<u>Title:</u>

Can Agricultural Intensification Help to Conserve Biodiversity? A Scenario Study for the African Continent

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- Land-use scenarios for Africa test tradeoffs between land sharing and land sparing
- The Biodiversity Intactness Index quantifies effects of agriculture on biodiversity
- Land sparing scenarios show higher values for the Biodiversity Intactness Index
- Complementary land systems studies at the local and regional level are required

Can Agricultural Intensification Help to Conserve Biodiversity? A Scenario Study for the African Continent

Abstract: Globally, the production of food, feed, bioenergy and biomaterials has increased considerably during the past decades. This was achieved by the expansion of agricultural land and the intensification of agricultural management. Due to the conversion of natural ecosystems and the increasing use of pesticides and fertilizers, these processes are recognized as important causes of biodiversity loss. This study focuses on the African continent and analyses the potentials to achieve a stable food provision for a growing population, and at the same time reduce further losses of biodiversity. These targets are important elements of the UN Agenda 2030. Using the spatially explicit land-use model LandSHIFT, we assessed the effectiveness of different land-sparing and land-sharing strategies to achieve these targets until the year 2030. The simulation results indicate that under the assumptions tested, the land sparing approach yields the most desirable results both, on the continental and the regional level. However, the land sharing/sparing framework in general and the research presented here are only analyzing the effect of two factors of many (food production and biodiversity conservation). Hence, they should not be understood to provide specific management recommendations. Further studies, from the regional to the local level, are required that apply a systems approach to understand and explain the multiple dimensions of sustainable food production on the African continent.

Keywords: land sharing; land sparing; Biodiversity Intactness Index; land systems; scenario analysis; Africa;

1. Introduction

Over the past decades, the expansion of agricultural land and the intensification of agricultural management have been indispensable for providing food, feed, bioenergy, and biomaterials for a growing world population (Foley et al., 2005; Rudel et al., 2009). Despite these efforts agricultural production in some sub-Saharan regions is not sufficiently stable to fulfil food demands adequately, often resulting in a high risk of malnutrition (e.g. Akombi et al. 2017; Bain et al 2013). At the same time, the resulting conversion of natural ecosystems and increased application of pesticides and fertilizers were identified as important causes for the loss of biodiversity (Balmford et al., 2012; Newbold et al., 2015).

In the light of the projected population growth in many African countries, together with a shift to richer diets and more material-intensive individual lifestyles, the improvement of access to and availability of food in these regions will be a central issue for scientists, practitioners and politicians in the coming decades (e.g., Godfray et al., 2010). In this sense, Laurance et al. (2014) expect that continuing expansion and intensification of agriculture in sub-Saharan Africa will even aggravate the current conflicts between food production and conservation of biodiversity.

The effectiveness of further intensification as a strategy to slow down the expansion of agricultural land and loss of natural vegetation while fulfilling food production requirements is heavily debated in the scientific literature (e.g., Laurance et al., 2014; Rockström et al., 2017; Tittonell and Giller, 2013). On the extremes, we find two opposing positions: (1) the land sparing approach advocates the implementation of highly intensified agricultural systems and a strict separation between managed and unmanaged land (Green et al., 2005); (2) the land sharing strategy favors ecosystem-friendly management practices with potentially lower crop yields but with less negative impacts on biodiversity, e.g., by limiting the application of fertilizer and pesticides (Phalan et al., 2011; Tilman et al., 2012). However, recent studies highlight the need for an integrated approach that supports sustainable intensification of agriculture to achieve both goals - a halt of cropland expansion and the conservation of a biodiversity in natural and agricultural systems (Fischer et al., 2014; Kassie et al., 2015; Tscharntke et al., 2012). Finding appropriate solutions to this problem is a key challenge to fulfil the goals defined by the "Sustainable Development Agenda" (Agenda 2030) of the United Nations (United Nations 2015). The UN recognizes the negative impacts of food insecurity and biodiversity loss on human development issues by including them as priorities in the "Sustainable Development Goals" (SDGs) for the period from 2015 until 2030. While SDG 2 "End of Hunger" addresses food security, SDG 15 "Life on Land" demands the preservation of biodiversity.

Land-change models in combination with the scenario technique can help to gain a better scientific understanding of these trade-offs by exploring trajectories of future agricultural development and their impacts on biodiversity. For example, Biggs et al. (2008) analyse land-use scenarios and their effects on biodiversity in Southern Africa, while van Soesbergen et al. (2017) focus on future agricultural development and its impacts on biodiversity in Uganda, Rwanda, and Burundi. Delzeit et al. (2017) and Newbold et al. (2016) present global studies analysing the trade-offs between cropland expansion and biodiversity. However, most of the modeling studies that explicitly compare land sparing and land sharing strategies either use highly idealized settings (e.g., Green et al., 2005) or are conducted on the landscape level (e.g., Deguines et al., 2014; Egan & Mortensen, 2012).

In the study presented in this paper, we address this research gap by applying an empirically driven, spatiotemporal simulation model for a continental scale analysis for Africa. Our objective is to assess the potential to reach both goals that are defined by SDG 2 and SDG 15 until 2030: An adequate food production to end hunger and the conservation of biodiversity. To achieve this, we conducted scenario-based simulation experiments, using the land-use model LandSHIFT (Alcamo et al., 2011; Koch, 2010; Rüdiger Schaldach et al., 2011). In the scenarios, the model used different crop production intensities to calculate the resulting expansion of agricultural land and loss of natural vegetation, respectively. Based in these model outcomes, we applied the Biodiversity Intactness Index (BII) (Scholes and Biggs, 2005) to quantify the effects of the calculated land-use changes on biodiversity losses.

2. Materials and Methods

2.1. Study Design

To understand the potential for reaching the two goals biodiversity conservation and reduced expansion of farmland, we use the spatiotemporal simulation model LandSHIFT (Alcamo et al., 2011; Schaldach et al., 2011; Schaldach and Koch, 2009) in the context of a scenario analysis for the African continent. The base year of our analysis is the year 2000. We run the simulation model for ten years, until 2010, and use the simulation output for this year to validate the model. We then run the validated model until 2030 to explore three scenarios with varying intensity levels for agricultural activities. We combine our spatial simulation results on land use and land cover with information from the GLOBIO-3 framework (Alkemade et al., 2009) and apply the Biodiversity Intactness Index (Scholes and Biggs, 2005) to explore the potential of reaching a halt of farmland expansion while simultaneously reducing the corresponding detrimental effects on biodiversity in Africa. **Figure 1** shows how the different analysis components described in the following sections form the workflow of our study.

