Balancing Climate and Biodiversity: Assessing the Socioeconomic Impacts of the 30-by-30 Target with Climate Warming Constraints

by

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Dedicated to my father, 林慶河*, who inspired my passion for science and nature through countless conversations and trips to the ocean shore, and whose unwavering support guided me every step of the way.*

I am deeply grateful.

Quiero dedicar este logro a mi familia y, en recuerdo de mi padre, Ching-Ho Lin, cuyo apoyo incondicional y confianza en mis capacidades han sido fundamentales para convertirme en la persona que soy hoy.

Gracias por siempre creer en mí.

謹以此篇論文獻給我人生前行最重要的導師—已在天上的　親愛的父親。

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ABSTRACT

Limiting global warming to 1.5°C will require significant land-use change. Various post-Paris Agreement strategies are rooted in land-based CO_2 removal. However, these strategies introduce potential mismatches with biodiversity conservation policies. Given this, this study evaluates the compatibility between the UN Kunming-Montreal Global Biodiversity Framework's "30-by-30" target—protecting 30% of land and oceans by 2030—and two climate change scenarios: "Current Trends" (CT), which extrapolates present climate policies through the century, and "Accelerated Actions" (AA), which seeks to stabilize average temperatures at 1.5°C. A multi-sector computable general equilibrium model (MIT Economic Projection and Policy Analysis) is employed with a 30-by-30 target that protects biodiversity-rich natural forest and grasslands while prioritizing subsidy-based transition to these land types. Subsequently, the analysis follows with a land use downscaling disaggregation model (Demeter) of 0.5 x 0.5 resolution projection to capture the spatiotemporal shifts resulting from the combined 30-by-30 and climate policy effects. The 30-by-30 biodiversity target is evaluated across an ensemble of socioeconomic scenarios and Demeter parameters to analyze their sensitivities to various climate targets and underlying downscaling model constraint characteristics. Under CT and AA, India and the Middle East will experience the largest GDP losses, up to tens of billions of dollars, as a result of combining the 30-by-30 target. Meanwhile, Brazil and Australia and New Zealand will experience billion-dollar magnitude growth. Outputs further magnify the distributional effects of the 30-by-30 target, where the Middle East and India will experience substantial food price increases ranging from 5-600% in certain agricultural products. These results highlight disparities for regions with deficient natural forest and grassland cover, but also the potential comparative advantage for strong agri-livestock regions that would benefit from increased food exports. Overall, these socioeconomic insights into the effects of a dual biodiversity-climate intervention can guide policymakers to develop complementary strategies that regulate policy ramifications, including food-price impacts and agriculture-induced deforestation.

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Abbreviations

AA Accelerated Actions

CT Current Trends

CGE Computable General Equilibrium model

EPPA MIT Economic Projection and Policy Analysis model

GDP Gross Domestic Product

GHG Greenhouse Gas

LULC Land Use Land Cover

nfors Natural Forest

ngrass Natural Grassland

PAs Protected Areas

Chapter 1

Introduction

Limiting global warming to 1.5°C will require significant land use change and development. With an increasing amount of interest in net-zero targets, public and private sectors seek to expand strategies that reduce and remove anthropogenic greenhouse gas (GHG) emissions (Calvin et al., 2023). A significant amount of these post-Paris Agreement nationally determined pathways (UNFCCC, 2015) are rooted in land-based carbon dioxide removal methods such as bioenergy crops, afforestation and reforestation, and nature-based solutions (Calvin et al., 2023; Dooley et al., 2024; Roe et al., 2019), not to mention increasing land use dedicated to solar and wind energy deployment (Diffendorfer et al., 2024). However, these technologies and strategies introduce potential concerns and mismatches with biodiversity and ecosystem conservation priorities (McManamay et al., 2021). This raises an important underpinning question and challenge for broader sustainability goals that seek to achieve multiple development and environmental targets: are large-scale climate actions compatible with biodiversity priorities?

Human development impacts nature-dependent economic activities by raising risks to key species and ecosystem services such as insect-driven pollination in agriculture, forest nutrient recycling for timber production, eco-tourism, and clean water filtration. These economic activities account for 1 to 3% of Gross Domestic Product (GDP), a number expected to reach up to 10% of GDP by 2030 for low to lower-middle-income agriculture-dependent countries (du Plessis, 2022; Gardes-Landolfini et al., 2024; Han et al., 2022). Beyond economic value, species richness and diversity carry profound and invaluable connections to the history and cultural foundation of Indigenous and local communities (Clark et al., 2014; Dudley et al., 2010). As a result, several policy frameworks set forth legal and community-based approaches to conserving ecosystems from human development.

Under increasing pressure to shield biodiversity value from human development, most nations have agreed to increase protected areas (PAs) in their respective jurisdictions (United

Nations Convention on Biological Diversity, 2022). This resulted in the formulation of the United Nations Kunming-Montreal Global Biodiversity Framework (KMGBF) Target 3, to ensure by 2030 that at least 30% of terrestrial, inland water, and coastal and marine areas are effectively protected and managed (UN Convention on Biological Diversity, 2022). Target 3 (also referred to as "30-by-30" target) further stipulates that PAs and other effective conservation measures must emphasize areas key to biodiversity and ecosystem functions while recognizing land rights of traditional Indigenous and local communities.

Despite international consensus, Target 3 was built heavily on conservation science, ecological analyses, and biophysical scientific data, failing to capture the social and economic feasibility and fairness that setting apart 30% of land from development could imply (Dinerstein et al., 2019; Robinson et al., 2024). Simultaneously, 30-by-30 remains increasingly vulnerable to land scarcity pressures, as human development and expanding climate change priorities risk undermining Target 3 itself. Therefore, these points raise the urgent need for model-based predictive investigations to quantify the socioeconomic tradeoff between these two land-competing policies and further inform more coherent and equitable implementation and governance strategies to reach a 30-by-30 biodiversity target.

The first chapter of this thesis addresses these gaps by expanding the MIT Emissions Prediction and Policy Analysis (EPPA) model to account for land use change pressures involved in reaching a 30-by-30 biodiversity target coupled with two climate change scenarios: Current Trends (CT), which projects present climate and anthropogenic emissions through 2100, and Accelerated Actions (AA) which sets forward more stringent goals to stabilize global temperatures at 1.5°C by 2100. The framework sets apart areas of high importance for biodiversity (i.e., natural forests and grasslands) by modeling a minimum of 30% of areas across each EPPA region protected from economic activities and urban expansion. In EPPA regions below 30% of high-biodiversity natural protected areas, a subsidy-based approach for land restoration was implemented to incentivize the transition of managed cropland and pastureland to protected natural forest and grassland, respectively.

Once the representation of the 30-by-30 biodiversity target is integrated into EPPA, the framework takes advantage of the CGE model properties in EPPA to clear market equilibrium across regions, economic sectors, and physical constraints. Therefore, the framework captures and analyzes the socioeconomic implications of Target 3 under Current Trends and Accelerated Actions, comparing them against their baseline climate-only scenarios. The model outputs are analyzed to interpret for shifts in GDP, household consumption, land use patterns, and food prices across EPPA regions and climate policies. These projections allow for further insight into the effects of a dual biodiversity-climate intervention that can guide policymakers to develop complementary strategies that govern and mitigate the policy ramifications in areas such as food security and deforestation leakage effects.

The second chapter of this thesis will focus on the geospatial downscaling component of the biodiversity target implementation. This further integrates the spatiotemporal algorithm application of Demeter into an integrated framework to disaggregate EPPA-generated socioeconomic data into geographic grids. EPPA's underlying computational framework was optimized to reach pressing global warming and protected area biodiversity targets for large economic regions within limited time frames; however, it cannot geographically track land transitions for detailed ecosystem delineation of PAs or account for overlaps with particular communities and Indigenous lands. The integration of a Demeter downscaling framework would allow for the aforementioned land type representations based on adjustable spatiotemporal parameters and a high 0.5 x 0.5 degree representation of the state and priority locations for natural lands and conservation. Therefore, the framework accounts for a more detailed delineation of protected areas and the evaluation of localized impacts on particular Indigenous lands and communities in proximity.

This work makes several contributions to the literature. While previous studies relied on sector-limited modeling through exogenously determined socioeconomic drivers (X. Li et al., 2024) or sectoral market clearing through partial equilibrium frameworks to simulate a 30-by-30 biodiversity target (Dolan et al., 2022), EPPA's capacity to simultaneously clear market equilibrium across regions, economic sectors, and physical constraints allows for economy-wide nuances and interactions projections. The implementation of this novel CGE and downscaling method in biodiversity policy modeling under climate change-related land pressures allows us to more appropriately characterize the potential patterns, socioeconomic effects, and compatibility of a dual biodiversity-climate change policy scenario to inform localized priorities as well as risks to local and underserved communities.

Chapter 2

EPPA Model

2.1 Literature Review

Previous regional and global studies suggest Computational General Equilibrium models (CGEs) as highly capable of capturing the socioeconomic effects of policy intervention in the context of ecosystem services and biodiversity, beyond well-established land use change and climate change socioeconomic modeling capabilities (A. Gurgel et al., 2024). Smaller regional CGE simulations can capture the economic effects of nature-based policies, as exemplified in the study of the impacts of the Wetland Reserve Program in Louisiana, USA (Olatubi & Hughes, 2002). Meanwhile, regional CGE modeling studies, such as Pattanayak et al. (2009), studying the effects of the Brazilian policy to expand national forests by 50 million acres, also suggest that CGEs can capture economic declines as well as sector-isolated impacts to certain groups and industries such as agriculture. Moreover, recent reports have stated the particularly well-suited state of CGEs integrated with Global Trade Analysis Project (GTAP) databases to capture economy-wide reactions and welfare impacts by policy simulation for biodiversity (Crossman et al., 2018; Johnson et al., 2023). This is due to CGE's ability to represent entire economies in an equilibrium baseline and under policy intervention scenarios. Therefore, the adaptable dynamic models can measure shifts and interactions inside and across economic sectors to reach a policy target, capturing the shockwave effects of regulatory intervention beyond the directly-regulated economic sector (US EPA, 2025).

EPPA's capacity to clear market equilibrium across regions, economic sectors, and physical constraints simultaneously, therefore differentiates it from other socioeconomic modeling approaches, such as system dynamics models which project regional carbon emissions estimates under exogenously determined socioeconomic drivers (X. Li et al., 2024). At the same time, EPPA expands on previous studies, such as Dolan et al. (2022), which instead rely on sectoral market clearing through a partial equilibrium framework to simulate the 30-by-30 biodiversity target.

Taking advantage of the previously mentioned CGE properties, the study aims to apply this novel approach to measure the global socioeconomic state and potential cross-sector trade-offs of a dual 30-by-30 biodiversity and climate change policy target. The scope focuses on terrestrial protected areas due to more complete land observational data and physical modeling capabilities that can account for these ecological systems. To quantify the impact of a 30-by-30 target, the study applied a similar method deployed by A. Gurgel et al. (2024) to measure global shifts in land use as a response to a range of climate policies. The method utilizes the MIT Economic Projection and Policy Analysis (EPPA) model for two climate scenarios: Current Trends (CT), which reflects present climate and anthropogenic GHG emission policies through the century, and Accelerated Actions (AA), which sets forward more stringent goals to stabilize global temperatures at 1.5°C by 2100.

Under CT and AA, EPPA can model regional distributional effects and policy ramifications of concern that a 30-by-30 biodiversity target would imply under climate policies, aiding policymakers to adopt complementary strategies to ensure an equitable and coherent roadmap to the dual policy implementation. EPPA has the capacity to leverage land use and cross-region trade to model potential shifts in food prices that a 30-by-30 target would impact on a particular region. Therefore, model simulations can aid policymakers in identifying potential regions most affected by a dual 30-by-30 target and climate policy to increase food security and affordability by optimizing regional agricultural sectors to appropriately increase crop yields that are projected to be at risk. Moreover, through EPPA's market-clearing capacity, the model can estimate the economic impact that these dual policies could have on regional developing economies; hence, helping inform effective distribution of funds destined for conservation in impacted low and lower-middle-income regions. Finally, EPPA's land use and reactive cross-sector clearing capabilities allow for accounting of deforestation leakage effects of a 30-by-30 biodiversity target, where higher restrictions and costs of land in a region could risk pushing natural forest and grassland depletion to other agricultural-exporting regions with abundant and cheaper natural land. Therefore, these projections could guide policymakers in the implementation of policy mechanisms to restrict or install deforestation-free import regulations.

2.2 Methodology

2.2.1 MIT Economic Projection and Policy Analysis (EPPA) model

The multi-regional and multi-sector projections extend from the MIT Economic Projection and Policy Analysis (EPPA) model version 6, a recursive-dynamic computable general equilibrium (CGE) model (A. Gurgel et al., 2016; Y.-H. Chen et al., 2015). EPPA simulates the socio-economic behavior and natural resources interplay and feedback in the global economy. In this version, EPPA encompasses further integration and links to modeling natural resources, including energy and land use. EPPA traces value and physical changes to these resources and their impact on socioeconomic factors, including predictions on land use change and greenhouse gas emissions under respective climate and land use interventions. The model exhibits these characteristics for 18 economic regions and 28 sectors, including 11 crop and livestock sectors in addition to the forestry industry and other primary factor inputs. The latter are further classified into depletable and renewable natural capital inputs in addition to labor and produced capital; cropland, pastureland, and managed forest lands are labeled as "produced" capital derivations from natural forestland (nfors) and natural grassland (ngrass).

This study focuses on two produced capital types: Cropland and pastureland, as leverage mechanisms to proxy shifts in land use. More specifically, EPPA considers the reversion of produced capitals to nfors and ngrass to reach biodiversity targets in the model. This approach was derived by taking assumptions on the 30-by-30 target and its inputs into the EPPA model. The scope will focus on reaching the terrestrial component of the 30% of protected areas by 2030. At the same time, with substantial shares of biodiversity (including more than 60% of vertebrate species) found in natural forests (Parr et al., 2014) and studies suggesting comparable biodiversity richness in natural grasslands (Petermann & Buzhdygan, 2021); consequently, biodiversity-rich areas are proxied as a combination of nfors+ngrass land classes with equal importance. Although not representative of crucial sparsely vegetated ecosystems such as deserts and tundras, EPPA's nfors+ngrass captures a comprehensive range of natural forest types (across temperate and tropical), natural grasslands (peatlands, wetlands, and grassy ecosystems), and mixed natural grassland and forest ecosystems such as savannahs, covering a majority of terrestrial biodiversity. Meanwhile, EPPA makes clear distinctions between nfors+ngrass and human-managed pasturelands, managed forests or forestry, croplands, and urban-developed areas. A final assumption into the modeling structure is its economic-first approach, EPPA increases the amount of protected natural forest and grassland by optimizing for cost-effectiveness while following an ideal protection regime for existing and future modeled protected areas. EPPA does not capture further incurred costs associated with illegal extraction, human development, and encroachment. Hence, these outputs present a conservative estimate for the costs of reaching 30-by-30, and could expect higher costs to protect specific biodiversity-rich areas with higher human development value or considerable investment to avoid illegal economic and development activities, while presenting an additional burden to achieving the 30-by-30 target.

EPPA sources economic data from the Global Trade Analysis Project Version 8 (GTAP 8) database (Narayanan et al., 2012). Historical economic trajectories are modeled recursively to 2010, 2015, and 2020, while future economic trajectories are projected in 5-year intervals from 2020 to 2100. Economic development factors are benchmarked against the International Monetary Fund's historical data and short-term Gross Domestic Product (GDP) projections (IMF, 2019). GTAP8 contains the world-scale Land Use and Land Cover Database Version 2, built from FAOSTAT production empirical data and additional cropland and pasture data (U. L. Baldos & Hertel, 2012; Ramankutty, 2012). Additionally, the model takes data from the Terrestrial Ecosystem Model (TEM) (Felzer et al., 2004) and historical land transitions (Hurtt et al., 2006) to complement GTAP8. Land use change and the evolution of natural lands into human-intervened or managed terrain are physically represented by a land use transformation approach (A. Gurgel et al., 2016), which allows for longer-term observations and large shifts in demand for land use.

EPPA is an economy-wide model useful for investigating direct and indirect shock-like repercussions of policy interventions (Carbone et al., 2022). The model explicitly solves multi-sector interactions and bilateral trade in goods among economic regions, accounting for: domestic production, exports, imports, government expenditures, investments, and household demand for final goods, ownership and supply of labor, and capital and natural resources. The model implements these recursive changes while complying with microeconomic and macroeconomic balances and principles. In a parallel process, EPPA projects the quantitative effects of policy intervention and economic transactions on physical values of energy (exajoules), emissions (tons), land use (hectares), and population (billions of people) (A. Gurgel et al., 2025). Hence, EPPA tracks the impact of renewable resources as a function of physical depletion and the use of natural resources. As an example, a scenario with stronger economic protectionism or less inter-region trade could lead to increased agricultural expansion and land development to satisfy intra-region food demand, thereby creating a cascading effect on the amount of cropland and pastureland, food prices, environmental impacts, and shifts in diet. EPPA then solves for a new adapted market and economic equilibrium based on these shifts in natural resource availability and depletion, capturing the shockwave effects of the intervention across sectors and regions. Similarly, the model is reactive to shocks such as income growth, trade openness, and cross-sector transactions.

In the model, natural to human-intervened land transitions (pastureland, cropland, or managed forests) are guided by land supply responses from previous calibrated land use change observations in literature (Hertel, 2011). A reverse transition can be gradual or direct: a gradual shift would transform "produced" capital land types into less heavily managed states (cropland into pastureland or managed forest) with continued sustained investment. Meanwhile, the current strategy applies direct transitions, which signal complete abandonment of the land and eventual return to natural grassland and forest protected areas with no further managed land investment. EPPA models these transitions after abandonment of economic activity and a time lag period that allows for geographically-dependent ecosystem regeneration (i.e., a cropland to tropical forest transition would take 20 years in Indonesia, whereas temperate forests in Russia would take 89 years) (Figure A.1).

2.2.2 Scenarios of combined climate and biodiversity targets

EPPA can project solutions under different climate change targets and settings. In order to represent land use change fueled by the increasing presence of renewable energies and state of decarbonization goals, the study models the KMGBF Target 3 in conjunction with both the Current Trends (CT) and Accelerated Actions (AA) scenarios (i.e., Paltsev et al. (2023)).

