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Key Points:
- There are trade-offs between SDGs related to food provision, climate change mitigation, and preservation of biodiversity in India
- Further agricultural intensification is required to help ensure food security and to slow the expansion of cropland and pasture in India
- Intensification efforts for agricultural production should be joined with specific measures to minimize biodiversity losses

Supporting Information:
- Supporting Information S1

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Agricultural Development and Land Use Change in India: A Scenario Analysis of Trade-Offs Between UN Sustainable Development Goals (SDGs)

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Abstract India has the second largest population in the world and is characterized by a broad diversity in climate, topography, flora, fauna, land use, and socioeconomic conditions. To help ensure food security in the future, agricultural systems will have to respond to global change drivers such as population growth, changing dietary habits, and climate change. However, alterations of how food is produced in the future may conflict with other UN Sustainable Development Goals (SDGs), such as the protection of land resources and climate change mitigation. It is crucial for decision-makers to understand potential trade-offs between these goals to find a balance of human needs and environmental impacts. In this paper, we analyze pathways of agricultural productivity, land use, and land-cover changes in India until 2030 and their impacts on terrestrial biodiversity and carbon storage. The results show that in order to meet future food production demands, agricultural lands are likely to expand, and existing farmlands need to be intensified. However, both processes will result in biodiversity losses. At the same time, the projections reveal carbon stock increases due to intensification processes and decreases due to conversions of natural land into agriculture. On balance, we find that carbon stocks increase with the scenarios of future agricultural productivity as modeled here. In conclusion, we regard further agricultural intensification as a crucial element to help ensure food security and to slow down the expansion of cropland and pasture. At the same time, policies are required to implement this intensification in a way that minimizes biodiversity losses.

1. Introduction

By area, India is the world's seventh largest country along with a population of about 1.3 billion people in 2015 (FAO, 2017a; UN-Pop, 2017). India is characterized by an immense diversity in climate, topography, flora, fauna, land use, and socioeconomic conditions (FAO, 2017b). During the past 140 years, India has experienced remarkable land use and land-cover changes including deforestation, cropland changes, and urban expansion (Roy et al., 2015; Tian et al., 2014). Over half of the territory is used as cropland, making India one of the largest producing countries of agricultural commodities worldwide (FAO, 2017a; Teluguntla et al., 2015). In 2016, the agricultural sector comprised 23% of the total economy, as measured by the gross domestic product, and employed around 59% of the country's total labor force (FAO, 2017b). Two thirds of the Indian population lives in rural areas (World Bank, 2016) and, with a relatively high poverty rate, is home to one of the largest populations (175.7 million) living below the World Bank's poverty line of $1.90 a day (World Bank, 2018).

India has experienced notable increases in agricultural productivity over the last decades (Chand & Parappurathu, 2012; Pingali, 2012). Nevertheless, there are still significant yield gaps for many crops across the countryside (Brahmanand et al., 2013; Sharma, 2016). The existence of yield gaps can be explained by many confounding factors, such as the prevalence of subsistence farming and poor access to chemical inputs, improved technology, and management techniques (Bhattacharyya et al., 2015; George, 2014; ICAR, 2015). India's food production needs to be increased substantially in the coming decades due to an expected population growth up to more than 1.6 billion in 2050 (UN-Pop, 2017) along with changing dietary preferences like a higher demand for animal-sourced products (Alexandratos & Bruinsma, 2012). This is an extremely challenging issue. Currently, India provides food to 18% of the world's population but occupies only 2.4% of the world's total land area (Bhattacharyya et al., 2015; Teluguntla et al., 2015). Studies such as Mauser et al. (2015) see large potential in India for increasing agricultural productivity by improving management practices and adopting new crop varieties. To realize these improvements, further investments in research and development (R&D) in the agricultural sector are required.

At the same time, possible negative environmental impacts due to agricultural intensification cannot be neglected (e.g., Ramankutty et al., 2018; Rockström et al., 2017; Springmann et al., 2018; Srivastava et al., 2016; Tilman et al., 2017; Tilman & Clark, 2014). India is still one of the richest nations in terms of biodiversity, and the remaining forest area (22% of the total area) represents a significant carbon stock that needs to be conserved as a means of climate change mitigation (Nadagoudar, 2016; Roy et al., 2015; Swaminathan & Bhavani, 2013; Tian et al., 2014). According to the IPCC (2014), India is likely to suffer from a higher frequency of extreme temperature and precipitation events. The cyclical monsoon system has been identified as one tipping element of the global climate system, which means that strong climate change might drastically change atmospheric circulation patterns globally (Lenton et al., 2008; Steffen et al., 2018). With such a systemic shift, there could be significant impacts on India's agricultural sector.

Thus, one of the main challenges facing India today is to develop strategies to sustain and improve living conditions of a growing population, while continuing to satisfy shifting consumption patterns and limit negative environmental outcomes (Nadagoudar, 2016; Roy et al., 2015; Swaminathan & Bhavani, 2013; Tian et al., 2014). The Sustainable Development Agenda of the United Nations (United Nations General Assembly, 2015) recognizes the negative impacts of food insecurity, biodiversity loss, and climate change on human development issues by including them as priorities in the Sustainable Development Goals (SDGs). While SDG 2 (*Zero Hunger*) addresses food security, SDG 15 (*Life on Land*) demands, among other things, the preservation of biodiversity and SDG 13 (*Climate Action*) focuses on climate adaptation and mitigation efforts. However, many scientific approaches that aim at informing policies to achieve the SDGs are sector-specific assessments and often disregard the interrelationships identified in multisectoral assessments (Obersteiner et al., 2016; Tagar et al., 2016). First attempts to systematically analyze interactions and trade-offs between SDGs were conducted by Pradhan et al. (2017) and Gao and Bryan (2017).

Spatially explicit simulation models are useful tools to explore the dynamics of future agricultural development, related land use change, and resulting environmental impacts (Alexander et al., 2017; Li et al., 2017; Prestele et al., 2016). For India, Schaldach, Priess, et al. (2011) use a spatially explicit land use model to assess the effects of biofuel development on land use change. While numerous global studies that include India as a subregion tackle the effects of land use change on either biodiversity (e.g., Delzeit et al., 2017; Kok et al., 2018; Newbold et al., 2016) or carbon storage (e.g., Popp et al., 2014), only a few studies are available that address effects on both impact categories (e.g., Eitelberg et al., 2016; Molotoks et al., 2018).

In this paper, we analyze a set of scenarios of future agricultural development in India and assess potential trade-offs between food production to prevent hunger (SDG 2), climate mitigation (SDG 13), and biodiversity (SDG 15). For our analysis we adapt and apply an integrated modeling framework that combines an economic model with different spatially explicit models. Since the UN Agenda defines 2030 as a target year to make substantial improvements in reaching the SDGs, we have chosen this year as the time horizon for the scenarios. In the following section the applied models and the scenario assumptions are described. This is followed by a section that describes our simulation results and a discussion of our main findings.

