What is possible versus how to get there: Integrating economic models with biophysical efficiency frontiers

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Introduction

Whether we stay within planetary boundaries depends largely on our economic choices of what and how much to consume (Richardson et al. 2023). Yet, economic activity is essential for producing the critical goods and services that make up the "social foundation" of the safe and just operating space for humanity (Rockström et al. 2023, Raworth 2017). Planetary boundary frameworks have emerged as a useful way for describing sustainability challenges, but it remains unclear how to assess, in specific terms, which policies are most effective at keeping us within the safe and just corridor. Two separate methodologies have emerged recently that aim to add specificity to the task of identifying what policies are best for keeping us within planetary boundaries. First, recent work identifies pareto-efficiency frontiers that quantify tradeoffs between environmental and economic values (Damania et al. 2023), calculating the frontier for 146 countries based on different land-use, land-management, and crop production choices. Frontiers are well suited to explore different conceptions of "what is possible." Second, researchers have created integrated earth-economy models that link computable general equilibrium (CGE) approaches with high-resolution earth systems and ecosystem services modelling (Banerjee et al. 2021, Johnson et al. 2023). This type of modeling does not consider optimization of the landscape but instead focuses on how specific policies play out, emphasizing "how to get there." In this paper, we discuss integrating Earth-economy models with efficiency frontiers to assess both what is possible and how to get there.

Specifically, this paper begins by discussing how the natural efficiency frontier is constructed and how to locate existing spatially-explicit scenarios of land-use in frontier space. Even the policies that aim to move towards the efficiency frontier fall far short of arriving, but we can quantify within the framework how much progress is made by different policies, calculated as the ratio of movement towards divided by total distance from the frontier. The policies considered in these scenarios were very limited in scope, aimed at decisions relevant to national-level policy. There exists additional potential to progress towards the frontier by considering smaller-scale, spatially-explicit policies. The second part of this paper discusses how these policies, especially when used in conjunction with the national-level policies, move significantly farther towards the optimal solutions. We conclude this paper with a discussion of future steps, including incorporating additional objectives like clean air and water and expanding the capacity for comprehensive welfare assessment, along with additional considerations that need to be considered when dynamics are considered.

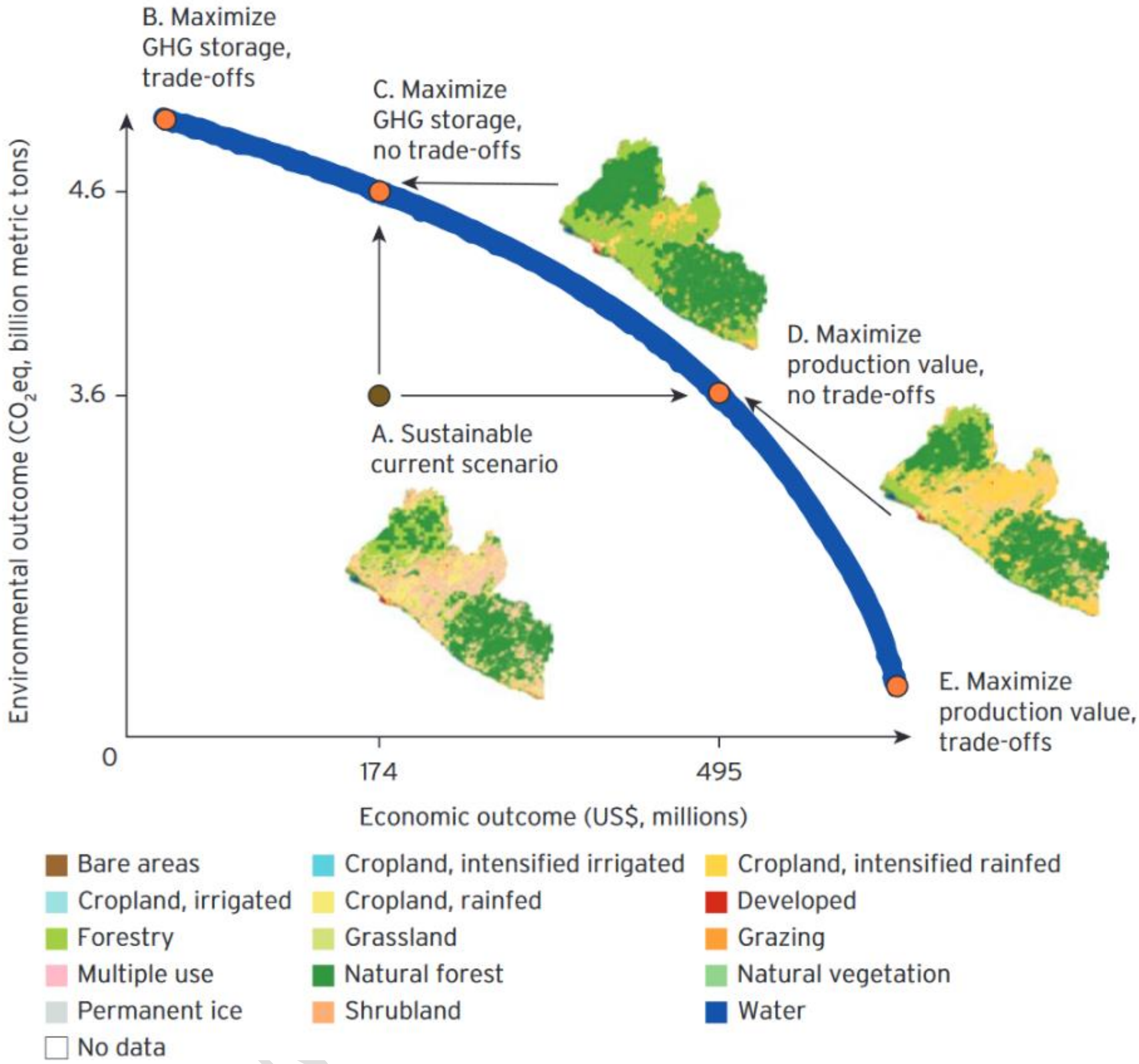
Methods

Natural Efficiency Frontier Construction

This research examines the impact of land use and management on economic outcomes, natural resources, and the ecosystem processes that deliver benefits to people, referred to as "ecosystem services." We use several models to analyze how alterations in the landscape affect biophysical processes (Chaplin-Kramer et al. 2019) and economic value from production systems such as agriculture, grazing, and forestry (Favero, Daigneault, and Sohngen 2020; Mueller et al. 2012). We use highly detailed spatial data with a resolution of 300 by 300 meter pixels, covering the entire globe.

