



Net0Pathways through impRoved IAMs across Sectors, diMensions, and scAles

Deliverable 5.1

Report on improved representation of biodiversity in IAMs, including release of model code and data

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November 2025



This project has received funding from the European Union's Horizon Europe programme under grant agreement No 101081604 - PRISMA. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Climate, Infrastructure and Environment Executive Agency (CINEA). Neither the European Union nor the granting authority can be held responsible for them.

Deliverable Title	Report on improved representation of biodiversity in IAMs, including release of model code and data
Deliverable number	5.1
Brief Description	The deliverable enhances biodiversity representation in IAMs by improving spatial resolution in land-use models, developing new impact assessment tools, expanding biodiversity indicators, and integrating ecosystem values into economic welfare analysis.
WP number	5
Lead Beneficiary	PIK
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Internal reviewer(s)	Cindy Azuero Pedraza (CMCC)
Deliverable Due Date	M35 (Nov 2025)
Actual Delivery Date	27 November 2025
Nature of the Deliverable	R – Document, report
Dissemination Level	PU - Public
KeyWords	Biodiversity modelling; Landuse Change; Spatial resolution; Ecosystem impacts; Biodiversity indicators

Date	Vers.	Contributors	Pages
30.10.2025	1	Miodrag Stevanović (PIK), Patrick von Jeetze (PIK), Sreyam Sengupta (IIASA), Mathijs Harmsen (PBL), Francesco Granella (CMCC), Alvaro Hahn Menacho (PSI), Romain Sacchi (PSI)	83
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Executive Summary

Humanity faces the dual, interconnected crises of climate change and biodiversity loss. The large-scale deployment of climate mitigation strategies, particularly land-demanding options like bioenergy with carbon capture and storage (BECCS), directly competes with the conservation and restoration of ecosystems. This competition for land creates complex trade-offs that are inadequately represented in the Integrated Assessment Models (IAMs) used to inform global policy. Current models often lack spatial detail, a diverse set of biodiversity indicators, and, crucially, the bidirectional feedbacks between economic activity, ecosystem health, and human welfare. This deliverable from the PRISMA project directly addresses these gaps, presenting a suite of methodological advancements and applied analyses that significantly enhance the capability to assess biodiversity impacts and synergies within a policy-relevant framework.

Key Research Contributions This report details several major innovations that move biodiversity modelling in IAMs beyond simple land-use proxies:

1. **High-Resolution Spatial Modelling:** We demonstrate the feasibility and power of coupling global landuse models (MAgPIE) with high-resolution spatial allocation tool (SEALS). This allows for the projection of land-use changes at a 300m resolution, enabling the assessment of impacts on specific habitats, landscape heterogeneity, and species' Area of Habitat (AOH).
2. **Integrated Systems Modelling:** We have linked the land-system model MAgPIE with the energy-system model MESSAGEix. This integration creates a unified framework to explore the competition for land between bioenergy for climate mitigation and conservation for biodiversity, endogenizing land-use impacts within energy system optimization.
3. **Bidirectional feedback between economic activity, ecosystem health, and human welfare:** We have advanced IAM methodology by directly integrating biodiversity loss into the RICE 50+ economic framework, allowing ecological change to influence economic outcomes rather than remaining an external assumption. It establishes a scalable approach for modeling two-way biodiversity–economy feedbacks to support more realistic global policy assessment.
4. **Novel Tools for Policy Assessment:** The deliverable includes the development and release of new, accessible tools:
 - a. A **Mean Species Abundance (MSA) emulator** that provides a fast, robust method for calculating biodiversity intactness, ideal for rapid scenario screening with IAMs.
 - b. The **edges Python framework**, which revolutionizes Life Cycle Assessment by enabling spatially explicit biodiversity impact assessment along global supply chains, linking remote environmental impacts to specific products and consumption patterns.

Major Findings and Policy Insights Our applied research, leveraging these new methodologies, yields several insights for designing effective and sustainable policies:

- **Dietary Shifts vs. Targeted Conservation:** While a global shift towards healthier, plant-based diets reduces agricultural land expansion and greenhouse gas emissions, it is insufficient on its own to halt biodiversity decline. We find that structural trends like landscape simplification continue unabated. Coordinated conservation policies—such as protecting 30% of land, maintaining semi-natural habitats in farmlands, and improving nitrogen use efficiency—are far more effective. A combined approach of partial dietary change and ambitious conservation delivers the most robust outcomes for biodiversity while minimizing socio-economic barriers like increased food prices.
- **Synergies between Climate and Biodiversity Goals:** Stringent biodiversity conservation policies are not a hindrance to climate mitigation but can reshape it for the better. By limiting the unsustainable expansion of bioenergy cropland, biodiversity protection forces an earlier phase-out of fossil fuels and a more rapid scaling of renewables like solar and wind. This results in climate mitigation pathways with a significantly reduced temperature overshoot and lower long-term warming, demonstrating that protecting nature enhances climate resilience.
- **The Economic Value and Equity of Natural Capital:** Climate change will cause significant economic damage through its impact on ecosystems. Our integration of natural capital into the RICE50+ model reveals that these damages are profoundly regressive. Approximately 90% of the economic losses from climate-driven ecosystem changes will be borne by the world's poorest 50% of countries, exacerbating global inequality. This underscores the urgent need for climate finance and justice mechanisms that address natural capital loss.
- **Uncovering Hidden Supply Chain Impacts:** The application of our edges framework to a case study of hydrogen production reveals how biodiversity impacts are displaced across the globe. The majority of impacts associated with hydrogen produced in Europe were traced back to mining activities for critical minerals in South Africa. This highlights the necessity of spatially explicit assessments to truly understand the biodiversity footprint of green technologies and ensure they do not simply shift environmental burdens.

Conclusion This deliverable provides a significant step forward in the analytical capacity to understand the complex interplay between human development, climate action, and biodiversity conservation. By providing enhanced models, finer spatial resolution, a broader set of biodiversity indicators, novel assessment tools, and a representation of bidirectional feedbacks between economic activity and biodiversity, we enable a more nuanced and integrated analysis of policy pathways. The findings consistently show that policies designed in silos are suboptimal; integrated strategies that simultaneously address climate mitigation, biodiversity conservation, and socio-economic equity are not only possible but essential. The methodologies and insights presented here are a critical step towards designing future



policies that are truly sustainable for both people and the planet, ensuring that the pursuit of one environmental goal does not inadvertently undermine another.

1 Introduction

1.1 Motivation

Human activities have transformed land and ecosystems at an unprecedented scale, making agricultural expansion, intensification, and land-use change the dominant global drivers of biodiversity loss and ecosystem degradation (Díaz et al., 2019; IPBES, 2019; Scherer et al., 2023). At the same time, achieving the Paris Agreement targets will require large-scale deployment of carbon dioxide removal (CDR) technologies, such as bioenergy with carbon capture and storage (BECCS), many of which directly compete with biodiversity conservation for land (IPCC, 2022; Frank et al., 2021; Wu et al., 2019). These challenges are also compounded with climate change itself, which alters ecosystem distribution and productivity, threatening the natural capital that underpins economic activity and human well-being (Bastien-Olvera et al., 2024; World Bank, 2021; Rockström et al., 2023). Globalized trade further amplifies these dynamics by displacing environmental impacts across regions and complicating the identification of effective intervention points (Chaudhary et al., 2015).

These converging pressures highlight the need for spatially explicit frameworks that can capture heterogeneity in biodiversity and ecosystems change under multiple drivers. Such approaches can support targeted and equitable mitigation strategies by integrating multiple drivers and feedbacks, identifying where interventions are likely to be most effective (Bulle et al., 2019; Sacchi et al., 2025). Reconciling climate mitigation and biodiversity targets under finite land and resource constraints is therefore a critical policy challenge. To address these complexities, integrated assessments are essential for understanding trade-offs across policy pathways, and for designing strategies that support both human and environmental well-being (Rockström et al., 2023; Pörtner et al., 2021).

Task 5.1 of the PRISMA project addresses these challenges by enhancing biodiversity representation in integrated assessment models (IAMs), improving spatial resolution, expanding biodiversity indicators, linking simplified impact tools, and integrating ecosystem and welfare dimensions to better evaluate land-use, mitigation, and climate impacts in a policy-relevant context.

1.2 Outline of the deliverable

The work is structured into five core chapters that collectively enhance our understanding of the synergies and trade-offs between human activities and ecosystem health.

Chapter 2 delves into the biodiversity consequences of human diets. Using a modeling framework that couples the global land-use model MAGPIE with the high-resolution spatial allocation tool SEALS, it compares the effects of a shift towards healthier, plant-based diets against a bundle of targeted conservation actions. Related to this, Chapter 3 integrates the land-use perspective with the global energy system. By linking MAGPIE with the energy-economy model MESSAGEix, it systematically explores the interplay between climate ambition

(defined by carbon budgets) and biodiversity ambition (measured by the Biodiversity Intactness Index, BII).

Chapter 4 introduces a practical software tool: a Mean Species Abundance (MSA) emulator. Developed by PBL, this simplified model replicates the core functionality of the more complex GLOBIO biodiversity model. It provides a fast, computationally efficient method for calculating terrestrial biodiversity intactness based on land use, climate change, and nitrogen deposition, making it ideally suited for direct coupling with IAMs for rapid and robust scenario analysis.

Chapter 5 shifts the focus to the product and supply chain level, introducing the novel edges Python framework. This tool advances Life Cycle Assessment (LCA) by enabling a spatially explicit evaluation of biodiversity impacts for every single exchange in a product's supply chain.

Finally, Chapter 6 consolidates the economic and welfare dimensions of biodiversity integration. It comprises three interconnected parts: a study quantifying the grossly unequal economic impacts of climate-driven natural capital loss on poorer nations; a framework for embedding biodiversity directly as a constraint or objective in land-use optimization models, demonstrating clear trade-offs between bioenergy cost and species extinction risk; and a comprehensive review of current IAMs that identifies critical gaps and proposes a forward-looking framework for creating models with fully bidirectional feedback between the economy and biodiversity.



2 Conservation outcomes of dietary transitions across different values of nature

Based on: von Jeetze et al. (2025), published in Nature Sustainability

2.1 Introduction

Over the past century, unprecedented changes in both character and scale of land used for food production have made agriculture by far the most prominent driver of biodiversity loss (Díaz et al., 2019; IPBES, 2019; Matson et al., 1997; Newbold et al., 2015). Today, the food sector is also the primary driver of nitrogen pollution, freshwater consumption and soil degradation (Borrelli et al., 2017; Poore & Nemecek, 2018). In addition, approximately one third of all greenhouse gas (GHG) emissions are linked to the food system. These emissions are mainly driven by CO₂ from land-use change, CH₄ from enteric fermentation and N₂O from managed soils and animal waste (Crippa et al., 2021). Population growth and the ongoing 'nutrition transition' towards higher intakes of resource-intensive foods, particularly from livestock, due to rising average incomes could further escalate the environmental pressures of food production (Bodirsky et al., 2020; Masters et al., 2016; Popp et al., 2017).

Recent assessments have shown that a reduction in the intake of resource-intensive livestock-based foods in favour of a variety of plant-based foods would not only provide substantial health benefits and a large reduction in food-related mortality, but would also significantly decrease the massive environmental burden of food production (Springmann et al., 2018; Willett et al., 2019). In terms of biodiversity conservation, several studies have also suggested substantial benefits of a shift towards healthier diets, in particular due to the enormous 'land-saving effect' as a result of changing agricultural demand (Scarborough et al., 2023; Springmann et al., 2018). However, biodiversity benefits depend not only on the quantity of land that is protected from conversion but more importantly on the type and location of conserved habitats (Brennan et al., 2022; Fisher et al., 2009; Jung et al., 2021; Strassburg et al., 2020). Moreover, biodiversity loss is not just confined to the conversion of natural habitats, but also pervasive in landscapes with a long history of human land use (Batáry et al., 2017; Poschlod & Braun-Reichert, 2017; Sánchez-Bayo & Wyckhuys, 2019; Seibold et al., 2019), where it has undermined the supply of critical nature's contributions to people (NCP) (IPBES, 2019).

Some of the principles that apply to other environmental outcomes of food production, such as an approximate linear scaling of CH₄ and N₂O emissions with livestock production levels (Humpenöder et al., 2022), may therefore not necessarily extend to biodiversity outcomes in relation to food demand shifts. Dietary changes may address specific drivers of biodiversity loss, such as reducing the loss of pristine habitats while other aspects, such as landscape simplification and NCP loss, are more closely related to broader structural trends in food production, like specialisation, intensification and the concentration of agricultural land (Coomes et al., 2019; Klasen et al., 2016; Matson et al., 1997). Despite the lively debate on demand-side interventions, particularly given their huge potential to reduce GHG emissions from agriculture (Bodirsky et al., 2022), only a few studies provided detailed analyses of the impacts of dietary shifts on biodiversity change (Henry et al., 2019; Williams et al., 2021).

Here, we apply a quantitative and spatially explicit modelling framework to assess how a shift towards healthier diets could affect various aspects of biodiversity change. Given that a shift towards healthier diets on a globally relevant scale is a complex and multifaceted challenge that involves various social, political and cultural dimensions (Fehér et al., 2020; Pohjolainen et al., 2015), we also assess different levels of convergence towards healthier diets, and compare the results with a bundle of alternative conservation actions. By contrasting multiple indicators of biodiversity with indicators of environmental change and socioeconomic aspects (Table 1), our study differs from previous assessments in terms of both the breadth and high granularity of the analysis.

The forward-looking open-source land and food system model MAgPIE (Model of Agricultural Production and its Impact on the Environment v4.6.11) forms the core of our modelling framework. MAgPIE is continually validated against observed data (Bodirsky et al., 2024) and has frequently been used to study questions related to food system sustainability (Humpenöder et al., 2022; Leclère et al., 2020; Soergel et al., 2021). It uses a wide range of socioeconomic and spatially explicit biophysical information to simulate global land-system dynamics over the 21st century (see Methods). To map projected land-cover changes at a scale relevant for assessing landscape and biodiversity change, we couple MAgPIE with the Spatial Economic Allocation Landscape Simulator (SEALS). SEALS uses empirically calibrated adjacency relationships, physical suitability and conversion eligibility information to allocate projected land-cover changes to a spatial resolution of 10arc seconds (300m × 300m at the equator). This enables us to relate coarse land-use change projections to fine-scale changes in specific habitats and landscape heterogeneity, and to assess key indicators for biodiversity change and the supply of NCP.

2.2 Methods

2.2.1 Models Description

The Model of Agricultural Production and its Impact on the Environment (MAgPIE) is a global, multiregional land-system model for assessing global land-use dynamics and their implications for sustainable development in the 21st century (Dietrich et al., 2019; Soergel et al., 2021). It spatially allocates agricultural commodity production to meet global demand for food, feed, bioenergy and biomass under biophysical and socioeconomic constraints, based on a recursive dynamic cost-optimisation approach. The model considers various cost components such as factor requirements (capital, labour, fertiliser), land conversion, transport, investment in agricultural productivity and irrigation costs. The model also accounts for depreciation and new investments in capital stocks for crop production in each time step, favouring historically cultivated locations while limiting the unrestricted relocation of production to areas with favourable climatic conditions but lack of required infrastructure. Trade flows are split between historical import and export patterns and comparative advantages in production, including trade costs. Spatially explicit biophysical information is derived from the dynamic global vegetation, crop and hydrology model LPJmL at a 0.5-degree spatial resolution based on historical climate data (Mengel et al., 2021) (no climate change effects). Vegetation, litter, and soil carbon stocks, as well as the water availability are taken from LPJmL4 (Schaphoff, Forkel, et al., 2018; Schaphoff, von Bloh, et al., 2018), while crop irrigation water requirements and yield patterns (cropland and grassland) are derived from LPJmL5 simulations with unlimited nitrogen supply (Lutz et al., 2019; von Bloh et al., 2018).

To address computational constraints, all model inputs at the 0.5-degree resolution are aggregated to spatial clusters for the optimisation using a k-means clustering algorithm (Dietrich et al., 2013). Socioeconomic constraints, such as trade patterns and interest rates, are defined at the scale of twelve model regions, with larger economies resolved individually and smaller ones grouped together. All major crop and livestock species, non-food agricultural commodities, and supply chain losses are included in MAgPIE. Land competition is modelled in terms of cost-effectiveness between crop and livestock production, and considering land conservation targets formulated in each scenario.

Following previous studies (Bodirsky et al., 2012; Popp et al., 2017; Schmitz et al., 2012; Stevanović et al., 2017; von Jeetze et al., 2023), several outcome indicators used here are directly derived from MAgPIE (Table 1). Net CO₂ emissions from land-use change are calculated based on carbon losses and uptake due to the conversion of forested and non-forest ecosystems and regrowth on abandoned agricultural land respectively between time steps (Humpenöder et al., 2018). CH₄ emissions include emissions from enteric fermentation, animal waste management, rice production, and the burning of agricultural residues, which are estimated from the level of ruminant livestock production, manure and the area of rice production. To estimate nitrogen surplus, we use a nitrogen budget approach (Bodirsky et al., 2012) that accounts for differences between organic and inorganic nitrogen inputs and removals through harvesting or grazing on agricultural land and for differences between excreted and recycled manure in animal waste management. On non-agricultural land we assume a stable state where nitrogen fixation equals surplus. Average annual crop yield changes are calculated from yield differences between time steps. These are driven by the relocation of cropland to higher yield areas and the relative cost-effectiveness of investing in irrigation or R&D for yield-increasing technologies (Dietrich et al., 2014), compared with other cost such as land conversion or transport. Food prices are derived from the shadow price (Lagrange multiplier) of producing one additional unit of food and multiplied with per-capita supply of agricultural food products (including waste) to obtain expenditure on agricultural products. A detailed documentation of the MAgPIE framework and the model source code are also made available online and openly accessible. The model code of the MAgPIE model is openly available under the GNU Affero General Public License, version 3 (AGPLv3) and accessible via GitHub (<https://github.com/magpiemodel/magpie>). The release version (MAgPIE 4.6.11), on which the present work is based, has been archived via Zenodo (<https://doi.org/10.5281/zenodo.8318615>; Dietrich et al., 2023). MAgPIE 4.6.11 has technical model documentation (<https://rse.pik-potsdam.de/doc/magpie/4.6.11/>), which has been compiled with the GAMS code documentation toolkit goxygen (Dietrich et al., 2020). The model results shown in this paper have been archived via Zenodo and can be accessed under <https://doi.org/10.5281/zenodo.10599896>.

We use the Spatial Economic Allocation Landscape Simulator (SEALS) to map simulated land-cover changes in MAgPIE at a scale relevant for assessing landscape and biodiversity change (Johnson et al., 2021, 2023; von Jeetze et al., 2023). SEALS spatially allocates projected land-cover changes from MAgPIE to a resolution of 10 arc seconds (field-scale), utilizing adjacency relationships, physical suitability, and conversion eligibility information. The initial state of the model landscape is defined by a high-resolution land use/land cover (LULC) map from the European Space Agency's Climate Change Initiative (ESA-CCI) for the year 2020. We therefore aggregate the 37 ESA-CCI land-cover classes into seven functional types, including cropland, grassland, forest, non-forest vegetation (e.g., shrubland or herbaceous cover), urban, barren



land, and water. Subsequently, we quantify the spatial adjacency strength for each functional type on neighboring land cover pixels, considering both distance and pixel agglomeration. The physical suitability for land-cover allocation is determined by high-resolution data on soil type and quality, topographic information, climate and travel time to the nearest market. In addition, allocation constraints are applied to prevent further cropland or pasture expansion in areas such as urban land, current protected areas or water bodies. In the BIOS scenario, expansion of crop, pasture and urban land is also prohibited in conservation priority areas in order to meet the 30×30 target of the GBF (see below). The overall suitability map is formed by combining adjacency relations, physical suitability, and conversion eligibility, where pixels are ranked based on their suitability. In an iterative process, land-cover changes are then allocated to the highest-ranked grid cells until all projected changes from MAgPIE between 2020 and 2050 are assigned to generate high-resolution land-cover maps for each modelled scenario. Specific coefficients for different adjacency relationships and physical suitability are determined by iteratively applying of the allocation algorithm on a time-series (2000–2010) of LULC maps from ESA-CCI. The coefficients most predictive on withheld data (2011–2015) are selected during this process.

2.2.2 Biodiversity and NCP Indicators

Landscape pollination sufficiency. Changes in configurational landscape heterogeneity and pollination sufficiency are derived based on fine-scale projections (300m × 300m at the equator) of land-cover changes using MAgPIE-SEALS coupling. Pollination sufficiency is defined by the presence of semi-natural habitat near cropland (Chaplin-Kramer et al., 2019; von Jeetze et al., 2023). To derive pollination sufficiency scores, we rank all cropland pixels by values between 0 and 1, based on the proportion of semi-natural habitat within a 2 km foraging radius typically found in wild pollinator communities. A value of 1 is assigned where the proportion of semi-natural habitat within the foraging range around cropland is >30 %, while values between 0 and 1 indicate a proportion of 0 to 30% (Chaplin-Kramer et al., 2019; Kremen et al., 2004; von Jeetze et al., 2023). Albeit this metric does not account for other important factors that affect wild pollinator abundance, such as pesticide applications, the presence of meta populations or the quality of nesting habitats or floral resources, multiple studies have shown that the amount of semi-natural habitat around cropland is a reliable proxy for wild pollination supply, as well as an important driver of biodiversity and other regulating NCP in various landscape contexts (Dainese et al., 2019; Estrada-Carmona et al., 2022; Kennedy et al., 2013; Klein et al., 2012; Perrot et al., 2021).

Soil loss by water erosion. Soil loss by water erosion is estimated using the Global Soil Erosion Modelling (GloSEM) platform. GloSEM uses a global Geographical Information System (GIS) implementation of the Revised Universal Soil Loss Equation (RUSLE) model, which has been developed and validated by Borrelli et al., 2017, 2020. In contrast to process-based soil erosion models, which have limited global applicability due to a lack of globally available fine-scale input data, GloSEM uses a parsimonious yet physically plausible approach to quantify soil erosion resulting from sheet and drill erosion processes at field scale. The accuracy of soil loss estimates using RUSLE-type models, such as GloSEM, has demonstrated to be suitable for most practical and policy applications (Borrelli et al., 2020). Similar to other RUSLE-type models, soil loss in GloSEM is determined by a driving force (rainfall erosivity), a resistance term (erodibility of the soil), as well as topographical and land cover information. Global rainfall erosivity maps were derived from the Global Rainfall Erosivity Database (GloREDa) using Gaussian process regression and covariates from the WorldClim database (Borrelli et al.,

2017; Panagos et al., 2017), while soil erodibility was estimated based on soil data from the ISRIC SoilGrids database (Hengl et al., 2014). Topographical information was obtained by processing DEM data using a two-dimensional GIS-based approach (Desmet & Govers, 1996). The land cover and management factor was calculated using separate approaches for cropland and non-cropland areas. For cropland, spatial cropping patterns from MAGPIE at the 0.5-degree level were utilized, and land cover factors were assigned to 20 crop functional types based on literature values (Borrelli et al., 2020). Subsequently, an area-weighted mean between all crop groups in each 0.5-degree grid cell was calculated and matched to projected fine-scale cropland maps from MAGPIE-SEALS. In non-cropland areas, land cover factors were estimated by combining literature values for forested and non-forested areas with potential annual vegetation and forest cover maps based on FCOVER data (Copernicus Global Land Service, 2021; Fuster et al., 2020) and tree cover data by Hansen et al., 2013, as detailed in von Jeetee et al., 2023.