2. Materials and Methods

2.1. Modeling Framework

Components of the modeling framework (Figure 1) include the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT; Robinson et al., 2015), the spatially explicit land use model LandSHIFT (Schaldach, Alcamo, et al., 2011), and two empirical models for the analysis of land use change effects on biodiversity (Alkemade et al., 2009, 2013; Biggs et al., 2008; Jenkins et al., 2013; Scholes & Biggs, 2005) and carbon stock changes in soils and vegetation (European Commission, 2010; European Parliament and Council, 2009; IPCC, 2006; JRC, 2010; Ruesch & Gibbs, 2008). This type of IMPACT-LandSHIFT model

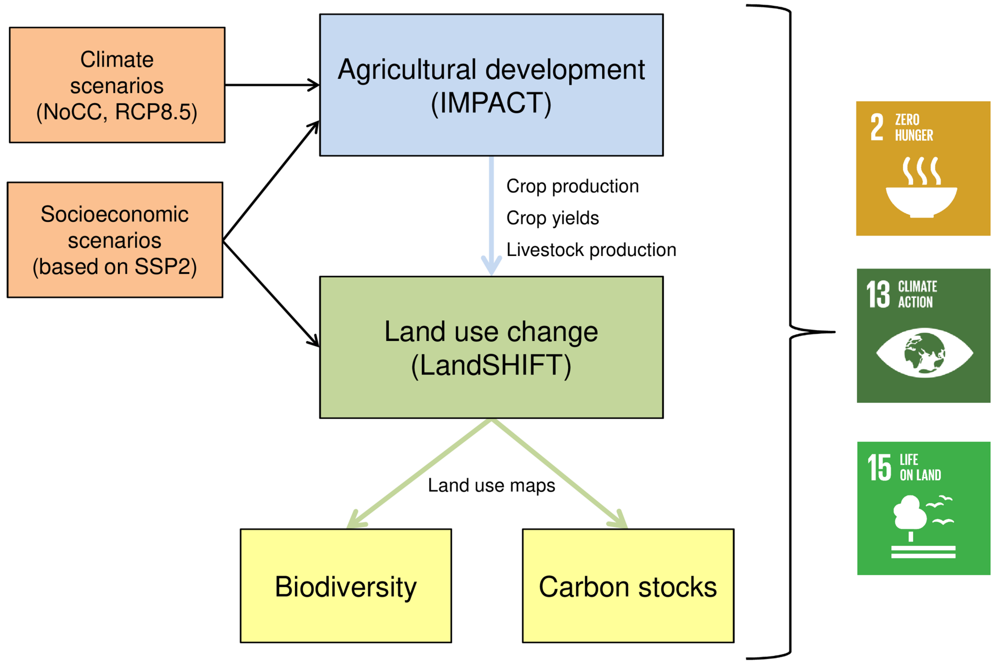

Figure 1. Modeling framework used for the scenario analysis.

coupling was already successfully implemented and applied for other scenario studies in Southeast Asia and East Africa (e.g., Mason-D'Croz et al., 2016; van Soesbergen et al., 2017). Both models are driven by exogenous climate and socioeconomic scenario data.

The IMPACT model is used for projecting changes in agricultural production and crop yields in India due to changing socioeconomic and climate conditions. IMPACT is an economic equilibrium model that calculates projections for global agricultural markets and trade and reflects changes of demands and production of agricultural goods in India and other countries as well as net trade. Internally crop yield changes due to climate and technological change are determined by the DSSAT suite of crop models (Hoogenboom et al., 2017; Jones et al., 2003) applied in MINK, a global gridded crop modeling approach (Robertson, 2017). The model output is passed to LandSHIFT and comprises country-level information on crop and livestock production as well as crop-specific yield changes. In the following, LandSHIFT translates this information into land use patterns, which then serve as input to the environmental impact assessment models. In this study, land use change is simulated on a raster with a cell size of 5 arcminutes (~9 × 9 km) at the equator. Table S0 in the supporting information summarizes the data and models used for our analysis.

2.2. Scenarios and Economic Modeling

For our analysis, we use four global scenarios (Table 1) that were developed as part of the CGIAR Global Futures and Strategic Foresight project, led by the International Food Policy Research Institute. The focus of that scenario exercise was to evaluate the effectiveness of different investment strategies in the agricultural sector with regard to food security under global change conditions up to the year 2050 (Rosegrant et al., 2017). All scenarios follow the Shared Socioeconomic Pathway 2 (SSP2) “middle of the road” assumptions on population and economic growth (Kriegler et al., 2014; Moss et al., 2010; van Vuuren et al., 2014). For this pathway, it is assumed that India's population will grow to more than 1.5 billion by the year 2030 while the economy is characterized by strong gross domestic product increases (Dellink et al., 2017; Samir & Lutz, 2017). In addition, the International Food Policy Research Institute scenarios combine these drivers with assumptions about different investments in R&D in the agricultural sector across the CGIAR research portfolio. These measures are assumed to comprise investments in advanced breeding techniques, including further advances in genomics as well as in efforts to increase the efficiency of scientific institutions to achieve productivity gains (Rosegrant et al., 2017).

Table 1
Main Characteristics of the Scenarios

Scenario grouping	Scenario	Scenario description
Reference	REF_HGEM	Reference scenario with RCP8.5 future climate using the HadGEM2-ES (HGEM)
	REF_NoCC	Alternative reference with no climate change (constant 2005 climate)
Productivity enhancement	MED	Medium increase in R&D investments across CGIAR portfolio; RCP8.5 future climate
	HIGH+RE	High increase in R&D investments across CGIAR portfolio plus increased research efficiency; RCP8.5 future climate

Note. See also Rosegrant et al. (2017).

The first two scenarios serve as reference cases with R&D investments following current trends and therefore directly represent the SSP2 storyline. The REF_NoCC scenario uses constant climate conditions around the year 2005 while the REF_HGEM scenario assumes climate change according to a RCP8.5 climate scenario (van Vuuren et al., 2011). In addition, two investment scenarios are specified. The MED scenario assumes an intermediate level of additional R&D investments by CGIAR centers while the HIGH+RE scenario considers a high increase in CGIAR investment plus an increased CGIAR research efficiency. Both investment scenarios assume climate change according to a RCP8.5 climate scenario. The crop modeling component of the IMPACT model (DSSAT and MINK) translates the climate change scenarios into a clear signal of what the impact of average climate change trends will be on crop yields. In addition, for each scenario the R&D investments are translated into crop yield increases following a logistic adoption pathway, based on historical trends and using expert judgment from regional CGIAR centers regarding the potential of crop productivity development for each region modeled. Then, the four scenarios are simulated using the IMPACT model. The scenario development process is described in detail in Robinson et al. (2015) and Rosegrant et al. (2017).

The effects of climate change (e.g., temperature and precipitation changes) were projected by the Hadley Centre Global Environment Model, version 2 (HadGEM2-ES (HGEM); Jones et al., 2011). We have chosen the RCP8.5 scenario and a reference case with 2005 climate conditions in order to investigate a broad corridor of potential climate change impacts on crop yields and to assess the robustness of the different investment strategies under climate change. As pointed out in section 2.1, country-level information that is passed from IMPACT to LandSHIFT includes crop and livestock production as well as the crop-specific yield changes in India.

2.3. Land Use Modeling

The LandSHIFT model is used to calculate spatial and temporal land use change due to crop cultivation, grazing, and urbanization. It has been validated and tested for India in the context of biofuel assessments (Schaldach, Alcamo, et al., 2011; Schaldach, Priess et al., 2011). The model is based on the concept of land use systems (Turner et al., 2007) and couples components that represent anthropogenic and environmental subsystems. Drivers of land use change are specified on the country-level, while the spatially distributed land use modeling is carried out on a regular grid. Cell-level information comprises land use type, human population density, landscape characteristics (e.g., terrain slope, potential yields, road infrastructure), and land use restrictions (e.g. protected areas). Table S2 gives an overview of the data sets used as model inputs for our analyses. During the simulation, LandSHIFT translates the country-level model input into spatial land use patterns. At the beginning of every time step, the suitability of each raster cell for the different land use types is determined based on the cell-level information. Thereafter, the model uses country-level data to determine and to allocate the land needed for each crop type, pasture, and settlement in the most suitable cells. The model results are raster maps that depict the spatial and temporal patterns of land use change until 2030 in 5-year time steps. Grid-level information on crop yields in the base year that are required for the spatial allocation of cropland is determined by the LPJmL model (Bondeau et al., 2007). In course of the scenario simulations, these values are adjusted according to the country-level information on crop-specific yield changes provided by the crop modeling component of the IMPACT model.