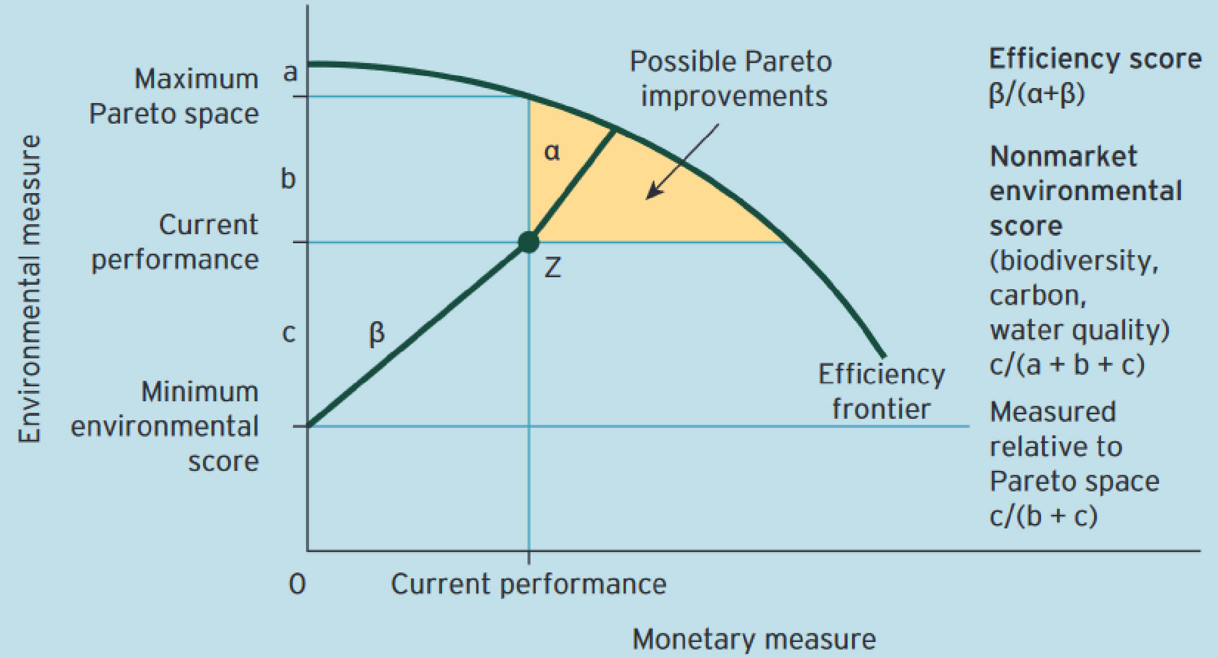
The overall concept of natural efficiency frontiers was originally documented in Polasky et al. (2008) for a small watershed and has recently been calculated at the global scale (Damania et al. 2023; Polasky et al., revise and resubmit at Science). The frontier plots feasible landscapes, represented by spatially-explicit land-use, land-cover (LULC) maps, locating them within the plot according to how well the landscape scores for different objectives. Typically, the horizontal axis represents values produced by the economy and captured via prices while the vertical axis represents an environmental value. Figure 1 (below) shows an example efficiency frontier, reproduced from Damania et al. (2023). Here we see the current landscape (brown dot) at a point inside the efficiency frontier, indicating that there exist pareto-improving reconfigurations of the landscape that could obtain higher values for both the economic axis and the environmental axis (here represented by a composite score for greenhouse gas emissions and biodiversity). Each point in the plot corresponds to a specific LULC map that was scored according to how it contributed to value for each of the axes. All points to the upper left of point A in figure 1 represent Pareto-improving reconfigurations of the landscape that attain higher values on both of the axes plotted while all points on the blue curve represent points that are Pareto-efficient, whereby it is not possible to improve on one axis without diminishing the value of the other axis. Along this curve, we see points that maximize the environmental objective overall (point B), maximize the environmental without any economic tradeoffs (point C), maximize economic value without any environmental tradeoffs (point D), and maximize production value overall.

Figure 1: Graphical illustration of a natural efficiency frontier



We extend the concept of the natural efficiency frontier to report a specific performance metric for any LULC map, summarized in figure 2. In this figure, point Z is the current landscape, all pareto-improving reconfigurations are plotted in yellow, and length α represents the distance from the current landscape to the frontier (technically, the specific point defined by the ray from the origin through Z to the frontier). The length β represents the distance between the current landscape and the minimum environmental score attainable (representing a worst-case scenario of complete natural degradation). The efficiency score for a given landscape, then, is defined as $E(LULC) = \frac{\beta}{\alpha+\beta}$. We also construct a metric for policy efficacy that calculates how far any given policy, represented by some alternative LULC map (point Z'), moves towards the Pareto-efficient set. We calculate this as $E(policy) = \frac{\alpha_{policy}}{\alpha}$ where α_{policy} is the distance from a landscape Z to Z'.

Figure 2: Performance metrics derived from the natural efficiency frontier



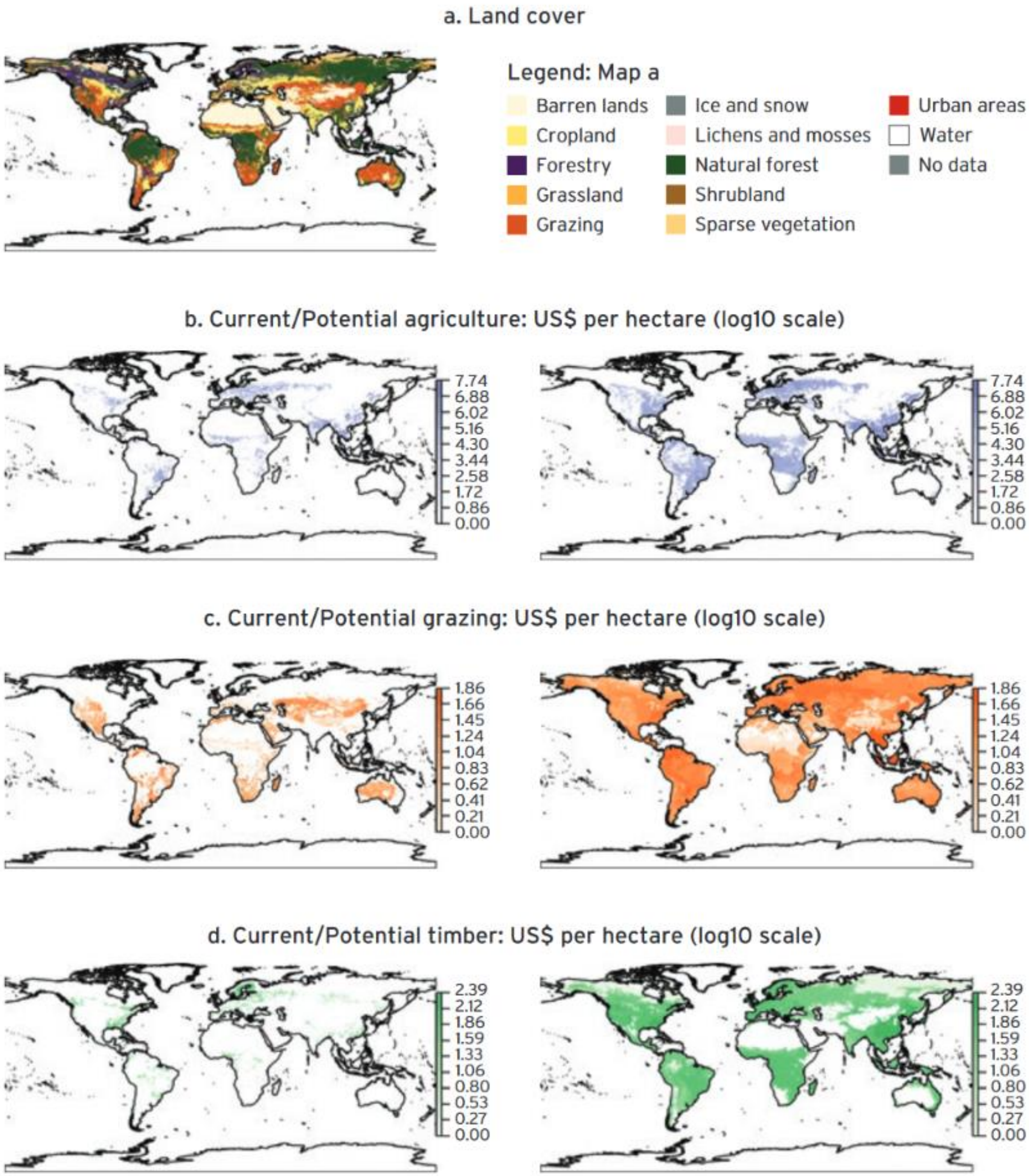
Source: World Bank.
Note: The upper curve shows the efficiency frontier, in which the maximum possible performance for the environmental measure is obtained for a given level of the monetary measure and vice versa. The shaded area is the Pareto space in which it is possible to improve both the environmental measure and the monetary measure relative to the current level of performance without sacrifice in the other measure.