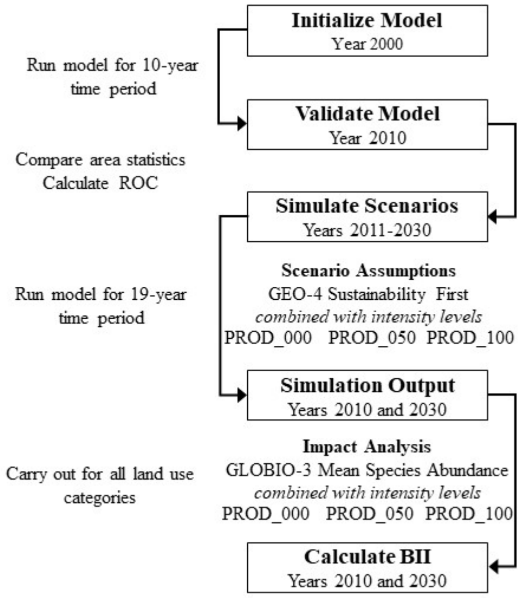

Figure 1. Workflow of the study describing the steps of the analysis.

2.2. Land-Use Modelling

We used the spatially explicit land-use model LandSHIFT to simulate land use/cover change at a spatial resolution of 5 arc minutes (approx. 9 km x 9 km at the Equator). LandSHIFT has been successfully applied to Africa in previous studies (e.g., Alcamo et al., 2011; Heubes et al., 2013; van Soesbergen et al., 2017). The model uses a cellular automata approach; it works on a regular raster and allocates land use to grid cells based on a weighted multi-criteria analysis, calculating potential suitability for different land-use activities (urban development, crop production, and livestock grazing). Based on population numbers, a population density is determined for each cell. If the population density exceeds a pre-defined threshold value, the dominant land use type on the respective cell is converted to urban. The same approach is applied for livestock grazing; forage consumption drives cell-level stocking density (SD) for grazing animals. A cell's land use type is converted to rangeland if the SD exceeds the pre-defined threshold. The output of LandSHIFT simulations consists of land use/cover maps, population density maps, and SD maps. Furthermore, a set of area and productivity statistics is included in the model output.

2.3. Scenario Description

We use the UNEP GEO-4 scenario Sustainability First (Rothman et al., 2007) as a basis for our simulation experiment. Sustainability First's storyline has a strong focus on significant improvements of human nutrition and food security and on preserving valuable ecosystems, which are the core components of the SDGs forming the basis of this study (SDGs 2 and 15). According to van Vuuren and Carter (2014), this scenario can be classified as a "global sustainable development" archetype and shares comparable assumptions with the Shared Socioeconomic Pathway 1: Sustainability – Taking the Green Road (e.g., O'Neill et al., 2017). Despite the availability of more recent scenarios, we chose a UNEP GEO-4 scenario because these scenatios are well documented and present clear ideas of how current social, economic, and environmental trends might develop in the future. Moreover, they are to the knowledge of the authors the only scenarios for the whole African continent that were developed in a participatory process together with regional stakeholders (Rothman et al., 2007).

To evaluate the effect of agricultural intensification on biodiversity, we combined the underlying assumptions for Sustainability First with three intensity levels for agricultural activities. These intensity levels are variations of the assumptions on increase in crop productivity specified for the Sustainability First scenario. We refer to the original assumption on productivity increase, which we consider optimistic, as **PROD_100**. The second level makes moderate assumptions on crop productivity increase by reducing the original increase by 50% (referred to as **PROD_050)**. For the third level, **PROD_000**, we define the productivity to remain at the year 2010 levels (i.e., no intensification of agricultural production). We use PROD_100, the scenario assumptions with the highest productivity increase as way to represent a land sparing approach, whereas we use PROD_000 as proxy for a land sharing approach.

2.4. Input Data

2.4.1. Model Initialization

The first step in our analysis was the construction of a gridded land-use map for the year 2000 with a spatial resolution of 5 arc minutes. We generated the map by merging census data on cropland and grazing area (FAO 2014) for each country with MODIS land-cover data (e.g., the location of arable land) (Friedl et al., 2002). This map formed the basis for estimating the parameter values for the suitability analysis of the three land-use activities modeled by LandSHIFT. We provide a detailed description of the model initialization process in **Appendix A**.

2.4.2. Scenario Assumptions

We derived input for LandSHIFT from Sustainability First scenario calculations. Model input data on the country level include population numbers, livestock numbers, crop production, and change in crop productivity due to agricultural intensification. Population projections for the GEO-4 scenarios were computed by the IFs model (Hughes, 1999). Under Sustainability First, Africa's population increases from approximately 0.8 billion in 2000 to about 1.48 billion in 2030. Future agricultural production and trade information was computed by the IMPACT model (Rosegrant et al., 2008). Production of the major crops increases from about 77 million metric tons to 172 million metric tons while crop productivity due to technological change and improved management practices are assumed to increase by 74% from an average grain yield of 1.34 t/ha to 2.33 t/ha. The production of grazing livestock rises from about 66 million livestock units in 2000 to 120 million livestock by 2030. The calorie availability per capita and day is assumed to increase from below 2,000 calories/day up to about 3,000 calories/day. Due to the scenario emphasis on biodiversity conservation, we excluded protected areas from being converted to settlement, cropland or rangeland.

2.4.3. Other Input Data

We initialized LandSHIFT with a historical land-use map (hereafter referred to as base map) representing the year 2000 (see section 2.4.1). Crop yields were provided through

LPJmL model simulations (Bondeau et al., 2007) for current climate conditions as described in Schaldach et al. (2011). Other input datasets in the LandSHIFT model include terrain slope (GAEZ; IIASA and FAO, 2000), population density (GRUMPv1; CIESIN, 2011), road network density (gROADSv1; CIESIN, 2013), river network density based on Lehner et al. (2006), the risk of tsetse fly occurrence (Wint and Rogers, 2000) and the location of nature conservation areas as defined in the world database on protected areas (IUCN and UNEP-WCMC, 2014). We used data on the spatial distribution of species diversity from Jenkins et al. (2013), who compiled a global gridded dataset on five arc minutes on vertebrate diversity differentiating between birds, mammals, and amphibians.

2.5. Model Validation

For model validation, we use a 10-year simulation period. We tested the plausibility of the suitability analysis and compared the calculated cropland extent with statistical country-level data for the year 2010. Hence, we validate our model on a spatial level different from the level on which the simulated process operates (i.e., grid cell level vs. country level). We provide a detailed description of the model validation process and results in **Appendix C**.

2.6. Biodiversity Intactness Index

We use the Biodiversity Intactness Index (BII) for quantifying the potential trade-offs between agricultural intensification (land sparing) and expansion of croplands and grazing lands (land sharing). The BII was developed initially for Southern Africa and describes species diversity at a particular point in space and time compared to the pre-colonial period before the year 1700 (Biggs et al., 2008; Scholes and Biggs, 2005).

