A framework for the cross-sectoral integration of multi-model impact projections: Land use decisions under climate impacts uncertainties

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Abstract

Climate change and its impacts already pose considerable challenges for societies that will further increase with global warming (IPCC, 2014a, 2014b). Uncertainties of the climatic response to greenhouse gas emissions include the potential passing of large scale tipping points (e.g. Lenton et al., 2008; Levermann et al., 2012; Schellnhuber, 2010) and changes in extreme meteorological events (Field et al., 2012) with impacts on a complex society (Hallegatte et al., 2013). Thus climate-change mitigation is considered a necessary societal response to avoid uncontrollable impacts (Conference of the Parties, 2010). On the other hand large scale climate-change mitigation itself implies fundamental changes in for example the global energy system. The associated challenges come on top of others that derive from equally important ethical imperatives like the fulfillment of an increasing food demand that may draw on the same resources. For example, ensuring food security for a growing population may require an expansion of crop land, thereby reducing natural carbon sinks or the area available for bio-energy production. So far available studies addressing this problem relied on individual impact models, ignoring uncertainty in crop- and biomes-model projections. Here, we propose a probabilistic decision framework that allows for an evaluation of agricultural management and mitigation options in a multi-impact-model setting. Based on simulations generated within the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) we outline how cross-sectorally consistent multi-model impact simulations could be used to generate the information required for robust decision making.

Using an illustrative future land-use pattern, we discuss the trade-off between potential gains in crop production and associated losses in natural carbon sinks in the new multi-crop and biomes-

models setting. In addition, crop and water model simulations are combined to explore irrigation increases as one possible measure of agricultural intensification that could limit the expansion of crop land required in response to climate change and growing food demand. This example shows that current impact-model uncertainties pose an important challenge to long-term mitigation planning and must not be ignored in long term strategic decision making.

1 Introduction

Climate change mitigation and rising food demand motivate competing responses (Falloon and Betts, 2010; Warren, 2011), resulting in, for example, competition for land between food and bio-energy production (Godfray et al., 2010a; Searchinger et al., 2008; Tilman et al., 2009). Given a certain level of global warming and CO2 concentration, the required area of land of food production is determined by: 1) food demand driven by population growth and economic development, 2) human management decisions influencing production per land area, and 3) biophysical constraints limiting crop growth and nutrients or water availability for irrigation under the management conditions considered. Similarly, the land area required to meet a certain climate mitigation target depends on: 1) the amount of energy to be produced as bio-energy and the required amount of natural carbon sinks, 2) human decisions determining the intensity of bio-energy production per land area, and 3) bio-physical constraints regarding the production of bio-energy per land area and potential losses of natural carbon sinks under climate change. We consider climate protection by bio-energy production and carbon storage in natural vegetation as examples of additional constraints on land-use (LU) that are relatively straightforward to quantify. However, other ecosystem services could impose further constraints that could be integrated if it is also possible to describe them in a quantitative manner based on available model outputs or external sources. For example, Eitelberg et al., 2015 have shown that different assumptions with regard to protection of natural areas can lead to a large variation of estimates of available crop land.

Assuming certain demands for food and energy (point 1), individual societal decisions (point 2) have to be evaluated and adjusted in the context of the competing interests. Here, we focus on the question of how the uncertainty in (bio-)physical responses to societal decisions (point 3) can be represented in this evaluation. Based on an illustrative analysis of multi-model impact projections from different sectors, we show that the uncertainties associated with future crop yield projections, changes in irrigation water availability, and changes in natural carbon sinks are considerable, and must not be ignored in decision making with regards to climate protection and food security. Due to the high inertia of energy markets and infrastructures mitigation decisions are long term decisions that may not allow for ad hoc decisions in the light of realized climate change impacts (e.g. Unruh, 2000).

Models already exist that couple surface hydrology, ecosystem dynamics, crop production (Bondeau et al., 2007; Rost et al., 2008) and agro-economic choices (Havlik et al., 2011; Lotze-Campen et al., 2008; Stehfest et al., 2013), which allow issues such as carbon-cycle implications of LU changes and irrigation constraints, to be addressed. These models provide possible solutions for LU under competing interests. However, integrative analyses usually rely only on individual impact models, without resolving the underlying uncertainties resulting from our limited knowledge of biophysical responses.

There is also a number of detailed, sector-specific studies covering a wide range of process representations and parameter settings not represented by single, integrative studies (Haddeland et al., 2011 (water); Rosenzweig et al., 2014 (crop yields); Sitch et al., 2008 (biomes)). A comprehensive integrative assessment, as requested by the Intergovernmental Panel on Climate Change (IPCC), must cover the full uncertainty range spanned by these models. Such an assessment should not only quantify uncertainties associated with climate model projections, but also account for the spread across impact models. However, so far a full integration of these sector-specific multi-model simulations has been hindered by the lack of a consistent scenario design.

Owing to its cross-sectoral consistency (Warszawski et al., 2013a), the recently launched Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP, www.isi-mip.org) provides a first opportunity to bring this multi-impact-model dimension to the available integrative analyses of climate change impacts and response options. Here we propose a probabilistic decision framework to explore individual societal decisions regarding agricultural management and climate change mitigation measures in the light of the remaining uncertainties in biophysical constraints. In this paper we will describe the additional steps required to provide a basis for robust decision making in the context of uncertainties in climate change impacts but not included into our analysis.

2 A probabilistic decision framework

Let us consider a certain greenhouse gas concentration scenario and its associated climate response described by a General Circulation Model (GCM); e.g. the Representative Concentration Pathway RCP2.6 (van Vuuren et al., 2011) in HadGEM2-ES, or any other pathway or climate model. In addition there already is a framework to combine this RCP with different story lines of socioeconomic development (e.g. population growth, level of cooperation etc.), the Shared Socioeconomic Pathways (SSP, van Vuuren et al., 2013), by proposing different political measures e.g. bringing a high population growth in line with a low emission scenario. Within the decision framework we assume that certain demands for food, bio-energy, and natural carbon sinks have been derived based on this process of merging an SSP with the considered RCP. Food demand could, for example, be derived from population numbers and the level of economic development by extrapolation from empirical relationships (Bodirsky et al., submitted). Given this setting, we propose a probabilistic decision framework that allows for an evaluation of agricultural management options determining food production (e.g. with regard to fertilizer input, irrigation fractions or selections of crop varieties), in combination with decisions about the intensity of bio-energy production and protection of natural carbon sinks. The approach is designed to account for uncertainties in responses of crop yields and natural carbon sinks to management, climate change and increasing atmospheric CO2 concentrations as represented by the spread of multi-model impact projections. Within this framework long term decisions could be based on the likelihood of fulfilling the demand for bio-energy production and natural carbon sinks while at the same time ensuring food security.

