Earth Syst. Dynam. Discuss., 6, 1129–1162, 2015
www.earth-syst-dynam-discuss.net/6/1129/2015/
doi:10.5194/esdd-6-1129-2015

Earth System Dynamics
Discussions
Open Access

Potential impact of climate and socioeconomic changes on future agricultural land use in West Africa

K. F. Ahmed[1], G. Wang[1], L. You[2], and M. Yu[1]

[1]Department of Civil and Environmental Engineering and Center for Environmental Sciences and Engineering, University of Connecticut, Storrs, CT, USA
[2]International Food Policy Research Institute, Washington, DC, USA

Received: 10 June 2015 – Accepted: 10 June 2015 – Published: 16 July 2015

Correspondence to: K. F. Ahmed (kfa09002@engr.uconn.edu)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

Agriculture is a key component of anthropogenic land use and land cover changes that influence regional climate. Meanwhile, in addition to socioeconomic drivers, climate is another important factor shaping agricultural land use. In this study, we compare the contributions of climate change and socioeconomic development to potential future changes of agricultural land use in West Africa using a prototype land use projection (LandPro) algorithm. The algorithm is based on a balance between food supply and demand, and accounts for the impact of socioeconomic drivers on the demand side and the impact of climate-induced crop yield changes on the supply side. The impact of human decision-making on land use is explicitly considered through multiple "what-if" scenarios. In the application to West Africa, future crop yield changes were simulated by a process-based crop model driven with future climate projections from a regional climate model, and future changes in food demand were projected using a model for policy analysis of agricultural commodities and trade. Without agricultural intensification, the climate-induced decrease in crop yield together with increase in food demand are found to cause a significant increase in agricultural land use at the expense of forest and grassland by the mid-century. The increase in agricultural land use is primarily climate-driven in the western part of West Africa and socioeconomically driven in the eastern part. Analysis of results from multiple decision-making scenarios suggests that human adaptation characterized by science-informed decision making to minimize land use could be very effective in many parts of the region.

1 Introduction

Land use and land cover change (LULCC) is an important factor responsible for observed global environmental changes (Foley, 2005; Pongtraz, 2010; Ellis, 2011). Although the terms – land use and land cover – are often exchangeable, they suggest different implications in climate change studies. Land use refers to utilization of land

ESDD
6, 1129–1162, 2015

resource by human for various socioeconomic purposes while land cover indicates the type of physical material at Earth's surface. Anthropogenic land use patterns have direct impact on land cover type. Both land use and land cover can be strongly linked with local and regional climate (Lambin, 2003; Kalnay and Cai, 2004; Mahmood, 2010; Mei and Wang, 2010). Agricultural activity is one of the most important processes driving LULCC in a region. During the pre-industrial period, addition of croplands was the primary response to increasing demand for food and other agricultural products. With the advent of modern agricultural technology, farmers adopted intensive crop farming to minimize the use of land area and slow down the rate of land cover changes (Burney, 2010). Nevertheless, globally the fraction of farmland, which comprises cropland and pasture, has been steadily increasing at the expense of forest (Burney, 2010; Hurtt et al., 2011). The average global GHG emission from agriculture was reported to increase by 1.6 % year^{-1} during 1961–2010 (Tubiello, 2013).

In addition to increasing the atmospheric concentration of greenhouse gases and therefore influencing global climate, LULCC also affects the regional or local climate by altering the water and energy budget at Earth's surface via changing albedo, Bowen ratio, and surface roughness (e.g. Xue and Shukla, 1993; Taylor et al., 2002; Hagos et al., 2014; Wang et al., 2015). Although there is a strong link between climate and LULCC, the dynamics of land use change is not explicitly represented in regional and global climate models, partly due to the difficulties in formulating the human decision-making processes influencing anthropogenic land use (Pielke, 2011; Rounsevell et al., 2014). Instead, anthropogenic land use is usually included as an external driver in climate models, which does not incorporate the potential adaptive measures. Using the Integrated Assessment Models (IAMs) is another approach to combine the socioeconomic aspects and the climatic systems into the same analytical framework. Projections from IAMs on future land use changes are often at the continental or regional scale and need to be downscaled to derive spatially distributed future land use scenario (Hurtt et al., 2011; West et al., 2014). Also because of their rather complex modeling framework with different sources of uncertainties involved, it is difficult to

ESDD
6, 1129–1162, 2015

engage IAMs in assessing relative roles played by climate and socioeconomic changes in projected LULCC (Ackerman, 2009; Rounsevell et al., 2014).

There are different approaches to modeling LULCC with a wide range of modeling perspectives (Agarwal et al., 2002; Parker et al., 2003; Verburg et al., 2006). Agarwal et al. (2002) reviewed and evaluated a set of 19 land use models with respect to spatial and temporal resolutions as well as human decision-making processes. They concluded that models involving more complex human decision-making are limited to lower resolution and extension in both space and time. In reviewing a number of methodologies of modeling LULCC, Parker et al. (2003) suggested to combine cellular model, which focuses on transitions in landscapes, with agent-based model, which represents human decision-making process, to incorporate anthropogenic elements in a spatially explicit modeling scheme. In projecting future agricultural land use, human decision-making is crucially important as farmers can adapt to a changing climate, especially if there is national policy or strategies in place to incentivize or guide adaptation. Moreover, different crops may have different responses to the same climate change scenario. Agent-based modeling approach, which considers the interaction between agents representing decision-makers with certain optimization schemes, has been used to represent the complex anthropogenic behaviors regarding land use changes (Parker et al., 2003; Verburg, 2006; Valbuena et al., 2010). However, application of agent-based approach in modeling land use change at a regional scale is limited because of its inherent complexity and larger data requirements (Valbuena et al., 2010).

Computable general equilibrium (CGE) and partial equilibrium (PE) models are often used to analyze land use patterns on a regional or global scale accounting for multiple natural and socioeconomic factors in an integrated modeling scheme. Schmitz et al. (2014) compared performances of ten global agro-economic models (six CGE and four PE models) in projecting future agricultural land use scenarios. Among these models, two PE models, the Model of Agricultural Production and its Impact on the Environment (MAgPIE) (Lotze-Campen et al., 2008) and the Global Biosphere

ESDD
6, 1129–1162, 2015

Management Model (GLOBIOM) (Havlik et al., 2011), are applicable for modeling land use and land cover changes on a spatially explicit scheme. MAgPIE simulates land use patterns at a spatial resolution of 0.5° based on an objective function to minimize the production cost for specific demand values. Input data to MAgPIE include grid-level crop yield data and regional demand for agricultural commodities. GLOBIOM simulates land use change scenario accounting for competition among agriculture, forestry and bioenergy on a spatially explicit scheme. In the integrated modeling approach, crop-specific yield information is supplied to GLOBIOM by the Environmental Policy Integrated Climate (EPIC) model (Valin et al., 2013; Leclère et al., 2014).

Although numerous studies, using different land use models which follow different approaches, integrated the climate-induced changes of agricultural productivity with socioeconomic changes in projecting the future land use scenario, most of them assess the land use change on national/sub-national levels and therefore do not provide gridded land use map needed by climate projection models (Schmitz et al., 2014). Moreover, most existing models and studies focus only on aggregated land use changes without providing information on individual crops. However, land use policymaking and strategic managements to ensure national or regional food security often require information for production of individual crops. Land use modeling at the individual crop level may help guiding policy making and long-term planning. In this study, we develop a land use projection (LandPro) algorithm that operates on a spatially explicit grid system with the capacity of quantifying land use changes at individual crop level to address the need of climate models for grid-based land use information. In the current application of LandPro to West Africa in evaluating the impact of future increase of food demand and the climate-induced crop yield changes on agricultural land use changes in the region, the mid-21st century projection is analyzed as an example.

Sub-Saharan Africa is extremely vulnerable to climate change impact because of its large dependence on natural resources, fragile economic infrastructure and limited capacity for mitigation and adaptation. Although local crop production provides the majority supply of staple foods, mostly rainfed agricultural system in Sub-Saharan

ESDD
6, 1129–1162, 2015

Africa is not prepared to adapt to projected future climate. Various studies predicted significant reduction in productivity of the major crops in the region under the changed climate scenario unless new technology and adaptation policy can counteract the adverse effect of climate variability (Schlenker and Lobell, 2010; Knox, 2012; Ahmed et al., 2015). Here we engage LandPro to address three questions: what would be the future distribution of crop areas in West Africa to satisfy the future country-level demand for foods with current agricultural practice?; what are the relative roles of socioeconomic factors and climate changes in driving future land use changes?; could land use optimization through human decision-making have considerable impact on the overall LULCC? Considering the fact that future crop yield is an input to LandPro algorithm, we also examine the sensitivity of our results to the selection of future climate data source used in projecting the future yield. Section 2 outlines the LandPro algorithm with its fundamental assumptions, and provides a brief description of the datasets used in this study. Section 3 presents the results, discusses the projected future change in land use patterns in the region and the key factor driving the change, and compares the agricultural land use map projected by our model with that of the Hurtt et al. (2011) dataset. Section 4 summarizes the results and presents the conclusion.

