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LIMITS

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Report on the comparison of land use consequences of ambitious mitigation strategies
Land-use related mitigation options – an evaluation of current IAM model results

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1 Introduction

Land-use related mitigation option can play an important role in comprehensive strategies to reduce greenhouse gas emissions. This not only includes options to reduce emissions directly related to land use (change), such as the CO_2 emissions from deforestation and the non-CO_2 emissions associated with crop production and livestock husbandry. It also includes options the reduce emissions in the energy system that lead to considerable land-use change such as bio-energy.

Still, most mitigation studies have concentrated on the options for greenhouse gas mitigation in the energy sector. Integrated assessment models are, however, more-and-more capable also to discuss the implications of climate policy for land-use and associated emissions. Examples of such integrated systems include the IMAGE integrated assessment model and the coupled MESSAGE-GLOBIOM, ReMIND-MagPIE and WITCH-GLOBIOM systems. As two systems include the GLOBIOM submodule, we focus here only on the MESSAGE-GLOBIOM system (results for the WITCH-GLOBIOM can directly be derived). In order to better to assess the policy messages suggested by these models as well as the quality of the different models it is necessary that the model outcomes are compared as part of so-called model comparison studies. This report describes the results of a model comparison study that was performed using a subset of the LIMITS models, as well as several US modelling group (Chapter 2). Next, Chapter 3-5 describe the results of recent model studies with these model systems using a common chapter lay-out.

2 Land-use transition for bioenergy and climate stabilization: Model comparison of drivers, impacts and interactions with other land use based mitigation options[1]

2.1 Introduction

Fossil fuel combustion, deforestation and other human activities have released large amounts of greenhouse gases into the atmosphere. IPCC's Fourth Assessment has shown that the associated changes in climate may potentially lead to considerable impacts on ecosystems and human societies (Parry et al., 2007). Climate change can be reduced through the mitigation of greenhouse gas emissions (Metz et al., 2007). Land-based mitigation strategies, especially the use of bioenergy, could have a potentially large role as part of an overall mitigation strategy (Rose et al., 2012). Biomass can be used to provide energy in many forms including heat, electricity, gaseous, solid and liquid fuels. Recently, bioenergy has received even more attention in combination with carbon dioxide capture and geologic storage (BECCS), which can lead to a net removal of CO2 from the atmosphere (Rose et al., 2013; Azar et al. 2010). However, large uncertainties exist on deployment levels of bioenergy and the impacts of large scale bioenergy on the land system, including resulting greenhouse gas emissions (e.g. Chum et al., 2011, Searchinger et al. 2008). The explicit modeling and analysis of integrated energy and land use systems is relatively new . Most analyses so far have been single-model studies (e.g. Popp et al. 2011a, van Vuuren et al. 2009, Wise et al. 2009) that do not accommodate a comparison of the various models' land use drivers, assumptions and impacts of large scale bioenergy deployment in a consistent way (Creutzig et al. 2012). In this paper, we use a multi-model approach, allowing comparison of drivers and results across different models, to assess the impacts of large scale bioenergy crop deployment on land use dynamics, carbon fluxes within the land use system and N2O emissions from fertilizer application in scenarios with and without climate change mitigation. In addition, the interaction of bioenergy with other land use based mitigation options is investigated. The model comparison framework of the Energy Modeling Forum's 27th Study (EMF 27; Kriegler et al., 2013) provides an opportunity to do this consistently, and do so in conjunction with the Rose et al. (2013) study that

[1] This Chapter has been published as: Popp, A. , Rose, S.K., Calvin, K., Van Vuuren, D.P., Dietrich, J.P., Wise, M., Stehfest, E., Humpenöder, F., Kyle, P., Van Vliet, J., Bauer, N., Lotze-Campen, H., Klein, D., Kriegler, E. (2014). Land-use transition for bioenergy and climate stabilization: Model comparison of drivers, impacts and interactions with other land use based mitigation options. Climatic Change. 123, 3-4, 495-509

analyzes the production, use, dependence, and value of bioenergy to climate change mitigation for these and the other EMF-27 models.

2.2 Methods

Here, we use a set of comparable scenarios developed using the GCAM (Clarke et al. 2007), IMAGE (Bouwman et al., 2006) and REMIND/MAgPIE (Popp et al. 2011a, Klein et al 2013) integrated assessment models (IAMs). All of these models have in common that they contain both a dedicated energy system and land use module that interact with each other. There are clear differences between these models however with respect to the modeling of biogeochemical processes and conditions and socio-economic processes and conditions; and the explicit coverage and detail of links and interactions between these two spheres, and the interaction with other land use based mitigation options. The remainder of this section introduces the model frameworks with a special focus on their land-use modules and reflects on their advantages and limitations.

2.2.1 Overview on integrated modeling frameworks

Here, we give an overview on the three integrated assessment frameworks and describe how the respective land-use modules interact with the energy and economy modules (see also Table 2.1).

The GCAM integrated assessment model links modules of the economy, the energy system, the agriculture and land-use system, and the climate. The agriculture and land-use component (Wise et al., 2011; Kyle et al., 2011) determines supply, demand, and prices for crop, animal and forestry production and bioenergy based on expected profitability. In doing so, the model determines land allocation across these categories, as well as pastureland, grassland, shrubland, and non-commercial forestland. The agriculture and land-use component of GCAM is fully-coupled with the energy, economic, and climate modules within GCAM; that is, all four components are solved simultaneously. In the version of GCAM used in the EMF27 study, bioenergy provides the linkage between the agriculture and land-use component and the energy component, with bioenergy produced by the land system and consumed by the energy system. The agriculture and land component is coupled to the economy through bioenergy and carbon prices. Carbon prices are imposed iteratively until the prescribed climate target is reached. The carbon prices influence the cost of fossil fuel energy technologies, and the profitability of land cover options. In particular, GCAM assumes the carbon price is applied to carbon stocks held in the terrestrial system, incentivizing land owners to increase these stocks. As a result, strong incentives exist to expand carbon stocks under a climate policy, resulting in significant afforestation. The agriculture and land-use component is connected to the climate through emissions (CO2 and non-CO2), which are produced by the land system and passed into

the climate system to calculate concentrations, radiative forcings, and other climate indicators.

The IMAGE framework (Bouwman et al., 2006) describes various global environmental change issues using a set of linked submodels describing the energy system, the agricultural economy and land use, natural vegetation and the climate system. The use of bioenergy plays a role in several components of the IMAGE system. First, the potential for bioenergy is determined using the land use model, which takes into account several sustainability criteria: the exclusion of forests areas, agricultural areas and nature reserves (see van Vuuren et al., 2009). To model the potential production of bioenergy (and food crops), an adapted version of the Agricultural Ecological Zones (AEZ) model is used that determines yields as a function of land and climate conditions and assumed changes in technology on a grid cell basis (0.5 degree). Based on these spatially explicit attainable yields, and other suitability considerations, land use is allocated. The information on potential yields, associated costs and potential greenhouse gas emissions is translated into bioenergy supply curves for the energy submodel of IMAGE. In the energy submodel, the demand for bioenergy is assessed by describing the cost-based competition of bioenergy versus other energy carriers (mostly in the transport, electricity production, industry and the residential sectors). Climate policy can be represented by introducing a carbon price that taxes fossil fuels, but also the greenhouse gas emissions associated with the production of biomass and its conversion into bioenergy. The resulting demand for bioenergy crops as output from the energy system is subsequently combined with the demand for other agricultural products as input for the land-use system to determine future land use. Finally, the emissions associated with land use and land-use change (including N2O emissions associated with fertilizer use and CO2 emissions from deforestation) and the energy system are used in the climate model (MAGICC-6) to determine climate change, which then affects all biophysical submodels, including future crop yields and bioenergy potential.

The ReMIND/MAgPIE integrated assessment framework (Popp et al. 2011a, Klein et al. 2013) provides a consistent system for the evaluation of bioenergy potentials and conflicts between economic development, food and bioenergy demand in different world regions. It consists of two components: ReMIND (Leimbach et al. 2010) and MAgPIE (Lotze-Campen et al. 2008, Popp et al. 2010). The multi-regional integrated assessment model, ReMIND, represents the energy-economy-climate system and covers a wide range of bioenergy and competing conversion technologies. The MAgPIE model consists of a global dynamic vegetation, land use and water balance model. To ensure a consistent application of these models, the land-use sector in ReMIND is represented by an emulation of MAgPIE. To create the emulation, MAgPIE was run to derive region specific response curves for bioenergy production costs, GHG emissions from land use and land use change and marginal abatement cost curves (MACs) for mitigation from avoided deforestation. Spatially explicit (0.5 degree resolution)

agricultural yields, carbon contents and water fluxes in MAgPIE come from the vegetation and hydrology model LPJmL (Bondeau et al 2007). The underlying dynamics of and implications for the land use sector due to bioenergy deployment can be evaluated in MAgPIE using the bioenergy demand and GHG prices for mitigation in the land use sector from ReMIND to MAgPIE for each scenario. ReMIND assumes an upper annual limit of 300 EJ per year for second-generation biomass use (Klein et al. 2013). This assumption is consistent with the upper end of potential 2050 deployment levels identified in the Intergovernmental Panel on Climate Change's Special Report on Renewable Energy Sources and Climate Change Mitigation (Chum et al., 2011).

2.2.2 Comparison of land use modules

Important details of the land use modules differ (see Table 2.1 for an overview). A brief comparison is given here. More detailed descriptions of each model's land modeling can be found in the SOM.

	GCAM	IMAGE	ReMIND/MAgPIE
Interactions of the LU module			
Energy module	Bioenergy demand	Bioenergy potential and bioenergy demand	Bioenergy demand
Economy module	Bioenergy prices and Carbon prices	Arable land	Bioenergy prices and Carbon prices
Climate module	GHG emissions	GHG emissions	GHG emissions
Land use dynamics			
Between economic units	Profit maximization	Cost minimization	Cost minimization
Between biophysical units	Profit maximization	Rule based approach	Cost minimization
Land types modeled			
Cropland	Dynamic	Dynamic	Dynamic
Bioenergy Cropland	Dynamic	Dynamic	Dynamic
Pasture	Dynamic	Dynamic	Constant
Forest	Dynamic	Dynamic	Dynamic
Managed Forest	Dynamic	Dynamic	Constant
Urban	Constant	Dynamic	Constant
Other Land	Dynamic	Dynamic	Dynamic
Spatial resolution (biophysical)	151 world regions	0.5 x 0.5 degree grids	0.5 x 0.5 degree grids
Spatial resolution (economic)	14 world regions	24 world regions	10 world regions
GHG emissions			

Land Use Change [CO2]	Yes	Yes (including regrowth of natural vegetation)	Yes
Livestock [CH4, N2O]	Yes	Yes	Yes
Cropland [CH4, N2O]	Yes	Yes	Yes
LU mitigation options			
Afforestation	Yes	No	No
Reforestation	Yes	No	No
Forest management	No	No	No
Avoided deforestation	Yes	No	Yes
Bioenergy	Waste, residues, 1st and 2nd generation bioenergy crops	Residues, 1st and 2nd generation bioenergy crops (only fast growing trees)	Residues, 2nd generation bioenergy crops
Agricultural Management [CH4, N2O]	Yes	Yes	Yes
Agricultural soil carbon management [CO2]	No	No	No
Crop yields			
Climate change impacts	No	Yes	No
Technological change	Exogenous	Exogenous	Endogenous
Irrigation	Yes	Yes (no irrigation for bioenergy crops)	Yes
Irrigation dynamics (efficiency increase, irrigation expansion)	No	Yes	Yes

Table 2.1: Overview and description of land modeling approaches in GCAM, IMAGE and ReMIND/MAgPIE.

First, the models describe economic decisions associated with bioenergy supply in different ways. In MAgPIE, land use decisions at the 0.5 x 0.5 degree grid are based on minimizing production costs. In GCAM, land is allocated to 151 biophysical regions based on profit-maximization. Finally, in IMAGE, food production is determined first by a macro-economic description, and subsequent decisions on regional bioenergy production are based on cost minimization. The final allocation of land-use at the 0.5 x 0.5 degree grid within a region follows a rule-based land mechanism that accounts for crop productivity and other suitability factors, such as proximity to existing agricultural land and water bodies. The models have fairly similar land type categories, but treat land pools differently. In GCAM and MAgPIE, urban land is considered to be static, while in IMAGE, a relationship with population density is used. In GCAM and IMAGE, pasture area is driven by demand for animal products, but it is constant in MAgPIE. The models differ in terms of geographic resolution at which differences in land quality and climatic conditions are taken into account for biophysical data inputs such as agricultural production, water availability for irrigation or carbon content of natural vegetation and agricultural crops. IMAGE considers this information at the level of 0.5 degree grid cells. In this application of MAgPIE, 0.5 degree data is aggregated to 200

clusters, whereas GCAM functions on the level of 151 regions. Agricultural yields in all models are assumed to change over time. Yield increases due to technological change are either considered mostly exogenously (GCAM and IMAGE) or treated endogenously (MAgPIE). In addition, in IMAGE, agricultural yields as well as carbon content of crops and natural vegetation are affected by climatic change. All models consider carbon fluxes of vegetation and soils and greenhouse gas emissions from agricultural management. In all models, carbon emissions from land use change occur if the carbon content of the previous land use activity exceeds the carbon content of the new land-use activity. Carbon uptake occurs if a more carbon-rich ecosystem replaces a less carbon-rich one. IMAGE assumes regrowth of natural vegetation and associated CO2 uptake on abandoned land. Land use based mitigation in the models is driven by GHG prices in the mitigation scenarios. However, the models produce different GHG price trajectories for a given policy (see Rose et al (this issue) for discussion of GHG prices and other cost metrics). There are differences in the land use based mitigation options available in the models. All models include production of dedicated bioenergy crops for deployment in the energy sector and mitigation of non-CO2 GHGs from agricultural production. However, the current IMAGE scenarios do not consider avoided deforestation, and afforestation/reforestation is only taken into account by GCAM. Importantly, the models differ in their assumptions on availability of land and water resources for dedicated bioenergy crops. In GCAM and MAgPIE, bioenergy crops will be allocated based on suitability of soil and climatic conditions and the competition with land needed for the production of other agricultural goods. In GCAM, all land is available. In MAgPIE, however, managed forests and pasture land are static and cannot be used for bioenergy production. Also, nature conservation areas are not available for cropland expansion. In contrast, IMAGE allows bioenergy crops only to be grown on land other than that required for food production, forests, nature conservation and urban areas (representing successful implementation of sustainability criteria). While all models consider irrigation for food crops, IMAGE, unlike GCAM and ReMIND/MAgPIE, assumes irrigation is unavailable for bioenergy crops, again due to sustainability considerations. GCAM includes both irrigated and rainfed croplands but only implicitly, that is, they are not distinct technology choices. The greatest flexibility for irrigation is in ReMIND/MAgPIE, which can shift production from irrigated to rainfed in response to economic or climatic drivers for all types of crop production.

2.2.3 Scenarios

In this paper we utilize five scenarios—one baseline and two stabilization scenarios from the EMF27 exercise (Kriegler et al., 2013), and two no bioenergy diagnostic reference scenarios (without and with climate policy). All three of the EMF27 scenarios include a full portfolio of mitigation technologies. The first scenario does not include climate change mitigation (Base FullTech), the second scenario limits the GHG (CO2 equivalent) concentration in the atmosphere to 550 ppm in 2100 (550 FullTech), and

the third scenario limits the GHG concentration to 450 ppm in 2100 (450 FullTech). The 'reference scenarios' are no bioenergy variants of Base FullTech and 450 FullTech. The reference scenarios represent a hypothetical future without bioenergy production but their input assumptions are identical to the corresponding scenarios otherwise. They serve as a point of reference for the assessment of land use, vegetation and soil carbon fluxes, and nitrous oxide emissions implications from bioenergy crops and other land use based mitigation measures. The models have not been harmonized in their socio-economic conditions that drive emissions, food, feed and energy demand.

2.3 Results

2.3.1 Bioenergy deployment

All models indicate that bioenergy deployment in the energy system increases over time in the baseline (Base FullTech) and climate policy scenarios (Fig. 1). By 2050, regional biofuel consumption is as much as 10%, 45%, and 70% of liquid fuel consumption across regions in GCAM, IMAGE, and REMIND respectively, while regional bioelectricity consumption is as much as 10%, 25%, and 20% of electricity consumption across regions in the three models respectively (Rose et al., 2013). Deployment grows with the stringency of the climate target. However, the levels and make-up of bioenergy deployment varies substantially across models. There is no single reason for the differences. The results derive from each models combination of plausible assumptions regarding, for instance, economic growth, available technologies, intensities (relationships between variables) and model structure. In GCAM and IMAGE, deployment increases steadily over time. In ReMIND/MAgPIE deployment levels remain constant in the first half of the century and then increase rapidly in the second half. In 2050, in the Base FullTech scenario, total global deployment levels range from 48-85 EJ/year (48 EJ in IMAGE, 53 EJ in ReMIND/MAgPIE and 85 EJ in GCAM) and increase to 109-231 EJ/year in 2100 (109, 231, and 138 EJ respectively). In the 450 FullTech scenario, 2050 global deployment levels increase to 129-228 EJ/year (142, 228, and 129 EJ respectively), with 2100 deployment of 255-324 EJ/year (255, 296, and 324 EJ respectively). Except of slightly higher deployment levels in 2100 in ReMIND/MAgPIE in the Base FullTech and in GCAM in the 450 FullTech scenario, deployment levels reported by the IAM models considered in this paper are in the range of the other 12 models applied in EMF27 that report 9-130 EJ/year in 2050 and 68-168 EJ/year in 2100 for the Base FullTech scenario and 94-207 EJ/year in 2050 and 205-300 EJ/year in 2100 for the 450 FullTech scenario (see Rose et al 2013). Not only the time path and level of bioenergy deployment differs across the 3 models but also the share of different biomass resources deployed. In IMAGE and ReMIND/MAgPIE, cellulosic bioenergy crops and residues are used as primary energy carriers. In GCAM 1st generation bioenergy crops are also used. In the Base FullTech scenario, GCAM deploys a considerable share of 1st generation bioenergy crops, but in the 450

FullTech scenario, this decreases. BECCS energy technologies play an important role in the three models. By mid-century, BECCS energy technologies dominate global bioenergy—67%, 50%, and 99% of primary energy in GCAM, IMAGE, and REMIND. By end-of-century, BECCS represents almost all bioenergy—97%, 86%, and 100% respectively (Rose et al. 2013). See Rose et al. (2013) for additional analysis of global bioenergy deployment for these and other models. Dedicated energy crops are of particular importance to land use dynamics, which is discussed next.