To describe the scheme, let us first consider a simplistic situation where the area required for food production and the area required for bio-energy production and natural carbon sinks are described in a “one dimensional” way, i.e. by their extent and independent of spatial patterns. Then the decision framework can be described by two probability density functions (pdfs, see Fig. 1): The red pdf (f) in the upper panel of Fig. 1 describes our knowledge of the required food-production area given the management option to be assessed under the considered RCP and climate model projection. The width of the distribution is fully determined by uncertainties in crop yield responses to the selected management and changes in climate and CO2 concentrations. Intensification of production, for example by increasing irrigation or fertilizer use, shifts the pdf to the left, since less land would be required to meet demand.

The blue pdf (c) illustrates our knowledge of the required land area to be maintained as natural carbon sinks, or used for bio-energy production, in order to fulfill the prescribed demands. In this case, the width of the distribution depends on, for example, uncertainties regarding the capacity of natural carbon sinks, the yields of bio-energy crops under climate change, and the efficacy of the considered management decisions. Assuming higher efficiency in bio-energy production per land area shifts the distribution to the right.

Mitigation strategies must now consider the physical trade-off between cropland area (F) and the area available for retention of natural carbon sinks and stocks or bio-energy production (N): N = T – F, where T = total available area. Assuming food demand will always be met, even at the expense of climate protection, the probability of climate protection failure (underproduction of bioenergy, or insufficient carbon uptake by natural vegetation) is given by

$$P = \int_{0}^{\infty}\int_{T-F}^{\infty} c(N)dN\, f(F)\, dF$$

Here, for any food production area F, the probability that more than the remaining area N = T - F is needed to fulfill the demand for bioenergy and carbon sinks, is described by the inner integral and the blue area in Fig. 1. The probability of climate protection failure given that food demand will always be fulfilled is the average of these probabilities of climate protection failure weighted according to the pdf describing the required food production area. In the case that the probability is higher than acceptable, the agricultural management decisions and mitigation measures must be revised and re-evaluated.

Assuming that the uncertainties in projected crop yields, bio-energy production and carbon sinks can be captured by multi-impact model projections, the probability can be approximated in the following two step approach.

Firstly, multiple crop model simulations (i) under the considered management assumptions and climate projections are translated into food production areas $L_{i,}$ fulfilling the considered demand (see yellow bars in Fig. 2). The translation could be done by agro-economic LU models such as MagPIE (Lotze-Campen et al., 2008) or GlOBIOM (Havlik et al., 2011). The diversity of these models used to determine “optimal” LU patterns based on expected crop yields, could be considered as an additional source of uncertainty in LU patterns. It could be implemented into the scheme by applying multiple economic models i.e. increasing the sample of LU patterns to n = number of crop models x number of economic models. However, since the differences in LU patterns introduced by different economic models may be due to different “societal rules” for land expansion, this component may rather be considered as belonging to the “socioeconomic decision” space. In this case they can be handled separately from the uncertainties introduced by our limited knowledge about biophysical responses as represented by the crop models. Most agro-economic models also account for feedbacks of LU changes or costs of intensification on prices, demand, and trade (Nelson et al., 2013). Since in our decision framework demand is considered to be externally prescribed, one could even introduce much more simplified, but highly transparent, allocation rules driven only by maximum yields, assumed costs of intensification or land expansion, and intended domestic production.

Then, each individual food production pattern leaves a certain land area N_i for bio-energy production and conservation of natural carbon sinks ($N_i = T - F_i$, green bars in Fig. 2). Increased irrigation could reduce the required food production area, leaving more area for bio-energy production and conservation of natural carbon sinks; but potential irrigation is limited by available irrigation water. These constraints can be integrated using consistent multi-water model simulations (j) which provide estimates of available irrigation water. Combining these with the individual crop model simulations leads to an array of individual estimates of the required land area F_{ij}.

Secondly, each land area $N_{ij} = T_{ij} - F_{ij}$ has to be evaluated by a set of crop- and biomes-model simulations to test whether it allows for the required bio-energy production under the assumed management strategy and the required uptake of carbon. These individual evaluations (illustrated in Fig. 2 by green tickmarks for success and red crosses for failure) allow for an estimation of the probability of climate protection failure in terms of the number of failures per number of impact model combinations. Again alternative decisions on bio-energy production could change the probabilities. Note that the intensity of bio-energy production will also be constraint by the available irrigation water (van Vuuren et al., 2009). Thus, though not indicated in Fig. 2, the evaluation may also build on multi-water model simulations similarly to the projected food production area.

For this kind of evaluation it is important that the required impact simulations are forced by the same climate input data, as done in ISI-MIP. Otherwise the derived LU patterns would be inconsistent. The flexible design of the ISI-MIP simulations furthermore allows for an evaluation of different LU patterns using a number of existing crop-model and biomes-model simulations, without running new simulations (see section 3).To date, the available crop-model and biomes-model simulations have not been translated into "required area for food production" or "required areas for bio-energy production and natural carbon sinks" except for a first attempt to quantify food production areas based on multiple crop and economic models (Nelson et al., 2013). However, in that study the setting was limited to four out of seven crop models and to a subset of simulations where CO_2 concentrations were held constant at present-day levels.