Area of habitat. The area of habitat (AOH) refers to the habitat available to a species within its geographic range (Brooks et al., 2019). We here produce vertebrate AOH maps for 6,374 amphibian, 9,124 bird, 5,351 mammal and 6,877 reptile species for the year 2020 and use land-cover projections based on the MAGPIE-SEALS framework to assess AOH changes under different land-use scenarios. Range polygons for each species were obtained from the IUCN Red List Database (IUCN, 2020) and from BirdLife International (BirdLife International and Handbook of the Birds of the World, 2021). In line with previous work we retained separate range polygons for resident, breeding, non-breeding, and uncertain seasonality during processing (Jung et al., 2021; Lumbierres, Dahal, Soria, et al., 2022), but aggregated the final results across all seasonal ranges of each species to simplify the presentation of our results. We further excluded all species ranges with unknown presence and of species with no habitat information. Habitat preferences for each species were derived from the IUCN Red List Database (IUCN, 2020) and reported based on the IUCN Habitats Classification Scheme (IUCN, 2012). In order to relate IUCN habitats to spatial land cover information we used the habitat-land cover model by Lumbierres et al. (2022). The model associates the habitat classes of the IUCN Habitats Classification Scheme with ESA CCI land cover classes and provides a translation table based on three different thresholds of positive association. We selected the threshold with the strongest habitat-land cover association, which in similar applications has shown to considerably reduce commission errors without compromising validation performance of the AOH estimates (Dahal et al., 2022; Lumbierres et al., 2022). For artificial degraded forest and plantation habitats, we chose the second strongest association threshold because none of the association values surpassed the threshold with the strongest association. Artificial degraded forest and plantation habitats were therefore associated with ESA CCI classes 12 (cropland, rainfed, tree or shrub cover), 20 (cropland, irrigated or post-flooding), and 190 (urban areas) (Lumbierres et al., 2022). Habitats classified as marginal or of no major importance in the IUCN Red List Database were omitted from the data. For abandoned agricultural land we followed the approach of Humpenöder et al. (2014) with updated parameters for the Chapman-Richards growth function by Braakhekke et al. (2019), which assumes the same carbon density and the same species pool as during natural succession. Thus, in early stages of the natural succession when the carbon density is below 20 tC ha⁻¹ the land is classified as non-forest vegetation (native grassland or shrubland) within the other land pool. After reaching a carbon density of 20 tC ha⁻¹, the land is classified as forest vegetation. We maintained this approach in the MAGPIE-SEALS coupling and classified

abandoned agricultural land in early successional stage as open habitat (native grassland or shrubland) and land in later successional stages as forest habitat.

The estimation of AOH changes followed a two-step approach including a pre-processing step and a scenario processing step. The pre-processing involved subtracting unsuitable elevation areas from the range (Brooks et al., 2019) and translating IUCN habitats to ESA CCI land cover classes for each species. Species' elevational range data was also obtained from the IUCN Red List Database and areas outside the elevational limits were subtracted based on WorldClim 1km elevation data (Fick & Hijmans, 2017). Some range polygons had no remaining areas within their species elevational limits and were therefore omitted from the data set. During the scenario processing step, unsuitable areas were subtracted from the pre-processed range polygons based on habitat preferences and land cover projections from MAGPIE-SEALS to produce final AOH estimates. AOH estimates for the year 2020 were directly derived from the ESA CCI land cover map. All calculations were performed using R (R Core Team, 2023) and the "terra" package (Hijmans, 2023). Due to the high computational load, the computations were run on a high performance cluster and parallelised with the packages foreach (Microsoft Corporation & Weston, 2023) and doParallel (Microsoft Corporation & Weston, 2023).

2.3 Future scenarios of dietary change and conservation action

In our scenario set we compare the effects of a partial and complete shift towards healthier diets with a bundle of conservation actions across different aspects of biodiversity change. Our reference scenario (SSP2-REF) follows the 'middle-of-the-road' shared socioeconomic pathway (SSP2) for the land-use sector (Popp et al., 2017) with moderate population and income growth. In our reference scenario, we also assume full compliance with currently implemented land policies, such as protected areas (PAs), but no climate mitigation policies in the landuse sector are assumed (such as Nationally Determined Contributions - NDCs). In our alternative scenarios we add a 50% (DIET50) and 100% (DIET100) convergence to a healthy reference diet as outlined by the EAT-Lancet Commission (Willett et al., 2019) by 2050, a set of targeted conservation measures to support biosphere integrity (BIOS), and a combination of a partial diet shift and targeted conservation action (DIET50-BIOS) to the reference case. The healthy reference diet is derived based on minimum per capita intakes of legumes, fruits, vegetables and nuts; maximum intakes of sugar, oils, poultry, eggs, red meat and dairy products; and a convergence to a healthy body mass index (20-25) (Springmann et al., 2018) (Figure 1). Within these limits, country-specific dietary patterns can still exhibit a considerable diversity. Conservation measures include area-based conservation in line with the 30x30 target of the Kunming-Montreal Global Biodiversity Framework (2022) (GBF), the conservation of at least 20% of semi-natural habitats in managed landscapes by 2030 (Garibaldi et al., 2020; Rockström et al., 2023; von Jeetze et al., 2023), a no net biodiversity loss scheme after 2030 whereby any decrease in biodiversity intactness (Leclère et al., 2020) must be compensated at the biome level, and increased nitrogen use efficiency on cropland (see Methods).

Indicator and unit	Definition	NCP dimension ^a	Reference
Food consumption, agricultural demand and land-use dynamics (MAgPIE)			
Calorie intake (kcal person ⁻¹ day ⁻¹)	Average calorie intake separated across 9 different food groups (Fig. 1a)	NCP 11	Bodirsky et al.(Bodirsky et al., 2020)
Agricultural demand (Gt DM year ⁻¹)	Total agricultural demand across 8 different demand categories (Fig. 1b)	NCP 11, 12 & 13	Popp et al.(Popp et al., 2017), Bodirsky et al.(Bodirsky et al., 2020)
Land-use change (Mha)	Net land-use change between 7 main land types (Fig. 2)	NCP 1, 11, 12 & 13	Popp et al.(Popp et al., 2017), Dietrich et al.(Dietrich et al., 2019)
Emissions (MAgPIE)			
CO ₂ emissions from land-use change (Gt CO ₂ year ⁻¹)	Carbon uptake and losses in terms of net CO ₂ emissions from land-use change, including carbon losses to the atmosphere from land conversion and carbon uptake from reforestation and natural regrowth on abandoned agricultural land.	NCP 4	Popp et al.(Popp et al., 2014), Humpenöder et al.(Humpenöder et al., 2018, 2022)
CH ₄ emissions from agriculture (Mt CH ₄ year ⁻¹)	CH ₄ emissions from enteric fermentation, animal waste management and rice production are calculated based on ruminant meat production, manure and area of rice cultivation. CH ₄ emissions from burning of agricultural residues are also accounted for.	-	Stevanović et al.(Stevanović et al., 2017)
Nitrogen surplus (Mt N year ⁻¹)	Nitrogen surplus on agricultural land is estimated based on the difference between organic and inorganic N inputs and removals through harvesting or grazing, while on non-agricultural land it is assumed that N fixation equals surplus. In animal waste management, N surplus is the difference between excretion and recycled manure.	-	Bodirsky et al.(Bodirsky et al., 2012)
Land productivity and food accessibility (MAgPIE)			
Average annual yield changes (% year ⁻¹)	The temporal development of agricultural yields is modelled endogenously based on cropland relocation and through the cost-effectiveness of investments into irrigation and research & development (R&D) investments into yield-increasing technological change relative to other cost components (e.g. land conversion or transport costs).	-	Dietrich et al.(Dietrich et al., 2014)
Expenditure on agricultural products (USD person ⁻¹ year ⁻¹)	Per capita expenditures in USD05 MER for agricultural commodities for food use, excluding the value-added in the supply chain. Food expenditure is derived from the country-level per-capita food use multiplied with the shadow price (Lagrange multiplier) of providing one additional unit of food in a world region.	-	Stevanović et al.(Stevanović et al., 2017)
Agricultural imports (Mt DM year ⁻¹)	A region imports agricultural commodities, if demand is not met by domestic production.	-	Schmitz et al.(Schmitz et al., 2012)
Biodiversity and regulating nature's contributions to people (NCP) (MAgPIE-SEALS)			
Configurational landscape heterogeneity & pollination sufficiency (unitless)	Cropland pixels (300m x 300m) are ranked by values between 0 and 1. 1 indicates >30% semi-natural habitat within 2 km around cropland. Values between 0 to 1 indicate a proportion from 0 to 30%. The presence of semi-natural habitat has shown to be positively associated with a range of important NCP such as pollination supply(Kennedy et al., 2013; Kremen et al., 2004) and an important driver of biodiversity(Estrada-Carmona et al., 2022).	NCP 1, 2 & 10	von Jeetze et al.(von Jeetze et al., 2023), Chaplin-Kramer et al.(Chaplin-Kramer et al., 2019)
Soil loss by water erosion (Pg year ⁻¹)	Soil loss by water erosion is estimated based on the Global Soil Erosion Modelling (GloSEM) platform. GloSEM is a large-scale Geographical Information System (GIS) version of the empirical, detachment-limited Revised Universal Soil Loss Equation (RUSLE) model. Soil loss by water erosion is a major driver of soil degradation, undermining the supply of critical soil-related material and regulating NCP(Vereecken et al., 2016).	NCP 8	von Jeetze et al.(von Jeetze et al., 2023), Borrelli et al.(Borrelli et al., 2020)
Area of habitat (AOH) change (ha)	The area of habitat (AOH) refers to the habitat available to a species within its geographic range. AOH changes are derived for 6,374 amphibian, 9,124 bird, 5,351 mammal and 6,877 reptile species and are based on a fine-scale allocation of land-cover projections and corresponding changes in the suitable habitat. Range shifts due to climatic changes could not be considered here.	NCP 1	Brooks et al.(Brooks et al., 2019), Lumbierres et al.(Lumbierres, Dahal, Di Marco, et al., 2022; Lumbierres, Dahal, Soria, et al., 2022)

^a NCP dimensions are define based on the IPBES conceptual framework(IPBES, 2019)

Table 1: Overview of outcome indicators assessed in this study and their NCP dimensions.



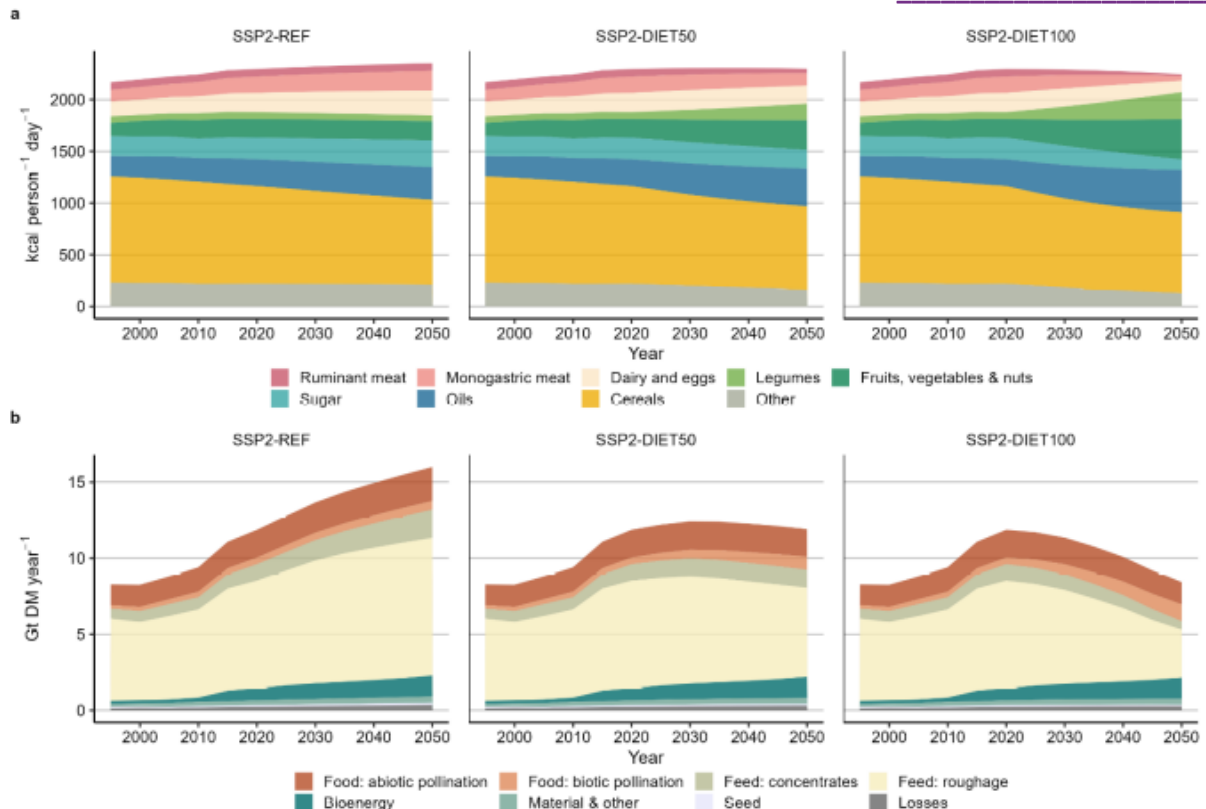


Figure 1: Global food consumption and agricultural demand. **a** Per-capita calorie intake per day across different food groups and for different levels of convergence towards recommended intake levels. In the reference scenario, calorie intake is derived from projected population growth, demographic changes, and per-capita income, while recommended intake levels in the two dietary change scenarios for the different food groups are taken from Springmann et al. (see Methods). **b** Overall changes in agricultural demand for different convergence levels towards the healthy reference diet separated into different demand categories. Food crops mediated by biotic pollination include oil crops such as sunflower or rapeseed, legumes and fruits, vegetables and nuts.

2.4 Land-system dynamics in the reference scenario

In our reference scenario (SSP2-REF), we consistently find a deterioration of the assessed indicators. Until 2050, global cropland and pasture area are projected to increase by 132 Mha and 30 Mha respectively (Figure 2). Similar to previous studies (Henry et al., 2019; Williams et al., 2021), our results show that these changes are largely driven by the expansion of agricultural land in tropical Africa, Asia and Latin America as a result of population growth and an increasing per capita food supply, in particular of meat and dairy products due to rising income. This transition could cause a global forest loss of over 123 Mha and a loss of 76 Mha non-forest ecosystems between 2020 and 2050. The continued expansion of agricultural land

could also keep annual CO₂ emissions from land-use change above 3 Gt CO₂ year⁻¹ until 2050, while global CH₄ emissions from agriculture and surplus of reactive nitrogen could rise to 264 Mt CH₄ year⁻¹ and 296 Mt Nr year⁻¹ respectively (Figure 3a-c).

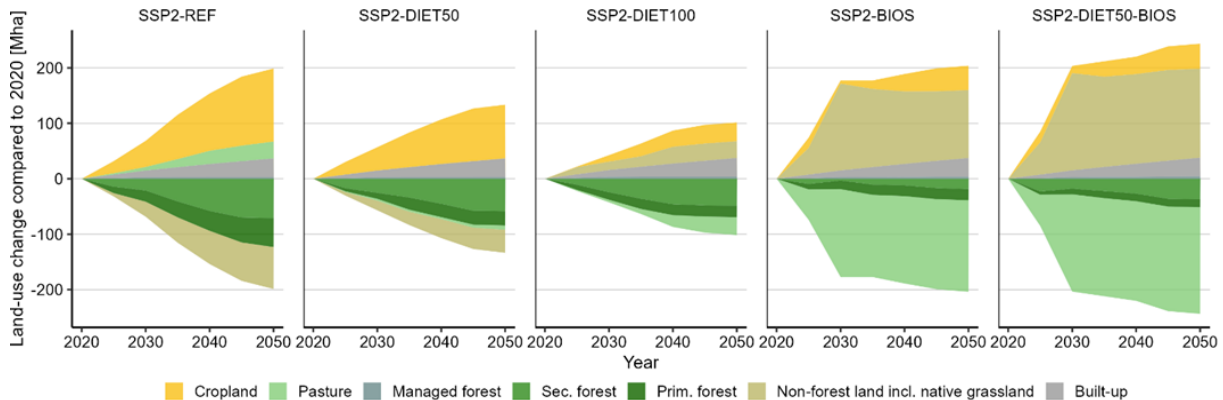


Figure 2: Global land-use change dynamics between 2020 and 2050 of primary land types. Global land cover in MAgPIE for the reference year 2020 contains 1603 Mha of cropland (food, feed and bioenergy crops), 3266 Mha of pastureland, 3975 Mha of forest and 3822 Mha of other non-forest vegetation, of which a total area of 1650 Mha was covered by protected areas.

The increased demand for agricultural land in SSP2-REF also puts further pressure on farmed landscapes, causing a further decline in the configurational heterogeneity of managed landscapes at the global scale (Figure 4). Configurational landscape heterogeneity is positively associated with a range of key regulating NCP (Dainese et al., 2019; Kennedy et al., 2013), such as wild pollination, and an important driver of biodiversity in managed landscapes (Estrada-Carmona et al., 2022; Tscharntke et al., 2021). Our data indicate that in 2020 the majority of cropland (1042 Mha) was situated in landscapes with low configurational heterogeneity and pollination sufficiency scores. By 2050, declining landscape heterogeneity in SSP2-REF further increases the total cropland area with low pollination sufficiency scores (Figure 4b), particularly in Sub-Saharan Africa (SSA; +39 Mha), Latin America (LAM; +8 Mha) and Asian countries excluding China and Japan (OAS; +7 Mha). This is especially concerning, since between 2020 and 2050 we also find high increases in the demand for highly nutritious, pollinator-dependent food crops, such as fruits, vegetables, nuts, legumes and oil crops in SSA (+163%), Middle East and North Africa (MEA; +65%), OAS (+46%) and India (IND; +41%).

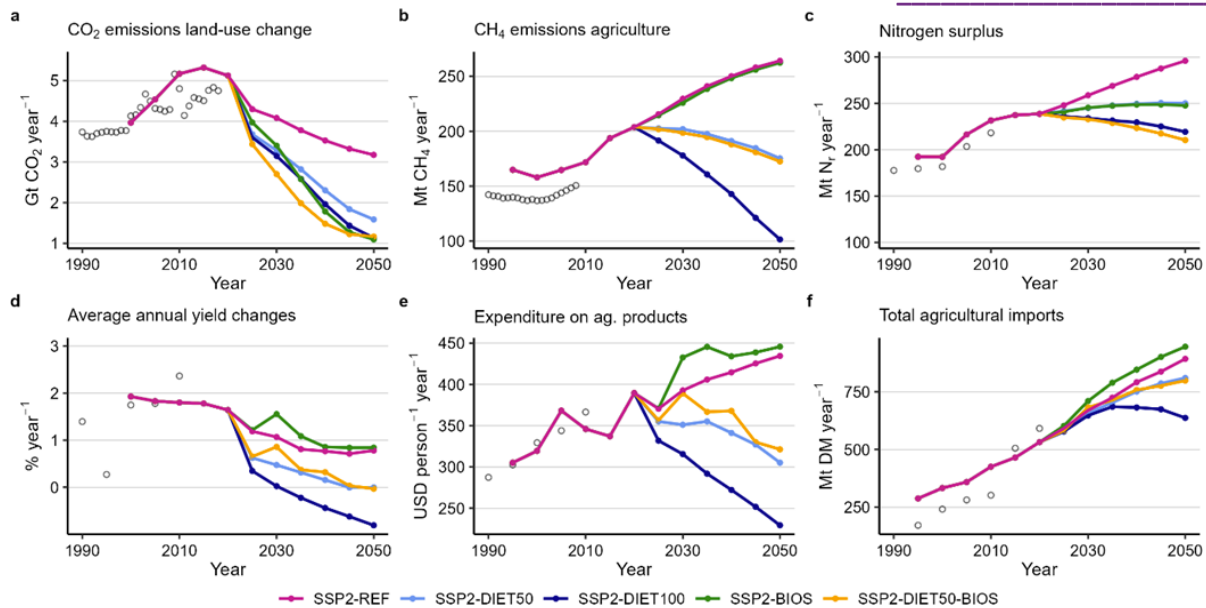


Figure 3: Global projections of environmental indicators, land productivity and food accessibility. a-f Outcomes projected by MAgPIE for (a) CO₂ emissions from land-use change, (b) CH₄ emissions from agricultural activities, (c) Nitrogen surplus estimated based on a budget approach on agricultural land and in animal waste management, (d) projected average annual crop yield changes, (e) expenditure on agricultural products for food use and (f) projected agricultural imports.

The reference scenario also shows a significant increase in global soil loss by water erosion from 44.2 Pg year⁻¹ in 2020 to 47.5 Pg year⁻¹ in 2050, mainly driven by the continued expansion of agricultural land (Figure 4d). However, it is important to note that, while still considerable, the reported increases in soil loss in SSP2-REF (+7.5 %) are notably lower than in previous projections also based on the Global Soil Erosion Modelling (GloSEM) platform (Borrelli et al., 2020; von Jeetze et al., 2023). This is explained by an improved representation of currently implemented land protection policies in the MAgPIE-SEALS framework (see Methods), advances in fine-scale land allocation and the different base year (2020 instead of 2015).