2 Model, data, and methodology

2.1 Algorithm for land use projection

The LandPro algorithm is developed based on the equilibrium between future demand and supply of food at the country level. In the application to the West African Sahel and Guinea Coast regions, 14 countries are included: Benin, Burkina Faso, Gambia, Ghana, Guinea, Guinea-Bissau, Ivory Coast, Liberia Mali, Niger, Nigeria, Senegal, Sierra Leone and Togo. The spatially explicit model, at a resolution of 0.5°, treats each country separately to calculate the gap between future demand of a particular crop and its supply from the local production based on future yield of the crop and the respective

ESDD
6, 1129–1162, 2015

present-day crop area at each pixel within the country.

$$D_{ij} = G_{ij} - \sum_{k=1}^{n} y_{ijk} a_{ijk} \quad (1)$$

where, D_{ij} is the future deficit for crop j in country i, G_{ij} is the future demand, y_{ijk} is future yield of crop j at pixel k and a_{ijk} is present-day area allotted for crop j at pixel k in country i with n number of 0.5° pixels.

The model is developed based on the assumption that agricultural land use will be prioritized over natural land use/land cover types to satisfy increased food demand in future decades. Therefore, the deficit will be overcome by means of increasing local production through the expansion of cropland at the expense of existing natural vegetation. Several rules are set to govern the conversion from naturally vegetated land to cropland, and multiple scenarios of decision making are considered. For example, in the best scenario with science-informed decision making:

1. Forest is preferred over grassland in making new land for crops, due to its generally more fertile soil and the need to preserve grassland for pasture use.

2. If the forest area within a country is completely exhausted and crop deficit still remains, the grass area will be used for conversion to cropland.

3. For multiple grid cells having the same type of natural vegetation, areas in grid cells with higher yield in future climate for a given crop will be used up to cultivate that particular crop before acquiring land from the next most productive grid cell, i.e., the order of land conversion follows the descending order of crop yield across grid cells within a particular country.

4. Naturally vegetated land is converted and allocated to crops following the descending order of crop deficit in a particular country. That is, the crop with the largest remaining gap between demand and production will be prioritized first.

ESDD
6, 1129–1162, 2015

Several alternative scenarios are constructed to test the sensitivity of the land use projection results by altering one or multiple rules listed above. For example, a worst scenario involves reversing the order mentioned in rule 3 and rule 4, and several intermediate scenarios represent different degrees of randomness in the decision making related to the rules.

The y_{ijk} in Eq. (1) is derived using the process-based crop model Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003). Future yield projected by the DSSAT are scaled by three factors. First, like any process-based model, outputs from the DSSAT associate with some bias. The ratio of the DSSAT-simulated present-day yield to a reference present-day yield dataset is used to correct the bias in the DSSAT-simulated future crop yield. Second, although the land use allocation model can account for any number of crops, sometimes due to data limitation or other reasons, only a subset of crops are considered. For example, instead of exhausting all crops existing, for simplicity, we consider only five major crops in West Africa – maize, sorghum, millet, cassava and peanut. These crops were chosen for their large present-day harvest area and high economic value in the region (Ahmed et al., 2015). To indirectly account for the existence of other crops ("minor crops"), the DSSAT-simulated future yield for major crops were scaled down using the ratio between major-crop harvesting area and all-crop harvesting area. In addition, mixed cropping systems commonly seen in West Africa are difficult to model explicitly. To indirectly account for the impact of mixed crops, a third factor, the ratio of total harvest area to the total area of physical land for crops, is used to scale up the DSSAT-simulated future crop yield. These can be summarized as follows:

$$y_{ijk} = y'_{\mathrm{DSSAT},ijk} \cdot \frac{y_{\mathrm{SPAM},ijk}}{y_{\mathrm{DSSAT},ijk}} \cdot \frac{A_{\mathrm{M},ik}}{A_{\mathrm{H},ik}} \cdot \frac{A_{\mathrm{H},ik}}{A_{\mathrm{P},ik}} \qquad (2)$$

where, y_{ijk} is the factored future yield, $y'_{\mathrm{DSSAT},ijk}$ is the DSSAT future yield, $y_{\mathrm{DSSAT},ijk}$ is the DSSAT present-day yield, $y_{\mathrm{SPAM},ijk}$ is the present-day yield according to the Spatial Production Allocation Model (SPAM) (You and Wood, 2006; You et al., 2014), $A_{\mathrm{H},ik}$ is

ESDD

6, 1129–1162, 2015

Agricultural land use in West Africa

K. F. Ahmed et al.

the total harvest area (summation of area allocated to all the individual crops) at pixel k in country i, $A_{\mathrm{P},ik}$ is the total physical area (excluding water body) and $A_{\mathrm{M},ik}$ is the total area allocated to the five major crops chosen for this study. Area data were also aggregated from the SPAM data which represents the geographic distribution of crop harvest area across the globe at a spatial scale of 5 min for the year of 2000 and 2005. SPAM was generated combining the Food and Agriculture Organization (FAO) national crop-specific data, population density, satellite imagery and other datasets. The implicit assumption is that these ratios will remain stationary in the future. Also note that brief descriptions of the reference present-day yield data and the land use land cover data are provided later in Sect. 2.4.

2.2 Projecting future crop yield

Agricultural land use in a region depends to a large degree on crop yield which is one of the essential inputs to the LandPro algorithm. In the application to West Africa, spatially distributed future yields of five major crops were used as the inputs that were simulated using the DSSAT version 4.5 at a spatial resolution of 0.5° across the region. The DSSAT was calibrated and run to simulate future yield for the period of 2041–2059 following the methodology of Ahmed et al. (2015) for cereal crops. For cassava and peanut, however, the DSSAT could not be calibrated satisfactorily following the same approach. Therefore, instead of calibrating the model, yield values of those two crops for the future DSSAT runs were adjusted by the ratio of country-level mean observed yield to the corresponding present-day mean of DSSAT-simulated yield. The mean observed yield values were calculated using the FAO country-level yearly yield data for 1980–1998 (FAOSTAT, 2014). Simulated yield values from 2041 to 2059 were averaged to provide the inputs to the LandPro algorithm to project the agricultural land use in 2050.

The future climate data required to drive the crop model was derived by dynamically downscaling the RCP8.5 climate of two general circulation models (GCMs) participating in the Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor

ESDD
6, 1129–1162, 2015

et al., 2012), the Model for Interdisciplinary Research On Climate – Earth System Model (MIROC-ESM) and the National Center for Atmospheric Research (NCAR) Community Earth System Model (CESM). The regional climate model RegCM 4.3.4 (Giorgi et al., 2012) coupled with the Community Land Model version 4.5 (CLM 4.5) (Oleson et al., 2010; Wang et al., 2015) was used to downscale the MIROC and CESM outputs to 50 km, which is then resampled to a 0.5° grid system. The dynamically downscaled climates were then bias-corrected using the Statistical Downscaling and Bias Correction (SDBC) method (Ahmed et al., 2013), and the Sheffield et al. (2006) data was used as present-day climate reference in the bias-correction algorithm.

2.3 Projecting future demand for local production

Future demand for local crop supply is one of the main inputs to the LandPro. Demand of crops in the West African countries in future years (from 2005 to 2050) was projected using the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) model (Rosegrant et al., 2012). The IMPACT was developed at the International Food Policy Research Institute (IFPRI) to investigate the supply-demand chain in the context of national food security in future decades. It can be used to project the future scenarios of supply, demand and price for more than 40 food commodities globally or regionally. For this study, IMPACT was run under the Shared Socioeconomic Pathway-2 (SSP2), a moderate pathway characterized by historical trends of economic development and medium population growth, according to IPCCC AR5. The future climate data used to drive IPMACT were derived from the RCP8.5 output of four GCMs, including GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, and MIROC-ESM. The average of the output from the four IMPACT runs was used as the input to the LandPro algorithm. Also, to project the mid-century land use scenario, future average of the demand during 2041–2050 was used. Note that the IMPACT projections include future scenarios for both the total demand (i.e., local demand assuming no international trade) and effective demand (i.e., net demand for local production after considering international trade) for a specific commodity in a country. Local production may satisfy

ESDD
6, 1129–1162, 2015

the total demand partially or fully. The deficit or surplus between the total demand and local production reflects the effect of international trading. For example, comparison of the time-series of total demand and local production of maize in Nigeria as projected by the IMPACT for 2005–2050 indicates an increasing trend for the portion of total demand to be met by international trading during the period (Fig. S1 in the Supplement).

