A COMPUTABLE GENERAL EQUILIBRIUM MODELLING APPROACH TO ASSESS BIODIVERSITY EFFECTS IN HIGHLY DETAILED GLOBAL LONG-RUN ANALYSIS

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Abstract

Model based ex-ante assessments are appropriate tools to comprehensively analyse biodiversity conservation efforts as they capture drivers of biodiversity loss and their interactions. In a global context, multi-regional dynamic Computable General Equilibrium (CGE) models represent a suitable starting point for these assessments. This paper implements two post-model biodiversity indicators in the modular and open-source CGE modelling platform CGEBox. It thereby contributes to assess conservation effects of large-scale policies and developments quantitatively rather than qualitatively. CGEBox is based on the Global Trade Analysis Project (GTAP) model and data. Both biodiversity indicators build on the land use results calculated with its Agro-Ecological Zone (AEZ) module. They differ in terms of the scoring systems applied. Structural changes in the socio-economic system can considerably impact biodiversity conservation. Thus, the GTAP-based Recursive Dynamic Economic Model (G-RDEM) is used in the analysis at hand to generate three baselines up to the year 2050. These follow exogenous assumptions of the Shared Socio-Economic Pathways (SSPs) 1 to 3. In this way, the biodiversity results are comprehensively analysed under different framework conditions, compared to each other, and tested for robustness. Preliminary results show that the two indicators set different foci due to their distinct scoring systems. This is reflected in significant differences in the absolute results of both indicators. In relative comparison over time, however, both indicators show comparable global trends. Biodiversity loss occurs in all three baselines. The indicator deterioration is particularly pronounced in tropical regions of Africa, Asia and South America. A comparison of the three baselines reveals that sustainable development is not necessarily ideal from a biodiversity conservation perspective. Both indicators show better results for about half of the regions in SSP3 than in SSP1.

Keywords: Biodiversity, Biodiversity Indicators, Computable General Equilibrium Model, Baseline Analysis, Long-Run Analysis

Introduction

Biodiversity, short for biological diversity, is a multidimensional term which describes the diversity of and between species as well as the diversity of ecosystems (UN 1992). It forms the basis of a multitude of different ecosystem services and is therefore of great importance for the health of the environment as well as for human well-being (MA 2005). Species extinction rates continue to increase all over the world (IPBES 2019). This let the United Nations Biodiversity Conference COP15 in December 2022 emphasise the need for immediate global action (CBD 2022). The drivers of biodiversity loss are manifold. Due to their interactions with each other, with socio-economic parameters and with the climatic system, it is difficult to make biodiversity forecasts and to predict the effects of conservation efforts (IPBES 2019; MA 2005). This is particularly the case in the global context, where unintended spill-over and leakage effects pose a risk for conservation (IPBES 2019). While biodiversity assessments have often been carried out qualitatively, there is a growing effort for quantitative alternatives (EC 2021; IPBES 2019). Model based ex-ante assessments capture drivers of biodiversity loss and their interactions. They are thus well suited to comprehensively analyse and evaluate conservation measures and to inform policy makers as well as the whole society. In a global context, multi-regional dynamic Computable General Equilibrium (CGE) models provide an appropriate starting point for ex-ante assessments. They represent the economy in detail and can be used to create scenarios depending on socio-economic or climatic development assumptions.

Previous and emerging efforts to use global CGE-based ex-ante analyses for biodiversity assessments frequently rely on model couplings. Thereby, two approaches are to be distinguished: loosed-coupled models (e. g. (Johnson et al. 2021)) and integrated assessment models (e. g. (Kapitza et al. 2021)). In contrast, this work proposes an approach to integrate biodiversity indicators post-model into the CGE analysis without resorting to other models. It thus ties in with efforts to develop Sustainable Development Goal (SDG) indicator frameworks for CGE analyses. Halting biodiversity loss is part of SDG 15 “Life on Land” (UN n. d.). However, biodiversity is so far not or only insufficiently addressed in these frameworks (Campagnolo et al. 2018; Liu et al. 2021; Philippidis et al. 2020; Wilts and Britz 2022).

This paper builds on the SDG indicator framework developed by Wilts and Britz (2022). It extends the modular and open-source Global Trade Analysis Project (GTAP)-based CGE modelling platform CGEBox (Britz and van der Mensbrugghe 2018) with two post-model biodiversity indicators. The land use and land management changes quantified with its Agro-Ecological Zone (AEZ) module form the basis of both. They differ in terms of the scoring systems applied. One indicator estimates the biodiversity goodness of a region based on its species richness (IUCN 2023; BLI 2023) and biodiversity scores found in the literature (Newbold et al. 2015). The other one calculates the potential species loss of a region based on so-called land use intensity characterisation factors (CFs) estimated by Chaudhary and Brooks (2018). As structural changes in the socio-economic system can have significant impacts in the context of biodiversity conservation, the GTAP-based Recursive Dynamic Economic Model (G-RDEM) (Britz and Roson 2019; Roson and Britz 2021) is used in the analysis at hand to generate three baselines up to the year 2050 with high regional and sectoral detail. These follow the exogenous Gross Domestic Product (GDP), demography and educational attainment projections of the Shared Socio-Economic Pathways (SSPs) 1 to 3. Thus, they depict different challenges for the adaptation and mitigation of climate change (Riahi et al. 2017). The results of both biodiversity indicators are comprehensively analysed and evaluated using the baselines.

This paper is structured as follows: Chapter 2 refers to the methodology applied. The data base and model set-up are briefly described before the development of the biodiversity indicators is explained in detail. Chapter 3 shows preliminary results of both biodiversity indicators and discusses them. Thereby, the focus is on the results of the SSP2 baseline, while the SSP1 and SSP3 baselines provide comparison points and outlooks where appropriate.

Methodology

Data Base and Modelling Framework

The SSP baselines in this analysis draw on the data base described in Wilts and Britz (2022). Building on the GTAP v10 data including power, emission and air-pollution information, the baselines start from a snapshot of the global economy in 2014. By means of an advanced multi-level split mechanism, the database is further expanded with agricultural and fishery detail. Irrigation water is added to the production factors and labor is subject to an educational specific gender split. The 141 GTAP regions are clustered into 31. Among these, 15 are individual countries putting focus on selected low- and middle-income countries. The rest is aggregated according to regional and/ or economic similarities (Wilts and Britz 2022). The CGE model applied in this analysis is build up on the open-source modelling platform CGEBox (Britz and van der Mensbrugghe 2018). This is based on the General Algebraic Modeling System (GAMS) replication of the GTAP standard model version 7 by van der Mensbrugghe (2018). However, its modular nature allows for a flexible model configuration. Numerous model extensions are available and can be combined if desired. In addition, structural changes to the standard model are possible and post-model tools can be activated. For a complete overview of the functions of CGEBox, please refer to its documentation (Britz 2022).

Land use change is the main driver of biodiversity loss according to the Organisation for Economic Co-operation and Development (OECD) (2018). The calculation of the biodiversity indicators thus requires the AEZ module to be activated. This is based on the AEZ model (Lee et al. 2009) and data (Baldos and Corong 2020) of the GTAP community. The AEZ definition of the Food and Agricultural Organisation of the United Nations (FAO) and the International Institute for Applied Systems Analysis (FAO 2022) is extended by three climate zones (tropical, temperate, and boreal), thereby distinguishing a total of 18 AEZs (Lee 2005). On this basis, land supply and demand of the model regions are disaggregated into AEZ sub-units. These show similar cultivation conditions and the production factor land, which is completely mobile in the GTAP standard model, is restricted to the AEZ sub-units. The CGEBox implementation goes beyond the GTAP one and replaces the traditional Constant-Elasticity-of-Transformation (CET) functional form by an additive one (aCET) as discussed in van der Mensbrugghe and Peters (2020). In this way, physical balancing is guaranteed while allocating the AEZ land stocks to the different production activities. Further, the original four-level nesting is extended to six nests differentiating the transformation elasticities of annual and perennial crops. In contrast to the GTAP model, the AEZ module in CGEBox also comprises a land buffer which enables a conversion of natural habitats into land in economic use (Britz 2022).

CGEBox, through G-RDEM (Britz and Roson 2019; Roson and Britz 2021), allows to analyse the biodiversity indicators under different socio-economic development scenarios. G-RDEM is a tool specifically designed for the generation and analysis of long-term baselines. It still builds on the GTAP standard model but replaces important features for this purpose. While the total factor productivity (TFP) shifter is endogenised, G-RDEM fixes GDP and population trends in each solve step. In doing so, it relies on exogenous GDP, demographic and educational attainment projections of the SSPs. To capture interaction effects between the core model and this exogenous assumptions, G-RDEM implements three features in the CGE modelling framework: A modified rank three implicit directly additive demand system (MAIDADS) in private consumption allows for income-dependent marginal budget shares and exponential Engel curves. The TFP shifter is sector-differentiated based on econometric work and a flexible nesting structure depicts substitution effects more precisely. In addition, G-RDEM updates relevant drivers of structural change in between two solve steps. The available labor force is adapted to the population and work force projections. In contrast, macro-saving rates, cost shares through time- and income-dependent input-output coefficients and endogenous expenditure shares of government and investment demand cannot be adjusted directly. In these cases, the update mechanism is based on econometrically determined correlations between the exogenous socio-economic projections and the parameters. The capital stock depends on GDP developments, updated saving rates and debt accumulation. It is adjusted in each solve step to the end stock of the previous one. Debt accumulation redefines the balance of payments so that international capital flows reflect past savings. Concerning land use, G-RDEM econometrically determines the development of the built-up area based on the socio-economic developments. In addition, it uses comprehensive FAO projections (FAO 2018) to correct for the particularly sensitive developments of crop yield and land. Figure 1 graphically summarises the set-up of the applied CGE model in the modelling platform CGEBox as well as the core mechanism of G-RDEM.