We calculate the BII on the cell level. Each cell represents an ecosystem with the cell's size being its areal extent, and its species richness being based on the sum of birds, mammals and amphibians as given by Jenkins et al. (2013). The calculation of a cell-level BII allows for the calculation of an average value of BII on different spatial levels of interested (landscape, watershed, country, or ecoregion). Biggs et al. (2008) define the Biodiversity Intactness Index as:

$$BII = \frac{\sum_i \sum_j \sum_k R_{ij} A_{jk} I_{ijk}}{\sum_i \sum_j \sum_k R_{ij} A_{jk}} \tag{1}$$

Equation 1 defines BII as the average impact across taxa *i*, ecosystems *j*, and land use types *k*. The impact is defined as the population abundance of a given species or group of species relative to the reference state I_{ijk}, weighted by the areal extent of each land use A_{jk} and the intrinsic species richness of the ecosystems affected R_{ij}. A BII close to 100% indicates that species abundance is on the pre-colonial level, while values near 0% indicate that species become extinct.

For estimating the impact *I* of a particular land-use, we combine LandSHIFT output with information from the GLOBIO-3 framework (Alkemade et al., 2009). The GLOBIO-3 database provides data, which specifies the respective reduction of mean species abundance (MSA) for different land use categories and use intensities (Table 1). The values for reduction of MSA are then mapped to LandSHIFT simulation output. For example, build-up area reduces the original MSA by 95%. Cultivated land is further subdivided into low-intensity agriculture with a reduction factor of 70% and high-intensity agriculture with a reduction factor of 90%. The proportions of low intensity and high intensity agriculture are based on Dixon et al. (2001). For Northern Africa the share of intensive agriculture is 64% while in Sub-Saharan Africa it accounts for only 24% (Table 2). We assign the class "extensive grazing" to cells where livestock density is lower than the defined threshold value, and which still have the land-cover type of the original ecosystem (e.g., Savannah). The threshold value was calculated by dividing the livestock (cattle) number by the rangeland area (FAO, permanent meadows and pasture) for each African country separately. The resulting country specific mean grazing densities were averaged over all countries within each modeled African region (North Africa, Western Africa, Central Africa, Eastern Africa and Southern Africa) with the result of a threshold value defining the intensity of the grazing management. Accordingly, the class "man-made pastures" includes cells with high stocking densities and the land-use type rangeland.

Table 1. Mean species abundance (MSA) values under different land-use types. The MSA values are based on (Alkemade et al., 2009) and (Biggs et al., 2008).

Land use type	MSA
Cropland	
Low input	0.30
Intensive	0.10
Grazing land	
Extensive grazing	0.70
Manmade pastures	0.10
Forest	
Primary forest	1.00
Lightly used forest	0.70
Secondary forest	0.50
Forest plantations	0.20
Natural vegetation	
Bare land	1.00
Savannah and grasslands (moderate use)	0.94
Urban	0.05

Table 2. Comparison of percentage of low and high intensity cropland in 2010 (Alkemade et al., 2009) and in 2030 as calculated by LandSHIFT for the three different productivity scenarios (PROD_000, PROD_050, and PROD_100).

	2010	PROD_000	PROD_050	PROD_100
Northern Africa				
Low input	36%	36%	11%	2%
High input	64%	64%	89%	98%
Western Africa				
Low input	76%	76%	59%	46%
High input	24%	24%	41%	54%

Eastern Africa				
Low input	76%	76%	54%	45%
High input	24%	24%	46%	55%
Central Africa				
Low input	76%	76%	55%	42%
High input	24%	24%	45%	58%
Southern Africa				
Low input	76%	76%	53%	38%
High input	24%	24%	47%	62%

2.7. Trade-Off Analysis

We used a geographic information system to analyse the effect of land-use change on biodiversity. For this purpose, we overlaid the four simulated raster maps–one for the year 2010 and three for the scenario simulations for the year 2030–with the gridded map of vertebrate diversity (Jenkins et al., 2013). We then combined this information with grid cell information on land-use type, population density, and livestock density, and calculated the BII for the five GEO-regions Northern Africa, Southern Africa, Eastern Africa, Western Africa, and Central Africa (see **Appendix A** for a list of the countries included in the different regions).

To calculate the BII, the fraction of intensive agriculture is required (see section 2.6). In the PROD_000 scenario (no agricultural intensification) the fractions of intensive agriculture is kept constant on the year 2000 level. For the intensification scenarios PROD_050 and PROD_100, we define the change in fractions of intensive agricultural based on the reduced extent of cropland as compared to the PROD_000 scenario. For example, in country A under PROD_000, cropland increases from 100 km² to 200 km² and under PROD_100 only to 150 km² which is 25% less area. Hence, the fraction of intensive agriculture under PROD_100 increases by 25% compared to PROD_000. Table 2 shows the fraction of low intensity and high intensity agriculture for the base year and the different scenarios. Starting point is the calculated 2010 map that was also used for model validation (see section 2.5).

The results of our scenario analysis are displayed on a GEO region level (Table 3). Based on the results from the scenario analysis, we further evaluate the sensitivity of the BII calculations to cropland intensification. For this purpose, we expanded the cases tested by adding assumptions on the agricultural intensity. For each scenario, we test the outcome under the assumption of all cropland being high intensity as well as all cropland being low intensity agriculture. This is realized by using the corresponding MSA values listed in Table 1.

3. Results

3.1. Land Use and Cover Change

Figure 2 displays the spatial pattern of changes in cropland and pasture as calculated by LandSHIFT. In year 2010 (Figure 2 panel (A)), the total cropland area is 1.6 Mkm² amounting to about 5% of the total land area. Pasture area is 1.76 Mkm² while more than 6.7 Mkm² is used as extensive grazing land. The spatial pattern of land-use change until 2030 for the PROD_000 and the PROD_100 scenarios are displayed in Figure 2 panels (B) and (C), respectively. The simulations show that new land use areas are mainly located in the northern part of the sub-Saharan regions.