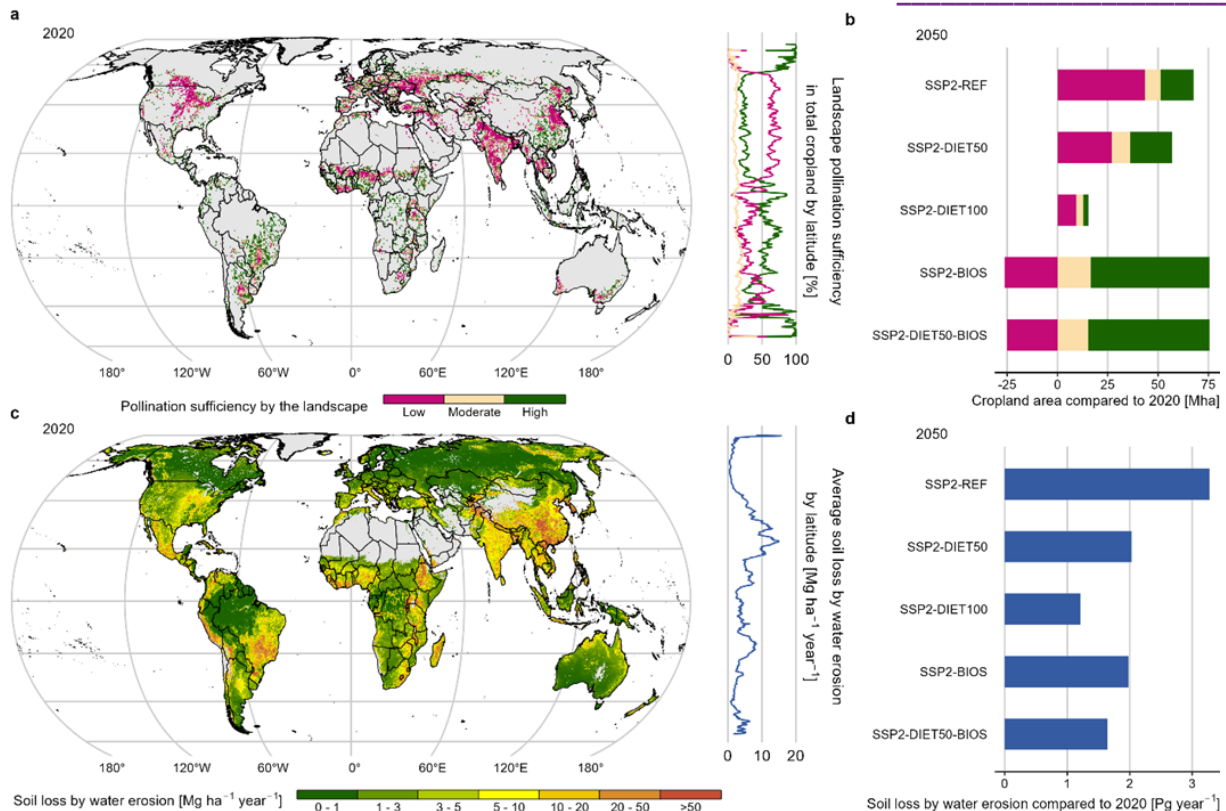


Figure 4: Landscape pollination sufficiency and soil loss by water erosion. **a, c** Spatial and latitudinal estimates for landscape pollination sufficiency scores and soil loss by water erosion for the reference year 2020. Spatial and latitudinal estimates for the year 2020 are directly derived from ESA CCI land cover maps. Soil loss estimates are based on the GloSEM platform (see Methods). **b, d** Projected changes in landscape pollination sufficiency (**b**) and soil loss by water erosion (**d**) between 2020 and 2050 based on MAgPIE-SEALS land cover projections.

Estimated AOH changes of vertebrate species are based on a fine-scale allocation of land-cover projections and corresponding changes in the suitable habitat within the range of each assessed species. AOH projections provide valuable information on potential habitat change and species extinction risk. They can also guide conservation efforts and have been proposed as an additional indicator for the IUCN Red List (Brooks et al., 2019; Lumbierres, Dahal, Soria, et al., 2022). To account for different habitat preferences, yet maintain clarity in the presentation of our findings, we report results separately for two broad habitat categories: forest and open habitat species. We find that in SSP2-REF, a total of 1774 species could experience a habitat loss of more than 5 %, of which 253 species are already vulnerable or endangered today (Figure 5a). Our results also show that 250 and 67 species respectively could lose more than 20 % and 40 % of their habitat by 2050 regardless of their Red List status (Figure 5b). Habitat loss predominantly affects small-ranged amphibians and birds in forest habitats, particularly in SSA, but open habitat birds in SSA, China (CHA) and OAS are also highly affected.

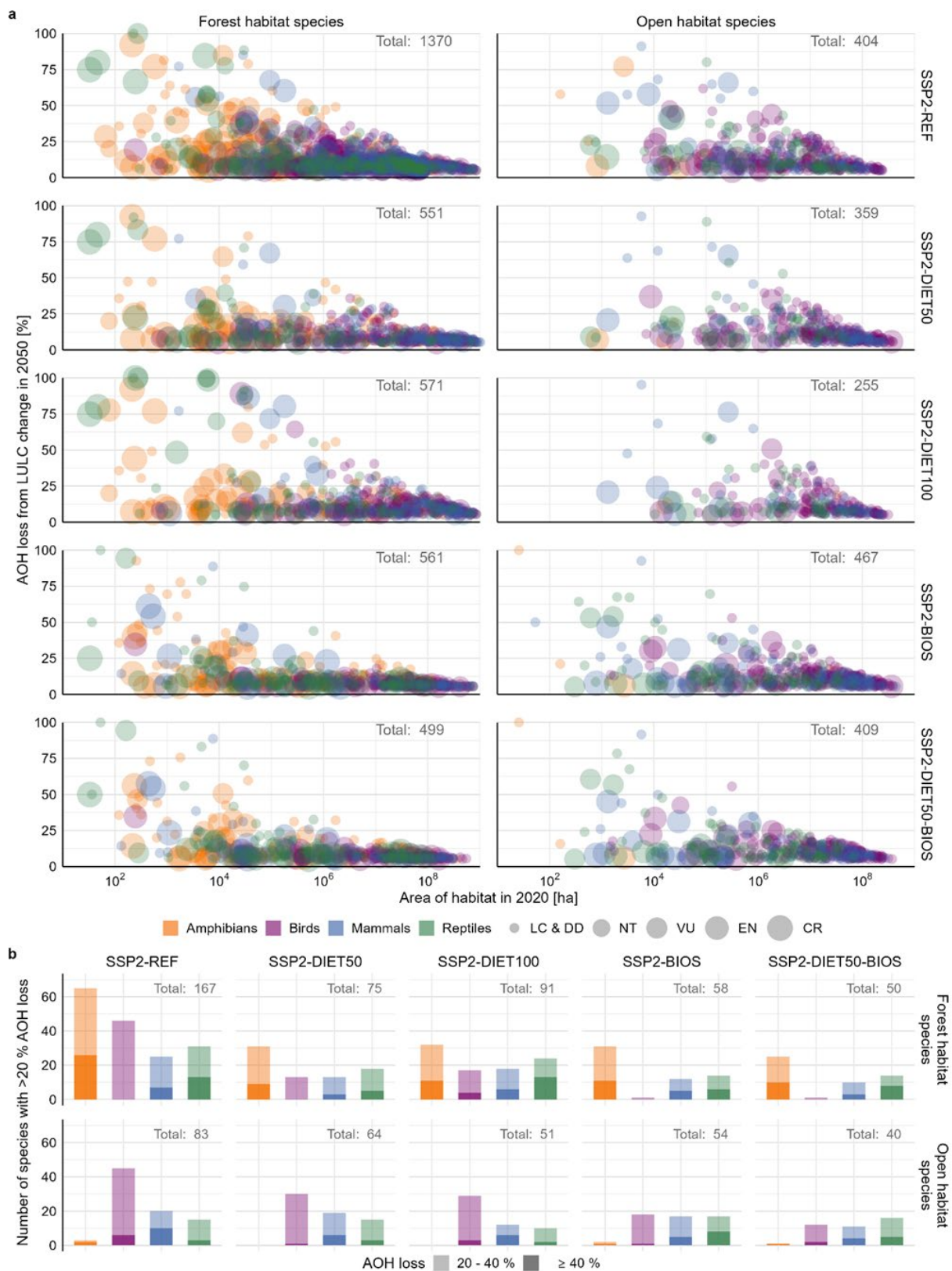


Figure 5: Projected changes in the area of habitat (AOH) between 2020 and 2050 across different species groups and habitat preferences. a Projected AOH losses (%) for forest and open habitat species in 2050 in relation to the estimated AOH in 2020. The size of the circles indicates the species' conservation status in the year 2020 according to the IUCN Red List Database. LC & DD: Least Concern and Data Deficient, NT: Near Threatened, VU: Vulnerable, EN: Endangered, CR: Critically Endangered. Only species with more than 5% AOH loss in 2050 are shown here. **b** Number of forest and open habitat species with more than 20% AOH loss by 2050 across modelled scenarios.

2.5 Conservation effects of dietary change

The assumed partial and full convergence towards a healthy reference diet in the DIET50 and DIET100 scenarios is associated with a reduction in average per capita calorie intake from livestock products of 33% and 66% respectively in 2050 (Figure 1a). The reduction in livestock-based food intake is compensated by an increase in plant-based food intake, in particular from legumes (+177% and +353% kcal person⁻¹ day⁻¹) and fruits, vegetables and nuts (+30% and +60% kcal person⁻¹ day⁻¹). This shift away from the consumption of livestock products is also reflected in the increased demand for pollinator-mediated crops, which increases from 21% of total dry matter food demand in SSP2-REF to 32% and 43% in the DIET50 and DIET100 scenarios respectively (Figure 1b).

Compared to SSP2-REF, the lower demand for feed concentrates in the DIET50 (-36%) and DIET100 (-71%) scenarios markedly reduces agricultural land expansion in LAM and OAS. In SSA, however, the cropland area in the DIET50 (+4 Mha) and DIET100 (+6 Mha) scenarios is larger than in the reference scenario, due to the much higher demand for nutritious plant-based foods and a lower land productivity. Significant cropland abandonment is only observed in the DIET100 scenario in CHA, Europe (EUR), reforming countries including Russia (REF) and the USA. The smaller agricultural area also leads to a reduction in soil loss by water erosion (-2.6% and -4.4%) and in CO₂ emissions from land-use change (-50% and -64%) in the DIET50 and DIET100 scenarios as compared to SSP2-REF. Similarly, CH₄ emissions from agriculture (-44% and -62%) and reactive nitrogen surplus (-15% and -26%) are also reduced due to the lower demand for livestock products in both diet change scenarios (Figure 3a & 3c).

In addition, the total number of vertebrate species with more than 20% habitat loss is roughly halved in both diet change scenarios relative to SSP2-REF, suggesting only marginal benefits in terms of habitat loss from full over partial convergence. This saturation of biodiversity benefits from reduced consumption of livestock products emerges because particularly in SSA land savings due to lower feed demand are offset by the shift from staple foods to more nutritious plant-based foods and a reduced land productivity. Crucially, we find that the total number of species with more than 40% habitat loss actually doubles in the DIET100 scenario

as compared to the DIET50 scenario (Figure 5b), largely due to the greater expansion of cropland in tropical Africa, which particularly affects forest-dwelling mammals and reptiles.

Our results also suggest that dietary shifts alone will not counteract structural trends in land use, such as landscape simplification, that undermine biosphere integrity (Estrada-Carmona et al., 2022; Rockström et al., 2023) and critical ecosystem functions (Dainese et al., 2019; Garibaldi et al., 2020; Tscharntke et al., 2021). We find that without additional measures a shift to plant-based foods could lead to further declines in landscape heterogeneity and pollination sufficiency scores, particularly in SSA and OAS. In SSA, cropland situated in simplified landscapes with low pollination sufficiency scores even increases by 8 Mha in the DIET100 scenario relative to the reference scenario. Projected demand for pollinator-dependent food crops, on the other hand, is 161% (DIET50) and 217% (DIET100) higher in SSA and 171 % (DIET50) and 237 % (DIET100) higher in OAS compared to SSP2-REF.

2.6 Targeted conservation action

In the BIOS scenario we assess the combined effects of a bundle of conservation measures that address different dimensions of biodiversity loss. In line with the targets set out in the GBF, these measures expand PAs to 30% of the global land surface and address key drivers of biodiversity loss outside of PAs. The assumed expansion of PAs prioritises land within Key Biodiversity Areas (Birdlife International, 2022) (KBAs), remaining unprotected habitat in Biodiversity Hotspots (BHs) and Ecoregions with a high beta-diversity (Dinerstein et al., 2020) (EBDs), and Critical Connectivity Areas (CCAs) as defined by Brennan et al. (Brennan et al., 2022). Conservation measures outside PAs include maintaining at least 20% of semi-natural habitats in agricultural landscapes by 2030; a no net biodiversity loss scheme after 2030 at the biome level (Olson et al., 2001); and finally a gradual increase of the nitrogen use efficiency on cropland until 2050.

We find that even if food demand remained unchanged from the reference scenario, these combined measures would already lead to substantial improvements in most assessed indicators that are comparable to or sometimes even exceed the effects of a partial or complete dietary shift. This is because by directly addressing immediate drivers of biodiversity loss, such as habitat conversion in conservation priority areas in SSA and OAS, these concerted measures also initiate spatial shifts in land-use patterns that make nature-related impacts less dependent on underlying factors such as population and income growth or dietary patterns.

The enlargement of PAs in the selected conservation priority areas, for example, has shown to be highly effective in reducing habitat loss for forest-dwelling species. We find that in the BIOS scenario the number of forest species affected by more than 20% habitat loss is reduced by two-thirds relative to the reference scenario and by 23% and 36% respectively as compared to the DIET50 and DIET100 scenarios (Figure 5). However, as land conversion shifts away from

forest habitats as a result of the conservation action, more open habitat species are overall affected by land conversion. The BIOS scenario therefore shows the highest number of open habitat species suffering a habitat loss of more than 5% (Figure 5a). The number of open habitat species with more than 20% of habitat loss, on the other hand, is still 35% lower than in the reference scenario, indicating that land-use impacts in the BIOS scenario are by and large more evenly distributed across species.

The overall higher level of land conservation compared to SSP2-REF also shows significant co-benefits regarding other indicators of environmental change. Together with the DIET100 scenario, the BIOS scenario has the lowest remaining CO₂ emissions from land-use change at just over 1 GtCO₂ year⁻¹ in 2050 and reductions in reactive nitrogen surplus that are comparable to the DIET50 scenario. The BIOS scenario also provides important co-benefits regarding soil loss by water erosion and is the only scenario that improves the structural heterogeneity of cultivated landscapes relative to 2020, which is directly influenced by the requirement of maintaining at least 20% of semi-natural habitats at the landscape scale. Hence, the cropland area with high pollination sufficiency scores shows a marked increase between 2020 and 2050 in almost all model regions. Only in SSA, the cropland area with low pollination sufficiency scores still continues to grow until 2050 due to the high demand pressure, but at a much slower rate than in the reference scenario. As the projected CH₄ emissions from enteric fermentation are directly linked to the level of dairy and ruminant meat production, they are not addressed by the conservation measures in the BIOS scenario and therefore remain unchanged compared to the reference scenario.

We also find that without changes in agricultural demand, particularly for livestock feed, socioeconomic barriers to conservation could become increasingly important. This especially pertains to higher food prices, which could drive up per capita food expenditure, but also to agricultural imports, which increase globally as a result of the conservation measures in the BIOS scenario (Figure 3d & 3e). Notable increases in food expenditure relative to SSP2-REF are observed in Canada, Australia and New Zealand (CAZ), EUR, LAM, REF and SSA. Higher food imports, on the other hand, would particularly be required in OAS and SSA, while food exports would increase in CHA, EUR, IND and REF relative to the reference scenario. Our results also show that these barriers would already be significantly reduced, if targeted conservation measures were accompanied by even a partial dietary change. We find that this shift, even when combined with ambitious conservation measures (DIET50-BIOS), would still lead to lower levels of required yield increases, food expenditures and food imports than in the reference scenario (Figure 3d-f), while ensuring significant improvements in all assessed dimensions of biodiversity loss.

2.7 Discussion

This study uses a quantitative and spatially explicit framework to assess how a transition to healthier diets would affect multiple aspects of biodiversity loss relative to targeted

conservation measures. We find that effective conservation will depend less on a convergence towards healthier diets than on coordinated measures that counteract structural trends in land-use dynamics and land allocation. This is because even after a shift towards healthier diets, population growth would remain the dominant driver of cropland expansion and landscape simplification in many countries in tropical Africa and Asia. Nonetheless, our results also show that a partial reduction in global livestock-based food intake of 33% relative to our reference scenario would significantly reduce important socioeconomic barriers to conservation action, such as higher food expenditure or increased imports.

Our analysis is an important addition to previous studies that have found substantial benefits for biodiversity from a decrease in livestock-based food intake, mainly due to reduced agricultural expansion (Henry et al., 2019; Williams et al., 2021). By including various aspects of NCP and biodiversity change at a high spatial granularity, our study provides a framework that allows for an integrated assessment of biodiversity impacts across different species groups, habitat types and NCP dimensions. Considering different conservation objectives and their potential trade-offs is particularly important when informing policy makers and the wider public about the potential consequences of alternative policy options. This is also illustrated by our assumptions regarding the expansion of protected areas in our BIOS scenario, which is critical to our scenario setup and therefore our projected outcomes. Our choice to expand protected areas in KBAs, BHs, EBDs and CCAs is informed by the current literature on conservation priority areas and seeks to balance different conservation objectives, taking into account areas of global importance as well as species migration (Brennan et al., 2022; Dinerstein et al., 2020). Yet it remains just one plausible implementation of the GBF's 30x30 target that exemplifies both the potential benefits and trade-offs of expanding PAs for different species groups. The strong positive effects for forest species found here, particularly forest birds, are largely the result of this choice. Likewise, the observed trade-offs of open habitat losses as a result of PA expansion suggest that open habitat species are widely neglected by prominent conservation priority layers (Stauder et al., 2023). These are key findings that can inform the debate on the balancing of different conservation objectives in the context of PA enlargement in line with the GBF.

A critical component of our modelling framework is the linkage between projected land-cover changes and AOH changes, which can be subject to mismatches and inaccuracies in both the land-cover data and species' associations with habitat and elevation (Lumbierres, Dahal, Di Marco, et al., 2022). However, the habitat-land cover model (Lumbierres, Dahal, Di Marco, et al., 2022) used here systematically reduces commission (false presence) errors and has shown to achieve high accuracies in AOH projections (Dahal et al., 2022). Also, future projections of AOH changes depend not only on projected losses of currently suitable habitats, for example due to cropland expansion, but also on our assumptions regarding habitat regeneration and restoration, e.g. following conservation measures. We here assume that habitat restoration is based on pre-industrial conditions, but in reality, restoration may also involve alternative management regimes and (normative) decisions about which habitats to

restore for particular species. In addition, habitats are not only defined by biophysical land cover but by a complex interplay of various factors. Changes in habitat quality, for example through management (Ernst et al., 2016), extraction (Benítez-López et al., 2017) or pollution by nutrients or pesticides (Sánchez-Bayo & Wyckhuys, 2019), could not be considered here. Climate change could also significantly impact both the quality and distribution of suitable habitats (Foden et al., 2013; IPBES & IPCC, 2021; Loarie et al., 2009) and may therefore interact with other drivers of habitat change (Foden et al., 2013; IPBES & IPCC, 2021). Drastic reductions in GHG emissions and land-based carbon uptake through ecosystem restoration (von Jeetze et al., 2023) are therefore critical to prevent climate-driven disruption of biodiversity (Trisos et al., 2020), while adaptive conservation approaches need to consider habitat connectivity and the dispersal of species along environmental gradients (Arroyo-Rodriguez et al., 2020; Beger et al., 2022; Brennan et al., 2022).

Our findings underline the global importance of coordinated and targeted conservation actions that address various dimensions of biodiversity decline. This also includes addressing trade-offs between different (normative) conservation objectives through an active and informed deliberation between scientists, policy-makers and the general public at various scales (Berkes, 2007; Pascual et al., 2021), as well as finding policy instruments that consider varying local contexts and guarantee the effectiveness of conservation measures. While conservation action produces considerable benefits for society at large (Johnson et al., 2023; Ouyang et al., 2020), local communities often face high costs that necessitate adequate compensation schemes for foregone opportunities (Green et al., 2018). This requires strengthening institutional capacities for the implementation and monitoring of conservation policies, e.g. to ensure that land use within a conservation priority area is in line with its conservation target (Meng et al., 2023).

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3 The effect of biodiversity conservation policies in addition to climate mitigation scenarios

3.1 Introduction

In the Paris Agreement, the global society defined the crucial goal to stay well below 2°C of global warming compared to pre-industrial levels and to pursue efforts to limit it to 1.5°C (UNFCCC, 2015). To do so, carbon dioxide removal (CDR) technologies will be essential, even more so if a temporary overshoot is to be limited, as indicated by the majority of such warming scenarios in the most recent, sixth IPCC Assessment Report (IPCC 2022, Riahi et al. 2021). Among the major land-based options are afforestation and reforestation, bioenergy with carbon capture and storage (BECCS), enhanced rock weathering (ERW), and biochar. Other methods include direct air carbon capture and storage (DACCS) as well as various ocean-based technologies.

In addition to climate mitigation, biodiversity conservation and recovery are essential goals humanity must work towards (IPBES 2019, Rockström et al. 2023, Pörtner et al. 2021). A primary driver of biodiversity loss is the conversion of natural habitats (Rockström et al. 2023, Hirata et al. 2024, Núñez-Regueiro et al. 2021, Van Vuuren et al. 2010, Immerzeel et al. 2014). Protecting biodiversity thus entails halting land conversion as well as active regeneration of already converted lands, as targeted by initiatives such as the UN Decade on Ecosystem Restoration. These efforts may be at odds with climate mitigation efforts and their land requirements (Wu et al. 2019, Frank et al. 2021).

That is because BECCS is a major contributor to climate mitigation in many scenarios compatible with the Paris Agreement (IPCC 2022), often at a scale that requires extensive and additional expansion of cropland for bioenergy crops such as *Miscanthus*. Implementing these expansions often hampers biodiversity conservation efforts (Wu et al. 2019, Frank et al. 2021, Braun et al. 2025), while stricter biodiversity conservation and thus reduced cropland expansion limit the available level of BECCS and thus the possible climate mitigation scenarios. At the same time, furthering biodiversity conservation may bolster other climate mitigation options, such as natural carbon sinks (Pörtner et al. 2021, Shin et al. 2022, Gorman et al. 2023).

It is thus essential to assess climate mitigation and biodiversity conservation scenarios in a common framework, considering both trade-offs and synergies, to understand where these different sustainability goals might support or hinder each other and how they can be balanced sustainably. Such interlinkages between different goals have so far only rarely been taken into account in policy discussions and integrated assessments (Rockström et al. 2023, Pörtner et al. 2021, Hirata et al. 2024, Van Vuuren et al. 2010, de Lamo et al. 2020).