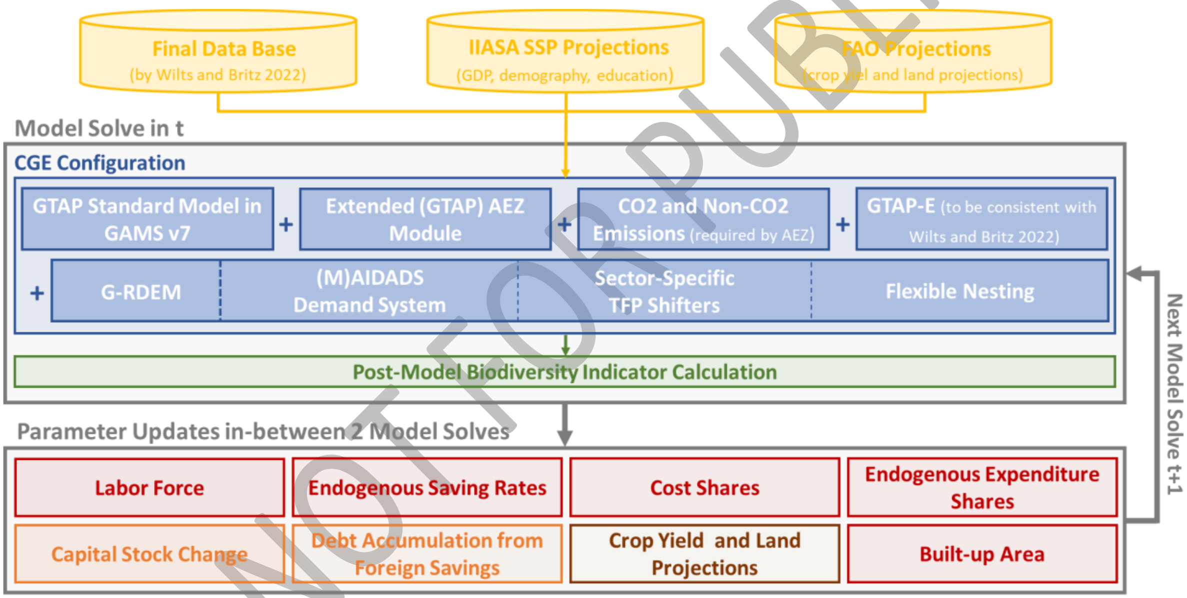


Figure 1: Model Configuration in CGEBox and G-RDEM Mechanism.

Source: Own illustration based on Britz and Roson (2019) and Wilts and Britz (2022).

Remark: The color differentiation in the lower field differentiates the update mechanism. Red fields are exogenous parameters which are updated in G-RDEM based on (econometrically estimated correlations with) the exogenous assumptions. Orange fields are endogenous parameters for which G-RDEM changes the update mechanism. The brown field relates to the FAO projections. Fixing crop yield and land projections requires to additionally endogenise the technology shift parameters.

In this analysis, G-RDEM is used to create three baselines with a two-year resolution up to 2050. The baselines differ in terms of the exogenous projections used and draw on SSP 1, 2 and 3. SSP1, which describes global sustainable development in its narrative, is characterised by high GDP growth, especially in low- and middle-income countries reducing global inequality.

Investments in education and health result in low population growth. SSP2 describes business-as-usual developments associated with medium GDP and population developments. The narrative of SSP3 refers to a development path of regional rivalry. This reduces global economic performance and GDP projections are comparatively low. Population trends are here high in low- and middle-income countries, while they are low in high-income countries (Riahi et al. 2017). In addition to the exogenous projections, G-RDEM implements scenario specific assumptions which follow the SSP narratives. These include the development of emission pricing (strong/ moderate/ no increase in SSP1/ SSP2/ SSP3) and the demand for animal products (strong/ moderate/ no reduction in SSP1/ SSP2/ SSP3). In the SSP3 scenario, further, preferences for regional products are increased.

Implementation of the Biodiversity Indicators

This paper implements two post-model biodiversity indicators in the modular and open-source CGE modelling platform CGEBox. At their core, both rely on the supported assumption that conversion from more natural to less natural land cover types is the main driver of biodiversity loss (OECD 2018). Therefore, land use cover changes (LUCCs) calculated by the AEZ module form the basis of both biodiversity indicators. Their highest spatial resolution is accordingly the AEZ sub-unit level of the model regions. Aggregations to country and AEZ level are also available. In addition to the LUCCs, both indicators consider land management intensity as another important driver of biodiversity loss (IPBES 2019). For this purpose, they both use the same management estimators. Despite the mentioned similarities, the structure of both indicators varies considerably due to different scoring systems applied. For this reason, the methodology of the two biodiversity indicators is described separately in the following two sub-chapters.

<u>Indicator 1: Composite Index of Biodiversity Goodness</u>

This indicator, hereinafter referred to as biodiversity indicator 1, estimates the biodiversity goodness of the considered region in a composite index. As described above, the LUCCs calculated by the AEZ module form the basis for the calculation of the biodiversity indicators. In this case, five habitat shares are calculated from the land use information. These record the proportion of a particular land cover (habitat) or a group of similar land covers (similar habitats) in the total land of the respective AEZ sub-unit, model region or AEZ. Table 1 provides information on which land cover types correspond to which habitat shares. An extended version of the table in appendix 1 further shows the GTAP and FABIO land use activities associated with the habitat shares.

Table 1: Composition of Biodiversity Indicator 1 (Composite Index of Biodiversity Goodness)

Habitat Share	GTAP-AEZ Land Cover	BDG Base Score	Potential Variation	BDG Final Score	Management Intensity Esimator
Natural Habitat Share (NHS)	Savanna Grassland Shrubland Unmanaged Forest Other Land	100	0	100	-
Managed Forest Share (MFS)	Forest	19	+ 65	19 - 84	*Land input in forest activity / dollar output of the same*
Cropland Share (CLS)	Cropland	74	- 50	24 - 74	Intermediate chemical demand of all cropland activities / cropland
Pastureland Share (PLS)	Pastureland	21	+ 63	21 - 84	*Land input in pasture activities / dollar output of of the same*
Built-up Land Share (BLS)	Built-up Land	1	0	1	-

Source: Own illustration.

Remark: BDG used as acronym for biodiversity goodness. Italic writing of the management intensity estimator explanation marks an inverse estimator. That is, a high value represents a low intensity of use.

In biodiversity indicator 1, the habitat shares act as weights to combine biodiversity goodness scores associated with the respective land covers into an index. For readability and interpretability, these scores, and thus also the composite index of biodiversity goodness itself, should lie in a value range between 1 (low biodiversity goodness) and 100 (high biodiversity goodness). To achieve this, the least favourable habitat share, the built-up land share (BLS), is assigned a biodiversity goodness score of 1. The most favourable habitat share, the natural habitat share (NHS), respectively, is given a score of 100. To establish a biodiversity scoring for the remaining three habitats, a comprehensive literature search was conducted. Newbold et al. (2015) calculate intensity-differentiated land use effects on terrestrial species richness. Although this publication leaves room for discussion, it remains unchallenged in its regional and methodological set-up to date. It thus forms the basis for the biodiversity goodness scores of managed forest, cropland and pastureland in this analysis.

In contrast to the natural habitats and the built-up area, the remaining three land covers are associated with economic land use activities. The model output thus provides information to estimate the corresponding land use intensities. Based on this, a biodiversity goodness base score and a potential score variation range are differentiated. The final biodiversity goodness scores can take on values between the base score and the sum of the base score and the score variation range. Which part of the variation range is added depends on the management intensity and further on regional species richness and is described in more detail below. Through this mechanism, the final biodiversity goodness scores for managed forest, cropland and pastureland differ from region to region.

Both, biodiversity goodness base score and variation range, are based on the values listed in Table SI1 of Newbold et al. (2015) in the "Species Richness" column for plantation forest, cropland and pasture. The score variation corresponds with the range from the lower limit of the 95% confidence interval at low use intensity to the upper limit at high use intensity. Whether the upper or lower limit is used as the base score depends on the estimator for management intensity and is also detailed below. Overall, the Newbold scores do not cover the entire range of values from 1 to 100. While the value for primary vegetation (minimal use) is 100, as aimed at, the lowest value for urban (intense use), which can be seen as comparable to the built-up area in the analysis is at hand, is 37.5. The scores listed in Table 1 thus do not exactly replicate the values shown in Table SI1 of Newbold et al. (2015). Rather, the Newbold scores have been standardised with the range of 37.5 to 100 to fit the target range of 1 to 100.

The score variation of the land covers in economic use depends primarily on the respective estimator for land management intensity. As listed in Table 1, it was possible to establish an intensity estimator in relation to land area only for cropland. Comparable attempts for managed forest and pastureland are too heavily distorted by outliers. Therefore, an inverse management intensity estimator is calculated in these cases. This sets the land input of the corresponding production activities in relation to their output. In this way, the effects of land rent changes are considered even without the land reference in the denominator. These estimators are inverse as a high land input value stands for a low intensity of use. All management intensity estimators are standardised, so that they take on values between 0 (low for regular estimator, high for inverse estimator) and 1 (high for regular estimator, low for inverse estimator). This allows the final biodiversity goodness score, which is composed of the biodiversity goodness base score and a part of the potential score variation range, to be determined using a simple linear function.