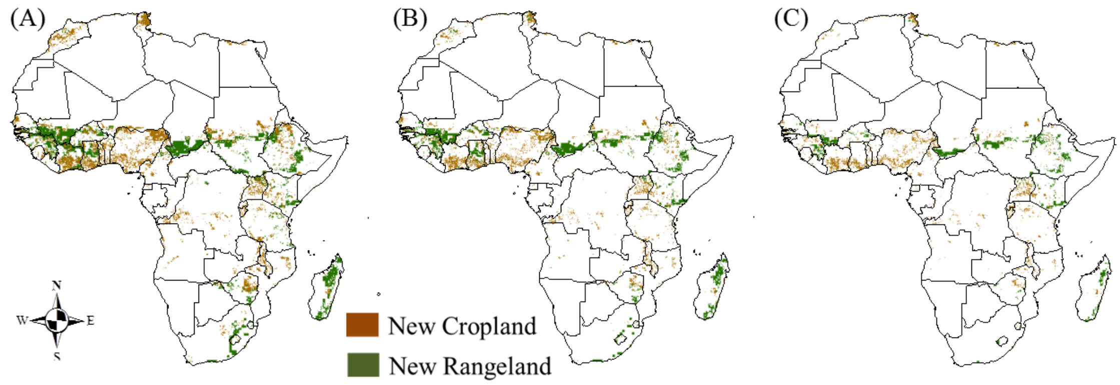

Figure 2. Spatial pattern of cropland and grazing land as calculated by LandSHIFT for (A) the year 2010, (B) for the year 2030 with yield increases from the Sustainability First scenario (PROD_100), and (C) for the year 2030 without yield increases (PROD_000).

Table 3 summarizes the areas for the different land-use categories on the continental level. For cropland areas, all scenarios display in area increase as compared to the year 2010. The area increase ranges up to 0.81 Mkm^2 for the PROD_000 scenario – the scenario with production intensity on the base year level. The scenarios with assumptions on productivity increase show considerable lower expansion of cropland area, with 0.35 Mkm^2 for the PROD_050 scenario and 0.12 Mkm^2 for the PROD_100 scenario.

Table 3. Absolute land-use areas in million square kilometres [Mkm^2] on the continental level for the three different scenarios of agricultural intensity.

Continental Africa	2010	PROD_000	PROD_050	PROD_100
Light grazing	6.78	6.15	6.20	6.53
Pasture	1.76	2.94	2.57	2.17
Cropland	1.60	2.41	1.95	1.72
Forest	2.25	2.15	2.19	2.21
Natural vegetation	16.28	14.99	15.73	15.98
Urban area	0.05	0.07	0.07	0.07

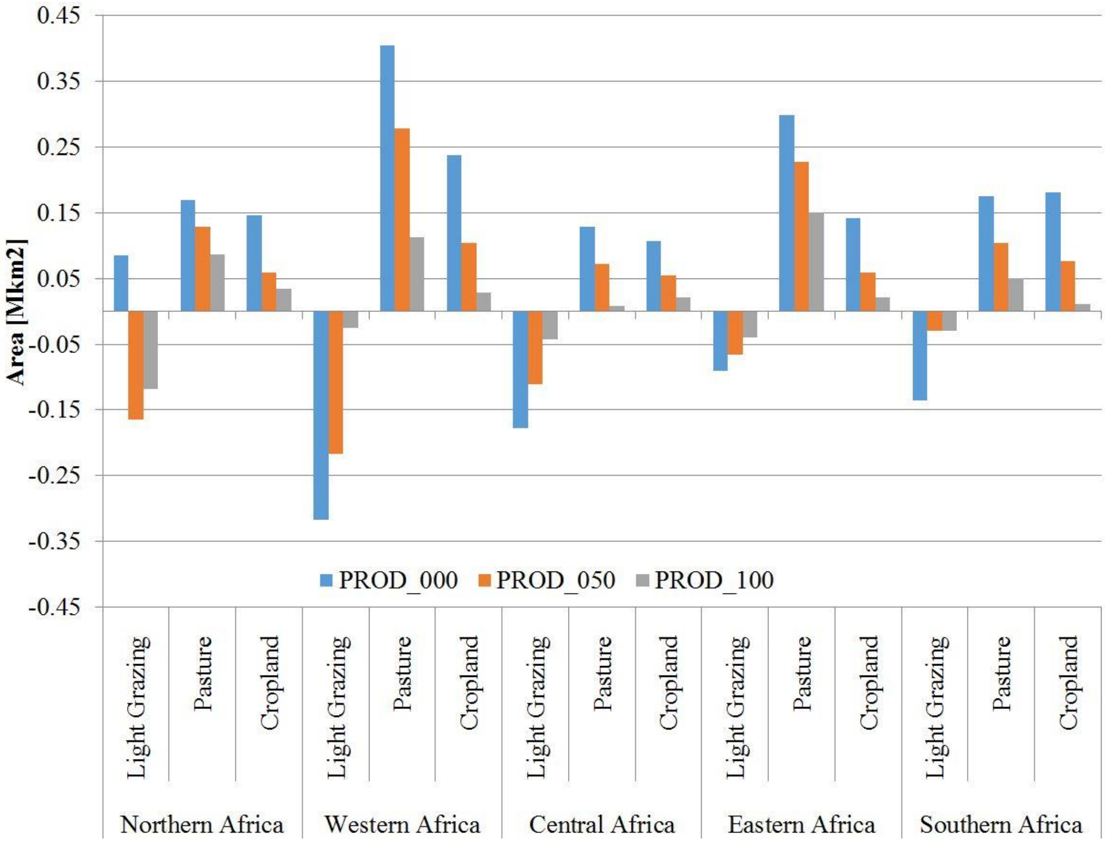

Figure 3. Changes in land-use categories on the regional level (GEO-4 regions as described in Appendix A, Table S1) for the different productivity scenarios. Values are provided in million square kilometres [Mkm^2].

On the continental level, the figures for pasture area show the same general trend between scenarios as the cropland areas (Table 3), with the lowest area increase for PROD_100 (0.41 Mkm^2) and the highest increase for PROD_000 (1.18 Mkm^2). On the regional level, we observe a similar trend (Figure 3). Additionally, the simulation results display a shift from extensively used grazing area to more intensively managed pasture in all scenarios with the former decreasing. In 2010, the fraction of pasture to total grazing land is 21%. In the PROD_000 scenario this fraction increases to 32%, in PROD_050 to 29% and in PROD_100 to 25%. Again, these trends can also be observed on the regional level (Figure 3). Here, Northern Africa is an exception; under the PROD_000 the results also indicate an increase in extensively used grazing area.

3.2. Effects of Land Use/Cover Change on Biodiversity

Figure 4 displays the relation between the Biodiversity Intactness Index (BII) and absolute area with a change in land use/cover on the regional level for the year 2010 (0 km^2 converted) and the three different productivity scenarios. For 2010, the BII ranges between 62% for Central Africa and 89% for Northern Africa. For all regions, the scenario simulations show a larger area converted from natural/forest to other land uses/covers with lower productivity level (Figure 3). As a result, we see a decrease in the BII from its value in 2010 over the PROD_100 and then the PROD_050 scenario, reaching the lowest values for the PROD_000 scenario (Figure 4). Central Africa shows the lowest decrease of all regions, with a BII of 89% in 2010 and a BII of 86% in 2030 for the PROD_000 scenario. The strongest BII decrease is projected for Eastern Africa, with a decline form 69% in 2010 to 57% in 2030 for the PROD_000 scenario. The BII values for Northern Africa stand out due to the large difference in converted area between the PROD_050 scenario and the PROD_000 scenario, resulting in a large reduction of BII values.