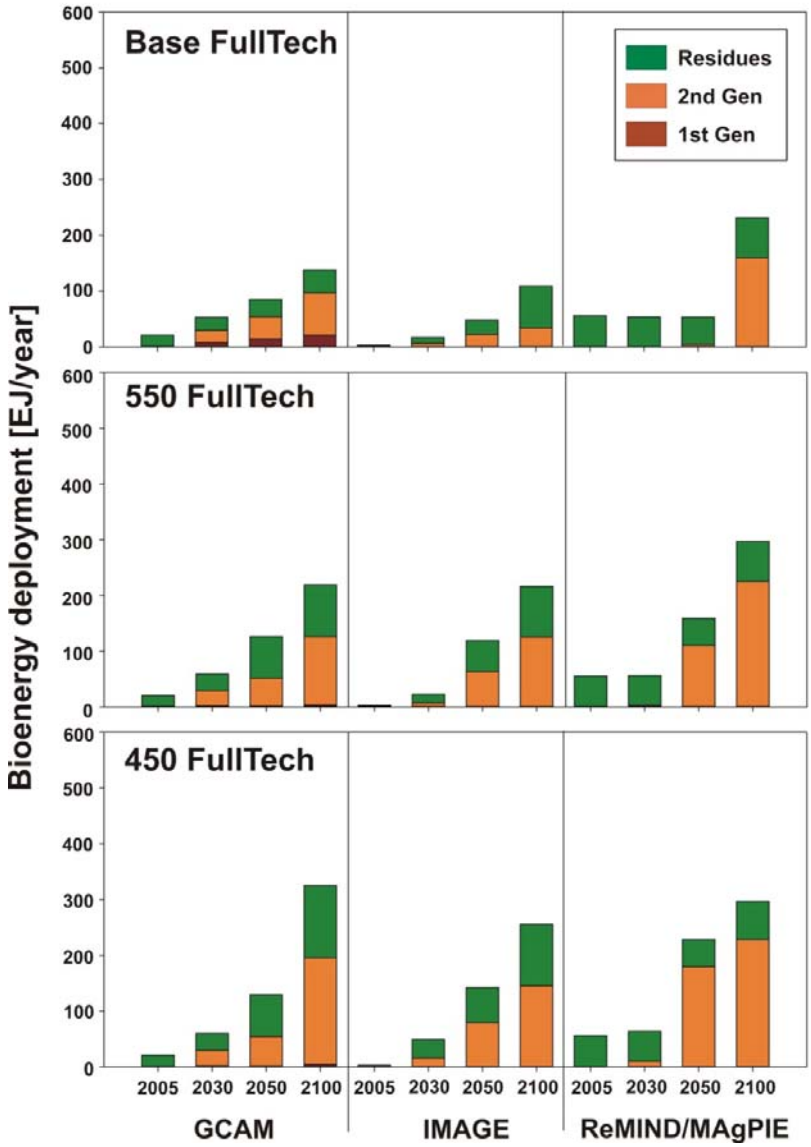

Figure 1.1: Global deployment of bioenergy feedstocks. Brown bars represent 1st generation bioenergy crops (such as maize, rapeseed or oilpalm), orange bars 2nd generation cellulosic bioenergy crops (such as poplar or Miscanthus) and green bars feedstock coming from residues. Traditional biomass is not included in this figure.

2.3.2 Land use dynamics

In the main text we present global land cover change results; however, in the SOM, we also provide results for five aggregate regions: OECD90 countries (OECD), reforming economies of Eastern Europe and the Former Soviet Union (REF), countries of the Middle East and Africa (MAF), countries of Latin America and the Caribbean (LAM), and Asian countries (ASIA) excluding countries already represented (Middle East, Japan and Former Soviet Union states). The discussion below considers both the global and regional results. We begin by discussing the base year. The initial allocation of land defines production and conversion opportunities for a model. The supplementary information indicates that the models have similar total land cover, but notably differ in their allocation in 2005. In GCAM and IMAGE, for instance, forest and other land dominate. Yet GCAM has 500 million more hectares (ha) of forests and 500 million less ha of cropland than IMAGE. Global pasture area in both models is similar. In contrast, global pasture area is most prominent in ReMIND/MAgPIE at the expense of 'other land' primarily, but also forest. ReMIND/MAgPIE has approximately 1.5 billion more hectares of pasture than the other models. Regionally, all models indicate that most pasture area but also other land can be found in MAF, forest area dominates in LAM, OECD and REF, and most cropland appears in ASIA and OECD (See Fig SI3). In general, dissimilarities in the base year across the models is caused by implementation of different land use data sources and categorizations, and use of different methodologies and definitions (e.g., pasture) in deriving the land use data sets (e.g. Ramankutty et al. 2008). For example, in contrast to IMAGE and ReMIND/MAgPIE where fallow cropland is accounted in the category of cropland, fallow cropland in GCAM is reported as other land, wherefore cropland in GCAM shows much lower numbers. The land cover allocation differences, along with differences in model structure, likely affect results. For instance, smaller cropland or forest area can imply higher productivity, larger land rents, as well as GHG intensity per hectare, while conversion constraints will have a greater impact the larger the land cover allocation (e.g., IMAGE's use of abandoned agricultural land and natural grass land, ReMIND/MAgPIE's fixing of pasture land).

Fig 2 shows that the models project very different global land cover conversion futures. In the baseline (Base FullTech), total cropland increases by 330 million ha by 2100 in GCAM (approximately the country area of India), compared to 530 million ha in ReMIND/MAgPIE, and a decrease of 180 million ha in IMAGE. IMAGE's result is driven by ongoing yield increases and a stabilizing global population in the second half of the century. Regionally, ReMIND/MAgPIE and GCAM project increases in cropland in all regions until 2100 with the highest increases in ReMIND/MAgPIE in LAM and in GCAM in ASIA (Fig SI6). Land use changes to 2030 and 2050 are also provided in the SOM. Globally, by 2100, energy crops represent 18 % of total cropland (non-energy and energy crop) in GCAM and ReMIND/MAgPIE and 10 % in IMAGE. In GCAM and ReMIND/MAgPIE bioenergy cropland is most prominent in ASIA and OECD in 2100. In addition, ReMIND/MAgPIE reports also high bioenergy cropland in LAM. In IMAGE

bioenergy cropland is most prominent in REF. Total Cropland expansion happens mainly at the expense of 'other land' and pasture in GCAM, and forest and other land in ReMIND/MAgPIE. In IMAGE, forest area increases substantial as cropland and other land contract and natural vegetation regrowth occurs. The baseline contraction of cropland in IMAGE frees up land for energy crops.

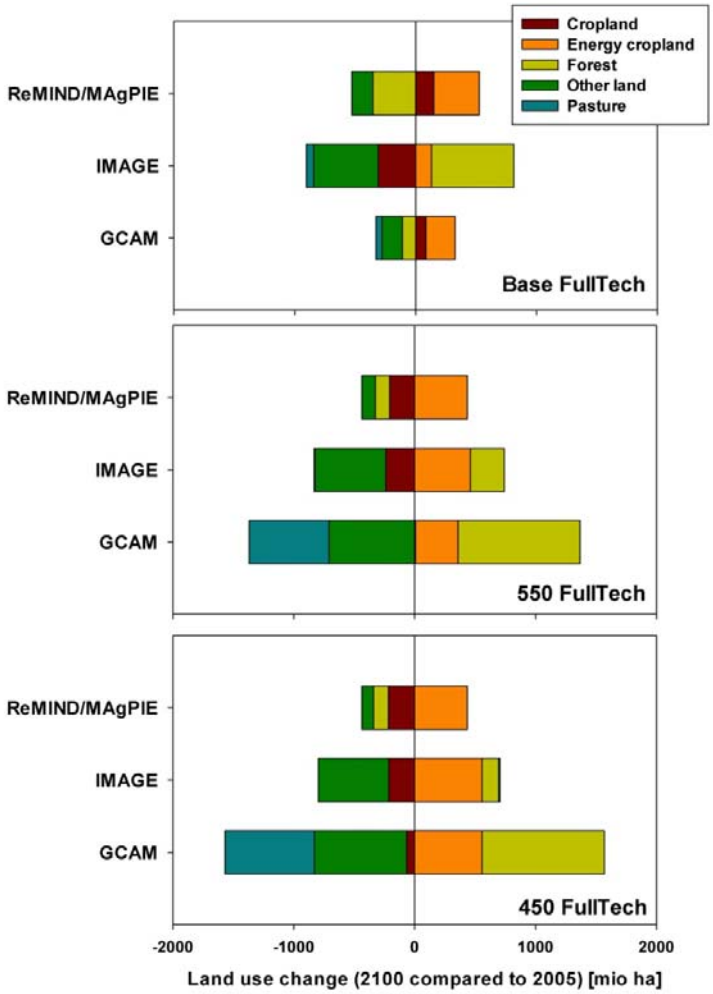

Figure 2.2: Change in global land pools [million ha] from 2005 to 2100 in GCAM, IMAGE and ReMIND/MAgPIE.

In the mitigation scenarios, bioenergy cropland expands significantly. Forests do as well, though for ReMIND/MAgPIE it appears as reduced forest loss (relative to the baseline). Non-energy cropland, other land and pasture are all affected, but to substantially different degrees across models. In IMAGE, total cropland (non-energy and energy) is 23 % (550 FullTech) and 28 % (450 FullTech) higher than in the Base

FullTech scenario in 2100. The main driver is bioenergy cropland that covers 26 % (550 FullTech) and 30 % (450 FullTech) of total cropland. In ReMIND/MAgPIE, non-energy cropland switches from expansion in the baseline to contraction in the mitigation scenarios, however there is very little difference in conversion levels and patterns between the mitigation scenarios. Here, the share of bioenergy cropland in total cropland increases to 24 % in 550 FullTech and 450 FullTech. In GCAM, total cropland expands at the cost of pasture and other land in both mitigation scenarios. Again, the main driver is bioenergy cropland, which uses 36 % of total cropland. In all models, bioenergy cropland increases strongly in ASIA, OECD, and REF by 2100 in the 450 FullTech scenario (Fig SI6). Global forest dynamics differ strongly across the different models in the 550 FullTech & 450 FullTech scenarios. In IMAGE, forest cover is globally 12 % lower compared to the Base FullTech scenario in 2100 as abandoned land is used for bioenergy crops, instead of regrown forests (450 FullTech scenario). Due to avoided deforestation, forest cover remains almost constant in ReMIND/MAgPIE in 550 FullTech & 450 FullTech. In GCAM, global forest cover even increases by 20 % until 2100 in the 550 FullTech & 450 FullTech scenarios due to afforestation and avoided deforestation, especially in MAF, REF and LAM. Overall, the land conversions reflect structural features of the models. Bioenergy land expansion is primarily cropland and other land in ReMIND/MAgPIE due to pasture constraints and avoided deforestation, while it is reduced cropland contraction and natural forest regrowth in IMAGE. In GCAM, it is reductions in other and pasture land.

2.3.3 Bioenergy yields

Current and projected future yields of bioenergy crops are important determinants for bioenergy potentials. The models consider different types of bioenergy crops, different types of management, different rates of future technological change and impacts of climatic change, as such a detailed analysis of agricultural yields is complicated. Instead, we focus on the overall simulated global energy yield (global bioenergy crop production divided by global bioenergy crop area) and its development over time for the scenario with most ambitious climate change mitigation (450 FullTech). Fig 3 shows that energy crop yields differ strongly across the models. In 2030, the highest yields of 491 GJ ha-1 year-1 are reported from ReMIND/MAgPIE. This is consistent with the fact that the model only considers cellulosic bioenergy crops and a large share is irrigated as the model shifts production from rainfed to irrigated for all types of crop production to minimize agricultural production costs. In GCAM, in 2030, lower yields of 273 GJ ha-1 year-1 result due to different assumptions about future management practices (e.g. irrigation). The lowest yields in 2030 are found in IMAGE (162 GJ ha-1 year-1). IMAGE only considers rain-fed woody crops and constrains bioenergy crops to marginal and abandoned land. Acreage required for food production, forests, and nature conservation is off limits. In all models, yields increase over time—by a factor of 1.6 from 2030 to 2100 in IMAGE, 1.2 in GCAM, and 1.1 in ReMIND/MAgPIE. These yield results are comparable with the wide range reported in the literature (see

Lewandowski et al. 2000, Fischer et al. 2005, Beringer et al. 2011, Hong et al 2011) where energy yield values range from 564 GJ ha-1 year-1 with irrigation and nitrogen supply to 291 GJ ha-1 year-1 without N supply and irrigation (e.g. Ercoli et al 1999).

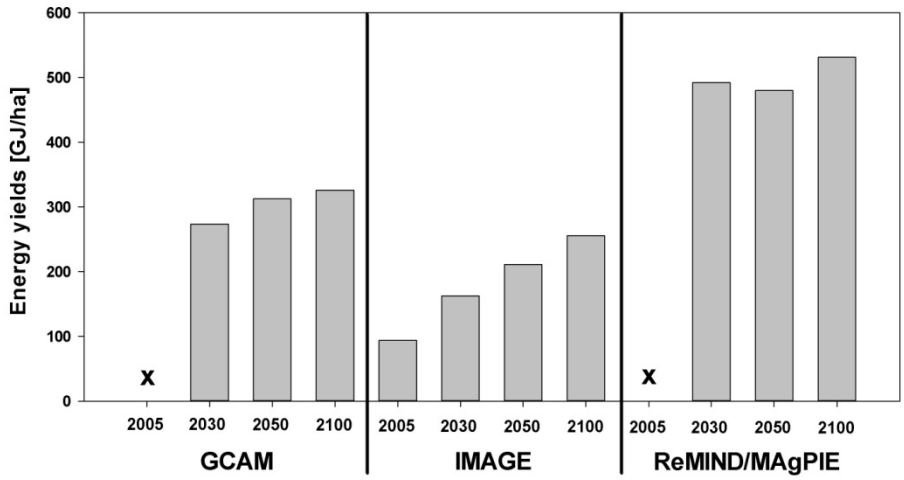

Figure 2.3: Global energy yields (global bioenergy crop production divided by global bioenergy crop area) for the *450 FullTech* scenario in GCAM, IMAGE and ReMIND/MAgPIE for the years 2005, 2030, 2050 and 2100. For GCAM and ReMIND/MAgPIE yields could not be calculated for 2005 as there are no bioenergy crops produced.

2.3.4 Greenhouse gas fluxes

Fig 4 presents the net land related greenhouse gas implications of bioenergy and other land use based mitigation measures—without and with climate policy. Shown are differences between the bioenergy scenarios (Base FullTech and 450 FullTech) and their respective no bioenergy reference scenarios. Comparing to a scenario without bioenergy provides a diagnostic that isolates the emissions implications of bioenergy. In Fig 4 we see very different emissions responses to bioenergy crops. In the Base FullTech comparison to reference, emissions of CO2 from land-use change and N2O are revealed for all models, with CO2 emissions dominating. However, the differences in the pattern of fluxes are stark. GCAM shows large initial CO2 emissions of 63 Gt CO2-equ cumulatively in the period 2005-2050 associated with early land conversion that declines with time as land conversion slows down (only 89 Gt CO2-equ cumulatively from 2005-2100). In contrast, dedicated bioenergy feedstocks aren't deployed in the ReMIND/MAgPIE baseline until the second half of the century, at which point increasing deployment produces increasing land-use emissions (52 Gt CO2-equ in the time period 2050-2100 alone). IMAGE has more modest bioenergy crop levels and also more modest CO2 emissions (10 Gt CO2-equ from 2005-2100) that occur as bioenergy crops prevent regrowth of natural vegetation on abandoned land and associated carbon uptake. N2O emissions, from the application of fertilizers for

non-energy and energy crop production, increase over time with bioenergy deployment and are highest cumulatively for GCAM (24 Gt CO2-equ), followed by ReMIND/MAgPIE (9 Gt CO2-equ) and IMAGE (3 Gt CO2-e) from 2005-2100. In the 450 FullTech comparison to reference, dedicated bioenergy deployment levels are much higher than in the baseline comparison. In IMAGE, the higher production of bioenergy crops reduces terrestrial carbon uptake by displacing regrowth of natural vegetation on abandoned land. On the other hand, ReMIND/MAgPIE reaches up to 250 EJ per year from energy crops; however, avoided deforestation prevents CO2 emissions from land-use change by restricting cropland expansion. In GCAM, a completely different dynamic plays out. It appears GCAM is releasing huge quantities of terrestrial carbon. However, the actual story is quite different. More afforestation is used for carbon sequestration in the land use sector when the energy system does not have the option to use bioenergy. Therefore, more carbon is stored in forests in the 450 FullTech reference scenario compared to the 450 FullTech scenario with bioenergy. Figure 2.4 shows the afforestation carbon opportunity cost of bioenergy. When bioenergy is available, GCAM chooses bioenergy, BECCS in particular, over additional afforestation for mitigation (176 GtCO2-equ from 2005-2100 of additional afforestation). While the land-use CO2 emissions stories vary widely, the models all project increases in land-use N2O emissions with bioenergy. However, it is important to note, as shown in Rose et al (2013), that the integrated perspective of these models finds that, despite increased land use CO2 and N2O emissions, bioenergy can still be a cost-effective climate stabilization strategy over the long-run.