To close this gap, we conduct a systematic scenario assessment of the global dynamics and the sustainable balance of bioenergy supply and demand for BECCS, alternative land-use activities for climate mitigation, and different ambition levels for biodiversity intactness. Our scenarios span thus the solution space for various ambitions regarding climate and biodiversity policies. Climate mitigation is quantified in terms of a carbon budget and the change of the average global temperature over the next 75 years, while biodiversity is quantified by the Biodiversity Intactness Index (BII). By running scenarios in an interlinked land-use and energy system constrained by various biodiversity intactness and thus conservation scenarios, a diverse set of climate-biodiversity narratives can be assessed, including business-as-usual biodiversity conservation with nearly unconstrained BECCS expansion as well as a strong focus on biodiversity conservation and, as a result, on natural carbon sinks.

3.2 Methods

3.2.1 The MESSAGEix-MAgPIE linkage

We utilize a newly implemented integrated assessment framework comprising detailed biophysical model of the land-use sector (the Model of Agricultural Production and its Impact on the Environment (MAgPIE (Dietrich et al. 2019))), and a bottom-up systems engineering model of the energy-economic systems (the Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGEix (Huppmann et al. 2019))). The two models are integrated via a MAgPIE land-use emulator that is implemented into MESSAGEix (as illustrated in figure 1). The two main dimensions of the land-use emulator are 1) the bioenergy demand (approximated through the variation of bioenergy prices) and 2) the stringency of climate policies (approximated through a GHG price on land-use activities).

The systematic representation of the solution space along these dimensions permits the endogenous representation of land-use consequences of bioenergy use in MESSAGEix. In practice, we compute a large ensemble of MAgPIE scenarios for this solution space. The scenarios are then added to MESSAGEix as dynamic vectors, representing internally consistent land-use transitions given specific GHG prices and bioenergy demands. Solutions of different MAgPIE scenarios can be blended over time with specific equations assuring that the path-dependency of land-use transitions in MAgPIE are retained in the emulator. Land-related GHG emissions of bioenergy use as well as related implications for the security of food supply and biodiversity become thus endogenous decision variables in the “extended” energy model.

For the scenario solution space, we utilize matrices comprising 84 bioenergy-carbon price combinations. Bioenergy production levels are modeled for seven price incentive scenarios starting from 0 US\$2005/GJ in 2020, linearly increasing to their targets ranging from 0 to 45 US\$2005/GJ in 2100. For each of these production scenarios, twelve carbon prices are introduced (0-103 US\$2005/tCO₂ in 2025, discounted at 5% per year to 0-4000US\$2005/tCO₂ in 2100).

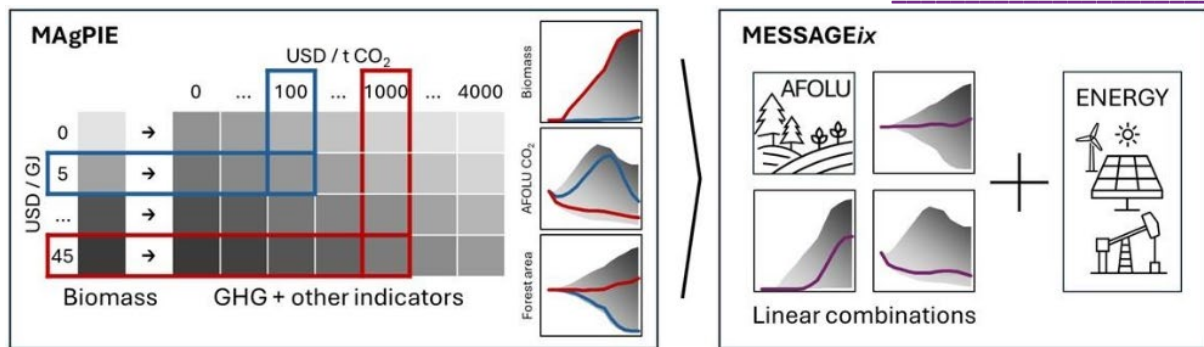


Figure 1. Conceptual implementation of MAgPIE land-use emulator in MESSAGEix. Left: In MAgPIE, two main steps create a scenario matrix to be implemented into MESSAGEix. Bioenergy price scenarios are solved to assess regional bioenergy production potentials. With these potentials fixed as demands, carbon price scenarios are solved. Each cell in the figure symbolizes one such bioenergy-carbon price combination, where the blue and red markings mark two specific examples. Per bioenergy-carbon price scenario, various land-use indicators endogenously calculated by MAgPIE, such as biomass production, CO₂ emissions, land-use change, and biodiversity outcomes (quantified by the Biodiversity Intactness Index (BII), explained in more detail below) are stored. The combination of all such scenarios creates a scenario space as shown in the example gradients, with the blue and red example scenarios highlighted within this space. Right: The full scenario matrix, including all indicators for all scenarios and regions, is implemented into MESSAGEix. As part of its optimization of the energy sector, its demand for bioenergy needs to be fueled by the land sector. To do so, MESSAGEix linearly combines (purple) the matrix scenarios. Despite the fact that a lot of land-use indicators (mentioned above) are passed to MESSAGEix, it does not use them for its cost optimization step. The only data MESSAGEix needs for this step are the bioenergy potentials, the GHG emissions, and their respective prices. The sum of the total profits from bioenergy production, and the total profits (losses) from GHG removal (resp. emissions) constitute the "land cost" that MESSAGEix sees from individual MAgPIE scenarios that comprise the matrix. Incorporating this land cost into its cost optimization is how MESSAGEix can precisely meet its bioenergy demand while also reflecting associated land-system impacts such as the accompanying land-use change and emissions.

3.2.2 Scenarios for biodiversity and climate protection

In order to explore the nexus of biodiversity conservation and climate mitigation, we employ a systematic scenario analysis investigating policy sets of various ambition regarding both targets. For each biodiversity scenario, we create a land-use emulator matrix, as described above and shown in Figure 1. Their setup varies in their biome-specific biodiversity conservation target, summarized in Table 1.

Biodiversity Scenario	Baseline protection	Low Ambition protection	Medium Ambition protection	High Ambition protection

Global BII Target (per Biome)	No Target	0.7	0.74	0.78
BII loss allowed (per Biome)	Yes	No	No	No
Protected Area	WDPA	WDPA + Biodiversity Hotspots	WDPA + Biodiversity Hotspots	WDPA + Biodiversity Hotspots

Table 1. Biodiversity conservation scenarios

Biodiversity conservation is quantified by the Biodiversity Intactness Index (BII), an indicator of intermediate complexity that is commonly used for biosphere integrity (Steffen et al. 2015). It represents the ratio of estimated supported biodiversity in a biome to the theoretical maximum if it were still untouched (Scholes et al. 2005). A BII of 1, for example, would be the theoretical maximum of biodiversity that could be achieved assuming that there would be no interference with Nature. In our scenarios, BII targets range from no target (leading to continued loss of BII over time) up to high ambition protection scenarios with a target of 0.78 per Biome. Conservation ambition is further expressed through additional land-conservation policies for higher ambition scenarios, protecting biodiversity hotspots (Myers et al. 2000). By comparison, the baseline ambition scenario without BII target efforts are limited to current protected areas as defined by the World Database on Protected Areas (WDPA) (IUCN, UNEP-WCMC 2022). In order to avoid high ambition protection scenarios hurting biomes with an already high BII by shifting production there, these scenarios do not allow biome-specific BIIs to drop below 2020 levels.

First, we develop a set of scenarios in order to understand how biodiversity conservation might be affected by climate policies in the land sectors (forest and agriculture). These scenarios assume baseline ambition for biodiversity protection in combination with different stringency for climate policies. In this setup, we analyze the full range of carbon price scenarios, looking at their impact on land-use and especially BII. The focus is on land-based policies, without additional demand for bioenergy of the energy sector, which is assumed to stay at current levels in these scenarios.

As a second step we investigate fully coupled scenarios with competition for land also for bioenergy. In these scenarios we assume additional biodiversity conservation efforts and vary the stringency of climate mitigation efforts to fully integrate both policy objectives. All four biodiversity scenario matrices are solved in MESSAGEix under various full-century carbon budgets, i.e., net emissions in the simulation period 2030-2110, to obtain cost-effective land-use transitions as well as energy supply and demand trajectories. The investigated budgets range from 300 to 1000 Gt cumulative CO₂ emissions, equating climate scenarios in line with a high likelihood to stay below 1.5 and 2 degrees warming, respectively (IPCC, WG1, AR6, 2023). We analyze integrated system indicators, such as the energy mix, land-use and emissions profile, and use the Model for the Assessment of Greenhouse Gas Induced Climate Change (MAGICC) (Meinshausen et al. 2011) to assess resulting peak and long-term global

surface air temperature (GSAT), i.e., the weighted average of near-surface air temperatures over land, oceans, and sea ice (IPCC, WG1, AR6, 2023).

3.3 Results

3.3.1 The impact of climate policy on biodiversity in the land-use sector

To assess the effect of climate change mitigation policies on biodiversity we analyze a representative set of mitigation scenarios from the Baseline biodiversity matrix, as shown in Figure 2. In MAgPIE, climate policies are implemented as an additional cost term, disincentivizing greenhouse gas emissions from the land-use sector. As such, the mitigation scenarios only vary in their carbon price, between 0 for the “Baseline” and 100 US\$2005/tCO₂ in 2025 for the “High Ambition” mitigation scenario, illustrating the gradually increasing effects of a core climate policy on land use and biodiversity. The goal here is to assess whether climate policy by itself - even in the absence of dedicated biodiversity protection - can have beneficial effects on biodiversity. Therefore, we only choose scenarios without any additional bioenergy demand, to remove the confounding effects of bioenergy production. The responses of these scenarios to the different climate mitigation policies result in cumulative emissions from the land sector of 366 (Baseline), 167 (Low Ambition), 76 (Medium Ambition), and -86 (High Ambition) Gt CO₂ by 2100 (Figure 2.A).

We find that increasing the carbon price protects and increases natural carbon storage, especially in forests. This is achieved by re-allocating agricultural activities and production to different (low-carbon) areas, where an increase in cropland has a lower carbon footprint even if more area is needed due to lower soil productivity. In addition, land-use intensity is increased through climate policies and technological-change investments, amplifying local production cost but also opening up more land for rewilding and afforestation.

A major insight from the scenarios is the significant co-benefits of land-based climate policies for biodiversity conservation and restoration. Climate policies induce protection and expansion of natural carbon sinks, which in turn increase the BII (see Figure 2, Panel B). These co-benefits are especially notable in the “High Ambition” climate policy scenario, where the historical downwards trend of BII is stopped as soon as climate policies are implemented. With continued climate policies biodiversity is recovering again and the BII is bending back up to its historical 1995 level and beyond (Figure 2.B), illustrating the large rewilding efforts resulting from stringent climate policies. This is due to the estimated high BII of natural carbon sinks, such as forested areas (Leclère et al. 2020). As such, rainforest areas such as the Amazon and Congo basins especially profit from the climate policy, while other areas and biomes not affected as much in the Baseline see a drop in biodiversity intactness over the century because additional production has been shifted there due to the lack of a general biodiversity conservation policy (Figure 2.Dii). We note the fact that MAgPIE prioritizes the restoration of natural forest ecosystems, as opposed to building plantation forests or bioenergy farms, is because there is no additional demand for timber, bioenergy, or other

plantation products. If we did have such additional demands on the land system, the beneficial effects of climate policy on biodiversity might have been much lower.

While far less impactful regarding BII than the “High” ambition mitigation scenario, the “Low” and “Medium” ambition scenarios highlight that even small mitigation policy changes can have significant biodiversity benefits. “Low” avoids most of the BII drop seen in the Baseline, while “Medium” shows early stabilization before bending back beyond the 2020 BII level. In contrast, the Baseline scenario without climate policy sees a continuous drop in BII, especially prominent in the Congo basin, India and South America (Figure 2.Di). This drop is driven by increasing food demands which, without price-competitive investments into intensification, leads to expansions of cropland and pasture into these biodiversity hotspots. In turn, in the “High” scenario, cropland decreases by 10% and pasture area by 20% relative to 2020 levels.

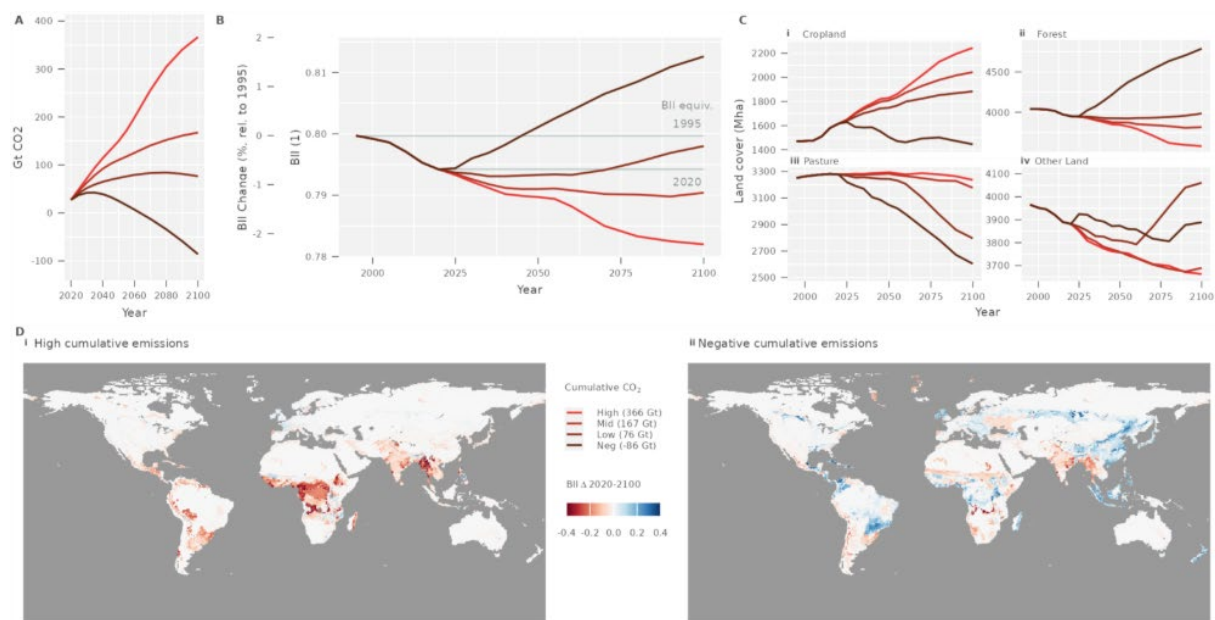


Figure 2. The impact of climate policy on biodiversity and land-use change. Top row: Cumulative land-use CO₂ emissions trajectories in four modeled climate change mitigation scenarios (A), associated changes in globally aggregated BII (B), and associated change in cropland, forest, pasture, and other natural land (C.i-iv). Bottom row: Disaggregated local changes in BII between years 2020 and 2100 in the high (i) and negative (ii) emissions scenario.

3.3.2 Sustainable Biomass Development Aligned with Biodiversity Protection

We have so far focused on the land sector perspective and have shown that climate protection leads to strong synergies for biodiversity if focusing on the land sector in isolation. From a fully integrated multi-sectoral perspective, however, trade-offs need to be taken into account, especially with respect to competition over land due to biomass products. In addition, the ambition to accelerate biodiversity conservation will likely change the land available for

mitigation activities. We thus move next here to the question of sustainable potential of bioenergy that could be deployable at different ambition levels for biodiversity protection.

We find that in absence of biodiversity protection, the global techno-economic bioenergy potential is vast, and can be as high as >600 EJ/yr by 2100 – an amount sufficient to satisfy today's primary energy demand of the entire planet (Energy Institute. Statistical Review of World Energy 2024). However, this level of biomass supply is unsustainable from the perspective of biodiversity protection. The potential thus plummets to less than half of this as soon as a stabilizing "stop loss" biodiversity conservation policy is enacted, keeping biome-specific intactness at or above the 2020 level (see. figure 3.A). Under the most ambitious biodiversity conservation and rewilding policy, the bioenergy potential drops further to about 100 EJ/yr, or about 15% of the pure techno-economic potential. This level of bioenergy is significantly lower than the mean primary energy supply from bioenergy in the stringent IPCC AR6 scenarios broadly consistent with limiting warming to 1.5 °C with no or low overshoot (C1 category) (Byers et al. 2022). From a spatial and regional perspective, sustainable bioenergy production in the order of 100 EJ can be achieved in dedicated and concentrated land areas with low biodiversity trade-offs (see right-hand panel figure 3.C). Tapping into the techno-economic potential would have major adverse effects due to intensive biomass production in all world regions (see left-hand panel of figure 3C).

In scenarios emphasizing biodiversity protection, cropland and pasture areas are strongly reduced and natural land expands by over 50% between 2020 and 2100 (see figure 3B). There is thus a dual effect pulling in opposite directions: biodiversity protection reduces the potential for bioenergy and BECCS, and at the same time it also improves the natural carbon sink of the planet by limiting deforestation and avoiding natural land degradation (see figure 3.B).



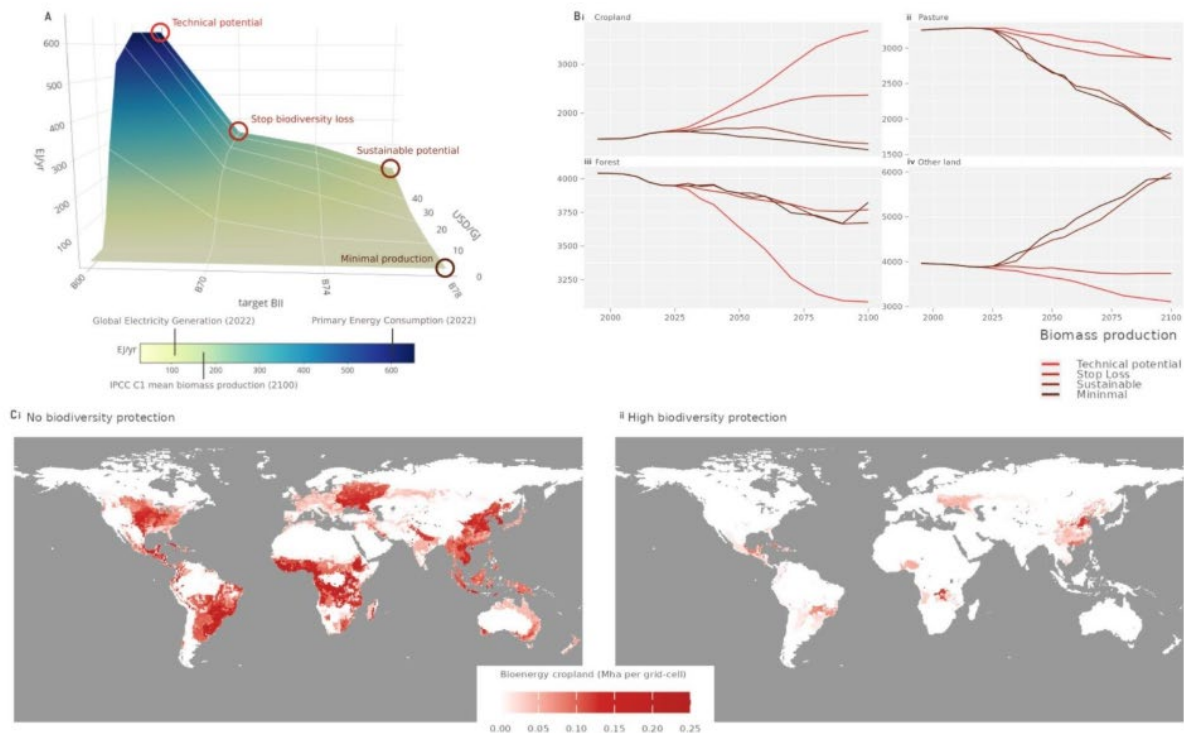


Figure 3. The impact of biodiversity policies on bioenergy availability and land-use change. Top row: Bioenergy potentials in 2100 dependent on biodiversity conservation ambition, expressed through target minimum biome-specific biodiversity intactness index. (A) “Techno-economic potential” marks a hypothetical bioenergy potential without considering biodiversity, stop “Stop biodiversity loss” marks the potential for a low BII target combined with a general BII loss prohibition policy after 2020, and “Sustainable” and “Minimal” production are associated with a high-ambition biodiversity scenario, where at different bioenergy price levels. B: Associated changes in cropland, forest, pasture, and other land. Bottom row: Disaggregated bioenergy production for techno-economic and sustainable potential.

3.3.3 Full integration of climate and biodiversity ambitions across the energy and land sector

We now explore characteristics of sustainable energy and land transitions that consider integrated biodiversity and climate policy targets. In order to disentangle the effect of the biodiversity target we systematically vary the biodiversity ambition from zero (baseline) to low, to medium and to high conservation ambition (cf., Methods).

We combine these biodiversity ambition levels with an illustrative climate target with a cumulative CO₂ budget of 1000 Gt CO₂ (from 2010 to 2100), which is estimated to limit global warming to below 2 °C with a likelihood of greater than 66% (IPCC, WG1, AR6, 2023). The results are shown in Figure 4.

We find that a high biodiversity protection target significantly changes the dynamics of the energy and land transformation towards limiting warming to 2C. Both the mix of the portfolio and the timing of mitigation options (see Figure 4) change when biodiversity is prioritized and thus bioenergy supply is limited and becomes more expensive. This incentivizes a more rapid upscaling of other renewable energy sources, such as solar and wind, which grants the energy system more flexibility and reduces its dependence on bioenergy towards the latter half of the century. This leads also to an earlier and more aggressive phase-out of fossil fuels and more stringent near-term emissions reductions, both of which serve to reduce reliance on BECCS-driven mitigation due to its limited availability and price-competitiveness. The share of forests and other natural land increases at higher levels of biodiversity protection and nearly doubles the forest carbon sink to 2.5 Gt CO₂/yr by 2100 compared to no biodiversity protection (roughly 1.5 Gt CO₂/yr). This partially offsets the reduced CDR potential from BECCS, which shrinks from nearly 70 to around 12 Gt CO₂/yr by 2100 under a high ambition biodiversity conservation policy (Figure 4). Overall this means that a sustainable climate transition which prioritizes biodiversity will reduce the risk of overshooting specific warming levels and also reduces the reliance on BECCS and other negative emissions technologies in the long-term.