Current Trends assumes that Paris Agreement Nationally Determined Contributions (NDCs) are implemented through the year 2030. This scenario best represents global commitments to limit greenhouse gas emissions, but falls short of stabilizing global climate warming. CT sets future characteristics by projecting energy use, emissions, electricity production, population growth, agricultural production, and climate behavior based on present climate change policies. The scenario considers nationally set decarbonization targets by countries and is aggregated or generalized for each EPPA region. In CT, global GHG emissions stay relatively constant initially, increasing from 47 gigatonnes of CO_2 equivalent (Gt CO_2e) in 2020 to about 48 Gt CO_2e in 2030 and then decreasing to 45 Gt CO_2e in 2050 because of policies in certain countries with more stringent emission constraints. Some of these policies are reflected in the following projections: A respective -26, -23, -35, and -45% for the United States (USA), Europe (EUR), Japan (JPN), and Brazil (BRA) changes in CO_2 emission relative to 2015 is expected by 2030 while -59, -44, -61, and -44% cuts are predicted for 2050 (Table A.1). At the same time, EPPA projects an overall food production increase of 90% from 2020 to 2050 (crop production by 70% and livestock by 61%). Global land-use endogenous trajectories remain relatively stable from 2020 to 2050, with natural forest and grassland areas decreasing by 1.4% and 3% respectively. Natural forest is expected to be converted into a 7.5% increase in cropland and natural grassland into a 1.8% increase in pastureland. Meanwhile, acreage dedicated to biomass is expected to increase by 46% by 2050 and occupy 3% of total cropland.

Accelerated Actions assumes an expansion to the Paris Agreement NDCs as well as enhancing climate policies in order to cap global warming at 1.5°C by 2100 with at least a 50% probability. This scenario takes into account a more stringent and stronger push to develop renewable sources of energy and decarbonization of the current electricity and transportation sectors, among others. The scenario is characterized by more aggressive emission targets than those submitted in NDCs. AA adjusts for ambitious policies that more rapidly invest in carbon emissions removal and reduction in greenhouse gas emissions, while considering similar projected population growth as CT. AA projects emissions to follow the same path as Current Trends until 2025, and then more ambitious policies reduce global GHG emissions to 18 Gt CO_2e by 2050 (a 62% decrease relative to 2020). Relevant to the 30-by-30 biodiversity horizon, the AA scenario produces relative changes in CO_2 emission by 2030 (relative to 2015) of -50, -45, -25, and -10% for USA, EUR, CHN, and AFR, respectively, while the changes reach -88, -73, -75, and -59% by 2050 (Appendix A.1). Agriculture in AA diverges in comparison to CT; the value of crop output is 5% lower than Current Trends, while the values of livestock and food output decrease by 9% and 5%, respectively. Globally, AA projects cropland to increase by 1% and pastureland to decrease by 4.2%, but land use for bioenergy increases by 44%.

To assess the socioeconomic impact of reaching 30% of protected areas by 2030, the project's approach takes advantage of this representation. CT and AA climate target simulations are augmented with the previously described nfors+ngrass proxy. The framework further utilized EPPA's ability to account for produced-to-natural land transitions with imposed subsidies to produce an increase in nfors+ngrass protected areas for EPPA regions that are below the 30% target set by the KMGBF Target 3 of PAs. Therefore, creating a matrix of scenarios that not only assesses individual impacts of climate and biodiversity targets, but also their combined effects.

Subsidies are financed endogenously by prioritizing intra-region public investment to increase the amount of protected areas by 2030. Ultimately, this is sourced from EPPA's modeled tax revenue for each economic region. Meanwhile, the volume of required subsidies per region is further quantified in monetary values of 2007 USD and is determined based on the difference between the price of the sought natural land type (i.e., natural grassland or forest) and the price of current managed land (i.e., pastureland or cropland), according to each region's land rent value (estimated total rental values of the land area divided by its total area). This approach prioritizes and assigns social welfare value to nfors+ngrass protected areas, while reflecting each EPPA region's land scarcity and pricing signals from supply and demand. EPPA was further modified to restrict transitions for subsidized lands, restricting newly subsidized nfors+ngrass from returning into a "produced" pastureland or cropland form. Similarly, already existing protected area coverage was sourced and aggregated from the World Database on Protected Areas (WDPA), and EPPA internalized with equal restrictions to subsidized PAs (World Database on Protected Areas (WDPA), 2025).

2.3 Results/Discussion

EPPA simulations show that the 30-by-30 target has evident winners and losers. The specific requirement to protect 30% of terrestrial lands with key importance for biodiversity and ecosystem services by 2030 leads to an increase in the protection of undeveloped natural lands and the commitment and direct transitioning of human-developed areas to PAs. Under this economic-first proxy for biodiversity-rich protected areas, EPPA prioritizes natural grasslands and forests, which host the majority of these species-dense areas. As a result, outputs show a substantial impact to regions that currently fall short of the 30-by-30 target, especially for EPPA economic regions with already low presence of natural grassland and forests such as India, the Middle East, and Other East Asia (Figure 2.1). In these regions, a low nfors+ngrass to total area ratio presents a challenge and a higher cost to pay for the conversion of developed cropland and pastureland to PAs.

This situation becomes evident when comparing Gross Domestic Product (GDP) change among EPPA regions for CT with subsidies to reach the 30-by-30 target versus a base CT scenario without. In the simulation results, modeled outputs observed that the Middle East (MES), India (IND), Other East Asia (REA), and Africa (AFR) experience the largest decreases of GDP at -10.42, -3.49, -1.65, and -0.81% respectively (Figure 2.2). This represents a substantial economic impact from these four regions that together compose 12.5% of the modeled global GDP. While this response can be attributed to MES, IND, REA, and AFR all having levels of nfors+ngrass below 30%, in certain EPPA regions, the consideration of other land classes, such as "barren" (which includes deserts) towards PAs could decrease the strong GDP impact of the 30-by-30 target.

In MES, the EPPA model was able to implement marginal changes up to 24.4% of protected areas before reaching a ceiling in the amount of nfors+ngrass that can be modeled for protected areas. MES's significant decrease in GDP can be traced to the natural scarcity of nfors+ngrass, which EPPA prioritizes for protected areas, leading to overly expensive subsidies. Desert lands are found in abundance across MES, providing crucial ecosystem functions and playing a role in regulating the climate. However, modeled outputs trigger

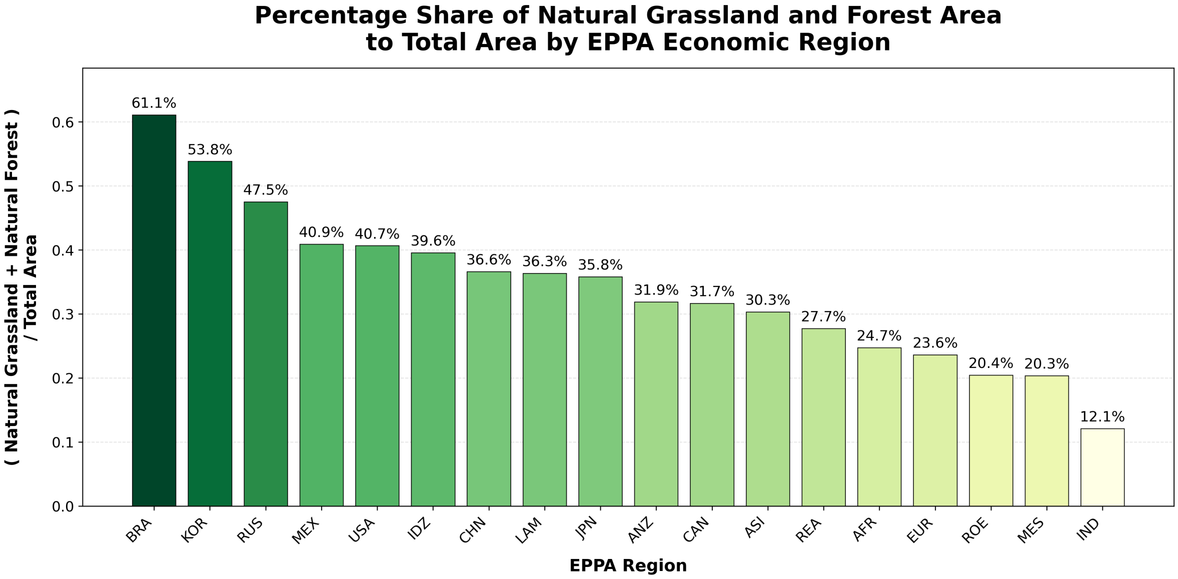


Figure 2.1: Natural Grassland and Forest Areas (nfors+ngrass) ratio to total area in each EPPA region.

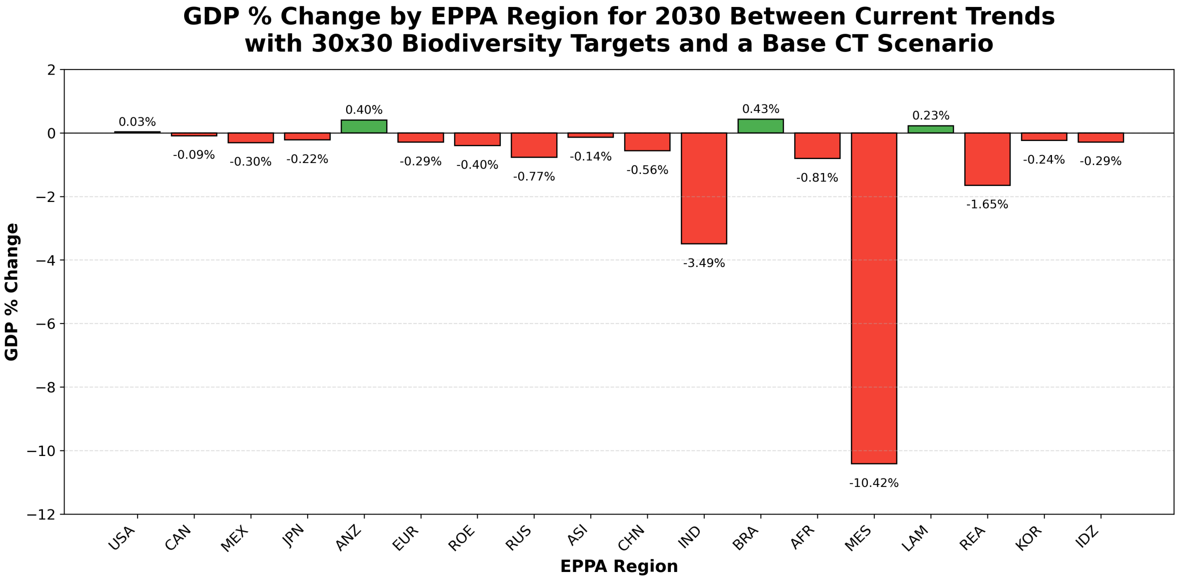


Figure 2.2: GDP percentage change for each EPPA region by 2030, subtracting GDP in a CT scenario with implemented 30-by-30 target subsidies from a base CT scenario without.

a discussion on how much desert land the Middle East and countries in the region should be allowed to contribute to their 30-by-30 targets. In this region, the abundance of deserts steers human development to a few areas rich in water and nutrients, often overlapping with biodiversity-rich areas. Hence, a balance must be struck between setting apart land for biodiversity and preventing overlabeling of low-biodiversity and economic value desert lands for protection.

To further analyze this question and test the addition of desert lands to the PA proxy method, sensitivity simulations were iterated through marginal increases in the amount of desert land counted toward 30-by-30 against required subsidies (Figure 2.3). In EPPA, desert lands are considered "barren", hence, are assumed to have a zero dollar cost to protect due to negligible economic value. At the same time, the model sets the "base" amount of MES protected areas at 20.35%, corresponding to the total nfors+ngrass that EPPA can set apart for protection in the region. Therefore, to measure the subsidy costs versus the percentage of desert counted toward 30-by-30, the regional sensitivity test iterated the amount of "zero value" desert land to compensate for the biodiversity target's gap. For example, at the 20.35% base, 9.65% of the desert is counted towards a 30-by-30, resulting in a 0 billion USD subsidy investment. However, at the next iteration, 20.60% of protected nfors+ngrass and a smaller 9.40% of desert is counted towards the biodiversity target, resulting in a more costly 2.08 billion USD subsidy. The iteration was varied until 24.4%, where physical model constraints limit further increases to protected nfors+ngrass. Hence, at least 5.6% of the desert must be counted as PAs to reach a physically feasible 30-by-30 target, while the inclusion of more would output a lower modeled GDP impact.

Figure 2.3 shows that MES experiences the largest jump in subsidy costs when the amount of desert counted towards 30-by-30 goes below approximately 5.8%, while costs tend to be lower and plateau at around 8% or more. Therefore, this informs the need for MES to adopt a regional variation to the 30-by-30 target, one where policymakers carefully balance protecting high biodiversity and ecosystem functions while sustaining an economy that operates in environments with abundant desert ecosystems and scarce natural grassland and forests that concentrate biodiversity.

Sharp decreases in GDP can also be due to high "produced" to "natural" land type transition costs, making it expensive to subsidize scarce cropland and pastureland conversion into aforementioned proxied methods for biodiversity-rich protected nfors+ngrass. In the case of India, highly valued pasturelands in India triggered a hike in pastureland to natural grasslands conversion subsidies, as EPPA is calibrated to give equal importance to protecting nfors and ngrass. However, due to India hosting one of the largest biodiversity-rich grasslands and simultaneously being the least protected and most misused land type (Dey et al., 2024),

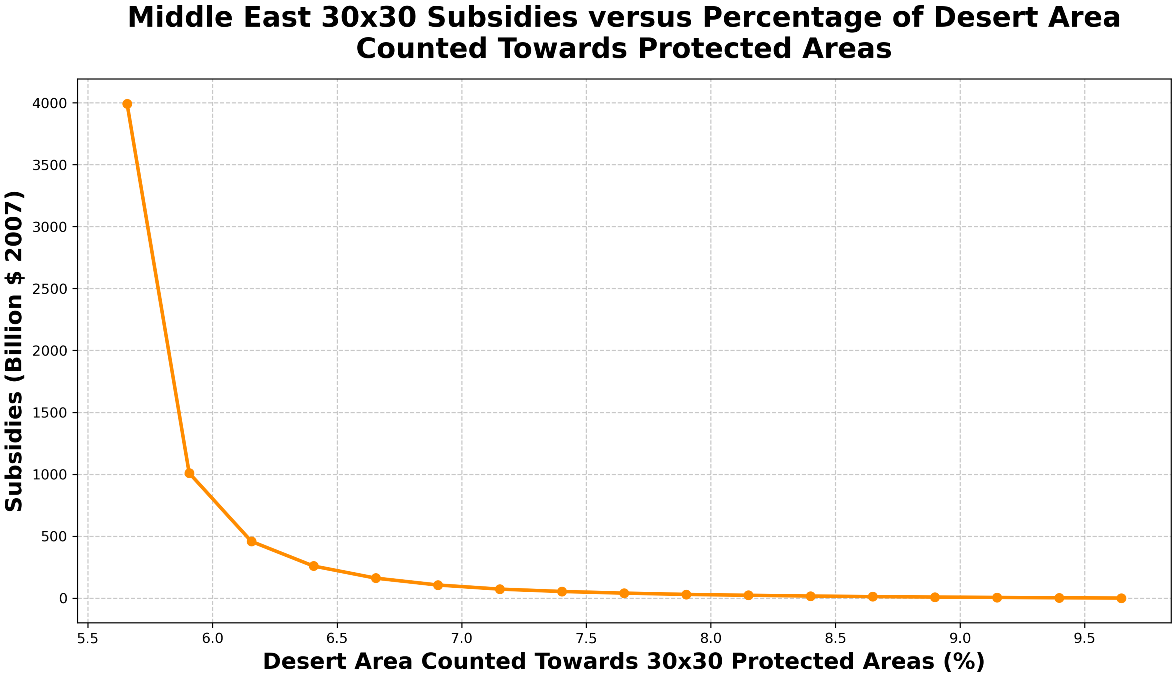


Figure 2.3: Compares the percentage of desert area in the MES counted as protected areas towards the 30-by-30 biodiversity target versus the required subsidies in billion 2007 US Dollars.

it was opted to maintain the modeling approach, which would require India to invest in protecting and restoring natural grassland coverage.

In contrast to IND and MES, regions such as Europe (EUR), Other of Eurasia (ROE), and Dynamic Asia (ASI) also require the implementation of subsidies to reach the 30-by-30 target under CT. However, lower transition costs to convert cropland and pastureland into protected biodiversity-rich natural forest and grassland result in much lower impacts on GDP, with decreases of -0.29, -0.40, and -0.14% respectively. At the same time, a decline in GDP is observed for China (CHN) and Japan (JPN), where available natural forest and grassland should lead to little or negligible subsidy investments to protect and restore areas with rich biodiversity. However, these export-heavy regions could be affected by negative trade effects. Regions such as IND, MES, and AFR that invest significantly in subsidies to restore natural forest and grassland could decrease trade, thus indirectly impacting them economically.

Modeled results also highlight a disparity between regions with strong versus weak agricultural and livestock export industries. As a contrast to previous EPPA regions, Brazil (BRA), Australia and New Zealand (ANZ), Latin America (LAM), and the United States of America (USA) embrace growths of 0.43, 0.40, 0.23, and 0.03% respectively in their overall GDP under the 30-by-30 CT scenario. Even with household consumption (total spending to meet the needs of the average household) decreasing across virtually all regions when comparing the CT 30-by-30 scenario versus CT alone (Figure 2.4), GDP increases in BRA, ANZ, LAM, and USA. Therefore, a higher GDP and lower household consumption for BRA, ANZ, LAM, and USA must be compensated for by increasing exports in trade. Hence, this case shows the comparative advantage of EPPA regions with strong agricultural and livestock industries, especially compared to those yet to reach the 30-by-30 target, in a Current Trends scenario.

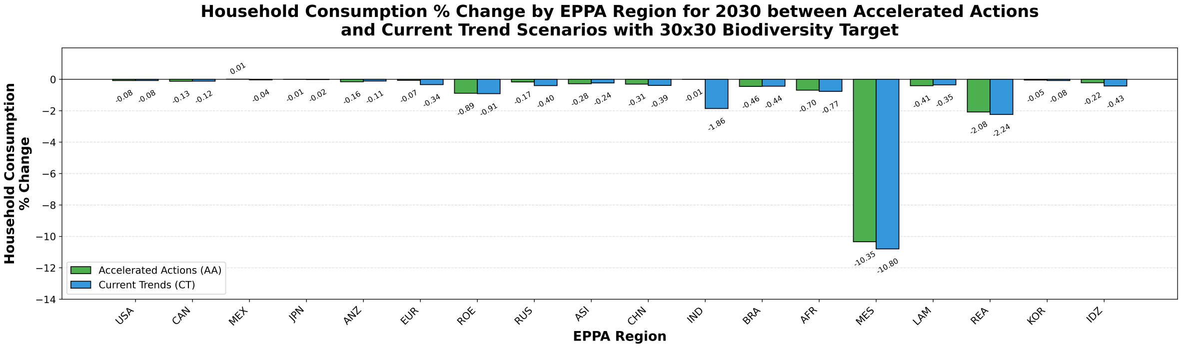


Figure 2.4: Household Consumption percentage change for each EPPA region by 2030, subtracting household consumption in a CT or AA scenario with implemented 30-by-30 target subsidies from their respective base CT or AA scenario without the target.