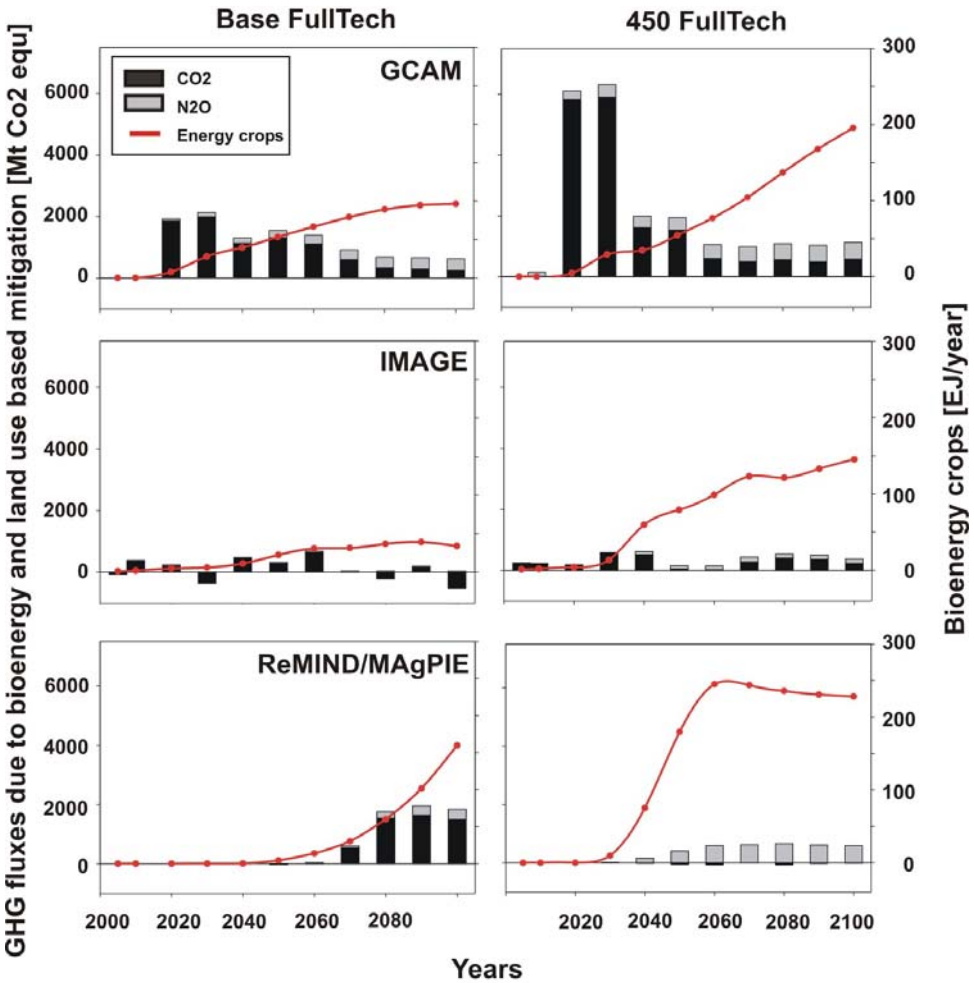

Figure 2.4: Bioenergy crop production (red line) and greenhouse gas (GHG) fluxes due to bioenergy production and other land use based mitigation options (improved agricultural management, avoided deforestation and afforestation) as a difference between the default scenarios with bioenergy (*Base FullTech* and *450 FullTech*) and the respective reference scenarios without bioenergy. GHG fluxes are shown for land use change (CO2 – black bars) and N2O emissions from nitrogen application (grey bars) from 2005 until 2100.

2.4 Conclusion

The land use sector could contribute significantly to climate change mitigation, for instance in the form of producing bioenergy (Rose et al. 2013, van Vuuren et al. 2009 Popp et al. 2011a) but also by afforestation/reforestation and avoiding deforestation (Wise et al. 2009, Rose et al. 2012). However, especially large-scale bioenergy crop production is seen to increase the competition for land, water, and other inputs, affecting land use dynamics and leading to deforestation, emissions from land use change and agricultural intensification. (e.g. Searchinger et al. 2008, Popp et al. 2012, Popp et al. 2011a, , Wise et al. 2009). We apply and compare three structurally different integrated assessment models (GCAM, IMAGE and ReMIND/MAgPIE) to explore drivers and impacts of bioenergy production on the global land system as well

as the interaction with other land use based mitigation options. The three models differ strongly in their assumptions and definitions of land cover distribution in 2005 and the availability of biomass resources for deployment in the energy system. They also include different sets of other land use based mitigation options (such as avoided deforestation and afforestation) that interact with bioenergy. We find that different choices of bioenergy feedstocks (1st vs. 2nd generation but also woody vs. herbaceous cellulosic), land use restrictions and current as well as future management (such as irrigation vs. rainfed) for bioenergy production significantly affect simulated bioenergy crop energy yields, with results ranging from 162-491 GJ ha-1 year-1 in 2030. Despite the dissimilarities, a number of robust findings emerge. In baseline scenarios without climate change mitigation, bioenergy cropland represents 10-18% of total cropland by 2100 and leads to cropland expansion, mainly at the expense of carbon richer ecosystems. Global CO2 emissions from land-use change range from 11 and 89 Gt CO2-equ cumulatively through 2100. The lowest emissions occur in IMAGE as bioenergy crops can only be grown on marginal and abandoned land, excluding carbon rich ecosystems such as forests. If also agricultural N2O emissions are considered, global co-emissions from baseline bioenergy production range from 14 to 113 Gt CO2-equ cumulatively through 2100. Disparities in these results derive from each models combination of plausible assumptions regarding, for instance, agricultural yields, economic growth, available technologies, intensities (relationships between variables) and model structure. In all models, dedicated bioenergy crops are seen as an important and cost-effective component of the energy system, especially in the scenario with the most ambitious climate stabilization targets (150-230 EJ/year in 2100). However, bioenergy interacts and competes with other land use based mitigation options. In general, bioenergy production leads to N2O emissions from fertilization but improved agricultural management (such as precision farming) increases the efficiency of nitrogen application and therefore reduces agricultural N2O emissions from both crop and bioenergy crop production (see also Popp et al. 2011b). The models also indicate that other land-demanding climate change mitigation measures (afforestation and avoiding deforestation) are cost-effective and prominent in scenarios with climate change mitigation. Simulations with ReMIND/MAgPIE show that avoiding deforestation, by pricing carbon emissions from land-use change, reduces forest loss in Latin America, Asia and Africa and hence co-emissions from bioenergy production. In addition to avoided deforestation and large scale bioenergy production, strong incentives exist under a climate policy to expand carbon stocks on land by afforestation in the GCAM simulations at the cost of pasture and other land. Overall, land demanding mitigation measures dominate land-use dynamics and enhance the competition for land and water by either restricting land availability for agricultural expansion (avoided deforestation) or spreading directly into agricultural land dedicated for food and feed production (bioenergy and afforestation). This analysis focused on potential bioenergy land use and GHG implications within climate management scenarios. However, other social dimensions will also be important and affect bioenergy's appeal and social acceptance, e.g., food prices, biodiversity and

nature conservation and water security. Basic biophysical (such as agricultural yields), techno-economic (such as conversion efficiencies in the energy system) and socio-economic conditions (such as food demand or trade of agricultural goods) strongly influence land-use outcomes and resulting bioenergy production as well as impacts. Therefore, it will be of key importance to reduce uncertainty in the outcomes and to improve our understanding of how bioenergy and other land use based mitigation perform and interact under different sets of techno-economic and socio-economic settings. Further research to address the issue of land use based climate change mitigation in general and specifically the issue of bioenergy will be crucial to inform decision-makers about robust strategies towards a more environmental-friendly future.

3 Analysis of land-use related mitigation options using IMAGE

3.1 Description of the IMAGE 3.0 model

Main purpose

IMAGE is an ecological-environmental model framework that simulates the environmental consequences of human activities worldwide. It represents interactions between society, the biosphere and the climate system to assess sustainability issues such as climate change, biodiversity and human well-being. The objective of the IMAGE model (version 3.0, released in 2014) is to explore the long-term dynamics and impacts of global changes that result from interacting demographic, technological, economic, social, cultural and political factors.

Brief description of the model
The IMAGE 3.0 framework addresses a set of global environmental issues and sustainability challenges. The most prominent are climate change, land-use change, biodiversity loss, modified nutrient cycles, and water scarcity. These highly complex issues are characterised by long-term dynamics and are either global issues, such as climate change, or manifest in a similar form in many places making them global in character. IMAGE is a simulation model: this means that is aims to describe processes of changes based on a set of rules that determine future investment and development patterns based on the information about the 'present' situation.

Important inputs into the system are assumptions on population and economic development. Next, two models describe the trends in the demand for key environmental services: energy and food demand. The global energy system model IMAGE-TIMER (Van Vuuren et al., 2007) has been developed to simulate long-term energy baseline and climate change mitigation scenarios. The model describes the investments in and use of different types of energy options influenced by technology development (learning-by-doing) and resource depletion. Inputs to the model are macro-economic scenarios and assumptions on technology development, preference levels and restrictions to fuel trade. For food and agriculture, the IMAGE system uses projections made by the computable-general-equilibrium MAGNET model. This model describes, in interaction with the main IMAGE framework, changes in food production and trade for a broad set of crops and animal products. The Terrestrial Environment System (TES) of IMAGE (Alcamo, 1994; Bouwman et al., 2006) computes land-use changes based on regional production of food, animal feed, fodder, grass, bio-energy and timber, with consideration of local climatic and terrain properties. Climate change affects the productivity of crops and induces changes in natural vegetation with consequences for biodiversity. TES represents the geographically explicit modelling of and use. The potential distribution of natural vegetation and crops is determined on the basis of

climate conditions and soil characteristics on a spatial resolution of 0.5 x 0.5 degree. It also estimates potential crop productivity, which is used to determine allocation of cropland to different crops. Emissions from land-use changes, natural ecosystems and agricultural production systems, and the exchange of carbon dioxide between terrestrial ecosystems and the atmosphere are also simulated. The Atmospheric Ocean System (AOS) part of IMAGE calculates changes in atmospheric composition using the emissions from the TIMER model and TES, and by taking oceanic carbon dioxide uptake and atmospheric chemistry into consideration. Subsequently, AOS computes changes in climatic parameters by resolving the changes in radiative forcing caused by greenhouse gases, aerosols and oceanic heat transport.

Land-use change and land-use related mitigation

Land use in the IMAGE model is described as a consequence of the interaction of various submodels:

- The LPJ model determining the potential production per grid cell for different crops and grasses at grid scale as a function of soil and climate characteristics. In time, the results are influenced by climate change and technology assumptions.
- The MAGNET agricultural economy model determining demand and production per region. This model also calculates investments into increase of agricultural productivity.
- The TIMER energy model determining the use and production of bio-energy based on the competition of different energy technologies and the potential production levels.

In determining land-use over time, the following model steps are taken:

- Information on production potential is provided to MAGNET and TIMER;
- Subsequently, the production levels and corresponding management factors (human investments in productivity) for food crops, livestock and bio-energy per region are determined. This allows to calculate land use per region.
- The production levels are assigned to the grid levels on the basis of different allocation rules. These rules include factors like productivity, proximity to existing agricultural areas and population.

This means that model is able to provide a dynamic description of land-use and land-use change in response to the demand for various agricultural and forestry products. Land use can also play an important role in mitigation strategies. Table 3.1 summarizes the land-use mitigation strategies currently represented in IMAGE.

Land-use related climate mitigation option	*Representation*
Bio-energy	Bio-energy is calculated on the basis of the crop model in IMAGE. Production levels are determined in the agro-economic model MAGNET and/or in the energy model TIMER.
Deforestation, reforestation, afforestation	Some experiments have been performed integration forestry measures as mitigation measure into IMAGE. A default method is, however, lacking in IMAGE 3.0
Reducing GHG emissions indirectly via changes in food demand or production	The IMAGE model can calculate the impacts of different agricultural scenarios by running the MAGNET agro-economic model in combination with the land-use model or introducing more ad-hoc changes in land-use consumption and production patterns
Reducing non-CO2	Non-CO2 emissions from agriculture are fully integrated into the models.

emissions from agriculture	Emissions can be reduced via mitigation strategies on the basis of their marginal costs. Emissions are also influenced by changes in land-use related activities.

Table 3.1: Land use mitigation strategies in IMAGE

3.2 Description of findings of IMAGE studies

3.2.1 Bio-energy

The IMAGE model was used to look into the potential of bio-energy but also the consequences of different bio-energy implementation strategies.

Bio-energy potential

The potential of bio-energy clearly depends on a range of assumptions on alternative land-use, sustainability criteria, assumptions on acceptable costs and climate change. To capture these factors in a transparent way, Hoogwijk et al. (Hoogwijk et al., 2009; Hoogwijk et al., 2005) introduced a method to calculate the potential for bio-energy within the context of different future scenarios that include assumptions of each of the factors mentioned above. These potential focus on both abandoned agricultural land (resulting mostly from declining population trends in the future) and potential land available for bio-energy, i.e. not-excluded on the basis of sustainability criteria. The latter, referred to as rest-land, mostly contains part of grass-type ecosystems (as for instance forests are excluded). The main purpose of the work was to show that the potential for bio-energy depends strongly on policy decisions and socio-economic trends in other areas (in particular food production). In the first publication, in 2005, relatively high potential were reported: For the year 2050 the geographical potential of abandoned land ranges was reported to range from about 130 to 410 EJ yr^{-1}, while for rest land the potential was from about 35 to 245 EJ yr^{-1}. In subsequent publications, the IMAGE model was used to explore the impact of more restrictive sustainability criteria and more realistic land-use scenarios. The resulting estimates for bio-energy typically show a range for 2050 for purposely grown bio-energy from 50-150 EJ yr^{-1} (Van Vuuren et al., 2010; van Vuuren et al., 2009) and 200-400 EJ yr^{-1} in 2100 (higher as a result of higher yields and, depending on the scenario, less population). Higher bio-energy potential was found to depend on development paths with high agricultural yields, dietary patterns with low meat consumption, a low population and/or accepting high conversion rates of natural areas. It was also explored how more strict sustainability criteria would impact these numbers. For instance, while in the OECD Reference scenario the default bio-energy potential was found to be 150 EJ yr^{-1}, 80 EJ yr^{-1}occurs in areas classified as from mild to severe land degradation, water stress, or with high biodiversity value (van Vuuren et al., 2009).

Degraded areas might also be an potential attractive area for second-generation bio-energy production as perennial energy crops would be impacted less by soil degradation than food crops providing the option of bio-energy production without substantial impacts on food production. Therefore, an estimate was made of the possible production

and yield of perennial energy crops on the degraded areas as a function of the type and degree of degradation (lightly degraded areas were not included, as these areas might be suitable for conventional food production) (Nijsen et al., 2012). It was found that the total global potential energy production on degraded lands was assessed to be slightly above 150 and 190 EJ yr-1, for grassy and woody energy crops, respectively. Most of this potential, however, is on areas currently classified as forest, cropland or pastoral land, leaving a potential of around 25 and 32 EJ yr-1 on other land cover categories. Most of this potential is located in China, Brazil, USA, Brazil, West Africa, East Africa, Russia and India.

Climate impacts of large-scale bio-energy production

As part of mitigation strategies, bio-energy can reduce greenhouse gas emissions by replacing fossil fuels. Several papers have shown, however, that large-scale bio-energy production may itself lead significant impacts. Such impacts might be the direct and indirect emissions of carbon dioxide as a result of land-use (related to a reduction of natural vegetation), the N_2O emissions associated with bio-energy production and the impacts on biophysical climate factors related to land use change.

The direct and indirect emissions of bio-energy has been studied extensively by various studies (Wicke et al., 2012). Most of these show that bio-energy production is likely to coincide with some net land-use related CO_2 emissions due to loss of natural vegetation (which is also found in empirical studies (Overmars et al., 2011)). In IMAGE, even if bio-energy production is restricted to using mostly abandoned agriculture land, emission can be attributed to bio-energy as natural vegetation would potentially regrow at the land used for bio-energy production in the alternative, reference, scenario. The resulting indirect "CO_2 emission factor" can also be estimated: in different IMAGE publication it was found to be around 3-5 kg CO_2/GJ for so-called second generation bio-energy (woody biomass) although it was also shown to depend strongly on the area used for bio-energy production and therefore both the volume of bio-energy production and the assumed land-use policies (Otto et al., 2014; Van Vuuren et al., 2007). For first-generation bio-energy, these emissions are likely to be considerably larger (Eickhout et al., 2008).

In addition to CO_2 emissions, the production of bio-energy crops will also likely to coincide with N_2O emissions associated with application of fertilizers and emissions during the conversion processes. Smeets et al. (2009) assessed the importance of these emissions for first-generation biofuels by applying a statistical model that uses spatial data on climate and soil. The results show that N2O emissions can have an important impact on the overall GHG balance of biofuels, though there are large uncertainties. The most important ones are those on the exact N_2O emissions related to fertilizer applications and the assumed reference system. It was found that ethanol produced from sugar cane and sugar beet and the use diesel from palm fruit are relatively robust GHG savers: these biofuels change the GHG emissions by -103% to -60% (sugar cane), -58% to -17% (sugar beet) and -75% to -39% (palm fruit), compared with conventional transportation fuels. For other fuels, however, the contribution might be either positive or negative based on the uncertainties mentioned above (this includes corn and wheat ethanol, rapeseed diesel and soybean diesel). It was also shown the optimized crop

management, which involves the use of state-of-the-art agricultural technologies combined with an optimized fertilization regime and the use of nitrification inhibitors, can reduce N2O emissions substantially and change the GHG emissions by up to -135 percent points (pp) compared with conventional management.
The bio-physical climate impacts of bio-energy production clearly depend on the location where bio-energy is produced. The IMAGE model was used in conjunction with the Speedy Climate model to explore an bio-energy strategy versus an afforestation strategy in the temperate zone (Schaeffer et al., 2006). As the bio-energy production was assumed to be a crop-based the impacts on albedo were found to be small. At the same time, the study also showed that given the large impacts for the alternative afforestation scenario, it is important to consider other climate impacts than just CO2 changes when discussing climate-change mitigation options that involve land-use changes. In fact, this may even involve impacts on atmospheric chemistry as it was found that land-use change could have significant impacts on atmospheric chemistry as well (Ganzeveld et al., 2010).

Different mitigation strategies involving the use of bio-energy
Bio-energy can be used in very different ways to substitute fossil fuels, resulting in different impacts on energy use and therefore greenhouse gas emissions. Main applications for bio-energy include the use of bio-energy as feedstock for electricity and hydrogen production, potentially in combination with carbon-capture-and-storage, the use of bio-energy to replace oil in transport, the use of bio-energy as energy source in industry and buildings and finally the use of bio-energy as feedstock to produce materials. In IMAGE, without climate policy bio-energy tends to typically be used most in transport in the absence of climate policy. This is a result of increasing prices of oil-based fuels due to depletion. However, if stringent climate policy is introduced – bio-energy is mostly used in the power sector especially in combination with carbon-capture-and-storage (Van Vuuren et al., 2007). Although other integrated assessment models often show rather distinct bio-energy application strategies, on average this is a pattern seen in several models (Rose et al., 2012; Rose et al., 2014; Van Vuuren et al., 2010).