Impact of biodiversity protection on land, energy, and emissions

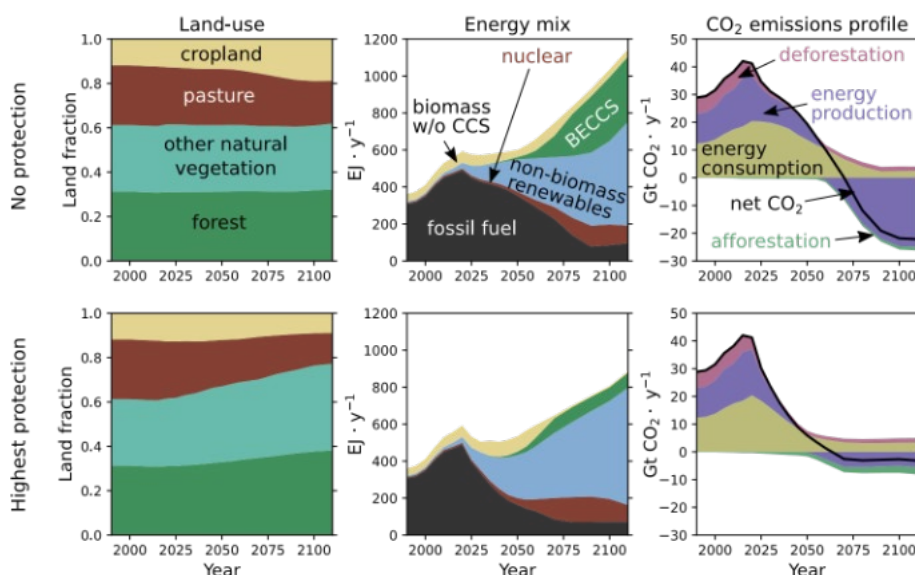


Figure 4. The impact of stringent biodiversity protection policy on global land-use, energy mix, and CO₂ emissions profiles. Top row, left to right: global land-use patterns, energy mix, and CO₂ emissions profile for the control scenario, which is constrained by a carbon budget but without biodiversity protection. Bottom row, left to right: the same indicator variables for the same carbon budget, constrained by the highest biodiversity protection scenario.

Effect of biodiversity policy on land-based CO₂ sink potentials

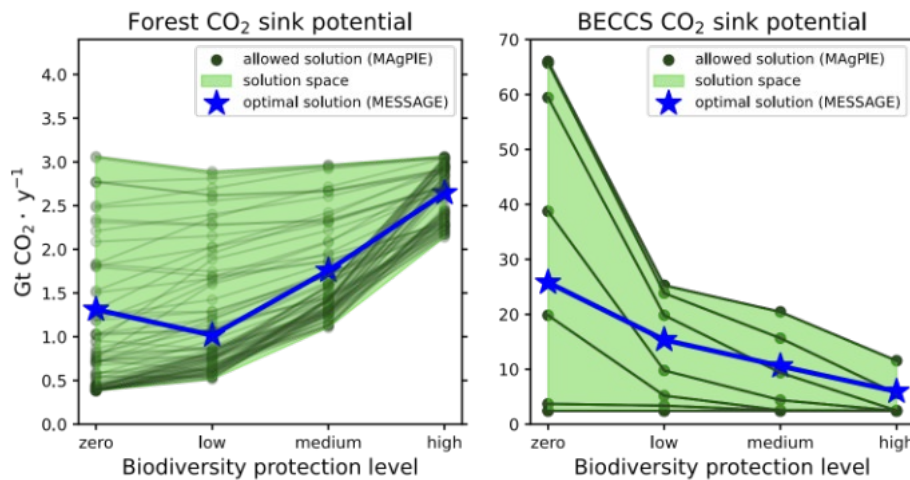


Figure 5. Effect of biodiversity protection on the mitigation potential of land CO₂ sinks by 2100 (left-hand panel), and the effect on the mitigation potential of BECCS (right-hand panel). The x-axis shows results across four levels of biodiversity conservation ambitions (see Table 1: Baseline, low, medium, and high). The uncertainty ranges for the CO₂ sink from forests (green area and black lines) represent 84 combinations of carbon and bioenergy prices that are used for defining the land-use emulator space. Each biodiversity policy scenario is created by systematically combining any one of seven different bioenergy price (and therefore demand) categories with any one of twelve greenhouse gas price categories, thus creating 84 different scenario combinations. Each of these scenarios represents a possible future evolution of the land system, and each of them has a corresponding value for the amount of CO₂ absorbed by forests in the year 2100 (Y-axis). This quantity is represented by the green dark dots, one for each of the 84 combinations. The dark green lines connect the dots to preserve visual continuity. The light green shaded region spans the range of possible forest sink potentials obtained from our simulations. All of the above are from simulations conducted in the land-use model MAGPIE. The dark blue line shows the cost-optimal forest sink potential in 2100, also considering the interactions between the land and energy systems, obtained by implementing the MAGPIE matrices through the energy-systems model MESSAGEix. When solved in MESSAGEix, we impose the additional constraint of a full-century cumulative CO₂ budget of 1000 Gt CO₂. Again, there are four such cost-optimal solutions, corresponding to the four different biodiversity conservation stringency levels. Right: the same concept, but this time showing the possible annual global CO₂ uptake potential of BECCS in the year 2100. Please note the different Y-axis – the hypothetically permitted BECCS potentials are an order of magnitude larger than the forest sink potentials, especially when biodiversity conservation policy is lax or non-existent.

3.3.4 Temperature implications of biodiversity protection policy

To investigate the effects of biodiversity conservation policies on global warming projections, the MESSAGEix model outputs are further analyzed in the simple climate model MAGICC to

obtain temperature trajectories. These show that stringent biodiversity conservation policy tends to minimize overshoot of the Paris Agreement warming limits. This is indicated in Figure 6, which compares two scenarios that are both constrained by a full-century carbon budget of 1000 Gt CO₂ but differ in their biodiversity conservation stringency. While both scenarios overshoot the stricter Paris limit of 1.5°C, the one without biodiversity protection has a median peak ΔT of around 2°C, whereas the scenario with biodiversity policy has a median peak ΔT of around 1.8°C. In addition, the scenario with biodiversity protection has about 75% chance to stay below the 2°C mark. This finding suggests that by limiting late-century CDR options, biodiversity conservation also creates more desirable outcomes for climate mitigation, and that these two objectives support each other.

In line with the results for the 1000 Gt budgets, stricter biodiversity conservation policies in general tend to result in lower peak temperatures for the same carbon budget, and thus a reduced overshoot of the Paris warming limits, as shown in Figure 7.A. While scenarios without additional biodiversity conservation policies can achieve a similar minimal ΔT overshoot as scenarios with such policies, they require much stricter carbon budget constraints to do so.

3.3.5 Long-term temperature implications

In addition to overshoot, the long-term temperature increase needs to be considered. For this study, it is defined as the global mean temperature reached at the end of this century, which is around the end of the time horizon of the models used. Figure 7 highlights both peak and long-term temperature for various combinations of carbon budgets and biodiversity conservation policies.

While more ambitious biodiversity conservation policies support a limited temperature overshoot, they also make lower full-century budgets unachievable. This is because many of these lower budgets require extensive CDR in the latter half of the century to balance out emissions, but biodiversity conservation policies limit the potential of CDR through BECCS. As a result, long-term warming levels of less than 1.2 °C are rendered unattainable by highly ambitious biodiversity conservation policies. However, keeping the long-term temperature below 1.5 °C, consistent with the Paris Agreement, remains feasible. Thus, even the strictest biodiversity conservation policy is compatible with the Paris goals.

One limitation of our analysis is that we have considered only one possible CDR technology, namely BECCS. In practice, we expect that a wider portfolio of CDR options will be available for implementation when the prerequisite technologies are suitably developed and scaled. Thus, it may be possible to attain lower overshoot (or avoid it entirely) while at the same time supporting keeping the full-century cumulative carbon budget low, provided BECCS is supported by other methods of CDR such as DACCS, enhanced rock weathering, and biochar. Such an analysis should be undertaken in a future study.

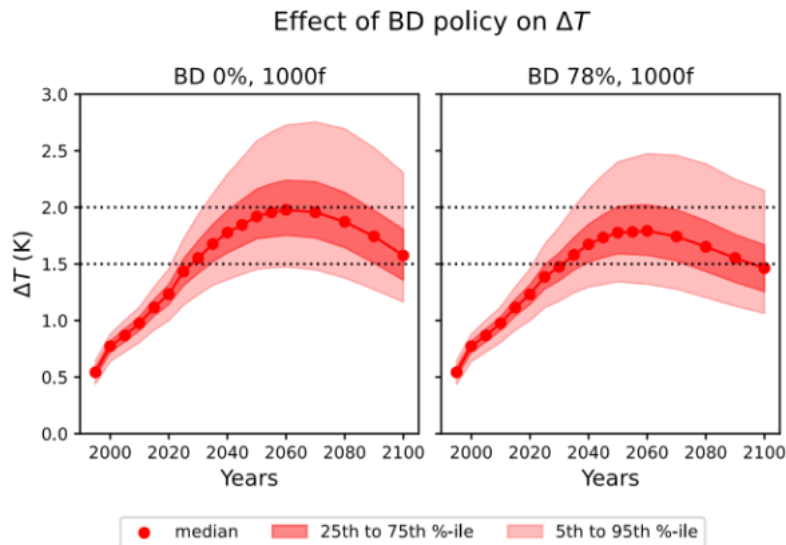


Figure 6. Effect of biodiversity policy on GMST increase. GMST profile for a full-century CO₂ budget of 1,000 Gt CO₂ in a scenario without biodiversity policy (left) and with the highest biodiversity protection (right). The darkest red dots show the median ΔT , the medium-dark shaded regions show the 25th to 75th percentiles, while the lightest shaded region represents the 5th to 95th percentiles. Abbreviations and variables: GMST - global mean surface temperature; BD - biodiversity policy strength (in units of BII constraint); 1000f - a full-century CO₂ budget of 1000 Gt; ΔT - the increase in GMST compared to pre-industrial levels.

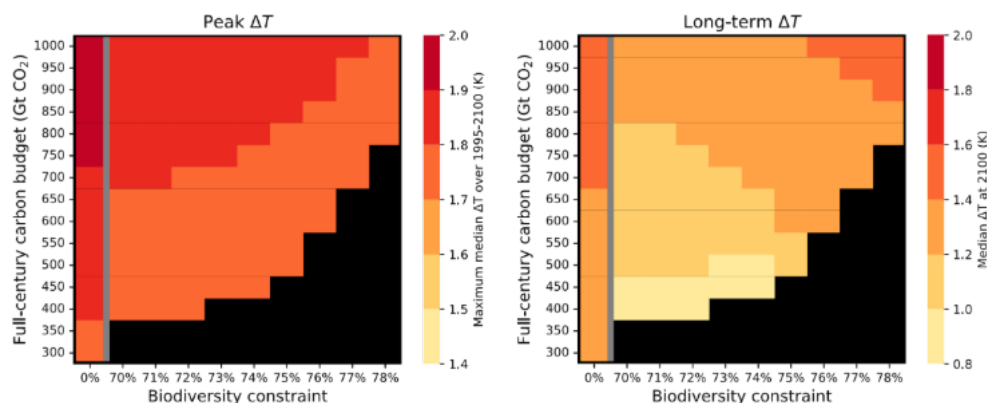


Figure 7. Effect of biodiversity protection and carbon budget on ΔT . Heatmap of peak ΔT (left) and EOC ΔT (right) for various combinations of biodiversity protection and full-century carbon budget scenarios. The black cells represent infeasible scenarios, i.e. combinations of biodiversity policy and full-century carbon budget for which the model fails to find any solution.

3.4 Discussion

In this study we have made a systematic assessment of the interactions of biodiversity conservation policy with land-based CDR methods such as afforestation and reforestation and BECCS. First, we assessed the effects of climate and biodiversity policy separately. Our results suggest that climate mitigation policy in the land sector does show co-benefits for biodiversity, but it alone is not sufficient to counteract biodiversity loss as it may result in shifting the loss

from biome to another. Conversely, biodiversity conservation policy has some beneficial effects for climate mitigation, such as the protection and expansion of natural carbon sinks, while also limiting the availability and cost efficiency of BECCS.

We further explored the effects of climate and biodiversity policy implemented together. The limited availability of bioenergy and associated CCS, which our model results projected to be an important source of renewable energy as well as terrestrial CDR, incentivizes the energy supply system to phase out fossil fuels earlier and invest in solar and wind technology. Emissions reduction also has to take place sooner since the negative emissions potential in the latter half of the century is reduced. The importance of the forest-based carbon sink increases, while the CDR from BECCS decreases. Biodiversity policy also reduces the duration and extent of overshoot.

Our results agree with previous studies suggesting that bioenergy cropland expansion poses a threat to biodiversity (Rockström et al. 2023, Hirata et al. 2024, Núñez-Regueiro et al. 2021, Van Vuuren et al. 2010, Immerzeel et al. 2014), with land-use change as the key driver of species loss. Further we re-confirm co-benefits of climate mitigation for biodiversity conservation, especially through forest and other natural land protection and expansion (Harvey et al. 2010, Pörtner et al. 2023). We build on this work with a systematic global assessment of bioenergy potentials under biodiversity conservation policies of varying degrees of stringency and the effects of these policies and potentials on the land-energy nexus and climate system. This analysis utilizes a set of bioenergy and emissions price scenarios which span a large range, modelled in the newly implemented MESSAGEix-MAGPIE integrated assessment framework. Utilizing this framework, we re-confirm a global limit for bioenergy production of around 100 EJ/yr in 2100 (Creutzig et al. 2015) under ambitious biodiversity policies, which is lower than other previous estimates (Van Vuuren et al. 2010). We further highlight co-benefits and trade-offs between biodiversity conservation and climate mitigation, such as the doubling of the forest carbon sink, and the palliative effect of biodiversity conservation on temperature overshoot driven by the more rapid and aggressive decarbonization needed to support these policies.

One obvious limitation of this study is that we do not consider any CDR technologies beyond BECCS. A full portfolio of CDR options would not depend so heavily on BECCS, and since BECCS has one of the highest land footprints of all commonly considered options, a more diverse portfolio would probably have a lower land footprint enabling even more ambitious combinations of biodiversity conservation and climate mitigation. Another limitation concerns the use of BII as a biodiversity indicator. Various indicators for ecosystem health exist (Burgess et al. 2024), and each of these captures some different aspect of it. BII is a relative metric that compares the species abundance of a given spatial location to the counterfactual situation without any human impact. As an indicator, BII is relatively straightforward for human understanding as well as numerical computation. However, BII would not respond to situations where the species composition, but not the abundance, were to change. One way to extend

the current analysis would be to use area-based metrics such as the Area of Habitat to complement the BII measurement. Another important conceptual limitation of our study is that we do not consider the impacts of climate change on biodiversity directly. Therefore, it is entirely possible our analysis underestimates the recovery of biodiversity because of climate change mitigation measures.

3.5 Conclusion

The next few years to decades will be crucial in how human society collectively responds to the climate and biodiversity crises. Our analysis suggests that despite the effectiveness of CDR technologies, there is no substitute to rapid decarbonization in the energy sector worldwide. Climate policies such as a carbon price are expected to incentivize afforestation and reforestation, which generally benefits terrestrial biodiversity. Biodiversity conservation policy in turn also benefits climate through protection and restoration of natural land. However, it limits the conversion of natural land to cropland for BECCS. Since the possibility of extensive CDR through BECCS in the latter part of the century is reduced, it becomes more important to mitigate emissions in the present and limit the duration and extent of overshoot beyond the limits set in the Paris Agreement.

International action on climate mitigation and biodiversity conservation is vitally important for the well-being of our planet and the biosphere. It is still very possible to avert the worst of both crises, but systematic measures must be taken as soon as possible. Other than reducing – and eventually eliminating – our dependence on fossil fuels, we need the means to remove carbon from the atmosphere, but this must not come at the cost of further biodiversity loss. Fortunately, our research shows that it is entirely possible to mitigate climate change while stopping the alarming loss of biodiversity. It will require a combination of bold actions such as rapid and aggressive decarbonization, investment into renewables such as solar and wind energy, restoration and legal protection of natural lands such as forests and grasslands, and support from still nascent but rapidly developing and scaling CDR technologies such as BECCS, and possibly others. Such measures will ensure that the world has a healthy natural carbon sink, long-term global warming stays within the Paris limits, and biodiversity loss is kept in check.

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3.8 Associated code development

MAGPIE emulator in MESSAGEix: https://github.com/iiasa/message_ix/tree/magpie_LU (this repo contains GAMS changes made to MESSAGEix to enable the MAGPIE linkage)

MAGPIE code changes: <https://github.com/magpiemodel/magpie/pull/639> (Enables bioenergy price incentives for 1st and 2nd generation biomass in MAGPIE)

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4 Mean Species Abundance emulator

PBL has developed a simplified tool for estimating biodiversity impacts (Ambrósio and Schuch, 2024, with [link to the model code](#); Ambrosio et al., 2024). This model emulates the mean species abundance (MSA) calculations of the GLOBIO model (Schipper et al., 2020). The GLOBIO biodiversity model is also developed by PBL and is designed to inform and support policy-makers by quantifying global human impacts on biodiversity and ecosystems. The model is tightly connected to PBL's IMAGE model: an integrated assessment model that simulates the global environmental consequences of human activities. The reasons behind the development of the emulator are to have an 1) easy to use / less data-intensive and 2) fast version of the original model that can be 3) directly coupled to the IMAGE-land model and other IAMs (as it uses common IAM output).

The MSA is a metric indicative of local terrestrial biodiversity intactness. It represents the average abundance of endemic species, relative to a no-impact reference case (see Figure 1 as an illustration). In both GLOBIO and in the developed emulator, abundance is affected by three key pressures: Climate change (CC), atmospheric nitrogen deposition and land use. GLOBIO also includes roads and hunting as pressures, which are not represented in the emulator.

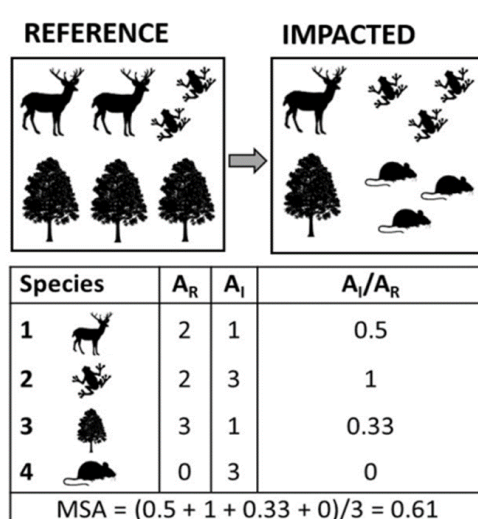


Figure 1 Illustration of the MSA concept

Unlike the original GLOBIO model, which calculates MSA based on vertebrates and plants, the emulator only uses plants for the indicator. The representation of the MSA of vertebrates in the emulator would be limited, as no information on species disturbance and fragmentation, as well as on hunting is available. Figure 2 shows how for plants, the emulator (IMAGE in the figure) closely resembles the outcomes from GLOBIO, while for vertebrates, the projections are not sufficient due to the lacking data.

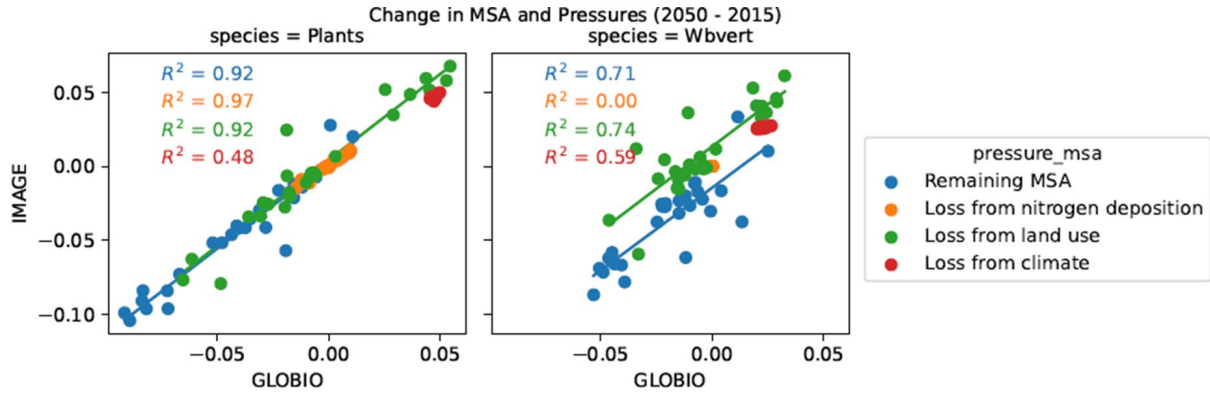


Figure 2 Change in MSA under various pressures in GLOBIO and in the emulator (i.e. IMAGE on the y-axis).

In the emulator, calculations are performed at the grid level, and the resulting MSA values are averaged at the region level. The CC pressure makes use of the global mean temperature values of the MAGICC6.3 climate model linked to IMAGE. Atmospheric nitrogen deposition is calculated based on NO_x and NH₃ emissions from agriculture, energy, and industry on nonagricultural and non-urban soils at the grid level. Land use is based on the share of different land-cover types from IMAGE-Land at the grid level, reclassified into the eight land-use classes required as input to GLOBIO: cropland-intense use, cropland-minimal use, pasture-intense use, pasture-minimal use, plantation, secondary vegetation, urban and natural land.

The MSA is calculated as follows (Schipper et al 2020), description from Ambrosio et al. 2024):

$$MSA_i = \prod_{x=1}^{x=m} MSA_{x,i}$$

where MSA_i is the terrestrial plants' MSA in grid cell *i* (5 arc-minute resolution, compared to a 10 arc-seconds resolution in GLOBIO) and MSA_{*x,i*} is the MSA corresponding to pressure *x* (CC, nitrogen deposition and land use). This calculation assumes that atmospheric nitrogen deposition does not have an additional impact on urban areas, cropland, and pastures. Hence, nitrogen deposition impacts are only included in grid cells with semi-natural and natural vegetation (Schipper et al 2020). The contribution of each pressure to the MSA loss within a specified grid cell is computed relative to the cumulative losses across all pressures. Subsequently, it is rescaled based on the total loss within the grid cell. Mathematically, this relationship is (Schipper et al 2020):

$$P_{x,i} = \left(1 - \frac{MSA_{x,i}}{\sum_{x=1}^m (1 - MSA_{x,i})} \right) \times (1 - MSA_i)$$

where $P_{x,i}$ is the contribution of pressure x to the loss in the MSA in grid cell i . Rescaling ensures that the sum of the MSA pressure-specific losses equals the grid cell's total MSA loss. MSA losses per cell and pressure contributions are then aggregated across grid cells 1 to n in any larger region, using an area-weighted mean value. To evaluate the differences in biodiversity impacts at the global and regional levels, we averaged the MSA and the contribution of the pressures at the global level and the level of two bioclimatic zones : (i) tropical forest (TF), accounting for TF and tropical woodlands; (ii) grassland and tropical non-forest (Grass & TnF), accounting for scrubland and savanna in the tropical region and grassland and steppe present beyond the tropical region.