Here we restrict our analysis to an illustration of the relevance of impact model uncertainties in the evaluation of different LU patterns and management assumptions and how this relates to crop/food production and natural carbon sinks/stocks. We use simulations from 7 global gridded crop models (GGCMs, Rosenzweig and Elliott, 2014), 11 global hydrological models (Schewe et al., 2013), and 7 global terrestrial bio-geochemical models (Friend et al., 2013; Warszawski et al., 2013b) generated within ISI-MIP to address the following questions:

1) how large is the inter-impact model spread in global crop production under different levels of global warming assuming present-day LU patterns and present day management (see Table S1,

SI)?; 2) how can multi-water model projections be used to estimate the potential intensification of food production due to additional irrigation and how does the induced uncertainty in runoff projections compare to the uncertainty in crop projections?; and 3) how large is the spread in projected losses in natural carbon sinks and stocks of an illustrative future LU pattern that gives a certain chance of meeting future food demand?

3 Data and Methods

3.1 Input data for impact model simulations

All impact projections used within this study are forced by the same climate input data (Warszawski et al., 2013a). For ISI-MIP, daily climate data from five General Circulation Models (GCMs) from the CMIP5 archive (Taylor et al., 2012) were bias-corrected to match historical reference levels (Hempel et al., 2013). Here, we only use data from HadGEM2-ES, IPSL-CM5A-LR and MIROC-ESM-CHEM (see Table S6 of the SI), since these models reach a global mean warming of at least 4 degrees w.r.t. 1980-2010 levels under the Representative Concentration Pathway RCP8.5 – the highest of the four RCPs (Moss et al., 2010). All model runs accounting for changes in CO2 concentrations are based on the relevant CO2 concentration input for the given RCP.

3.2 LU patterns and food demand

As present day reference for agricultural LU pattern we apply the MIRCA2000 irrigated and rainfed crop areas (Portmann et al., 2010). They describe harvested areas as a fraction of each grid cell. The patterns are considered to be representative for 1998-2002. Simulated rainfed and fully irrigated productions within each grid cell were multiplied by the associated fractions of harvested areas and added up to calculate the simulated production per grid cell. Historical LU patterns are subject to large uncertainties (Verburg et al., 2011). Alternative maps are for example provided by (Fritz et al., 2015). Here, we use the MIRCA2000 patterns as they make our estimated changes in production consistent to the spatial maps of relative yield changes provided by Rosenzweig et al., 2014. In addition, the total agricultural area derived from MIRCA2000 is consistent with the area of natural vegetation as described by the MAgPIE model and used as reference for the analysis of the biomes model projections of changes in carbon fluxes and stocks (see this section below).

As an illustrative future LU pattern we use a projection of the agro-economic LU model MAgPIE (Lotze-Campen et al., 2008; Schmitz et al., 2012) generated within the ISI-MIP-AgMIP cooperation and published in (Nelson et al., 2013). The model computes LU patterns necessary to fulfill future food demand (Bodirsky et al., submitted). Here, food demand is calculated from future projections of population and economic development (Gross Domestic Product, GDP) under the “middle of the road” Shared Socioeconomic Pathway (SSP2, https://secure.iiasa.ac.at/web-apps/ene/SspDb) (Kriegler et al., 2010). The associated LU projections are based on the historical and RCP8.5 simulations by HadGEM2-ES and associated yields generated by LPJmL (Nelson et al., 2013). The pattern is based on fixed CO_2-concentration (370 ppm) crop-model simulations. MAgPIE accounts for technological change leading to increasing crop yields (applied growth rates are listed in Table S4 of the SI), while our analysis is based on crop-model simulations accounting for increasing levels of atmospheric CO_2 concentrations but no technological change. In the context of our study the pattern is only considered a plausible example of a potential future evolution of land use. However, it does not assure consistency between food demand and production for different crop yield projections. To achieve consistency individual crop model projections would have to be translated into individual LU patterns as described in Section 2 and Fig. 2.

The present day reference for the total area of natural vegetation is taken from the 1995 MAgPIE pattern. The MAgPIE model is calibrated with respect to the spatial pattern of total cropland to be in line with other data sources, like the MIRCA2000 dataset (Schmitz et al., 2014). That means that the area of natural vegetation assumed here is not in conflict with the total area of harvested land described by MIRCA2000 and used here to calculate crop global production based on the crop model simulations. However, the patterns of individual crops may differ, due to the underlying land use optimization approach. Future projections of the total area of natural vegetation are taken from the MAgPIE simulation described above.

3.3 Impact model simulations

Crop models

Our considered crop model ensemble (see Table 1) represents the majority of GGCMs currently available to the scientific community (run in partnership with the Agricultural Model Intercomparison and Improvement Project (AgMIP, Rosenzweig et al., 2012). In their complementarity, the models represent a broad range of crop growth mechanisms and assumptions (see Table 1 and S1 for more details). While the site-based models were developed to simulate crop growth at the field scale, accounting for interactions among crop, soil, atmosphere, and management, the agro-ecosystem models are global vegetation models originally designed to simulate global carbon, nitrogen, water and energy fluxes. The site-based models are often calibrated by agronomic field experiments, whilst the agro-ecosystem models are usually not calibrated (LPJ-GUESS), or only on a much coarser scale such as national yields (LPJmL). The agro-ecological zone model (IMAGE) was developed to assess agricultural resources and potential at regional and global scales.

The crop modelling teams provided "pure crop" runs, assuming that the considered crop is grown everywhere, irrespective of current LU patterns but only accounting for restriction due to soil characteristics. For each crop annual yield data are provided assuming rainfed conditions and full irrigation not accounting for potential restrictions in water availability. In addition modelling groups provided the amount of water necessary to reach full irrigation except for PEGASUS and IMAGE. This design of the simulations makes the projections highly flexible with regard to LU patterns that can be applied in post-processing as described in Section 3.2.

The quantity projected differs from model to model, ranging from yields constrained by current management deficiencies to potential yields under effectively unconstrained nutrient supply (Table 1 and Table S1 of the SI). Therefore, we only compare relative changes in global production to relative changes in demand. Since simulated yield changes may strongly depend on, for example, the assumed level of fertilizer input in the reference period, we consider this aspect as a critical restriction. In this way, the analysis presented here is an illustration of how the proposed decision framework could be filled, rather than a quantitative assessment.

The default configuration of most models includes an adjustment of the sowing dates in response to climate change, while total heat units to reach maturity are held constant, except for in PEGASUS and LPJ-GUESS. Three models include an automatic adjustment of cultivars.