2.4. Model Initialization

LandSHIFT is initialized with a gridded land use map representing the year 2005. This base map is produced by merging of land-cover data from the GlobCover 2009 data set with data on the physical extent of different crop types and permanent meadows and pastures from the UN Food and Agricultural Organization FAO (ESA, 2010; FAO, 2017a). In contrast to the land-cover data set, the base map distinguishes 12 different crop types and includes a spatial allocation of pastureland. The information on the relative share of the various crop types in the total cropland area per country is derived from the input data on harvested area on country-level for the year 2005 from IMPACT. The conversion from harvested area of a crop, as specified by IMPACT, to its physical area allocated in the base map is done on a per-country basis and is kept constant for the simulation period. For this purpose, harvested area is multiplied by the ratio of total physical cropland area (FAO) over total harvested area of all crops (as derived from IMPACT). Hence, LandSHIFT assumes the same cropping intensity for all crop groups in a country, which is a clear simplification of our modeling approach as intensities may vary between cropping systems. In this study, all cropping systems have an intensity factor of 0.63, which is kept constant during the simulation period. For pasture, initialization data, that is, livestock numbers and permanent area of meadows and pasture, are taken from FAO. Table S3 shows the mapping of the GlobCover 2009 land-cover types to the land use types in the LandSHIFT model and the area that they occupy in the base map.

An important outcome from the data merging process is that the cropland area depicted in GlobCover 2009 strongly exceeds the physical cropland area given in the statistical data. As a consequence, excess cropland cells are classified as set-aside in the base map. To further specify the actual land use, we overlay the base map with a regional land-cover product (Roy et al., 2015) at a spatial resolution of 30 m × 30 m and calculated the mean fraction of different land-cover types within the 5-arcmin cells. As a result of this GIS analysis, we characterize these cells as a mosaic of less intensive subsistence farming with higher field margin vegetation and/or agroforestry (20%) and fallow land/natural vegetation, especially lightly used forests and secondary forests (80%).

2.5. Assessment of Impacts on Biodiversity

We use the Biodiversity Intactness Index (BII) for quantifying the impact of land use change on biodiversity. The BII is an indicator of the average abundance of a large and diverse set of organisms in a given geographical area, relative to reference populations in the preindustrial period (Scholes & Biggs, 2005). The BII was originally developed for analyses in Southern Africa (e.g., Biggs et al., 2008). In recent publications related to the Planetary Boundary concept, it has been proposed as a suitable indicator to measure the loss of species diversity in large-scale assessments (Steffen et al., 2015) and applied for continental and global analyses (Koch et al., 2019; Newbold et al., 2016).

Calculations of the BII are carried out for the land use maps generated by LandSHIFT. Here, each cell represents an ecosystem with its areal extent being the cell size and its species richness described by the sum of bird, mammal, and amphibian species. Spatially explicit data on species richness is derived from the global data set by Jenkins et al. (2013). The BII at the country-level is determined by summing up the individual grid cell values (equation (1)).

$$\mathrm{BII} = \frac{\sum_{\mathrm{i}}\sum_{\mathrm{j}}\sum_{\mathrm{k}}\mathrm{R_{ij}A_{jk}I_{ijk}}}{\sum_{\mathrm{i}}\sum_{\mathrm{j}}\sum_{\mathrm{k}}\mathrm{R_{ij}A_{jk}}} \tag{1}$$

According to equation (1) (based on Scholes & Biggs, 2005), the BII on the country-level is defined as the average impact across taxa *i*, ecosystems *j*, and land use types *k*. The impact I_{ijk} is defined as the population abundance of a given species or group of species relative to the reference state, 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 at a preindustrial level, while values close to zero indicate that most species have become extinct or that their abundance has fallen to minimal levels compared to the undisturbed habitat.

For estimating the impact *I* of a particular land use type on species abundance, we use information from the GLOBIO model (Alkemade et al., 2009, 2013) that specifies the respective reduction of Mean Species

Table 2
Mean Species Abundance Under Different Land Use Types

Land use type	MSA
Cropland	
Low input	0.3
Intensive	0.1
Grazing land	
Extensive grazing (grassland)	0.7
Intensive grazing (pasture)	0.3
Man-made pastures (pasture)	0.1
Forest	1.0
Other natural vegetation	1.0
Set-aside (tree cover/other natural vegetation/cropland)	0.5
Urban	0.05

Note. The parameter values are taken from Alkemade et al. (2009, 2013).

Abundance (MSA). Urban land reduces the original MSA by 95%. Cultivated land was further subdivided into low-intensity agriculture with a reduction factor of 70% and high-intensity agriculture with a reduction factor of 90%. Table 2 summarizes the MSA values used for the analysis. The proportions of low- and high-intensity agriculture are based on Alkemade et al. (2009). For India the share of intensive agriculture is 57%. Similar to cropland, pasture is subdivided into intensive grazing and man-made pastures. As there was no specific data available about the areal distribution of both types, intensive grazing and man-made pastures are assumed to have the same area share as the cropland types (Table 3).

BII changes over time are driven by land conversion and intensification of crop cultivation and pasture management. To portray the effect of agricultural intensification, the fractions of low input and intensive cropland, as well as the fractions of intensive grazing and man-made pastures, are changed over the simulation period. We assume that the projected yield increases depicted in the scenarios will be accomplished to a large extend by the expansion of intensive agriculture that is characterized by the cultivation of high productive crop varieties that successively become available until 2030 (see section 2.2), but very likely also by high inputs of mineral fertilizer, improved pest control and a strong degree of mechanization with negative effects on biodiversity (e.g., Bhattacharyya et al., 2015; Srivastava et al., 2016). At the same time, we assume that these measures are accompanied by an improved soil carbon management in order to decrease soil erosion and to prevent loss of soil fertility as a prerequisite to increase crop yields in the long term (see section 2.6).

The fraction of intensive cropland in 2030 is estimated as follows: For the REF_NoCC scenario we assume that this fraction increases by the mean yield growth rate of all crops between 2010 and 2030 from 57% to 85% (see section 3.1). Since the REF_HGEM scenario is characterized by similar changes of agricultural management practices (resulting in lower crop yield under climate change), the fraction of intensive cropland has the same value as under the REF_NoCC case. For the two investment scenarios that are both characterized by higher yield increases, we assume a further gradual increase of the fraction of intensive cropland to 90% under MED and 95% under HIGH+RE (Table 3).

In contrast, the fraction of man-made pastures in 2030 is determined by multiplying half of the livestock density growth rate of each scenario from 2010 to 2030 with the relative proportion of man-made pastures in 2010. Half of the growth rate is used because we assume that livestock systems in India will change to more intensive systems with higher proportions of animal housing that cause less grazing pressure (Table 3).