Ambrósio et al. (2024) demonstrated the use of the emulator. Their study identifies effective strategies for recovering biodiversity to 2020 levels while mitigating CC, using scenarios from the IMAGE database. Results show that combining protected areas with stringent climate mitigation policies yields the most positive outcomes for biodiversity and climate. Supply and demand measures, such as reducing food waste and meat consumption, further improve outcomes.

The tool provides an easy to use, fast and relatively model-accurate representation of the MSA for plants, a common biodiversity indicator. With a coarser resolution than the model it emulates (GLOBIO), it is particularly useful for IAM studies aimed at a general understanding of sustainability linkages, rather than for in-depth studies.

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5 Advancing the assessment of land use impacts on ecosystems in Environmental Life Cycle Assessment (LCA) - Implementation in regionalized life cycle impact assessment and link to IAM

5.1. Objective

Land use and land use change are among the most important drivers of terrestrial biodiversity loss (Scherer et al., 2023). Assessing these pressures is therefore essential to guide strategies to halt and reverse biodiversity decline. Yet, the degradation of natural habitats and associated biodiversity loss frequently occur far from the point of consumption because of globalized trade and increasingly complex supply chains (Chaudhary et al., 2015).

Environmental Life Cycle Assessment (LCA) provides a comprehensive framework to quantify environmental impacts along global supply chains and to inform decisions that minimize trade-offs across environmental categories or regions (Mutel et al., 2019). While traditionally focused on greenhouse gas emissions, recent advances have extended LCA to account for impacts on biodiversity. However, the regional nature of land-use pressures on ecosystems requires spatially explicit approaches to capture the variability of impacts across regions and biomes (Chaudhary et al., 2015).

The life-cycle community has continuously developed regionalized LCIA methods, among them IMPACT World+ (Bulle et al., 2019), to provide globally consistent, spatially resolved characterization factors at the country and biome levels for assessing the impacts of land use and transformation on biodiversity. Despite these advances, integrating regionalized methods into full LCA models remained computationally demanding, as it typically requires GIS-based spatial data or extensive flow duplication. Consequently, a gap persists between methodological development and practical implementation, limiting the consolidation of regionalized impact assessment in mainstream LCA practice.

To address this challenge, we developed *edges*, a computational framework that extends life cycle impact assessment to the exchange level. Each interaction in the life-cycle network, whether involving the environment or the technosphere, can receive its own characterization factor (Sacchi et al., 2025). This exchange-resolved approach enables the application of regionalized impact assessment methods such as IMPACT World+ or LC-Impact without requiring explicit GIS integration. By allowing characterization factors to depend on both the emitting and receiving activities and their respective locations, *edges* captures the geographic and relational structure of life-cycle networks. Building on this framework, we can quantify

impacts and pressures on ecosystems associated with the land footprint of energy technologies and infrastructure deployment supply chains, enabling a spatially differentiated assessment of impacts on biodiversity.

5.2. Methodology

5.2.1. Edges

We developed the *edges* Python library (Sacchi et al., 2025), which enables life cycle impact assessment at the level of individual exchanges between processes rather than aggregated node or flow levels. In this exchange-resolved formulation, characterization factors (CFs) are applied directly to each exchange, preserving the contextual information of both the emitting and receiving processes, including their location, classification, and interconnections within the technosphere and biosphere.

The *edges* framework implements several key capabilities for regionalized LCIA:

- *Exchange matching*: CFs are matched to exchanges using criteria including node name, matrix ('biosphere' or 'technosphere'), and metadata (location, classification), applying to both supplying and consuming nodes.
- *Regional mapping*: Exchanges are mapped to CF regions through (i) direct matching, (ii) association (e.g., 'Canada' for 'Québec' when Quebec-specific CFs are unavailable), (iii) dynamic resolution for composite regions (e.g., Rest of World), and (iv) fallbacks to global averages.
- *Composite region handling*: CFs for inventory regions like 'RER' (Europe) or 'RoW' (Rest of World) are calculated dynamically as weighted averages of constituent areas. The weighting keys vary by method and can include resource consumption, population, GDP, area, or other relevant metrics. For 'RoW' regions specifically, the CF is computed based on all non-overlapping regions, excluding those for which region-specific inventories exist in the database.
- *Uncertainty representation*: Supports multiple distribution types (normal, lognormal, gamma, beta, triangular, uniform, discrete empirical) for Monte Carlo sampling and error propagation. For composite regions, *edges* uses nested distributions: at each Monte Carlo iteration, it first selects a constituent country with weighted probability, then samples a CF value from that country's distribution.

This exchange-resolved approach enables the application of regionalized impact assessment methods without requiring explicit GIS or flow duplication. It occupies an essential methodological space between conventional node-based LCIA and fully spatially explicit, GIS-integrated models, providing a robust yet accessible solution for regionalized and relational life cycle assessments.

5.2.2. IMPACT World+

Within this framework, we implemented the biodiversity-related impact categories of the

IMPACT World+ method (Bulle et al., 2019), which provides globally regionalized characterization factors for land occupation and land transformation. The method builds on the Countryside Species-Area Relationship (SAR) model (Chaudhary et al., 2015), which accounts for habitat heterogeneity and species-specific responses to land use impacts. Unlike the classic SAR (which assumes that no species survive on human-modified land), this model considers the affinity of different taxonomic groups to various land-use types. This recognizes that some species can survive in agricultural or managed landscapes.

While the IMPACT World+ methodology is designed to operate at multiple spatial resolutions, the implementation available in *edges* provides characterization factors aggregated at the country level. These country-level CFs represent weighted averages across the biomes and ecoregions within each country. The method covers five taxonomic groups (mammals, birds, reptiles, amphibians, and vascular plants) aggregated into overall biodiversity indicators across six land-use types: intensive forestry, extensive forestry, annual crops, permanent crops, pasture, and urban land.

Within *edges*, we have implemented four complementary IMPACT World+ indicators for biodiversity assessment:

1. **Land occupation, biodiversity (damage level):** quantifies the damage to biodiversity from ongoing land occupation, expressed in potentially disappeared fraction of species $\times$ area $\times$ time per $\text{m}^2 \cdot \text{yr}$ occupied;
2. **Land occupation, biodiversity (midpoint level):** provides a midpoint proxy for occupation impacts, expressed in m^2 arable land equivalent-yr per $\text{m}^2 \cdot \text{yr}$ occupied;
3. **Land transformation, biodiversity (damage level):** quantifies the damage from land transformation (i.e., land use change), accounting for both immediate species loss and the time required for ecosystem recovery, expressed in $\text{PDF} \cdot \text{m}^2 \cdot \text{yr}$ per m^2 transformed;
4. **Land transformation, biodiversity (midpoint level):** provides a midpoint proxy for transformation impacts, expressed in m^2 arable land equivalent per m^2 transformed.

The damage-level indicators directly quantify potential biodiversity loss. In contrast, the midpoint indicators serve as proxies when uncertainty in damage modelling is a concern or when comparability with other midpoint-based assessments is desired.

5.2.3. Enhanced countryside SAR with land use intensities and fragmentation (Scherer et al. 2023)

In addition to IMPACT World+, we have also integrated the biodiversity characterization factors developed by Scherer et al. (2023) in the context of the [UNEP Life Cycle Initiative's Global Guidance for Life Cycle Impact Assessment \(GLAM\) project](#), which advances the field through three key enhancements: finer spatial resolution, explicit consideration of land use intensities, and incorporation of habitat fragmentation effects.

Scherer et al. provide characterization factors at the ecoregion level (825 terrestrial ecoregions) for five distinct taxonomic groups: plants, amphibians, birds, mammals, and

reptiles. These taxonomic groups are also integrated in *edges* under an aggregated Eukaryota indicator. Aggregated country-level CFs are additionally provided.

While Chaudhary et al. (2015) distinguish six broad land use types, Scherer et al. refine this by distinguishing three land use intensity levels (minimal, light, intense) within each of five broad land types (cropland, pasture, plantations, managed forests, urban), creating 15 habitat combinations per ecoregion. This enhancement recognizes that, for example, lightly managed cropland has substantially different biodiversity impacts than intensively managed cropland with high fertilizer and pesticide inputs.

Within *edges*, we have implemented two indicators provided by Scherrer et al. to address different land-use activities.

1. **Land occupation, biodiversity (damage level):** For land *occupation* (ongoing use of land), the CFs have units of PDF/m² (Potentially Disappeared Fraction of species per square meter). When multiplied by inventory flows that report both area and duration of occupation (m²·yr), the result is an impact in PDF·yr.
2. **Land transformation, biodiversity (damage level):** For land *transformation* (conversion from one land use type to another), the CFs have units of PDF·yr/m² and are applied directly to the transformed area (m²), also yielding impacts in PDF·yr. It includes the time needed for the ecosystem to regenerate and therefore has a time dimension. When land is converted (e.g., from forest to agricultural land), the CF accounts for the initial biodiversity loss and the time required for the system to recover naturally.

5.2.4. Uncertainty

Within *edges*, uncertainty is represented differently for the two methods, reflecting both their underlying data structures and the framework's approach to handling composite regions (e.g., "RER" for Europe, "RoW" for Rest of World).

For both IMPACT World+ and Scherer et al. (GLAM), composite regions are resolved dynamically. When an exchange refers to a composite region, *edges* computes its CF on the fly as a weighted average of all constituent countries or areas, using land area as the weighting key. For "Rest of World" regions specifically, *edges* calculates the CF from all remaining non-overlapping countries, excluding those already represented individually in the database.

In IMPACT World+, uncertainty arises mainly from this dynamic regional resolution. Since the method operates at the country level, *edges* represents uncertainty in composite regions through nested probability distributions. During each Monte Carlo iteration, a constituent country is randomly selected with a probability proportional to its land area, and its corresponding country-level CF is applied. Because the implementation relies on country-aggregated CFs rather than ecoregion-level data, some spatial detail is necessarily lost compared to the original IMPACT World+ model.

In contrast, the Scherer et al. implementation captures within-country spatial heterogeneity by directly using CFs defined at the ecoregion level. Each country is associated with multiple ecoregion CFs, weighted by the ecoregion's share of the country's total area. These area fractions were precomputed for all country–ecoregion combinations. When a flow is mapped to a country, the uncertainty distribution for its CF includes all ecoregions within that country, each sampled according to its area-weighted probability.

For example, if a land occupation flow occurs in Brazil, the uncertainty distribution draws from all CFs corresponding to Brazil's ecoregions. Each ecoregion contributes according to its share of Brazil's total land area, and one is randomly selected at each Monte Carlo iteration. This approach captures the variability in which specific ecoregions might be affected, preserving the within-country biodiversity variation across biomes and landscapes. This is particularly fitting in the common case where the precise location of a process in a country is unknown.

As a result, the Scherer et al. method achieves substantially finer spatial resolution in uncertainty representation than IMPACT World+, since it distinguishes 825 terrestrial ecoregions rather than approximately 200 countries. Both approaches leverage *edges'* capability to represent uncertainty through flexible probability distributions without requiring GIS integration or explicit spatial modeling.

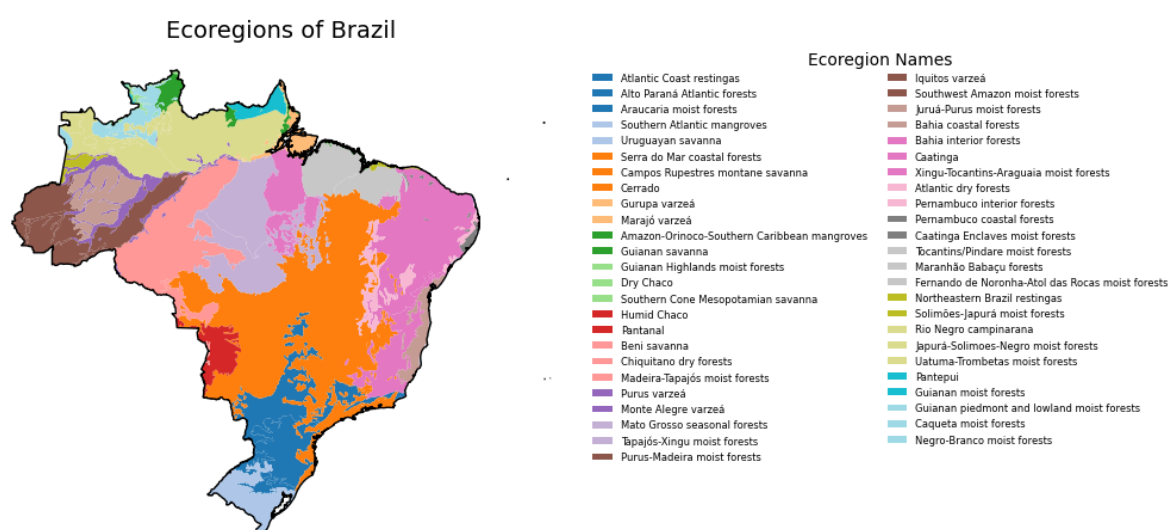


Figure 1. Spatial distribution of terrestrial ecoregions within Brazil. The map illustrates the 49 distinct ecoregions that occur within Brazil's borders. In the implementation of Scherer et al. (2023) characterization factors within *edges*, country-level uncertainty distributions are constructed as discrete empirical distributions weighted by the percentage of country area occupied by each ecoregion. This spatial heterogeneity enables Monte Carlo sampling to capture within-country biodiversity variation across different biomes and landscapes. When a land use inventory flow is attributed to Brazil, one of these ecoregions is randomly selected

during uncertainty propagation according to its area-weighted probability, reflecting the variability in which specific ecoregion within the country might be affected by the land use activity.

5.3. Repositories and Usage

Both IMPACT World+ and Scherer et al. (2023) biodiversity methods are implemented within the open-source *edges* library, maintained by PSI and available at: <https://github.com/Laboratory-for-Energy-Systems-Analysis/edges>

All characterization factors are distributed as JSON-based CF definitions that can be directly loaded into *edges*. To illustrate the workflow, we applied the biodiversity indicators of both approaches to the production of one kilogram of hydrogen by proton exchange membrane (PEM) electrolysis using electricity from offshore wind in France. The case study demonstrates how the exchange-resolved implementation enables spatially differentiated biodiversity assessment along the entire hydrogen supply chain, including material supply – from mineral mining and refining to component manufacture – needed for the infrastructure of the product system (electrolyzer, wind turbine, electricity transmission lines, etc.), electricity supply for the operation of the electrolyzer, and waste treatment.

Figure 2 showcases the IMPACT World+ biodiversity assessment. It reveals that life-cycle biodiversity impacts from hydrogen production are highly concentrated geographically. For both land occupation and transformation, South Africa dominates the impact profile, accounting for the majority of impacts across all three panels. This concentration stems primarily from iridium mining activities in platinum group metal mines, which are essential for the electrolyzer's catalyst layer, as well as hard coal mining operations. Additional contributions come from other mining activities (including the treatment of tailings and the processing of various mineral resources) and from forestry operations that supply materials throughout the supply chain.

The error bars, representing spatial variability in characterization factors, are notably absent for country-specific assessments but appear for "Rest-of-World" (RoW) and global (GLO) regions. As explained in Section 5.2.4, this pattern reflects the composite nature of these regions: whereas country-specific exchanges are matched to specific characterization factors with well-defined spatial boundaries, RoW and GLO exchanges represent weighted aggregations across multiple countries, each with distinct characterization factors. The Monte Carlo analysis samples from these regional distributions, producing the observed uncertainty ranges that capture spatial heterogeneity within these composite regions.

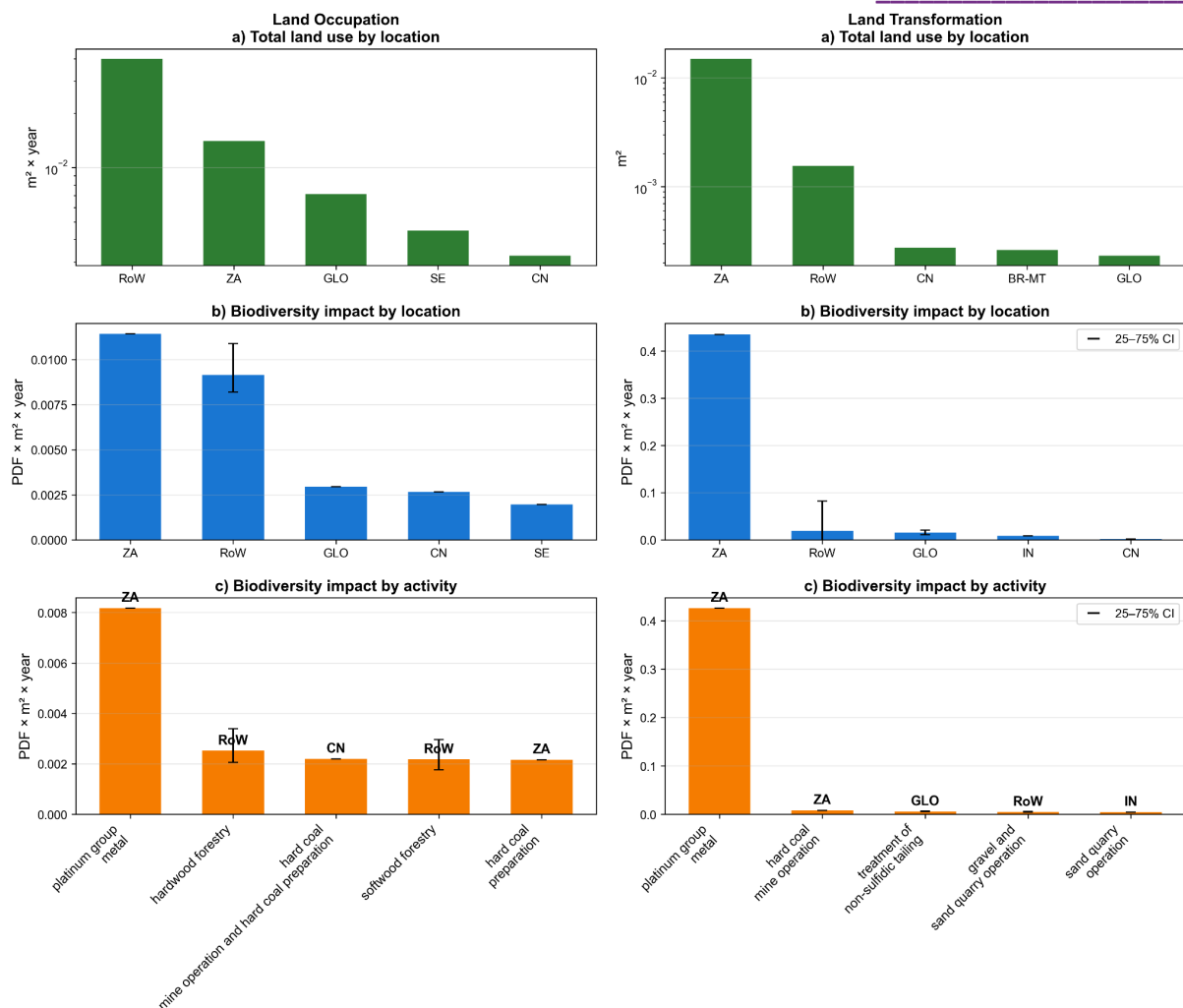


Figure 2. Land occupation and land transformation impacts on terrestrial biodiversity for producing one kilogram of hydrogen through water electrolysis using offshore wind power in France, assessed using IMPACT World+. Values represent mean impacts across 10,000 Monte Carlo iterations, with error bars showing the 25th to 75th percentile range. Note that only the uncertainty associated with the spatial resolution of CFs is considered, not that stemming from inventories. Panel (a) shows the top five countries where land occupation/transformation occurs; panel (b) displays the top five countries experiencing the greatest biodiversity impacts; and panel (c) identifies the top five activities contributing most to biodiversity impacts within the hydrogen production supply chain. Country codes above bars in panel (c) indicate where each activity occurs (CN = China, IN = India, RoW = Rest-of-World, SE = Sweden, ZA = South Africa). Both occupation and transformation impacts are expressed in PDF x m² x year.

Figure 3 showcases the implementation of Scherer et al.'s biodiversity assessment. This species-specific assessment provides additional taxonomic resolution while revealing similar geographic patterns. Land use totals in panel (a) differ slightly from Figure 2 because the

Scherer et al. implementation includes only land occupation and transformation flows that could be matched to the method's land use classification system, following the matching approach described in (Scherer et al., 2021). Unmatched flows represent land uses that do not correspond to any of the five broad categories (cropland, pasture, plantations, managed forests, and urban land) nor to any of the three intensity levels (minimal, light, and intense) defined in the method.

Consistent with IMPACT World+ results, South Africa is the main contributor to biodiversity impacts, again driven by iridium mining. Panel (b) shows total impacts disaggregated by taxonomic group. Panels (c) and (d) show that mining activities, along with hardwood and softwood forestry operations, are the main contributors to impacts on biodiversity in the hydrogen supply chain. Figure 3 shows wide uncertainty ranges, which primarily reflect the spatial variability of CF across the numerous ecoregions aggregated within the RoW and GLO regions. The substantial share of impacts occurring in these broad regions suggests that the current geographic resolution ofecoinvent may be too coarse to capture the spatial detail required by biodiversity impact assessment methods. This limitation is especially pronounced for hydrogen production, where most biodiversity-related impacts stem from mining and forestry activities — sectors whose ecological consequences depend strongly on local environmental conditions.