2.4 Present-day land use and crop yield data

To quantify the bias in crop yield simulated by DSSAT (Eq. 2), the grid-level dataset of present-day yield from SPAM for the year of 2005 were used as the reference data. The present-day harvest area for five major crops and total physical land area at each 0.5° pixel in West Africa used as inputs to LandPro were also obtained from the SPAM 2005 dataset. In addition to crop area, the present-day fractions of forest area and grassland at each grid cell are also needed to provide the initial condition for the LandPro algorithm for projecting future land use. The fractional coverage of each of these three land cover types at each grid cell was obtained from the global land surface data developed by Lawrence and Chase (2007) which combined various satellite products and other datasets to derive the present-day global distribution of plant functional types at a 0.05° resolution. However, crop fraction in the Lawrence and Chase (2007) dataset was estimated according to historical crop area data generated by Ramankutty and Foley (1999) and it shows a considerable deviation from the SPAM crop fraction. Since crop area information for this study were prescribed according to SPAM, crop fraction in Lawrence and Chase (2007) was updated accordingly and the fractional coverage for forest and grassland were adjusted proportionally.

3 Results and discussions

The reduction in crop yield as a result of climate change and the increasing demand for food in future years are expected to cause an increase in the agricultural land

ESDD
6, 1129–1162, 2015

use, leading to a substantial shift in land cover in West Africa as projected by the LandPro algorithm (Fig. 1). The present-day land use distribution shows majority of the agricultural activity occurring in the eastern part of West Africa and the extensive presence of forest area in the southwest, especially along the coast. Although grassland exists almost over the entire region, they are more dominant further inland to the north. The LandPro algorithm projects further increase in crop areas in the eastern part of West Africa which would result in a complete depletion of forest and grassland in future decades. The western and central parts of West Africa would also experience noticeable increase in cropland. However, most of the increment would occur at the expense of forest area, with generally a lower degree of grassland depletion. In Nigeria, the country-average crop area percentage is projected to increase from 39.44 to 84.46 % under MIROC-driven climate and to 80.87 % under CESM-driven climate (Table S1 in the Supplement). In the western part of the region along the coast, the largest increase in cropland is projected to occur in Gambia (44.97 and 39.23 % under the MIROC- and CESM-driven climates respectively). Along the Gulf of Guinea, west of Nigeria, Benin would also experience a large increase of crop area by 37.34 % (MIROC) and 40.91 % (CESM). In Niger, crop production is clustered only to the south since the vast northern part of the country is mostly covered by desert. Therefore, although the model projects a small change in the fractional coverage of cropland averaged over the entire country, the magnitude of the projected increase of agricultural land use in the south is much larger. For most countries, the LandPro projections for aggregated land use change driven by downscaled climates from the two GCMs are very similar. The inter-model difference is much smaller than the inter-country difference of land use changes.

To assess the relative importance of climate and socioeconomic factors in driving the future land use changes, we also conducted LandPro simulations considering only the socioeconomic changes in the region and excluding the impact of climate-induced crop yield changes. In order to do so, the LandPro was run with the future demand and present-day crop yield (as opposed to the future yield used for the initial run) as

ESDD
6, 1129–1162, 2015

inputs. Since the crop yield values remain unchanged, outputs from this run, namely LandPro-SE, reflect the impact of socioeconomic changes on agricultural land use ignoring the climate-induced changes in yield (Fig. 2). The difference between the future changes in crop area from the LandPro-Total run (considering both climate and socioeconomic factors) and the LandPro-SE run indicate the changes in crop area projected by LandPro considering only climate change (LandPro-CC). Under both the MIROC-driven and CESM-driven regional climates, the socioeconomic changes tend to have a stronger impact on future land use transition than the changes in crop yield in the eastern part of the region. In the western part near the coast, however, the impact of crop yield changes is more dominant, which can be attributed to the larger yield loss resulting from a larger future warming in that part of the region (Ahmed et al., 2015). In the central part of the region, the climate-induced expansion in crop area tends to be somewhat more evident under the CESM-driven climate.

Food demand determined by socioeconomic factors is the most important driver for land use. The land use changes shown in Fig. 2 were predicted using LandPro driven by changes in the net demand for local production projected by IMPACT (referred to as "Local Production" experiment). To test the sensitivity of LandPro to the production demand, future changes in agricultural land were also predicted using the total demand projected by IMPACT (as if there would be no international trading) as the driver (referred to as the "Total Demand" experiment), and using a demand that features a future increase half as fast as the projection by IMPACT (referred to as the "50 % Change" experiment). Spatial patterns of absolute changes in crop area percentage are essentially similar for both the net demand and total demand experiments (Figs. 3 and 4, for the MIROC- and CESM-driven climates respectively). The magnitude of changes is generally larger in the case of total demand since most of the countries in the region depend on import to satisfy the demands which exceed local production. The land use changes are expectedly smaller for the "50 % Change" experiment. However, spatial patterns of the relative importance of climate change and socioeconomic changes can noticeably vary according to demand scenarios. For example, under the

ESDD
6, 1129–1162, 2015

MIROC-driven climate, in the northeast part of Nigeria (East of 10° E and North of 8° N), changes in crop are projected to be dominated by socioeconomic changes to satisfy total demand (Fig. 3). In contrast, in satisfying either the net demand or 50 % future changes of total demand, changes in crop area would be controlled by climate-induced changes in crop yield while the impact of socioeconomic changes would be negligible. Thus, fraction of future land use change attributed to climate change tends to vary spatially within a country depending on the future demand values. However, magnitudes and spatial patterns of the fraction of climate-induced crop area expansion across the regions for all three demand scenarios are generally similar under both of the GCM-driven climate scenarios.

The dependence of future land use patterns on the magnitude of demand can be attributed to two factors which govern LandPro algorithm – the present-day distribution of forest and grass, and the differences between present-day and future ranking of grid cells according to their respective yield values. Since the LandPro scenario experimented on uses up forest area over the entire country before it starts to consume grassland, grid cells with grass in the present-day are not converted to crop area until the demand reaches a threshold value. Therefore, with present-day yield, although many grid cells dominated by grass do not experience any change in land use in satisfying lower demand, they are converted to crop area when demand is higher. However, with generally lower yield in future climate, those grid cells need to be converted to cropland even to satisfy a lower level of demand. Furthermore, a grid cell with a lower rank for present-day yield may become higher-ranked for future yield values and vice versa, leading to a difference in spatial variability of climate-induced land use changes for different demand values. The comparison among country-average values of climate-induced land use changes for different demand scenarios also highlights the uncertainty in LandPro in determining the fraction of changes attributable to climatic factors (Fig. 5). For a particular country, the total demand would usually necessitate a larger increase in total crop area than the net demand for local production, whereas the magnitude of the increase would be the lowest in the case

ESDD
6, 1129–1162, 2015

Agricultural land use in West Africa

K. F. Ahmed et al.

of 50 % changes of the total demand. Exception can be found for export countries. The relative importance of climate and socioeconomics changes as drivers of land use change and how it varies spatially are relatively stable across the three simulations, with the exception of several countries. For example, under the MIROC-driven climate changes, in Gambia, Senegal and Togo, the fraction of climate-induced changes to total crop area changes projected by LandPro to satisfy the 50 % increase in total demand is larger than the projected changes for other two demand scenarios. Under the CESM-driven climate, the climate-induced change in agricultural land use is the largest for the "50 % change" experiment in the case of Burkina Faso as well.