Daioglou et al (2014b) recently explored how the use of bio-energy in different sectors in IMAGE would impact bio-energy use on greenhouse gas emissions. Interestingly, they found that this not only depends on the fuels that are replaced in the different sectors, but also whether this leads to the use of the replaced fuels in other sectors (as a result of reduced depletion of fossil fuels). For instance, replacing oil in transport was found to lead to relatively little leakage (as oil does not have a strong competitive position in most other sectors) while replacing natural gas in other end-use sectors would lead to increased use of natural gas in other sectors. Overall, bio-energy was found to have strongest impact on emission in the power sector (given the option of combining it with CCS). Daioglou et al (2014b) also pointed out that the emission reduction potential of bioenergy may be limited due to high demand of bioenergy in uses which have low emission reduction potential when compared to power with CCS.
The use of bio-energy with CCS as part of mitigation strategies was studied in much more detail in several other publications (Azar et al., 2010; van Vuuren et al., 2013).

This technology is found to be very important in low greenhouse gas concentration strategies given its ability to create negative emissions. In fact, both stylized calculations and IMAGE model runs show that without the possibility of negative emissions, pathways meeting the 2 °C target with high probability need almost immediate emission reductions or simply become infeasible. At the same time, the potential for negative emissions was found to be uncertain given the uncertainties related to both bio-energy supply and storage resources. Based on the bio-energy potentials (see above), it was estimated that BECCS is probably limited to around 0 to 10 GtCO2/year in 2050 and 0 to 20 GtCO2/year in 2100.

Bio-energy can also be used to produce chemicals and plastics. This can be quite an important sector for bio-energy as it is expected that the global gross demand for feedstocks more than triples from 30 EJ in 2010 to over 100 EJ in 2100. It was found in IMAGE calculations, that if biomass is used, it can reduce carbon emissions by up to 20% in 2100 compared to the reference development (Daioglou et al., 2014a), although the sector is rather small compared to other sectors in terms of using bio-energy.

3.2.2 Afforestation, reforestation and avoiding deforestation

Human policies to increase forest cover are another important form of land-use based mitigation action. Using the IMAGE model, Strengers et al.(2006) and van Minnen et al. (2006), estimated the use of possible contribution of reforestation and afforestation strategies worldwide. It was found that theoretically, the contribution of such strategies could be very large but this would significantly depend on assumptions of agricultural land use. Under a business-as-usual scenario, the theoretical potential for mitigation actions was estimated to be 2.7 GtC yr^{-1} in 2100 assuming harvest when the mean annual increment decreases and assuming no environmental, economic or political barriers. However, taking such barriers into consideration would reduce the potential by at least 60%. It was also found that taking into account land and establishment costs, the largest part of the potential up can be supplied below 200 $/tC making this option relatively attractive.

Avoiding deforestation might also have an important contribution to mitigation. At the moment, “REDD” (Reducing Emissions from Deforestation and Forest Degradation in Developing Countries) has already been suggested as an attractive instrument to avoid greenhouse gas emissions at relatively low costs. However, cost estimates differ greatly in the literature, as they depend on the approach chosen, for example: giving an economic stimulus to entire countries, taking landowners as actors in a REDD framework, or starting from protecting carbon-rich areas. The IMAGE model was used to estimate the potential for REDD and the associated costs specifically focusing on the protection of carbon-rich areas (thus avoiding the use of these areas as agricultural land) (Overmars et al., 2014). The opportunity costs of reducing deforestation within the framework of REDD were assessed using an integrated economic and land-use modelling approach comprising the global agro-economic model in the IMAGE framework (LEITAP) and the biophysical parts of the IMAGE model. The model runs were done by increasing the protected areas in consecutive runs starting off with the

most carbon rich lands. The associated impacts on the growth of GDP were calculated with LEITAP, while the net reduction in carbon dioxide emissions were calculated in the IMAGE land cover model. The results showed that globally a maximum of around 2.5. Gt carbon dioxide emissions could be avoided, annually. However, regional differences in opportunity costs are large and were found to range from about 0 to 3.2 USD per tonne CO_2 in Africa, 2 to 9 USD in South America and Central America, and 20 to 60 USD in Southeast Asia. These results are comparable to other studies that have calculated these costs, in terms of both opportunity costs and the regional distribution of emissions reduction

Finally, it should be noted that strategies changing forest cover of the earth are likely to have consequences for biophysical climate factors. We explored this using the IMAGE model in conjunction with the climate model Speedy specifically for afforestation strategies in the temperate zone (Schaeffer et al., 2006). Here is was found that the albedo-induced impact of the forest policy was as large as the mitigation by CO2 changes and thus totally offsetting a positive impact. Further, an atmospheric circulation change in the carbon-plantation scenario weakens the supply of moisture from the oceans to North Africa and central Eurasia, leading to changes in precipitation patterns. It is, however, not expected that afforestation strategies outside the temperate zone with have similar severe impacts.

3.2.3 Reducing greenhouse gas emissions indirectly by changing food demand and production

The agriculture sector forms a major source of greenhouse gas emissions, both as a result of deforestation and land-use related non-CO_2 emissions. Changes in food demand and production can therefore contribute to climate change mitigation. Important factors here include changing dietary patterns and reducing food waste, changes in livestock production, yield changes and trade policies.

The impact of diet change mostly concerns meat consumption. Changing dietary patterns might be attractive for a number of reasons including biodiversity protection (meat production is responsible for the lion's share of global land use) and improving human health (consumption levels in rich countries are above the levels recommended for health reasons). The IMAGE model was used to explore the potential impact of dietary changes on achieving ambitious climate stabilization levels (Stehfest et al., 2009), assuming that no economic feedbacks would occur. It was found that a global food transition to less meat could have a dramatic effect on land use. Up to 2,700 Mha of pasture and 100 Mha of cropland could be abandoned, resulting in a large carbon uptake from regrowing vegetation. Additionally, methane and nitrous oxide emission would be reduced substantially. A global transition to a low meat-diet (assuming no economic feedbacks) would reduce the mitigation costs to achieve a 450 ppm CO2-eq. stabilisation target by about 50% in 2050 compared to the reference case. In a subsequent study (Stehfest et al., 2013), the impact of possible economic feedbacks was explored using two different economic models (IMPACT and LEITAP), coupled to IMAGE, to examine different options to reduce the environmental impact of agriculture:

dietary changes (less meat and dairy), increased production efficiency, and reduced food waste. In both models, all options resulted in a reduction in agricultural land use and greenhouse gas emissions, as well as in agricultural commodity prices. However, both models also showed that the impacts could be lower than the theoretical environmental gains would actually be achieved, due to price feedbacks leading to increased consumption and less intensive production. Importantly, also large differences were found between the IMPACT and LEITAP model calculations, showing the importance of model uncertainty – specifically regarding international trade, the assumptions on technological change, and the treatment of agricultural expansion.

Changes in trade policies themselves could also impact greenhouse gas emissions. One may argue that removing trade barriers could reduce greenhouse gas emissions by allowing food to be produced at high yield (potentially low costs) areas. However, it should be noted that also labour costs play an important role – and low costs regions may therefore have lower yields (potentially as result of lower investment in agricultural management). Moreover, transitions in production patterns could also be associated with emissions. Calculations using the IMAGE model coupled to LEITAP showed that in this system the latter set of dynamics dominate over the former (Verburg et al., 2009). As a result, trade liberalisation leads to an increase in total greenhouse gas emissions by about 6% compared to the reference scenario value in 2015. The increase in CO2 emissions are caused by vegetation clearance due to a rapid expansion of agricultural area; mainly in South America and Southeast Asia. This pattern is observed up to 2050.

3.2.4 Reducing non-CO2 emissions from agriculture/land-use

The agriculture sector is responsible for a large share of the non-CO_2 emissions. The IMAGE model can also be used to determine the optimal strategies in reducing non-CO_2 emissions based on assumptions on the overall objective and the value assigned to non-CO_2 emissions (substitution metric, such as GWPs). The reductions of non-CO2 greenhouse gases in mitigation scenarios are determined on the basis of so-called marginal abatement costs curves. For these curves, estimates on technology change and total abatement potential are crucial. The curves used in IMAGE are based on an literature review regarding the future maximum attainable reduction potentials and costs (Lucas et al., 2007). These MACs have been used in a large number of multi-gas analysis for stabilising greenhouse gas concentrations. These show that including non-CO2 mitigation options (including those associated with agriculture) reduces the overall costs compared to situations where no development is assumed (3-21% lower in 2050 and 4-26% lower in 2100 in our analysis). It should be noted that methane and nitrous oxide emissions from land use-related sources are not easy to abate and therefore the estimated abatement potential in 2100 is restricted to around 60% and 40%, respectively.

3.3 Integrated strategies and overall conclusions

In several IMAGE paper, overall mitigation strategies are described. These papers obviously also address the role of land-use related mitigation option.

Above all, these paper show the crucial role of bio-energy in mitigation strategies. As shown in several IMAGE papers, with the current system targets as low as 2.6 W/m2 can only be reached if the combination of bio-energy and CCS are available. Excluding bio-energy from the mitigation portfolio implies that only targets above 3.0 W/m2 are 'feasible' (Van Vuuren et al., 2007; van Vuuren et al., 2011). Regarding the role of forestry based measures, IMAGE 2.2/2.3 based scenarios showed a limited contribution of afforestation and reforestation measures. In these papers, it was discussed however that such strategies need to be evaluated with alternative land-use strategies (such as bio-energy). As more recent IMAGE work does not include forestry-related mitigation strategies as part of the portfolio, in general mitigation scenarios show a small increase in land-use change related emissions compared to the baseline scenario (as a result of bio-energy use) but, across the century, a rapid decline compared today's emissions (as a result a peak in global population and resulting implications for agriculture). For non-CO_2, the IMAGE results show that there is a substantial contribution – but there is an interesting time dynamic. Early in the scenario, reducing non-CO_2 emissions plays a rather important role compared to other options as several non-CO_2 emissions categories have relatively low abatement costs. However, over time the limited reduction potential of mostly the land-use related non-CO_2 sources imply that non-CO_2 emissions are reduced less than CO_2 emissions.

4 Analysis of land-use related mitigation options using MagPie

4.1 Brief introduction of the model system, main characteristics, main LUC options included[2]

4.1.1 Land-use model MAgPIE

The Model of Agricultural Production and its Impacts on the Environment (MAgPIE) is a spatially explicit, global land-use optimization model (Lotze-Campen *et al* 2008, Popp *et al* 2010). The objective function of MAgPIE is the fulfilment of food crop, livestock and material demand at least costs under consideration of biophysical constraints, socio-economic conditions and climate polices. Demand is income elastic, but price-induced changes in demand are not reflected. Major cost types in MAgPIE are factor requirement costs (capital, labor, and fertilizer), land conversion costs, transportation costs to the closest market, investment cost for technological change (TC), and costs for GHG emission rights. The cost minimization problem is solved in 10-year time steps until 2095 in recursive dynamic mode by varying the spatial production patterns, by expansion and contraction of agricultural land, and by investing in yield-increasing technological change (Dietrich *et al* 2012, Lotze-Campen *et al* 2010). Technological change increases the yields of all crops within a region by the same factor. The costs for enhancing the yields in a specific region increase with the level of agricultural development of the particular region; i.e., the higher the actual yields in a region the higher the costs for one additional unit of yield increase (Dietrich *et al* 2014). The model distinguishes ten economic world regions with global coverage: Sub-Saharan Africa (AFR), Centrally Planned Asia including China (CPA), Europe including Turkey (EUR), states of the former Soviet Union (FSU), Latin America (LAM), Middle East/North Africa (MEA), North America (NAM), Pacific OECD including Japan, Australia, New Zealand (PAO), Pacific (or Southeast) Asia (PAS), and South Asia including India (SAS). Socio-economic constraints like trade liberalization and forest protection as well as climate polices are defined at the world region level. In contrast, biophysical constraints such as crop yields, carbon density and water availability, derived from the global crop growth, vegetation and hydrology model LPJmL (Bondeau *et al* 2007, Müller and Robertson 2014), as well as land availability (Krause *et al* 2013), are introduced at the grid cell level (0.5 degree longitude/latitude;

[2] The description of the MAgPIE model is based on text taken from Klein D, Humpenöder F, Bauer N, Dietrich J P, Popp A, Bodirsky B L, Bonsch M and Lotze-Campen H 2014 The global economic long-term potential of modern biomass in a climate-constrained world *Environ. Res. Lett.* 9 074017 and Humpenöder F, Popp A, Dietrich J P, Klein D, Lotze-Campen H, Bonsch M, Bodirsky B L, Weindl I, Stevanovic M and Müller C 2014 Investigating afforestation and bioenergy CCS as climate change mitigation strategies *Environ. Res. Lett.* 9 064029

59199 grid cells). Due to computational constraints, all model inputs in 0.5 degree resolution are aggregated to 500 simulation units for the optimization process based on a k-means clustering algorithm (Dietrich *et al* 2013).

Land types in MAgPIE consist of cropland, pasture, forest and other land (e.g. non-forest natural vegetation, abandoned agricultural land, deserts, urban land). In the initial year 1995, the global land area consists of 1438 Mha cropland, 2913 Mha pasture, 4235 Mha forest and 4321 Mha other land (12907 Mha in total). In general, all land types are free for conversion in the optimization, with the exception of urban land (1% of total land area) and 12.5% of the initial global forest area (mainly undisturbed natural forest) that lies within currently protected areas. In addition, 30% of the initial global forest area is reserved for wood production (FAO 2010). Altogether, about 86% of the world's land surface is freely available in the optimization of the initial time-step.
MAgPIE calculates emissions of the Kyoto GHGs carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) (Bodirsky *et al* 2012, Popp *et al* 2010, 2012a). CO_2 emissions from land-use change reflect the difference in carbon stocks between simulation time steps. For instance, if forest is converted to cropland for agricultural expansion, carbon stocks decrease, which results in CO_2 emissions. In case agricultural land is abandoned, ecological succession leads to regrowth of natural vegetation carbon stocks along sigmoid growth curves, which results in CO_2 uptake from the atmosphere (Humpenöder *et al* 2014). N_2O land-use emissions mainly depend on animal waste management and the efficiency of organic and inorganic fertilizer use for crop production. CH_4 land-use emissions originate from livestock management (enteric fermentation, animal waste) and paddy rice production.

4.1.2 Land-based mitigation options in MAgPIE

Pricing of GHG emissions
Pricing of GHG emissions aims to reduce GHG emissions from the land system. To this purpose, GHG emissions (tCO_{2eq}) are multiplied with a price on GHG emissions ($/$tCO_{2eq}$). The resulting cost term is added to the cost minimizing objective function of MAgPIE. Therefore, pricing GHG emissions in MAgPIE provides economic incentives to reduce GHG emissions from land-use (e.g. improved fertilizer application and better livestock management) and land-use change (e.g. less deforestation).

4.1.3 Bioenergy

Bioenergy is expected to play an important role in the future energy mix, in particular in climate change mitigation scenarios. First of all, bioenergy can substitute fossil fuels. Second, the combined use of bioenergy with Carbon Capture and Storage (CCS) technology can remove CO_2 from the atmosphere. The use of bioenergy in the energy system as low-carbon energy carrier and/or Carbon Dioxide Removal (CDR) technology is strongly interlinked with the land system since bioenergy crop production requires fertile land.

MAgPIE takes global demand for bioenergy as input. Bioenergy can be produced from dedicated herbaceous and woody bioenergy crops (2nd generation bioenergy). The model endogenously allocates bioenergy production, based on cost-effectiveness, to the ten economic world regions. Hereby, bioenergy production competes for land with all other land-use activities, such as food production.

Afforestation
Juvenile trees absorb more CO_2 from the atmosphere than they respire. Therefore, afforestation, i.e. planting new trees, is another land-based option for CDR.
In MAgPIE, afforestation is incentivized by the extension of CO_2 emissions pricing towards negative emissions. To this purpose, negative CO_2 emissions resulting from afforestation activities are multiplied with a price on CO_2 emissions. The resulting negative term lowers the costs in the objective function of MAgPIE, which is cost minimization. The model endogenously decides about location and timing of afforestation under consideration of competing land-uses, such as food and bioenergy production.

4.2 Description of findings of MagPIE studies

4.2.1 Bio-energy (potential, effectiveness as mitigation option)[3]

Introduction
Energy from biomass as a substitute for fossil energy is not only supposed to improve energy security. Several studies investigating the transition of the energy system under climate change stabilization targets consider bioenergy a large-scale and cost-effective mitigation option (Riahi *et al* 2007, Calvin *et al* 2009, Luckow *et al* 2010, van Vuuren *et al* 2010a, Rose *et al* 2013). In particular bioenergy with CCS (BECCS) may significantly reduce stabilization costs since its negative emissions compensate emissions from other sources and across time (van Vuuren *et al* 2010b, 2013a, Kriegler *et al* 2013a, Azar *et al* 2010b, 2013, Klein *et al* 2013). The amount of realizable negative emissions directly depends on the amount of biomass available. Thus, the biomass potential and its cost become crucial factors that affect overall mitigation costs (Rose *et al* 2013, Klein *et al* 2013). While the scientific consensus on the importance of bioenergy for climate change mitigation is strong (Rose *et al* 2013), high uncertainties remain regarding the biomass potential (Chum *et al* 2011). This is mainly due to uncertainties about future developments of agricultural yields, demand for food and feed, and availability of land and water for agricultural production. In particular, there are only few global studies attributing costs or prices to the estimated bioenergy

[3] Klein D, Humpenöder F, Bauer N, Dietrich J P, Popp A, Bodirsky B L, Bonsch M and Lotze-Campen H 2014 The global economic long-term potential of modern biomass in a climate-constrained world *Environ. Res. Lett.* **9** 074017

potential (Hoogwijk 2004, Hoogwijk *et al* 2009, van Vuuren *et al* 2009). The purpose of this study is to provide supply price curves for lignocellulosic biomass that can serve as a basis for the economic assessment of bioenergy in climate change mitigation scenarios.