These results highlight the potential negative ramifications of a 30-by-30 target without supplementary policies. The EPPA simulated responses indicate that implementation of a biodiversity target could incite cross-region shifts in land use change. For example, an increase of protected areas in regions such as India and the Middle East could result in deforestation leakage to other regions or countries, fueled by a decrease in available cropland and pastureland. These regions could resort to trade imports in agricultural and animal food products, which increases deforestation and expand land use in regions with strong agricultural and livestock industries. This effect potentially risks displacing deforestation and ecosystem destruction to regions such as the United States, Brazil, and Latin America. A concern exacerbated for regions with lax environmental regulations in law or in enforcement. This pattern is further shown in Figure 2.5, where most of the EPPA regions that experience a gain in GDP under a CT scenario with 30-by-30 targets in comparison to the base CT, also experience percentage point increases in regional shares of land dedicated to cropland, pastureland, or both; patterns that show an increase in supply as a response to cross-region increases in demand.

To avoid the deforestation leakage effects modeled in EPPA, it is imperative that supplementary policies govern the import of agricultural products from regions with lax deforestation regulations to avoid potential net biodiversity habitat loss. These policies could

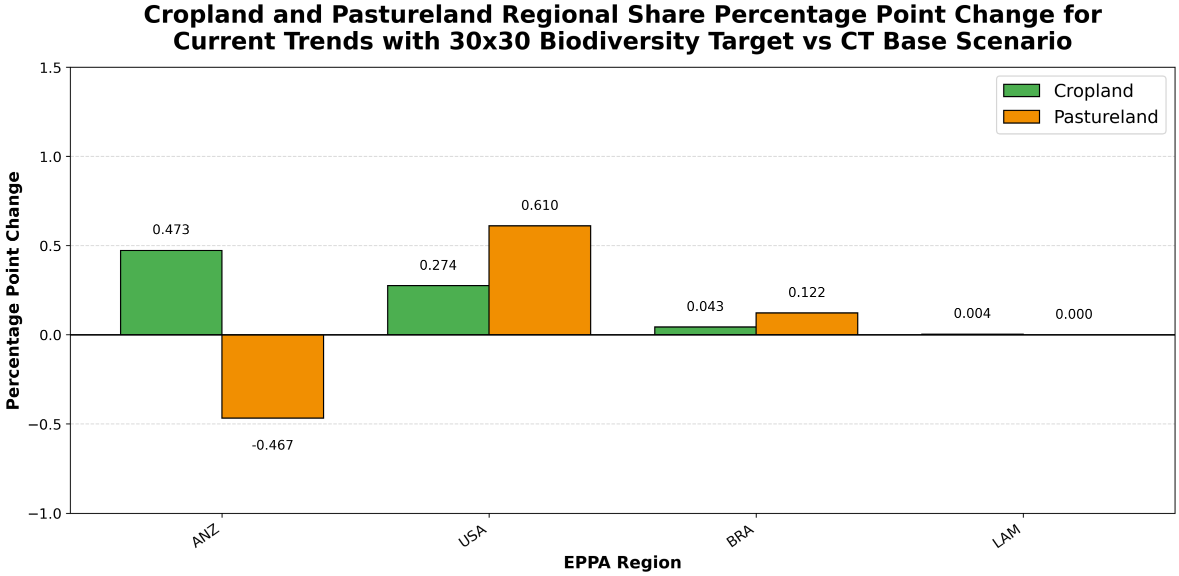


Figure 2.5: Cropland and Pastureland Regional Share Percentage Point Change for EPPA regions that gain in GDP under a Current Trends (CT) 30-by-30 biodiversity target scenario in comparison to one without.

reflect current deforestation-free import regulations, such as the EU Deforestation Regulation (EUDR), where conditions require EU importing businesses to demonstrate that commercialized products are not produced illegally or under destructive practices (B. Li et al., 2025). This increased scrutiny on traceability and entry of 6 imported agricultural commodities and their derivatives, therefore, incentivizes producers abroad to adopt regulation-compliant and sustainable deforestation-free practices to continue operating in the market. Modeled EPPA outputs can further inform these regional priorities for the implementation of similar deforestation-free import guards, where India and the Middle East remain top priorities. Previously raised points on the 30-by-30 impact on GDP and land scarcity, in addition to IND and MES' already high volumes of imports on agricultural products (FAOSTAT, 2026), factor into concerns of potential future deforestation-fueled agricultural imports. Therefore, this highlights a priority to set supplementary deforestation-free market import policies in these regions.

EPPA outputs further show that food security risks will be a point of concern in the future development of a 30-by-30 biodiversity target under Current Trends. To measure regional vulnerability to this shift, the method only analyzed agricultural product classifications or crop outputs that comprised more than 1% of household spending to be considered as relevant or sensitive to price changes (i.e., if buying wheat comprises <1% of the household spending in Brazil, then it would not be considered in the analysis). With this consideration, most developed regions were filtered, while among the remaining regions the sharpest upticks were observed in food prices for IND, MES, AFR, and ROE. Figure 2.6 shows that MES will experience the most dramatic single category food price increase, with the category for fish, raw milk, and wool increasing up to approximately 620%. Meanwhile, the price shift with the largest impact will be for vegetables, fruits, and nuts which rise by a near 120%, but comprise a larger fraction of the average household's spending in the Middle East. Similarly, across other impacted regions, it is observed that agricultural products such as vegetables and fruits, fish, and raw milk that compose the largest fraction of the average household consumption will see increases in prices of about 5-10%. As these values are an average of the household consumption across a spectrum of different incomes, this 5-10% increase in price could make crucial products such as vegetables, fruits, and nuts inaccessible to low-income households in AFR and IND. Therefore, potentially deteriorates the nutrition and health of lower-income households. The captured distributional effects of a 30-by-30 target under CT on food accessibility and nutrition, therefore, require the implementation of supplementary food policies in key regions such as AFR, IND, MES, and REA. Furthermore, regional investment strategies should focus on yield intensification technologies and practices that secure the future supply of crops such as vegetables, fruits, and nuts that are projected to become considerably less accessible under a 30-by-30 biodiversity target under current climate policies.

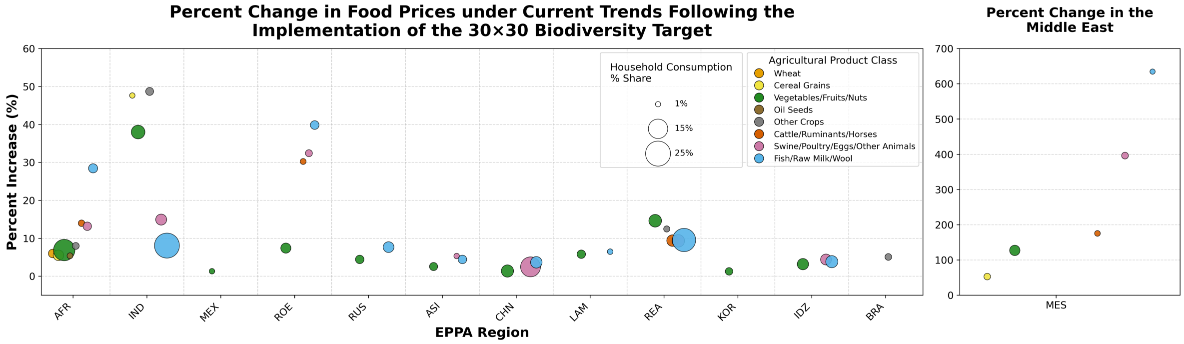


Figure 2.6: Percent change in food prices under Current Trends following the implementation of a 30-by-30 biodiversity target. Analyzed components consider only agricultural categories that compose more than 1% of household consumption. The size of the circle depicted represents a crop classification and scales with the household consumption fraction of that agricultural category.

In Accelerated Actions (AA) with subsidies for 30-by-30 versus AA alone, the scenario observed similar patterns to Current Trends (CT) under the same model assumptions. GDP experiences similar decrease and gain patterns across EPPA regions, although at smaller proportions in comparison. For AA, the case observed a contraction of -10.21, -2.30, -1.50, and -0.61% in MES, IND, REA, and AFR, respectively. Meanwhile, strong agriculture and pastureland regions such as BRA, ANZ, LAM, and USA observe GDP increases of 0.34, 0.31, 0.22, and 0.02% (Figure 2.7). These simulated changes in GDP are despite a generalized fall in household consumption across all EPPA regions in AA (Figure 2.4) (except for a small increase in Mexico). Hence, similar to Current Trends, agricultural and animal exports to areas experiencing decreases in food production—such as MES, IND, and REA—will likely increase. In Figure 2.8, visualized EPPA outputs further observed similar shifts in land use for regions that experience a gain in GDP under AA with the 30-by-30 target, where most regions experience an increase in percentage share of land dedicated to cropland, pastureland, or both. Finally, for regions such as ROE, EUR, and ASI that also required subsidies to reach the 30-by-30 target, GDP responses show a contraction of -0.24, -0.23, and -0.13%, respectively.

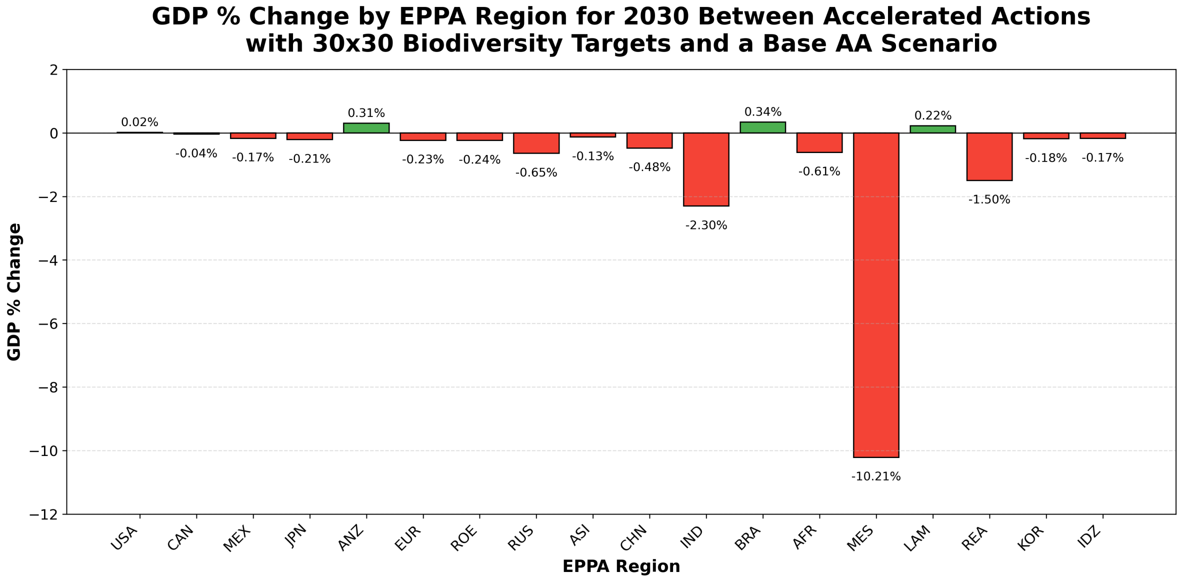


Figure 2.7: GDP percentage change for each EPPA region by 2030, subtracting GDP in an Accelerated Actions scenario with implemented 30-by-30 target subsidies from a base AA scenario without.

When comparing the AA 30-by-30 scenario to AA alone, the modeled results show similar patterns to Current Trends outputs. This case observed sharp decreases in GDP for IND and MES, which could be related to limitations in the method to proxy protected areas and the cost of land conversion under the assumptions for modeled biodiversity-rich nfors+ngrass PAs. Furthermore, even though the impacts on GDP and household consumption are lower in comparison to Current Trends, the AA case continues to observe a similar socioeconomic pattern that suggests the potential for deforestation leakage, especially for MES and IND. Therefore, under an AA scenario, these regions would continue to require similar deforestation-free import regulations to prevent net global biodiversity and ecosystem

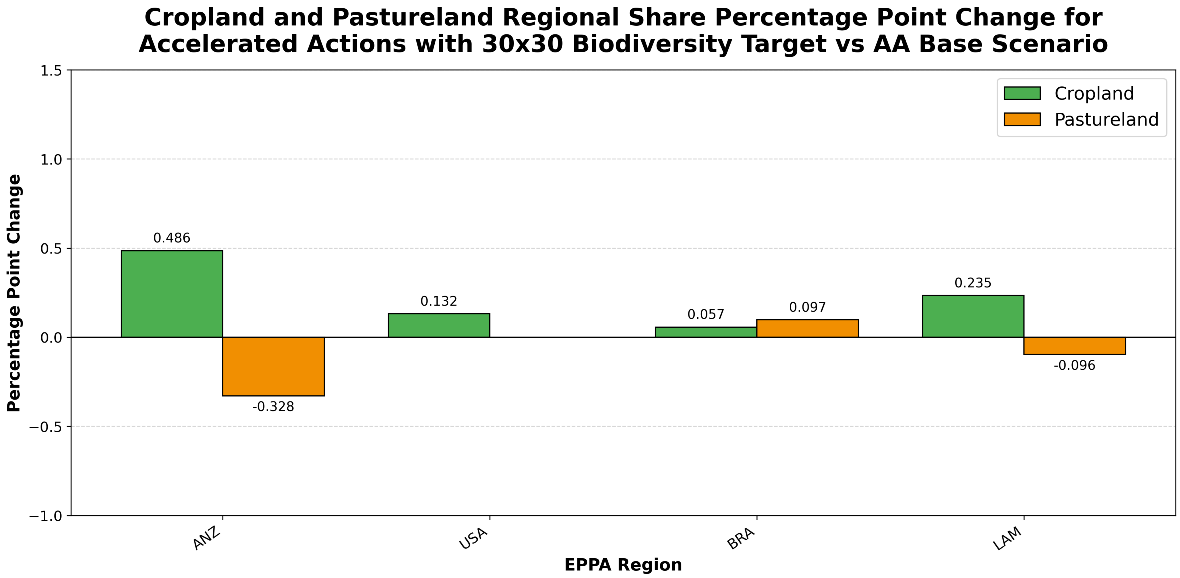


Figure 2.8: Cropland and Pastureland Regional Share Percentage Point Change for EPPA regions that gain in GDP under an Accelerated Actions (AA) 30-by-30 biodiversity target scenario in comparison to one without.

loss, as well as consideration of desert land PAs toward achieving the 30-by-30 target.

In terms of the distributional effect on food prices of the 30-by-30 target under AA, the scenario observes responses similar to those established in CT. MES will continue to present the largest increase in price for a single agricultural product class, with fish, raw milk, and wool rising to approximately 600%. Meanwhile, in Figure 2.9, it is observed that the patterns for crop types with the largest household consumption shares continue to hold similar behaviors across EPPA regions, albeit with slight shifts in certain agricultural sectors and a generally smaller increase in food prices across EPPA regions.

Comparing AA with CT scenarios shows that weak climate change policies result in higher costs to reach the 30-by-30 biodiversity target. Despite similarities in GDP changes as a result of the 30-by-30 target, GDP growth and decreases are both reduced in the AA scenario (Table 2.1). This results from more stringent climate change policies set in AA, indirectly impacting GDP. AA's higher carbon taxes and clean energy technology investment policies result in overall reduced household consumption and a change in GDP in comparison to CT (Table 2.1 and Figure 2.4); consequently, reducing land use change. Subsidy costs to transition pastureland and cropland into protected natural grass or forest are therefore lowered. Table 2.1 shows that AA reduces subsidy burdens on GDP contraction the most for the yet-to-reach 30-by-30 regions with low ngrass+nfors, such as MES, IND, REA, and AFR. Four regions that intersect 15 of 36 global biodiversity hotspots, forests, and other habitats representing just 2.5% of Earth's surface but supporting more than half of the

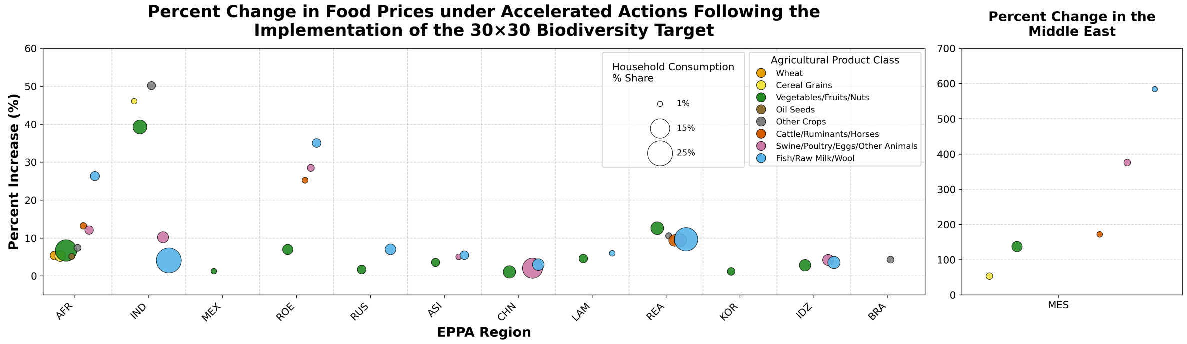


Figure 2.9: Percent change in food prices under Accelerated Actions following the implementation of a 30-by-30 biodiversity target. Analyzed components consider only agricultural categories that compose more than 1% of household consumption. The size of the circle depicted represents a crop classification and scales with the household consumption fraction of that agricultural category.

world's endemic plants and nearly 43% of bird, mammal, reptile, and amphibian species as endemic (Hoffman et al., 2016; Stork & Habel, 2014; Conservation International, 2025). Modeled AA, however, also lowers GDP growth for regions with strong agriculture and livestock industries such as BRA, ANZ, LAM, and USA; albeit, all still experience overall comparative advantage and relative growth. A result that could be triggered by smaller streams of inter-regional trade associated with more stringent climate change policies and lower consumption.

In AA, household consumption tends to decrease at similar proportions as CT. However, it is observed that some regions could experience either a smaller decrease or a larger decrease for some EPPA regions (Table 2.2). The variation could result from some regions presenting fewer climate mitigation options due to geographical and physical factors, hence, also increasing the costs for some regions to comply with the more stringent AA climate policy.