The LandPro algorithm explicitly considers multiple scenarios of human decision-making (as reflected by the order of land conversion in rules 3 and 4 mentioned in Sect. 2.3), which is a major source of uncertainty in projected future land use changes. To assess such uncertainties, we evaluated whether human decision regarding agricultural land use optimization can influence the future land use change in West Africa based on alternative decision scenarios. In agricultural expansion, the selection of areas to cultivate from naturally vegetated land is one major uncertainty in human decision-making for land use. Therefore, apart from the best scenario simulated by the initial run, two alternative projections of future land use distribution, including the worst scenario and an intermediate scenario, were conducted by altering the order of crop area selection based on future crop yield in rule 3 in LandPro. The worst scenario assumes that the conversion from natural vegetation to cropland by farmers follows the ascending order of crop yield, while the selection is random for the intermediate scenario. Comparison of these alternative scenarios with the best scenario reveals noticeable differences, with both alternative scenarios generally involving more cropland (Fig. 6). The cropland expansion is minimized if farmers utilize the areas with higher future yield first before engaging the less productive land, whereas the opposite approach would maximize the amount of cropland usage (Table S2, using MIROC as example). The difference among multiple future scenarios of agricultural land use, which depends on the farmers' decision regarding the

ESDD
6, 1129–1162, 2015

selection of crop area, implies an adaptive potential to minimize the conversion of naturally vegetated land based on appropriate knowledge of future crop yield. We also performed sensitivity analysis of LandPro projections to input demand (as shown in Figs. 3 and 4) in the case of worst scenario of agricultural land use regarding the order of crop area selection. With the alternative cropping order, the relative importance of climate and socioeconomic factors in driving the future land use change considerably changes in many parts of the region for all the demand scenarios (Fig. S2, using MIROC as example). This implies that land use decision-making can play a significant role in determining future agricultural land use changes.

Prioritization of the crops by farmers with respect to the sequence of land allocation in a particular country reflects another uncertainty related to human decision-making. For the best scenario run, the land was allocated to the crops according to the descending order of future crop deficits as stated in rule 4. Several alternative scenarios were examined with LandPro. In alternative 1, the prioritization in rule 4 follows the ascending order of deficits in a specific country; in alternative 2, in all of the countries, the priority for land allocation was given to the cereal crops first (maize, sorghum and millet) followed by cassava and peanut; in alternative 3, the reverse order of alternative 2 is used. Under the MIROC-driven climate, spatial maps of crop area distribution from the multiple alternative runs indicate that prioritization of the crops as a land use optimization technique would have little impact on the projected future land use land cover changes (Fig. 7). The difference in country-average future crop area percentage from different runs is negligible as compared to the absolute magnitude in a particular country (Table S3). The results are qualitatively similar for the projections based on the CESM-driven climate changes.

To test the performance of LandPro, we compared the LandPro projections with the crop area distribution in 2050 projected by Hurtt et al. (2011, henceforth H11) data. H11 projected future (2005–2100) land use scenarios following four Representative Concentration Pathways (RCPs) according to the Fifth Assessment Report (AR5) of the Intergovernmental panel on Climate Change (IPCC), and created a unique grid-

ESDD
6, 1129–1162, 2015

level dataset for both the historical land use and the future carbon-climate scenarios. However, the impact of future climate changes on land use and land cover changes was not explicitly accounted for. Therefore, the future change in crop area according to the H11 data is conceptually comparable to our LandPro-SE projection. The comparison shows that the increase in croplands projected by LandPro-SE is substantially higher, especially in the agriculture-dominated eastern part of the region (Fig. 8). Although noticeable differences exist also in the spatial patterns projected by the two data sets, both projections show consensus with larger increase in the southeastern part of the region. The challenges and uncertainty in quantifying land use are also reflected by the difference in the present-day crop areas between SPAM and H11. For the present-day land use distribution in 2005, the two data sets exhibit noticeable discrepancy over the region dominated by agriculture. This highlights the typical inconsistency between land use maps generated by different methodologies (You et al., 2014).

4 Summary and conclusions

A land use and land cover change algorithm (LandPro) was developed to study the future expansion of agricultural land and the resulting loss of naturally vegetated land, and was applied to West Africa as a case study. LandPro integrates the impact of climate change on crop yield and future socioeconomic scenarios to construct a spatially gridded land cover map, and a spatial scale of 0.5° is used in the case study. Without accounting for the farmers' adaptive potential to address the negative impact of future warming and changes in precipitation pattern on crop productivity, the model projects a large increase in agricultural land use under the future climate scenario. The increase in cropland would occur at the expense of natural vegetation cover, both of which could further modify the regional climate. Not considering the farmers adaptive potential and the technological advancements, which could reduce rate of crop area expansion by increasing the yield, is one of the limitation of this study. However, in Sub-Saharan Africa, more than 80 % of the agricultural growth since 1980 was attributed

ESDD
6, 1129–1162, 2015

to crop area expansion instead of increase of productivity over already existing agricultural land (The World Bank, 2008). Considering the vulnerability of agricultural infrastructures in the region, despite the potential scope of improving yield to minimize land use change, addition of new crop area is likely to be a prevailing strategy for agricultural growth in the near future. Multiple possible adaptive measures by the farmers to minimize the harvest area were also analyzed addressing the uncertainties involved in human decision-making process. Although prioritization among the crops in allocating the available land for their cultivation might have no or minimal impact in optimizing the land use, a specific order of selecting cultivation area based on future crop yield might effectively reduce the total loss of naturally vegetated land. However, despite some effectiveness of land use optimization, the large degree of overall land use change emphasizes the need for more effective adaptation policy to slow down the regional agricultural land use expansion.

Our results also indicate spatial heterogeneity of land use change dynamics which can be dominated by different controlling factors in different parts of West Africa. Climate change impact on crop yield would considerably vary across the region resulting in large variability in the spatial pattern of future yield loss. While the agricultural land use could be dominated by the projected yield loss in some parts of the region, the projected increase in food demand would be of greater importance in the land use change dynamics in other regions. However, future projections from LandPro imply that farmers' decision-making can alter the relative importance of different factors in driving future land use changes. Therefore, although LandPro demonstrated robustness to multiple future climate scenarios, the projection from the model can be more sensitive to other future scenarios of supply and demand of food. Despite the fact that the IMPACT was run for multiple climate and socioeconomic scenarios in projecting the future demand, the uncertainties involved in the IMPACT projection can be considered as a limitation of this study. Apart from the uncertainties involved in the model setup, not considering any historical trend in land use transitions is another limitation of this study.

ESDD
6, 1129–1162, 2015

K. F. Ahmed et al.

The LandPro algorithm provides a preliminary framework for the projection and analysis of future agricultural land use. LandPro offers two clear advantages. It provides spatially distributed land use information needed by climate models as the lower boundary condition; also it can be conveniently used for future land use information at the individual crop level that is needed for national and regional land use and food security policy analysis. The algorithm can and will be further developed to overcome existing limitations pointed out earlier. In this study, LandPro was used to evaluate the land use change over several decades without the transient process. The same model can also be suitably applied in a stepwise mode to investigate the transient trend in land use change which is the topic of our future research.

The Supplement related to this article is available online at doi:10.5194/esdd-6-1129-2015-supplement.

Author contributions. K. F. Ahmed and G. Wang designed the study, analyzed the results and wrote the paper. L. You and M. Yu provided the data. L. You commented on methods and results.

Acknowledgements. Funding support for this study was provided by National Science Foundation (AGS-1049017, AGS-1048967).

References

Ackerman, F., DeCanio, S. J., Howarth, R. B., and Sheeran, K.: Limitations of integrated assessment models of climate change, Climatic Change, 95, 297–315, doi:10.1007/s10584-009-9570-x, 2009.

Agarwal, C., Green, G. M., Grove, J. M., Evans, T. P., and Schweik, C. M.: A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice, GTR NE-297, U.S.D.A., Forest Service, Northeastern Research Station, Newton Square, PA, 61 pp., 2002.

ESDD

6, 1129–1162, 2015

Agricultural land use in West Africa

K. F. Ahmed et al.

Ahmed, K. F., Wang, G., Silander, J., Wilson, A. M., Allen, J. M., Horton, R., and Anyah, R.: Statistical downscaling and bias correction of climate model outputs for climate change impact assessment in the US northeast, Global Planet. Change, 100, 320–332, 2013.

Ahmed, K. F., Wang, G. L., Miao, Y., You, L. Z., and Koo, J.: Potential impact of climate change on cereal crop yield in West Africa, Climatic Change, in press, 2015.

Boysen, L. R., Brovkin, V., Arora, V. K., Cadule, P., de Noblet-Ducoudré, N., Kato, E., Pongratz, J., and Gayler, V.: Global and regional effects of land-use change on climate in 21st century simulations with interactive carbon cycle, Earth Syst. Dynam., 5, 309–319, doi:10.5194/esd-5-309-2014, 2014.

Burney, J. A., Davis, S. J., and Lobell, D. B.: Greenhouse gas mitigation by agricultural intensification, P. Natl. Acad. Sci. USA, 107, 12052–12057, doi:10.1073/pnas.0914216107, 2010.