A major concern about the sustainability of large-scale bioenergy production is its potential to induce deforestation. First, deforestation causes carbon emissions and counteracts the objective of emission mitigation if no effective forest protection regime is in place (Wise *et al* 2009a, Popp *et al* 2011a, 2012b, Calvin *et al* 2013). Second, deforestation entails substantial biodiversity loss as forests are the most biologically diverse terrestrial ecosystems (Turner 1996, Hassan *et al* 2005). Both adverse effects could be considerably mitigated if GHG emissions from the land-use sector (including non-CO_2 emissions such as N_2O from fertilizer use) would be equally priced with energy emissions. In case of a GHG price regime comprising energy *and* land-use/land-use change emissions, the strong demand for bioenergy and pricing of terrestrial emissions are likely to coincide, and the GHG pricing is likely to affect the availability and productivity of land for bioenergy, and thus bioenergy prices for a given level of demand. However, to our knowledge the available literature on bioenergy potentials does not consider GHG pricing in the land-use sector (Hoogwijk 2004, Hoogwijk *et al* 2005, 2009, Smeets *et al* 2007, Erb *et al* 2009, van Vuuren *et al* 2009, Dornburg *et al* 2010, Haberl *et al* 2010, Beringer *et al* 2011). Therefore, this study investigates the impact of GHG prices on the potential and the supply prices of bioenergy.

Methods

We simulate the outcome of climate policy by applying GHG taxes and bioenergy demand scenarios as exogenous parameters to the MAgPIE model. While bioenergy demand is varied in order to derive the bioenergy supply price curves, the GHG tax is varied for the sensitivity analyses of the supply curves.

The bioenergy supply price curves are derived by measuring the price response of the MAgPIE model to 73 different global bioenergy demand scenarios. Each bioenergy demand scenario yields a time path of regional allocation of bioenergy production and global bioenergy prices. For each region and time step the supply curve was fitted to the resulting 73 combinations of bioenergy production and bioenergy prices.

The global uniform GHG tax on CO_2, N_2O and CH_4 emission in the tax30 scenario starts in 2015 increasing by 5% per year (2020: 30 \$/tCO_2eq, giving the scenario its name, 2055: 165 \$/tCO_2eq, 2095: 1165 \$/tCO_2eq). It is close to CO_2 prices required to reach low stabilization targets at 450 ppm CO_2eq (Rogelj *et al* 2013a, IEA 2012, Luderer *et al* 2013). The CO_2 tax applies only on land-use change emissions from deforestation, i.e. CO_2 emissions from the conversion of other potentially carbon rich ecosystem are not part of the GHG pricing mechanism. The N_2O and CH_4 taxes are calculated from the CO_2 tax using the GWP100 (IPCC 2013). In the tax0 scenario there is no GHG tax.

Deviating from the general model description, the livestock sector is not modeled explicitly in this study. Therefore, pasture land is fixed at its initial value and not available for land conversion during the optimization. Considering this, about 7900 Mha

(~ 61 %) of the world's land surface is freely available in the optimization of the initial time-step, of which about 3000 Mha are suitable for cropping.

Results

Figure 4.1 shows the globally aggregated supply curves for 2055 and 2095. The colored bars at the bottom show the underlying regional bioenergy production pattern for the sample scenario (145 EJ in 2055 and 240 EJ in 2095). Without a GHG tax in the land-use sector bioenergy in 2055 can be supplied starting at 5 $/GJ. The sample scenario shows that conditions of bioenergy production differ across regions. Without a GHG tax, the major bioenergy producers are the tropical regions AFR and LAM (Figure 4.1 bottom) which offer access to large areas of forest that can be converted to high productive land for crop and bioenergy production. CPA and NAM contribute most of the remaining part. There are only minor contributions of EUR, FSU, and PAS and almost none of PAO and MEA.

Introducing a global uniform GHG tax substantially increases supply prices for biomass by about 2 $/GJ at low bioenergy demands (below 30 EJ/yr) and 5 $/GJ at medium to high demands (above 120 EJ/yr) in 2055 (Figure 4.1). In 2095 the tax increases bioenergy prices by 10 $/GJ. The price-elevating effect of a GHG tax can be separated into two components: a steepening of the supply curve due to land exclusion and a translation effect due to non-CO_2 co-emissions from bioenergy. The steepening of the supply curve is caused by the component of the GHG tax that affects the carbon emissions from land conversion (CO_2-price) since it effectively stops deforestation and thus reduces the amount of land available for the expansion of bioenergy production. The translation effect is caused by pricing nitrogen emissions that accrue from fertilizer use for bioenergy crop cultivation. The translation effect applies to all regions and is stronger in 2095 than in 2055 since the GHG tax is substantially higher (1165 vs. 165 $/t$CO_{2eq}$). Regions where no forest land is used in the tax0 scenario, such as CPA, PAS, and SAS, are only affected by this N_2O-price effect. The supply curves of regions that deforest in the tax0 scenario *additionally* show a steepening due to CO_2 pricing of forest land (strongest in AFR and LAM). This is reflected in the reallocation of the bioenergy production depicted at the bottom of Figure 4.1: production shifts from AFR and LAM mainly to PAS, CPA and SAS under the GHG tax.

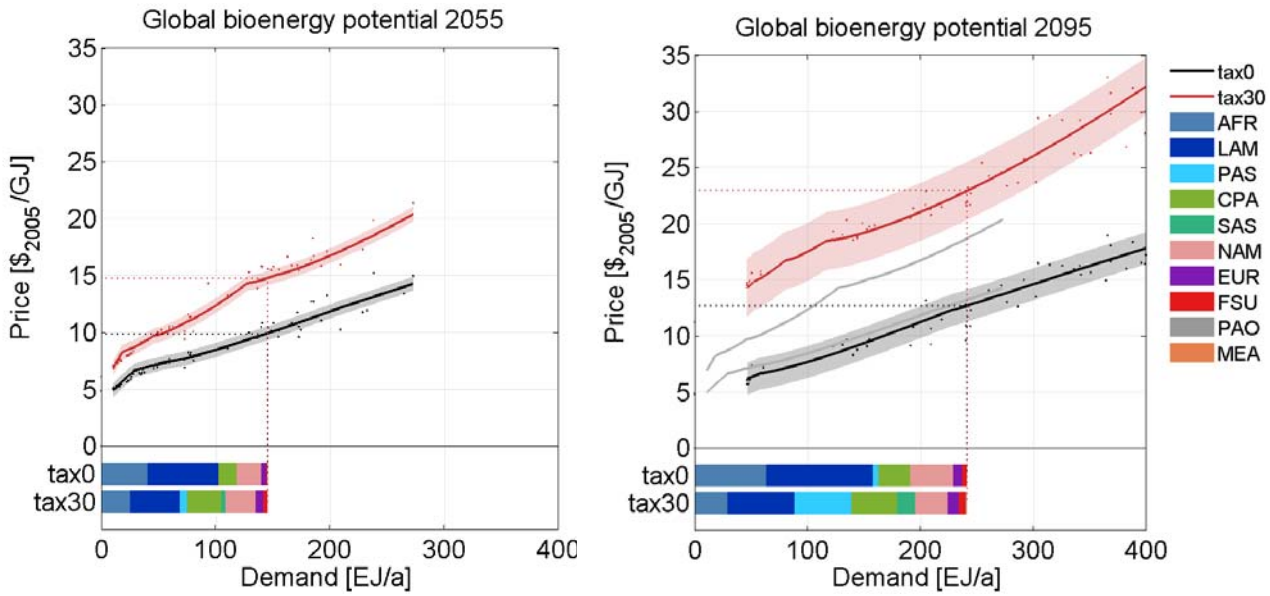

Figure 4.1: Globally aggregated bioenergy supply curves for 2055 (top left) and 2095 (top right) without (black line) and with a global uniform GHG tax (red line). The gray lines in the 2095 figure (right) indicate the position of the 2055 supply cures. The colored bars at the bottom show the underlying regional bioenergy production pattern for the sample scenario (145 EJ in 2055 and 240 EJ in 2095). The shaded areas in the upper part indicate the standard deviation of the aggregated fit. Since the fit in 2095 is based on higher demand values than the 2055 fit, the absolute value of the spread is larger in 2095, as is the standard deviation.

Figure 4.2 shows the global land cover in 2095 and the initial value in 2005 for the four land types that are subject to the optimization in MAgPIE (top) and their changes from 2005 to 2095 (bottom). Bioenergy production requires substantial amounts of land, almost 500 million ha (Mha) for 240 EJ in 2095. With and without tax this is predominantly realized by crop land reduction (intensification) and usage of other land. Without a GHG tax, bioenergy causes only little additional deforestation (-55 Mha, in LAM mainly), since large amounts of accessible forest are already cleared for food and feed production (-250 Mha), (tax0 Bio vs. tax0 NoBio). Bioenergy deployment without GHG tax reduces cropland globally by 300 Mha (-17 %) in 2095, mainly in AFR, LAM, CPA, and NAM. Under the GHG tax, bioenergy and food production cannot access high productive forest land in AFR and LAM since it is effectively protected by the tax. Therefore, bioenergy plantations are partly pushed out of regions that formerly had access to forest (300 Mha in AFR and LAM). In parts this is compensated by further expansion into other land (-100 Mha), since other land is not part of the assumed GHG emissions pricing mechanism.

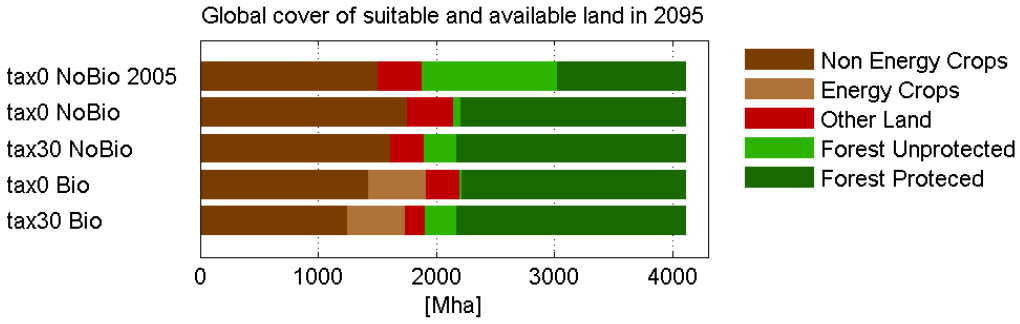

Figure 4.2 Global cover of land suitable and available (except protected forest) for agricultural production in 2095 with initial value of 2005 (top). Global changes in land cover between 2005 and 2095 (bottom).

Figure 4.3 shows the carbon emissions from the land-use sector cumulated from 2005 to 2095 separated into emissions from food and energy crop production. Without the GHG tax food production accounts for roughly 234 $GtCO_2$ (80 %) of total emissions mainly caused by deforestation in AFR (120 $GtCO_2$) and LAM (70 $GtCO_2$). Since the GHG tax almost stops deforestation it substantially reduces carbon emissions from food crop production by 56 % (to 102 $GtCO_2$). Remaining carbon emissions are caused by conversion of other land. The production of bioenergy causes additional emissions. If forest is not protected by the GHG tax, bioenergy emissions account for 63 $GtCO_2$, mainly due to deforestation in LAM (40 $GtCO_2$). Under the GHG tax there is no deforestation for bioenergy, but substantial expansion into other land, predominantly in PAS (73 $GtCO_2$). This leakage effect increases bioenergy emissions by 54 % to 97 $GtCO_2$ cumulated from 2005 to 2095.

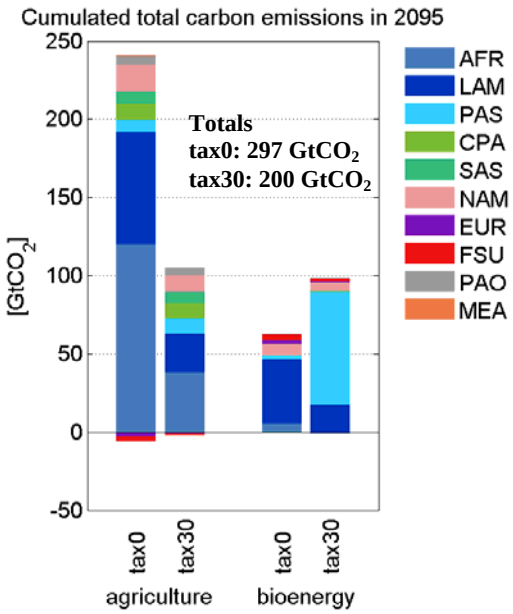

Figure 4.3: CO_2 emissions from land-use change due to bioenergy production and other agricultural activities cumulated from 2005 to 2095.

Conclusion

Climate policy not only increases the demand for bioenergy as several studies show (Rose *et al* 2013, Calvin *et al* 2009, van Vuuren *et al* 2010a), it could also substantially increase supply prices of biomass raw material as the present study shows (+5$/GJ in 2055, +10 $/GJ in 2095). This is mainly due to the fact that large amounts of high-productive forest land are *de facto* excluded by the GHG tax, since expanding into forests would entail substantial carbon emissions and related emission costs. Imposing the GHG tax thus prevents deforestation, lowers carbon emissions, reduces land available for bioenergy production and increases the opportunity costs of land that is in competition with food production. N_2O emissions from fertilizer use further increase bioenergy prices. The GHG tax also reduces the emissions in the case of no bioenergy demand, because the agricultural demand alone is a strong driver for cropland expansion. The bioenergy prices presented in this study emerge under full land-use competition with other crops and are therefore higher than pure production costs on abandoned land found by Hoogwijk *et al* (2009) and Vuuren *et al* (2009).

4.2.2 Reforestation/afforestation (potential, effectiveness as mitigation option, possible side-effects)[4]

Introduction

Recent modeling exercises indicate that the achievement of ambitious climate targets, such as the 2°C target, relies on the availability of CDR options (Edenhofer *et al* 2014, Kriegler *et al* 2014). Two land-based CDR option are currently high on the scientific agenda: bioenergy with CCS and afforestation (Tavoni and Socolow 2013). Both options make use of the accumulation of carbon in growing biomass through photosynthesis (carbon sequestration). Bioenergy with CCS removes carbon from the atmosphere by capturing the carbon released during the combustion of biomass and storing the captured carbon in geological reservoirs underground (biological carbon sequestration and geological storage). Afforestation utilizes the carbon storage capacity of natural vegetation to store the carbon that has been absorbed during the growth of trees (biological carbon sequestration and storage). Therefore, a unit of land can be used several times for CDR though bioenergy with CCS, but just once for CDR through afforestation. This study explores the CDR potential of bioenergy with CCS and afforestation, and the associated land requirement throughout the 21st century with the MAgPIE model.

[4] The findings presented in this section are published as: Humpenöder F, Popp A, Dietrich J P, Klein D, Lotze-Campen H, Bonsch M, Bodirsky B L, Weindl I, Stevanovic M and Müller C 2014 Investigating afforestation and bioenergy CCS as climate change mitigation strategies *Environ. Res. Lett.* 9 064029

In the literature, studies focus on the standalone mitigation potential of bioenergy CCS (Azar *et al* 2010a, Popp *et al* 2011b, Klein *et al* 2014, Kriegler *et al* 2013b, van Vuuren *et al* 2013b) and afforestation (Strengers *et al* 2008, Reilly *et al* 2012) or investigate both at the same time (Wise *et al* 2009b, Calvin *et al* 2014, Edmonds *et al* 2013). However, the standalone and combined effects of bioenergy CCS and afforestation on land-use and carbon dynamics have not been analysed so far with a common methodological approach. Looking at both, the standalone and combined mitigation potential, provides insight into potential trade-offs like competition for land or path dependencies, which are important for the evaluation of afforestation and bioenergy CCS as mitigation strategies.

Methods

In this study, afforestation and bioenergy with CCS are both incentivized by a tax on GHG emissions that is extended towards negative CO_2 emissions.

We assume a GHG tax (Tax30) on Kyoto gases (CO_2, N_2O, CH_4) that increases non-linearly at a rate of 5% yr^{-1} (Kriegler *et al* 2013b). The GHG tax has a level of 30 $\$/tCO_{2eq}$ in 2020 and starts in 2015. The resulting GHG tax with prices of 102 $\$/tCO_{2eq}$ in 2045 and 1165 $\$/tCO_{2eq}$ in 2095 is close to GHG price trajectories required to limit global average temperature increase to 2°C above pre-industrial levels with a probability of 50% (Rogelj *et al* 2013b). The N_2O and CH_4 taxes are calculated from the CO_2 tax using the GWP100 (IPCC 2013).Afforestation in MAgPIE is implemented as managed regrowth of natural vegetation. The regrowth of natural vegetation follows sigmoid (S-shaped) growth curves, which reflects the limited carbon storage capacity of natural vegetation. Based on a planning horizon of 30 years, the model calculates potential annual carbon sequestration due to afforestation. These negative CO_2 emissions are multiplied with the CO_2 tax. The resulting negative term lowers the costs in cost-minimizing objective function of MAgPIE. Therefore, the CO_2 tax provides an economic incentive for afforestation in MAgPIE. In addition, costs for afforestation activities, such as planting or monitoring are considered.

Demand for bioenergy in this study does not rely on exogenous trajectories, but is derived endogenously as a response to the GHG tax. The mechanism is similar to afforestation. First, the model calculates annual carbon sequestration due to use of bioenergy with CCS. Subsequently, these negative CO_2 emissions are multiplied with the CO_2 tax and enter the objective function of the model as negative term. In addition, costs for bioenergy production are considered. The geological carbon storage capacity is constrained at the regional level, which adds up to 3960 $GtCO_2$ at the global level (Bradshaw *et al* 2007). We assume a lifetime of the CCS technology of 200 years (Szulczewski *et al* 2012) and therefore limit the annual geological injection of carbon to 0.5% yr^{-1} in terms of the geological carbon storage capacity, which results in an annual realizable geological injection rate of about 20 $GtCO_2$ yr^{-1} globally. The value of energy produced due to bioenergy CCS is deliberately disregarded in this study.

We investigate four scenarios, which cover two dimensions: GHG tax and availability of carbon removal options (Table 4.1). In the business as usual scenario (BAU), no tax on GHG emissions is applied, i.e. there is no incentive to avoid GHG emissions. In the

mitigation scenarios, the GHG tax penalizes all positive GHG emissions from the land-use system and rewards negative CO_2 emissions from afforestation in AFF, from bioenergy CCS in BECCS, and from both in AFF+BECCS.