Reaching the 30-by-30 biodiversity target is still significantly less costly than reaching an AA climate target under PAs modeling assumptions. Setting CT with no 30-by-30 biodiversity target as the baseline, outputs were compared across absolute GDP changes for implementing a 30-by-30 biodiversity policy, an AA climate policy, and a compounded scenario where both are applied (AA with 30-by-30) (Figure 2.10). The figure shows that in most EPPA regions, the 30-by-30 policy produces a smaller impact on GDP relative to the more aggressive AA climate policy scenario. The one exception is MES, where the absolute negative change in the region due to 30-by-30 could be comparable to that resulting from meeting the AA climate target. Overall, modeled results signal the possibility that two major concurrent international targets, the 30-by-30 protected areas biodiversity target in addition

Table 2.1: Percentage Point Difference between Current Trends (CT) and Accelerated Actions (AA) for GDP percentage change in each scenario.

EPPA Region	**CT % Change in GDP**	**AA % Change in GDP**	**Percentage Point Difference (AA% - CT%)**
ANZ	0.40	0.31	-0.09
BRA	0.43	0.34	-0.09
LAM	0.23	0.22	-0.01
USA	0.03	0.02	-0.01
JPN	-0.22	-0.21	0.01
ASI	-0.14	-0.13	0.01
CAN	-0.09	-0.04	0.05
EUR	-0.29	-0.23	0.06
KOR	-0.24	-0.18	0.06
CHN	-0.56	-0.48	0.08
IDZ	-0.29	-0.17	0.12
RUS	-0.77	-0.65	0.12
MEX	-0.30	-0.17	0.13
REA	-1.65	-1.50	0.15
ROE	-0.40	-0.24	0.16
AFR	-0.81	-0.61	0.20
MES	-10.42	-10.21	0.21
IND	-3.49	-2.30	1.19

Table 2.2: Percentage Point Difference between Current Trends (CT) and Accelerated Actions (AA) for Household Consumption percentage change in each scenario.

EPPA Region	**CT % Change in Household Consumption**	**AA % Change in Household Consumption**	**Percentage Point Difference (AA% - CT%)**
ANZ	-0.11	-0.16	-0.05
BRA	-0.44	-0.46	-0.02
LAM	-0.35	-0.41	-0.06
USA	-0.08	-0.08	0.00
JPN	-0.02	-0.01	0.01
ASI	-0.24	-0.28	-0.04
CAN	-0.12	-0.13	-0.01
EUR	-0.34	-0.07	0.27
KOR	-0.08	-0.05	0.03
CHN	-0.39	-0.31	0.08
IDZ	-0.43	-0.22	0.21
RUS	-0.40	-0.17	0.23
MEX	-0.04	0.01	0.05
REA	-2.24	-2.08	0.16
ROE	-0.91	-0.89	0.02
AFR	-0.77	-0.70	0.07
MES	-10.80	-10.35	0.45
IND	-1.86	-0.01	1.85

to a global warming mitigation climate policy, could present no further significant economic burdens on GDP for most regions when deployed.

These outputs are true under an economic-first conservative estimate, which models an nfors+ngrass proxy method for biodiversity-rich protected areas and assumes a 30-by-30 where PAs do not incur further costs associated with unlawful misuse. Therefore, modeled 30-by-30 implementation costs could be considerably higher due to the funding costs associated with preventing PAs from illegal human development and encroachment. At the same time, the model focuses on the direct costs associated with protecting and regenerating PAs; therefore, EPPA does not capture future ecosystem services benefits, such as pollination and water filtration at the boundary of the PAs. However, any future human intervention or extraction benefits, such as timber, are disabled. Although this experiment seeks to compare direct absolute changes in GDP produced by the climate policy and the 30-by-30 target (individually) against their combined climate and biodiversity intervention, their fundamental cost structures differ. Therefore, the sequence and interaction between implementing the AA target first and then the 30-by-30 or vice versa, could have repercussions on the GDP change of the other (i.e., the implementation of an AA target could produce lower weather impacts on cropland yield, consequently, lowering their land value and costs to regenerate them into forests under a 30-by-30).

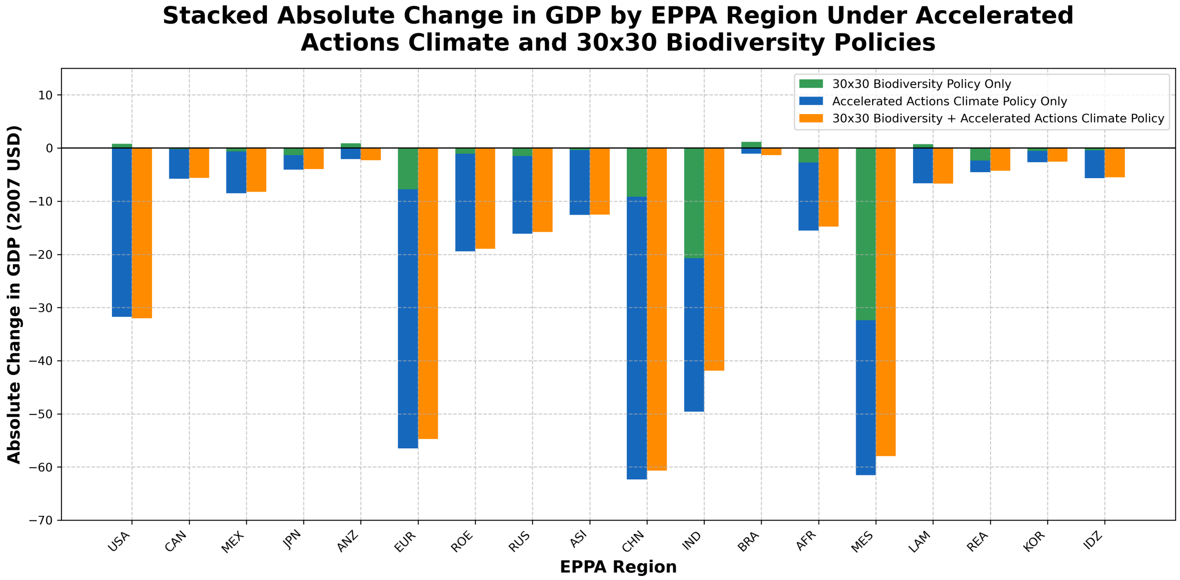


Figure 2.10: Bar plot representation of the absolute change in GDP by EPPA region benchmarked against a base Current Trends without 30-by-30 baseline scenario. Bars represent a 30-by-30 biodiversity policy only (green), Accelerated Actions climate policy only (blue), and a concurrent scenario with 30-by-30 and Accelerated Action climate policies (orange).

2.4 Conclusion

This study investigated how simultaneous climate change targets and a "30-by-30" global biodiversity goal could affect the economy and social systems across global economic regions. The 30-by-30 target was applied to a dynamic multi-sectoral and multi-regional CGE model with expanded natural resource allocation capabilities (EPPA), which also simulated the world economy for two climate change target scenarios (CT and AA). These climate change scenarios highlight a world economy that follows the present Paris Agreement to the end of the century (CT) and a more stringent scenario that stabilizes global average temperatures at 1.5°C by 2100 with 50% probability (AA).

Modeled outputs show that a weaker climate change policy could lead to higher costs to reach the 30-by-30 target. Projections in EPPA showed that in the AA scenario, intra-region GDP decreases less across economic regions relative to CT under the 30-by-30 target (Table 2.1). Higher taxation on carbon and investment for decarbonization could reduce consumption and consequently disincentivize land conversion of natural capital. As a result, with the more stringent AA climate target, the concurrent 30-by-30 goal would require fewer subsidies to reach the biodiversity target in MES, IND, REA, and AFR. Four regions that intersect 15 of 36 global biodiversity hotspots, supporting more than 50% and 43% of endemic plant and vertebrate (bird, mammal, reptile, and amphibian) species, respectively.

Modeled results under the current protected areas proxy method show that a 30-by-30 biodiversity target has a lower absolute GDP impact at the regional level than reaching the more stringent AA climate policy. Hence, it signals the feasibility of deploying both biodiversity and climate goals simultaneously, as well as adding incentive for economic regions to protect valuable biodiversity and ecosystems without significantly impacting their GDP. However, these results are conservative estimates, as previously discussed limitations in the proxy method to account for costs from increasing protected areas could suggest a higher modeled estimate.

Regions with low amounts of natural grassland and forest hosting high biodiversity and ecosystem functions experience the largest negative changes in GDP. In the case of MES, the region was only able to total 24.4% of protected areas before reaching a physical ceiling in the amount of natural lands that can be protected in the modeling process. However, further sensitivity simulations with EPPA highlighted how the inclusion of desert areas (lands considered "less biodiverse" yet still harbor important natural ecosystems) outside of the outlined nfors+ngrass proxy method for biodiversity-rich PAs can have a substantial and beneficial impact on GDP losses. Taken together, these results offer an important context on how much desert areas should nations within regions such as the MES be allowed to contribute towards any PA 30-by-30 target. As land rich in fertile soil and water resources for agriculture often overlaps with scarce biodiversity-rich areas, governance and policy decisions must balance between protecting land for biodiversity while avoiding overlabeling of low-value and biodiversity desert areas toward the 30-by-30 goal.

AA and CT outputs highlight a potential for 30-by-30-triggered deforestation leakage effect. The study found that increases in protected areas in major developing economies (i.e., MES, IND, REA, and AFR) could result in potentially a deforestation leakage to other EPPA regions. A decrease in available land for agriculture and livestock could increase reliance on agricultural and animal products imports to compensate for food demand. Therefore, such a one-dimensional 30-by-30 policy dynamic risks simply redirecting ecosystem degradation to large food producer regions such as BRA, ANZ, LAM, and the USA at a comparative advantage. This response pattern is seen in the EPPA results as an increase in the regional share of land dedicated to cropland and pasturelands across the four regions that gain the most in GDP after the implementation of the 30-by-30 biodiversity target. If the 30-by-30 target is to prevent net global loss in biodiversity, supplementary policies that counter these deforestation leakages will need to be in place. Governance must establish domestic efforts to curb potential deforestation concealed in food imports from regions often at a comparative advantage due to lax environmental regulations or abundant natural resources. Regional policymakers should establish deforestation-free import regulations similar to the EUDR, which dictate this precondition as a leverage for the commercialization of imported agricultural commodities. Therefore, pushing commodity producers abroad to shift away from ecosystem-destructive practices to maintain access to the market. Modeled EPPA outputs further inform the regional prioritization of these deforestation-free import regulations. For IND and MES under the CT and AA scenario, it was observed that the 30-by-30 impact on GDP and increased cropland and pastureland scarcity, in addition to their high volume of imports on agricultural products, make them vulnerable to deforestation-fueled agricultural imports. Therefore, this suggests a priority to establish supplementary deforestation-free market import policies in these regions first.

Under CT and AA, the study further analyzed the distributional effects on food prices that the 30-by-30 biodiversity target could generate. The outputs show that across EPPA regions such as AFR, IND, and REA, the projected post-30-by-30 increase in food prices could reach 5-10% for vegetables and fruits and fish and raw milk, which comprise the largest fraction of the average household consumption in those regions. As this value is a mean of household consumption spanning all incomes, this 5-10% increase could make agricultural products such as vegetables, fruits, and nuts inaccessible to low-income households in AFR and IND. Therefore, significantly deteriorates the accessibility to a quality diet and nutrition in lower-income households. To address this potential projection, key regions such as AFR, IND, MES, and REA will need to prioritize regional food policies that invest in yield intensification technologies and techniques to secure the future supply of nutrition-essential crops projected to become less accessible under the 30-by-30 target.

There remain uncertainties in the previously outlined simulations, which require further investigation. Despite EPPA's ability to project economic and social responses to policy interventions, it carries limitations in measuring direct localized impact. The model's underlying computational framework was optimized to reach pressing global warming and protected area biodiversity targets for large economic regions within limited time frames; however, it cannot geographically track land transitions for detailed ecosystem delineation of PAs or account for overlaps with particular communities and Indigenous lands. In the case of delineating ecosystems, the proxy method based on biodiversity-rich protected nfors+ngrass could be significantly improved by the integration of high-resolution tools. This would expand conservative estimates to evaluate for unaccounted costs and benefits that reflect the real state of protected areas. Hence, accounting for both positive ecosystem services benefits at the boundary of protected areas, as well as costs from their proximity to urban areas and risk of human encroachment and development. In the case of overlapping with community lands, EPPA is not able to distinguish ownership of developed agricultural and pastureland, which could lead to results that reflect unintentional conversion of traditional Indigenous farmed lands. However, ongoing investigations aimed to integrate these EPPA results with downscaling tools will effectively distribute regional projections to finer spatial resolutions, allowing the model framework to account for more detailed cost-benefits of protected areas and evaluate their localized impacts on particular Indigenous lands and communities in proximity.

Chapter 3

Demeter Model

3.1 Literature Review

EPPA's underlying computational framework was optimized to reach dual climate and biodiversity goals within limited time frames and socioeconomic parameters; however, it cannot geographically track land transitions and the detailed state of PAs or overlaps with particular communities and Indigenous lands. Therefore, this investigation aims to overcome this limitation by downscaling EPPA land use projections (e.g., grassland and forests) and the detailed extent of crops and vegetation, representing the distribution patterns and shifts that coupled conservation and climate targets have on land use and key land types such as food crops.

Projecting land use change to a finer spatial resolution at pixel-level transitions for parcels of land is challenging. Previous efforts attempted to project Integrated Assessment Models (IAMs) and Multi-Sector Dynamics (MSD) models to higher spatial resolution; however, these often lacked predictive capacity (Alexandratos & Bruinsma, 2012; Luo et al., 2023). The literature suggests that several frameworks address the downscaling of land use change from IAMs to higher spatial resolution (A. Gurgel et al., 2025). The most prominent among these methods is Hurtt et al. (2020), which downscales land use land cover (LULC) from various IAMS and couples them with Earth System Models (ESM) at higher resolutions. Previous studies also attempted to construct partial equilibrium models with high-resolution economic and environmentally driven downscaling decisions on land use (U. L. C. Baldos et al., 2020); however, a limitation to this approach is often in the versatility and reliability to adapt downscaling to alternative modeling frameworks. These downscaling algorithm representations to finer spatial resolution could often be "hard-coded" to specific modeling structures, lacking general equilibrium effects and competition among alternative LULC (A. Gurgel et al., 2025). Le Page et al. (2016) aimed to minimize these limitations by developing Demeter, a downscaling algorithm that generates finer resolution land use projections by integrating aggregated outputs produced by IAMs. This downscaling algorithm was constructed for a specific IAM context, but was aimed to remain versatile enough to be adapted for other models and pixel resolutions.

A range of studies have applied Demeter to downscale IAM projections, such as the Global Change Analysis Model (Calvin et al., 2019) and GCAM-USA (Binsted et al., 2022), to produce high-resolution LULC change representations across socioeconomic and climate scenarios (M. Chen et al., 2020; Vernon et al., 2018). Meanwhile, more recently, A. Gurgel et al. (2025) extended the use of Demeter by harmonizing its interoperability with EPPA, designing a Multi-Sector Dynamics (MSD) framework that integrates EPPA aggregated regional outputs to a 0.5 degree grid scale localized projections, creating a socioeconomic economy-wide IAM modeling to a high-resolution LULC projection pipeline. In the following pages, this thesis builds on previous literature and aims to extend contributions to understand two main points: 1) The localized impacts and state of land use as a result of competing land pressures from a 30-by-30 biodiversity target coupled with current climate targets, and 2) measure the EPPA to Demeter pipeline sensitivity to varying parameters and socioeconomic scenarios.

3.2 Methodology

Demeter is an open source model designed to distribute land use projections from economic models to higher resolution representations by modeling land transitions at a pixel level in fractional and physical units (M. Chen et al., 2019; Le Page et al., 2016; Vernon et al., 2018). The downscaling algorithm evaluates land allocation based on pixel suitability characteristics and user-imposed constraints and transition rules to project LULC types. Demeter solves for land use across sequential allocations, allowing for previously produced maps to influence future land projections (A. Gurgel et al., 2025). Therefore, this approach presents an advantage over statistical methods, as it explicitly accounts for and allocates LULC based on pixel-level spatial and temporal relationships between natural and human-managed land. Therefore, Demeter's land allocation at time steps t for $t > 1$ is based on the previous (t - 1) time step projected spatial map, whereas at $t = 1$ or the initial map, it is modeled after a base data map.

In Demeter, the user can further set constraints or rules depending on different priorities for the case scenario. Spatial constraints are defined at the pixel level, p, for each land type, l, on a scale from 0 to 1. The user can assign a low constraint value, which would cue Demeter to allow a pixel for more degrees of freedom in land allocation derived from the base map or previously produced (t - 1) map and proximity to other pixels of the same land type. In other words, a low constraint allows for more allocation of a land type based on previously present pixels. Meanwhile, a high constraint value for a pixel in a particular land type would force Demeter to follow an input user value. The latter is detailed in the user input fine resolution constraint file, which is also scaled from 0 to 1, where every pixel can be assigned a value toward a preferred land type. This study takes advantage of this property to guide Demeter to make land allocations based on RESOLVE 2017 Ecoregion and World Database on Protected Areas (WDPA) data. In preparation, the biome and PA data were first rasterized for every land pixel p, and depending on the amount of the cell that is occupied by the biome, a 0 to 1 value was assigned. For example, if p intersects a tropical and subtropical moist broadleaf forest biome, then a higher user-input value is assigned for forest land use in that pixel while grassland land use would be lower; the opposite would occur for a pixel that contains a tundra biome with extensive grasslands. This is followed by a weighted average calculation for pixels that contain a combination of biomes, where scaled values for forest and grassland would be adjusted accordingly to the amount of area occupied by each biome. Pixels with protected areas are assigned a fine resolution constraint close to 0 to avoid future land use changes to that pixel.

Additional parameters allow Demeter to further govern downscaling priorities. Intensification ratio (IR) represents the ideal fraction of LULC for a particular land type that populates pixel p, while the remainder (1- IR) represents the extensification ratio. In other words, IR limits the fraction amount of a land type to be allocated in a pixel before moving on to allocating a surrounding pixel. Finally, Process Order allows users to choose the sequence by which Demeter assigns land types (i.e., forest, grasslands, or corn) to pixels.