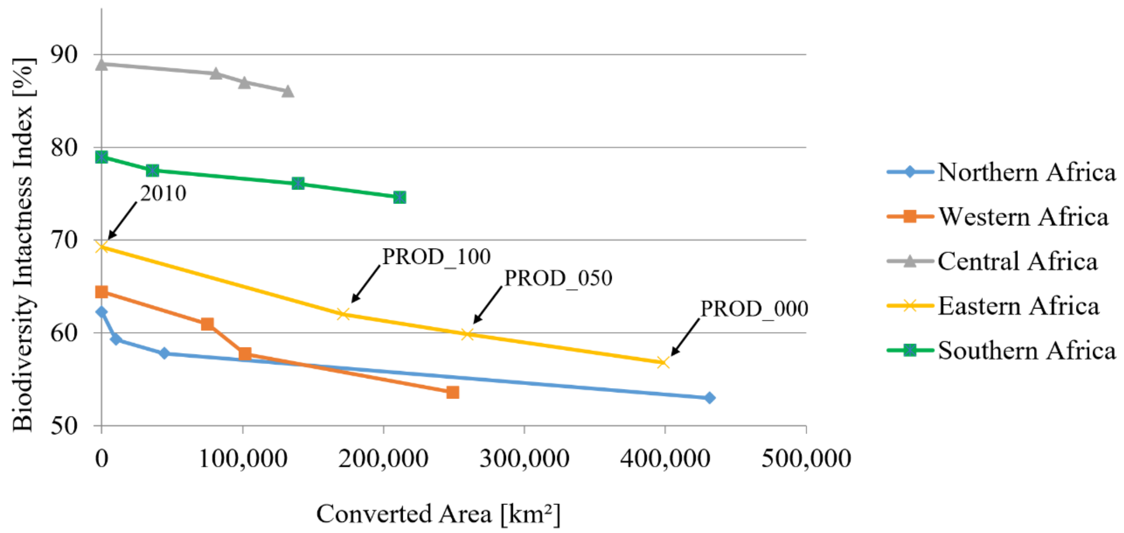

Figure 4. Area converted from natural land cover (e.g., grassland, shrubland, barren land and forest) to other land uses/covers and Biodiversity Intactness Index (BII) on the regional level for the year 2010 and for the year 2030 under the three productivity scenarios. As illustrated for Eastern Africa, in all regions the lowest area conversion is under PROD_100, followed by PROD_050 and PROD_000.

3.3. Effects of Land-Use Intensity on Biodiversity

Figure 5 visualizes the simulation results for the trade-off analysis assuming different management practices for cropland intensities combined with the different productivity scenarios (see section 2.7). For the individual regions, we see the same trend as described in section 3.2, with the highest BII values for the PROD_100 scenario and the lowest values for the PROD_000 scenario. Within each scenario, the value of low-input agriculture marks the upper end of the calculated BII range and the value of intensive agriculture marks the lower end of the calculated BII range. In general, the results indicate no overlap between the ranges for the different productivity scenarios. However, there is one exception for Western Africa. Here, the lowest detrimental impact from PROD_050 (60%) is slightly higher than the highest detrimental impact from PROD_100 (59%). Compared to the PROD_000 scenario, the other two scenarios display smaller variation in the BII across all regions.

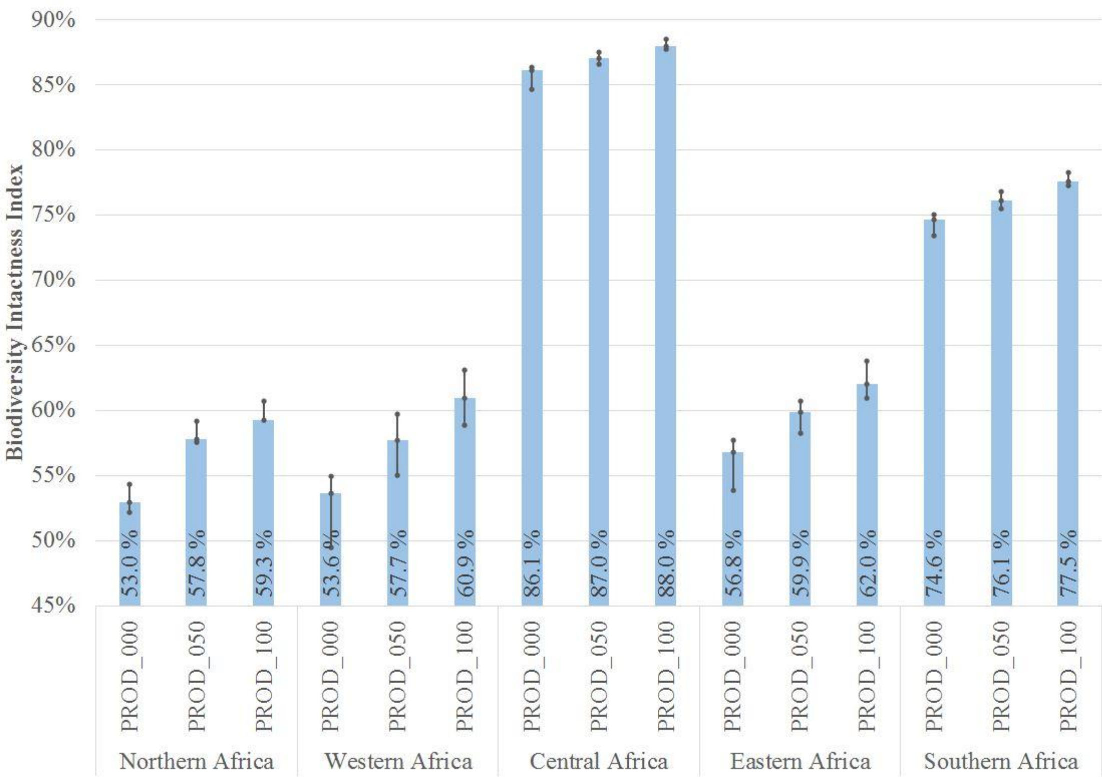

Figure 5. Results for testing the response of Biodiversity Intactness Index (BII) value to varying levels of cropland intensity connected to Mean Species Abundance (MSA) values. The upper end of the BII range reflects an MSA value of low-input agriculture (0.3), the lower end of the BII range reflects an MSA value of intensive agriculture (0.1). The bars (and values listed at the bottom of the bars) display the level of impact by calculated intensification as described in section 2.7.