Secondly, to further differentiate land management impacts depending on local species stocks, the management intensity estimators are offset against species richness figures of the regions under consideration. The intensity estimators are thereby weighted by factor three to establish a ranking which rates poor management as less favourable for biodiversity than low species richness. This follows the assumption that biodiversity-poor regions can recover under good management, whereas poor management results in particularly high biodiversity loss when species richness is high. The species richness figures of the regions under consideration are calculated using GIS analysis. Spatially explicit species occurrence data from the International Union for Conservation of Nature (IUCN) and BirdLife International (BLI) (BLI 2023; IUCN 2023) are mapped to the GTAP-AEZ shape and species richness statistics are calculated. The results are available for the post-model calculation of biodiversity indicator 1 as GAMS Data Exchange (GDX) format. They are adjusted to the country aggregation of the database when imported into the modelling platform by weighting them with area shares. Like the management intensity estimators, the species richness figures are standardised to take values between 0 (low) and 1 (high). It is to be noted that records of the comprehensively assessed taxonomic classes mammalia, amphibia and aves are used for the calculation of total regional species richness. Information on the regional richness of endangered and endemic species is also available. This includes reptilia in addition to the three taxonomic groups just mentioned.

The complete calculation of biodiversity indicator 1 is summarised in the following formula:

$$
\begin{aligned}
(1)\quad BiodiverisityIndicator1_{r,t} = {} & NHS_{r,t} * 100 \\
& + MFS_{r,t} * [\ 19 + 65 * (\ 3 * MI(MF)_{r,t} + SR_r\ ) \,/\, 4\ ] \\
& + CLS_{r,t} * [\ 74 - 50 * (\ 3 * MI(CL)_{r,t} + SR_r\ ) \,/\, 4\ ] \\
& + PLS_{r,t} * [\ 21 + 63 * (\ 3 * MI(PL)_{r,t} + SR_r\ ) \,/\, 4\ ] \\
& + BLS_{r,t} * 1
\end{aligned}
$$

With: r for region, t for solve step, MI for management intensity estimator, MF,CL and PL for the land cover types corresponding to the equally named habitat shares

Indicator 2: Potential Species Loss

This indicator, hereinafter referred to as biodiversity indicator 2, calculates the regions' potential species loss per 1000 ha. For this purpose, the land use results of the AEZ module are offset against CFs published by Chaudhary and Brooks (2018). These estimate terrestrial potential species loss per square metre through long-term land use for five taxonomic groups (mammalia, amphibia, aves, plantae and reptilia) and five land covers (managed forest, plantation, cropland, pasture and built-up) under three management intensities (minimal, light, intense) and cover up to 804 ecoregions. In addition to this high resolution, the CFs are also available at country level and for the total species population. Further, land occupation and land transformation CFs are distinguished (Chaudhary and Brooks 2018). Despite the fact that the CFs by Chaudhary and Brooks (2018) are based on 2005 land use data, these are the most recent CFs to cover such a level of detail to the best of the authors knowledge. They are ideally suited for the present paper, as the land use categories considered, except of plantations, correspond to the GTAP-AEZ land use categories.

For the calculation of biodiversity indicator 2, the land transformation CFs at country level have been assigned to the GTAP regions. While the highest (worst) CFs are assumed for built-up area, a base CF and a potential CF variation range are determined for each GTAP region for the remaining three land covers, analogous to the score differentiation in biodiversity indicator 1. Whether the base CF corresponds to the lowest (best) or the highest (worst) CF depends, again, on the respective management intensity estimators summarised in Table 1. Cropland therefore uses the highest CF as the base value, whereas managed forest and pastureland use the lowest CF due to the inverted nature of the intensity estimator.

To create a reference point, CFs rely on the assumption that there is no species loss in natural habitats. Therefore, natural land cover types are not considered in the calculation of biodiversity indicator 2. The land use information for managed forest, cropland, pastureland and built-up area is multiplied with the respective CFs. In a next step, the potential species loss of the region is summed over the four land covers and related to the total area of the region under consideration in 1000 ha. As with biodiversity indicator 1, the management intensity estimators are used in standardised form. In this way, the part of the potential CF variation that is added to the base CF can again be determined by means of a simple linear regression. Also analogous to the other indicator, the geographical resolution of biodiversity indicator 2 is initially the AEZ sub-unit of the region under consideration. However, aggregations at country and AEZ level are also available.

The following formula 2 summarises the calculation of biodiversity indicator 2:

$$(2) \qquad \begin{aligned} PSL_{MF,r,t} &= LU_{MF,r} * (BaseCF_{MF,r} - MI(MF)_{r,t} * VarCF_{MF,r}) \\ PSL_{CL,r,t} &= LU_{CL,r} * (BaseCF_{CL,r} + MI(CL)_{r,t} * VarCF_{CL,r}) \\ PSL_{PL,r,t} &= LU_{PL,r} * (BaseCF_{PL,r} - MI(PL)_{r,t} * VarCF_{PL,r}) \\ PSL_{BU,r,t} &= LU_{BU,r} * (BaseCF_{BU,r} + 1 * VarCF_{BU,r}) \end{aligned}$$

$$BiodiveristyIndicator2_{r,t} = [PSL_{MF,r,t} + PSL_{CL,r,t} + PSL_{PL,r,t} + PSL_{BU,r,t}] / TotalLU_{r}$$

With: PSL for potential species loss, LU for land use, Va for Variation, BU for built-up area r, t, and MI as in formula (1)

Preliminary Results

As described in Chapter 2.1, the three baselines differ primarily in terms of the exogenous GDP, population and FAO projections which feed back to many other model parameters. How this influences land use and land management as the basis of both biodiversity indicators is graphically summarised in the Appendices 2 and 3. The figures there first depict the situation in the base year 2014, followed by the changes in the three baselines from 2014 to 2050.

Beginning with the land use results, the North Africa Aggregate (NAfrica), Canada, the Former Soviet Union (FUSSR) and Ethiopia show notably high shares of land not in economic use (savanna grassland, shrubland, unmanaged forest and other land[1]) with more than 70% in the base year. In contrast, Germany, South Africa, the Rest of the European Union Aggregate (EU), the Philippines and Bangladesh reveal the lowest shares of this land cover class, also referred to as unmanaged land, with less than 30%. On average across regions, the unmanaged land cover share decreases over time by -15.51% in the SSP1 baseline, -16.07% in the SSP2 baseline and -16.53% in the SSP3 baseline. The highest losses are seen in Bangladesh, Ghana, Nigeria, the Association of Southeast Asian Nations (ASEAN), India and the Rest of Africa Aggregate (RoAfrica) across all baselines. Additionally, in the SSP3 baseline, the Philippines record a strong natural habitat decline. Despite their high unmanaged land cover shares, the NAfrica, the FUSSR, Canada and the Australia and New Zealand Aggregate (ANZ) show low reductions in this land cover. The latter even reports a rise (+1.82%) in the SSP3 baseline. Further notable exceptions showing increases in the unmanaged land cover are South Africa (+9.73%) in the SSP3 baseline and Vietnam (+0.78%) and Mercosur (+0.72%) in the SSP1 baseline.

The unmanaged land cover losses from 2014 to 2050 are due to increases in the shares of the four remaining land cover classes managed forest, cropland, pastureland and built-up area. Concerning the managed forest share, reference is to be made to the definition of managed forest by Sohngen et al (2008) which underlies the GTAP-AEZ data. This defines forest within a radius of ten kilometres from infrastructure as managed and therefore distorts the share (Sohngen et al 2008). The aggregate of the left-over OECD countries (RoOECD) shows by far the highest managed forest share in 2014 with 51.48%. This is followed by the ASEAN, the EU, the Philippines and Germany, reporting shares between 26% and 37%. At the lower end of the managed forest share in the base year are the NAfrica, Kenya, the ANZ and the Mercosur aggregate with shares of less than 10%. Over time, the average increase across regions is strongest in the SSP1 baseline with +29.87%, followed by the SSP2 baseline with +19.04% and the SSP3 baseline with +7.89%. Due to the high GDP growth, total consumption (of luxury goods) increases in the SSP2 and especially in the SSP1 baseline. This is also reflected in the demand for wood. Added to this is the high increase in emission prices in these two baselines. At country level, the managed forest increases in Malawi and Kenya in the SSP1 baseline are particularly high (+153.63% and +138.89%). However, especially Kenya records only a very

[1] In the GTAP database, other land includes rock, ice and desert (Baldos and Corong 2020).

small managed forest share. Nicaragua, Argentina, the RoAfrica and Bangladesh also show above-average managed forest share growth across the SSPs. Nigeria and the Philippines are notable cases as they show declines in in the respective share in all three baselines.