Dimensions beyond two can be visualized by including multiple plots (example below shown in figure 1) or by aggregating different objectives into one composite value plotted on the axis. Visualization aside, the concept of optimizing for n-dimensional efficiency frontiers scales to high values of n.

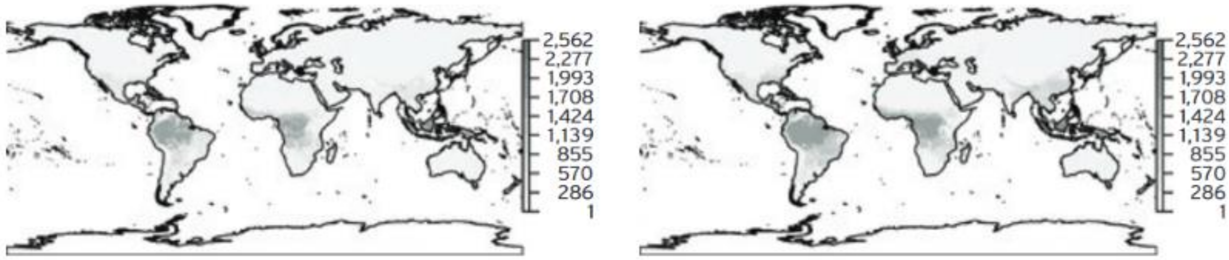
Economic and environmental return

The value reported on each plotting axis (or frontier dimension) depends on a series of economic and environmental return functions. The choice variables are represented by the LULC map, while the returns from any specific choice of land-use within a pixel depends on spatially-explicit return maps, shown in figure 3 below. Panel A shows the current land-cover, panels B to D report returns for marketed goods (economic value) while E to G report returns for non-marketed goods (environmental value). Specifically, the figure shows the current (left) and potential (right) value attainable for the following agriculture, grazing, timber, carbon storage, and two metrics of biodiversity.

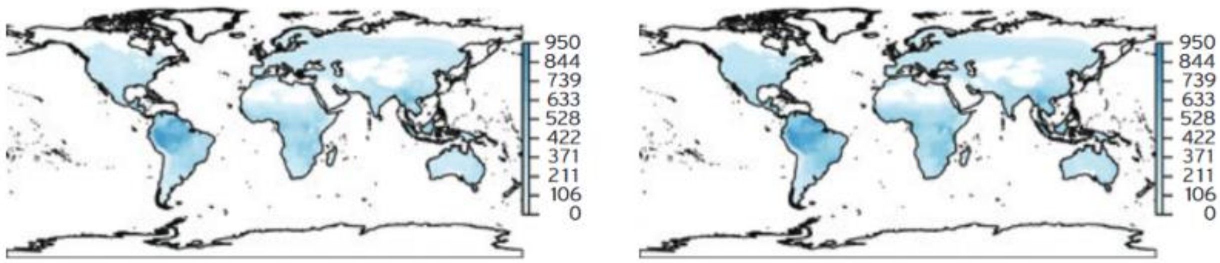
Figure 3: Land cover with current and potential returns



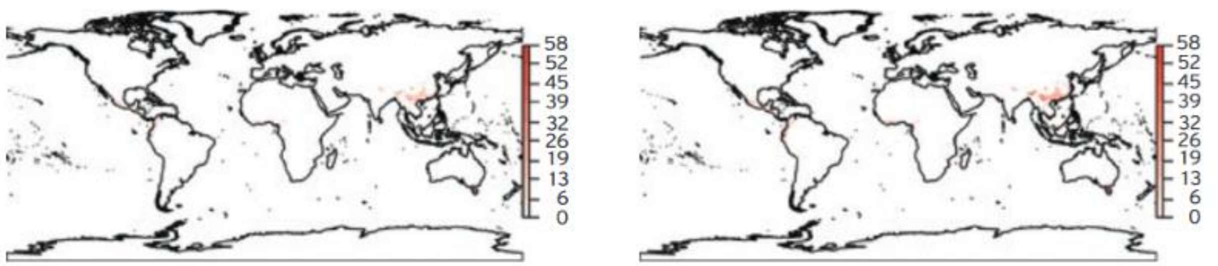
e. Current/Potential carbon: Tonnes of carbon per hectare



f. Current/Potential species richness: Number of vertebrate species per pixel



g. Current/Potential T/E richness: Number of threatened and endangered vertebrate species per pixel



Source: World Bank.

To calculate biophysical returns, we use the InVEST model from the Natural Capital Project, supplemented by model extensions and a collection of globally consistent biophysical and socio-economic data (~300m2 at the equator), to analyze the impacts of current sustainable land use and 13 land-use and land-management alternatives (LU-LM alternatives) on land-based climate mitigation, biodiversity, and production value. The LU-LM alternatives applicable to each pixel include either maintaining or shifting to current agriculture, natural habitat, forestry, grazing, intensive agriculture rainfed, and intensive agriculture irrigated. Overall, the LU-LM alternatives consist of different combinations of management practices such as current extensification practice, rainfed intensified extensification, irrigated intensified extensification, rainfed intensified fixed area, and irrigated intensified fixed area. In improving current practices and ensuring sustainability, we impose a series of constraints – preventing land-based economic activities related to cropping, grazing, and forestry into any IUCN class I-IV protected area, restricting crop management alternatives to only include rainfed cropland if irrigation is considered unsustainable, not allowing expansion of intensified cropland into pixels with average slope >10°. Considering associated constraints, the optimization technique selects among sustainable current sustainable land use or one of the 13 LU-LM alternatives for each land parcel to achieve outcomes along the efficiency frontier.

We used the European Space Agency land use/land cover map as the current landscape map with augmented sustainability practices or constraint factors for 146 countries with adequate globally available and consistent datasets. Sustainable current is the adjusted baseline condition used with the optimization of various LU-LM alternatives. To be sustainable current, a country prohibits unsustainable irrigation, removes existing cropland from land in IUCN classes I-IV and VI, allows current economic uses on IUCN class V, and more specifically allows grazing and forestry expansion in IUCN class VI.