Water models

The considered water model ensemble comprises four land surface models accounting for water and energy balances, six global hydrological models only accounting for water balances and one model ensuring energy balance for snow generation (see Table 2 and Table S3 of the SI). Following the ISI-MIP protocol all modelling teams were asked to generate naturalized simulations excluding human influences. Here we aggregate the associated runoff projections over one year and so called Food Production Units (FPU, Kummu et al., 2010) representing intersections between river larger basins and countries (see Fig. S7 of the SI for the definition of the FPUs). In this way we create an approximation of the water available for irrigation (see Section 3 of the SI for a detailed description of the calculation of the available crop specific irrigation water).

For illustrative purposes we assume that irrigation water (plus a minor component of water for industrial and household uses) is limited to 40% (Gerten et al., 2011) of the annual runoff integrated over the area of one FPU. In addition, we assume a project efficiency of 60%, where 60% of the irrigation water is ultimately available for the plant. The available water is distributed according to where it leads to the highest yield increases per applied amount of water, as calculated annually. The information is available at each grid cell from the “pure rainfed” and “full irrigation” simulations provided by the crop models and the information about the irrigation water applied to reach “full irrigation”. To generate probabilistic projection each crop model projection is combined with each water model projection (see SI for more details). Our approach only accounts for renewable surface and groundwater. Model simulations account for the CO2 fertilization effect on vegetation if this effect is implemented in the models.

Biomes models

Similar to the crop model the biomes modelers provided “pure natural vegetation” runs not accounting for current or future LU patterns but assuming that the complete land area is covered by natural vegetation wherever that is possible due to the soil characteristics. In this way potential LU patterns can be applied and tested in post-processing. The main characteristics of the considered models are listed in Table 3 (and Table S5 of the SI for some more detail). Here, we use the ecosystem-atmosphere carbon flux and vegetation carbon as two of the main output variables provided by the models. Both are aggregated over the area of natural vegetation as described by the MAgPIE projection introduced in Section 3.2. To quantify the pure LU induced changes the annual carbon stocks and fluxes under fixed 1995 LU are compared to the associated values assuming an expansion of agricultural land as described by MAgPIE.

Biophysical simulations are based on HadGEM2-ES and RCP8.5. All simulations account for the CO2 fertilization effect. Results for the simulations where CO2 is held constant at year 2000 levels are shown in the SI. Our approach does not account for the carbon released from soil after LU changes (Smith, 2008). While agricultural land can be considered as carbon neutral to first order (cultivated plants are harvested and consumed), the conversion process emits carbon to the atmosphere as soil carbon stocks typically degrade after deforestation (Müller et al., 2007).

3.4 Partitioning of the uncertainty budget associated with crop production changes

To separate the climate-model-induced uncertainty from the impact-model uncertainty, the GGCM-specific spread of the relative crop production changes at different levels of global warming is estimated by the standard deviation of the GGCM-specific mean values. These are calculated over all climate model- (and RCP-) specific individual values (e.g. colored dots in Fig. 3), or all water-model-specific individual values, in case of the production under maximum irrigation. The climate model or water-model-induced spread is estimated as the standard deviation over the individual deviation from these GGCM means.

4 Results and Discussion

4.1 Adaptive pressure on future food production

GGCMs project a wide range of relative changes in global wheat, maize, rice and soy production at different levels of global warming and associated CO_2 concentrations (first column of each global mean warming box in Fig. 3). At 4°C the GGCM spread is more than a factor 5 larger than the spread due to the different climate models (see Table 4, estimated as described in Material and Methods). This is partly due to the bias correction of the climate projections, which includes a correction of the historical mean temperature to a common observational data set (Hempel et al., 2013), and may depend on the selection of the three GCMs. However, the results suggest that the inter-crop-model spread will also be a major component of the uncertainty distribution associated with the area of crop land required to meet future food demand.

Despite considerable uncertainty, it is evident that even if global production increases arising from optimistic assumptions about CO_2 fertilization, this effect alone is unlikely to balance demand increases driven by population growth and economic development (assuming that the observed relationship between per capita consumption patterns and incomes holds in the future and ignoring demand-side measures (Foley et al., 2011; Parfitt et al., 2010)).All GGCMs show a quasi-linear dependence on global mean temperature across the three different climate models, considered scenarios and range of global mean temperature changes (Fig. S5-S6 of the SI). Values range from -3 to +7%/°C for wheat, -8 to +6%/°C for maize, -4 to +19%/°C for rice and -8 to +12%/°C for soy (Table S2 of the SI, c.f. Rosenzweig et al., 2014 for an update of the IPCC-AR4 Table 5.2 (Easterling and et. al, 2007)). It is not necessarily clear that crop-production changes can be expressed in a path-independent way as a function of global mean temperature change. In particular, CO_2 concentrations are expected to modify the relationship with global mean temperature. However, for the 7 GGCMs and the RCP scenarios considered here, the path dependence is weak (Fig. S1-S4 of the SI). This suggests that the red pdfs shown in Fig. 1, or the associated sample of LU patterns, could also be determined for specific global warming (and CO_2) levels, but relatively independent of the specific pathway.

The disagreement in the sign of the change in crop production in Fig. 3 arises predominantly from differences in the strength of the CO_2 fertilization effect. Projections based on fixed CO_2 levels show a smaller spread and a general decrease in global production with increasing global warming (Table S2 and Fig. S6 of the SI). Given the ongoing debate about the efficiency of CO_2 fertilization, in particular under field conditions (Leakey et al., 2009; Long et al., 2006; Tubiello et al., 2007), and the fact that most models do not account for nutrient constraints of this effect, projections are likely to be optimistic about the growth-promoting effects of increased atmospheric CO_2 concentrations.

3.2 Irrigation potential

Using different means of intensifying crop production on existing crop land, the red uncertainty distributions in Fig. 1 can be shifted to the left. As an example, we show how multi-water-model simulations could be combined with crop-model simulations forced by the same climate input to estimate the uncertainties in the potential production increase due to expansion of irrigated areas, using only present-day agricultural land. The effect is constrained by 1) biophysical limits of yield response to irrigation, and 2) water availability.