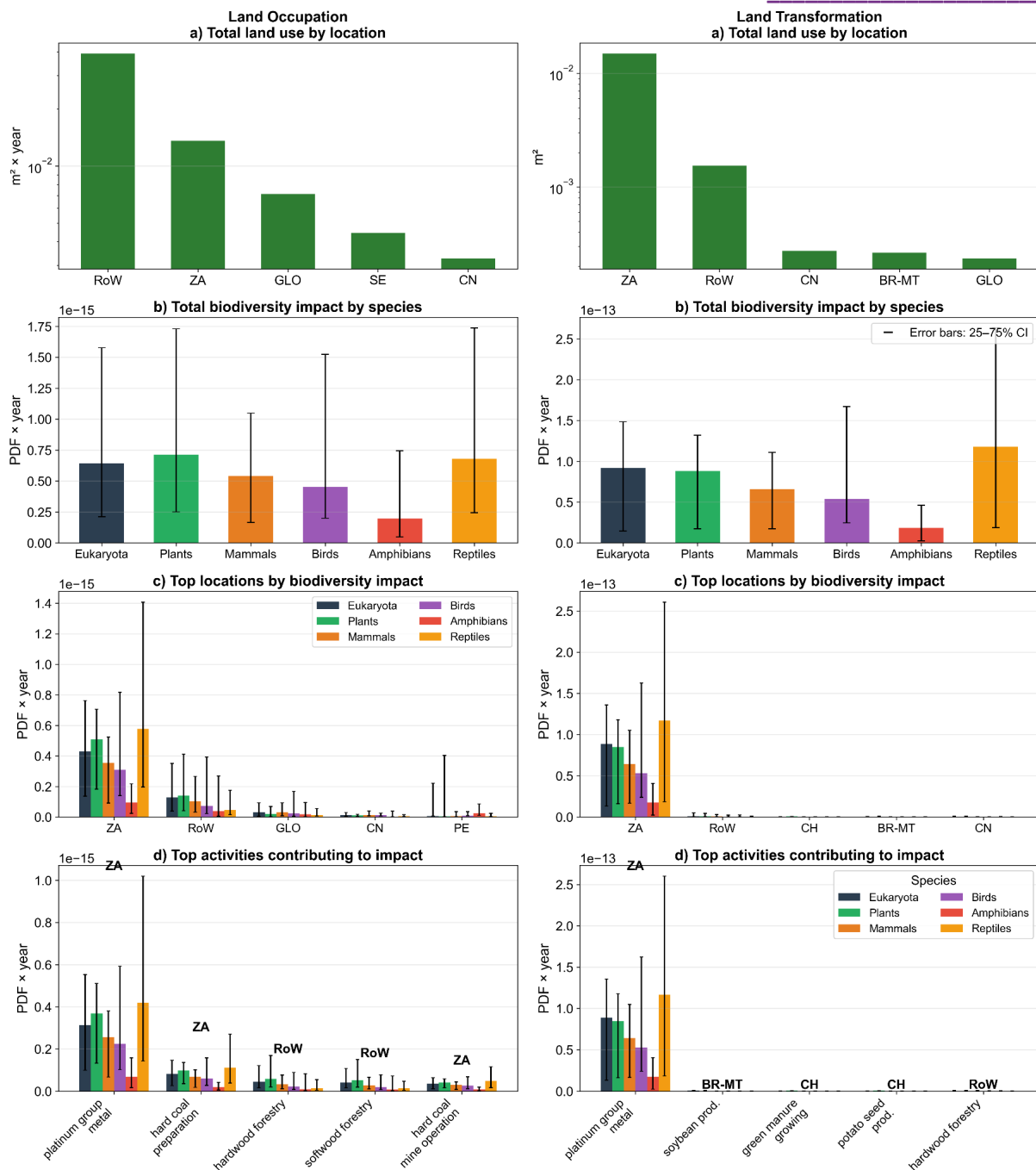


Figure 3. Land occupation and land transformation impacts on terrestrial biodiversity for producing one kilogram of hydrogen through water electrolysis using offshore wind power in France, assessed using the Scherer et al. (2023) method. Values represent mean impacts across 10,000 Monte Carlo iterations, with error bars showing the 25th to 75th percentile range. Panel (a) shows the top five countries where land occupation/transformation occurs; panel (b) displays total biodiversity impacts disaggregated by taxonomic group (eukaryota represents impacts assessed at the aggregate taxonomic level across all species, while

individual groups show impacts on plants, mammals, birds, amphibians, and reptiles); panel (c) shows the top five countries experiencing the greatest biodiversity impacts with species-level detail; and panel (d) identifies the top five activities contributing most to biodiversity impacts, with species-specific contributions indicated by color. Country codes above bars in panel (d) indicate where each activity occurs (BR-MT = Brazil- Mato Grosso, CA-QC = Québec, CH = Switzerland, CN = China, PE = Peru, RoW = Rest-of-World, ZA = South Africa,). All impacts are expressed in PDF × year.

5.4. Outlook

The case study demonstrates the capability of the exchange-resolved approach to track biodiversity impacts along the entire supply chain, far from the place of consumption. The hydrogen produced in France shows its primary biodiversity impacts occurring in South African platinum mines, a connection that would remain obscured without spatially explicit impact assessment. This transparency enables identification of both the activities causing impacts and the regions experiencing biodiversity loss, providing actionable information for supply chain interventions and sourcing decisions.

The results also highlight opportunities to improve the spatial resolution of biodiversity impact assessment in life cycle studies. The case study reveals that hydrogen production derives most of its biodiversity impacts from forestry and mining activities, sectors where site-specific ecological conditions can vary substantially. Enhanced geographic resolution for these extractive and forestry activities would reduce uncertainty in impact assessments. Developing country- and subnational-specific inventory data for mining operations and forestry practices, particularly in biodiversity-rich regions, would enable more precise characterization of impacts. Where feasible, linking specific mining sites, forestry concessions, and industrial facilities to their corresponding terrestrial ecoregions would allow direct application of spatially differentiated characterization factors without relying on composite regional averages.

5.5. Conclusion

By resolving characterization factors at the level of exchanges, *edges* enables context-aware life cycle impact assessment without relying on full GIS integration. The framework supports regionalized, relational, and scenario-based modeling while maintaining transparent, extendable logic through JSON-based and symbolic characterization factor definitions. Beyond established methods such as IMPACT World+ and Scherer et al. (2023), this structure also provides a flexible basis for integrating new sources of information, including satellite-derived indicators of land disturbance or habitat loss. Such data can be translated into exchange-specific characterization factors, for example, for mining or infrastructure activities, thereby expanding the potential of *edges* to represent spatial and temporal patterns of biodiversity pressure in a globally consistent way.

The case study on hydrogen production demonstrates how this approach enables tracking of

biodiversity impacts across complex supply chains, revealing how production in one region may drive biodiversity impacts in another, thereby providing essential insights for informed decision-making in sustainable technology development.

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6 Modelling biodiversity feedback in the economy

6.1 Unequal Climate Impacts on Global Values of Natural Capital

Climate change represents one of the most significant challenges to global economic stability and environmental well-being, with far-reaching implications that extend beyond direct temperature and precipitation effects. While substantial research has examined the immediate impacts of climate change on sectors such as agriculture, energy, and infrastructure, the economic consequences of climate-driven changes to terrestrial ecosystems and their associated benefits remain incompletely understood. This knowledge gap is particularly critical given that ecosystems generate both market goods (such as timber) and non-market benefits (such as recreation, water regulation, and cultural services) that are essential for human welfare.

This chapter, based on Bastien-Olvera et al. (2024), addresses this critical gap by providing novel comprehensive global assessment of how climate change will affect the economic value of natural capital across countries and regions. Published in *Nature*, this research represents a significant advancement in understanding the distributional impacts of climate-induced ecosystem changes on human well-being, with important implications for climate policy and international cooperation.

Natural capital, defined as the stock of natural resources and ecosystem services that provide value to humanity, constitutes a substantial portion of national wealth, particularly in lower-income countries. The World Bank estimates that natural capital accounts for up to 47% of total wealth in low-income countries compared to only 3% in high-income countries (World Bank, 2021). This disparity suggests that climate-induced changes to natural capital may have profoundly unequal distributional consequences, potentially exacerbating existing global inequalities.

6.1.1 Methods

The research employs an innovative methodological framework that combines multiple modeling approaches to assess climate impacts on natural capital. We integrate dynamic global vegetation models (DGVMs) with economic valuation techniques and a regionally explicit integrated assessment model to project how climate-driven changes in terrestrial vegetation will affect both market and non-market ecosystem benefits globally.

The methodology consists of three sequential phases. First, we develop country-specific estimates of natural capital values per hectare for different biomes using the Values of Ecosystem Goods and Services (VEGS) database combined with World Bank natural capital accounts. Second, we project future changes in natural capital based on climate-driven biome shifts as modeled by three DGVMs (LPJ-GUESS, ORCHIDEE-DGVM, and CARAIB). Third, we incorporate these projections into an extended version of the RICE50+ integrated assessment

model (Gazzotti et al, 2021), to estimate economic impacts on gross domestic product (GDP) and non-market benefits.

6.1.1.1 Economic Valuation

We distinguish between two types of natural capital based on World Bank accounting practices. Market natural capital (mN) represents the projected value from timber revenues, while non-market natural capital (nN) encompasses biome-related recreational services, water resources, non-timber forest products, and the inherent value of protected areas. To distribute country-level natural capital values across different biomes, we employ random forest algorithms trained on subsets of the VEGS database. This approach allows us to estimate the relative contribution of each biome to total natural capital values while accounting for country-specific characteristics such as GDP per capita and biome coverage patterns.

6.1.1.2 Dynamic Global Vegetation Models

We use outputs from three process-based DGVMs that simulate the establishment, growth, disturbance, competition, and mortality of different vegetation types under changing climate conditions. These models provide projections of biome distributions under different warming scenarios, incorporating the effects of changing atmospheric CO₂ concentrations, temperature, and water availability on ecosystem structure and function. The DGVMs operate under the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) 2b Protocol, using fixed 2005 land-use conditions to isolate the effects of climate change on natural vegetation from direct anthropogenic land-use changes. This approach enables us to focus specifically on climate-driven ecosystem shifts while controlling for other drivers of ecosystem change.

6.1.1.3 Integration with RICE50+ Model

The study extends the open-source RICE50+ integrated assessment model. The extended model, termed “Green RICE50+,” implements the Dasgupta Review’s framework for including natural capital in economic production functions (Dasgupta, 2021). In this framework, GDP is computed using a Cobb-Douglas production function that includes labor, manufactured capital, and market natural capital as factors of production, modulated by a global environmental good providing regulating and maintenance ecosystem services. This approach captures both the direct contribution of natural resources to economic output and the indirect role of ecosystem services in supporting productive activities.

6.1.2 Key Findings

The analysis reveals substantial and unequally distributed impacts of climate change on natural capital values globally. Under the Shared Socioeconomic Pathway SSP2-6.0 scenario, the study projects that the annual population-weighted mean global flow of non-market ecosystem benefits will be reduced by 9.2% by 2100 relative to a baseline scenario without climate change. The global population-weighted average change in GDP by 2100 is projected to be -1.3% of baseline GDP.

These impacts exhibit clear geographical patterns that reflect both biophysical changes in ecosystem structure and the economic importance of natural capital in different regions. Tropical regions are expected to experience net losses in vegetated area, while higher latitudes and Central Asia will likely see net gains in vegetation cover. However, the economic implications of these changes depend critically on the existing economic structure and natural capital dependence of affected regions.

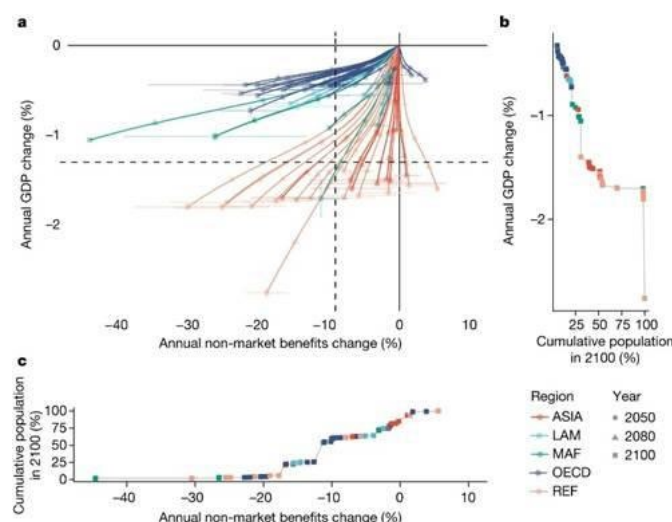


Figure 1 Market and non-market impacts under the SSP2-6.0 scenario.

Additionally, we find that approximately 90% of the economic damage from climate-driven changes to natural capital will be borne by the poorest 50% of countries and regions, while the wealthiest 10% experience only 2% of these losses. This distributional pattern reflects the greater reliance of lower-income countries on natural capital for economic production and well-being. In many developing countries, natural capital constitutes a larger fraction of total national wealth, making these economies more vulnerable to climate-induced ecosystem changes. The regressive nature of these impacts could further exacerbate global economic inequalities and complicate international climate negotiations.

The research identifies significant variations in climate impacts across different biome types and geographical regions. Boreal biomes are projected to expand into high-latitude areas previously characterized by sparse vegetation, while temperate biomes advance poleward. Grasslands show net losses in tropical and temperate areas, with corresponding expansion of forest biomes in some regions.

The study reveals that only five regions globally are expected to receive net benefits from ecosystem shifts under climate change. Changes in non-market benefits are not strongly correlated with country per-capita income or geographic region, indicating that climate impacts on ecosystem services may affect both lower-income and higher-income countries, though with different magnitudes and mechanisms.

When contextualized within broader estimates of climate economic impacts, the findings suggest that roughly one-tenth of total climate damages by 2100 could be linked to impacts on terrestrial ecosystem ranges. This represents a substantial previously unquantified

component of climate change costs, highlighting the importance of incorporating ecosystem impacts into comprehensive climate damage assessments.

The research also demonstrates the potential for positive feedbacks between ecosystem changes and economic productivity. Regions experiencing vegetation carbon content increases may see enhanced non-market benefits, while areas losing vegetation face compounding economic losses. These dynamics suggest that climate adaptation strategies focused on ecosystem conservation and restoration could provide significant economic returns.

Code and data to replicate the analysis, results and figures are publicly available at <https://doi.org/10.5281/zenodo.8303029>. Source data are provided with the paper at <https://www.nature.com/articles/s41586-023-06769-z#Sec18>.

6.1.3 Conclusions

The study represents a significant advancement in understanding and quantifying the economic impacts of climate change on natural capital globally. By demonstrating that climate-driven ecosystem changes will have substantial and unequally distributed economic consequences, we highlight an important but previously under-quantified dimension of climate impacts.

The methodological framework developed in this research provides a foundation for incorporating ecosystem considerations into integrated assessment models, directly supporting the objectives of Task 5.1. The approach demonstrates how to combine ecosystem modeling with economic valuation while maintaining the spatial and temporal scope necessary for global policy assessments.

The finding that ecosystem-related climate impacts are regressive has important implications for climate policy and international cooperation. The concentration of damages among lower-income countries and regions suggests that ecosystem considerations should be central to climate justice discussions and international climate finance mechanisms.

The research also demonstrates the importance of natural capital conservation and restoration as climate adaptation strategies. The economic benefits of maintaining ecosystem services under changing climate conditions provide strong justification for investments in ecosystem-based adaptation approaches. As the scientific understanding of ecosystem-climate-economy interactions continues to advance, the integration of these insights into policy frameworks will be essential for effective climate response strategies.

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6.2 Incorporating Biodiversity Impacts in Land Use Decision Models

This chapter presents our framework for incorporating biodiversity impacts into land use optimization models, addressing the critical need to integrate ecological considerations into land use decision-making processes. Our methodology directly supports an improved representation of biodiversity and its relation with land-use change in Integrated Assessment Models (IAMs) and it's based on (Azuero-Pedraza et al., 2024). Mathematical formulation and data for the case study can be found in the supplementary section of (Azuero-Pedraza et al., 2024).

6.2.1 Introduction

We developed a comprehensive framework addressing the need to integrate biodiversity considerations into land use change decision-making models. The simultaneous environmental crises of climate change and biodiversity loss require coordinated responses that consider both challenges simultaneously, taking advantage of synergies while addressing trade-offs. Land represents a critical intersection between economic and ecological systems, where decisions affect human communities through agriculture and forests while impacting ecosystems through habitat transformations.

Current approaches to assessing biodiversity impacts typically employ ex-post analysis, taking resulting land cover from optimization models and subsequently estimating biodiversity impacts. This approach fundamentally misses opportunities to reduce biodiversity impacts as part of the decision-making process. Our framework moves beyond this limitation by incorporating biodiversity considerations directly into the optimization process, enabling proactive biodiversity conservation within economic planning.

6.2.2 Biodiversity Measurement and Modeling Approach

The countryside species-area relationship (cSAR) (Pereira and Dally, 2006; Proença and Pereira, 2013; Pereira et al., 2014) serves as our ecological model for quantifying biodiversity impacts. This approach belongs to the family of Species-Area Relationship models derived from ecological studies and widely used in Life Cycle Impact Assessment (LCIA). The cSAR model assumes that when transforming natural habitat, some species may adapt to human-modified habitats, meaning not all affected species will be lost completely. This nuanced approach provides more realistic estimates of biodiversity impacts compared to standard species-area relationships.

Our biodiversity indicator $Slost_{g,l}^{cSAR}$, estimated with the cSAR model is based on species richness, specifically the number of regional species committed to extinction due to habitat loss (See). For taxonomic groups indexed by g , ecoregions indexed by l , and land use types indexed by i , the species loss calculation incorporates original habitat areas, species affinity values for different land use types, and species-area relationship slopes that describe habitat loss impact rates. This indicator represents a risk of extinction rather than instantaneous loss, reflecting biodiversity at the taxonomic level while acknowledging that regional extinctions do not necessarily imply global species loss. The indicator can only represent deterioration in biodiversity relative to pristine scenarios, as no new species can be created.

$$Slost_{g,l}^{cSAR} = Sorg_{g,l} \left[1 - \left(\frac{\sum_{i \in U} h_{g,i,l} A_{i,l}}{Aorg_l} \right)^z \right] \forall g \in G, l \in L$$

We established eight criteria for incorporating biodiversity measures into land use optimization models. These include: (1) mathematical relationships between drivers and indicators, (2) spatial explicitness, (3) data availability, (4) future projection capabilities, (5) taxonomic group representation, (6) nonlinear impact accounting, (7) previous applications for validation, and (8) scientific validation through peer review. The cSAR model satisfies all these criteria, providing adequate mathematical relationships to associate land use change variables with potential species loss while allowing spatially explicit assessment of nonlinear biodiversity impacts.

We acknowledge several important limitations of the cSAR model. It ignores potential species migration responses to habitat disturbances, particularly relevant for mobile species like birds. It operates at the species level without accounting for population effects that respond more rapidly to environmental changes. The model applies uniform affinity values within taxonomic groups, missing vulnerability differences among species, and assumes uniform species distribution throughout ecoregions. Additionally, uncertainties exist in input parameters, particularly species richness indicators affected by sampling efforts and undersampling issues.

6.2.3 Implementation Approaches for Optimization Models

We developed six distinct approaches for incorporating biodiversity impacts into optimization models, combining three mathematical representations with two implementation strategies. The three mathematical representations include characterization factors (CF), piecewise linear approximation (LaP), and direct nonlinear implementation (cSAR). The two implementation strategies involve constraint approaches and objective function approaches.

The characterization factor (CF) approach employs Life Cycle Impact Assessment methodology, assuming linear biodiversity impacts. Characterization factors estimate biodiversity impact per unit of land use transformation, measured as potential species loss per unit area transformed to specific land use types. These factors are derived from the cSAR model using average assessment approaches, providing computational efficiency through linearity while potentially underestimating impacts due to the linear assumption.

The piecewise linear approximation (LaP) method linearizes the cSAR function while maintaining nonlinear impact characteristics. This approach introduces breakpoints and weights to approximate the curved relationship between habitat availability and species loss. Implementation requires additional decision variables and constraints, increasing model complexity but preserving nonlinear relationships within linear programming frameworks. Our analysis shows this method provides good approximations while slightly overestimating impacts compared to the true nonlinear function.

Direct nonlinear implementation (cSAR) incorporates the cSAR function without modification, creating nonlinear programming problems. This approach maintains mathematical accuracy while potentially increasing computational complexity. The convex nature of the cSAR function ensures compatibility with convex optimization frameworks, supporting efficient solution procedures.

Constraint approaches define upper limits on acceptable biodiversity loss, treating biodiversity protection as a hard constraint within optimization. This method guarantees specific biodiversity protection levels while allowing optimization of other objectives within biodiversity bounds. Objective function approaches integrate biodiversity impacts directly into optimization targets, enabling explicit trade-offs between biodiversity protection and other goals such as cost minimization or production maximization.

6.2.4 Ethical Considerations and Aggregation Choices

We discuss the underlying ethical assumptions in biodiversity impact aggregation across taxa and spatial units. Different aggregation approaches embody distinct value judgments about species equivalence and spatial priorities. Global aggregation across taxa and ecoregions implies equal valuation of different species types and locations, allowing optimization models to trade mammal species loss in one region against plant species conservation in another region if economically advantageous.

Taxa-specific constraints prevent trading between different taxonomic groups while allowing spatial trading within groups. This approach recognizes biological distinctiveness between taxonomic categories while maintaining spatial flexibility. Combined taxa and spatial constraints eliminate all trading opportunities, ensuring protection for each taxonomic group within each ecoregion individually. While this approach provides maximum protection specificity, it reduces model flexibility and may create infeasibility issues.

Regional versus global species loss indicators present another ethical choice with practical implications. Regional indicators give equal weight to species loss across all ecoregions, encouraging biodiversity protection everywhere but potentially ignoring endemic species vulnerability. Global indicators prioritize areas with high endemism levels, focusing protection efforts on regions where local extinctions contribute most to global species loss while potentially neglecting less endemic regions.

The choice between constraint and objective function approaches represents a fundamental philosophical decision about biodiversity valuation. Constraint approaches guarantee minimum biodiversity protection levels, treating biodiversity as a non-negotiable requirement within economic planning. Objective function approaches enable explicit trading between

biodiversity and other values, requiring quantitative biodiversity valuation but providing greater flexibility in balancing multiple objectives.

6.2.5 Case Study: Bioenergy and Climate Change Mitigation

We demonstrated our framework through a comprehensive case study examining bioenergy production for climate change mitigation under various biodiversity protection scenarios. The study addresses the large-scale bioenergy deployment needed to meet climate goals while considering associated biodiversity impacts from habitat conversion. Our model determines optimal land cover allocations for woody biomass production while incorporating biodiversity constraints as described in our framework.

The linear programming model optimizes land use transformations from current to future land cover across global ecoregions and land use types including annual crops, permanent crops, pastures, extensive forests, intensive forests, and urban areas. Land allocation decisions consider transformation costs, biomass yields, and biodiversity impacts for four taxonomic groups: amphibians, birds, mammals, and reptiles. Multiple biomass demand scenarios ranging from 4,221 to 17,024 million tons per year represent different climate mitigation ambition levels.

Our Pareto frontier analysis (See Figure 2) reveals critical trade-offs between transformation costs and biodiversity impacts. The high biodiversity impact, low cost scenario minimizes economic costs while accepting higher species loss. The low biodiversity impact, high cost scenario prioritizes biodiversity protection despite increased economic burden. Between these extremes, we identify intermediate solutions offering improved outcomes with modest cost increases achieving substantial biodiversity benefits.

Specific results demonstrate that moving from the cost-minimizing solution toward moderate biodiversity protection achieves 22.5% reduction in biodiversity impacts with only 9.4% cost increase. Conversely, modest relaxation of strict biodiversity protection reduces costs by 54% while increasing biodiversity impacts by only 3%. These findings highlight significant opportunities for improving biodiversity outcomes without proportional economic penalties.