2.6. Assessment of Carbon Storage Changes

Land use change within the simulation period is determined by comparing the scenario-specific raster maps for 2010 and 2030 generated by LandSHIFT. Land use change occurs if the land use type of a cell in 2030 is

Table 3
Shares of Intensive and Low Input Cropland (Alkemade et al., 2009) and Intensive Grazing and Man-Made Pastures in 2010 and in the Scenarios 2030 (Own Assumptions)

		REF_HGEM	REF_NoCC	MED	HIGH+RE
	2010	2030	2030	2030	2030
Cropland					
Low input	43%	15%	15%	10%	5%
Intensive	57%	85%	85%	90%	95%
Grazing land (pasture)					
Intensive grazing	43%	29%	29%	25%	5%
Man-made pastures	57%	71%	71%	75%	95%

different from its land use type in 2010. The resulting annualized CO_2 emissions (e_l) are calculated according to equation (2).

$$e_l = (CS_R - CS_A)^* F^* \frac{1}{Y}, \tag{2}$$

where
e_l = annualized emissions from carbon stock change due to land use change [tCO_2/a],
CS_R = carbon stock in soil and vegetation on cell-level in 2010 [tC],
CS_A = carbon stock in soil and vegetation on cell-level in 2030 [tC],
F = factor for the conversion of C to CO_2 (default = 3.664), and
Y = annualizing of carbon stock changes over a 20-year period [a].

The methodology, derived from the EU Renewable Energy Directive, is based on the 2006 IPCC Guidelines for Tier 1 calculation of land carbon stocks (European Parliament and Council, 2009; IPCC, 2006). In the first step, the carbon stocks in soil and vegetation for each raster cell in the years 2010 (CS_R) and 2030 (CS_A) are determined. Information regarding soil, climate, and land use type, as well as the related values for soil organic carbon and vegetation carbon stocks, is derived from the data presented by (European Commission (2010), IPCC (2006), JRC (2010) and Ruesch & Gibbs (2008). In the second step, the change in carbon stocks during the simulation period is obtained by subtracting CS_A from CS_R. In the last step, the annual emissions related to these carbon stock changes are calculated for a time frame of 20 years by dividing total emissions into 20 equal parts. A positive sign indicates the release of CO_2 to the atmosphere while a negative sign stands for uptake of CO_2 from the atmosphere.

Equation (3) illustrates the rule for the calculation of carbon stocks, which takes into account organic carbon in mineral soils and in the above and belowground vegetation compartments (European Commission, 2010):

$$CS_{R/A} = SOC_{ST}^* F_{LU}^* F_{MG}^* F_I + C_{VEG}^* A, \tag{3}$$

where
$CS_{R/A}$ = carbon stock in soil and vegetation on cell-level associated with the reference/actual land use [tC],
SOC_{ST} = standard soil organic carbon in the 0- to 30-cm topsoil layer [tC/ha],
F_{LU} = land use factor reflecting the difference in soil organic carbon associated with the type of land use compared to the standard soil organic carbon [−],
F_{MG} = management factor reflecting the difference in soil organic carbon associated with the principal management practice compared to the standard soil organic carbon [−],
F_I = input factor reflecting the difference in soil organic carbon associated with different levels of carbon input to soil compared to the standard soil organic carbon [−],
C_{VEG} = above and belowground vegetation carbon stock [tC/ha], and
A = factor scaling to the area concerned [ha].

The carbon stock estimates for SOC_{ST} and C_{VEG}, as well as the land use factor F_{LU}, are defined by the specific land use, climate, and soil type on each cell. Furthermore, the selection of the values used for the F_{MG} and F_I factors is based on expert knowledge from scientists of the Institute for Social and Economic Change and on descriptions of land management systems in India given by Bhattacharyya et al. (2015). To calculate not only the carbon stock changes due to land use conversions but also the modifications of C stocks due to management practice changes on the remaining agricultural land, the factors F_{MG} and F_I are changed over the simulation period for the different scenarios. Tables S4–S6 in the supporting material include the values used for the respective factors in our study. In the starting year of our simulations, both intensive and low input cropland is subject to full tillage and low residue return after harvest. This reflects current management practices in the Indian agricultural sector with a high share of small farm holders who often have limited access to equipment and technology. In many cases, these farmers are not able to afford costly inputs and often make use of suboptimal agricultural practices due to poor agricultural education, such as excessive tillage,

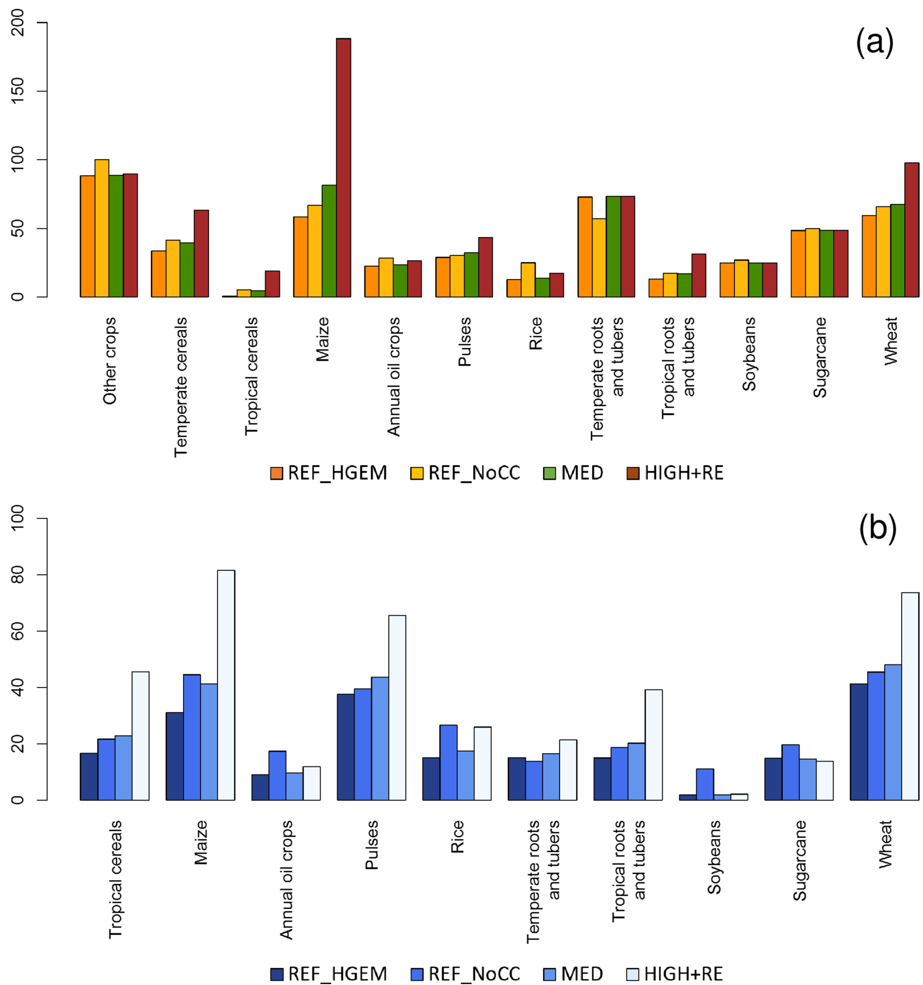

Figure 2. Changes in (a) crop production in % and (b) increases in crop yields in % due to investments in agricultural R&D and climate change between 2010 and 2030 under the four scenarios for India. Simulation results from the IMPACT model.

unbalanced use of mineral fertilizer and pesticides, and inadequate crop residue inputs (Bhattacharyya et al., 2015; ICAR, 2015). As pointed out in the previous section, in our scenarios, the successive intensification of cropland with higher yields is supported by advancements in soil management that in consequence lead to increasing soil carbon stocks (see Lal, 2004). The reference scenarios (REF_HGEM and REF_NoCC) both assume full tillage but in combination with medium input of crop residues. Crop cultivation in the MED scenario is carried out with reduced tillage and medium input of crop residues while the HIGH+RE scenario combines reduced tillage with high residue inputs.