3.2.1 EPPA Scenarios

In this study, the framework adapted a series of EPPA scenarios developed by A. C. Gurgel et al. (2021a) that cover high and low values for 6 different stressors that capture potential divergences from a Business As Usual (BAU) scenario, which contains no climate change policies. Where stressors are defined as socio-economic and environmental drivers that influence land use decisions and therefore lead to higher or lower needs for managed lands (e.g., croplands). To create a more representative application of the scenarios, the approach implemented 6 different high and low scenarios under the Current Trends (CT) with 30-by-30 biodiversity projections to reflect present climate change policies, emissions reductions, and biodiversity commitments as described in Chapter 1. Moreover, the methods also consider a combined stressors scenario or high all, which inflicts the greatest force or pressure on EPPA regional land allocations under a CT 30-by-30 target scenario. Conversely, a low all scenario, which reflects the low stressors across all scenarios, was also implemented.

This ensemble of 14 high and low socioeconomic stressor scenarios (Table 3.1) covers a range of possible drivers and stressors affecting future projected land use described in previous literature (Hertel, 2011; Stehfest et al., 2019). In the low trade scenario, trade barriers were increased by 50%, while in the high trade scenario, they were reduced by 50%. In the low climate impacts scenario on crop yield and livestock, productivity, and pasture yields were adjusted to reflect the average impacts from global gridded crop models in Blanc (2017), which often tend to produce increased crop yields A. C. Gurgel et al. (2021b). In the high climate impacts scenario, the case assumes a central value of crop yield impacts from the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment report (Porter et al., 2014), which observes mainly negative effects on yield but varying across regions. Yield changes were extracted from the Global Gridded Crop model and IPCC for staple crops such as rice, wheat, maize, and soybean; Other Crops (OCR) and pasture and livestock are assumed to have a simple average change in yields from the previous four major crops, following an approach by A. C. Gurgel et al. (2021b). In terms of low yield constraint, the scenario assumes a higher rate of increase in exogenous crop yields due to faster research and development (R&D) and diffusion, while a high yield constraint represents a lower rate in R&D and therefore lowered research-assisted increase in agricultural yields. These yield improvement rates further correspond with the literature (Ray et al., 2013). For low meat demand, the stressor was determined by decreases in income elasticity of demand for meat, which results in decreased meat demand in developed countries; an opposite change in income elasticity is considered for a high meat demand scenario. Low and high population growth scenarios assume a population growth 1% lower and higher in comparison to the adapted CT baseline, respectively. Likewise, low and high economic growth assume 20% lower and higher GDP growth in comparison to the baseline.

3.2.2 Linking EPPA and Demeter

Localized pixel-level LULC changes are dependent (to some degree) on economic drivers projected at regional and global levels that are represented in EPPA. Meanwhile, sub-regional nuances and finer resolution differences are captured by the base map applied in Demeter. The latter reflects LULC at the benchmark or initial time step from which Demeter contextualizes early land allocation time steps. This base map is combined with previously described Demeter parameters and assumptions (e.g., Intensification Ratio or Process Order) to produce pixel-level land use projections consistent with existing spatial patterns;

Table 3.1: EPPA scenario names and brief descriptions of high and low cases derived from socioeconomic stressors applied to a Current Trends (CT) 30-by-30 baseline.

Scenario	**Brief Explanation**
Current Trends (CT) with 30-by-30	Baseline scenario with current climate change policies and 30-by-30 biodiversity targets
low trade	Reduced trade due to 50% higher import tariffs globally
low clim. imp. crops & livest	Positive climate impacts on crop and pasture yields from Global Gridded Crop Models
low yield constraint	Higher annual increase in crop yields (1.5% per year)
low meat demand	Changing diet toward lower income elasticity on meat demand
low pop. growth	Lower population growth (1% lower than CT baseline)
low econ. growth	Lower GDP growth (20% lower than CT baseline)
low all	Combined low scenario impacts
high trade	Increased trade due to 50% lower import tariffs globally
high clim. imp. crops & livest	Negative climate impacts on crop and pasture yields from IPCC local crop models
high yield constraint	Negative annual increase in crop yields (0.5% per year)
high meat demand	Changing diet toward higher income elasticity on meat demand
high pop. growth	Higher population growth (1% higher than CT baseline)
high econ. growth	Higher GDP growth (20% higher than CT baseline)
high all	Combined high scenario impacts

previous studies have prescribed similar approaches to Demeter downscaling in the continental United States and global land use downscaling (M. Chen et al., 2020; A. Gurgel et al., 2025).

The schematic (Figure 3.1) and main steps to integrate the Demeter-EPPA framework for higher resolution LULC projections are derived from A. Gurgel et al. (2025) and described as follows:

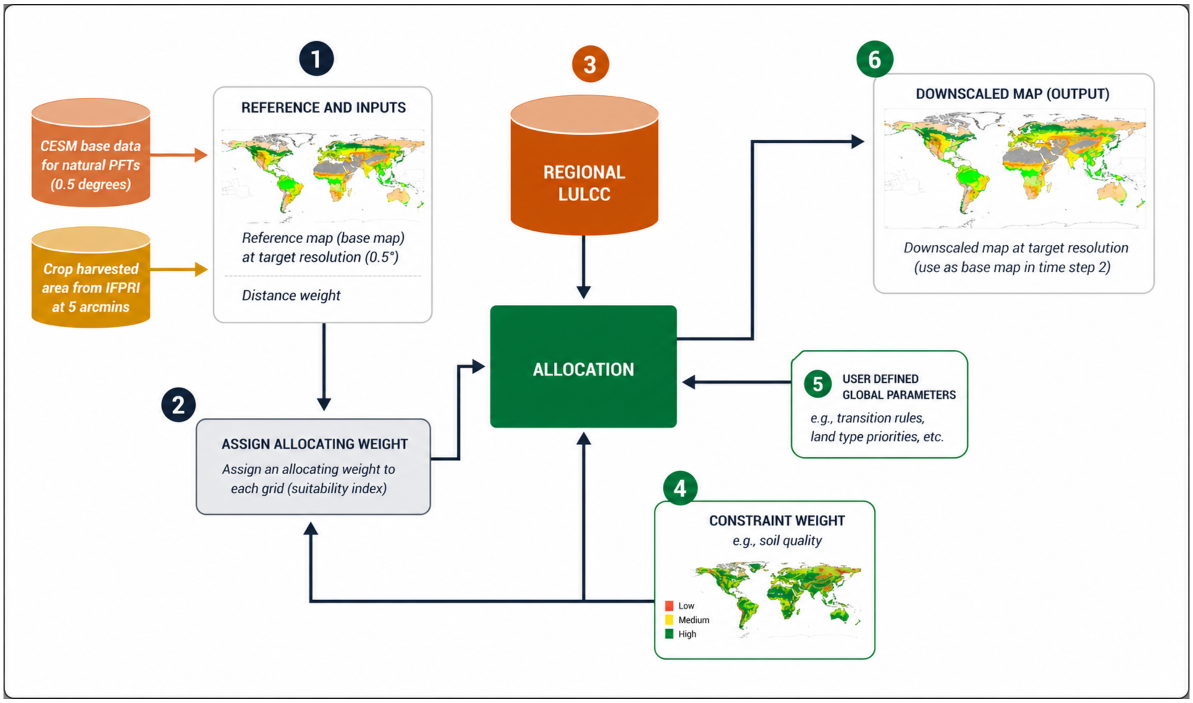


Figure 3.1: Schematic outlining the Demeter-EPPA harmonized model framework pipeline sequence and inputs to downscale LULC projections to the pixel-level observations.

1. Demeter requires an initial base map for LULC at time step t = 1. The model was initialized with a map from the Community Land Model (CLM 5.0), which is harmonized with fine-resolution crop harvest data from IFPRI MapSPAM.

2. According to this initial base map, Demeter sets initial spatial allocation constraints and its complementary kernel density (1 - allocation constraint) value. A high kernel density determines future land use change for land type l to expand around neighboring pixels that have the same land type l or expansion to new surrounding pixels (low kernel density).

3. Demeter intakes regional LULC projections from EPPA, defining net regional land use change across 5-year time steps.

4. Additionally, the user can define fine resolution constraints (e.g., ecoregion and protected area-based constraints) to more explicitly guide Demeter to downscale particular land types to selected pixels.
5. The user can further set transition rules through global-level parameters to project LULC across sequential allocations, giving transition priority to certain land types along with regional parameters for LULC change to determine allocation constraints in each pixel. EPPA regional land use allocations are not affected by Demeter transition rules. Meanwhile, the linking of the Demeter and EPPA acts in conjunction to capture regional economic signals while also considering the spatial characteristic suitability at the pixel-level and other set constraints (as explained in point 4).
6. Steps 1-5, therefore generate the "gross" land use maps for all land types at the pixel-level and a final map of LULC at a user-defined time step 1, which serves as a base map for time step t+1.

In order to harmonize the Demeter and EPPA models, the linked approach had to adjust land type categories to extend compatibility across the framework. The Demeter base map treats forest as a broad land use category; therefore, mapping EPPA natural and managed forests into a single land category. Similarly, Demeter does not distinguish natural grassland and pasturelands, which are combined into a single category as a result of the EPPA to Demeter pipeline. Finally, Demeter tracks crop types at a higher detail, which allows for the separation of EPPA-generated cropland projections to be separated into individual crops such as corn, wheat, and paddy rice, among others. These details are described more fully in Table 3.2.

3.2.3 Sensitivity Analysis

To test the impact of Demeter and EPPA scenarios on the final LULC map, this study implemented a sensitivity analysis that tests the Demeter-EPPA integrated framework across downscaling parameters and economic stressors. For Demeter, three variables, including the Allocation Constraint, Intensification Ratio, and Process Order, were adjusted; in addition to the ecoregion and protected areas-based fine resolution constraints. Allocation constraint and intensification ratio were varied to cover all combinations through a parametric sweep from 0 to 1 at 0.1 variations (both parameters are increased by 0.1 until all combinations from 0 to 1 are reached). For Process Order, the method varied allocation order for land types following a Default Process Order for Demeter as tested by M. Chen et al. (2020) and two experimental energy-first and food production-first sequences, which are defined in

Table 3.2: Land use harmonization and mapping between Demeter and EPPA land use categories to establish an integrated Demeter-EPPA linked framework.

Land use categories in EPPA	**Land use categories in Demeter**	**EPPA-Demeter aggregated land use categories**
Natural Grassland	Pasture and Grazing Land	Pasture and Grazing Land
Pasture and Grazing Land		
Natural Forest	Forests	Forests
Managed Forest		
Cropland		
Paddy Rice	Paddy Rice	Paddy Rice
Coarse Grains	Corn	Corn
Oil Seeds	Oil Seeds	Oil Seeds
Wheat	Wheat	Wheat
Sugar Crops	Sugar Crops	Sugar Crops
Vegetables & Fruits	Vegetables & Fruits	Vegetables & Fruits
Plant Based Fibers	Plant Based Fibers	Plant Based Fibers
Other Crops	Other Crops	Other Crops
Biomass		
Other Land Uses	Other Land Uses	Other Land Uses

Table 3.3. For EPPA, as previously mentioned, a 14 high and low stressor scenarios ensemble was adapted from a Current Trends (CT) climate change policy scenario with the 30-by-30 biodiversity target.

Table 3.3: Demeter downscaling land type sequences for user-inputted Process Order Scenarios

Default	**Energy First**	**Food First**
Other	Forest	Forest
Wheat	Grassland	Grassland
Corn	Other	Corn
Paddy Rice	Corn	Wheat
Other Crop	Sugar Crops	Paddy Rice
Oil Seeds	Oil Seeds	Vegetable and Fruits
Sugar Crops	Wheat	Sugar Crops
Plant Based Fibers	Other Crops	Oil Seeds
Vegetables and Fruits	Paddy Rice	Other Crops
Forest	Vegetable and Fruits	Plant Based Fibers
Grassland	Plant Based Fibers	Other

3.3 Results/Discussion

Sensitivity tests show that downscaled final output maps can be influenced by both varying Demeter allocation constraint and intensification ratio parameters; however, their sensitivities vary significantly by EPPA region and crop type. The study focuses on grassland and forest parameters that govern areas that are key to protected areas. To represent and facilitate comparison across a large number of final outputs generated from a combination of Demeter parameters and EPPA stressor scenarios (121 combinations across 12 stressor scenarios, respectively), the final outputs were represented in the form of heatmaps by spatial correlation. In each heatmap, vertical axes represent EPPA regions and horizontal axes represent the variation across EPPA stressor scenarios. Values in each cell represent the spatial correlation between the EPPA stressor scenario and region with a set of Demeter parameters against the same combination of configurations in the Current Trends (CT) baseline. This represents the similarity for each pixel across every cell in the two maps to be compared. To summarize the high dimension of output data, model outputs were represented as minimum spatial correlation and mean spatial correlation heatmaps. Minimum spatial correlation corresponds to selecting the Demeter parameters (allocation constraint + intensification ratio) and EPPA stressor scenario and region combinations against their CT 30-by-30 baseline counterpart (Figure 3.2) that produces the lowest spatial correlation.

In terms of mean spatial correlation, the value represented in each cell is obtained from the average of every spatial correlation across all 121 combinations of Demeter parameters under a particular EPPA stressor (12 scenarios) and region configuration. Finally, the colorbar feature represents low spatial correlation between the two configurations in a yellow tone and progresses to green and then blue in the middle and high spatial correlation spectrum; the lower end of the color bar was adjusted to the spatial correlation value and not equally scaled across heatmaps to highlight differences more clearly. These heatmap representations were applied across three different Demeter Process Orders—Default, Energy First, and Food First.

For grassland with a Default Process Order (Figure 3.3), the lowest minimum spatial correlation was observed at 0.543 in India (IND) under a high all EPPA stressors scenario. Due to the stark difference between the lowest value and other scenarios across IND, this discrepancy could signal a strong effect from a land-demanding high all scenario in India and Demeter parameters (allocation constraints and intensification ratio). As previously established in Chapter 1, IND requires a significant amount of subsidies to expand a considerable number of PAs by restoring managed land, including cropland and pastureland, into protected natural forest and grassland. However, this increasing amount of land for reaching a 30% of protected areas by 2030 target could conflict with other land demands established by socioeconomic drivers such as population, GDP, and agriculture-related land use, leading to significant shifts in LULC. As high all represents the combination of several land-intensive driver scenarios, such as increasing populations, trade tariffs, yield constraints, and meat demand, among others; this could result in a compounded effect that produces a substantial shift in LULC in regions—such as India—nearing the limit of its land use allocation for managed lands.

The strong effects of a high all scenario for India can be further visualized in Figure 3.4. In this image, it can be observed that IND experiences a substantial shift in the distribution of grassland when comparing the differences between pixels in a high all EPPA stressor scenario and the baseline CT scenario under the minimum spatial correlation case. The figure shows major decreases in grassland across the middle-west and central regions of the country, while the western end and northern parts of IND experience an increase in grassland.

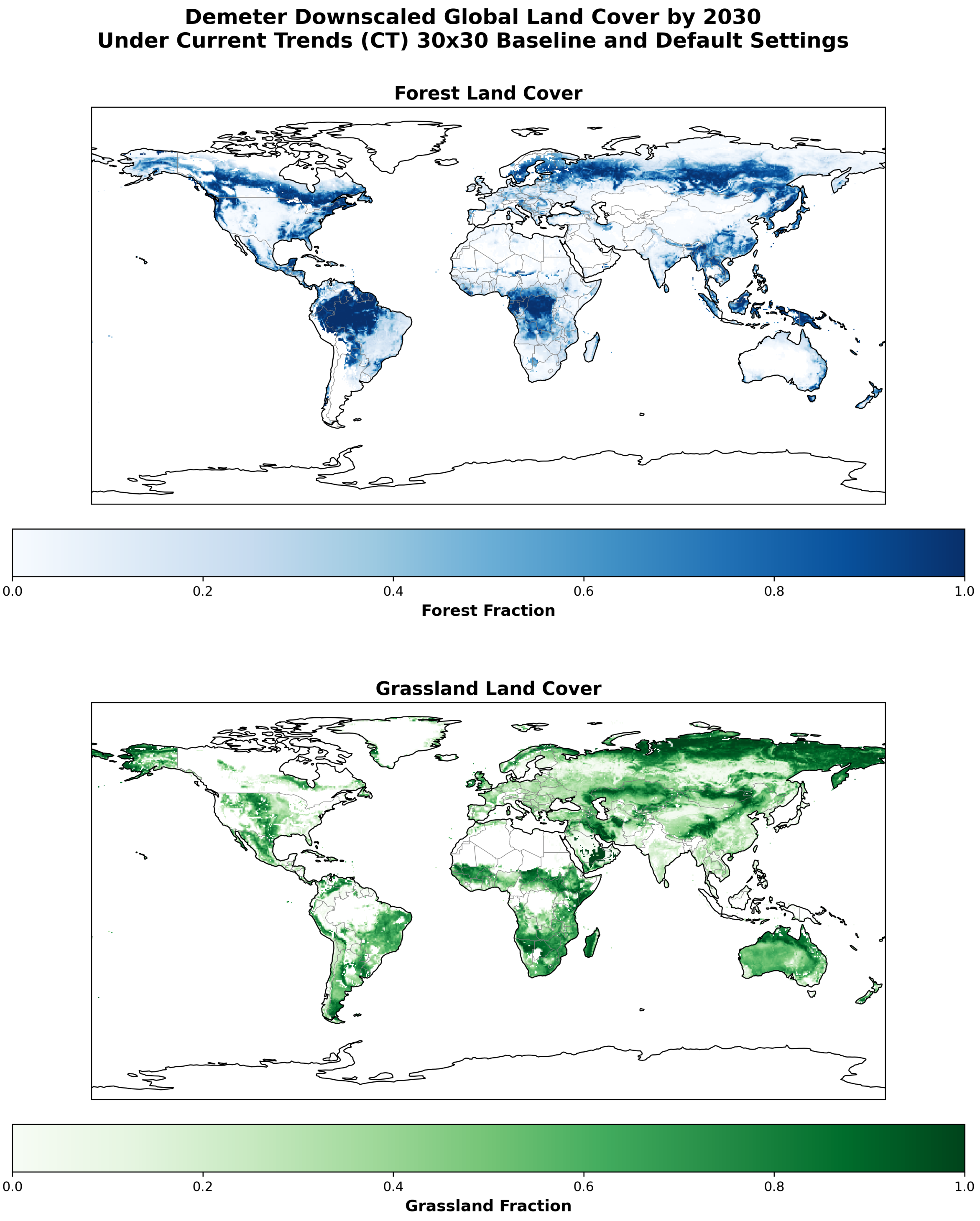
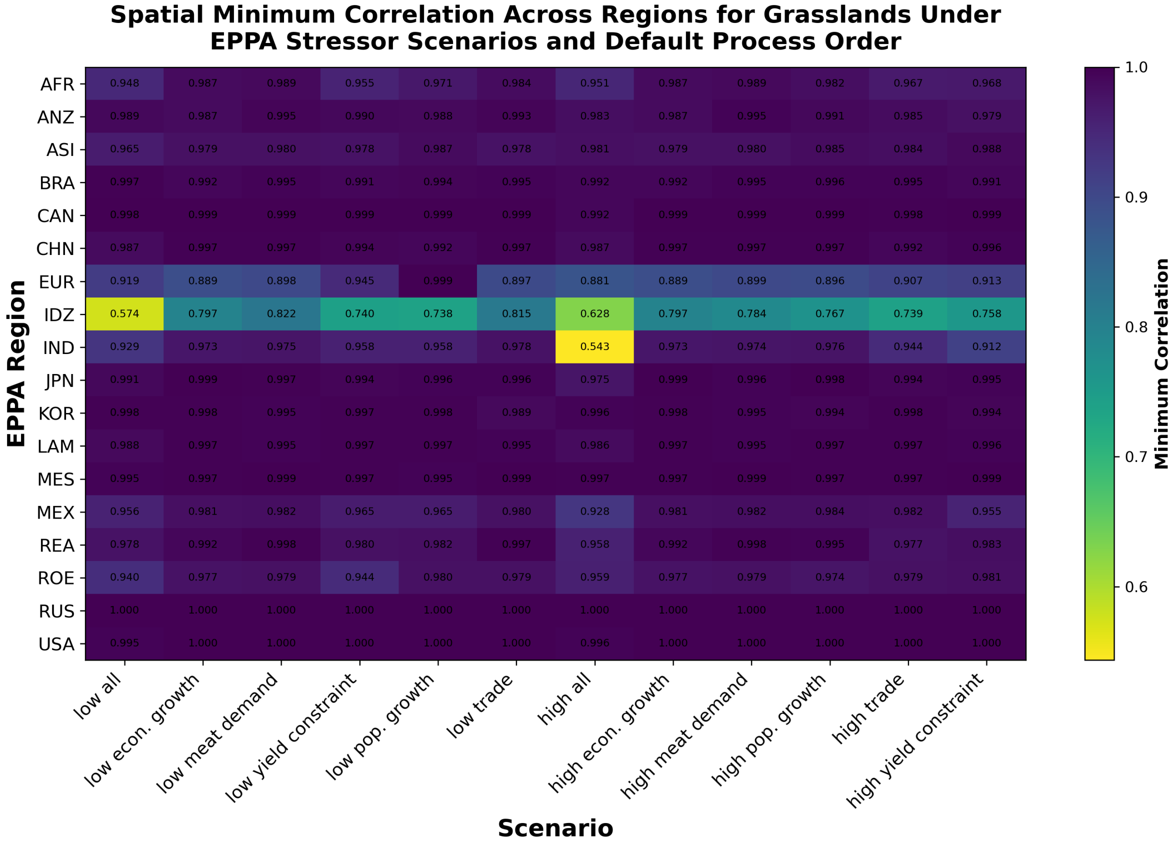