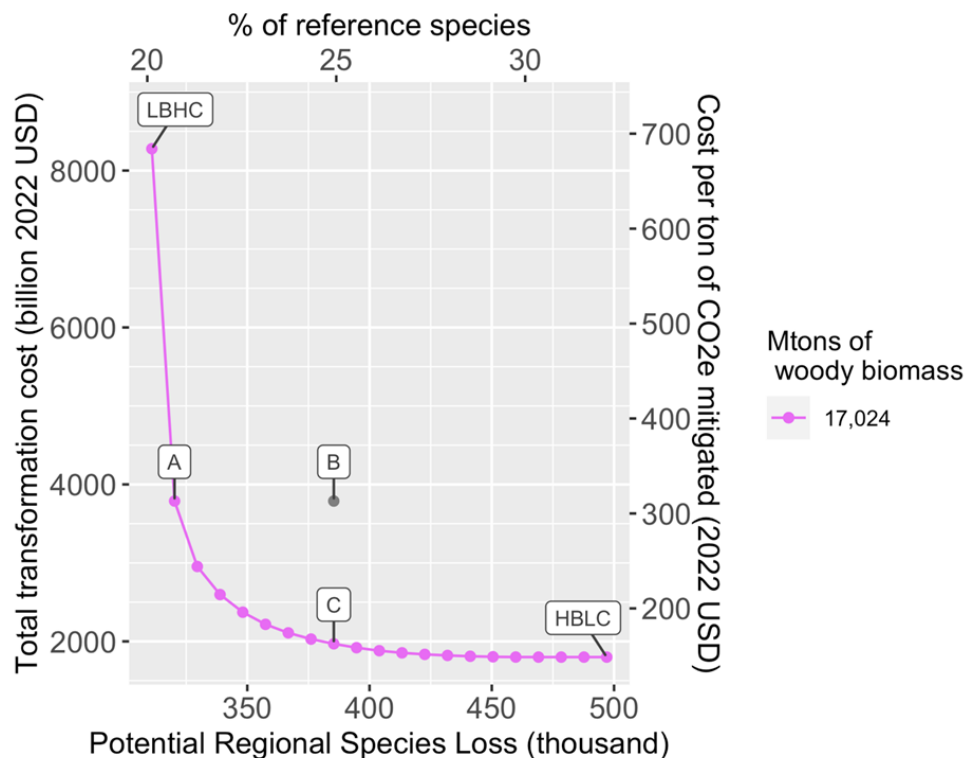


Figure 2: Pareto frontier for the highest biomass demand (17 Bt) showing cost of land use transformation in the y-axis and biodiversity impacts on the x-axis. High Biodiversity impact Low Cost (HBLC) point minimizes costs, whereas Low Biodiversity impact High Cost (LBHC) minimizes biodiversity impacts

6.2.6 Methodological Comparison and Validation

Our comparative analysis of the three mathematical implementation approaches reveals distinct accuracy and computational trade-offs. The characterization factor method significantly underestimates biodiversity impacts due to its linear assumption, with increasing errors as habitat availability decreases. The range of estimated biodiversity impacts narrows considerably compared to nonlinear approaches, potentially misleading decision-makers about true environmental consequences.

The piecewise linear approximation provides excellent estimation accuracy while maintaining linear programming benefits. Slight overestimation occurs, particularly at low habitat availability levels, but overall performance closely matches the true nonlinear function. Implementation complexity increases through additional variables and constraints, but computational benefits of linear programming often justify this overhead.

Direct nonlinear implementation maintains mathematical accuracy while requiring nonlinear programming capabilities. Computational performance depends on specific model characteristics and solution algorithms. For models already employing nonlinear programming, this approach provides accuracy without additional conceptual complexity.

The increasing marginal cost of biodiversity protection emerges consistently across all methodological approaches and biomass demand levels. This finding reflects the economic reality that initial biodiversity protection measures target the most cost-effective opportunities, with subsequent protection requiring increasingly expensive interventions. This pattern supports economic theory predictions while providing practical guidance for policy development.

6.2.7 Benefits of Integrated Decision-Making

Our integrated approach provides substantial advantages over traditional ex-post biodiversity assessment methods. Direct integration enables identification of solutions with improved outcomes that pure cost optimization would miss. We identify specific mechanisms through which optimization models achieve biodiversity benefits, including preferential transformation of human-modified lands over natural habitats when biodiversity constraints become active.

The integrated framework reveals both synergies and trade-offs between climate mitigation and biodiversity protection. Some land use changes support both objectives simultaneously, such as reforestation initiatives that provide biomass while creating habitat. Other interventions create conflicts requiring explicit trade-off evaluation, such as transforming natural areas into intensive biomass plantations.

Challenge identification represents another integration benefit, revealing situations where even biodiversity-optimized scenarios may struggle to meet conservation targets due to high biomass demands. Our case study demonstrates that minimizing biodiversity impacts while satisfying ambitious bioenergy targets still results in significant natural land transformation, highlighting fundamental tensions between large-scale renewable energy deployment and biodiversity conservation.

6.2.8 Framework Extensions and Future Developments

Our methodology provides a foundation for incorporating additional biodiversity indicators and drivers into land use optimization models. Current focus on habitat loss-driven species extinction could expand to include population-level indicators responding more rapidly to environmental changes. Integration of multiple indicators would require careful consideration of potentially conflicting signals and appropriate aggregation approaches.

Additional drivers of biodiversity loss including climate change, pollution, overexploitation, and invasive species present opportunities for framework extension. Each driver requires well-defined mathematical relationships with biodiversity indicators suitable for optimization model incorporation. Life Cycle Impact Assessment approaches provide starting points, but capturing nonlinear relationships remains challenging for drivers beyond habitat loss.

6.2.9 Policy Implications and Decision Support

Our framework provides direct support for policy development by enabling quantitative assessment of biodiversity-economy trade-offs under different regulatory approaches. Constraint-based implementations support evaluation of biodiversity protection standards and their economic implications. Objective function approaches facilitate analysis of biodiversity pricing mechanisms and payment for ecosystem services schemes.

Nature-based solutions providing both carbon sequestration and biodiversity benefits become explicitly quantifiable, supporting integrated policy development. However, measurement and verification challenges require careful attention to ensure policy effectiveness.

Sectoral policy applications span agriculture, forestry, energy, and urban development planning. Each sector presents specific opportunities for biodiversity integration within existing economic optimization frameworks. Agricultural policies could balance food security and biodiversity through spatially explicit land use planning incorporating ecological constraints. Energy system expansion could minimize biodiversity impacts while meeting renewable energy targets through optimized siting and technology selection.

6.2.10 Conclusions and Research Implications

Our framework represents a significant methodological advancement in integrating biodiversity considerations into economic decision-making models. The approach provides practical tools for incorporating ecological constraints and objectives into land use optimization while maintaining computational tractability. Successful implementation requires careful attention to underlying ethical assumptions and methodological choices affecting policy recommendations.

The biodiversity crisis demands urgent integration of ecological considerations into economic planning processes. Our framework provides immediately applicable tools supporting this integration while acknowledging current limitations and future development needs. Continuous refinement incorporating additional biodiversity indicators, drivers, and spatial scales will enhance policy support capabilities.

Broader adoption of integrated biodiversity-economy modeling requires sustained collaboration between ecological and economic research communities. Data availability improvements, particularly for species distribution and habitat affinity parameters, remain critical for expanding framework applications.

The methodology presented here contributes to reversing biodiversity loss trends by enabling proactive conservation integration into economic planning. Rather than treating biodiversity protection as an external constraint or afterthought, our approach makes ecological considerations integral to optimization processes. This integration supports development of economically efficient biodiversity conservation strategies while maintaining economic development objectives.

Future research priorities include expanding taxonomic coverage, incorporating additional ecological processes, and addressing uncertainties in biodiversity impact predictions. Validation studies comparing model predictions with observed outcomes would strengthen scientific credibility and policy relevance. Economic valuation improvements would enhance objective function implementations and support comprehensive cost-benefit analysis of biodiversity conservation investments.

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6.3 Improving Biodiversity Representation in Integrated Assessment Models: A Comprehensive Review and Methodological Framework

The interconnected crises of biodiversity loss and climate change represent two of the most pressing challenges facing humanity, with their complex interactions demanding sophisticated analytical approaches that can inform integrated policy responses (Pörtner et al., 2023, 2021; WWF, 2022; Ferreira et al., 2018). Within this context, we have undertaken a comprehensive analysis of how biodiversity has been incorporated into Integrated Assessment Models (IAMs), examining 33 papers published between 2006 and 2025 to understand current practices, identify critical gaps, and propose methodological improvements for enhanced biodiversity representation. This chapter is based on (Azuerop-Pedraza et al., 2025)

We categorized the reviewed studies across five key dimensions that capture the essential characteristics of biodiversity representation: the type of biodiversity indicators used, the drivers of biodiversity loss considered, the modeling approach employed, the degree of integration within the IAM framework, and the spatial resolution of the analysis. This multidimensional assessment provides a structured foundation for understanding how biodiversity has been conceptualized and operationalized within different IAM architectures.

The first category refers to whether the study explicitly used a biodiversity indicator or if it was proxied by other elements (e.g. ecosystem services). The second category refers to the direct drivers of biodiversity loss included (i.e. habitat loss, climate change, pollutants, invasive species, overexploitation). The third examines whether an explicit or an economic modeling approach was used. The fourth refers to a post-processed versus an endogenous representation. Finally, the fifth refers to the spatial scale of the analysis.

6.3.1 Current State of Biodiversity Representation in IAMs

Our review encompassed two primary categories of IAMs (Weyant, 2017; Bosetti, 2021): Detailed-process IAMs (DP-IAMs) and Benefit-Cost IAMs (BC-IAMs), reflecting fundamental differences in model architecture, purpose, and approach to biodiversity integration. Among the 33 papers analyzed, 28 focused on DP-IAMs while only 5 addressed BC-IAMs, revealing a significant imbalance in research between these model types. Figure 3 summarizes the results.



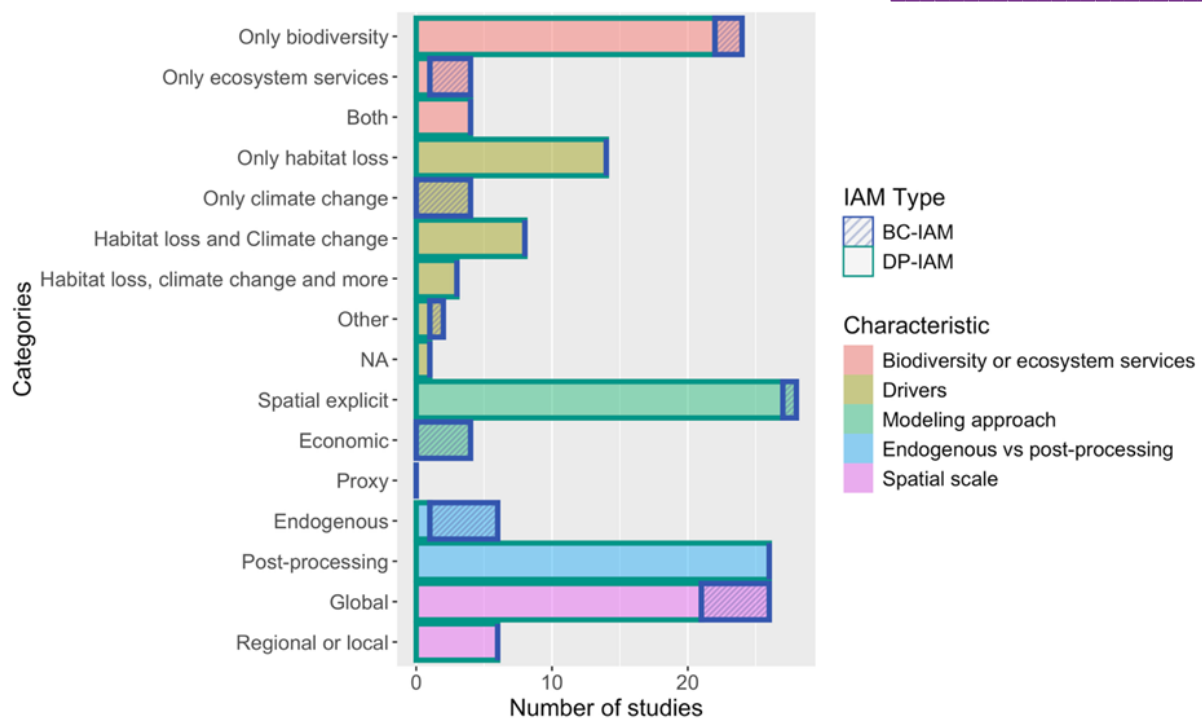


Figure 3: characteristics summary of reviewed literature. Total number of studies: 33.

6.3.2 Detailed-Process IAMs

DP-IAMs dominate the current literature on biodiversity representation, utilizing spatially explicit models that typically estimate biodiversity indicators through post-processing analysis focused on habitat loss and climate change impacts at global scales. These models, including IMAGE, BLUES, MAGNET, MESSAGE, AIM, GCAM, POLES, and REMIND, along with associated land-use models such as GLOBIOM and MAGPIE, have developed sophisticated approaches to linking land-use change projections with biodiversity indicators.

Regarding drivers, all of DP-IAMs studies have represented habitat loss, with some (41%) also including climate change. Pollutants, invasive species or overexploitation effects are still lacking.

The spatial resolution of DP-IAM biodiversity analyses varies considerably, ranging from 30 meters to 200 kilometers, with the majority of studies (33%) employing 50-kilometer resolution. This variation in spatial resolution reflects different research objectives and computational constraints, though it also introduces challenges for comparing results across studies and for policy applications requiring fine-scale spatial information.

Regarding biodiversity indicators, we found that species richness accounts for 33% of indicators used in DP-IAMs, followed by suitable area indicators (18%) and Mean Species Abundance or similar composite indices (16%). This distribution reflects both data availability constraints and the varying conceptual approaches to measuring biodiversity impacts. Most studies utilize community-based models rather than species-based approaches, primarily due to data limitations and computational efficiency considerations.

DP-IAMs still need to improve the representation of biodiversity impacts. Focus should be placed on representing more drivers, improving regional data availability, addressing uncertainty, and using more than one biodiversity indicator. Moreover, all efforts have concentrated on terrestrial ecosystems, lacking freshwater and marine ecosystems. However, a major gap for DP-IAMs is the lack of representation of how changes in biodiversity affect the economic system, limiting policy analysis and misrepresenting the dependence of the economic system on nature.

6.3.3 Benefit-Cost IAMs

BC-IAMs, exemplified by models such as FUND, DICE/RICE, and PAGE, represent biodiversity and ecosystem services quite differently from DP-IAMs. These models focus on capturing the economic welfare implications of biodiversity loss through damage functions that translate environmental changes into monetary costs or utility impacts. However, we found that biodiversity implementation in BC-IAMs remains at an early stage of development.

In BC-IAMs we can find both attempts trying to use biodiversity indicators such as FUND (Brooks and Newbold, 2014), but most have focused on representing ecosystem services (ES). In general, these types of models lack a spatial representation of biodiversity impacts and instead use economic valuation and correlative damage functions, described as the economic approach. These simplified functions directly associate the impacts of drivers of biodiversity loss into the economy, allowing an endogenous representation of the nature-economy connection. 3 of the 5 studies analyzed have focused on provisioning ES and non-use values, 2 included supporting and regulating ES, and only one included cultural ES.

All studies have focus only on the impacts due to climate change, excluding the other drivers from their analysis.

The challenge of biodiversity representation in BC-IAMs stems partly from the need to translate complex ecological changes into economic terms that can be integrated into welfare functions. Current implementations typically rely on “expert guesses” or simplified relationships rather than empirically grounded damage functions, highlighting a critical research need for better quantification of biodiversity-economic relationships.

The spatial resolution limitations of BC-IAMs also constrain their ability to capture local and regional variations in biodiversity values and ecosystem service provision. Unlike DP-IAMs, which can utilize spatially explicit representations, BC-IAMs typically operate at aggregate spatial scales that obscure important heterogeneity in both ecological and economic conditions.

6.3.4 Cross-Cutting Methodological Challenges

Several challenges affect both DP-IAM and BC-IAM approaches to biodiversity representation. The connection between biodiversity indicators and ecosystem service provision remains poorly understood and inadequately modeled across both model types. This limitation is particularly significant given the growing policy emphasis on nature-based solutions and ecosystem service valuation.

Data quality and availability represent persistent constraints across all model types. Comprehensive biodiversity monitoring data remain limited, particularly for developing regions and marine ecosystems, constraining model development and validation efforts. Similarly, empirical data on the relationships between economic activities and biodiversity impacts are often insufficient for robust model parameterization.

The integration of multiple drivers presents computational and methodological challenges that most current studies have addressed only partially.

6.3.5 Methodological Approaches for Enhanced Biodiversity Integration

Building on our analysis of current practices and limitations, we propose a comprehensive methodological framework for improving biodiversity representation in IAMs. This framework addresses both the technical challenges of modeling complex biodiversity-economy interactions and the practical requirements for policy-relevant analysis.

6.3.5.1 From Economic Systems to Ecosystems: Improving Impact Pathways

The representation of how economic activities translate into biodiversity impacts requires strengthened methodological approaches that capture both direct and indirect pathways. This requires developing functional relationships that link specific economic activities to multiple biodiversity pressures, moving beyond the current focus on land-use change and climate change to also include pollution and overexploitation.

To improve impact pathways, one possibility is to take advantage of existing development with land use models. The enhancement involves land use models to calculate biodiversity indicators and include this in its look up tables. Biodiversity indicators should then include as many drivers as possible. Once in the look-up tables, simple response functions could be constructed and included in the IAM. In the equation B is the biodiversity indicator and Q_{wbio} is the demanded quantity of biomass for the energy system. This relationship changes depending on the carbon price p_c .

$$B = f(Q_{wbio} | p_c)$$

A similar possibility is the use of emulators of more complex biodiversity models.

Another alternative, for climate change drivers, is to take advantage of the correlative approaches already used by BC-IAMs to construct damage functions on biodiversity due to climate change. An important component here is to keep a spatial explicit component and rely on empirical data.

For overexploitation, a good starting point is to start representing fish in marine ecosystems, which may connect with the agricultural sector and shifting diets. Extension of land use models in this regard will be a next step.

For pollutants, both air and water pollutants, the integration of life cycle assessment (LCA) approaches offers promising opportunities for quantifying the full environmental footprint of economic activities, including impacts on biodiversity through material extraction, manufacturing processes, and fertilizer use.

In general, we emphasize the need to use more than one biodiversity indicator, ideally representing more than one dimension of biodiversity. For example, one species-based (e.g. species richness, PDF, Red List Index (RLI), ESH) and one population-based (e.g. MSA, BII, LPI). Moreover, extending the use of functional diversity indicators will allow for a more straightforward connection with ecosystem services and therefore with the feedback into the economic system.

6.3.5.2 From Ecosystems to Economic Systems: Valuation and Welfare Integration

Once a representation of how the economic system affects biodiversity, there are various methods to represent how this change affects the economic system. A first approach will be to impose upper limits on biodiversity loss using hard constraints. This can be considered as a sustainability limit representation. Other is to represent a more explicit connection to the economic system and let the economic agents decide how much biodiversity loss is acceptable.

The explicit connection to the economic system can be done, from a modeling perspective, (1) affecting the production of goods, (2) affecting the utility function from consumers, (3) affecting both, and (4) using damage functions to affect welfare functions. In the review, we describe Natural Capital (Barbier, 2019; Dasgupta, 2021) as an example of the first approach, an extension of utility functions as a reflection of how much humans in the economic system care or value ecosystems, and damage functions as an approach for macro-economic models that uses a welfare function.

6.3.5.3 Integrated Bidirectional Approaches

The most promising methodological advancement involves developing fully integrated approaches that capture bidirectional relationships between economic systems and biodiversity. This integration requires modeling frameworks that simultaneously optimize economic outcomes and ecological constraints, moving beyond the current paradigm of post-processing biodiversity impacts from economic scenarios.

We propose implementing dynamic feedback mechanisms that allow biodiversity changes to influence economic decisions in within the model solution. This approach would require expanding the state variable space of IAMs to include biodiversity indicators alongside traditional economic variables such as capital, labor, and technology. The resulting model would endogenously determine both economic development pathways and biodiversity outcomes through simultaneous optimization.

The implementation of such integrated approaches presents significant technical challenges, particularly regarding model complexity and computational tractability. We recommend beginning with simplified representations that capture the most critical feedbacks, such as the relationship between agricultural productivity and pollinator populations, before expanding to more comprehensive biodiversity-economy interactions.

Spatial heterogeneity represents a crucial consideration for integrated approaches, as both economic activities and biodiversity impacts exhibit substantial geographic variation. We propose utilizing nested modeling approaches that combine global economic optimization

with regionally specific ecological models, allowing for detailed representation of local biodiversity impacts within a globally consistent economic framework.

6.3.6 Conclusions

This comprehensive review reveals both the significant progress made in incorporating biodiversity considerations into IAMs and the substantial opportunities for methodological advancement that remain. Our analysis of 33 studies demonstrates that DP-IAMs have developed sophisticated approaches for representing biodiversity impacts through spatially explicit modeling and post-processing analysis, while BC-IAMs have begun exploring biodiversity integration through expanded damage functions and welfare measures.

The critical gaps we identified point toward several high-priority research directions. The underrepresentation of multiple biodiversity drivers beyond habitat loss and climate change requires expanded modeling approaches that capture pollution, invasive species, and overexploitation impacts.

Furthermore, DP-IAMs should concentrate in establishing the relationship between biodiversity status and the economic system. BC-IAMs specifically, the current reliance on simplified damage functions and limited empirical evidence highlights the urgent need for expanded valuation research and more comprehensive welfare function specifications. The integration of multiple ecosystem service categories, non-use values, production function effects, and a more spatial explicit model represents critical enhancements for improving policy relevance and analytical robustness.

The methodological approaches we propose offer concrete pathways for addressing these limitations through enhanced spatial integration, bidirectional feedback mechanisms, and comprehensive valuation frameworks. The implementation of these approaches in IAMs will enable more integrated policy analysis that simultaneously addresses climate and biodiversity objectives, supporting the development of more effective and efficient environmental policies.

Our work demonstrates that significant technical and empirical advances are both necessary and feasible for substantially improving biodiversity representation in IAMs. The urgency of both climate and biodiversity crises demands rapid progress in developing analytical tools that can support integrated policy responses. Enhanced biodiversity representation in IAMs represents a critical component of this analytical infrastructure, enabling policymakers to better understand trade-offs, identify synergies, and design more effective interventions that address multiple environmental objectives simultaneously.

6.3.7 References

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