The cropland share in 2014 is highest in Bangladesh with 61.21%, followed by India with 53.75% and Nigeria with 44.5%. Five more regions report shares between 30% and 40%: the Philippines, Germany, Malawi, Vietnam and Ghana. In contrast, the Rest of the Andes Aggregate (RoAnden), the ANZ, Bolivia, Canada and the NAfrica show cropland shares below 5% and Brazil, the RoAfrica, the RoOECD, the FUSSR and South Africa below 10%. The average increase across regions from 2014 to 2050 is highest in the SSP3 baseline with +26.69%, followed by the SSP2 baseline with +17.31% and the SSP1 baseline with +13.64%. Across all SSPs, the increases are most pronounced in the RoAfrica, Kenya, Nigeria, Ghana and Ethiopia. The remaining African countries, against this, only show moderate increases. China is the only country to record a decline in the cropland share in all three baselines. In addition, Vietnam, the ANZ, Germany, the Philippines and the EU show declines or only moderate increases in the SSP1 and the SSP2 baseline. Behind the cropland developments are not only GDP-driven demand and technology changes. Due to the emission pricing, land rents increase significantly more in the SSP1 than in SSP2 baseline, while they remain at a low level in the SSP3 baseline. Further, the FAO projections correct land productivity according to the SSP narratives (SSP1 > SSP2 > SSP3). The same drivers are behind the development of the pastureland share. However, GDP effects (demand for luxury goods due to high GDP growth) are more important in this case. The base year pastureland share is highest in South Africa, Mercosur, the ANZ and China, at more than 40%. In contrast, Vietnam, the RoOECD, ASEAN, Canada, India and Bangladesh report shares below 5% and the Philippines, Indonesia, the FUSSR and the NAfrica below 10%. The average increase in this share over time across regions is strongest in the SSP2 baseline with +8.61%, followed by the SSP1 baseline with +7.1% and the SSP3 baseline with +3.96%. At region level, Bangladesh and the Philippines report high pastureland growth in all three baselines. In the SSP3 baseline, Indonesia is to be added to this list. Nigeria, in contrast, shows the sharpest decline in the pastureland share in all three baselines.

The built-up area share is low compared to the other land cover shares, ranging from less than 0.1% in Ethiopia, Malawi, Kenya and the RoAfrica to 6.77% in Germany. The RoOECD, the EU, the USA and Vietnam also show high built-up area shares of more than 1%. According to the GDP and population projections, the increases in this share are highest in the SSP1 baseline with +95.46% on average across regions. This is followed by +86.71% in the SSP2 baseline and +76.42% in the SSP3 baseline. The increases in all three baselines are particularly high in Central Africa (all African regions except North Africa and South Africa) and Asia Pacific (Bangladesh, India, Vietnam, Philippines, Indonesia). In contrast, already highly developed regions are experiencing lower urban growth.

With a view to the management intensity estimator results, the global picture for managed forest in 2014 is in the upper midfield of the rating scale. Only Bolivia, Vietnam, Canada, the USA and the ANZ report slightly worse values than the rest of the world. Except of Canada, the EU and the ANZ, the forest management estimator deteriorates globally in all three baselines from 2014 to 2050. The decline is particularly strong in Africa and Asia Pacific. A comparison of the changes in the three baselines is inconclusive in this case. Europe, North America, Russia and the Rest of the World Aggregate (RoW) perform better in the SSP1 baseline than in the SSP2 baseline and worse in the SSP3 baseline. The opposite is true for the other regions. The cropland management estimator shows very low values for most countries which might be due to standardisation effects. The use of chemicals in agriculture is so high in some countries (China, rest of OECD aggregate, South America) that the management intensity in the other countries appears low in relation. Over time, the cropland management intensity deteriorates in all three baselines. These effects are particularly pronounced in the RoAfrica and India in the comparison of the regions and in SSP1 in the comparison of the baselines. In contrast, the SSP3 baseline even shows slight improvements in cropland management in some cases, for example in the EU or China. The pastureland intensity estimator assesses the global baseline situation in 2014 as very poor. Thereby, the worse results for Africa and India are striking. The indicator relates the land input of pasture production activities to their output. It does not consider that pasture output can also be produced in stables. It therefore seems to be biased in favour of industrial agriculture. Nevertheless, the pastureland management intensity estimator deteriorates over time with a particular pronunciation in Africa and Asia Pacific. Against this, the EU and North America perform relatively well while the left-over regions rank in between. In comparison of the baselines, poorer scored regions in SSP2 worsen in SSP1 while higher scored regions improve. In contrast, the ratings of the regions in the SSP3 baseline converge in comparison to the SSP2 baseline.

The following Figures 2 and 3 summarise how land use and management are reflected in the two biodiversity indicators. The top map in both figures depicts the situation in the base year while the three following maps report the changes in 2050 in the three SSP baselines.

Figure 2: Biodiversity Indicator 1

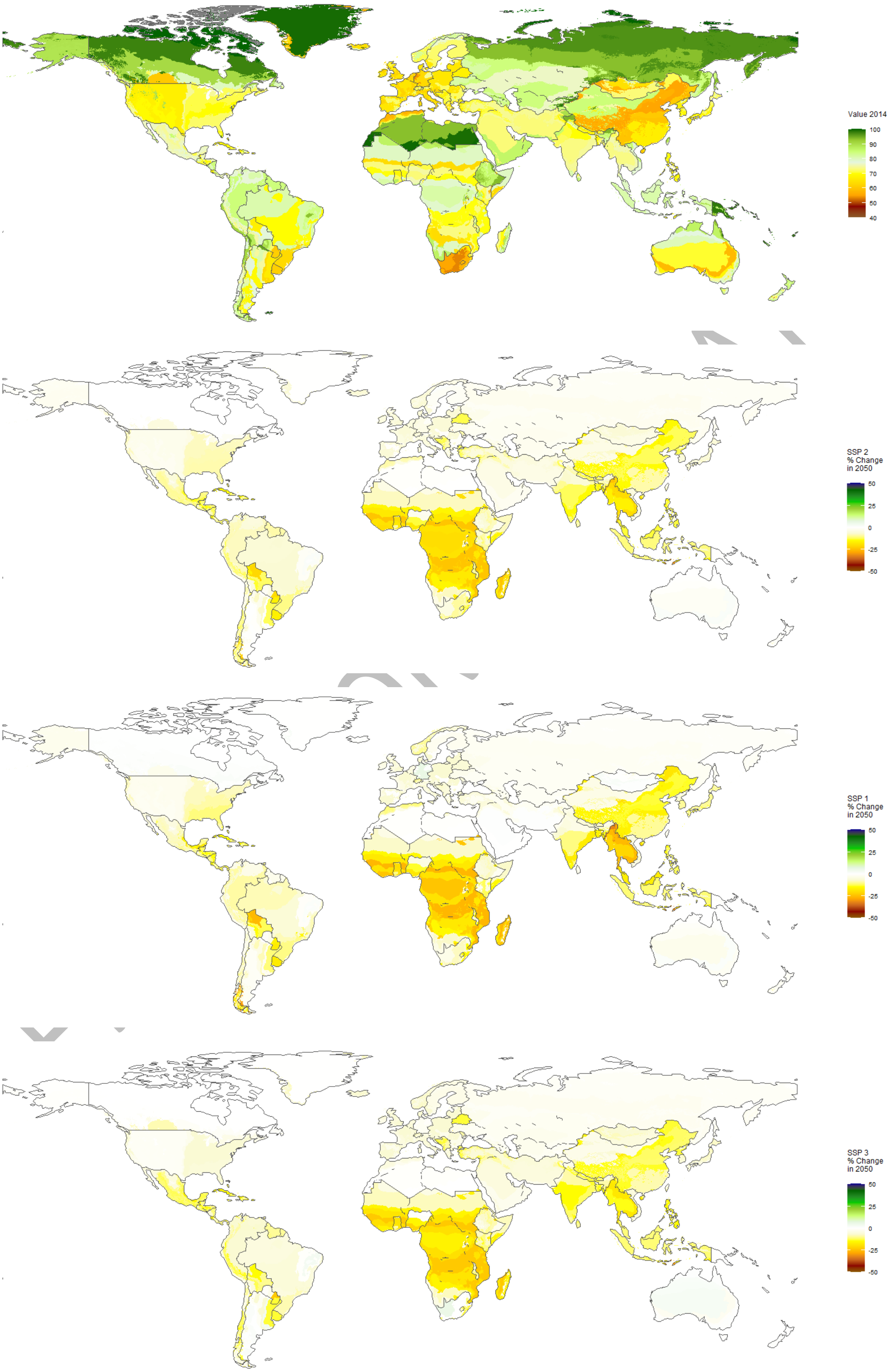
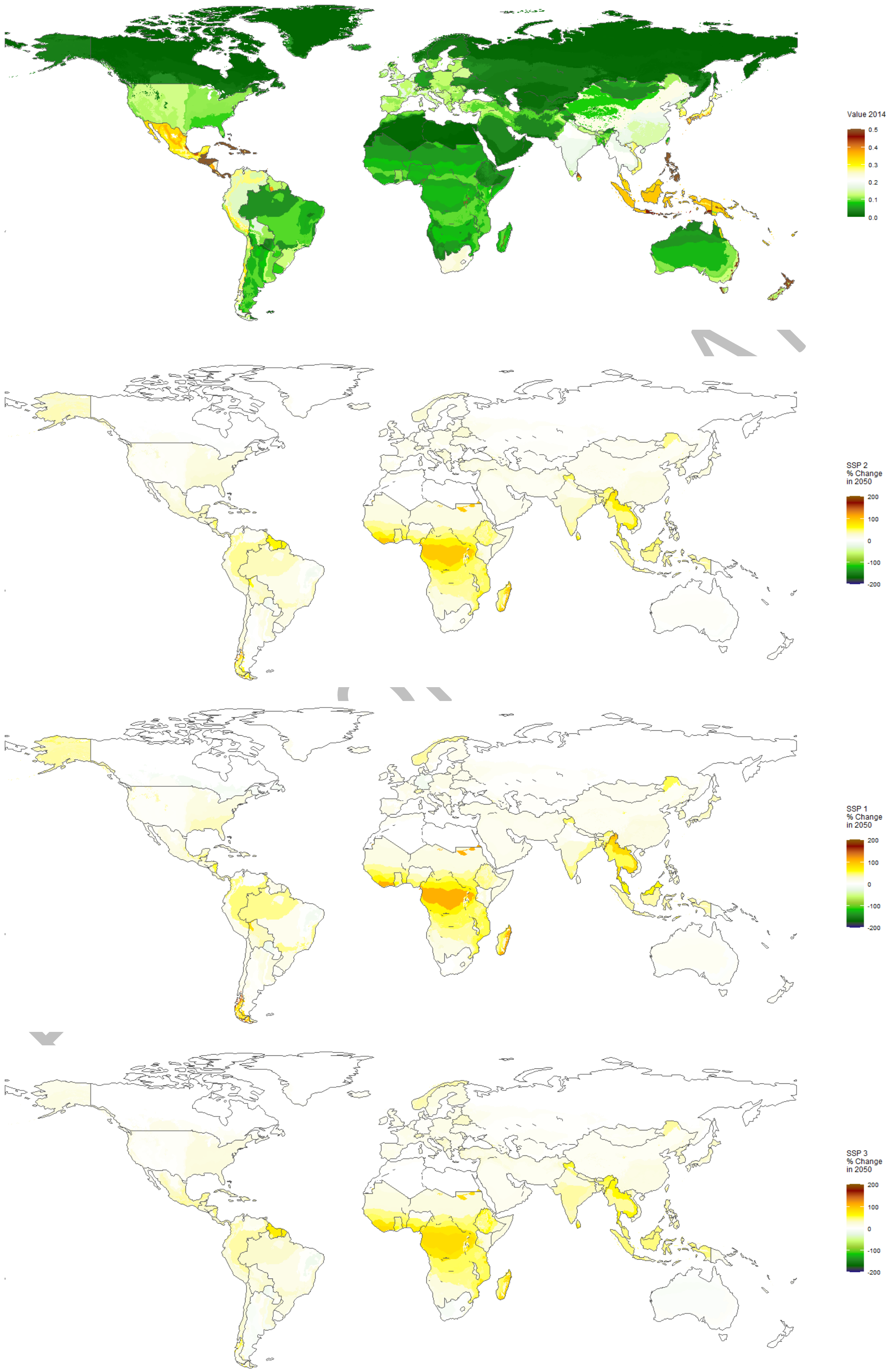