While potential expansion of irrigation (or reduction, in the case of insufficient water availability for full irrigation of currently-irrigated areas) could compensate for the climate-induced adaptive pressure projected by some GGCMs (second column of each global mean warming level in Fig. 3), the feasible increase in global production is insufficient to balance the relative increase in demand by the end of the century. In the case of rice, which is to a large extent already irrigated (SI, Fig. S3), the imposed water limitation reduces production in comparison to full irrigation on currently irrigated areas for some of the GGCMs (see Elliott et al., 2013 for a more detailed discussion of limits of irrigation on currently irrigated land). In terms of Fig. 1, additional irrigation shifts the red uncertainty distributions to the left. However, even with this shift, it remains unlikely that the currently cultivated land will be sufficient to fulfill future food demand.

The spread of projections of global crop production under additional irrigation is dominated by the differences between GGCMs rather than the projections of available water (the partitioning of uncertainty is described in the Materials and Methods section). Based on the HadGEM2-ES, RCP8.5 climate projections, the GGCM-induced (5 models provide the necessary information) spread at 4°C is at least a factor of 4 larger than the spread induced by the hydrological models (see Table 2).

The production levels shown in Fig. 3 do not reveal whether the increase is mainly biophysically limited by potential yields under full irrigation, or by water availability. Further analysis (see SI, Fig. S8 and Fig. S9) shows that production under the highly optimistic assumptions regarding water distribution is relatively close to production under unlimited irrigation on present day crop areas with the exception of wheat.

3.4 Effect of LU changes on global crop production

Intensification options are certainly not exhausted by additional irrigation. For example, other possibilities include improved fertilizer application, switching to higher yielding varieties, or implementing systems of multiple cropping per year. Historically, most of the long-term increase in crop demand was met by a variety of intensification strategies (Godfray et al., 2010b; Tilman et al., 2011). However, the expansion of arable land may become more important in light of further increasing demand and possibly saturating increases in crop yields (Alston et al., 2009; Lin and Huybers, 2012). A recent study (Ray et al., 2013) suggests that observed increases in yields will not be sufficient to meet future demand.

To illustrate the potential to increase yields via LU change, we apply a LU pattern generated by the agro-economic LU model MAgPIE for the year 2085 (Materials and Methods) in combination with the water distribution scheme discussed above (see third column of each global mean warming bin in Fig. 3). There is a very large spread in the relative changes in crop production w.r.t. 1980-2010 reference values, reaching standard deviations of 31% for wheat, 84% for maize, 80% for rice, and 79% for soy, at 4°C. In one case there is even a reduction in production. This may be due to the fact that MAgPIE's optimization scheme results in highly-concentrated agricultural patterns by 2085, exaggerating regional features of the GGCM simulations (Fig. S10-S13 of the SI) and means at the same time that optimal LU pattern derived from individual crop models may strongly differ. In terms of Fig. 1 these results indicate a very wide uncertainty distribution associated with the area required for food production.

The relative increase in production by some crop models exceeds the projected demand increase. However, in spite of the strong expansion of cultivated land, with particularly high losses in the Amazon rainforest (see Fig. S15 of the SI), the lower ends of the samples still do not balance the projected demand increase in 2050 (except for wheat).

3.4 Effect of LU changes on natural carbon sinks and stocks

The increase in production by LU changes comes at the cost of natural vegetation. The considered illustrative reduction of the area of natural vegetation reaches 480 Mha in 2085 compared to 1995 levels. This corresponds roughly to the land area spared due to obtained yield increases in wheat and maize during the last 50 years (Huber et al., 2014). For all but one vegetation model (Hybrid) the reduction of the area of natural vegetation (Fig. S15 of the SI) means a loss of carbon sinks. There is a wide spread in losses, in some cases reaching 50% compared to the reference period (see Table 6). For the Hybrid model, natural vegetation even turns into a carbon source (Friend et al., 2013) by mid-century (Fig. S16 of the SI), which means that a reduction in natural vegetation leads to an increase in the global carbon sink. Overall the models show a spread in the reduction in carbon sinks from 0 to 0.5 Pg /yr (see Table 6 and Fig. 4a). The direct reduction of the vegetation carbon stock reaches a multi-model median of about 85 Pg (about 8.5 years of current CO_2 emissions) by the end of the century compared to a simulated increase in vegetation carbon of about 100 to 400 Pg in pure natural vegetation runs under the same climate change scenario (Friend et al., 2013). The multi-model spread of maximum LU change induced reductions reaches 32 to 121 Pg (see Table 6 and Fig. 4b).

4 Conclusion

The competition between food security for a growing population and the protection of ecosystems and climate poses a dilemma. This dilemma is fundamentally cross-sectoral, and its analysis requires an unprecedented cross-sectoral, multi-impact-model-analysis of the adaptive pressures on global food production and possible response strategies. So far uncertainties in biophysical impact projections have not been included in integrative studies addressing the above dilemma because of a lack of cross-sectorally consistent multi-impact model projections. Here we propose a decision framework that allows for the addition of a multi-impact-model dimension to the available analyses of climate change impacts and response options. The concept allows for an evaluation of different (agricultural) management decisions in terms of the probability of meet a pre-described amount of carbon stored in natural vegetation and bio-energy production under the constraint of a pre-described food demand that have to be fulfilled. The probability is determined by the uncertainty of the biophysical responses to the considered management decision, climate change and increasing levels of atmospheric CO2 concentrations. The proposed framework allows for an evaluation of selected management option but does not include an optimization to find a best solution in view of conflicting interests as provided by usual integrated assessment studies. In this regard it is similar to the integrated framework to assess climate, LU, energy and water strategies (CLEWS) (Howells et al., 2013) while the approach considered here does not include an economic assessment.

To date, a quantification of this probability has been inhibited by the lack of cross-sectorally consistent multi-impact-model projections. Here, simulations generated within ISI-MIP were used to illustrate the first steps to addressing the gap. The spread across different impact models is shown to be a major component of the uncertainty of climate impact projections. In the case of multiple interests and conflicting response measures, this uncertainty represents a dilemma, since ensuring one target with high certainty means putting another one at particularly high risk.

