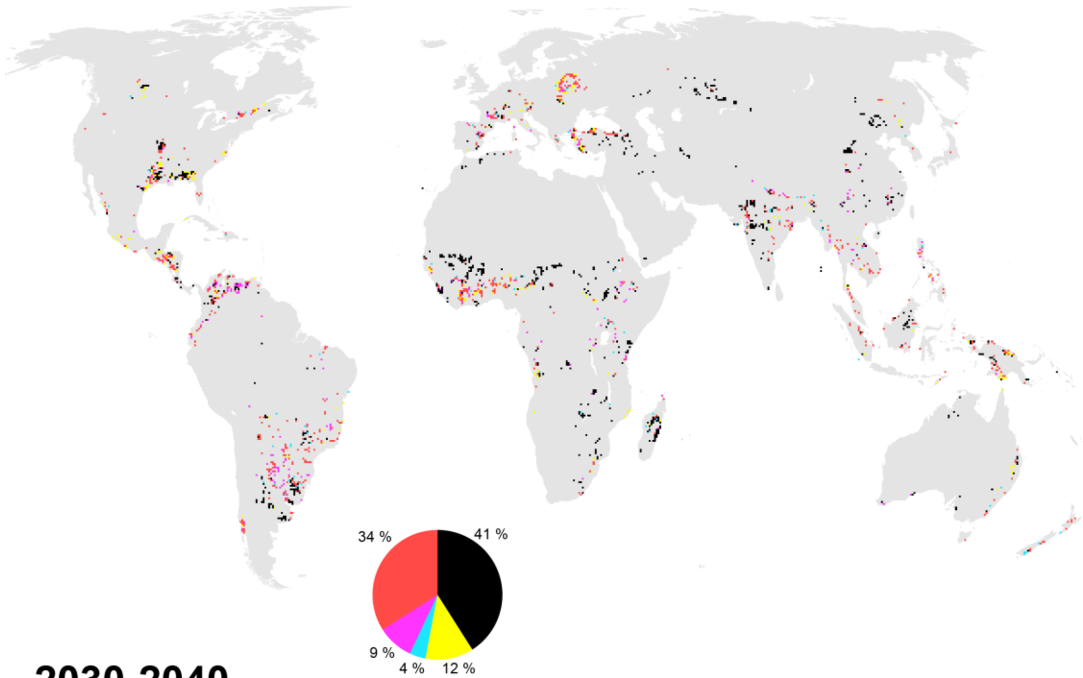
Figure S3: Classification rules applied to each ca. 0.5 x 0.5 degree grid cell to identify a predominant reduction of a particular source LULC type.

S3 Additional Results


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


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

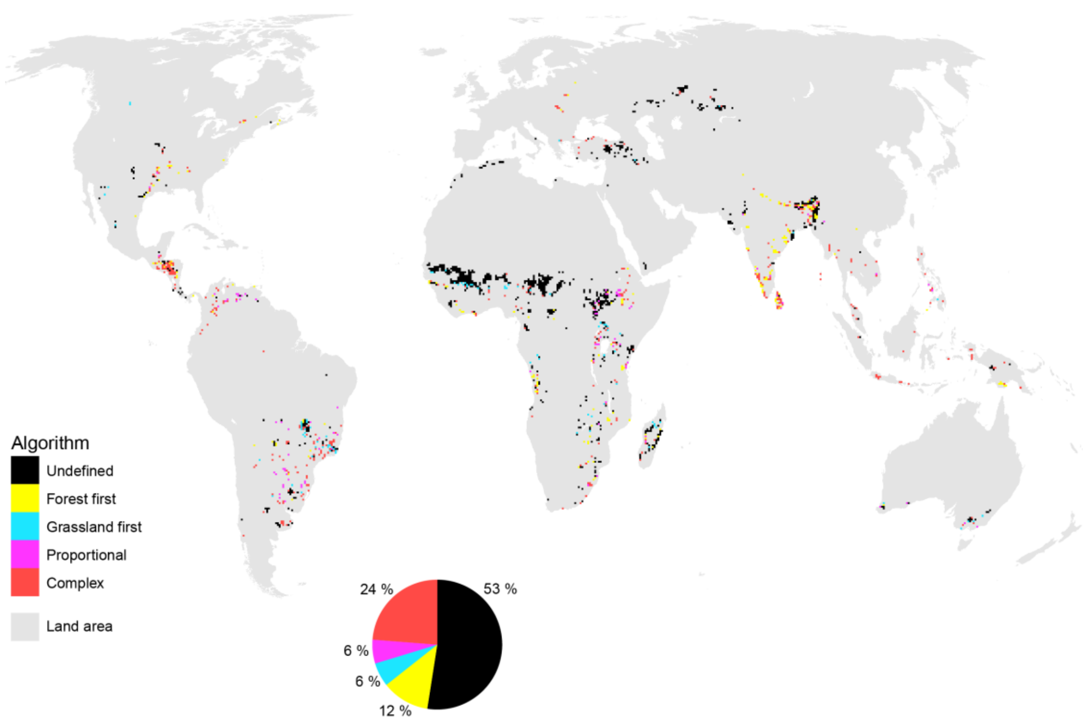


Figure S4: Transitions from natural vegetation to cropland as shown by the CLUMondo model (FAO 3 demand scenario) from 2000 to 2040 in decadal time steps. Colored grid cells represent areas with at least 10 % of cropland expansion within a ca. 0.5 x 0.5 degree grid cell. Grid cells are classified to forest first (yellow), grassland first (cyan), proportional (magenta) and complex reduction (red) algorithm as described in the text (for details see SI). Black grid cells denote areas where the validity of none algorithm could be detected.

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