In the scenario exercise with the IMPACT model (Rosegrant et al., 2017), yield growth for perennial crops, not being a focus of that analysis, are held constant and result in a production-weighted average increase in yield of about 10%. Therefore, we assume for all scenarios similar changes in F_{MG} and F_I from medium inputs in 2010 to high inputs of crop residues in 2030.

In the case of pasture, the methodology employed allows changes in management inputs only for improved grassland, which is defined as "sustainably managed land with moderate grazing pressure" (European Commission, 2010). Input changes for pasture are not included in this study because of the high grazing densities simulated in all scenarios. Increases in livestock densities are assumed to lead to higher rates of land degradation (F_{MG} changes).

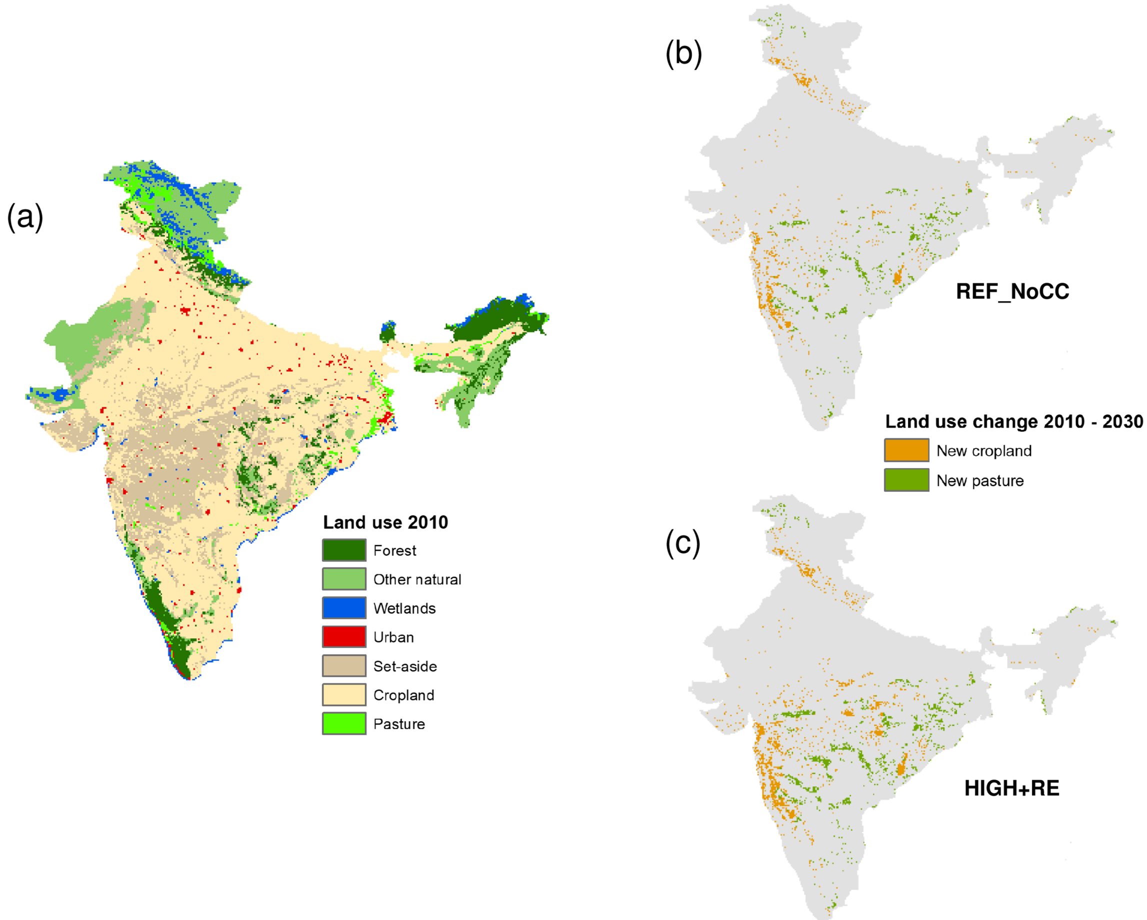

Figure 3. Land use map for the base year 2010 (a) and maps depicting the expansion of cropland and pasture between 2010 and 2030 for (b) the REF_NoCC scenario and (c) the HIGH+RE scenario. For better visualization, the 12 crop types are aggregated to one land use type "Cropland."

3. Results

3.1. Agricultural Development Until 2030

Changes in agricultural production and crop yields are simulated using the IMPACT model. Crop yields, driven by investments in agricultural R&D and climate change, as well as crop production, driven by population growth and changes in global and regional demand, are projected to increase in all scenarios (Figure 2).

The comparison of the reference scenarios (REF_HGEM and REF_NoCC) illustrates that, looking at India as a whole, climate change has a negative effect on the yields of nearly all modeled crops. Exceptions are temperate roots and tubers, which benefit from the changing climate. Spatially aggregated yields of all crops show a lower growth rate from 2010 to 2030 for the climate change scenario (+41%) compared to the no climate change scenario (+48%). A similar trend can be observed when looking at the growth rates of total crop production. Under climate change, less is produced (+43%) than under a no climate change pathway (+50%). Considering the futures for different crop groups under both scenarios, some crops will become increasingly important while others will be less cultivated. Increases in yields and production are greatest for cash crops, such as vegetables and cotton, as well as for wheat.

In contrast, the investment scenarios, which follow the climate assumptions of REF_HGEM but with an accelerated level of investments in agricultural R&D, result in higher yield increases compared to the NoCC reference scenario. Out to 2030, the yields of crops in aggregate for the MED and HIGH+RE scenarios increase by 43% and 54%, respectively. Total production is projected to increase by 46% and 55% for MED and HIGH+RE, respectively, compared to the base year 2010. Especially in the HIGH+RE scenario, increases in

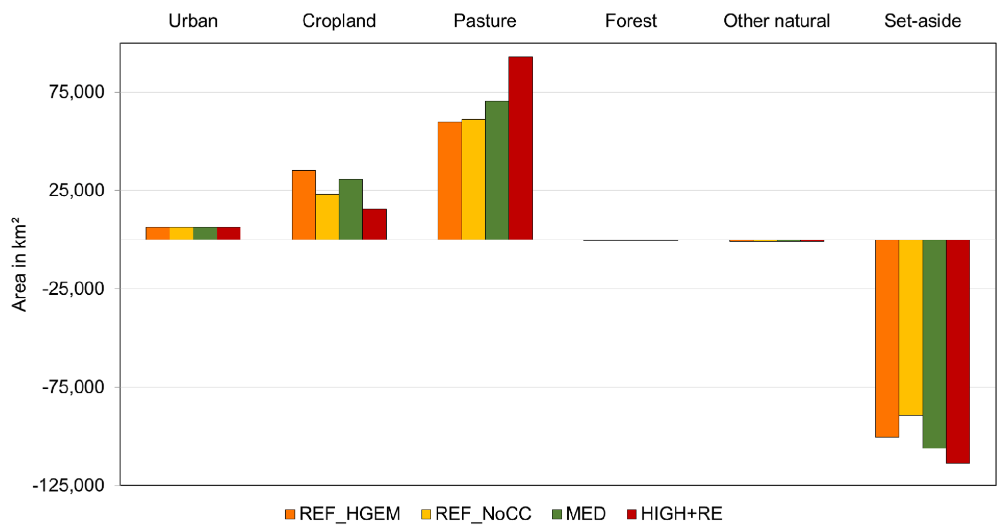

Figure 4. Area change from 2010 to 2030 for the four studied scenarios in km^2.

yield and production for maize and wheat are especially strong. Comparing the reference scenarios with the MED scenario, we see that the modestly higher investments in agricultural R&D are not able to curb all negative effects of climate change. The HIGH+RE scenario, however, more than mitigates the adverse climate change impacts on agriculture.