Economic Returns

To pinpoint areas suitable for productive livestock grazing and forestry, we adjusted the baseline ESA map by integrating pixel locations identified as permanent meadows and pastures from Food and Agriculture Organization (FAO) data, along with a global map indicating the proportion of each pixel expected to be pasturelands. Subsequently, we utilized a global raster indicating the probability of a pixel being a grazed pasture, as outlined by Hoskins et al. (2016), to prioritize pixels within viable Land Use and Land Cover (LULC) classes for designation as 'grazed' within our sustainable current landscape, as referenced in Polasky et al. Eventually, our area of grazing is equivalent to the area under permanent meadows and rangelands in each country.

To ascertain which pixels are presently managed for timber production, we acquired a global raster of forest management data from Lesiv et al. (2022). This dataset categorizes global forest lands into six distinct categories: (1) primary forests, (2) naturally regenerating forests, (3) planted forests, (4) plantation forests, (5) agroforestry, and (6) oil palm plantations. For pixels classified within ESA forested categories classes, we utilized this map to determine their management status. Pixels falling into category 1 were regarded as natural forests with no timber activity. Those in categories 2 and 5 were considered forestry on natural lands. Categories 3 and 4 were interpreted as plantation forests. Category 6, designated as oil palm plantations, was excluded from the timber production value and added to the cropland value.

Climate returns

We use the InVEST Carbon Storage and Sequestration model to assess the carbon storage potential of different LU-LM alternatives, focusing on only above-ground and belowground biomass. Carbon densities vary geographically, influenced by factors such as land cover and natural vegetation types. Agriculture BMPs are considered, but intensification itself is treated as not affecting carbon storage. For forestry, we reduced the carbon stored in forest classes in half to reflect the fact that timber is periodically harvested, which reduces above-ground that grows back slowly while trees mature, while grazing lands are not ascribed with a change in carbon storage, given conflicting evidence on the impact of grazing on carbon stock (ref). However, changes in land cover due to grazing are accounted for according to Spawn et al. (2020). In cases where cropland carbon storage is overestimated, the carbon storage is capped at the potential natural habitat type. Methane emissions from livestock are converted to carbon dioxide equivalents (CO2e) and adjusted for long-term emissions, with the net greenhouse gas storage calculated by subtracting long-term methane emissions from carbon stocks (Polasky et al.,).

Biodiversity returns

We use the Species Threat Abatement and Restoration (STAR) metric to evaluate the potential impact of investments in reducing species extinction risk. While Mair et al. (2021) establish a STAR threat abatement metric and a STAR restoration metric, in this analysis we only consider the STAR threat abatement metric. Applying the formula below, a global STAR threat abatement (STAR-T) score is defined for each species, which can be totaled across all species to indicate the global effort required to reduce threats until all species reach the Least Concern status. STAR-T can also be disaggregated spatially by using the currently available Area of Habitat (AOH) for each species in a specific location, serving as a proxy for the population proportion in that area.

The modeling framework for developing the STAR score uses publicly available data on species' extinction risk categories, threats classification, species' Area of Habitat (AOH) estimated using species' available habitat within its range, habitat associations, elevation limits, and current and historical land cover maps (Mair et al, 2021). Mair et al (2021) study obtained species' threat classification and extinction risk categories data for amphibians, birds, and mammals from the IUCN Red List and utilized 5-km-resolution species' AOH rasters to determine the extent of current and restorable AOH for species. Current and historical AOHs were calculated based on the European Space Agency Climate Change Initiative (ESA CCI) land use and cover maps, respectively dated 2015 and 1992. These maps were reclassified to match the habitat classes from IUCN Red List assessments. Range maps of species were then overlaid with land cover and digital elevation maps to map AOH within each species' range, constrained by their elevation range as per the IUCN Red List data.

The STAR score is calculated using a specific formula that considers various factors related to threats, AOH, and extinction risk to 5,359 species including 2,055 amphibians, 1,957 birds and 1,347 mammals. Species categorized as data deficient and those classified as Least Concern were excluded from the analysis due to insufficient information regarding threats and their extinction risk classification.

$$T_{t,i} = \sum_{s}^{Ns} P_{s,i} W_s C_{s,t}$$

where Ps, i is the current AOH of each species s within location i (expressed as a percentage of the global species' current AOH), Ws is the IUCN Red List category weight of species s (Near Threatened = 1; Vulnerable = 2; Endangered = 3; Critically Endangered = 4)7,8, C is the relative contribution of threat t to the extinction risk of species s, and Ns is the total number of species at location i. (Mair et al., 2021).

The STAR score is derived and analyzed based on several key assumptions. These include factors like restorable Area of Habitat (AOH) – assuming lost habitats can be restored, excluding threats that occurred in the past and are uncertain or unlikely to recur or have an unexpected impact on population decline, and utilizing equal steps weighting instead of relative extinction risk weights for enhanced extinction risk improvement opportunities. These assumptions are crucial in applying the STAR score to assess the potential impact of action targets on species conservation outcomes, supporting global conservation and sustainability objectives such as the Global Biodiversity Framework (GBF), Sustainable Development Goals (SDGs), and the Paris Agreement (Mair et al., 2021). The effective application of STAR necessitates verifying the presence and distribution of threatened species, improving threat assessment, and addressing uncertainties through sensitivity analyses.