Figure 3: Biodiversity Indicator 2



The upper maps in Figures 2 and 3 show distinct color schemes illustrating a different assessment of the AEZ sub-units and regions by the two biodiversity indicators. The base year situation seems to be better assessed by biodiversity indicator 2 compared to biodiversity indicator 1. However, two things are to be noted in this regard: Firstly, the two biodiversity indicators take on different value ranges. Biodiversity indicator 1 is scaled to a potential value range of 1 to 100 and realises scores between 49.35 and 100 in 2014. Values below 49.35 are not achieved because the lowest-scoring built-up area share is only small, even at AEZ sub-unit level. Further, the scores of lands in economic use only take on a section of their possible value range in the base year due to the standardisation with the management intensity estimators which all deteriorate over time. Although some individual scores below 49.35 are reported, these are buffered in the final composite index by other, higher-scoring habitats. Biodiversity indicator 2 records a base year potential species loss per 1000 hectare between 0 and 2.84. In this small range of values, high scores seem to be outliers. The 95% quantile of the results of biodiversity indicator 2 in 2014 is 0.53 and the 75% quantile is 0.2. Due to the outliers, the visual differentiation between regions with low base year results is lost and a large part of the upper map in Figure 3 appears in green colors. To make effects visible at all, the color scaling in this graphic is set to the range of values between 0 and 0.5 which covers 93.15% of the base year results of biodiversity indicator 2. AEZ sub-units exceeding the value of 0.5 are found in the ANZ, the Philippines, Indonesia and the Central America aggregate and are colored identically to the value 0.5. Secondly, it is to be considered that the two indicators capture different perspectives on biodiversity. A good (high) biodiversity indicator 1 as a composite index of biodiversity goodness describes regions where land cover and management are in favor of biodiversity. In these regions, biodiversity loss may be comparatively low, but species richness can also be stable or even improving. In contrast, biodiversity indicator 2 as an estimator of potential species loss grasps only negative biodiversity situations. A good (low) biodiversity indicator 2 stands for low species loss compared to other regions.

Focusing on the relative assessment of the regions and AEZ sub-units instead of the different color schemes, it appears that both biodiversity indicators rate NAfrica, Canada, the FUSSR and Ethiopia, and thus the regions with above-average unmanaged land cover, as particularly good. At the level of the AEZ sub-units, there is also a high degree of agreement in the top ranking of the two indicators mainly dominated by a high share of unmanaged land. In contrast, the two indicators diverge for the regions rated worst. In the case of biodiversity indicator 1, unmanaged land cover also appears to have a strong influence in this regard. The five regions with the lowest occurrence of natural habitats (Germany, South Africa, EU, Philippines, Bangladesh) are among the seven regions assigned the lowest scores. The other two regions in this listing are China and the Mercosur aggregate. The proportion of natural land cover in these two regions is only slightly higher than in the five regions mentioned before. In addition, China and the Mercosur aggregate show a comparatively high share of pastureland which is generally rated poor as described above. Considering the worst scores of biodiversity indicator 1 on a disaggregated level, AEZ sub-units belonging to the seven regions just mentioned also dominate. In addition, some AEZ sub-units of other model regions characterised by high pastureland shares are also scored poorly. In biodiversity indicator 2, in comparison, a low unmanaged land cover share seems to be of less importance. The regions with the highest natural habitat deposits are ranked between the 5th and the 31st place at the aggregate level of the model regions. As described in the previous paragraph, particularly high (poor) values of biodiversity indicator 2 are found at the AEZ sub-unit level in the ANZ, the Philippines, Indonesia, and the Central America aggregate. This suggests that the CFs used by this indicator to score land use and management place high importance on endemic species richness. At the aggregate level, the Philippines, Indonesia, and the Central America aggregate are also rated as the three regions worst for biodiversity. The ANZ further comprises AEZ sub-units which are rated less negative and thus buffer the average score of this region.

Comparing the ranking of the remaining regions between the two biodiversity indicators, less clear tendencies can be seen at both the aggregated and the disaggregated levels. As already visible in the comparison of the regions scored best and worst, the assessment by biodiversity indicator 1 tends to rely more on the land use and management conditions described above than biodiversity indicator 2. Its ranking corresponds with the ranking of the unmanaged land cover share. Deviations from this occur either in the case of extremely poor management conditions reflected in the score of the respective land cover or in the case of high shares of other, lower scored land covers. Brazil, for example, shows the seventh largest stock of land not in economic use but is ranked 12th by biodiversity indicator 1 as its management of cropland and pastureland is evaluated poorly. In this way, the biodiversity indicator 1 ranking of all aggregated regions and AEZ sub-units can be explained. In contrast, the midfield ranking of biodiversity indicator 2 shows some positions which cannot be understood based on the land use and management results described above. For example, this indicator ranks Germany as the fifth best country although it has neither high unmanaged land cover nor above-average land management. This suggests that the reason for the ranking here, as for the ranking of the worst scored regions, seems to be the CFs. At this point, it is again to be emphasised that biodiversity indicator 2 is not a measure of general biodiversity quality but of the potential loss of species observed in a region. Aspects such as the substitutability of a species or its adaptability to human intervention seem to be of greater importance than land use and management.

Looking at the change in the two biodiversity indicators in the three SSP baselines by 2050, there is a higher degree of agreement than in the ranking comparison. Both indicators predict the direction of change identically for the aggregated model regions in all scenarios. At the AEZ sub-unit level, the SSP-specific forecasts of both indicators each match for more than 90% of the regions. As can be seen in the three lower maps in Figures 2 and 3, negative biodiversity effects predominate globally in all three scenarios. On average across regions, biodiversity indicator 1 in the SSP2 baseline predicts a deterioration of -6.39% for the year 2050. In the SSP1 baseline, this deterioration amounts to -6.31% and in the SSP3 baseline to -6.04%. Biodiversity indicator 2 shows an average increase of +20.45% in the SSP2 baseline, of +19.54% in the SSP3 baseline and of +19.53% in the SSP1 baseline. Despite the positive signs, these values correspond to indicator deteriorations as a higher potential species loss is poor for biodiversity. Depending on the scenario and the indicator considered, 85% to 92% of the regions show a reduction of the respective biodiversity indicator. This is in all cases particularly pronounced in tropical regions of Africa and Asia-Pacific. In these regions, as described above, the loss of natural land cover in favor of economic land use is particularly pronounced. In addition, there is an extreme increase in the intensity of managed forest and pastureland management. South America also shows biodiversity loss in its tropical regions. However, this is comparatively low, especially in biodiversity indicator 2. One consequence of the described global biodiversity development is that improvements are only evident in a few AEZ sub-units, regardless of the socio-economic framework conditions. Figures 2 and 3 further indicate that positive biodiversity effects are much less pronounced than negative ones. Biodiversity indicator improvements are for example evident in parts of South America and the ANZ. In these regions, management practices deteriorate but land is being released from economic use and consequently the unmanaged land cover share increases. Comparing the three baselines at the level of AEZ sub-units, both biodiversity indicators agree on the evaluation of the SSP1 and the SSP3 baseline relative to the SSP2 baseline in more than 85% of the cases. Biodiversity indicator 1 predicts an improvement in the SSP1 baseline compared to the SSP2 baseline for 141 of the 292 regions, biodiversity indicator 2 for 153. In the case of the SSP3 baseline, these figures are 155 and 138 respectively. There are 25 AEZ sub-units in which the SSP1 baseline and the SSP3 baseline do not develop in opposite directions under biodiversity indicator 1 and 21 under biodiversity indicator 2. To fully understand the drivers of these developments, a case-by-case analysis is necessary. However, in the hotspots of biodiversity change, a conclusion can be drawn directly: The SSP1 baseline leads to higher biodiversity deterioration compared to the SSP2 baseline, the SSP3 baseline to lower. This shows that it is not the land use or land management effects alone that influence the change in the two biodiversity indicators over time, but their interaction.