By 2030, the production of livestock in India increases drastically under all scenarios. In the reference scenarios, we find an increase from 4.56 million livestock units (LU) in 2010 up to 12.45 million LU under REF_HGEM and 12.62 million LU under REF_NoCC, respectively. In contrast under MED, livestock numbers increase to 14.91 million LU while under HIGH+RE we find 24.78 million LU. However, it is important to note that livestock production is not only dependent on free-roaming grazing on rangelands and pasture. Mixed or industrial livestock systems include the feeding of livestock with crops or crop byproducts and the keeping of livestock in stables (Alkemade et al., 2013).

3.2. Land Use Change by 2030

The extent and spatial pattern of land use change are calculated with the LandSHIFT model. Figure 3a shows the land use pattern in the base year 2010 aggregated to seven major classes. Figures 3b and 3c depict the expansion of cropland and pasture until 2030 for the REF_NoCC and the HIGH+RE scenarios.

Cropland and pasture areas expand in all scenarios (Figure 4). Most of the expansion takes place on land previously covered by set-aside land (Table S7–S10). This land use type accounts for a large proportion of the total land area in India and is mainly located in Central and West India. The largest increase of cropland area occurs in the REF_HGEM scenario, with an increase from 2010 to 2030 of 35,302 km^2 (2.1%) to a total of 1,730,990 km^2. The higher crop productivity in the REF_NoCC scenario, assuming a constant 2005 climate, allows future food demands to be met with an expansion of cropland area of only 22,990 km^2. Also, in both investment scenarios, cropland expansion is lower than under REF_HGEM, with absolute increases of 30,672 km^2 (MED) and 15,605 km^2 (HIGH+RE). The key reason behind this moderate expansion of cropland area in all scenarios is the projected increase of crop yields due to agricultural intensification.

Pasture area grows from 59,964 km^2 in 2010 to an extent ranging from 119,823 km^2 (+99.8%) under REF_HGEM and 152,913 km^2 (+155%) for the HIGH+RE scenario in 2030. Stocking density increases from 63 LU/km^2 in 2010 up to 93 LU/km^2 under REF_HGEM and 94 LU/km^2 under REF_NoCC. Under the investment scenarios, this increase is even higher with 103 LU/km^2 (MED) and 148 LU/km^2 (HIGH+RE). Total decreases of set-aside area until 2030 due to cropland and pasture expansion are in a range between 113,724 km^2 (HIGH+RE) and 89,294 km^2 (REF_NoCC).

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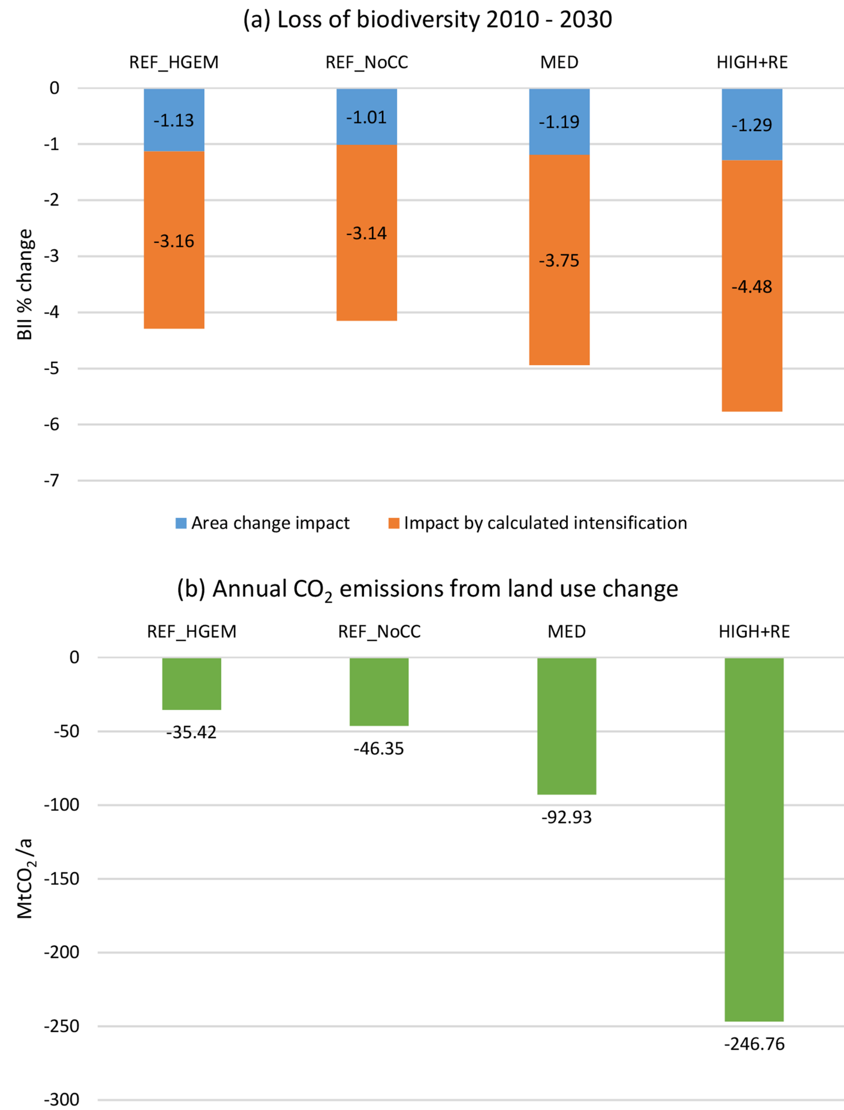

Figure 5. (a) Change in Biodiversity Intactness Index (BII) due to converted natural land and agricultural intensification from 2010 to 2030 for all scenarios. (b) Annualized CO_2 emissions in million metric tons [Mt/a] from land use change and agricultural intensification for all scenarios during the period 2010 to 2030.

For all scenarios, the losses of forest and other natural land are relatively small. The forest area decreases by 264 km^2, while other natural land is reduced by 786 km^2. Urban area grows in all scenarios by more than 6.9%, equal to an absolute increase of 6,220 km^2.

3.3. Impacts of Land Use Change on Biodiversity

The BII for India in the year 2010 is 41.67%. Changes of BII in our scenarios are driven by the conversion of natural and set-aside land to cropland, pasture, and urban area as well as by the intensification of cropland and pasture. Figure 5a gives an overview of BII changes due to these impacts.

The impacts of the expansion of agricultural and urban land on the BII are relatively small across all scenarios. Under REF_NoCC, the scenario with the lowest expansion of agricultural area, the BII decreases by 1.01%, followed by the REF_HGEM scenario with a decrease of 1.13%. The two investment scenarios show significantly higher expansion rates, especially of pasture, into set-aside areas leading to larger decreases of the BII (MED: −1.19%; HIGH+RE: −1.29%).