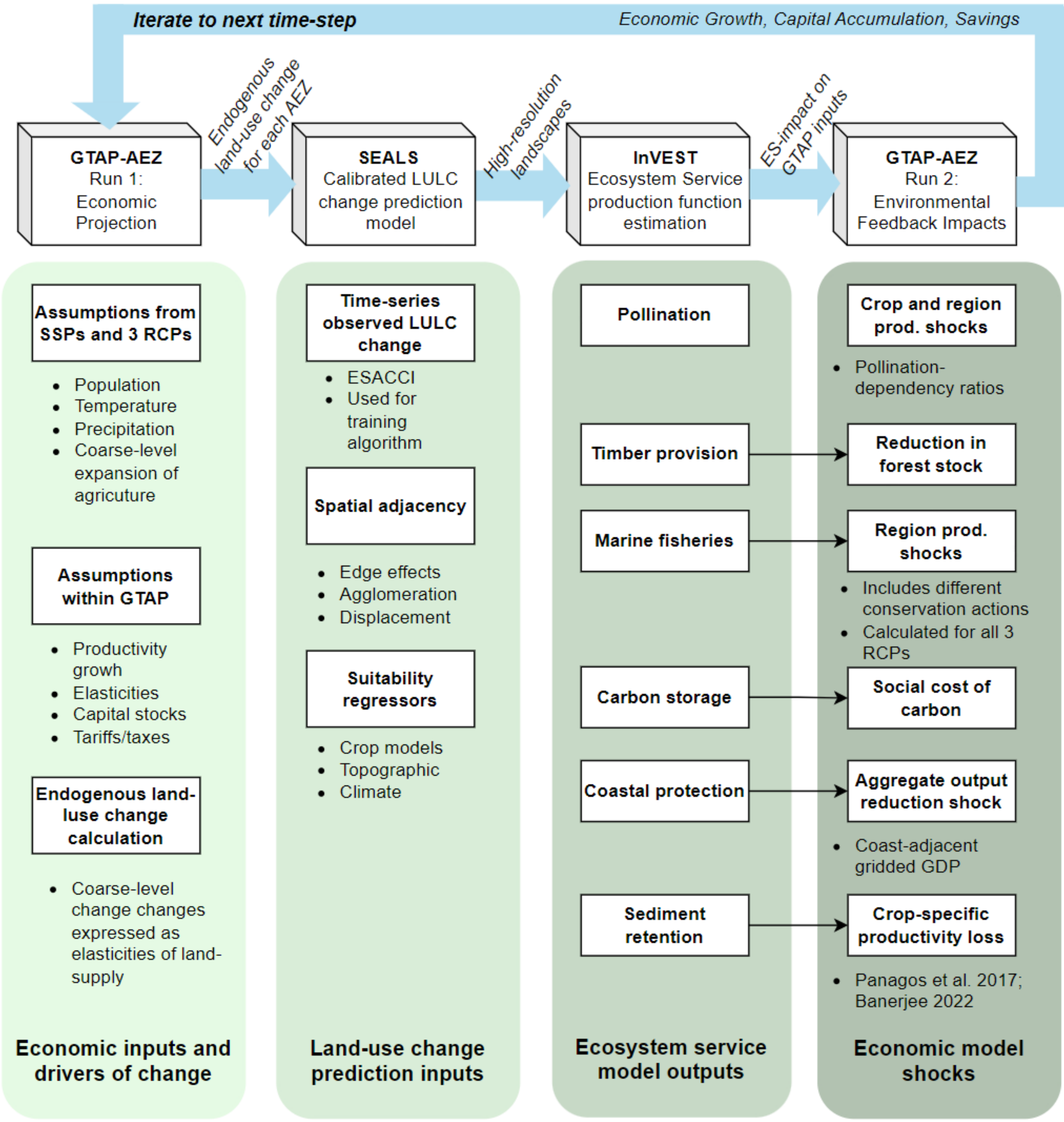
With these potential activities defined, we calculated the efficiency frontiers for nearly all (190) countries on earth, discussed in more depth in the results section.

Policy modeling and scenario development

Knowing what Pareto-improving reconfigurations of the landscape is a conceptually compelling description of “what is possible” on the landscape. However, it does not, specify “how to get there,” namely the policies that might generate the societal changes that lead to the reconfigured landscape. To assess policies, we need models that relate agents’ behavior (production, consumption, savings, taxation, etc.) to economic and biophysical changes.

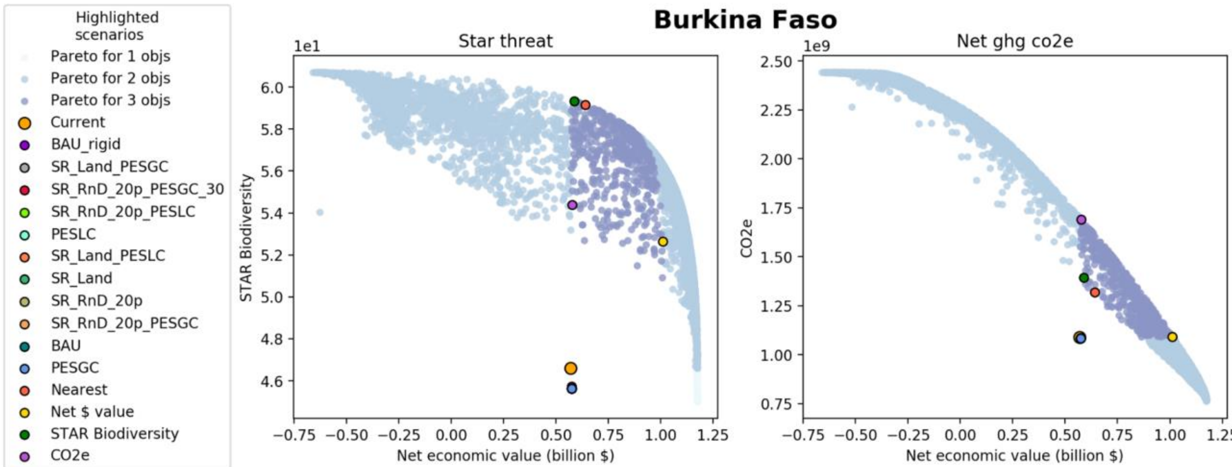
To do this, we use GTAP-InVEST, an Earth-Economy model that calculates how economic activity affects the environment, and vice versa, on global to local scales. The model integrates a computable general equilibrium (CGE) model, a land-use change (LUC) model, and an ecosystem services (ES) model, InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs), provided by the Natural Capital Project. The economic model is a new variant of GTAP-AEZ (Agroecological Zones) model, which calculates equilibrium prices, quantities, GDP, trade and many other economic variables, and most notably for this exercise, endogenously calculates how land is used in different sectors and how natural land is brought into economic use through agricultural, pasture and managed forest expansion. The LUC component is the Spatial Economic Allocation Landscape Simulator (SEALS) model, which downscales regional estimates of land-use change from GTAP-AEZ to a high enough resolution (300m) to run ecosystem service models. Finally, the ES model is InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs), provided by the Natural Capital Project, which takes the downscaled land-use, land-cover maps from SEALS to calculate changes in ecosystem service provision. These ecosystem service changes are then further expressed as shocks to the economy and used as inputs into a second run of GTAP-AEZ, which calculates how losses of ecosystem services affect economic performance. Details of this model are described in figure 4.