Deng, X., Zhao, C., and Yan, H.: Systematic modeling of impacts of land use and land cover changes on regional climate: a review, Advances in Meteorology, 2013, 1–11, doi:10.1155/2013/317678, 2013.

Division, E. S., Ridge, O., and Ridge, O.: The relationship between land-use change and climate change, Ecol. Appl., 7, 753–769, 1997.

Ellis, E. C.: Anthropogenic transformation of the terrestrial biosphere, Philos. T. R. Soc. A, 369, 1010–1035, doi:10.1098/rsta.2010.0331, 2011.

FAOSTAT: Database on Agriculture, Food and Agriculture Organization of the United Nations, Rome, Italy, available at: http://faostat3.fao.org/home (last access: June 2014), 2014.

Foley, A.: Estimating historical changes in global land cover? Croplands historical have converted areas, Global Biogeochem. Cy., 13, 997–1027, 1999.

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E. A., Kucharik, C. J., Monfreda, C., Patz, J. A., Prentice, I. C., Ramankutty, N., and Snyder, P. K.: Global consequences of land use, Science, 309, 570–574, 2005.

Giorgi, F., Coppola, E., Solmon, F., Mariotti, L., Sylla, M. B., Bi, X., Elguindi, N., Diro, G. T., Nair, V., Giuliani, G., Cozzini, S., Guttler, I., O'Brien, T. A., Tawfik, A. B., Shalaby, A., Zakey, A. S., Steiner, A. L., Stordal, F., Sloan, L. C., and Brankovic, C.: RegCM4: model description and preliminary tests over multiple CORDEX domains, Clim. Res., 52, 7–29, 2012.

ESDD

6, 1129–1162, 2015

Agricultural land use in West Africa

K. F. Ahmed et al.

Havlik, P., Schneider, U. A., Schmid, E., Böttcher, H., Fritz, S., Skalsk'y, R., Aoki, K., Cara, S. D., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., and Obersteiner, M.: Global land-use implicationsof first and second generation biofuel targets, Energ. Policy, 39, 5690–5702, 2011.

Havlik, P., Valin, H., Mosnier, A., Obersteiner, M., Baker, J. S., Herrero, M., Rufino, M. C., and Schmid, E.: Crop productivity and the global livestocksector: implications for land use change and greenhouse gas emissions, Am. J. Agr. Econ., 95, 442–448, 2013.

Houghton, B. R. A., Woods, T., Box, P. O., and Hole, W.: Revised estimates of the annual net flux of carbon to the atmosphere from changes in land use and land management 1850–2000, Tellus B, 55, 378–390, 2003.

Hurtt, G. C., Chini, L. P., Frolking, S., Betts, R. a., Feddema, J., Fischer, G., and Wang, Y. P.: Harmonization of land-use scenarios for the period 1500–2100: 600 years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands, Climatic Change, 109, 117–161, doi:10.1007/s10584-011-0153-2, 2011.

Jones, J., Hoogenboom, G., Porter, C., Boote, K., Batchelor, W., Hunt, L., and Ritchie, J.: The DSSAT cropping system model, Eur. J. Agron., Vol. 18, 235–265, doi:10.1016/S1161-0301(02)00107-7, 2003.

Kalnay, E. and Cai, M.: Impact of urbanization and land-use change on climate, Nature, 423, 528–532, doi:10.1038/nature01675, 2003.

Knox, J., Hess, T., Daccache, A., and Wheeler, T.: Climate change impacts on crop productivity in Africa and South Asia, Environ. Res. Lett., 7, 034032, doi:10.1088/1748-9326/7/3/034032, 2012.

Lambin, E. F., Geist, H. J., and Lepers, E.: Dynamics of land-use and land-cover change in tropical regions, Annu. Rev. Env. Resour., 28, 205–241, doi:10.1146/annurev.energy.28.050302.105459, 2003.

Lawrence, P. J. and Chase, T. N.: Representing a new MODIS consistent land surface in the Community Land Model (CLM 3.0), J. Geophys. Res., 112, G01023, doi:10.1029/2006JG000168, 2007.

Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P., Conway, T. J., Doney, S. C., Feely, R. A., Foster, P., Friedlingstein, P., Gurney, K., Houghton, R. A., House, J. I., Huntingford, C., Levy, P. E., Lomas, M. R., Majkut, J., Metzl, N., Ometto, J. P., Peters, G. P., Prentice, I. C., Randerson, J. T., Running, S. W., Sarmiento, J. L., Schuster, U.,

ESDD
6, 1129–1162, 2015

Sitch, S., Takahashi, T., Viovy, N., van der Werf, G. R., and Woodward, F. I.: Trends in the sources and sinks of carbon dioxide, Nat. Geosci., 2, 831e836, doi:10.1038/ngeo689, 2009.
Leclère, D., Havlík, P., Fuss, S., Schmid, E., Mosnier, A., Walsh, B., and Obersteiner, M.: Climate change induced transformations of agricultural systems: insights from a global model, Environ. Res. Lett., 9, 124018, doi:10.1088/1748-9326/9/12/124018, 2014.
Lotze-Campen, H., Müller, C., Bondeau, A., Rost, S., Popp, A., and Lucht, W.: Global food demand, productivity growth, and the scarcity of land and water resources: a spatially explicit mathematical programming approach, Agr. Econ., 39, 325–338, 2008.
Mahmood, R., Quintanar, A. I., Conner, G., Leeper, R., Dobler, S., Pielke, R. A., and Syktus, J.: Impacts of land use/land cover change on climate and future research priorities, B. Am. Meteorol. Soc., 91, 37–46, doi:10.1175/2009BAMS2769.1, 2010.
Mei, R. and Wang, G.: Rain follows logging in the Amazon? Results from CAM3–CLM3, Clim. Dynam., 34, 983–996, doi:10.1007/s00382-009-0592-x, 2009.
Murray-Rust, D., Dendoncker, N., Dawson, T. P., Acosta-Michlik, L., Karali, E., Guillem, E., and Rounsevell, M.: Conceptualizing the analysis of socioecological systems through ecosystem services and agent-based modelling, Journal of Land Use Science, 6, 83–99, doi:10.1080/1747423X.2011.558600, 2011.
Olesen, J. E. and Bindi, M.: Consequences of climate change for European agricultural productivity, land use and policy, Eur. J. Agron., 16, 239–262, doi:10.1016/S1161-0301(02)00004-7, 2002.
Oleson, K. W., Lawrence, D. M., Bonan, G. B., Flanner, M. G., Kluzek, E., Lawrence, P. J., Levis, S., Swenson, S. C., Thornton, P. E., Dai, A., Decker, M., Dickinson, R., Feddema, J., Heald, C. L., Hoffman, F., Lamarque, J. F., Mahowald, N., Niu, G.-Y., Qian, T., Randerson, J., Running, S., Sakaguchi, K., Slater, A., Stockli, R., Wang, A., Yang, Z.-L., Zeng, X., and Zeng, X.: Technical description of version 4.0 of the Community Land Model, NCAR Tech. Note NCAR/TN-478+STR, 257, available at: http://www.cesm.ucar.edu/models/ccsm4.0/clm/CLM4_Tech_Note.pdf, last access: May 2015, 2010.
Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., Deadman, P., Manson, S. M., and Hall, S.: Multi-agent systems for the simulation of land-use and land-cover change: a review, Ann. Assoc. Am. Geogr., 3, 314–337, doi:10.1111/1467-8306.9302004, 2002.
Pielke, R. A., Pitman, A., Niyogi, D., Mahmood, R., McAlpine, C., Hossain, F., Klein Goldewijk, K., Nair, U., Betts, R., Fall, S., Reichstein, M., Kabat, P., and de Noblet-