Moreover, due to the different assumptions regarding agricultural intensification, there are further decreases of the BII across all scenarios. Increases in crop yields are assumed to be realized e.g. with high productive crop varieties and improved nutrient and soil management (see section 2.5) whereas increasing livestock density results in higher pressures on grassland ecosystems. Due to its high fraction of intensive cropland and man-made pastures, the strongest decrease of BII due to agricultural intensification can be found in the HIGH+RE scenario with −4.48%. In contrast, the REF_NoCC scenario shows the lowest decrease of BII by −3.14% and is characterized (together with REF_HGEM) by the smallest fraction of intensive cropland and man-made pasture.

Summarizing the effect of both processes, we see that the HIGH+RE scenario exerts the highest pressure on species abundance of amphibians, birds, and mammals for the year 2030 in India with the BII decreasing to 35.9%.

3.4. Impacts of Land Use Change on Carbon Storage

Similar to the biodiversity losses, carbon stock changes are driven both by processes of land conversion, such as conversion from forest to agriculture, and by the intensification of agricultural management.

As shown in Figure 5b, the calculated annual CO_2 emissions have negative values under all scenarios representing a net uptake of CO_2 from the atmosphere. As a result, soil carbon stocks are increasing. The REF_HGEM scenario shows the lowest annual uptake of CO_2 (−35.42 $MtCO_2$/a), followed by the REF_NoCC scenario (−46.35 $MtCO_2$/a). As the assumptions regarding increases in agricultural management and livestock grazing in both scenarios were similar, differences in CO_2 uptake can be attributed to the different expansion rates of agricultural land. In the REF_HGEM scenario, more set-aside land with relatively high carbon stocks in vegetation and soil are converted to cropland and pasture due to depressed yields under climate change conditions.

Under the investment scenarios, the additional improvements of agricultural management, including reduced tillage practices, have a significantly positive effect on the rates of CO_2 uptake. Under the MED scenario, the annual uptake is 92.93 $MtCO_2$/a while the HIGH+RE increases this to 246.76 $MtCO_2$/a.

In summary, under our scenario assumptions regarding the improvements in agricultural management practices on cropland, we calculate a strong uptake of carbon from the atmosphere. As this uptake is higher than carbon losses due to the conversion of set-aside and natural land, we find a net carbon sink in agricultural soils.

4. Discussion and Conclusions

Socioeconomic factors, such as population and economic growth, are main drivers for increasing future food demands in India. Under the different scenarios modeled here, the projected crop production growth ranges from 43% to 55% between 2010 and 2030. At the same time, livestock production is projected to more than double. These results are supported by the findings of other studies, like the “Vision 2050” done by the Indian Council of Agricultural Research (ICAR, 2015). Food provision in India will face problems similar to those in China, the other major player in Asia in that significant changes of agricultural policies and management practices are required to realize the necessary production increases in a more sustainable way (Yu & Wu, 2018). Our results also highlight that climate change affects Indian food supply in a negative manner and that higher future R&D investments in the agricultural sector can trigger food production increases that will offset these losses in productivity.

To meet the future crop production demands and SDG 2 (*Zero Hunger*), our study shows that, in India, crop yields must increase and cultivated lands must expand. In addition, the huge increases in demand for animal products require additional pastureland. The results suggest that most conversions to cropland and pasture take place on set-aside land that, according to our GIS-analysis, consists of a mosaic of extensive farming and remaining natural vegetation (Roy et al., 2015; Tian et al., 2014). However, when comparing crop production growth with agricultural land expansion, it becomes apparent that in all scenarios more than 90% of the projected crop production growth comes from increasing crop yields. The HIGH+RE scenario projects the highest yield increases and lowest cropland expansion. Since climate change has negative impacts on the yield of nearly all modeled crops, the REF_NoCC scenario projects higher yields than the climate change scenario, REF_HGEM. Modest investment increases in agricultural R&D under the MED scenario are not enough to counteract climate impacts by 2030, but the stronger investment scenario in HIGH+RE more than compensates for the climate change effects and will also help bolster livelihood resilience. Compared to cropland, pasture requires not only much more land but also intensification in the form of higher stocking densities, which helps to limit the expansion of this land use type.

The modeled trend toward less agricultural land expansion and concurrent improvements in crop yields per ha is confirmed by Bhattacharyya et al. (2015) and ICAR (2015). As India is a land scarce country, only a few options for the expansion of agricultural land are available. Today, small-scale mixed farming (e.g. as part of the set-aside land category) is the most important agricultural system. Compared to other countries like China or Brazil, productivity is low. As these small-scale farmers often do not have access to technologies and the financial resources necessary for further investments, a shift to more commercial-orientated farming systems or the organization of small farmers into producer companies is likely. Importantly, India should be recognized as a special case when considering future scenarios of agricultural intensification. Since there is little land into which agriculture can expand (see above), expanding production will come almost solely from closing yield gaps (GYGA, 2019). The scenarios modeled here use growth trends that are in line with generally accepted yield trends that will not exceed biophysical limits (Robinson et al., 2014; Rosegrant et al., 2017). In regions such as Sub-Saharan Africa and Latin America, there are critical land use considerations (Pellegrini & Fernández, 2018) that we generally will not encounter in India. In these other regions, the land use effects of agricultural intensification need to be addressed through appropriate policy measures (Kreidenweis et al., 2018; Popp et al., 2017). While we regard the results of our assessment to be specific to India, the model-based approach we have developed can be adapted to other country-level and even global studies.

Although our study focused on agricultural development, we could demonstrate that urban sprawl dynamics will also play an important role in future land use change in India. Urban expansion is projected to take place on every land use type, including forest areas and cropland. According to ICAR (2015), more than 50% of India's population will reside in cities by 2050. Here a more detailed assessment is required.

The analysis of potential trade-offs between achieving future food demands, the protection of biodiversity, and biological carbon storage as a means of climate change mitigation is strongly related to the 2030 Agenda of Sustainable Development. In our study, we concentrated on the effects of future land use change in India, triggered by the aim to provide food for all (SDG 2) while at the same time conserving biodiversity (SDG 15) and carbon storage (SDG 13). Using empirical modeling approaches, we could assess selected environmental effects from cropland and pasture expansion as well as from agricultural intensification. It is important to note that the scope of our trade-off analysis is far from being comprehensive and that future research should incorporate a larger set of SDGs (e.g., Gao & Bryan, 2017). Here we see two aspects with a direct relation to agricultural development that are particular important for India. First to mention are trade-offs between irrigation water requirements for crop cultivation and water requirements for households of the steadily growing urban population (Flörke et al., 2018) that can be linked to SDG 6 (*Clean Water and Sanitation*) and SDG 11 (*Sustainable Cities and Communities*). The second example is the impact of intensive agriculture on water pollution and eutrophication due to the input of pesticides and nutrients to water bodies and groundwater (Agrawal et al., 2010; Bhagowati & Ahamad, 2018), related to SDG 6 and SDG 14 (*Life Below Water*).

The results of the biodiversity impact assessment indicate that both agricultural land expansion and intensification lead to a decreasing BII. The strongest impact can be observed in the HIGH+RE scenario. The expansion of pasture into set-aside (mosaic) land is calculated to have the highest area change impact on biodiversity. The decrease can be explained due to the fact that the species richness of set-aside areas with a mosaic of extensive cropland and nature areas is likely to be higher than on intensively used pasture and cropland (Brooker et al., 2016). The strongest negative impact on biodiversity is generated by agricultural intensification. The modeled pasture intensification concurs with studies from Alkemade et al. (2013) and Tscharntke et al. (2005), who identify the removal of biomass, trampling and destruction of root systems, and replacement of wild grazers by livestock as important driving factors. Cropland intensification, as Tscharntke et al. (2005) point out, promotes monocultures of high-yield varieties and increasing input of fertilizers and pesticides, which are the main factors for the loss of important habitat functions within agricultural areas.