4. Discussion

In this study, we applied the land sharing/land sparing framework as introduced by Green et al. (2005) and conducted scenario simulations with the LandSHIFTmodel with a five arc min resolution for the African continent. We used the GEO-4 Sustainability First scenario (Rothman et al., 2007) to drive our simulations because it is a good match for our emphasis on two of the SDG, namely Zero Hunger and Life on Land (United Nations, 2015). We furthermore combined the scenario with different assumptions on yield increases due to technological change to represent land sharing and land sparing. The simulation results, including simulations on demands for urban area, cropland, and grazing land, allowed us to quantify area required for food production. We then combined the simulation results with indicators from GLOBIO (Alkemade et al., 2009) and data on species abundance (Jenkins et al., 2013) to calculate the Biodiversity Intactness Index (Scholes and Biggs, 2005), which we used as a way to quantify the trade-offs between biodiversity conservation and production intensity, and hence land sharing/sparing. While there have been several studies exploring the impacts of land-use change on biodiversity in different African regions (e.g., Biggs et al., 2008; van Soesbergen et al., 2017) and on the global level (e.g., Jantz et al., 2015; Newbold et al., 2016), this study is the first one to analyse potential trade-offs and conflicts between between the two extremes of the land sharing/sparing framework on the continental level for Africa.

4.1. Effects of Agricultural Intensity

The major outcome of our analysis is, that under the scenario assumptions tested, and given the use of BII as indicator for quantifying trade-offs between land sharing and sparing, the land sparing approach (i.e., highly intensive agricultural activities) provided the best results for the BII. This applies for both, the continental and the regional level. Our results indicate that the lower land demand through intensification leads to lower biodiversity losses (= higher BII values) even if local impacts on species abundance are considerably stronger than in the low- and non-intensification case. Even when we assume 100% of biodiversity loss under full intensification, the impact level would still be lower than the hypothetical case of no intensification without any negative effects on biodiversity intactness.

These results underline the importance of increasing crop productivity and more effective grazing management as a prerequisite for slowing down the loss of natural ecosystems on the continental level. They confirm the findings from other scenario analyses (e.g., Kok et al., 2018; Tilman et al., 2017) and empirical studies that show the advantages of land sparing for biodiversity conservation (Hulme et al., 2013; Phalan et al., 2011). In the light of the existing high discrepancy between actual and achievable yields with an improved agricultural management (Tittonell and Giller, 2013), the scenario assumptions regarding the maximum crop yield increases until 2030 seem plausible, at least from the technological point of view (Mauser et al., 2015). However, as Ray et al. (2012) point out, it is uncertain whether these potentials can be realized. Additionally, other authors stress potentially negative climate impacts on crop yields (Challinor et al., 2007; Schlenker and Lobell, 2010) which will demand specific adaptation measures in agriculture. These uncertainties are reflected in the two sub-scenarios with lower yield increases.

4.2. Reflecting on the Land Sharing/Sparing Framework

Fischer et al. (2014) discuss key priorities for moving forward with the land sharing/land sparing framework. Specifically, they recommend to structure the discussion around land scarcity over food production and to acknowledge the limitations of trade-off analyses when using the land sharing/sparing framework. According to Fischer et al. (2014), discussing land scarcity instead of food production will help to avoid criticism for disregard of the role of food security and food sovereignty. Discussing land scarcity acknowledges that not all agricultural production is for food and that the economic demand for agricultural products is higher than the requirements for the actual need for food (Fischer et al., 2014). The LandSHIFT model (Schaldach et al., 2011; Schaldach and Koch, 2009) is well suited to analyze land scarcity at the larger scale. Our study analyses availability of area required to fulfil the demand for different agricultural activities. We found that at the continental and regional scale, there was no scarcity of land suitable to produce the required demand for agricultural commodities. However, the availability of land for crop production does not guarantee the on-the-ground implementation of agriculture in a way that actually fulfils the demand. For this point, we consider the discourse around food security and food sovereignty as complementary. While our simulations showed that it is realistic to assume—at least under the assumptions specified for the tested scenarios—that sufficient land resources are available to meet the demand for agricultural products, studies on the regional and local level revolving around the topics of food security and food sovereignty are required to implement fair and sustainable food production in Africa and to achieve the SDGs of

Zero Hunger and Life on Land (e.g., Garibaldi et al., 2017; Nijbroek and Andelman, 2016; Waha et al., 2018).

Fischer et al. (2014) point out that, while there is an intellectual value to trade-off analyses for land sharing/sparing, these analyses have limited value to inform real-world decision making. More specifically, the authors emphasize that land management decisions are typically not made based on the two factors production and diversity, but are more likely a "wicked" problem. These are problems where no single best solution exists (Game et al., 2014). There is, however, a value to trade-off analyses. They can help to identify situations where an increase in one factor leads to no or minimal detrimental effects on the other factor (Fischer et al., 2014). Applying this advantage to our simulation results, we can see that reflected in the regional differences (Figure 4, 5). When analyzing the difference between the production intensities, we can see that for Central and Southern Africa the effect of different agricultural intensities on biodiversity conservation is less pronounced as compared to Northern, Eastern, and especially Western Africa. This means that for Central and Southern Africa there exist allocations of crop production where highly intensive agricultural activities have a relatively small negative effect on biodiversity conservation. However, a trade-off analysis like ours provides no guidance on which allocation or intensity level is the "socially preferable" one (Egli et al., 2018; Fischer et al., 2014, p.151).

4.3. Study Limitations and Next Steps

While we were able to identify important findings on land sharing/sparing trade-offs for the African continent, there are some limitations to our study approach. The first major limitation is that the effect of future climate on crop yields and biomass productivity was not considered in this study. Since it is likely that a change in climatic conditions will have a detrimental effect on crop yields (e.g., Challinor et al., 2007), our simulation results may underestimating the amount of cropland and grazing area required to fulfill future needs for food and feedstock production. At the same time our modelling approach only considers the increase of stocking densities on grazing land but neglects other mechanisms of intensification such as a change in the feed basket towards a larger share of crops and residues (Herrero et al., 2013) which might significantly reduce the demand for pasture and rangeland (Weindl et al., 2015).

Another limitation of our analysis is the use of species diversity and richness data for mammals, amphibians and birds (Jenkins et al. 2013). Other taxa with important ecological functions such as plants, funghi and arthropods were not considered. Also, while many studies on land sharing/sparing use species richness, it may not be the most suitable descriptor of biodiversity (Phalan, 2018). This is because species richness does not indicate changes in species composition and population size (Hillebrand et al., 2018; Matthews et al., 2014). One way to avoid this issue would be to follow the recommendations of Hill et al. (2016) and Mace et al. (2014) who suggest to use multiple indicators to capture different dimensions of biodiversity loss.