ESDD
6, 1129–1162, 2015

Ducoudre, N.: Land use/land cover changes and climate: modeling analysis and observational evidence, WIREs Climate Change, 2, 828–850, 2011.
Pongratz, J., Reick, C. H., Raddatz, T., and Claussen, M.: Biogeophysical versus biogeochemical climate response to historical anthropogenic land cover change, Geophys. Res. Lett., 37, 8, doi:10.1029/2010GL043010, 2010.
Robinson, S., van Meijl, H., Willenbockel, D., Valin, H., Fujimori, S., Masui, T., Sands, R., Wise, M., Calvin, K., Havlik, P., Mason d'Croz, D., Tabeau, A., Kavallari, A., Schmitz, C., Dietrich, J. D., and von Lampe, M.: Comparing supply-side specifications in models of global agriculture and the food system, Agr. Econ., 45, 21–35, 2014.
Ronneberger, K. E.: The global agricultural land-use model KLUM – a coupling tool for integrated assessment, PhD thesis, University of Hamburg, available at: https://www.mpimet.mpg.de/fileadmin/publikationen/Reports/BzE_26.pdf, last access: May 2015, 2006.
Rosegrant, M. W.: International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) Model Description, International Food Policy Research Institute, available at: http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/127162, last access: May 2015, 2012.
Rounsevell, M. D., Annetts, J., Audsley, E., Mayr, T., and Reginster, I.: Modelling the spatial distribution of agricultural land use at the regional scale, Agr. Ecosyst. Environ., 95, 465–479, doi:10.1016/S0167-8809(02)00217-7, 2003.
Rounsevell, M. D. A., Arneth, A., Alexander, P., Brown, D. G., de Noblet-Ducoudré, N., Ellis, E., Finnigan, J., Galvin, K., Grigg, N., Harman, I., Lennox, J., Magliocca, N., Parker, D., O'Neill, B. C., Verburg, P. H., and Young, O.: Towards decision-based global land use models for improved understanding of the Earth system, Earth Syst. Dynam., 5, 117–137, doi:10.5194/esd-5-117-2014, 2014.
Schlenker, W. and Lobell, D. B.: Robust negative impacts of climate change on African agriculture, Environ. Res. Lett., 5, 014010, doi:10.1088/1748-9326/5/1/014010, 2010.
Schmitz, C., van Meijl, H., Kyle, P., Nelson, G. C., Fujimori, S., Gurgel, A., and Alin, H.: Land-use change trajectories up to 2050: insights from a global agro-economic model comparison, Agr. Econ., 45, 69–84, doi:10.1111/agec.12090, 2014.
Schröter, D., Cramer, W., Leemans, R., Prentice, I. C., Araújo, M. B., Arnell, N. W., Bondeau, A., Bugmann, H., Carter, T. R., Gracia, C. A., de la Vega-Leinert, A. C., Erhard, M., Ewert, F., Glendining, M., House, J. I., Kankaanpää, S., Klein, R. J. T., Lavorel, S., Lindner, M., Metzger, M. J., Meyer, J., Mitchell, T. D., Reginster, I., Rounsevell, M., Sabaté, S., Sitch, S., Smith, B., Smith, J., Smith, P., Sykes, M. T., Thonicke, K., Thuiller, W., Tuck, G., Zaehle, S.,

and Zierl, B.: Ecosystem service supplyand vulnerability to global change in Europe, Science, 310,1333–1337, 2005.

Sheffield, J., Goteti, G., and Wood, E. F.: Development of a 50-yr, high resolution global dataset of meteorological forcings for land surface modeling, J. Climate, 19, 3088–3111, 2006.

Smith, P., Haberl, H., Popp, A., Erb, K.-H., Lauk, C., Harper, R., and Rose, S.: How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals?, Glob. Change Biol., 19, 2285–2302, doi:10.1111/gcb.12160, 2013.

Stéphenne, N. and Lambin, E. F.: A dynamic simulation model of land-use changes in Sudano-sahelian countries of Africa (SALU), Agr. Ecosyst. Environ., 85, 145–161, doi:10.1016/S0167-8809(01)00181-5, 2001.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, B. Am. Meteorol. Soc., 93, 485–498, doi:10.1175/BAMS-D-11-00094.1, 2012.

Tubiello, F. N., Salvatore, M., Rossi, S., Ferrara, A., Fitton, N., and Smith, P.: The FAOSTAT database of greenhouse gas emissions from agriculture, Environ. Res. Lett., 8, 015009, doi:10.1088/1748-9326/8/1/015009, 2001.

Valbuena, D., Verburg, P. H., Bregt, A. K., and Ligtenberg, A.: An agent-based approach to model land-use change at a regional scale, Landscape Ecol., 25, 185–199, doi:10.1007/s10980-009-9380-6, 2010.

Valin, H., Havlík, P., Mosnier, A., Herrero, M., Schmid, E., and Obersteiner, M.: Agricultural productivity and greenhouse gas emissions: trade-offs or synergies between mitigation and food security?, Environ. Res. Lett., 8, 035019, doi:10.1088/1748-9326/8/3/035019, 2013.

Veldkamp, A. and Lambin, E.: Predicting land-use change, Agr. Ecosyst. Environ., 85, 1–6, doi:10.1016/S0167-8809(01)00199-2, 2001.

Verburg, P. H.: Simulating feedbacks in land use and land cover change models, Landscape Ecol., 21, 1171–1183, doi:10.1007/s10980-006-0029-4, 2006.

Verburg, P. H., Kok, K., Pontius Jr., R. G., and Veldkamp, A.: Modeling land-use and land-cover change, in: Land-Use and Land-Cover Change, Springer, Berlin, Heidelberg, 117–135, 2006.

Verburg, P. H., Neumann, K., and Nol, L.: Challenges in using land use and land cover data for global change studies, Glob. Change Biol., 17, 974–989, doi:10.1111/j.1365-2486.2010.02307.x, 2011.

Wang, G. L., Miao, Y., Pal, J. S., Rui, M., Bonan, G., Levis, S., and Thornton, P.: On the development of a coupled RegCM-CLM-CN-DV model and its validation in West Africa, Clim. Dynam., doi:10.1007/s00382-015-2596-z, online first, 2015.
World Bank: Investment in Agricultural Water for Poverty Reduction and Economic Growth in Sub-Saharan Africa. A collaborative programme of ADB, FAO, IFAD, IWMI and World Bank, Synthesis Report, available at: http://siteresources.worldbank.org/RPDLPROGRAM/Resources/459596-1170984095733/synthesisreport.pdf, last access: May 2015, 2008.
You, L. S. and Wood, S.: An entropy approach to spatial disaggregation of agricultural production, Agr. Syst., 90, 329–347, doi:10.1016/j.agsy.2006.01.008, 2006.
You, L. S., Wood, S., Wood-Sichra, U., and Wu, W.: Generating global crop distribution maps: from census to grid, Agr. Syst., 127, 53–60, 2014.

ESDD
6, 1129–1162, 2015

Agricultural land use in West Africa

K. F. Ahmed et al.

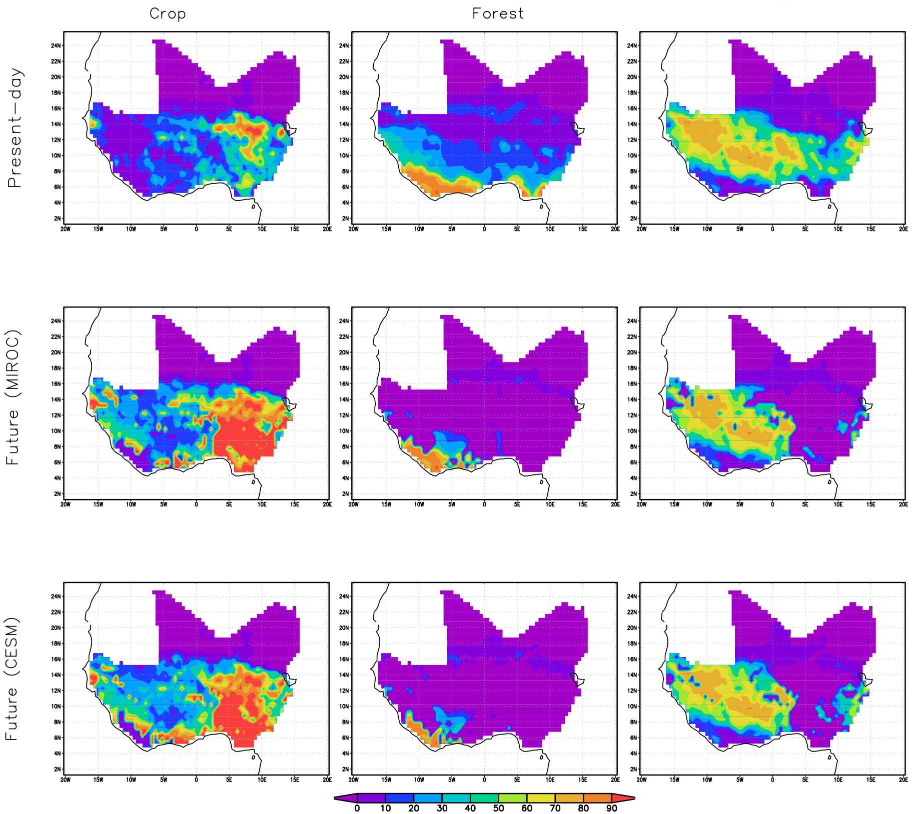

Figure 1. Spatial distribution of crop, forest and grass coverage (%) in 14 West African countries from present-day (year 2005) observation (top row) and future projection by the LandPro algorithm for mid-21st century under two GCM climate – MIROC (middle row) and CESM (bottom row).