The results of the two biodiversity indicators, their development over time and the comparison of the different scenarios provide interesting insights. In the further process of this research, they need to be verified against literature findings and results of other emerging approaches to assess biodiversity at a global scale. Additionally, their implications for policy design and decision making are to be discussed.

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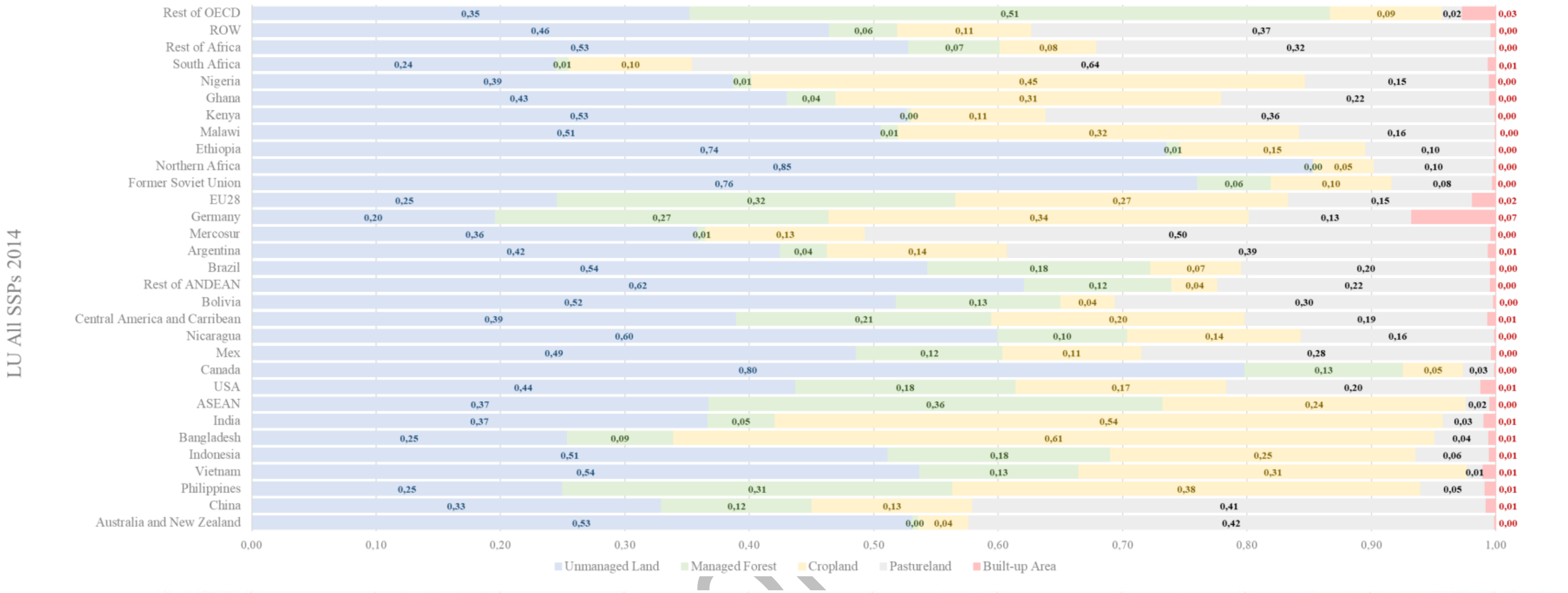
APPENDIX 1: EXTENDED TABLE 1

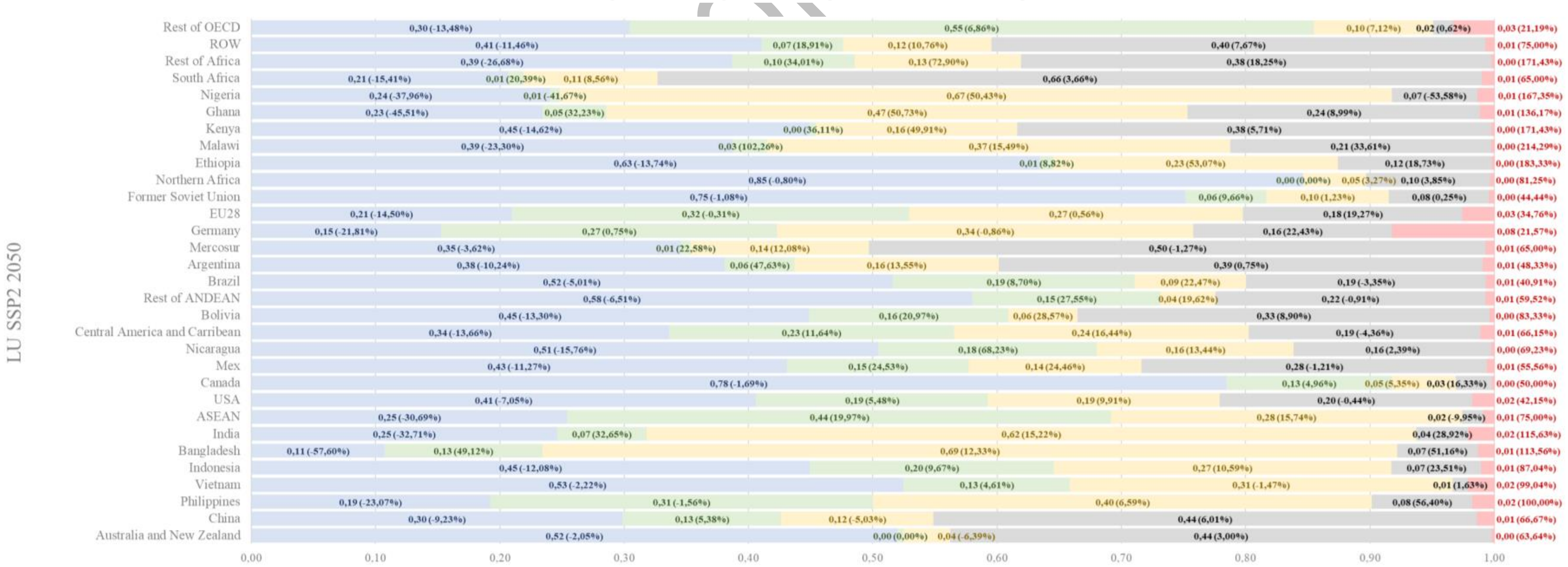
Habitat Share	GTAP-AEZ Land Cover	GTAP-AEZ Land Use (Economic)	FABIO Land Use Split	BDG Base Score	BDG Score Variation	Management Intensity Esimator
Natural Habitat Share (NHS)	Savanna Grassland Shrubland Unmanaged Forest Other Land	-	-	100	0	-
Managed Forest Share (MFS)	Forest	-	-	19	+ 65	Land input in forest activity / dollar output of the same
Cropland Share (CLS)	Cropland	Paddy Rice (pdr) Wheat (wht) Other Cereal Grains (gro)	Paddy Rice (pdr) Wheat (wht) Sorghum (sorg) Barley (barl) Maiz (maiz) Oats (oat) Rye (rye) Other Cereals (ocer)	74	-50	Intermediate chemical demand of all cropland activities / cropland area
		Vegetables, Fruits, and Nuts (v_f)	Potatoes (pota) Other roots and tubers (rttb) Leguminosae (leg) Tomatoes (toma) Other vegetables (oveg) Citrus fruits (citr) Apples (appl) Grapes (grap) Bananas and plantains (banp) Other fruits (fruit) Rest of v_f (v_fo)			
		Oil Seeds (osd)	Soy bean (soy) Palm oil fruit (palm) Rape seed (rape) Olives (olv) Other oilseeds (oso)			
		Sugar Cane/ Beet (c_b) Plant-Based Fibres (pfb) Other Crops (ocr)	Sugar Cane/ Beet (c_b) Plant-Based Fibres (pfb) Cocoa beans (coco) Teas (teas) Coffee beans (coff) Rest of ocr (ocro)			
Pastureland Share (PLS)	Pastureland	Cattle, Sheep, Goats and Horses (ctl) Raw Milk (rmk) Wool and Silk-Worm Cocoons (wol)	Cattle for meat (cattle) Other ruminant for meat (orum) Raw Milk (rmk) Wool and Silk-Worm Cocoons (wol)	21	+ 63	Land input in pasture activities / dollar output of of the same
Built-up Land Share (BLS)	Built-up Land	-	-	1	-	-