Figure 3.2: Demeter projected global grassland and forest land cover maps for a Current Trends (CT) 30-by-30 baseline under default settings.

Due to Demeter's aggregation of pastureland and natural grassland into a single category, Demeter cannot directly quantify the conversion of natural grassland into pastureland and vice versa. However, changes occur in areas that agree with India's LULC distribution (NRSC, 2024). Moreover, significant changes observed in the western end of India result in potential negative changes associated with Asia's largest tropical grasslands—The Banni Grasslands—home to biodiversity-rich ecosystems but also several documented misuses and anthropogenic interventions that imperil local species and ecological functions (Dey et al., 2024).



EPPA Region	low all	low econ. growth	low meat demand	low yield constraint	low pop. growth	low trade	high all	high econ. growth	high meat demand	high pop. growth	high trade	high yield constraint
AFR	0.948	0.987	0.989	0.955	0.971	0.984	0.951	0.987	0.989	0.982	0.967	0.968
ANZ	0.989	0.987	0.995	0.990	0.988	0.993	0.983	0.987	0.995	0.991	0.985	0.979
ASI	0.965	0.979	0.980	0.978	0.987	0.978	0.981	0.979	0.980	0.985	0.984	0.988
BRA	0.997	0.992	0.995	0.991	0.994	0.995	0.992	0.992	0.995	0.996	0.995	0.991
CAN	0.998	0.999	0.999	0.999	0.999	0.999	0.992	0.999	0.999	0.999	0.998	0.999
CHN	0.987	0.997	0.997	0.994	0.992	0.997	0.987	0.997	0.997	0.997	0.992	0.996
EUR	0.919	0.889	0.898	0.945	0.999	0.897	0.881	0.889	0.899	0.896	0.907	0.913
IDZ	0.574	0.797	0.822	0.740	0.738	0.815	0.628	0.797	0.784	0.767	0.739	0.758
IND	0.929	0.973	0.975	0.958	0.958	0.978	0.543	0.973	0.974	0.976	0.944	0.912
JPN	0.991	0.999	0.997	0.994	0.996	0.996	0.975	0.999	0.996	0.998	0.994	0.995
KOR	0.998	0.998	0.995	0.997	0.998	0.989	0.996	0.998	0.995	0.994	0.998	0.994
LAM	0.988	0.997	0.995	0.997	0.997	0.995	0.986	0.997	0.995	0.997	0.997	0.996
MES	0.995	0.997	0.999	0.997	0.995	0.999	0.997	0.997	0.999	0.997	0.997	0.999
MEX	0.956	0.981	0.982	0.965	0.965	0.980	0.928	0.981	0.982	0.984	0.982	0.955
REA	0.978	0.992	0.998	0.980	0.982	0.997	0.958	0.992	0.998	0.995	0.977	0.983
ROE	0.940	0.977	0.979	0.944	0.980	0.979	0.959	0.977	0.979	0.974	0.979	0.981
RUS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
USA	0.995	1.000	1.000	1.000	1.000	1.000	0.996	1.000	1.000	1.000	1.000	1.000

Figure 3.3: Grassland spatial minimum correlation for each EPPA region and EPPA socioeconomic stressor scenario under a Default Process Order.

In the case of Indonesia in Figure 3.3, a different effect from that of India is observed. Here, the minimum spatial correlation seems to show decreased values across all EPPA stressor scenarios, which signals that Demeter parameters (allocation constraint + intensification ratio) significantly influence minimum spatial correlation. At the same time, low and high all incur more significant drops in spatial correlation, showing a potential joint effect of Demeter parameters and EPPA's socioeconomic drivers.

To further comprehend the effects that Demeter and EPPA parameters contribute to

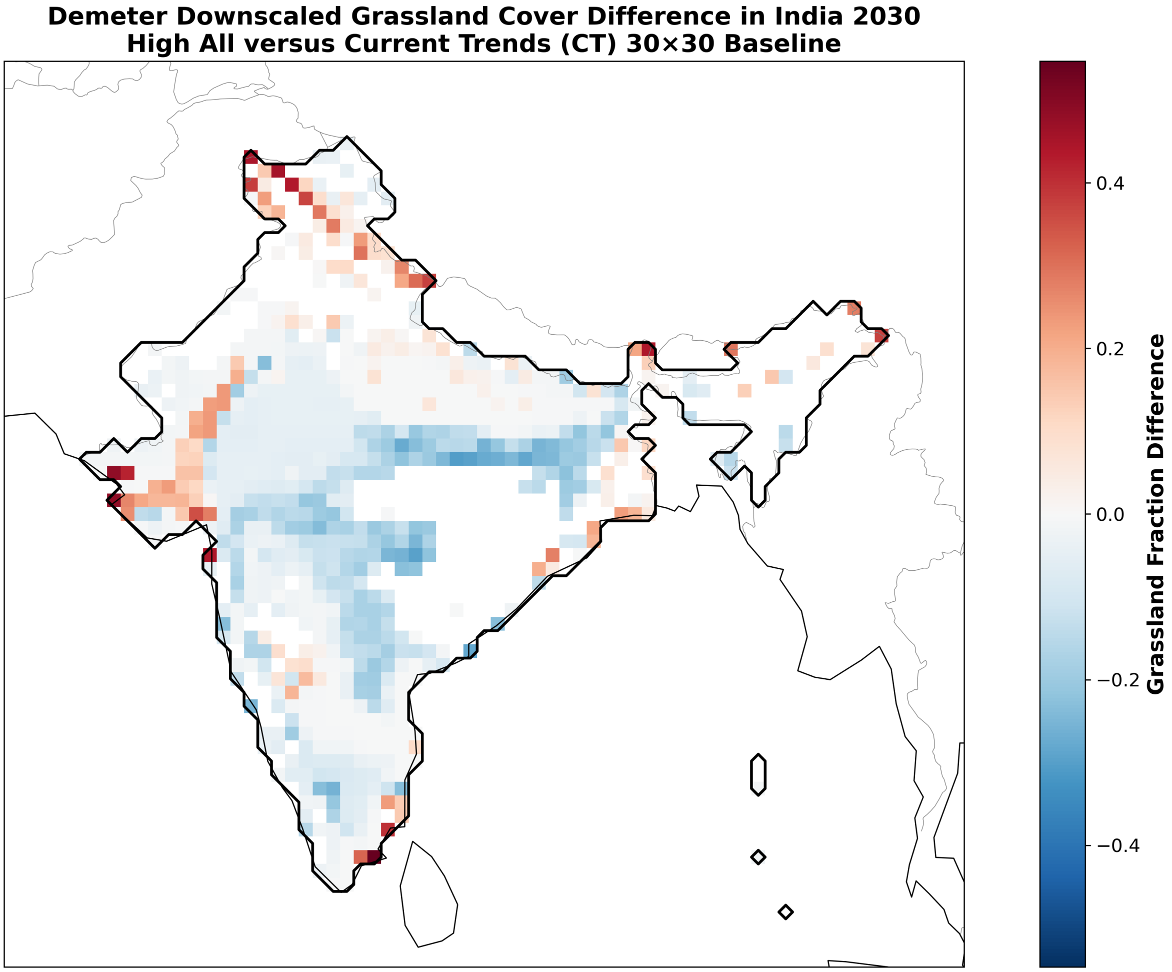


Figure 3.4: Grassland cover difference between high all and Current Trends (CT) 30-by-30 baseline for Demeter downscaled India 2030 land projections.

downscaling projection heatmaps, mean spatial correlation for grasslands was further visualized (Figure 3.5). From this, it was observed that a similar pattern to Figure 3.3 holds in mean spatial correlation heatmaps; however, spatial correlation values across India and Indonesia increase. This signals that the previous minimum spatial correlation was produced by a specific configuration of Demeter parameters that led to a considerably lower spatial correlation and, therefore, a more significant shift in projected LULC. Nonetheless, at a mean spatial correlation of 0.808 in India under high all and 0.761 and 0.8181 in Indonesia under low all and high all, the persistent pattern shows a continued strong influence of EPPA's socioeconomic drivers over downscaling projections in IND and IDZ.

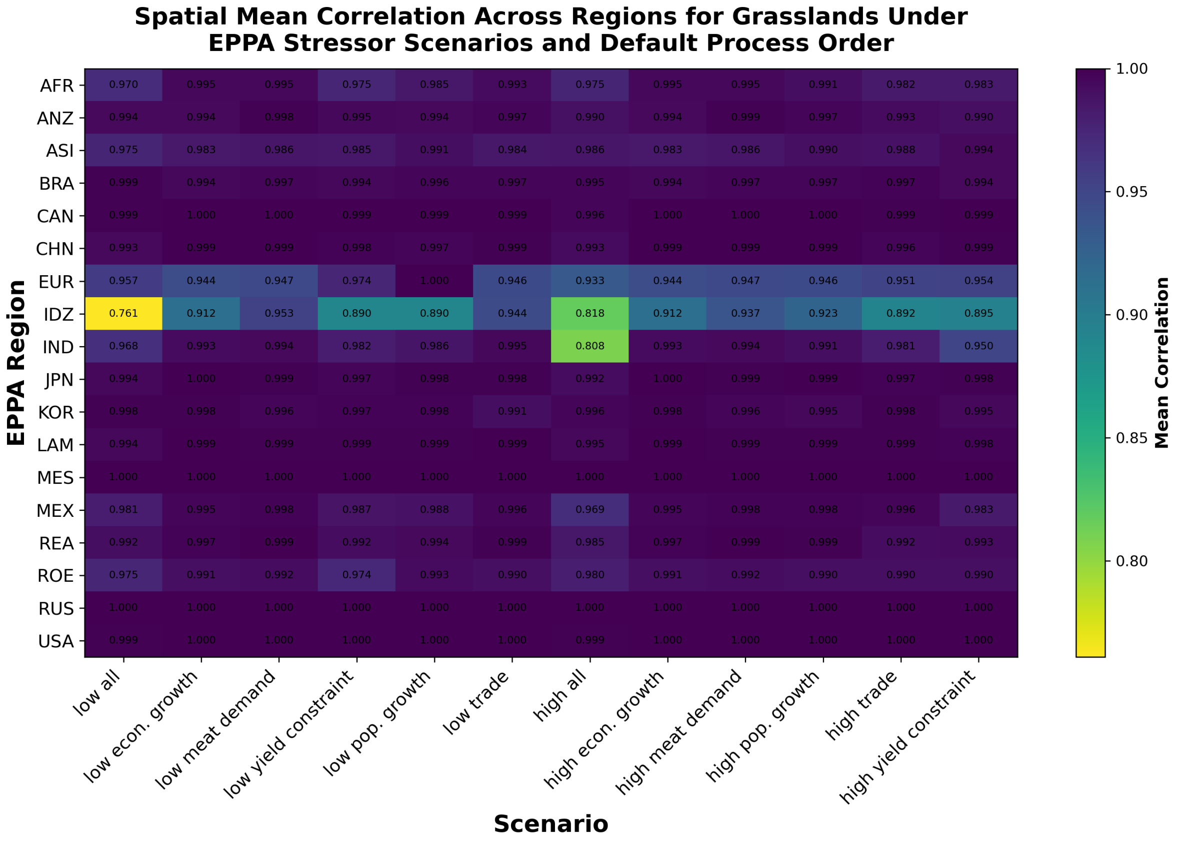
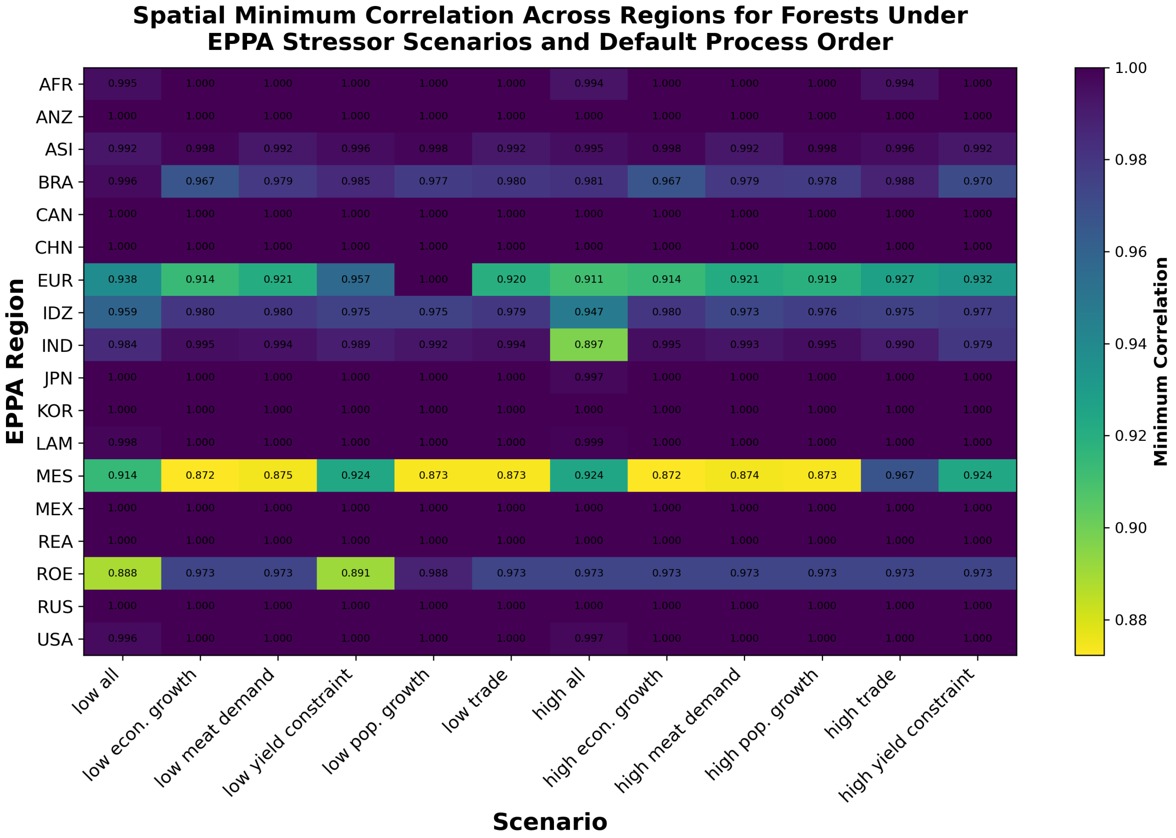


Figure 3.5: Grassland spatial mean correlation for each EPPA region and EPPA socioeconomic stressor scenario under a Default Process Order.

In the case of forests with a default Demeter treatment order (Figure 3.6), a less dramatic decrease in minimum spatial correlations was observed. The lowest spatial correlations occur in the Middle East (MES) and hover around 0.87 across various EPPA stressor scenarios. This could be explained by the dominance of the Demeter allocation constraint and intensification ratio parameters over the variations produced by different EPPA stressors to drive change in LULC. An analogous situation in Europe (EUR), Indonesia (IDZ), and

Other Eurasia (ROE) occurs. Similar to the heatmap in grasslands, in India, an isolated lower minimum spatial correlation under the high all scenario is observed. This could be due to the continued effect of land scarcity in the region, which results in compounded effects on land use change from the various drivers in a high all scenario against an already land-strained region for managed lands under a 30-by-30 and CT climate targets.