ESDD
6, 1129–1162, 2015

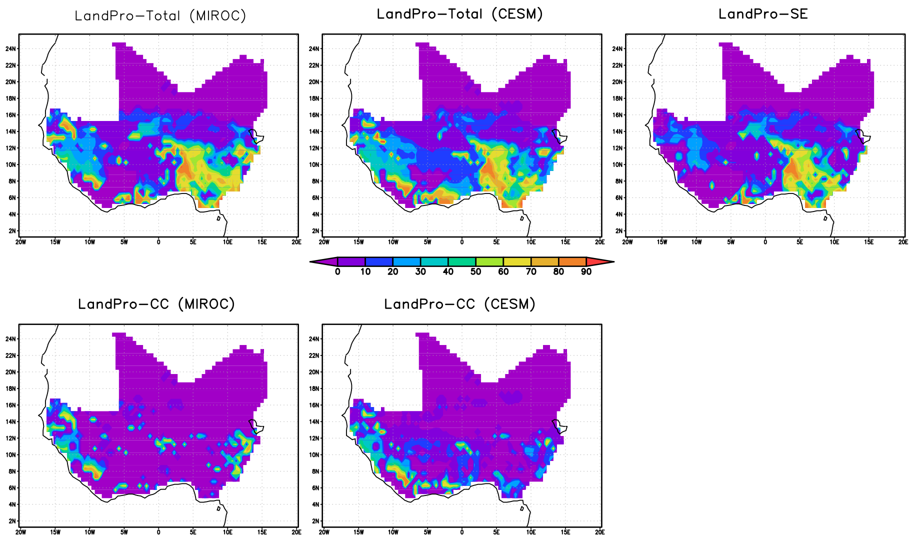

Figure 2. Future changes in crop area distribution according to the LandPro projections accounting for total change (LandPro-Total), socioeconomic change (LandPro-SE) and climate change (LandPro-CC) in West Africa under the MIROC-driven and CESM-driven future climate.

ESDD
6, 1129–1162, 2015

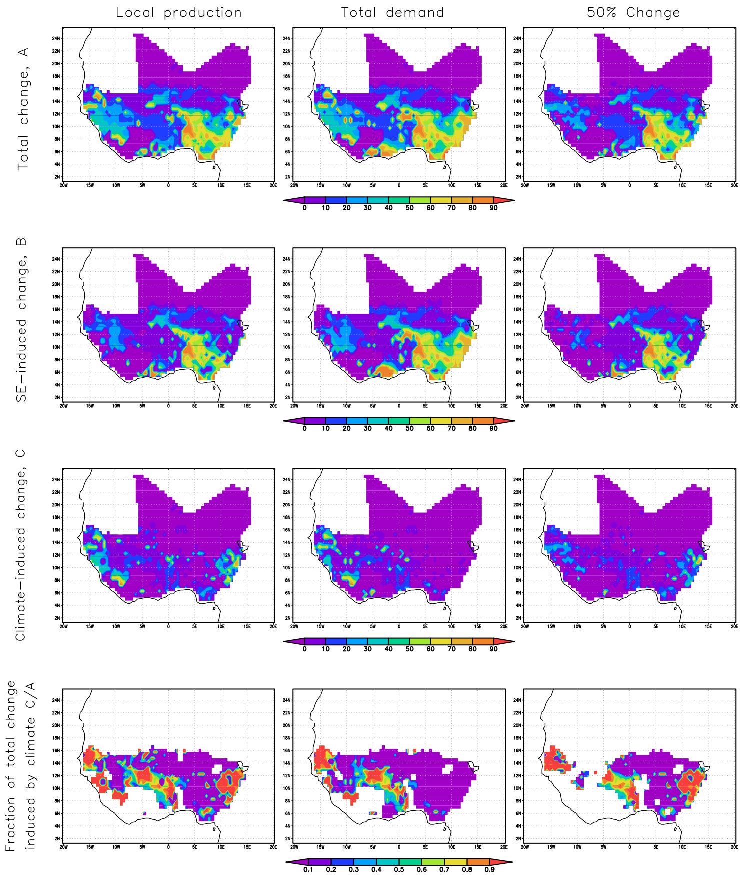

Figure 3. Sensitivity of land use change pattern to the demand values used as input to LandPro under the MIROC-driven climate. 1st row: absolute magnitude of total change for three future scenarios of demand; 2nd row: change due to socioeconomic factors; 3rd row: change due to climatic factors; 4th row: fraction of climate-induced change to total change.

ESDD
6, 1129–1162, 2015

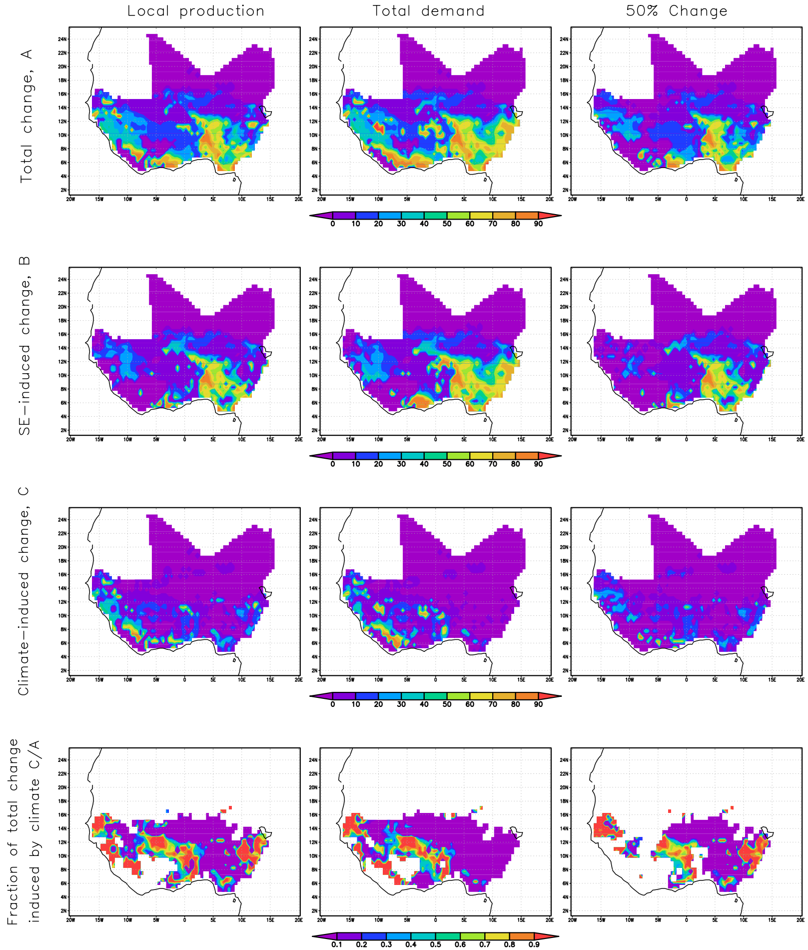

Figure 4. As in Fig. 3, but for CESM-driven climate. (Note that the SE-induced changes in both Figs. 3 and 4 are same.)

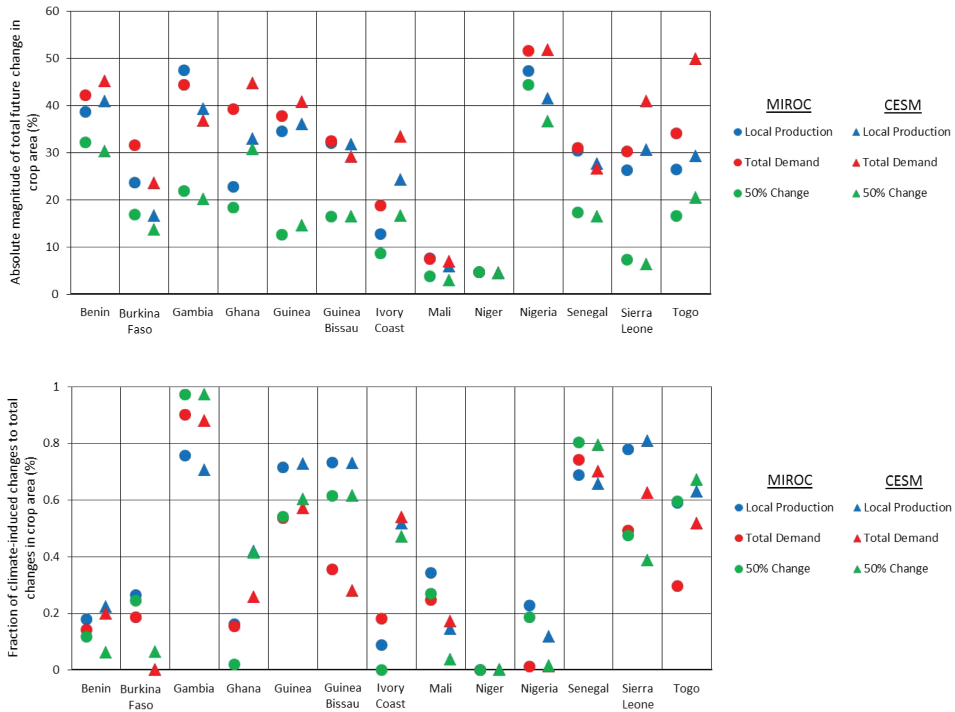

Figure 5. Country-average values of total change in crop area (top) and fraction of climate-induced changes to total change (bottom) according to three future scenarios of demand under the MIROC- and the CESM-driven climate.