In consequence, according to the selected scenarios and the methodology used in our study, we can identify a clear trade-off between the increasing food production in India and the protection of biodiversity. The calculated BII is below the values from Hill et al. (2018) and Newbold et al. (2016) who determine a BII of 0.485 for South Asia, though it is still of the same magnitude, so we feel confident it is a reasonable estimate. Also, the decrease of BII in our scenarios is larger than projected by Hill et al. (2018) under an SSP2 scenario in combination with RCP4.5 for that region. The REF_HGEM scenario follows the relatively more severe RCP8.5 as represented by the HadGEM model, so these stronger climate change impacts on BII appear reasonable. However, these differences could have several explanations. For example, the values describing the impact of each land use type, especially regarding different intensity levels, on biodiversity that were used to calculate the BII may be imprecise or could be oversimplified. Hui et al. (2008) identify this factor as a main component of uncertainty for determining the BII. The proportions of low input and intensively used agriculture in the year 2010 based on the regional estimates for South Asia from Alkemade et al. (2009) are in the same order of magnitude as data from the Indian national statistical office. According to that, 44% of agricultural land is currently cultivated by small and marginal farmers (Kumar et al., 2018) corresponding well to the 43% of low input farming in that we assume in our study. In contrast, the assumption concerning the fractional increases of intensive agriculture during the scenario period represents only one possible way to estimate future developments. We feel this was a conservative approach, however. At last, it is important to note that (1) our study takes into account only vertebrate diversity and neglects, for example, insects, soil biota, and plants, which are crucial components of the ecosystem, and (2) that the BII has only a limited perspective on biodiversity as it, for example, does not consider functional aspects (e.g., Steffen et al., 2015). In consequence we suggest that future analyses should be expanded to other taxa and apply a mixture of different indicators to give a more complete picture of human pressures and impacts (e.g., Hill et al., 2016; Mace et al., 2014).

Under all scenarios, we find an annual net CO_2 uptake from the atmosphere. These results can be explained by (1) the expansion of new agricultural land predominantly into mosaic land cover with a relatively low carbon content and (2) the projected immense intensification of all farming systems in India. Indeed, most area conversions from natural land to human-modified land—such as cropland, pasture, and urban land—lead to decreasing carbon stocks and net CO_2 emissions (Arneth et al., 2017). However, due to our assumptions regarding increased sustainable soil management in agriculture, India has the potential to achieve high carbon accumulations in cropland soils. Higher inputs in the form of manure or crop residues improve soil fertility and increase soil organic pools. At the same time, changes toward reduced tillage practices lead to less soil disturbance and thus diminished releases of carbon to the atmosphere (Lal, 2004; Liao et al., 2015; Srivastava et al., 2016; Tittonell & Giller, 2013). In contrast to the identified trade-offs between food production (SDG 2) and biodiversity (SDG 15), these newly created carbon sinks directly contribute to climate change mitigation (SDG 13), indicating synergies with food production. A clear limitation of our study is that we only considered CO_2 and neglected other greenhouse gas emissions from agriculture, for example, CH_4 emissions from livestock management and paddy rice cultivation as well as N_2O emissions from fertilizer applications (IPCC, 2006), which may counteract the benefits seen in this scenario analysis.

The key objective of our study was to contribute to gaining a better understanding of trade-offs between the different SDGs in India and to unravel the underlying mechanisms and interdependencies between agricultural development, land use change, and environmental impacts. For this purpose, we have developed a relatively simple but, as we believe, transparent and easy to follow study design. Starting with SSP2 as a background scenario, we vary investments in agricultural R&D to obtain three clearly defined future pathways with different levels of agricultural intensification that in the next step are analyzed in regard of their consequences for the considered SDGs. A broader type of analysis, for example, to investigate how the depicted investment strategies would play out in different SSP worlds, was beyond the scope of this paper. Our motivation for the selection of only two climate scenarios was similar. As pointed out earlier, the intention was to investigate a large corridor of potential climate change in the year 2030, in our case defined by an RCP8.5 scenario with a clear negative impact on crop yields and a no climate change scenario without considerable changes. In this sense, uncertainties of future development trends are addressed by exploring the defined scenario space using the presented modeling framework.

Our study does not systematically quantify uncertainties of the structure and parameters of the applied models, which limits its usefulness as an information source for real-world decision making processes or risk assessments (Uusitalo et al., 2015). Parameter and data uncertainties exist on all levels of our model chain. Regarding the modeling of land use change processes with LandSHIFT, Göpel et al. (2018) show for a case study in Brazil how the utilized satellite-based land-cover products as well as the method used to estimate model parameters affect the calculated land use patterns. For addressing uncertainties in the structure of the crop and climate models, ensembles that apply multiple data sets and simulation models would be a promising route to further refine our study design (e.g., Semenov & Stratonovitch, 2010; Rosenzweig et al., 2013; Wallach et al., 2018). Sources of uncertainties in determining the parameters of the two empirical environmental impact models were already summarized in the previous paragraphs, and in further studies these should be systematically assessed by means of sensitivity and uncertainty analysis (Crosetto et al., 2000; Gao et al., 2017). In the field of social-ecological systems modeling, the paper of Gao et al. (2016) demonstrates how a variance-based global sensitivity analysis method can be applied to assessing uncertainties from a set of global change scenarios. However, it is important to note that a full uncertainty analysis would require taking into account the propagation of uncertainties through the different levels of our model chain, which would be a demanding task that was beyond the scope of this paper. In addition to conducting a numerical uncertainty analysis, we regard collecting and using more detailed regional specific soil and biodiversity data as a crucial step for further improving the reliability of our model results. A first step in that direction was done by the integration of knowledge from Indian field experts into our analysis, for example, regarding the classification of set-aside land.

Another promising field for future research is the refinement of the structure of our modeling framework that is currently based on a linear coupling of separate models. This effort should include the implementation of a mutual feedback mechanism between land use change processes on grid-level (LandSHIFT) and economic processes on country-level (IMPACT) in order to simulate effects such as the influence of reduced land availability due to urbanization on land management or on market prices and trade of agricultural commodities more realistically (see Long & Qu, 2018). In addition, a process-based ecosystem model could replace the IPCC Tier 1 approach to allow for more detailed analysis of soil management and climate effects of soil carbon storage (e.g., Del Grosso et al., 2016). At this point it is important to note that more sophisticated models typically require input data in a high level of detail that is often not available in large-scale studies (Ruane et al., 2017).

In conclusion, considering its limitations, it is important to emphasize that the results of our study should not be interpreted as forecasts but as potential development pathways under the assumptions made in the underlying scenarios. In this light, they can provide valuable new insights on how the agricultural sector and land use in India may evolve during the coming decade, and on the consequences for conflicts and synergies between the investigated SDGs. Our findings indicate that the intensification of agriculture will play a crucial role in improving food security in India (SDG 2). It is likely that this intensification will lead to a significant change of the farm structures as small subsistence farms will be transformed into larger units. Nevertheless, this pathway seems to be inevitable in order to countervail the expansion of cropland and pasture. Consequently, Indian agricultural and environmental policies should aim at supporting farmers in the implementation of sustainable intensification measures to minimize biodiversity losses and to foster soil carbon sequestration as a means to improve soil fertility and to reduce greenhouse gas emissions from agriculture.

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