	GHG tax	Carbon removal option(s)
BAU	-	-
AFF	Tax30	Afforestation
BECCS	Tax30	Bioenergy CCS
AFF+BECCS	Tax30	Afforestation and bioenergy CCS

Table 4.1: Scenario definitions; GHG tax: Tax30 has a level of 30 $/tCO_{2eq}$ in 2020, starts in 2015 and increases by 5% yr^{-1}; Carbon removal option(s): available option(s) for generating negative CO_2 emissions rewarded by the GHG tax;

Results

In 1995, global land cover (12907 mio ha) consists of food crop (1425 mio ha), pasture (3073 mio ha), forest (4235 mio ha) and other land (4174 mio ha) (Figure 4.4). In the BAU scenario (no GHG tax), food crop area increases by about 300 mio ha globally until 2095, mainly at the expense of forestland. In the second half of the century, pasture area decreases due to stabilizing livestock demand in combination with average yield increases of about 0.48% yr^{-1}, leading to an increase of abandoned agricultural land. In the mitigation scenarios, the GHG tax on land-use change emissions keeps forestland almost constant over time. Afforestation emerges as cost-efficient mitigation strategy from 2015 (start of GHG tax at 24 $/tCO_{2eq}$) and increases, mainly at the expense of pasture and food crop area, to 2773 mio ha in AFF until 2095. Endogenous yield increases, accompanied by changes in spatial production patterns, compensate for the reduced agricultural area. In AFF, the cost–efficient level of average yield increases in the agricultural sector is 1.21% yr^{-1} throughout the 21st century. Bioenergy CCS comes into play much later than afforestation, as it is cost-efficient first in 2065 (270 $/tCO_{2eq}$). Bioenergy area increases to 508 mio ha until 2095 in BECCS, mainly at the expense of food crop area. Total dedicated bioenergy production, mainly herbaceous crops, stabilizes at 237 EJ yr^{-1} until 2095. In the combined setting, AFF+BECCS, afforestation area (2566 mio ha) is slightly smaller compared to AFF, while bioenergy area (300 mio ha) is almost halved compared to BECCS. Despite the smaller bioenergy area, bioenergy production remains at 237 EJ/yr in 2095 in AFF+BECCS, which is reflected in a higher level of average yield increases in AFF+BECCS (1.37% yr^{-1}) compared BECCS (1% yr^{-1}).

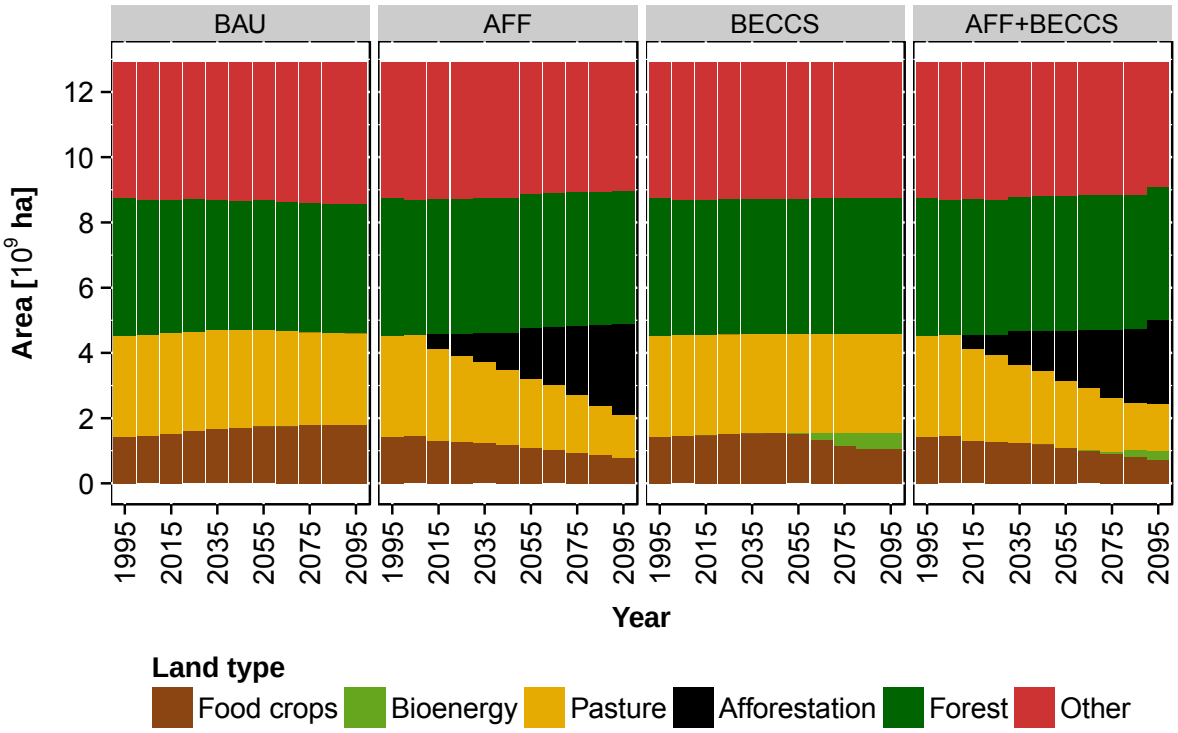

Figure 4.4. Time-series of global land-use pattern (10^9 ha) for BAU, AFF, BECCS and AFF+BECCS and six land types.

In the BAU scenario, CO_2 emissions from the land-use system accumulate to 177 $GtCO_2$ until 2095 (Figure 4.5). The peak in mid-century is mainly caused by deforestation, while the following decline in CO_2 emissions is due to ecological succession on abandoned agricultural land. In the mitigation scenarios, the described land-use dynamics lead to net carbon removal from the atmosphere. More precisely, carbon is detracted from the atmosphere by photosynthesis and is either biologically sequestered via afforestation or geologically sequestered via bioenergy CCS. In AFF, land conversion into afforestation area increases cumulative CO_2 emissions in 2015, followed by continuous carbon removal of about 10 $GtCO_2$ yr^{-1} throughout the 21st century. Until 2095, carbon removal in AFF accumulates to 703 $GtCO_2$. In BECCS, cumulative CO_2 emissions are almost constant until bioenergy CCS becomes cost-efficient as mitigation strategy in 2065 at GHG prices of 270 $/$tCO_{2eq}$. From 2065, carbon removal in BECCS is about 20 $GtCO_2$ yr^{-1}, which cumulates to 591 $GtCO_2$ until 2095. In AFF+BECCS, carbon dynamics are similar to AFF until bioenergy CCS becomes competitive as mitigation option in addition to afforestation in 2055. Carbon removal in AFF+BECCS is about 25 $GtCO_2$ yr^{-1} in from 2065 to 2095, which results in cumulative carbon removal of 1000 $GtCO_2$ until 2095. In 2095 in BECCS and AFF+BECCS, the constraint on the annual geological carbon injection rate is binding (20 $GtCO_2$ yr^{-1}), while cumulative carbon storage capacity (3960 $GtCO_2$) would last for approximately another 150 years. Bioenergy yield gains go along with increased fertilizer use, which drives N_2O emissions. In 2095, cumulative N_2O emission in

BECCS and AFF+BECCS are about 30-50 $GtCO_{2eq}$ higher compared to BAU or AFF, although N_2O emissions are penalized by the GHG tax.

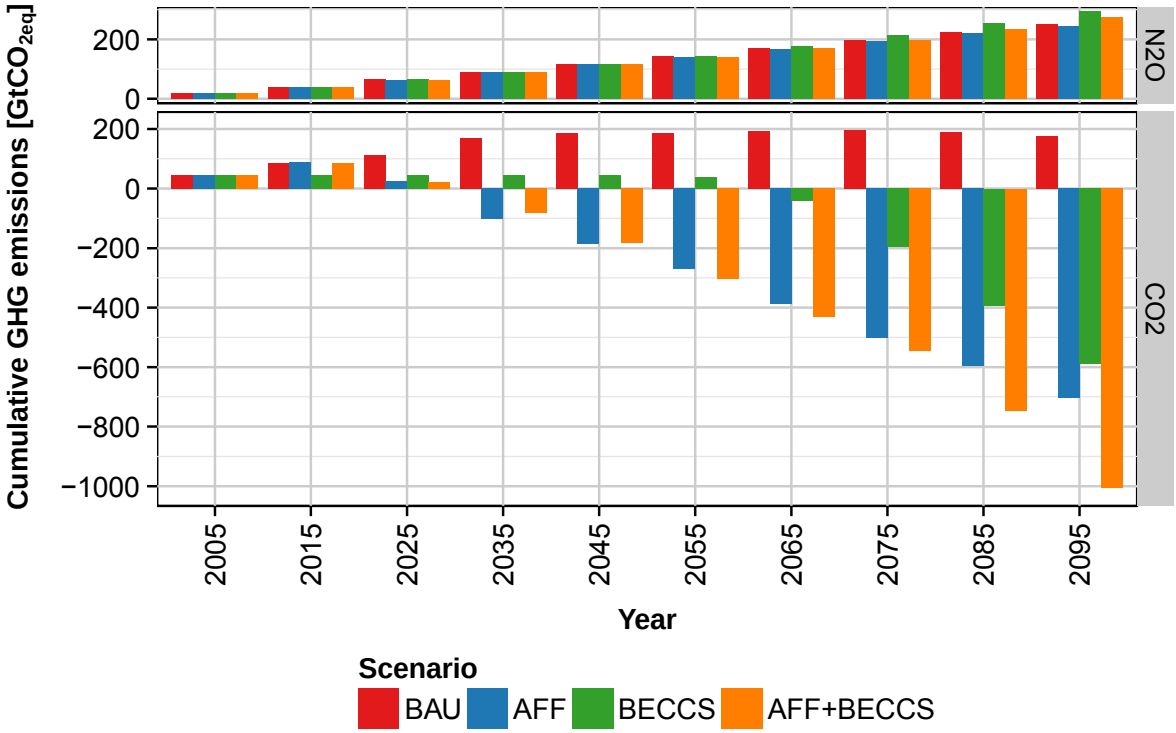

Figure 4.5. Time-series of global cumulative N_2O and CO_2 emissions ($GtCO_{2eq}$) from the land-use system for BAU, AFF, BECCS and AFF+BECCS.

In order to test the stability of our results, we perform sensitivity analyses with crucial exogenous parameters (Table 4.2). Figure 4.6 shows the results in terms of land and carbon dynamics at the global level.

The constraint on the annual geological carbon injection rate is crucial for the scenarios with bioenergy CCS. With 1 $GtCO_2$ yr^{-1} and 20 $GtCO_2$ yr^{-1} the constraint is binding, which indicates that the mitigation potential of bioenergy CCS is mostly limited by the annual geological carbon injection rate. However, with a potential of 396 $GtCO_2$ yr^{-1} the constraint is not binding, which indicates that the potential of bioenergy CCS is also limited by other factors like land availability and costs associated with bioenergy production. Bioenergy production is 530 EJ yr^{-1} in HIGH, compared to 237 EJ yr^{-1} in DEFAULT and 4 EJ yr^{-1} in LOW. In the combined setting, AFF+BECCS, land demand is similar for all parameter settings, while the difference in carbon removal is about 500 $GtCO_2$. This can be explained by considering that in the combined setting in HIGH average annual yield increases are at 1.5% yr^{-1} compared to 1.25% yr^{-1} in LOW.
The carbon removal potential is highly sensitive to different levels of the GHG tax, which is the only driver for land-based mitigation in this study. In general, different GHG tax trajectories influence the point in time when bioenergy CCS and afforestation are cost-efficient, which translates into different mitigation potentials in 2095. While

bioenergy CCS is cost-efficient starting from carbon prices of 165 $/tCO_{2eq}$, afforestation emerges as cost-efficient at prices of 6 $/tCO_{2eq}$. In AFF+BECCS, the range of sensitivity for the mitigation potential is about 900 $GtCO_2$. In general, the degree of sensitivity decreases with higher GHG tax levels, especially for afforestation.
Lower annual discount rates (4%) mostly affect the carbon removal potential of bioenergy CCS as lower discount rates facilitate long term investments in R&D translating into agricultural yield increases. On the contrary, higher discount rates (10%) increase the charges for credit, which is reflected in average annual technological change rates of 1.25% yr^{-1} in HIGH and 1.45% yr^{-1} in LOW. The range of sensitivity for the mitigation potential is about 200 $GtCO_2$ for BECCS and 300 $GtCO_2$ for AFF+BECCS.

In terms of land, the time horizon for investment decisions mostly affects afforestation. With a time horizon of ten years, afforestation area accumulates to about 1500 mio ha, while with a time horizon of 30 or 50 years afforestation area is about 3000 mio ha, which translates into a difference in carbon removal of about 300 $GtCO_2$. The mitigation potential of bioenergy CCS is also affected as a shorter lifetime of investments in CCS infrastructure increases the costs associated with bioenergy CCS.
When bioenergy yields are fixed at their initial level, bioenergy CCS is less attractive as mitigation strategy. In BECCS, bioenergy production is reduced to 74 EJ yr^{-1} in LOW compared to 237 EJ yr^{-1} in DEFAULT, which results in a reduction of the mitigation potential of about 500 $GtCO_2$ until 2095. In the combined setting, AFF+BECCS, bioenergy CCS is no longer competitive with afforestation when bioenergy yield are not allowed to increase in the future, which reduces the mitigation potential in LOW compared to DEFAULT by about 300 $GtCO_2$.

	CCS capacity globally [Gt CO_2]	GHG tax in 2020 (2095) [US$/$tCO_{2eq}$]	Time horizon [years]	Discount rate [% yr^{-1}]	Bioenergy yields [-]
LOW	198	5 (194)	10	4	Static
DEFAULT	3960	30 (1165)	30	7	Variable
HIGH	79200	50 (1942)	50	10	-

Table 4.2: Parameter settings for sensitivity analysis. "DEFAULT" characterizes our default parameter settings used in this study. "LOW"/"HIGH" characterize lower/higher parameter values compared to "DEFAULT".

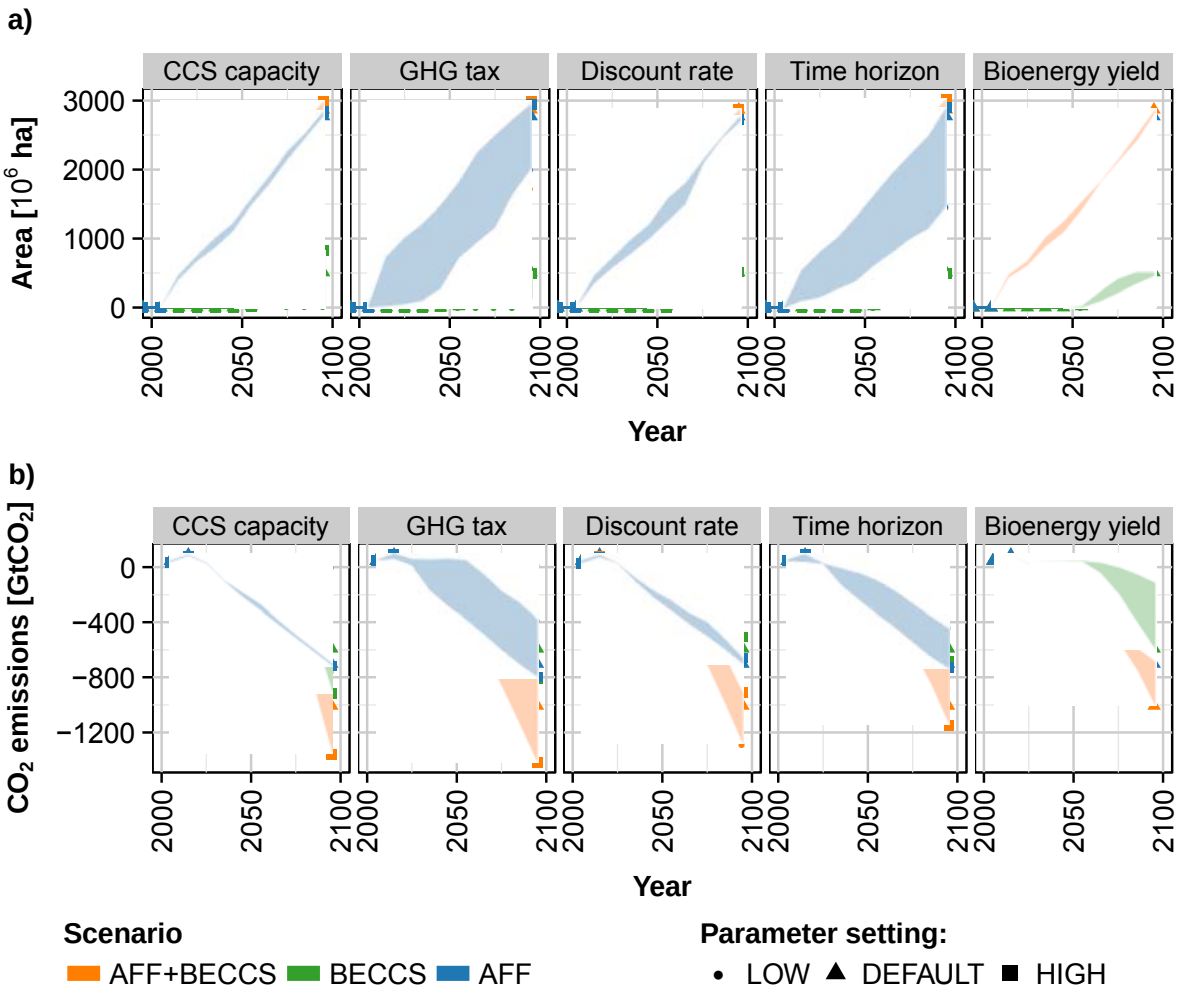

Figure 4.6. Time-series of sensitivity analysis for AFF, BECCS and AFF+BECCS at the global level. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, Discount rate, Time horizon, Bioenergy yield) are described in Table 4.3. The shaded areas span the whole range of sensitivity in the respective scenario in terms of a) area in use for land-based mitigation (10^6 ha) and b) cumulative CO_2 emissions ($GtCO_2$).