ESDD
6, 1129–1162, 2015
Agricultural land use in West Africa
K. F. Ahmed et al.

ESDD
6, 1129–1162, 2015

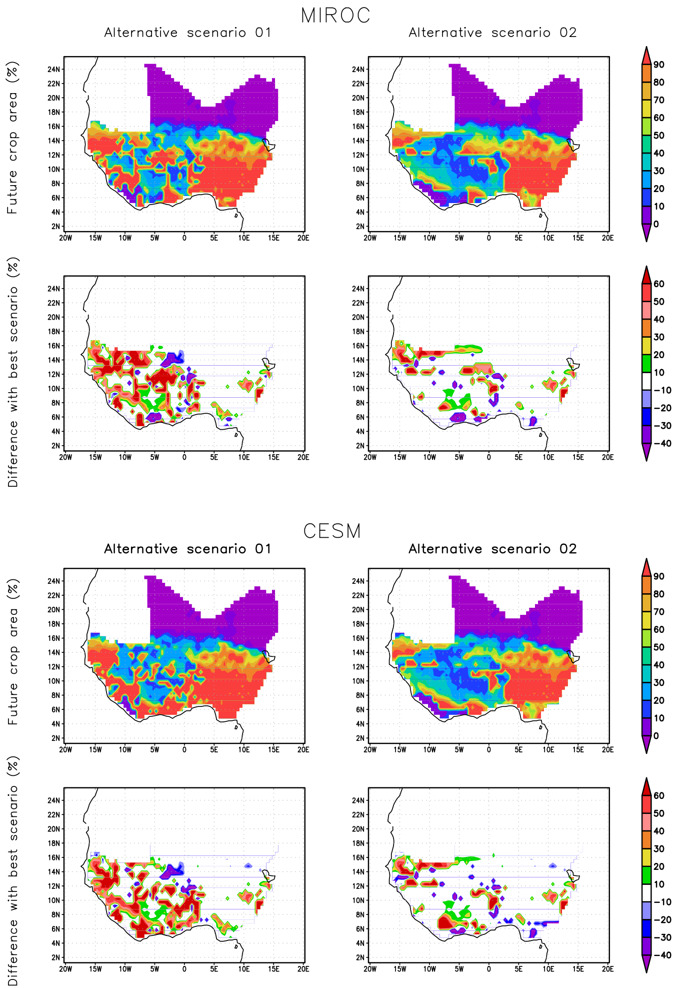

Figure 6. Spatial maps of future crop area percentage (1st and 3rd rows) in the West Africa (under the MIROC- and the CESM-driven climate) projected by the LandPro algorithm following two alternative scenarios with respect to selecting the remaining grid cells for conversion to agricultural land based on the order of yield and their respective differences (2nd and 4th rows) with the initial run which follows descending order of yield (best scenario). Alternative scenario 01: ascending order of yield; alternative scenario 02: random order.

ESDD
6, 1129–1162, 2015

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

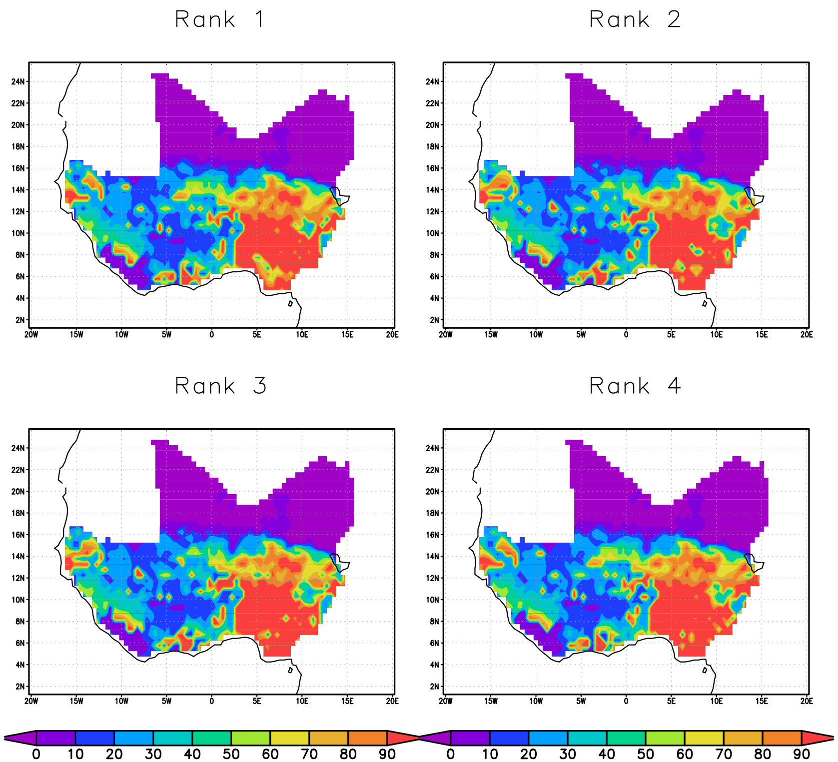

Figure 7. Spatial maps of future crop area coverage (%) in the West Africa under the MIROC-driven climate as projected by the LandPro algorithm following four different rankings of crops prioritized by the farmers to optimize agricultural land use. Rank 1: descending order of country-level crop deficit (initial run); rank 2: ascending order of country-level crop deficit; rank 3: maize, sorghum, millet, cassava, peanut; rank 4: peanut, cassava, millet, sorghum, maize.

ESDD
6, 1129–1162, 2015

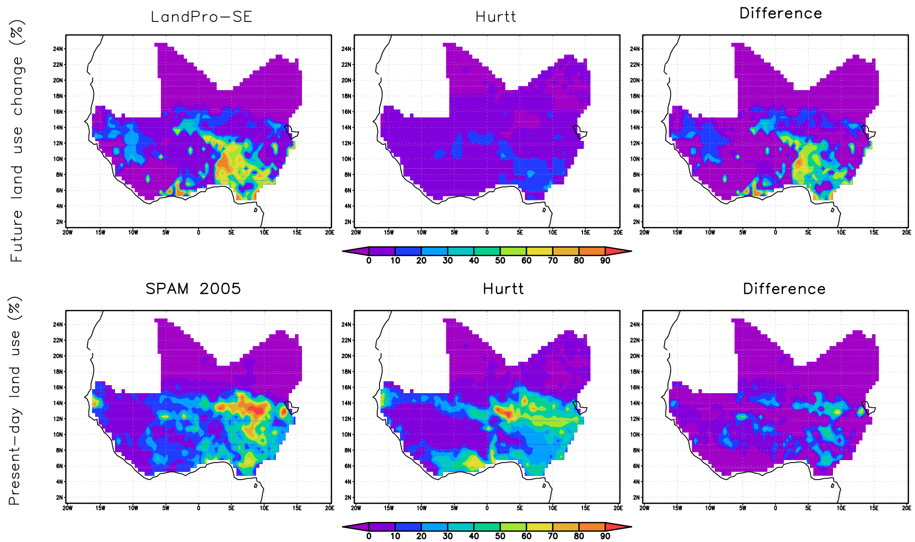

Figure 8. Future changes in crop area distribution according to the LandPro projections accounting for only socioeconomic changes (LandPro-SE) and Hurtt et al. (2011) data (top row). Comparison of the SPAM present-day (2005) crop area with respective Hurtt et al. (2011) data (bottom row).

ESDD
6, 1129–1162, 2015