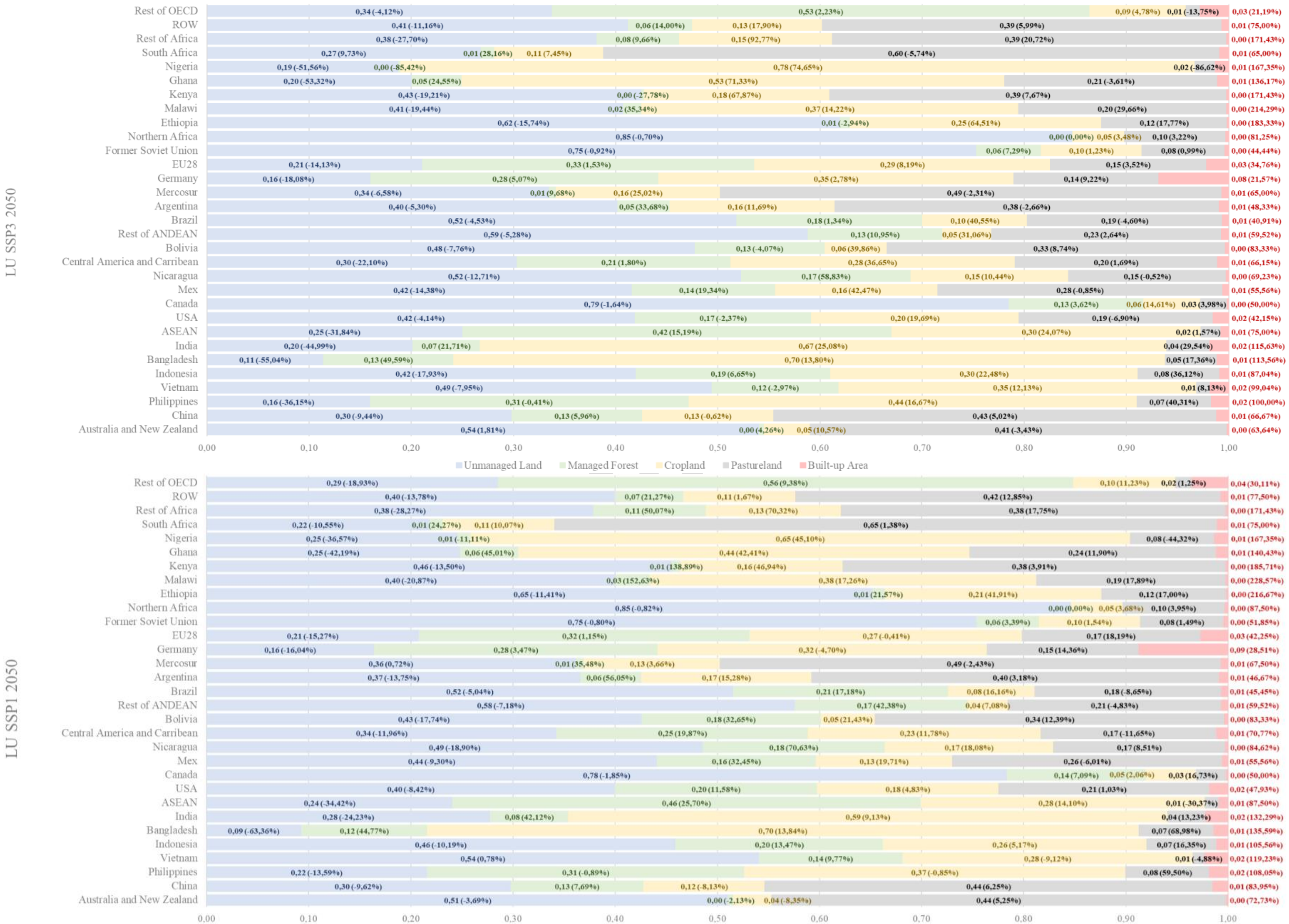
Source: Own illustration.

Remark: BDG used as acronym for biodiversity goodness. Italic writing of the management intensity estimator explanation marks an inverse estimator. That is, a high value represents a low intensity of use. All cropland activities are additionally split into rainfed and irrigation activities.

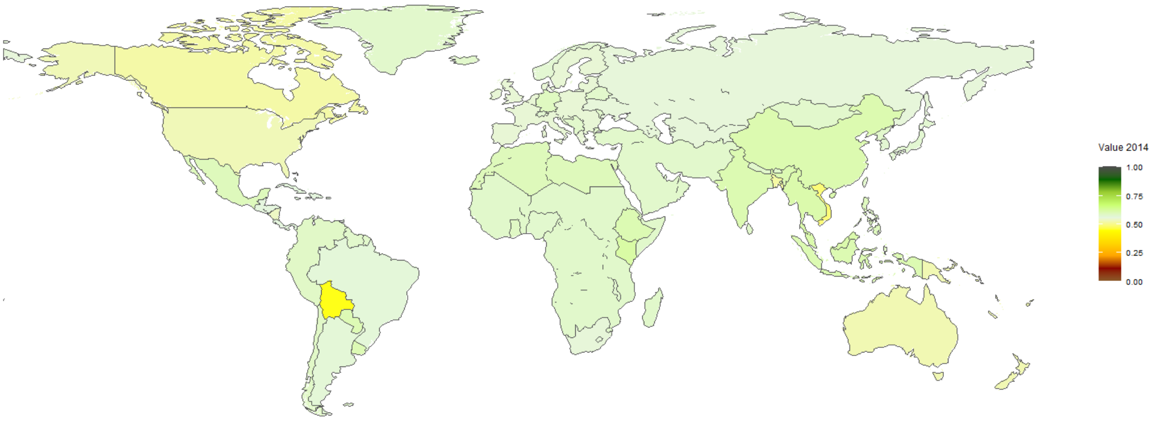
APPENDIX 2: REGION'S LAND USE SHARES (AND CHANGES IN 2050 COMPARED TO BASE YEAR 2014)