Conclusion

As single mitigation strategy, afforestation is cost-efficient at relatively low carbon prices (6 $\$/tCO_{2eq}$), while bioenergy CCS only becomes competitive at higher carbon prices (165 $\$/tCO_{2eq}$). By end-of-century, global area for land-based climate change mitigation is more than five times larger in case of afforestation (~2800 mio ha) compared to bioenergy CSS (~500 mio ha). Despite the dissimilarities in land demand, cumulative carbon removal by end-of-century is similar for afforestation (703 $GtCO_2$) and bioenergy CCS (591 $GtCO_2$). This can be explained by considering that, contrary to afforestation, yield-increasing technological change can enhance carbon removal per unit area of bioenergy CCS – at the expense of additional N_2O emission due to increased fertilizer use, which reduces the mitigation effect of bioenergy CCS throughout the century by about 30-50 $GtCO_{2eq}$. The combination of afforestation and

bioenergy CCS leads to higher cumulative carbon removal (1000 $GtCO_2$ in AFF+BECCS) compared to scenarios with single mitigation strategies. But carbon removal in the combined setting is less than the sum of carbon removal in the standalone settings, indicating that afforestation and bioenergy CCS compete for land. Although bioenergy area is halved compared to the standalone setting, biomass production and thereby carbon removal due to bioenergy CCS is maintained – at the cost of additional yield increases. The sensitivity analysis shows that land-based mitigation is very sensitive to different levels of GHG taxes. Different GHG tax trajectories influence the point in time when bioenergy CCS and afforestation are cost-efficient, which results in different mitigation potentials in 2095. Moreover, the mitigation potential of bioenergy CCS highly depends on the development of future bioenergy yields and the availability of geological carbon storage, while for afforestation projects the length of the crediting period is crucial.

5 Analysis of land-use related mitigation options using GLOBIOM

5.1 Brief introduction of the model system, main characteristics, main LUC options included

Model description

The Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) and the Global Biosphere Management Model (GLOBIOM) were jointly used in the most recent LIMITS study to model the agricultural and forestry (henceforth AF) sector worldwide, under different scenarios about climate change mitigation efforts. The energy-focused MESSAGE model offers a general picture of the AF role against the larger economy-wide mitigation efforts, whereas the AF-specific GLOBIOM provides details concerning AF's involvement in greenhouse gases (GHG) emissions abatement. The integration of the two models was firstly applied in Reisinger *et al.* (2013), which looked into the implications of using fixed- and time-dependent climate change metrics for GHG abatement costs and regional/sectoral participation in global GHG mitigation.

GLOBIOM (Havlík *et al.* 2014) is a recursive dynamic partial equilibrium model that simulates global land use competition between agricultural, forestry, and bioenergy uses with a 5 arc-minute pixel spatial resolution. Data on the quality and availability of six land cover types are incorporated in the model: cropland, grassland, short-rotation tree plantations, managed forest, unmanaged forest, and other natural land. The model determines the optimal land use and resources allocation for and among 30 economic regions, via maximizing the sum of consumer and producer surpluses along the modeling period. Policy-induced changes in the comparative profitability of different land-based economic activities potentially drive the land use change. Details on the land use change options could be found in Havlik *et al.* (2011).

Description of the scenarios used here to present GLOBIOM results

To show the use of land-based mitigation options and their consequences based on the GLOBIOM model, two scenarios were implemented – the reference scenario (REFL) that assumed zero planned mitigation efforts and the 2 degree stabilization (2DEG) scenario that followed the RCP 2.6 assumptions (representative concentration pathway with the target to limit radiative forcing to 2.6 W/m^2 by 2100).

As shown in Table 5.1, both scenarios shared the SSP2-SPA0 (shared socioeconomic pathways 2 – shared policy assumptions 0) assumptions that indicate middle-level

mitigation and adaptation challenges/efforts for the future (O'Neill *et al.*, 2014; Kriegler *et al.*, 2014). Specifically, for SSP2, factors such as population growth, economic growth, energy intensity of the economic system, carbon intensity associated with energy supplies, and etc. that determine the mitigation capacity of a society are at intermediate level, compared with SSP1 (low mitigation challenges) and SSP3 (high mitigation challenges). Also, on challenges to adaptation, factors that influence the exposure to changes in future climates, sensitivity of the hazards, as well as the adaptive capacity of a society, are at the middle level as well. The SPA0 assumption then indicates that the carbon market mechanism fully functions globally, covering both land use and energy sectors. While it is true that global cooperation on carbon pricing and the incorporation of land use as a mitigation component is limited today and may remain so for the foreseeable future, the SPA0 assumption was used here for simplicity of analyses and to gain an initial understanding of how AF land use would perform for abatement, should the GHG mitigation institution is fully enforced.

Scenario Name	SSP Assumption	SPA Assumption	RCP Assumption	Time Horizon
REFL (Reference Baseline)	SSP2	SPA0	None	2000 – 2100 with 10-year time steps
2DEG (2 degree stabilization)	SSP2	SPA0	RCP 2.6 (carbon price would be present)	2000 – 2100 with 10-year time steps

Table 5.1 Scenarios Used in the LIMITS Study

As mentioned earlier, the AF-based abatement required for achieving RCP 2.6 was determined by MESSAGE and GLOBIOM together, as they model the integration of AF and energy sectors. The details on AF mitigation activities were directly provided by GLOBIOM. In the findings below, we focus on the model outcomes in 2050, since by then the 2DEG concentration pathway differs sufficiently enough away from REFL and 2050 is relevant for analyzing mid-term mitigation and land use.

5.1.1 Bio-energy (potential, effectiveness as mitigation option)

Considerable increases in biomass-based energy would occur under the 2DEG scenario, relative to REFL. By 2050, the biomass-based energy amounted up to 113 EJ/year, accounting for 18% of the total world primary energy use. The Global Energy Assessment (GEA, 2012) and Lauri *et al.* (2014) gave similar projections on bioenergy's contribution.

Accompanying the bioenergy increase were the expansions of short-rotation tree plantations and forests worldwide (Figure 5.1). Latin America, Africa, and Asia were

the major places seeing these rises. The shares of cropland and grassland declined accordingly in these regions, resulting in decreases in crop and livestock production levels that present food security risks.

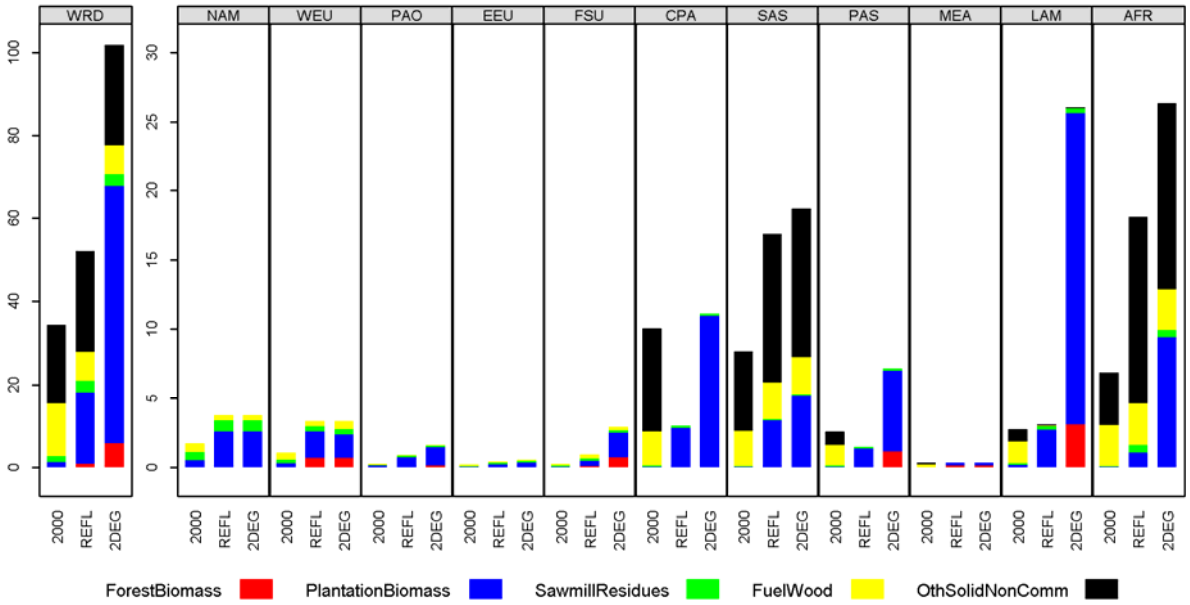

Figure 5.1. Biomass supply for bioenergy [EJ primary]

In earlier studies, Havlik *et al.* (2011) simulated the options of sourcing bioenergy feedstock from agriculture alone, forestry alone, and marginal lands only. The marginal land refers to land that is not attractive for either primary agricultural production or conventional forestry production. The study showed that from a GHG emissions abatement perspective, the marginal land option would perform the best among the three options. For example, it would cause the least amount of deforestation. Nonetheless, it still had implications on food security, as the expansion of dedicated bioenergy feedstock plantation would compete with traditional agricultural land.

More recently, Mosnier *et al.* (2013) examined the impacts of US Renewable Fuels Program (RFS2) on global GHG emissions. Their study found that should the biofuel mandate volumes be set higher than the current levels, a net increase in global GHG emissions would occur, as the imbalance between the reduction in emissions within the US and the policy-induced emissions in the rest of world would then take place. Increases in agricultural productivity were considered to be the premises for future biofuel development.

5.1.2 Avoiding deforestation (potential, effectiveness as mitigation option, possible side-effects)

In addition to the bioenergy contribution to GHG abatement, the LIMITS study showed that the exercising of carbon prices under the 2DEG scenario would create GHG abatement opportunities in conventional AF activities also. Specifically, the carbon price imposed costs on agricultural production in general and transferred revenues to the forestry sector. The asymmetric impacts had thus led to an increasingly more competitive forestry sector. By 2050, an accumulative amount of over 160 million ha of forest land was saved from deforestation. Compared with Havlik *et al.* (2011) which showed limited area of avoided deforestation for milder bioenergy scenarios versus baseline, the 2DEG scenario in the LIMITS study appeared to have altered the relative competitiveness of AF activities aggressively, resulting in a significantly expanded forestry sector.

Earlier, Frank *et al.* (2013) concerned the effectiveness of sustainability criteria embedded in the Renewable Energy Directive (RED) by the European Union (EU). The study found that by implementing RED, lands with high biodiversity would get lost and additional GHG emissions would occur. The study called for a policy design that widens the range of agricultural commodities and member countries to be regulated and/or effectively affected by the bioenergy policy. Bottcher *et al.* (2013) suggested that, to better address the sustainability issue associated with the bioenergy deployment, policies can focus on land use directly – namely, preventing deforestation as well as biodiversity loss.

Mosnier *et al.* (2014) used Congo Basin as a case study to explore the challenges of avoiding deforestation and/or forest degradation in that area. As pointed out in Mosnier *et al.* (2014), the drivers of deforestation were mostly outside of the forestry sector. Increasing agricultural demand, improvements in infrastructure that improves market access and trade, as well as enhancing local agricultural production competitiveness, can all result in deforestation in the Congo Basin region in the future. Delicate balances between food security, local socioeconomic development, and the goal of keeping forests thus present policy challenges for this region.

5.1.3 Reforestation/afforestation (potential, effectiveness as mitigation option, possible side-effects)

In the LIMITS study, the presence of the 2DEG mitigation efforts encouraged faster afforestation and reforestation relative to REFL also. On par with the size of avoided deforestation, by 2050, over 150 million ha of additional afforestation and reforestation occurred relative to REFL, contributing to a greater build-up of carbon sinks.

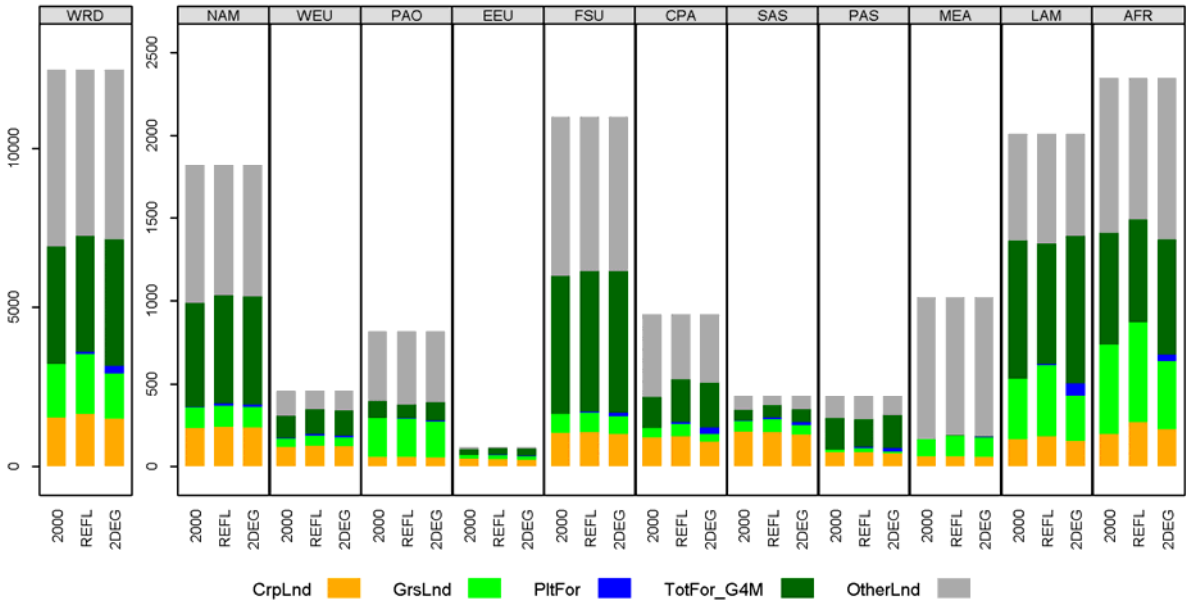

Figure 5.2. Land cover [Mha]

This finding corresponds to Bottcher *et al.* (2013) in the sense that the bioenergy deployment drives up the energy wood price, making forestry production more valuable, and consequently inducing more afforestation and/or reforestation.

5.1.4 Forest management (same area, different management system… potential, effectiveness)

In the LIMITS study, the avoided deforestation and increases in afforestation and reforestation together resulted in a larger forest land base under 2DEG (Figure 5.2). Forestry production thus increased correspondingly, in particular the wood for energy use. Figure 5.3 shows the overall increases in industrial wood production under 2DEG relative to REFL.

Consistent with Lauri *et al.* (2014) and Kraxner *et al.* (2013), the share of managed forest also increased as a response to rising bioenergy demand. Therefore, in general, the LIMITS study depicted a larger and more intensely managed forestry sector under RCP 2.6 assumptions. The improvements in forestry management – to reduce emissions from forest degradation – were also discussed in Mosnier *et al.* (2013) as an out-of-the box strategy for balancing agricultural market development and local GHG emissions abatement.

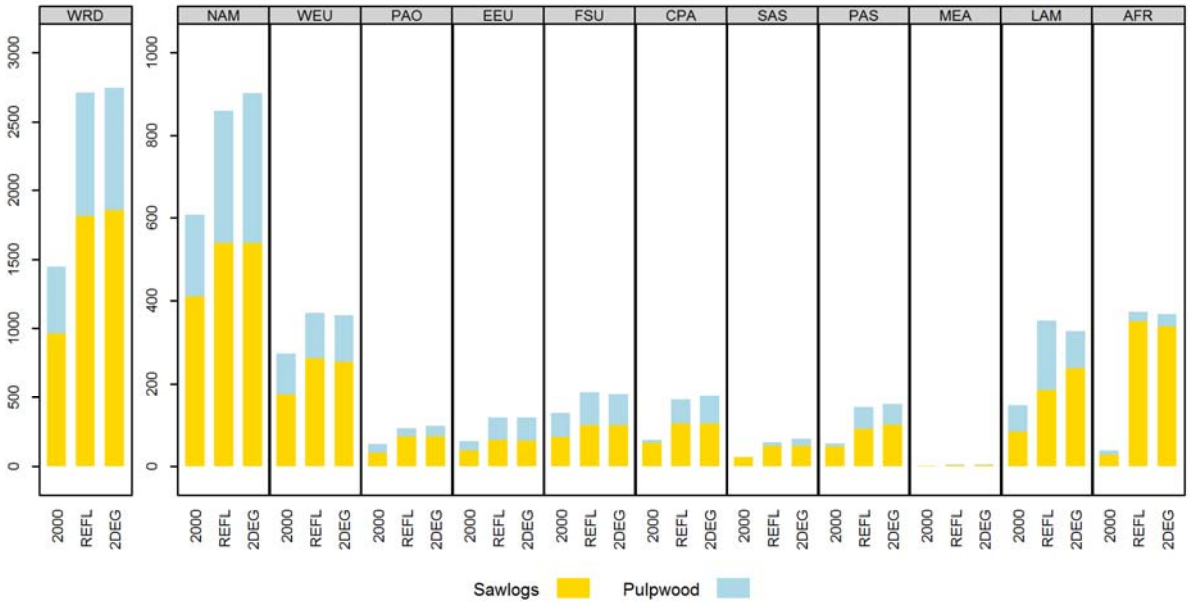

Figure 5.3. Industrial round wood production [Mm3]

5.1.5 Reducing food demand via diet change, reduced waste

Bottcher *et al.* (2013) pointed out that with GDP and population growth alone, the food demand can cause considerable increases in GHG emissions because of the inevitable need to expand agricultural production. Mosnier *et al.* (2013b) also discussed the dilemma of agricultural production and/or trade increases versus GHG mitigation via reducing deforestation.

In the LIMITS study, part of the mitigation comes from cutting down the agricultural production: the presence of 2DEG carbon price negatively influenced the agricultural sector in Africa and Asia (Figures 5.4 and 5.5) and benefitted the forestry sector in Latin America and North America.

The tangible market effects were then the 2DEG-induced remarkable price increases in agricultural products (Figure 5.6). Specifically, sizable price increases for livestock commodities occurred in Asia, Middle East, Latin America, and Africa. Price increases for crop commodities were relatively milder. Nonetheless, in Asia where people traditionally consume more crop and less animal protein, crop commodity prices exhibited substantially larger increases than the rest of world.