For a full quantification of the probability distributions illustrated in Fig. 1 multiple crop-models simulations have to be translated into a pdf of the “required food production area” given certain demands accounting, for example, for changing trade patterns (Nelson et al., 2013). This translation has already started within the AgMIP-ISI-MIP cooperation and will enable the generation of a probability distribution of the required food production area. However, current estimates (Nelson et al., 2013) are based on crop model runs that do not account for the CO2-fertilization effect and only a limited number of models provide explicit LU patterns in addition to the aggregated area. In addition, not all models are adjusted to reproduce present day observed yields rendering the analysis presented here illustrative rather than a robust quantitative assessment.

To estimate the associated probability of climate protection failure, carbon emissions due to the loss of natural carbon sinks and stocks, particularly including effects of soil degradation, must be quantified. Therefore, the set of demand-fullfilling LU-patterns has to be provided as input for multi-model biomes simulations. ISI-MIP is designed to facilitate this kind of cross-sectoral integration, which can then be employed to fulfill the urgent demand for a comprehensive assessment of the impacts of climate change, and our options to respond to these impacts and socio-economic developments, along with the corresponding trade-offs.

Our illustration of the uncertainty dilemma is by no means complete. In addition to the irrigation scheme considered here, a more comprehensive consideration of management options for increasing crop yields on a given land area is required. To this end, the representation of management within the crop model simulations needs to be harmonized to quantify the effect of different management assumptions on crop-model projections. For example, similar to the rainfed vs full irrigation scenarios, low fertilizer vs high fertilizer input scenarios could be considered allowing for a scaling of the yields according to the assumed fertilizer input. However, not all crop models explicitly account for fertilizer input.

In the longer term initiatives as ISI-MIP will contribute to filling the remaining gaps and finally allow for a probabilistic assessment of cross-sectoral interactions between climate change impacts. For example, the current second round of ISI-MIP will include biomes and water model simulations accounting for LU changes generated based on different crop model projections (see ISI-MIP2 protocol, www.isi-mip.org).

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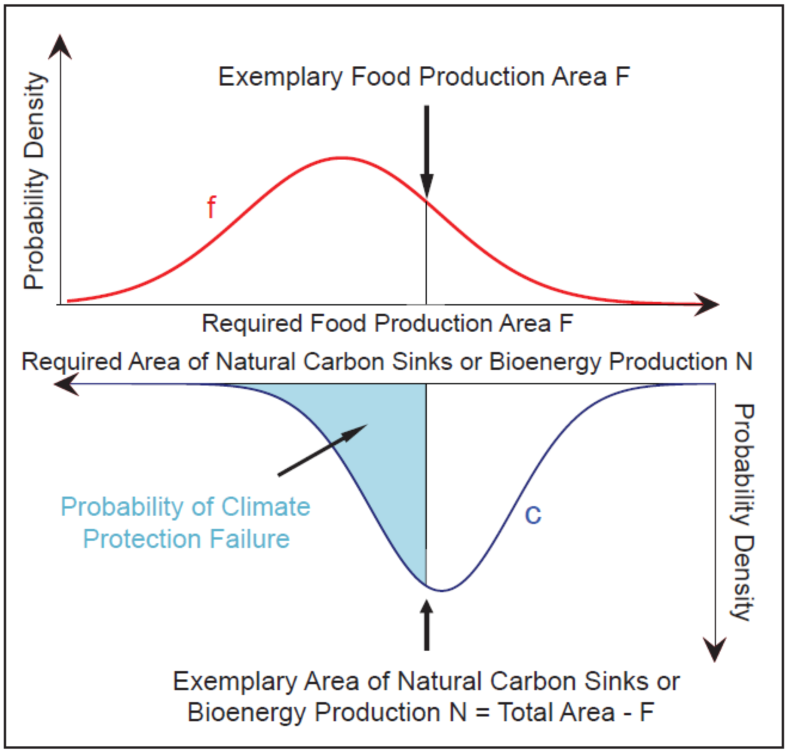

Figure 1. Concept of a probabilistic decision framework allowing for an evaluation agricultural management decisions under uncertainty of biophysical responses. Red pdf: Uncertainty associated with the area of crop land required to fulfill future food demand. Blue pdf: Uncertainty associated with the (natural) carbon sinks and stocks required to ensure climate protection.

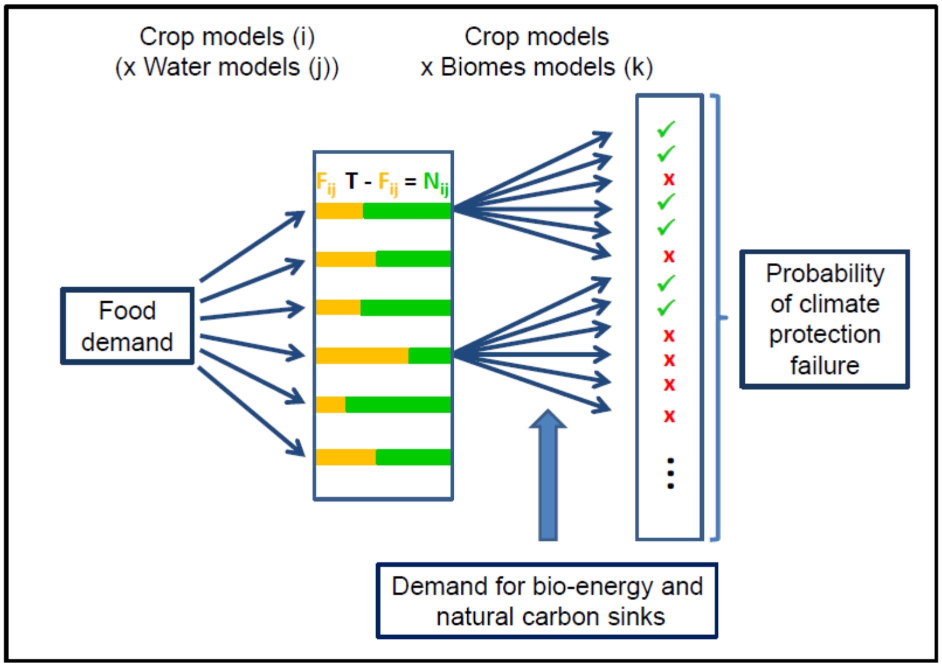

Figure 3. Implementation of the probabilistic decision framework based on multi-model impact projections. Step 1: Food demand is translated into required food production area (F) based on multi-crop model simulations (i) (potentially combined with multiple water model simulations (j) to account for irrigation water constraints) under a fixed management assumption (yellow bars). T = Total land area available for food or bio-energy production and conservation for natural vegetation. N = Land area left for bio-energy production or natural vegetation assuming future food demand will always be fulfilled (green bars). Step 2: Each pattern N_{ij} is evaluated whether it is sufficient to fulfill a pre-scribed demand for natural carbon sinks and bioenergy production based on multiple crop and biomes model simulations (green tickmarks agreement and red crosses for failure).