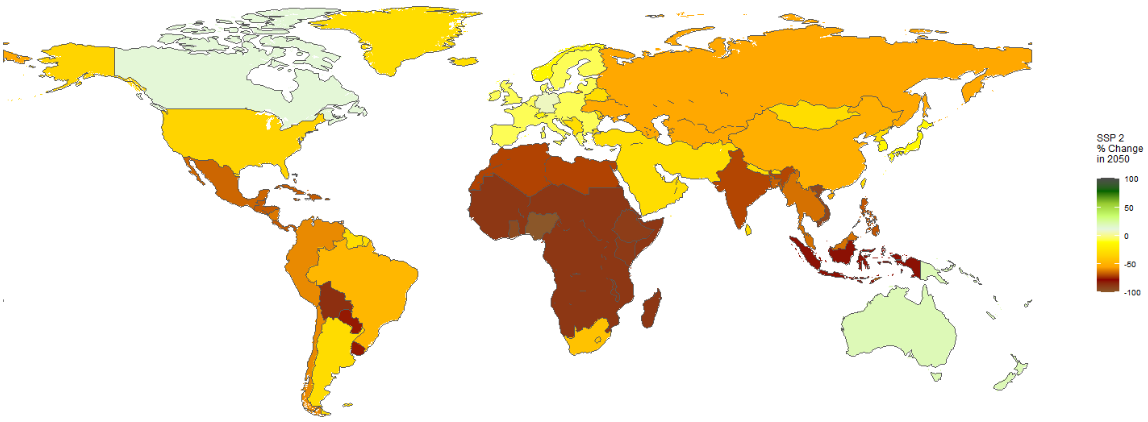


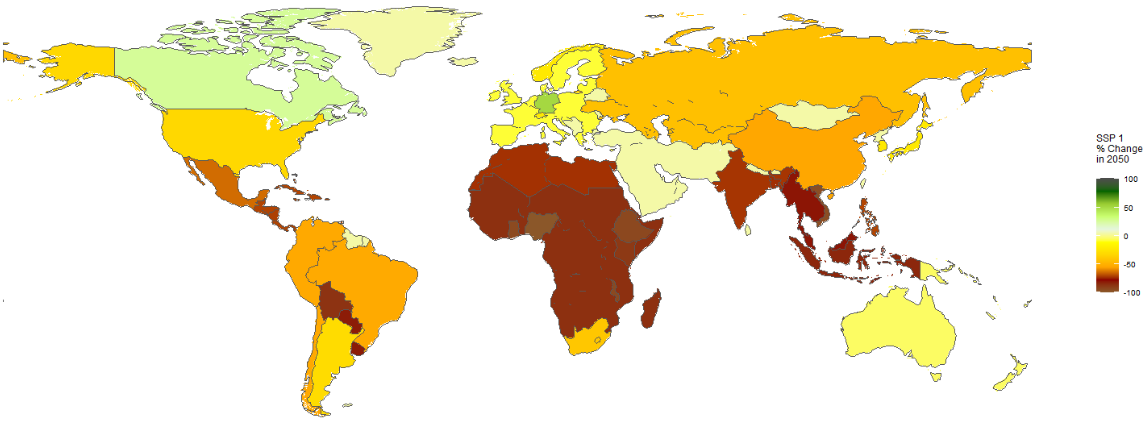


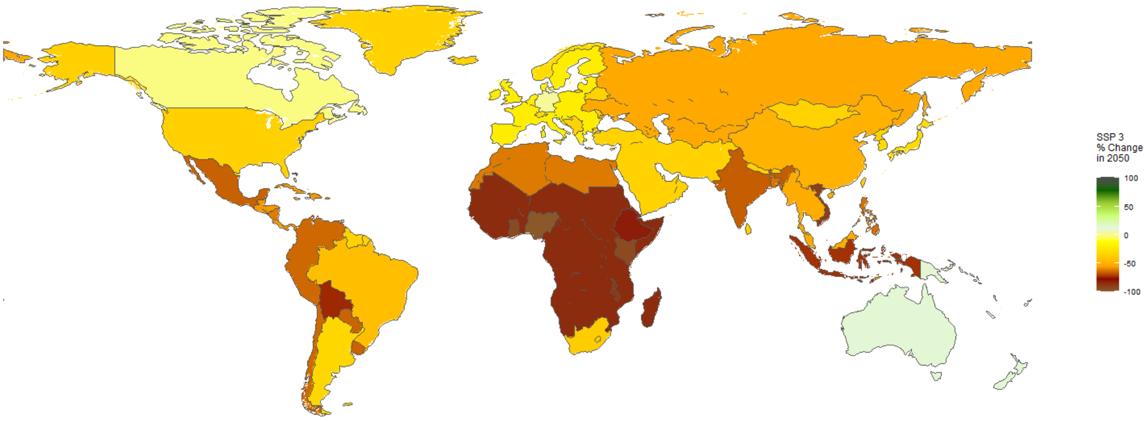

LU SSP3 2050
Rest of OECD
ROW
Rest of Africa
South Africa
Nigeria
Ghana
Kenya
Malawi
Ethiopia
Northern Africa
Former Soviet Union
EU28
Germany
Mercosur
Argentina
Brazil
Rest of ANDEAN
Bolivia
Central America and Carribean
Nicaragua
Mex
Canada
USA
ASEAN
India
Bangladesh
Indonesia
Vietnam
Philippines
China
Australia and New Zealand
0,00 0,10 0,20 0,30 0,40 0,50 0,60 0,70 0,80 0,90 1,00
Unmanaged Land
Managed Forest
Cropland
Pastureland
Built-up Area
LU SSP1 2050
Rest of OECD
ROW
Rest of Africa
South Africa
Nigeria
Ghana
Kenya
Malawi
Ethiopia
Northern Africa
Former Soviet Union
EU28
Germany
Mercosur
Argentina
Brazil
Rest of ANDEAN
Bolivia
Central America and Carribean
Nicaragua
Mex
Canada
USA
ASEAN
India
Bangladesh
Indonesia
Vietnam
Philippines
China
Australia and New Zealand
0,00 0,10 0,20 0,30 0,40 0,50 0,60 0,70 0,80 0,90 1,00

APPENDIX 3: FOREST MANAGEMENT INTENSITY ESTIMATOR

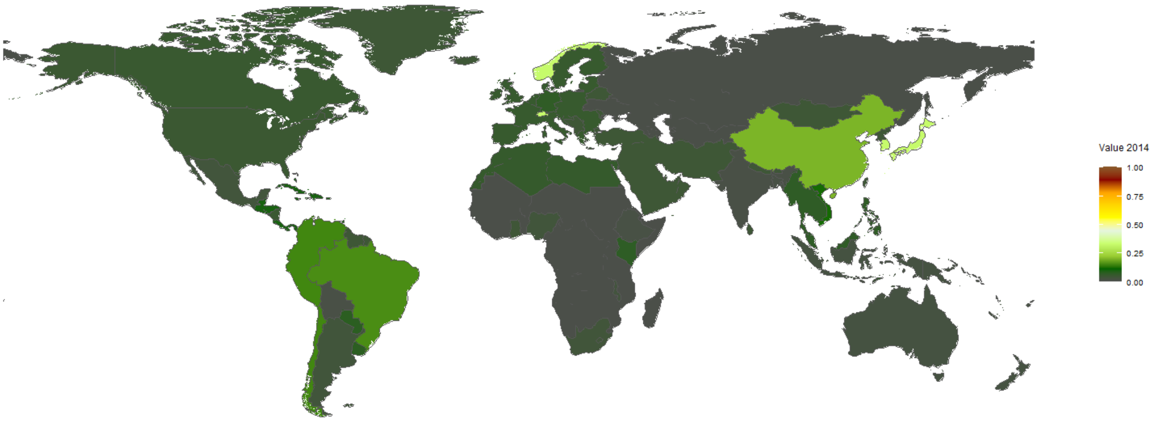


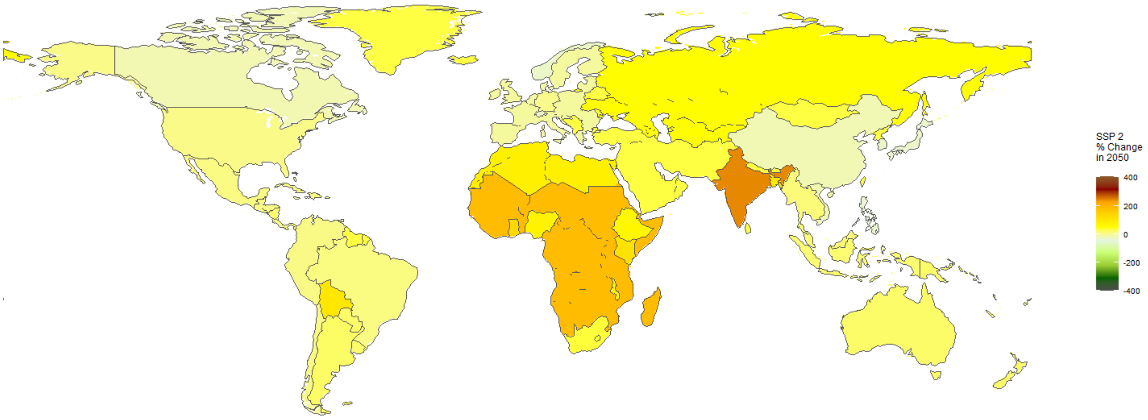


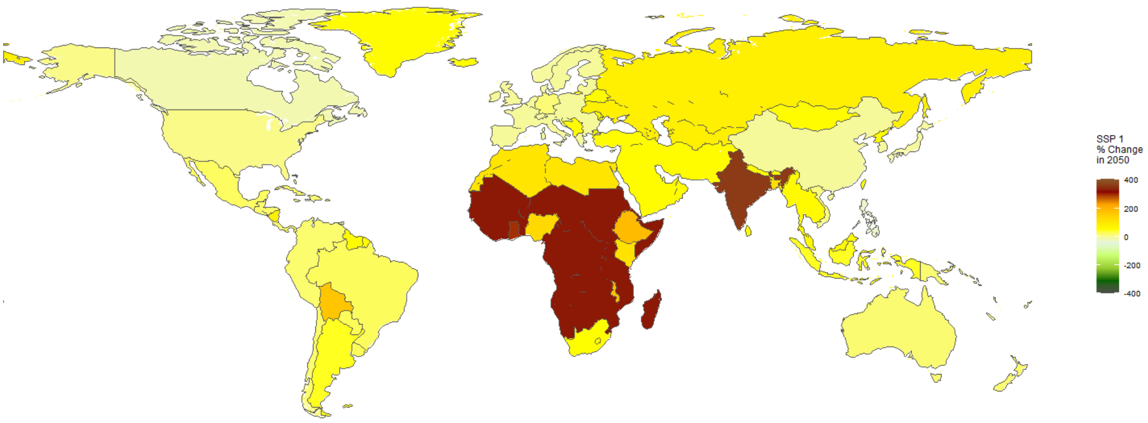


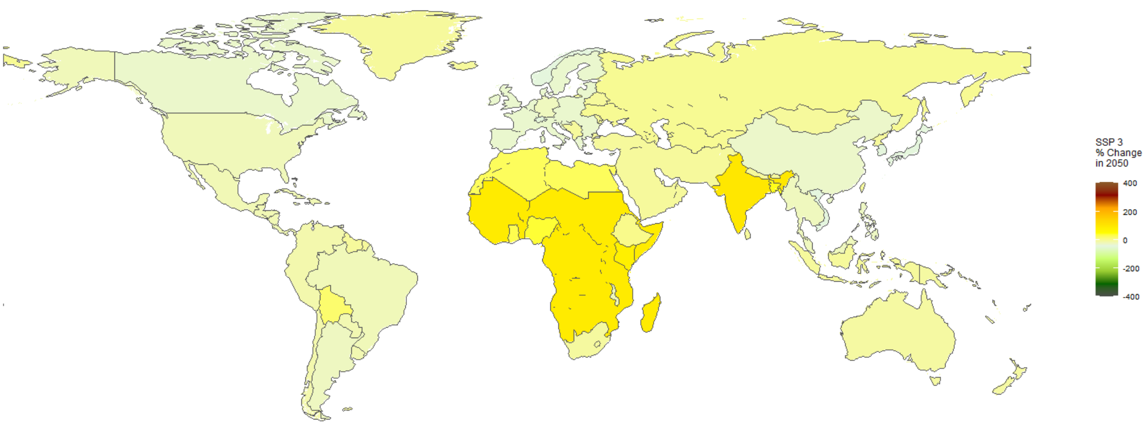


APPENDIX 4: CROPLAND MANAGEMENT INTENSITY ESTIMATOR









APPENDIX 5: PASTURELAND MANAGEMENT INTENSITY ESTIMATOR