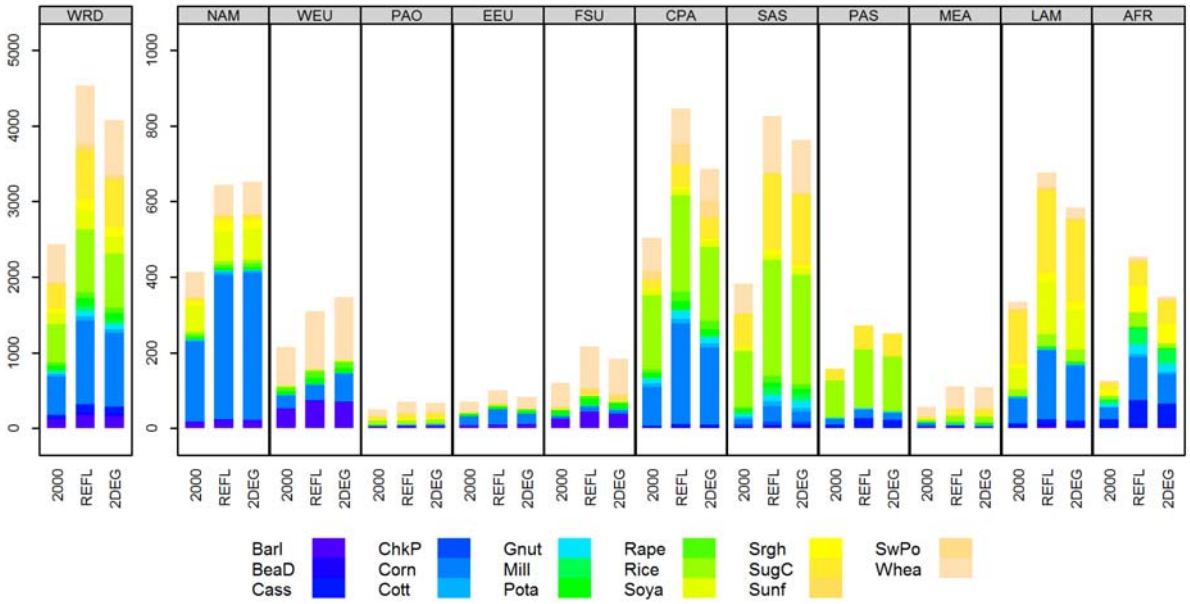

Figure 5.4. Crop production [tDM]

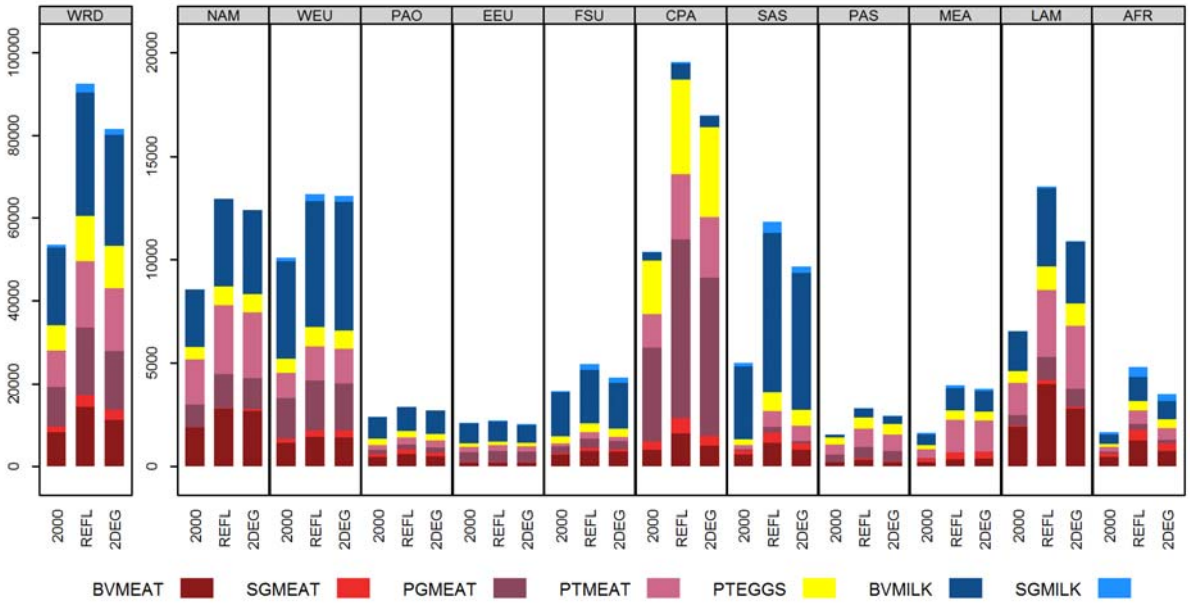

Figure 5.5. Livestock production [t protein]

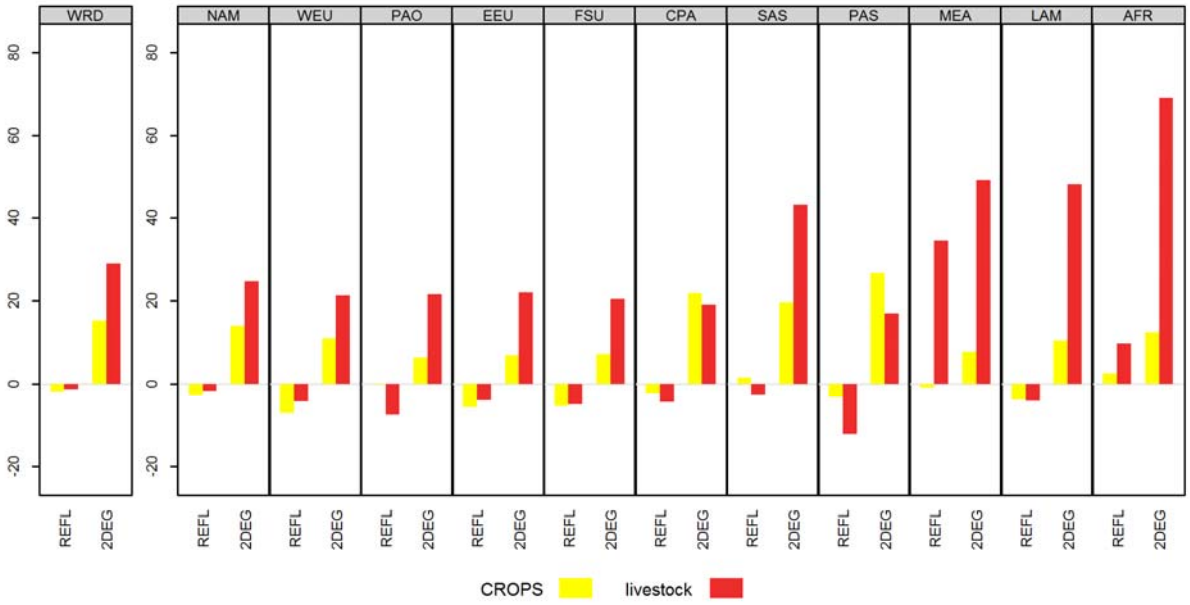

Figure 5.6. Agricultural commodity price index (% change compared to 2000)

The overall declining crop and livestock production levels, plus the less affordable prices, presented threats to food security – physically and economically. Africa turned out to be the region being most adversely hit under the 2DEG scenario.

Results above largely focused on reducing GHG emissions by decreasing the absolute demand for agricultural products, which would then naturally raise concerns about the really varying food security impacts.

Valin *et al.* (2013) suggested that improving agricultural production yields can help mitigate both the GHG emissions and the potential food security issues. Specifically, crop yield increases provide the food security benefits, while improvements in the efficiency of raising livestock help reduce the GHG emissions. Havlik *et al.* (2014) reached similar conclusions in that mitigating GHG emissions via the livestock sector does not have to call for less meat consumption, but by adopting more efficient livestock production systems and practices.

5.1.6 Reducing non-CO2 emissions from agriculture/land-use

LUC can be a critical contributor to GHG abatement, by either reducing GHG emissions or building greater GHG sinks. In earlier works, avoided emissions from preventing natural land conversion (Havlik *et al.* 2014) and preventing grassland conversion (Havlik *et al.* 2013) were found to be a major component for GHG abatement.

In the latest LIMITS study, LUC was also projected to be a significant contributor for 2DEG mitigation. At regional level, Latin America and Africa saw the majority of the LUC CO_2 mitigation taking place, as they host large amounts of forests. Developed regions like North America also experienced significant LUC CO_2 mitigation.

Simulating the agricultural contribution to GHG mitigation using MESSAGE-GLOBIOM, Reisinger *et al.* (2013) found that abatement of agricultural non-CO2 emissions can help reduce the global abatement costs considerably.

In the LIMITS study, the mitigation potential associated with reducing agricultural CH4 and N2O emissions was milder relative to that of LUC. Nonetheless, under the 2DEG scenario, Asia, Latin America, and Africa still exhibited noteworthy reductions in CH4 and N2O emissions, implying a more GHG efficient and/or a downsized agricultural sector. In terms of environmental impacts, the 2DEG scenario resulted in significantly reduced usage of fertilizer, which then contributed to agricultural N2O emissions reduction and soil protection. Developing regions like Asia, Latin America, and Africa incurred these changes.

As discussed in previous studies, agricultural productivity improvements (Mosnier *et al.* 2014; Mosnier *et al.* 2013; Valin *et al.* 2013) could help alleviate the pressure that agriculture places on land and other resources, and reduces the demand for inputs such as fertilizer that causes non-CO2 emissions.

5.1.7 Conclusions

Summarizing the findings in the LIMITS study, the 2DEG scenario caused global land use to shift toward forests and bioenergy plantations, fostering the role of LUC in GHG mitigation. The LUC abatement was however two-fold: one is enhancing GHG sinks via forest land increase, realized through avoiding deforestation or enlarging afforestation and reforestation; the other is expanding short-rotation tree plantations, for bioenergy, reducing GHG emissions via fossil fuels replacement.

The earlier GLOBIOM studies that examined biofuels and land use have followed such a path: initially the feasibility of sourcing 1st and 2nd generation biofuel feedstocks from different land uses were explored. In Havlik *et al.* (2011), trade-offs with conventional agricultural and forestry production were weighed against the “marginal land” option that does not directly compete for land with the AF sector. Short-rotation biomass plantation was then found to be a relatively ideal candidate for large-scale bioenergy deployment, from the GHG abatement perspective.

The sustainability issue associated with indirect land use change was also investigated, because the interconnectedness of the global agricultural and forestry trade can materialize the spillover effects caused by biofuel policies in one region. Frank *et al.* (2013) found that the sustainability criteria proposed in EU’s RED do not necessarily guarantee sustainability, largely due to deforestation and biodiversity loss issues. Bottcher *et al.* (2013) further pointed out that biofuel policies should target on land use directly, if authentic, net GHG mitigation benefits are to be reaped. Mosnier *et al.* (2013) studied the implications of US’ RFS2 program and suggested a delicate balance

between the emissions saving within the US and the policy-induced emissions elsewhere in the world. Mosnier *et al.* (2014) investigated future scenarios concerning the fate of forests in the Congo Basin region. Improvements in forest management was discussed as an outlet to address the dilemma of future agricultural development and potential deforestation.

To summarize the AF strategies in studies reviewed above, short-rotation plantation biomass on marginal land, more intensive use of existing forests or improvements in managing forests, as well as increases in agricultural productivity, can ease the land use change issue to some extent, helping to obtain real GHG mitigation benefits.

Besides the biofuel and the land use change aspects, agricultural non-CO2 emissions were also shown to have noteworthy abatement potential. In the LIMITS study, the shrinking cropland and grassland under the 2DEG scenario reduced the sheer size of crop and livestock production, cutting down N2O emissions originated from fertilizer use and agricultural soils, as well as CH4 emissions from livestock raising and rice production. Valin *et al.* (2013) and Havlik *et al.* (2014) then suggested that the agricultural non-CO2 emissions savings could come from either reducing agricultural demand or improvements and shifts in agricultural production practices. The latter ameliorated the food security concerns associated with GHG mitigation.

Across the regions, Latin America and Africa had the greatest GHG mitigation potential for both LUC and agricultural non-CO2 emissions. Mitigation in Asia then focused more on the agricultural non-CO2 aspect. Developed regions in general showed moderate opportunities for AF mitigation.

While the AF sector bears considerable GHG mitigation potential, the regional differences in abatement approaches have policy implications for global and local development. In particular, the AF mitigation in developing regions can imply a trade-off with local food security. The reduced supply of crop and livestock products, together with the price rises, potentially present malnutrition risks to these regions, with Africa most adversely affected. The presence of carbon price also asymmetrically imposes costs on agricultural production and subsidizes forestry, creating further regionally varying effects through shifting benefits/costs between regions and sectors. As pointed out in Reisinger *et al.* (2013), appropriate policies that govern how mitigation in agriculture should take place globally is perhaps more important, because of the political economy impacts that global GHG mitigation can impose in the real world.

6 Conclusions

This deliverable describes the findings of integrated assessment modelling experiments regard the use of land-use related mitigation options. First, Chapter 2 describes a model comparison study regarding the results for land-based mitigation options in REMIND/MAGPIE, GCAM and IMAGE. In subsequent studies and literature review in Chapter 3-5, the application of the IMAGE, MAGPIE and GLOBIOM modelling framework and results were discussed.

There are considerable differences between these model systems, in terms in model structure, key assumptions and model outcomes. Table 6.1 summarizes some of the key differences. As indicated in the table, the models differ as well in terms of the mitigation options that can be evaluated.

	GCAM	IMAGE	ReMIND/MAgPIE	GLOBIOM
Interactions of the LU module				
Energy module	Bioenergy demand	Bioenergy potential and bioenergy demand	Bioenergy demand	Bioenergy potential and bioenergy demand
Economy module	Bioenergy prices and Carbon prices	Arable land	Bioenergy prices and Carbon prices	Bioenergy prices and Carbon prices
Climate module	GHG emissions	GHG emissions	GHG emissions	GHG emissions
Land use dynamics				
Between economic units	Profit maximization	Cost minimization	Cost minimization	Profit maximization
Between biophysical units	Profit maximization	Rule based approach	Cost minimization	Profit maximization and Rule based approach
LU mitigation options				
Afforestation	Yes	No	Yes	Yes
Reforestation	Yes	No	No	Yes
Forest management	No	No	No	Yes
Avoided deforestation	Yes	No	Yes	Yes
Bioenergy	Waste, residues, 1st and 2nd generation bioenergy crops	Residues, 1st and 2nd generation bioenergy crops (only fast growing trees)	Residues, 2nd generation bioenergy crops	Residues, 1st and 2nd generation bioenergy crops
Agricultural Management [CH4, N2O]	Yes	Yes	Yes	Yes
Agricultural soil carbon management [CO2]	No	No	No	Yes
Crop yields				
Climate change impacts	No	Yes	No	No
Technological change	Exogenous	Exogenous	Endogenous	Exogenous
Irrigation	Yes	Yes (no irrigation for bioenergy crops)	Yes	Yes

Irrigation dynamics (efficiency increase, irrigation expansion)	No	Yes	Yes	

Table 6.1: Overview and description of land modeling approaches in GCAM, IMAGE, ReMIND/MAgPIE and GLOBIOM.

The results described in the different chapters indicate that dedicated bioenergy crops and biomass residues form a potentially important and cost-effective input into the energy system. A starting point here are estimates of the so-called bio-energy potential, based on technical considerations only, on the basis of competition with other land-use types or the actual implementation potential as part of mitigation scenarios. In the early 2000s often very high bio-energy potentials were reported (in the order of 500-1000 EJ or even higher). Recent studies of the models described in this report typically provide considerably lower numbers. There are two important reasons for this: 1) estimates account for sustainability considerations and 2) are based on less optimistic yield assumptions for food crops. Typically, values for bio-energy supply now range in the order 100-300 EJ (see the Chapter 3 for an evaluation from a more technical perspective using the IMAGE model, while Chapter 4 describes an evaluation using MAgPIE in which also the impact of competition with other land-use is accounted for, leading mainly to substantially higher bio-energy prices. The actual use of bio-energy in scenarios is somewhat lower. Also taking the supply of residues for bio-energy into account typical values are in the order of 100-200 EJ in 2050 and 100-300 EJ in 2100 in ambitious mitigation scenarios (see results described for the model systems in the respective chapters). In the baseline scenarios (without climate policy) numbers are lower. The models typically show that for mitigation targets use of bio-energy in the power sector in combination with CCS becomes attractive.

The energy production per hectare differs significantly across the models, also depending on the use of residues and technology assumptions. A typical range across the models is 200-500 EJ/ha. This implies that considerable land is needed to produce the bio-energy numbers mentioned above, in stringent mitigation scenarios this might be in the order of 500 Mha (e.g. compared to around 1600 Mha for crop production for food and other products today). In REMIND/MAGPIE, GCAM and GLOBIOM, this is associated with substantial increases in land prices and/or prices for agricultural and forestry products . This also means that bio-energy crops could easily reach prices in the order of 10-20$/GJ. In all models, it also leads to an emission flux – either directly from the grid cells producing bio-energy or, indirectly, as a result of replacement of other agricultural activities. The size of this carbon flux strongly depends on assumed mitigation policies. For first generation crops without sustainability restrictions emissions might, on a global scale, actually be higher than those of the replaced fossil fuels. However, for second generation and woody bio-energy products mostly considered in IAM models as part of mitigation strategies these impacts are considerably smaller. The models also report that N_2O emissions associated with bio-energy may for some crops be substantial, for both the overall mitigation potential and (if impacted by climate policy) bio-energy costs.

The models have also looked into REDD, reforestation and afforestation strategies. These options are typically found to be competitive at relatively low carbon prices, and may therefore form an important part of a mitigation strategy. MAGPIE, for instance, reports a substantial potential for afforestation at 6 $/t$CO_2$-eq. This also means that for those models that use these options as part of their integrated modelling climate-policy driven afforestation could have significant impact on land use (up to 1000s Mha) (unless restrictions are introduced). Also in GLOBIOM, as a result of an increase of the price of forests products, a substantial increase in forest cover is reported.

In terms of the role of reducing non-CO_2 gas emissions, both IMAGE and GLOBIOM report detailed abatement opportunities. For instance, simulating the agricultural contribution to GHG mitigation using MESSAGE-GLOBIOM, Reisinger *et al.* (2013) found that abatement of agricultural non-CO2 emissions can help reduce the global abatement costs considerably. This result was also reported by the IMAGE model team. At the same time, it should be noted that emission reduction potential for non-CO_2 gases is limited – and that emissions reductions are typically less than for other GHG emission sources.

Finally, mitigation scenarios may have consequences for dietary patterns. The GLOBIOM results show that mitigation scenarios may have a negative impact on food security if it leads to higher land prices. This was reported earlier as well by the GCAM and MAgPIE modelling team. The IMAGE team explored in contrast if deliberate dietary changes (in high income countries mostly) could have a positive impact on reducing greenhouse gas emissions. Here, substantial impacts were identified.

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