Figure 4: Model formulation of GTAP-InVEST

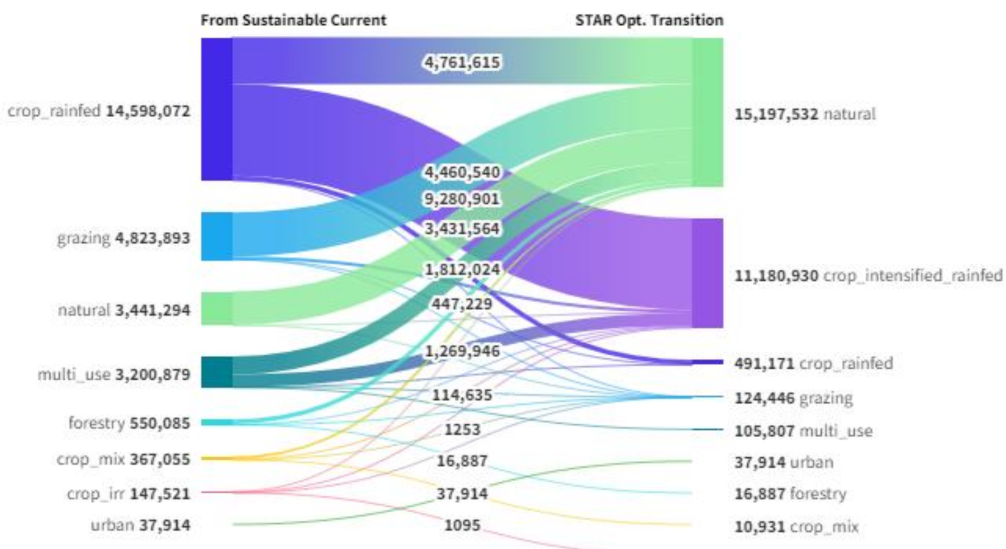


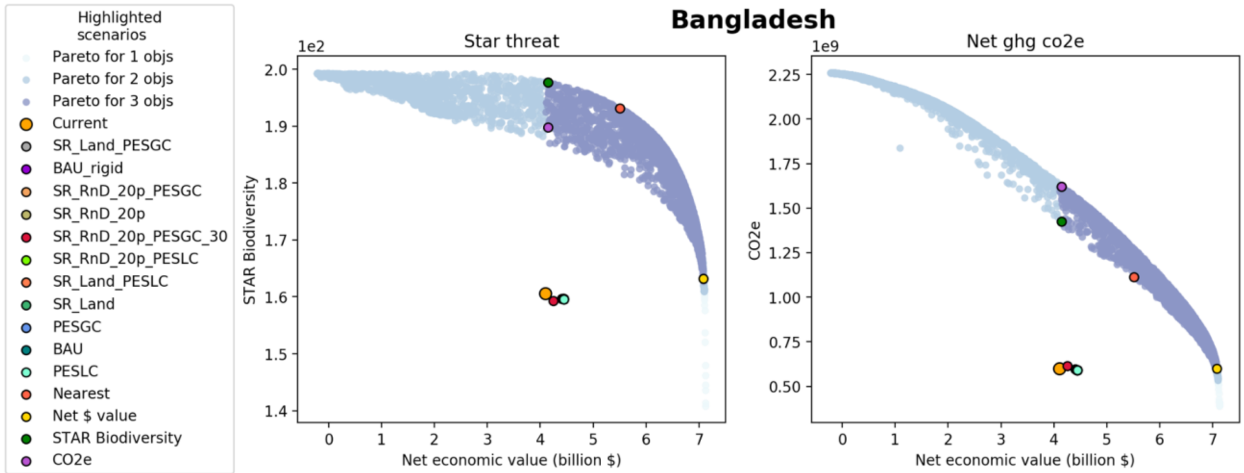
Results

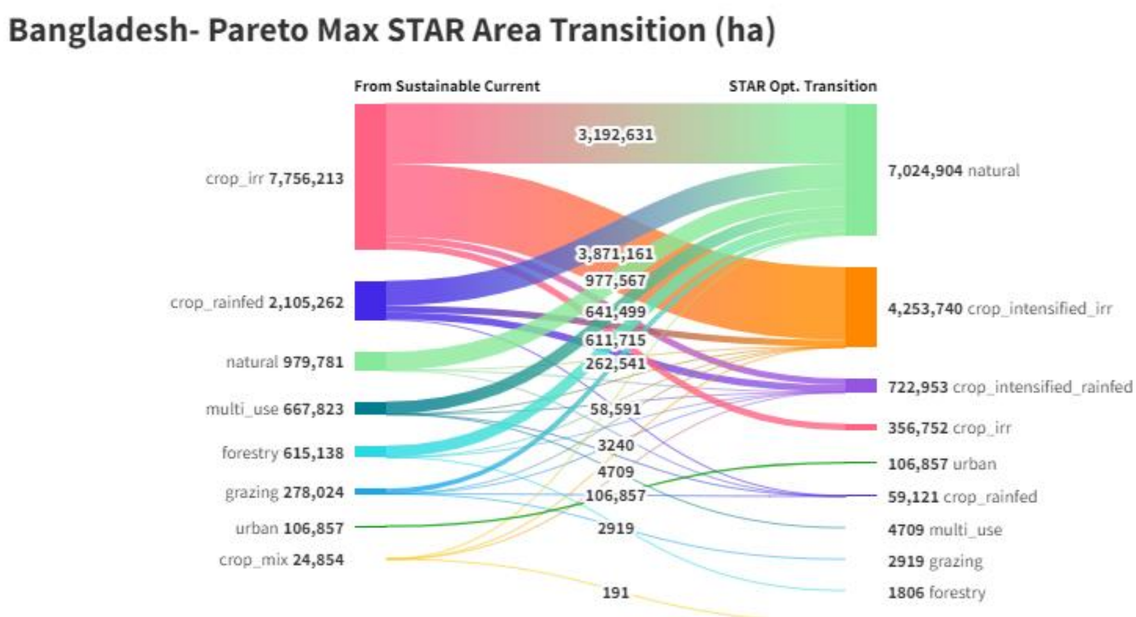
To be completed ASAP.

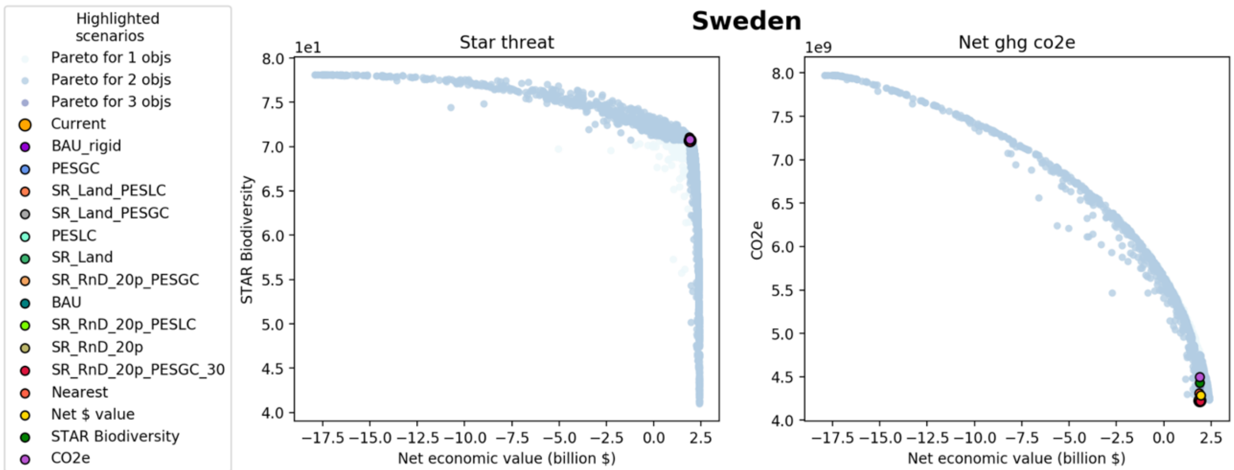


Burkina Faso- Pareto Max STAR Area Transition (ha)