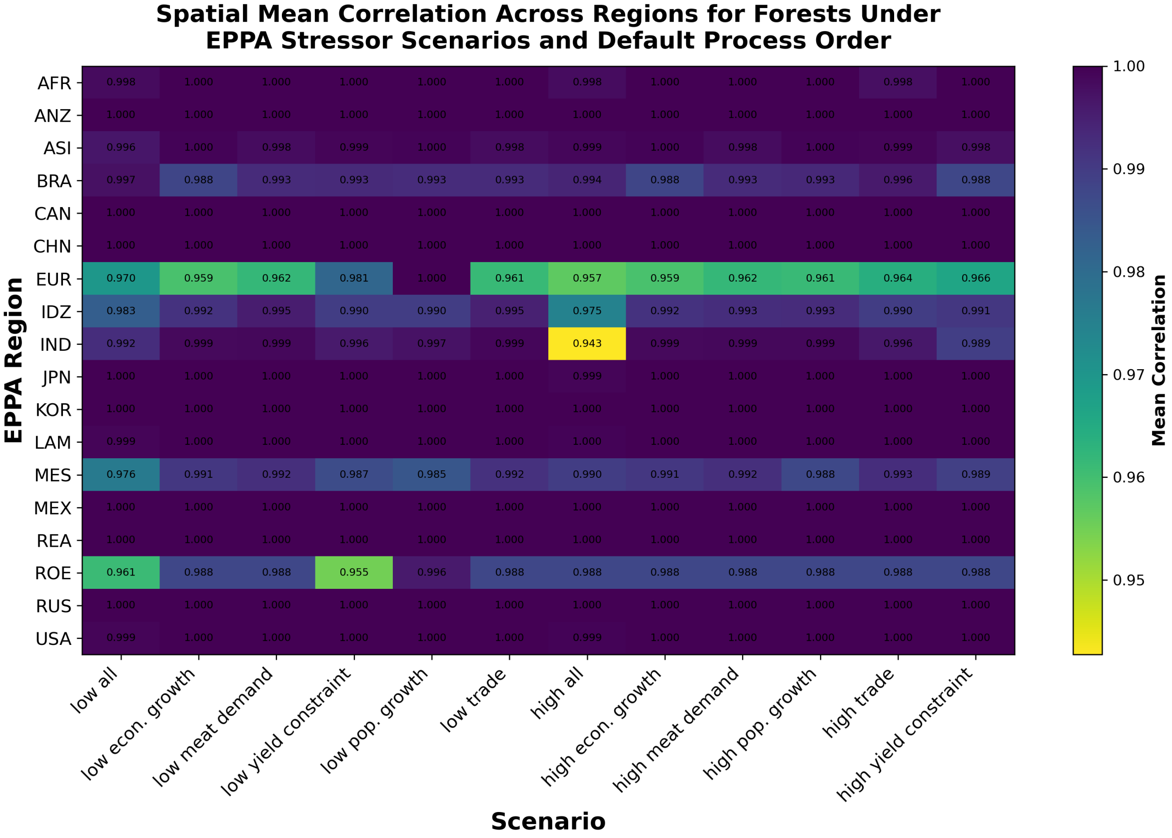


	low all	low econ. growth	low meat demand	low yield constraint	low pop. growth	low trade	high all	high econ. growth	high meat demand	high pop. growth	high trade	high yield constraint
AFR	0.995	1.000	1.000	1.000	1.000	1.000	0.994	1.000	1.000	1.000	0.994	1.000
ANZ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ASI	0.992	0.998	0.992	0.996	0.998	0.992	0.995	0.998	0.992	0.998	0.996	0.992
BRA	0.996	0.967	0.979	0.985	0.977	0.980	0.981	0.967	0.979	0.978	0.988	0.970
CAN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CHN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
EUR	0.938	0.914	0.921	0.957	1.000	0.920	0.911	0.914	0.921	0.919	0.927	0.932
IDZ	0.959	0.980	0.980	0.975	0.975	0.979	0.947	0.980	0.973	0.976	0.975	0.977
IND	0.984	0.995	0.994	0.989	0.992	0.994	0.897	0.995	0.993	0.995	0.990	0.979
JPN	1.000	1.000	1.000	1.000	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000
KOR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LAM	0.998	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
MES	0.914	0.872	0.875	0.924	0.873	0.873	0.924	0.872	0.874	0.873	0.967	0.924
MEX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
REA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ROE	0.888	0.973	0.973	0.891	0.988	0.973	0.973	0.973	0.973	0.973	0.973	0.973
RUS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
USA	0.996	1.000	1.000	1.000	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000

Figure 3.6: Forest spatial minimum correlation for each EPPA region and EPPA socioeconomic stressor scenario under a Default Process Order.

For the mean spatial correlation of forests with a default Demeter treatment order heatmap (Figure 3.7), it can be observed that the previous patterns continue to hold. However, considering that the mean spatial correlation averages across all Demeter allocation constraints and intensification ratio combinations, higher and more consistent spatial correlations across EUR, IDZ, IND, and ROE regions could indicate that land use is not considerably governed by Demeter parameters in these regions. The lowest spatial correlation in the Middle East is 0.976 and indicates that EPPA socioeconomic drivers tested through varying stressor scenarios do not have a strong influence on MES's projected LULC. Similar increases in EUR, IDZ, and IND's high all scenarios compared to their counterpart in the minimum spatial correlation heatmap also signal that, in the case of forests under a Default

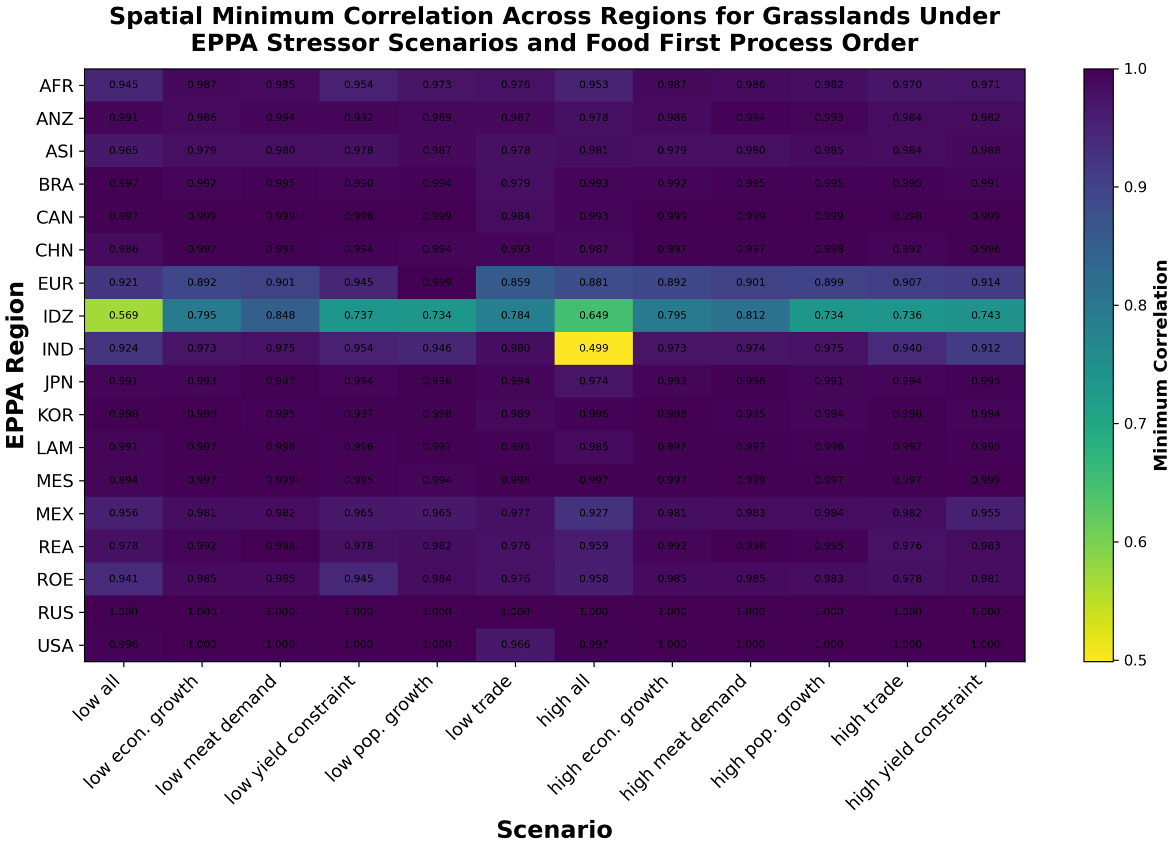
Process Order, Demeter parameters play a smaller role in their sensitivity.



EPPA Region	low all	low econ. growth	low meat demand	low yield constraint	low pop. growth	low trade	high all	high econ. growth	high meat demand	high pop. growth	high trade	high yield constraint
AFR	0.998	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	0.998	1.000
ANZ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ASI	0.996	1.000	0.998	0.999	1.000	0.998	0.999	1.000	0.998	1.000	0.999	0.998
BRA	0.997	0.988	0.993	0.993	0.993	0.993	0.994	0.988	0.993	0.993	0.996	0.988
CAN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CHN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
EUR	0.970	0.959	0.962	0.981	1.000	0.961	0.957	0.959	0.962	0.961	0.964	0.966
IDZ	0.983	0.992	0.995	0.990	0.990	0.995	0.975	0.992	0.993	0.993	0.990	0.991
IND	0.992	0.999	0.999	0.996	0.997	0.999	0.943	0.999	0.999	0.999	0.996	0.989
JPN	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
KOR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LAM	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MES	0.976	0.991	0.992	0.987	0.985	0.992	0.990	0.991	0.992	0.988	0.993	0.989
MEX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
REA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ROE	0.961	0.988	0.988	0.955	0.996	0.988	0.988	0.988	0.988	0.988	0.988	0.988
RUS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
USA	0.999	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000

Figure 3.7: Forest spatial mean correlation for each EPPA region and EPPA socioeconomic stressor scenario under a Default Process Order.

To further evaluate the effects of Demeter Process Orders on the EPPA-Demeter linked framework's land allocation downscaling, similar minimum and mean spatial correlation heatmaps were generated to compare Default Process Order against that of an Energy and Food First approach, which show the effects to a change in the sequence of land types by which Demeter solves land allocation projections as detailed in the previous Table 3.3. When comparing the default scenario against the Food and Energy First heatmaps, the principal patterns hold. According to the heatmap for grasslands under a Food First Process Order (Figure 3.8), the lowest minimum spatial correlation continues to correspond to IND, while IDZ experiences a similar lower spatial correlation pattern across EPPA scenarios when compared to the Default Process Order in Figure 3.3. However, some of the lower spatial correlation values observed in the Default Process Order become smaller under a Food-First approach. Therefore, showing that adjusting the sequence by which Demeter solves for land allocations can produce changes to the final land allocation outputs, although at a smaller scale compared to the effects of adjusting allocation constraint and intensification ratio parameters. Moreover, observed shifts in spatial minimum correlation values were starker when comparing a Default Process Order to a Food or Energy First (Figure 3.9) heatmap than between the latter two cases, although still showing slight differences.



EPPA Region	low all	low econ. growth	low meat demand	low yield constraint	low pop. growth	low trade	high all	high econ. growth	high meat demand	high pop. growth	high trade	high yield constraint
AFR	0.945	0.987	0.985	0.954	0.973	0.976	0.953	0.987	0.986	0.982	0.970	0.971
ANZ	0.991	0.986	0.994	0.992	0.989	0.987	0.978	0.986	0.994	0.993	0.984	0.982
ASI	0.965	0.979	0.980	0.978	0.987	0.978	0.981	0.979	0.980	0.985	0.984	0.988
BRA	0.997	0.992	0.995	0.990	0.994	0.979	0.993	0.992	0.995	0.995	0.995	0.991
CAN	0.997	0.999	0.999	0.998	0.999	0.984	0.993	0.999	0.999	0.999	0.998	0.999
CHN	0.986	0.997	0.997	0.994	0.994	0.993	0.987	0.997	0.997	0.998	0.992	0.996
EUR	0.921	0.892	0.901	0.945	0.999	0.859	0.881	0.892	0.901	0.899	0.907	0.914
IDZ	0.569	0.795	0.848	0.737	0.734	0.784	0.649	0.795	0.812	0.734	0.736	0.743
IND	0.924	0.973	0.975	0.954	0.946	0.980	0.499	0.973	0.974	0.975	0.940	0.912
JPN	0.991	0.993	0.997	0.994	0.996	0.994	0.974	0.993	0.996	0.991	0.994	0.995
KOR	0.998	0.998	0.995	0.997	0.998	0.989	0.996	0.998	0.995	0.994	0.998	0.994
LAM	0.991	0.997	0.998	0.996	0.997	0.995	0.985	0.997	0.997	0.996	0.997	0.995
MES	0.994	0.997	0.999	0.995	0.994	0.998	0.997	0.997	0.999	0.997	0.997	0.999
MEX	0.956	0.981	0.982	0.965	0.965	0.977	0.927	0.981	0.983	0.984	0.982	0.955
REA	0.978	0.992	0.998	0.978	0.982	0.976	0.959	0.992	0.998	0.995	0.976	0.983
ROE	0.941	0.985	0.985	0.945	0.984	0.976	0.958	0.985	0.985	0.983	0.978	0.981
RUS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
USA	0.996	1.000	1.000	1.000	1.000	0.966	0.997	1.000	1.000	1.000	1.000	1.000

Figure 3.8: Grassland spatial minimum correlation for each EPPA region and EPPA socioeconomic stressor scenario under a Food First Process Order.

In the case of forests, a similar behavior to grasslands under the Energy and Food First Process Orders occurs. Patterns hold when comparing the heatmaps of default (Figure 3.6) to Food and Energy First cases (Appendix A.2 and A.3). However, there are slight changes to the minimum spatial correlations where for example across the MES, the minimum spatial correlation, these values for forest experience small increases when comparing Food and Energy First to the Default Process Order case. Similar to grasslands, shifts to spatial correlation are also stronger when comparing the Default Process Order and the Energy and Food First cases than among the latter.

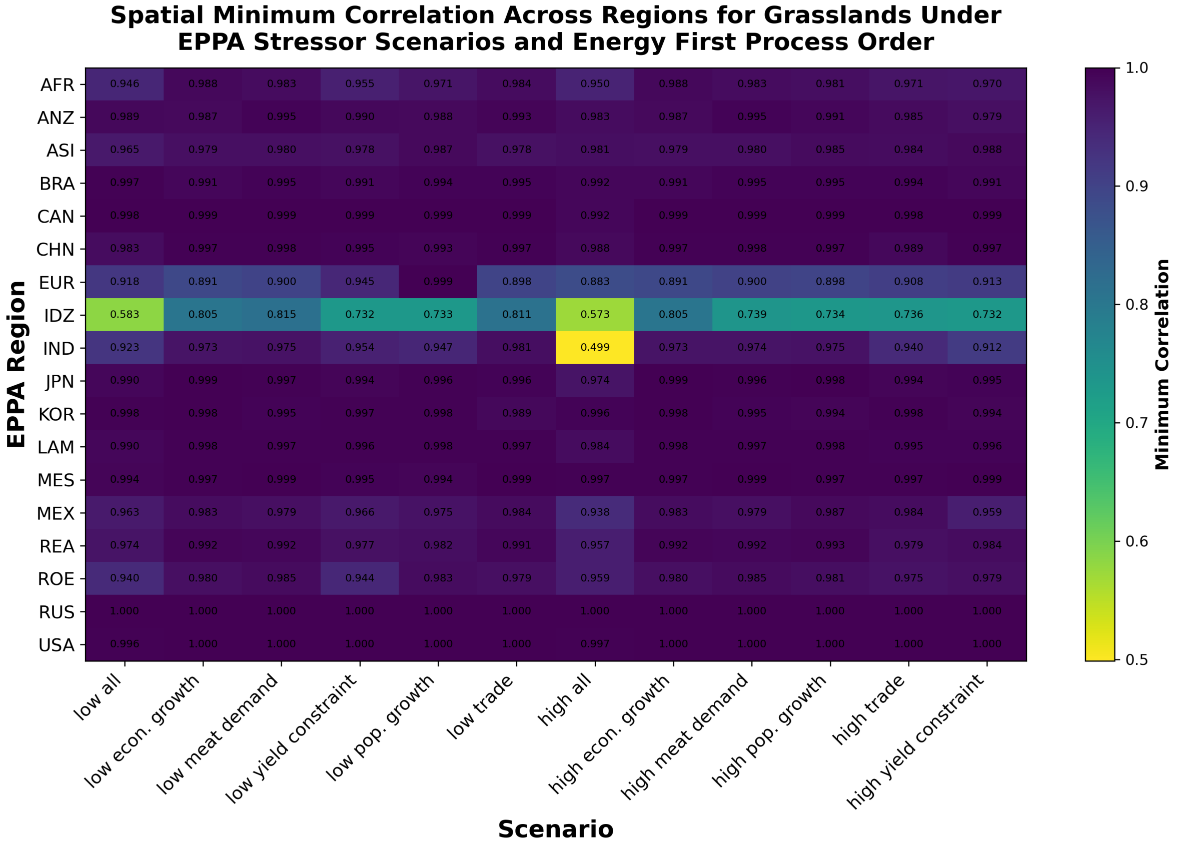


Figure 3.9: Grassland spatial minimum correlation for each EPPA region and EPPA socioeconomic stressor scenario under an Energy First Process Order.

3.4 Conclusion

This chapter shows the value of linking the EPPA model with Demeter to better understand how global-scale economic and policy decisions translate into finer resolution land projection. While EPPA captures how economies respond to climate and biodiversity goals at a regional aggregated level, Demeter aims to model where those projected changes are likely to happen at the pixel level. This combination makes it possible to move beyond broad trends and examine how land use shifts in localized areas, central to evaluating the effects of a compounded 30-by-30 and CT climate targets.

Spatial correlations across the range of land-use projections highlight that LULC outcomes are not determined by a single factor. Instead, they result from the interaction between socioeconomic drivers and stressors (such as population growth, trade restrictions, and agricultural demand) and user-defined rules to allocate land during the model downscaling process. In some regions, particularly India and Indonesia, under a Default Process Order, these interactions lead to considerable shifts in land use patterns—especially for grasslands. Under more extreme scenarios, such as high all, where multiple pressures occur simultaneously, these regions experience larger LULC shifts when compared to their CT baseline counterpart. This indicates potential difficulties in balancing conservation targets with higher rates of growing demand for food and land, suggesting that changes can lead to substantially different land use outcomes in regions where land is already heavily managed.

Not all land types respond in the same way. Forest patterns tend to remain more consistent across different scenarios and show higher minimum and mean spatial correlation values. Therefore, this indicates that user-set Demeter parameters (allocation constraint and intensification ratio) and EPPA socioeconomic stressor scenarios in the EPPA-Demeter framework play a weaker role in determining LULC distribution for forests. This contrast between forests and previous grassland behavior highlights the importance of evaluating land types separately, as each responds differently to modeling configurations. This could be closely linked to land categories such as grasslands, experiencing increased risk and pressure from anthropogenic interventions and development. Therefore, higher sensitivities to land use treatment rules and socioeconomic-driven configurations may result.