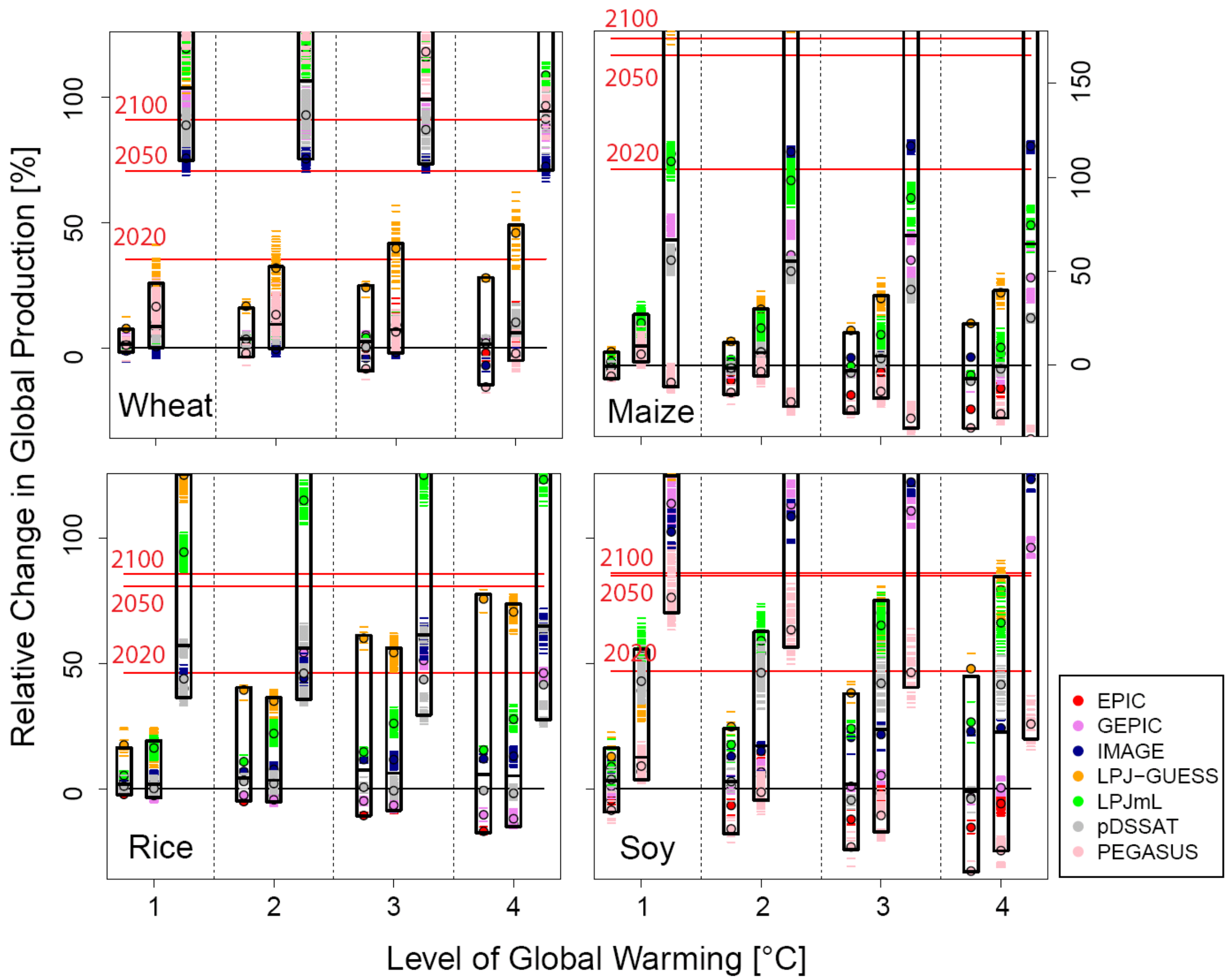

Figure 3. Adaptive pressure on global crop production and effects of irrigation and LU adaptation. Relative changes in crop global production (wheat, maize, rice, soy) at different levels of global warming with respect to the reference data (global production under unlimited irrigation on currently-irrigated land; averaged over the 1980-2010 reference period). Horizontal red lines indicate the relative change in demand projections for the years 2020, 2050, and 2100 due to changes in population and GDP under SSP2. First column of each global mean warming block: change in global production under fixed current LU patterns assuming

unlimited irrigation restricted to present-day irrigated land. Second block: relative change (w.r.t. reference data) in global production assuming potential expansion of irrigated land accounting for irrigation water constraints as projected by 11 water models (for details see SI). Third column: Based on the same water distribution scheme as column 2 but applied to the 2085 LU pattern provided by MAgPIE. EPIC is excluded from the LU experiment as simulations are restricted to present-day agricultural land. Color coding indicates the GGCM. Horizontal bars represent results for individual climate models, RCPs, GGCMs, and hydrological models (for column 2 and 3). Colored dots represent the GGCM-specific means over all GCMs and RCPs (and hydrological models). Black boxes mark the inner 90% range of all individual model runs. The central black bar of each box represents the median over all individual results.

Table 1: Short characterisation of the applied Global Gridded Crop Models. More details are provided in the SI (Table S1).

Global Gridded Crop Model	Model type	Reference level
EPIC	site based crop model	potential yields
GEPIC	site based crop model	present day yields
IMAGE	agro-ecological zone models	present day yields
LPJ-GUESS	agro-ecosystem model	potential yields
LPJmL	agro-ecosystem model	present day yields
pDSSAT	site based crop model	present day yields
Pegasus	agro-ecosystem model	present day yields

Table 2: Short characterisation of the applied water models. More details are provided in the section 3 of the SI.