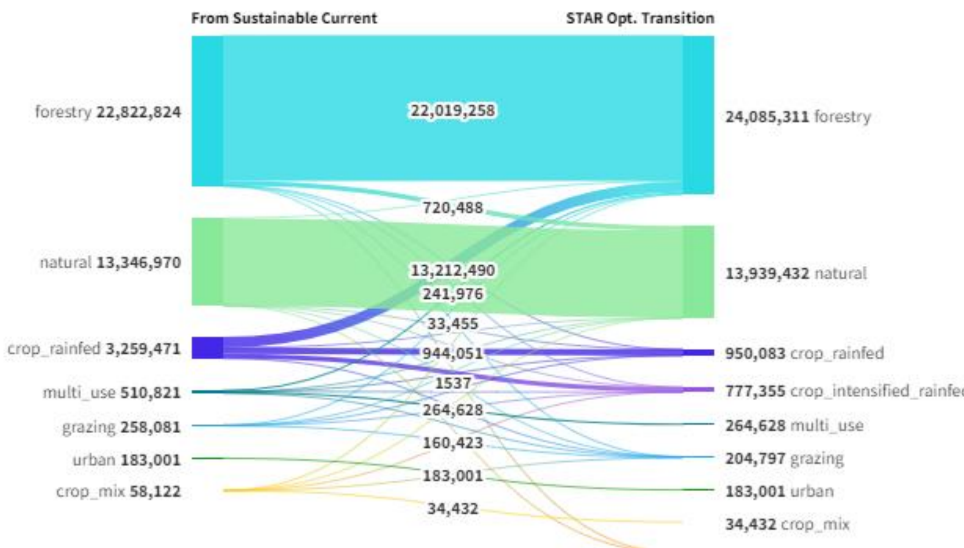



Bangladesh
Highlighted scenarios
Pareto for 1 objs
Pareto for 2 objs
Pareto for 3 objs
Current
SR_Land_PESGC
BAU_rigid
SR_RnD_20p_PESGC
SR_RnD_20p
SR_RnD_20p_PESGC_30
SR_RnD_20p_PESLC
SR_Land_PESLC
SR_Land
PESGC
BAU
PESLC
Nearest
Net $ value
STAR Biodiversity
CO2e
Star threat
1e2
STAR Biodiversity
Net economic value (billion $)
Net ghg co2e
1e9
CO2e
Net economic value (billion $)

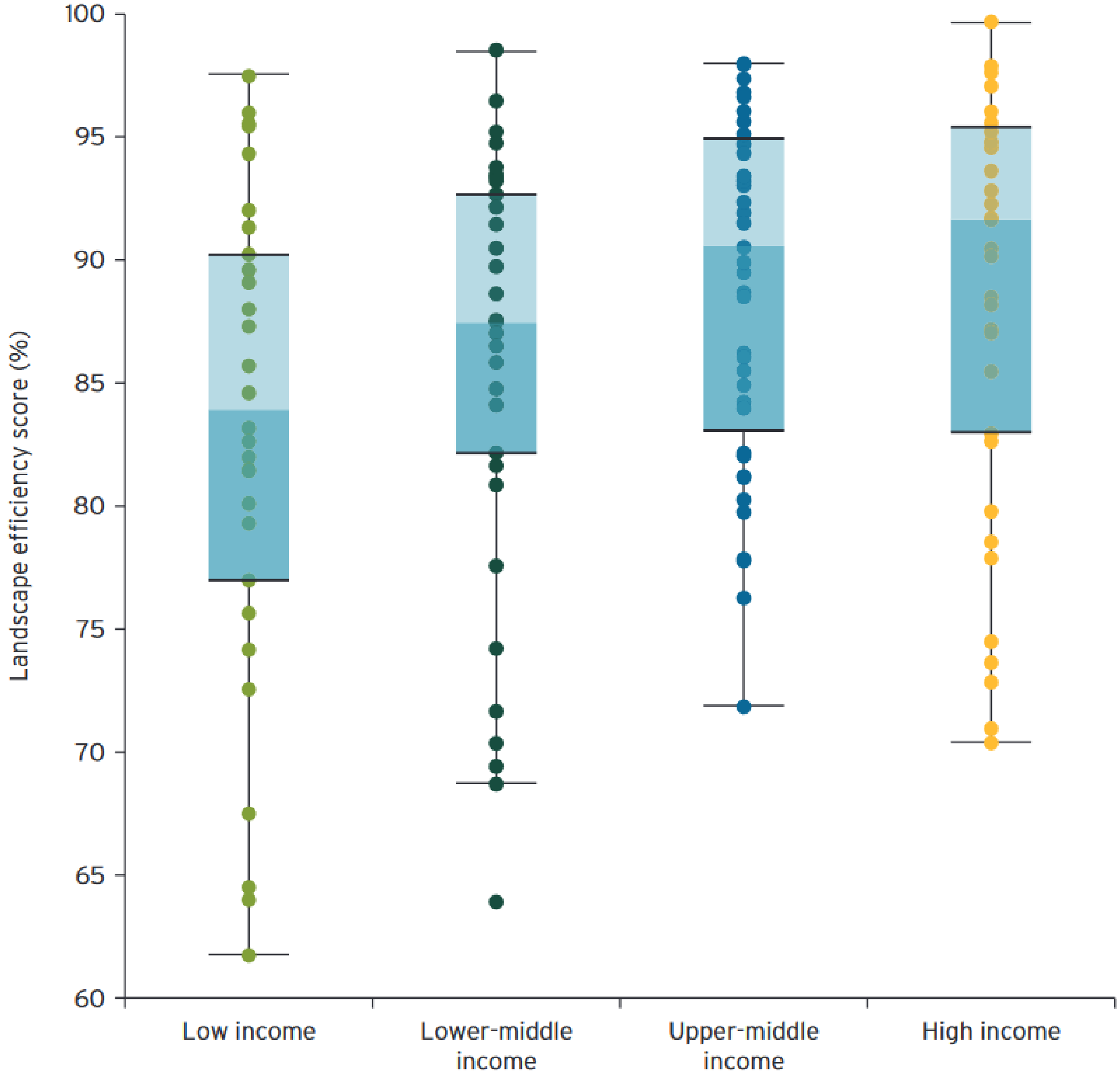

Bangladesh- Pareto Max STAR Area Transition (ha)
From Sustainable Current
STAR Opt. Transition
crop_irr 7,756,213
crop_rainfed 2,105,262
natural 979,781
multi_use 667,823
forestry 615,138
grazing 278,024
urban 106,857
crop_mix 24,854
3,192,631
3,871,161
977,567
641,499
611,715
262,541
58,591
3240
4709
106,857
2919
191
7,024,904 natural
4,253,740 crop_intensified_irr
722,953 crop_intensified_rainfed
356,752 crop_irr
106,857 urban
59,121 crop_rainfed
4709 multi_use
2919 grazing
1806 forestry



Sweden- Pareto Max STAR Area Transition (ha)