Our next steps will focus on improving the current limitations of our study. The use of information on other taxa such as plants, fungi and arthropods was hindered by the availability of data with a continental coverage. The same applies to the use of multiple indicators for biodiversity as suggested by Hill et al. (2016) and Mace et al. (2014). This shortcoming can be addressed as soon as suitable data for the African continent becomes available. Hence, we will focus our efforts on a more detailed assessment of climate change effects on food production. Specifically, we suggest the use of climate scenario simulations for the different RCPs (Moss et al., 2010) to prepare simulations of potential future crop productivity under different climate conditions. This would allow the quantification of the possible effect of changes in climate on crop yields, and hence more detailed estimates of area demand for food production.

5. Conclusions

As with every scenario study, it is important to emphasize that our results are not forecasts but projections of future developments valid only for the assumptions made for the tested scenarios. The value of our study lies in the improved understanding of the availability of land resources for future food production, and in quantifying how different production intensities affect biodiversity (specifically species abundance). Our method of combining land change simulations with data from the GLOBIO-3 database on mean species abundance to create a density-yield curve and using the Biodiversity Intactness Index is a new way to quantify land sharing and land sparing trade-offs for large-scale simulation studies. Our findings highlight the importance of agricultural intensification for achieving the SDGs Zero Hunger and Life on Land. However, agricultural intensity and biodiversity conservation are only two of many factors to consider when making decisions about food production. When taking into account social and political factors, the land sparing approach might not be the favourable option. While the potential for food production is given, many efforts on the national, regional, and local levels will be required to achieve the SDGs and the best possible outcomes for human well-being.

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Supplementary material

Appendix A - Model initialization and spatial units

The first step of the modelling exercise was the construction of a gridded land-use map (base-map) for the year 2000. Statistical information on crop cultivation on country level was merged with MODIS land-cover data (e.g. location of arable land). Grazing land was distributed by merging FAO data (permanent meadows and pastures) with country-level livestock numbers according to the net primary productivity on each cell as calculated by LPJmL (Bondeau et al., 2007). The result is a land-use map with grid-level information on the spatial distribution of different crop types as well as area used for grazing. Based on this base-map the parameter values for the suitability analysis of the three land-use activities modelled by LandSHIFT were estimated as described in Appendix B.

Table A1: Grouping of the African countries in GEO-regions (Rothman et al. 2007)

Central Africa	Eastern Africa	Northern Africa	Southern Africa	Western Africa
Central African Republic	Burundi	Algeria	Angola	Benin
Chad	Ethiopia	Egypt	Botswana	Burkina Faso
Congo	Eritrea	Libya	Lesotho	Gambia
Dem. Rep. of Congo	Djibouti	Morocco	Malawi	Ghana
Equatorial Guinea	Kenya	Sudan	Mozambique	Guinea
Gabon	Madagascar	Tunisia	Namibia	Cote D'Ivoire
Sao Tome and Principe	Rwanda		South Africa	Liberia
	Somalia		Swaziland	Mali
	Uganda		Tanzania	Mauritania
			Zambia	Niger
			Zimbabwe	Nigeria
				Guinea-Bissau
				Senegal
				Sierra Leone
				Togo

Appendix B - Estimation of model parameter values

In the LandSHIFT model the preference of each grid cell for the different land-use types is determined with a multi-criteria analysis according to the following equation (Schaldach et al., 2011):

$$\psi_k = \underbrace{\sum_{i=1}^{n} w_i \; p_{i,k}}_{suitability} \times \underbrace{\prod_{j=1}^{m} c_{j,k}}_{constraints} \qquad , with \sum_i w_i = 1, \;\; and \;\; p_{i,k}, c_{j,k} \in [0,1] \tag{1}$$

The factors p_i reflect the most important geographical and biophysical drivers that affect suitability for a particular land-use type. The factor-weights w_i determine the importance of each factor at grid cell k, while c_j determine constraints for changing the land-use type of a cell. Both p_i and c_j are normalized by value functions transforming the factor values to a co-domain from 0 to 1.

Constraints c_j are applied in cells that are designated as nature conservation areas or according to possible transitions of land-use types. For example, it is assumed that a cell formerly used as rangeland is more suitable for being converted to cropland than a forest cell. Furthermore the risk of tsetse fly occurrence limits the suitability for rangeland.

LandSHIFT distinguishes between the three land-use activities settlement (METRO), crop cultivation (AGRO) and grazing (GRAZE). Each of these activities implements its own evaluation scheme. For METRO and GRAZE the factors (Table B1) were deduced from literature sources as described in Alcamo et al. (2011).

Table B1: Suitability factor weights for the two land use activities METRO and GRAZE for Africa.

Activity	Factor/constraint	Description	Default factor weight
METRO	Factor	Terrain slope	0.4
	Factor	Road infrastructure	0.6
	Constraint	Land use transition	
	Constraint	Conservation area	
GRAZE	Factor	Terrain slope	0.2
	Factor	River network density	0.2
	Factor	Grassland NPP	0.2
	Factor	Proximity to cropland	0.2
	Factor	Population density	0.2
	Constraint	Land use transition	
	Constraint	Conservation area	
	Constraint	Tsetse fly abundance	

In contrast, for AGRO the factor weights were determined for each of the five GEO-regions individually, based on the land-use data of the country with the largest cropland area within each region. For this purpose we used is the criteria importance through inter-criteria correlation (CRITIC) method proposed by Diakoulaki et al. (1995). An example of its application can be found in Schaldach et al. (2013). The method involves four steps. The first step is to calculate the standard deviation σ for each parameter p_i according to the initial land-use and land-cover pattern represented in the base map. This standard deviation is an expression for the contrast intensity of each parameter p_i in respect to the other parameters. The second step is to determine the linear correlation coefficient (c_{ij}) between all parameters p_i. When these correlation coefficients are summed up according to equation (2), the second step acquires a measure of the conflict created by parameter p_i with respect to the rest of the parameters.

$$\sum_{j=1}^{n}(1 - c_{ij}) \tag{2}$$

The third step is to aggregate the previously quantified information (contrast intensity and conflict) into one term following equation (3). This term (Inf_i) is an expression for the information carried by each parameter p_i.

$$Inf_i = \sigma_i * \sum_{j=1}^{n}(1 - c_{ij}) \tag{3}$$

The fourth and last step involves the calculation of w_i for each parameter p_i. This is accomplished by normalizing the resulting values Inf_i for each parameter p_i to 1 according to equation (4).

$$w_i = \frac{Inf_i}{\sum_{j=1}^{n} Inf_j} \tag{4}$$

The parameter values obtained for the five regions with the CRITIC method are summarized in Table B2.