The sensitivity testing of Demeter parameters indicated that stricter land allocation and/or land-use intensity can have a large impact on final mapping projections. Similarly, changing the Process Order in which land types are allocated also affects projection, although these shifts are often smaller in comparison. From the sensitivity runs, an EPPA-Demeter downscaling pipeline, land projections of aggregated socioeconomic IAM model outputs (such as EPPA) remain responsive to user-defined parameters and transition rules. Therefore, initial Demeter model settings are non-trivial and lead to significant shifts in final LULC mapping projections.

Overall, these findings show that achieving climate and biodiversity goals at the same time involves real tradeoffs at an intra-model level and varies across regions. A target like protecting 30% of land by 2030 cannot be fully understood without considering where that land is located and the pressures that exist in each economic region. The EPPA–Demeter framework helps reveal these spatial differences, making it a useful tool for identifying where conflicts between conservation and development are most likely to arise. However, equally important, sensitivity tests have determined that model configurations and prioritizations play a key role in effectively guiding downscaling projections and providing more reliable mapping outputs.

Chapter 4

Conclusion

This thesis investigated the integration of novel global socioeconomic CGE models with spatial downscaling algorithms to better understand the interaction and effects of a compounded climate and biodiversity target on economic and social system outcomes. The harmonization of EPPA and Demeter extends socioeconomic projections and allows for a dual climate and biodiversity target projection, creating a pipeline to move beyond aggregated regional outcomes and evaluate localized land use change effects at a finer spatial resolution.

At global and regional scales, EPPA modeling outputs suggest that achieving biodiversity and climate goals simultaneously is feasible, but not without potential tradeoffs. A more stringent Accelerated Actions (AA) climate policy can benefit from reduced economic burden of reaching a 30-by-30 biodiversity target, in comparison to a Current Trends (CT) scenario with the same biodiversity policy implementation, by decreasing land use conversion pressures. However, model outputs observed distributional effects across EPPA regions. Areas with limited natural land and pressure from development, such as the Middle East and India, face a higher economic burden and greater difficulty in balancing socioeconomic parameters such as family consumption, GDP, and food prices. Meanwhile, regions with land-abundant and strong agricultural sectors may experience relative economic gains due to increased agricultural production and exports fueled by demand in natural land-scarce regions, resulting in cross-regional deforestation leakage.

At the spatial pixel level, outputs further show that LULC projections are shaped by interactions between socioeconomic drivers (such as population growth, trade tariffs, and food demand) and user-determined assumptions in the Demeter downscaling process parameters. In regions like India, these interactions can lead to substantial shifts in land use patterns, particularly for grassland, which was determined to be more spatially sensitive due to present anthropogenic land use and development pressures. However, this behavior was observed to be specific to particular land types. In the case of forest patterns, these tended to remain more stable across socioeconomic stressors and observed overall higher spatial correlation values, therefore also showing to be less sensitive to changes in Demeter parameters.

Sensitivity analyses show that user-set model configurations play a key role in land allocation projection through shifts in intensification ratio and allocation constraints. At the same time, the sequence by which the user prioritizes land allocations or Process Order in the downscaling pipeline further shows marginal changes in output land projections. These findings demonstrate that initial Demeter user assumptions have an impact result over outputs drawn in the EPPA-Demeter modeling framework. Hence, careful parameter selection in initialization and modeling assumptions is essential for producing reliable projections.

Beyond model harmonization and sensitivity analysis, the EPPA-Demeter framework points to broader economic and environmental implications. The implementation of a simultaneous climate change and biodiversity target could potentially contribute to increased food prices in vulnerable regions while expanding agriculture and deforestation in others through trade. Therefore, these dynamics inform the need for complementary policies that target these potential ramifications through strategies that incentivize investment in agricultural intensification research in affected regions and implement deforestation-free market import policies or accounting mechanisms to ensure net-positive progress towards a 30-by-30.

Overall, this study demonstrates that achieving climate and biodiversity goals simultaneously requires a coupled socioeconomic and spatially grounded approach. Global and regional-scale EPPA modeling provides key insights to inform top-down policies to counter potential compounded effects and ramifications of a dual climate change and biodiversity policy. At the same time, an EPPA-Demeter pipeline allows the user to understand how policy decisions interact with localized pressures and constraints. Therefore, the harmonized EPPA-Demeter framework provides a valuable and novel tool for capturing these dynamics and the trade-offs among conservation, human development, and climate change policies that might arise, and how they could be addressed. This study emphasizes that both modeling and policy design feed into each other to shape outcomes and projections, reinforcing the need for an integrated and regionally informed approach to environmental and biodiversity policy planning that takes into account socioeconomic and human well-being parameters.

Appendices

Appendix A

Appendix

Figure A.1: Average maturation age for forests in each EPPA region. Forest maturation age is used to estimate the time lag or regeneration period that allows forest ecosystems to bounce back or regrow to their natural functions after being deforested (Sohngen, 2007). Natural grasslands are assumed to have a time lag or regeneration period of 5 years to return to their natural maturation state.

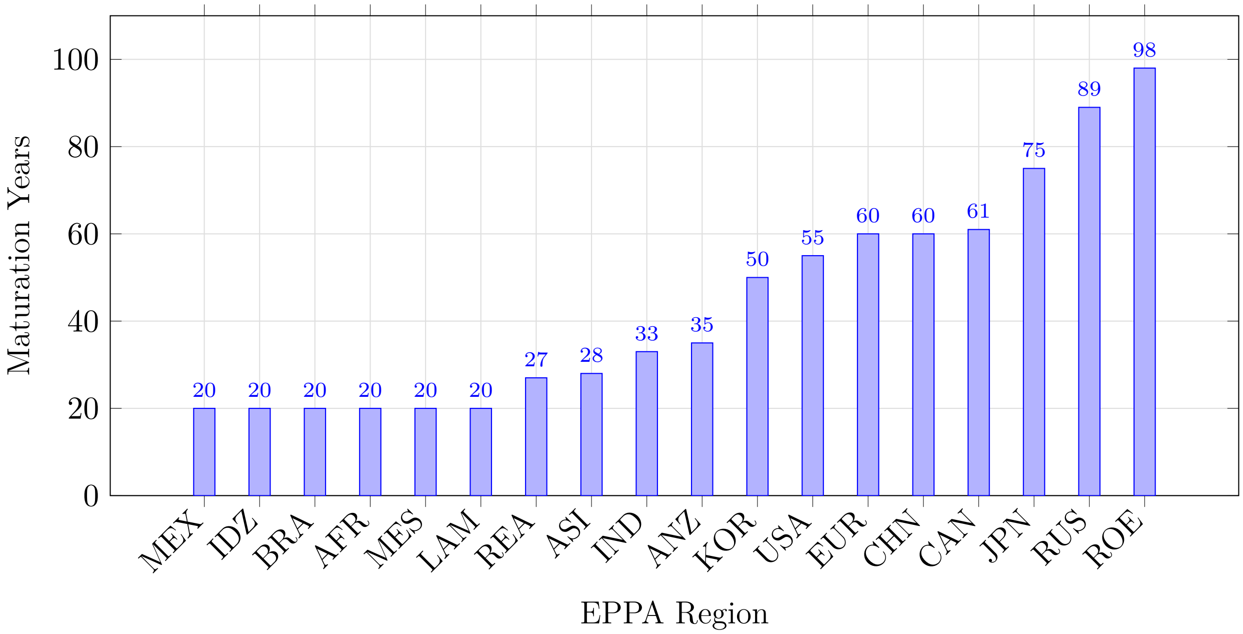


Table A.1: Carbon emission and greenhouse gas emission (GHG) projections for 2030 and 2050 relative to 2015 for each EPPA economic region under Current Trends (CT) and Accelerated Actions (AA). Adapted from the MIT Center for Sustainability Science and Strategy (CS3) (formerly MIT Joint Program on the Science and Policy of Global Change) 2023 Global Change Outlook.

EPPA Region	**Current Trends (CT)**				**Accelerated Actions (AA)**			
	CO_2 emissions		**GHG emissions**		**CO_2 emissions**		**GHG emissions**	
	2030	**2050**	**2030**	**2050**	**2030**	**2050**	**2030**	**2050**
USA	-26%	-59%	-25%	-52%	-50%	-88%	-45%	-79%
EUR	-23%	-44%	-27%	-46%	-45%	-73%	-45%	-71%
CAN	-17%	50%	-17%	-49%	-35%	-82%	-34%	-80%
JPN	-35%	-61%	-36%	-61%	-45%	-81%	-46%	-81%
KOR	-17%	-51%	-18%	-50%	-25%	-67%	-26%	-66%
ANZ	-8%	-39%	-17%	-40%	-22%	-78%	-30%	-72%
CHN	10%	-22%	10%	-20%	-25%	-75%	-22%	-67%
IND	38%	47%	37%	59%	-2%	-50%	8%	-13%
BRA	-45%	-44%	-36%	-35%	-48%	-85%	-41%	-76%
IDZ	17%	0%	13%	6%	1%	-62%	-4%	-55%
MEX	16%	26%	2%	12%	-23%	-71%	-30%	-68%
RUS	1%	-5%	-7%	-15%	-23%	-91%	-26%	-85%
ASI	15%	39%	11%	31%	-21%	-71%	-22%	-66%
AFR	-7%	15%	-5%	19%	-10%	-59%	-10%	-45%
MES	1%	41%	-5%	24%	-26%	-64%	-29%	-64%
LAM	-7%	-5%	-10%	-10%	-24%	-65%	-25%	-60%
REA	21%	59%	13%	43%	12%	-65%	4%	-50%
ROE	25%	66%	13%	-38%	-16%	-77%	-23%	-75%

Table A.2: Allocation constraint weights assigned to forest and grassland land types by biome. The score represents the allocation constraint weight applied under the corresponding land type. WDPA areas were restricted from allocation changes by applying a 0 value.

Biome ID	**Biome Name**	**Forest Weight**	**Grassland Weight**
WDPA	Protected Areas	0	0
1	Tropical & Subtropical Moist Broadleaf Forests	0.90	0.10
2	Tropical & Subtropical Dry Broadleaf Forests	0.90	0.15
4	Temperate Broadleaf & Mixed Forests	0.90	0.20
5	Temperate Conifer Forests	0.90	0.15
7	Tropical & Subtropical Grasslands, Savannas & Shrublands	0.20	0.80
8	Temperate Grasslands, Savannas & Shrublands	0.20	0.80
9	Flooded Grasslands & Savannas	0.20	0.90
10	Montane Grasslands & Shrublands	0.10	0.95
11	Tundra	0.01	0.99
12	Mediterranean Forests, Woodlands & Scrub	0.90	0.20
13	Deserts & Xeric Shrublands	0.01	0.10
14	Mangroves	0.90	0.15

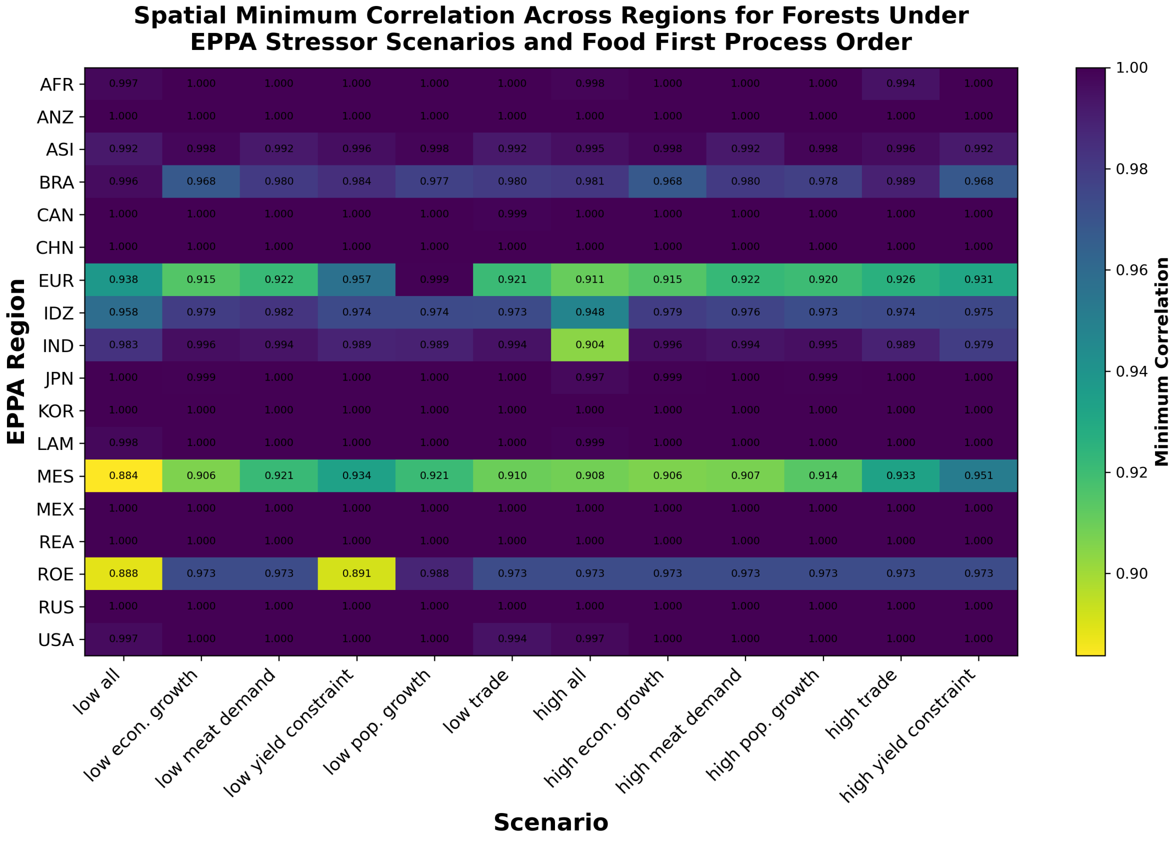
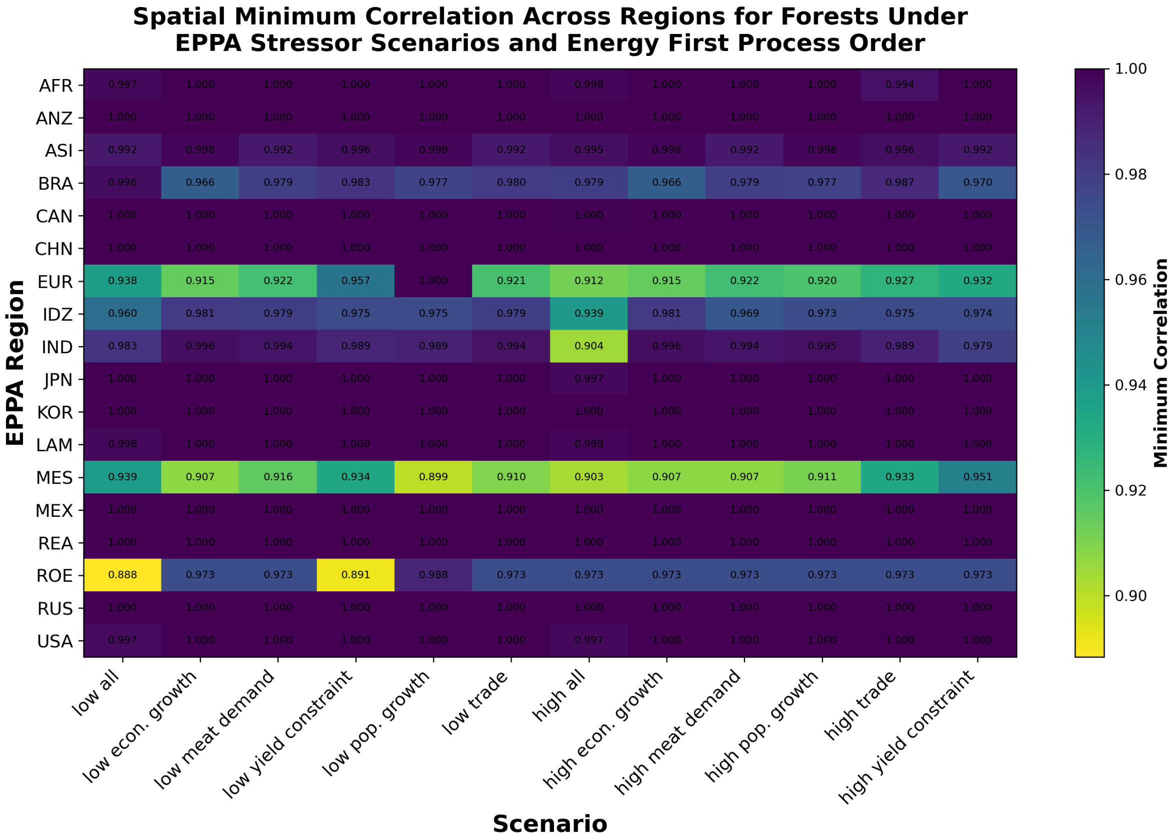


Figure A.2: Forest spatial minimum correlation for each EPPA region and EPPA socioeconomic stressor scenario under a Food First Process Order.



EPPA Region	low all	low econ. growth	low meat demand	low yield constraint	low pop. growth	low trade	high all	high econ. growth	high meat demand	high pop. growth	high trade	high yield constraint
AFR	0.997	1.000	1.000	1.000	1.000	1.000	0.998	1.000	1.000	1.000	0.994	1.000
ANZ	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ASI	0.992	0.998	0.992	0.996	0.998	0.992	0.995	0.998	0.992	0.998	0.996	0.992
BRA	0.996	0.966	0.979	0.983	0.977	0.980	0.979	0.966	0.979	0.977	0.987	0.970
CAN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CHN	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
EUR	0.938	0.915	0.922	0.957	1.000	0.921	0.912	0.915	0.922	0.920	0.927	0.932
IDZ	0.960	0.981	0.979	0.975	0.975	0.979	0.939	0.981	0.969	0.973	0.975	0.974
IND	0.983	0.996	0.994	0.989	0.989	0.994	0.904	0.996	0.994	0.995	0.989	0.979
JPN	1.000	1.000	1.000	1.000	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000
KOR	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
LAM	0.998	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000	1.000	1.000
MES	0.939	0.907	0.916	0.934	0.899	0.910	0.903	0.907	0.907	0.911	0.933	0.951
MEX	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
REA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ROE	0.888	0.973	0.973	0.891	0.988	0.973	0.973	0.973	0.973	0.973	0.973	0.973
RUS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
USA	0.997	1.000	1.000	1.000	1.000	1.000	0.997	1.000	1.000	1.000	1.000	1.000

Figure A.3: Forest spatial minimum correlation for each EPPA region and EPPA socioeconomic stressor scenario under an Energy First Process Order.

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