Distribution of landscape efficiency scores, by country income group



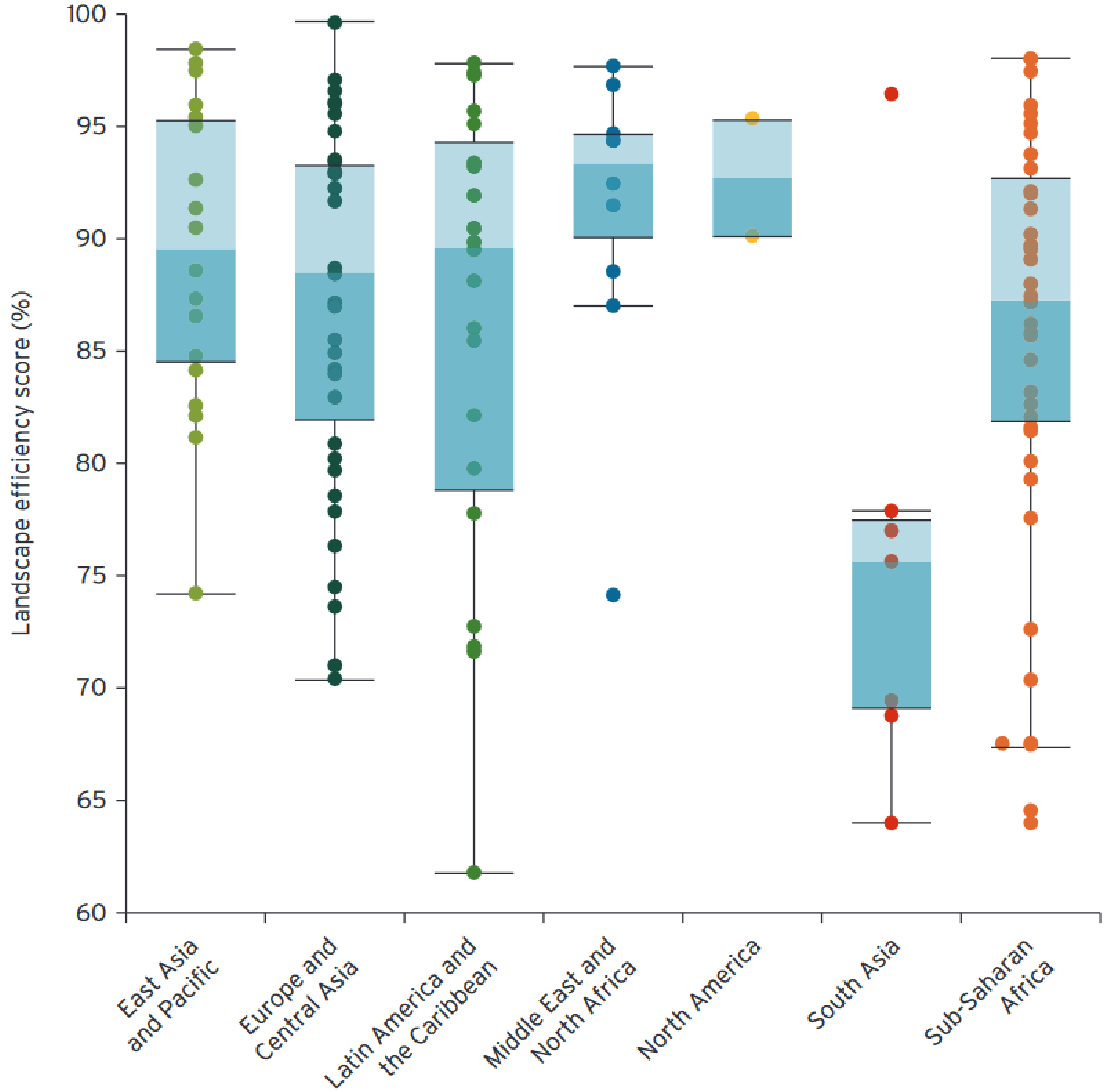
Source: World Bank.
Note: Circles represent individual country scores. The mean value across countries in each income group is indicated by the horizontal line that extends across the box. Inside the box, the upper, light blue portion is the second quartile (25th–50th percentile), and the lower, dark blue portion is the third quartile (50th–75th percentile). Outer lines are useful for identifying outliers.

Landscape efficiency scores, by country income group

Country income group	(1) Mean economic efficiency within the Pareto space[a] (%)	(2) Mean carbon efficiency within the Pareto space (%)	(3) Mean biodiversity efficiency within the Pareto space (%)
Low income	47.5	74.2	77.6
Lower-middle income	51.7	78.9	81.0
Upper-middle income	55.1	83.0	84.9
High income	72.6	77.9	86.6

Source: World Bank.
Note: Numbers closer to 100 indicate higher levels of efficiency.
a. The Pareto space refers to outcomes where improvements in one of the key dimensions can be made without sacrifice in the other two dimensions.

Distribution of landscape efficiency scores, by region



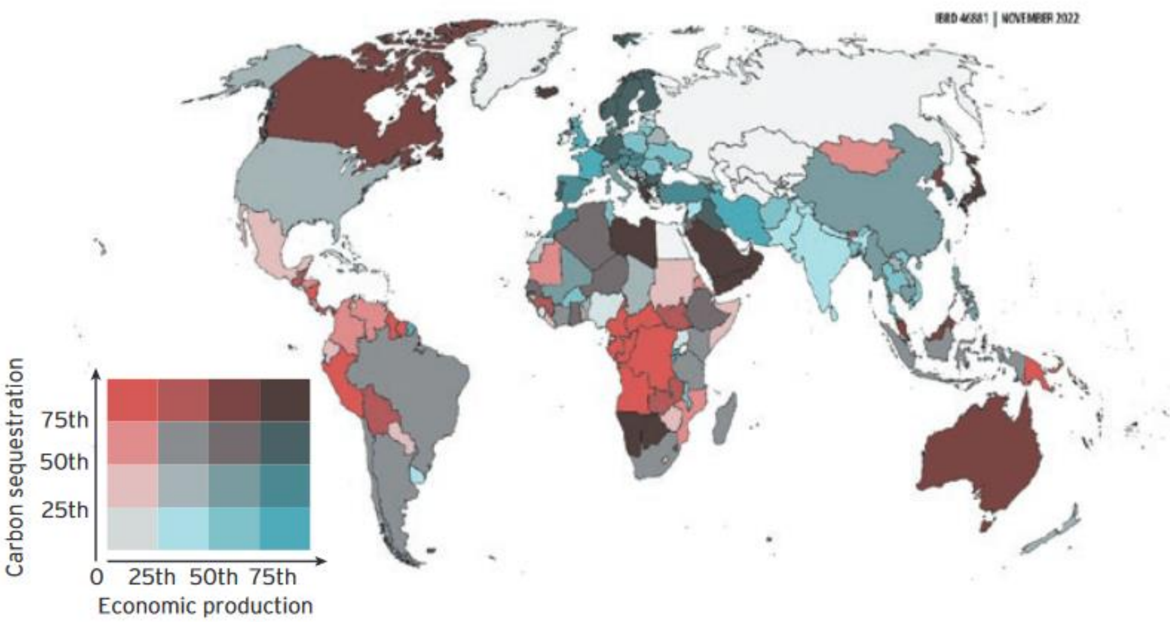
Source: World Bank.
Note: Circles represent individual country scores. The mean value across countries in each income group is indicated by the horizontal line that extends across the box. Inside the box, the upper, light blue portion is the second quartile (25th–50th percentile), and the lower, dark blue portion is the third quartile (50th–75th percentile). Outer lines are useful for identifying outliers.

Landscape efficiency scores, by region

Region	Mean economic efficiency within the Pareto space (%)	Mean carbon efficiency within the Pareto space (%)	Mean biodiversity efficiency within the Pareto space (%)
East Asia and Pacific	62.8	83.7	86.1
Europe and Central Asia	72.3	75.2	87.5
Latin America and the Caribbean	37.4	82.0	83.3
Middle East and North Africa	76.9	83.5	79.4
South Asia	53.0	60.2	79.2
Sub-Saharan Africa	46.7	79.8	78.2

Source: World Bank.
Note: Numbers closer to 100 indicate higher levels of efficiency.

MAP 3.1
Country performance across economic efficiency and carbon sequestration efficiency in Pareto spaces



Source: World Bank.
Note: No data is available for the countries shaded in the palest gray.

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