Table B2: Suitability factor weights for the land-use activity AGRO and the identified regions of Africa.

Suitability factor	Central Africa	Eastern Africa	Northern Africa	Southern Africa	Western Africa
Slope	0.145	0.182	0.206	0.131	0.078
Proximity to agriculture	0.118	0.068	0.056	0.093	0.142
Population density	0.316	0.290	0.390	0.006	0.299
Road infrastructure	0.181	0.147	0.163	0.204	0.158
Crop yield	0.180	0.261	0.227	0.239	0.257

Appendix C - Model validation

Validation of the LandSHIFT model was done for the model assumptions regarding the cell suitability for cropland (suitability validation) and the calculated quantity of cropland expansion (Schaldach et al., 2011).

a) Validation of the suitability analysis

Cropland suitability is one of the key factors in land-use change decision making since it determines the most qualified sites for agricultural expansion or abandonment. Thus, it is important to test a models ability to compute this suitability. For the purpose of this study, two spatial methods to compare the accuracy of crop suitability calculation with estimates of the real location of areas used for agricultural cultivation were applied. LandSHIFT calculates cropland suitability as function of input variables within a range from 0 to 1. The real location of cropland is derived from the initial land use map for the year 2000.

The first method compares the frequency distributions of calculated cropland suitability on observed cropland grid cells to non-cropland grid cells. Our hypothesis is that cropland is located on grid cells with a high suitability rating since we expect that cropland has the highest priority compared to other kinds of land use. Non-cropland should be located on grid cells with lower suitability for crop cultivation respectively. The results as shown in Table C1 verify our hypothesis. The values show that the mean suitability of cropland cells is higher as for non-cropland cells.

Table C1: Results from the suitability evaluation.

GEO-region	Mean suitability Non-cropland	Mean suitability Cropland	AUC
Northern Africa	0.40	0.51	0.881
Western Africa	0.36	0.52	0.846
Central Africa	0.35	0.55	0.794
Eastern Africa	0.34	0.53	0.874
Southern Africa	0.31	0.51	0.821

The second method is the calculation of the relative operating characteristics (ROC) of the simulated crop suitability map against the base land use map. The ROC metric allocates proportions of correctly and incorrectly classified spatial predictions (Pearce and Ferrier, 2000; Pontius Jr and Schneider, 2001). In this context, computed values of crop suitability are ranked and compared, whether or not they correspond to a grid cell that is either cropland or not. A cell is a true positive, if it has been observed as cropland grid cell and a false positive if the grid cell has been identified as non-cropland. This process is applied to all cropland grid cells. The measure of performance for the ROC test is the area under the resulting curve (Figure C1). A value of 1.0 indicates a perfect fit of the current cropland distribution with areas identified as most suitable by the model. If the suitability for crop cultivation would be randomly distributed among cropland and non-cropland cells, the area under curve would be 0.5. This part of the evaluation has been done for the five African regions separately. We find AUC values between 0.794 (Central Africa) and 0.881 (Northern Africa) that indicate that the cropland cells of the initial map can predominantly be found on locations with high suitability and are not randomly distributed (Table C1, Figure C1).

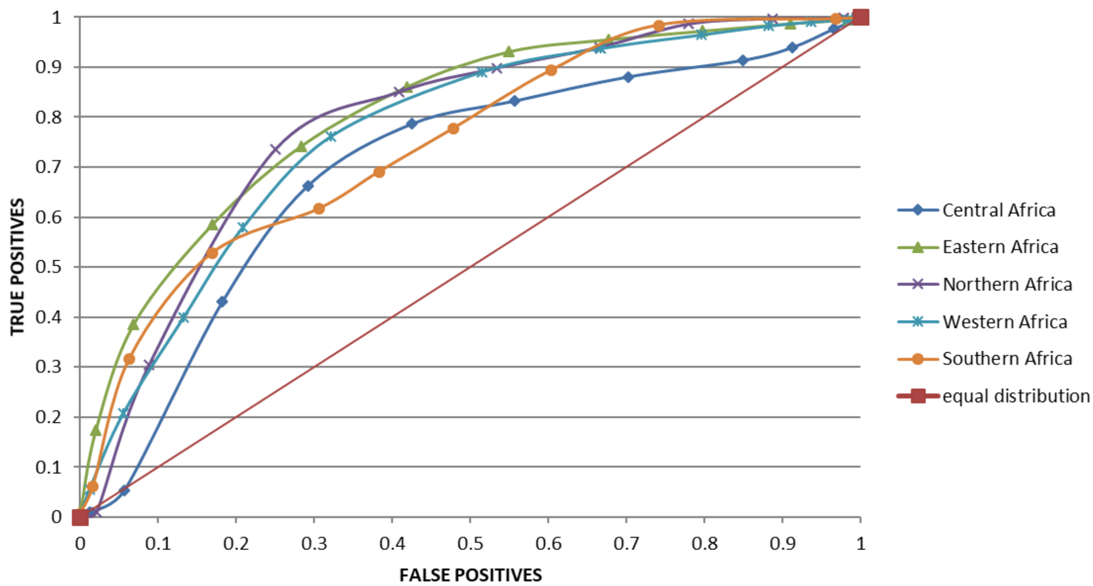

Figure C1: Relative Operating Characteristics (ROC) curves for the five different GEO-regions.

b) Validation of model output

In contrast to the first method for testing model performance, which was focused on the location of change, the second method involves the test for the correct quantity of change. Cropland area is used as the indicator here because an independent set of country scale estimates has been made available from the UN Food and Agriculture Organization (FAO 2014). Model efficiency ME (Janssen and Heuberger, 1995; Loague and Green, 1991) has been selected as the degree of agreement between the LandSHIFT model results and the observed FAO data on country level. A value of 1.0 indicates perfect agreement between modeled and observed values. The model is run from 2000 until 2010 with statistical data for agricultural production from FAO as input. Then the calculated cropland area for each country in 2010 is compared to FAO statistics (n=51). Table C2 summarizes the results. We find ME values between 0.69 (Northern Africa) and 0.98 (Western Africa) indicating that the model has a high skill to reproduces the observed quantities of cropland change on country level.

Table C2: Model efficiencies calculated for the years 2000 and 2010.

Geo-region	ME 2000	ME 2010
Africa Total	0.98	0.96
Central Africa	0.91	0.96
Eastern Africa	0.77	0.96
Northern Africa	0.89	0.69
Southern Africa	0.96	0.86
Western Africa	0.97	0.98