Global water model	Energy balance	Dynamical vegetation changes
DBH	Yes	No
H08	Yes	No
JULES	Yes	Yes
LPJmL	No	Yes
Mac-PDM.09	No	No
MATSIRO	Yes	No
MPI-HM	No	No
PCR-GLOBWB	No	No
VIC	Only for snow.	No
WaterGAP	No	No
WBM	No	No

Table 3: Short characterisation of the applied biomes models. More details are provided in section 6 of the SI.

Global vegetation model	Represented cycles	Dynamical vegetation changes
LPJmL	water and carbon	yes
JULES	carbon	yes
JeDI	water and carbon cycle	yes
SDGVM	water and carbon, below ground nitrogen	no
VISIT	water and carbon	no
Hybrid	carbon and nitrogen	yes
ORCHIDEE	carbon	Not in the configuration used for ISI-MIP

Table 4: Comparison of the crop model induced spread in global crop production to the climate model induced spread at different levels of global warming in comparison to the 1980-2010 reference level. Global production is calculated based on present day LU and irrigation patterns not accounting for constraints on water availability (MIRCA2000, Portmann et al., 2010).

	1°C	2°C	3°C	4°C
	wheat			
crop model induced spread of global production	3%	6%	10%	13%
climate model induced spread of global production	2%	2%	2%	2%
	maize			
crop model induced spread of global production	4%	9%	14%	18%
climate model induced spread of global production	2%	2%	2%	2%
	rice			
crop model induced spread of global production	7%	16%	26%	33%
climate model induced spread of global production	2%	1%	2%	2%
	soy			
crop model induced spread of global production	8%	14%	22%	28%
climate model induced spread of global production	4%	4%	3%	4%

Table 5: Comparison of the crop model induced spread in global crop production to the water model induced spread at different levels of global warming in comparison to the 1980-2010 reference level. Global production is calculated based on present day LU but extended irrigation

patterns according to water availability described by the water models (section 3.3 and section 3 of the SI).

	1°C	2°C	3°C	4°C
	wheat			
crop model induced spread of global production	8%	10%	13%	17%
water model induced spread of global production	4%	4%	4%	4%
	maize			
crop model induced spread of global production	7%	11%	16%	21%
water model induced spread of global production	3%	3%	3%	3%
	rice			
crop model induced spread of global production	9%	18%	27%	36%
water model induced spread of global production	1%	2%	2%	2%
	soy			
crop model induced spread of global production	23%	30%	35%	41%
water model induced spread of global production	3%	3%	4%	3%

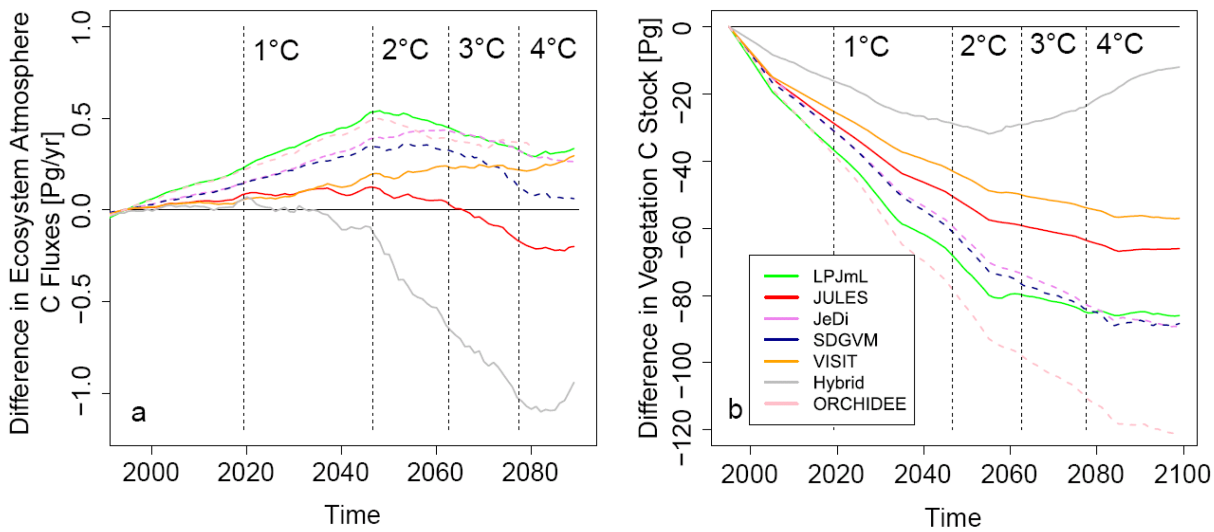

Figure 4. (a) Loss of carbon sinks (ecosystem-atmosphere C flux) due to reduction of natural vegetation and (b) associated changes in the vegetation C stock (Cveg). Colored lines represent 20 year running means of the differences of these variables between the LU change scenario and the reference scenario (fixed 1995 area of natural vegetation). Positive values indicate higher ecosystem-atmosphere C fluxes and a reduction in Cveg under LU change, respectively. Color coding indicates the different bio-geochemical models. Solid (dashed) lines represent simulations based on dynamic (static) vegetation patterns. Results are based on the historical and RCP8.5 simulations by HadGEM2-ES. Dashed vertical lines: Years where the global mean temperature change with respect to 1980-2010 reaches 1, 2, 3, and 4°C.

Table 6: Maximal loss of carbon sinks and the vegetation carbon stock as estimated for the illustrative LU change scenario (based on colored lines in panel (a) and (b) of Fig. 4). The

maximum of the transient changes (column 2 and 4) is compared to mean values of the C-fluxes and the C-stock averaged over the reference period 1980-2010 (column 3 and 5).

Model	Max Δ C sink [Pg/yr]	Ref [Pg/yr]	Max Δ Cveg [Pg]	Ref [Pg]
LPJmL	0.5	-1.4	86	201
JULES	0.1	-0.6	67	148
JeDI	0.4	-0.7	89	141
SDGVM	0.3	-0.6	89	161
VISIT	0.3	-0.7	57	126
ORCHIDEE	0.5	-0.7	121	224
Hybrid	0.0	-0.6	32	137