Supplemental Information for
Developed economies are growing while reducing their environmental impacts

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Zenodo link (data tables, code, etc.): https://zenodo.org/records/18499827

S.1 Data

Table S1. World Bank 2021 Income Group Classifications (144 countries)

High-Income Countries (45 countries, ~1.27 billion people in 2023): Australia, Austria, Bahrain, Barbados, Belgium, Canada, Chile, Croatia, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Luxembourg, Malta, Netherlands, New Zealand, Norway, Oman, Poland, Portugal, Puerto Rico, Qatar, Saudi Arabia, Seychelles, Singapore, Slovenia, South Korea, Spain, Sweden, Switzerland, Trinidad and Tobago, United Arab Emirates, United Kingdom, United States, Uruguay
Upper-Middle-Income Countries (36 countries, ~2.64 billion people in 2023): Albania, Argentina, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Dominica, Dominican Republic, Ecuador, Equatorial Guinea, Gabon, Guatemala, Iraq, Jamaica, Jordan, Lebanon, Libya, Malaysia, Mauritius, Mexico, Montenegro, Namibia, North Macedonia, Panama, Paraguay, Peru, Romania, Russia, Saint Lucia, Serbia, South Africa, Thailand, Turkey
Lower-Middle-Income Countries (42 countries, ~3.50 billion people in 2023): Algeria, Angola, Bangladesh, Benin, Bolivia, Cambodia, Cameroon, Cape Verde, Comoros, Congo, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Eswatini, Ghana, Haiti, Honduras, India, Indonesia, Iran, Kenya, Laos, Lesotho, Mauritania, Mongolia, Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Palestine, Philippines, Sao Tome and Principe, Senegal, Sri Lanka, Tanzania, Tunisia, Vietnam, Zambia, Zimbabwe
Low-Income Countries (21 countries, 0.81 billion people in 2023): Afghanistan, Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of Congo, Ethiopia, Gambia, Guinea, Guinea-Bissau, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Sierra Leone, Sudan, Togo, Uganda

2021 World Bank income group classifications (based on Gross National Income (GNI) per capita in current US dollars using the Atlas method, with thresholds updated on July 1, 2021 and reflecting 2020 GNI per capita values):

- Low-income economies: GNI per capita less than $1,045
- Lower-middle-income economies: GNI per capita $1,046 – $4,095
- Upper-middle-income economies: GNI per capita $4,096 – $12,695
- High-income economies: GNI per capita greater than $12,695

Gross Domestic Product (1960 to 2023)
Gross Domestic Product (GDP) per capita is the average economic output per person in a country per year. This data is adjusted for inflation and for differences in living costs between countries and set to international-$ at 2011 prices.

Data Cleaning:
Maddison GDP data (constant international-$ 2011, PPP) were combined with World Bank GDP data (constant 2021-$ international, PPP) (Bolt & Van Zanden, 2025; World Bank, 2025). Maddison was missing data for ARE (United Arab Emirates) for 1991 and 1992, and linear interpolation was used to fill in the gaps (Bolt & Van Zanden, 2025). GDP data from Maddison was combined with GDP from World Bank data to create a GDP dataset with values from 1950 to 2023. The World Bank data was used to calculate growth rates from 2022 to 2023 to get 2023 GDP values in international-$ at 2011 prices. Population data from Our World in Data (OWID) was used to get GDP per country. A partial panel of GDP per capita data (constant international-$ 2005, PPP) from EconStats was used to convert the combined cleaned GDP data (constant international-$ 2011, PPP) to 2005 constant international-$ PPP for Figure 4 (EconStats, 2025).

Population (1960 to 2023)
Data for human population by country came from OWID which combined datasets from the Historical Database of the Global Environment (HYDE 2023), Gapminder (2022), and UN World Population Prospects (UN WPP, 2024). A country's population is typically estimated using the cohort-component method ($\text{Population}_t = \text{Population}_{t-1}$ + Births - Deaths + Immigration - Emigration), except when a census is conducted.

HYDE is a historical database that combines population estimates with land-use data, providing spatially explicit population maps over long time spans, from 10,000 BCE to near present (Klein Goldewijk, 2023). Gapminder draws on existing historical demographic sources and interpolates/adjusts for consistency. Their population series is a composite built from other sources including from the Maddison Project Database (*Gapminder*, 2022). The UN WPP is the UN's official demographic estimation and projection framework. The UN WPP takes national census data, vital statistics (births, deaths), demographic and health surveys, and other administrative records submitted by governments, to estimate populations within countries. Beyond the present, the UN WPP uses variant scenarios to project future population through 2100 (UN, 2024a, 2024b).

Material Footprint Data (1970 to 2024)
The material footprint data comes from the Global Material Flows Database provided by the International Resource Panel and is measured in metric tons (IRP, 2024; UNEP, 2023). Material Footprint (MF) is the attribution of global material extraction to domestic final demand of a country. The total material footprint is the sum of the material footprint for biomass, fossil fuels, metal ores, and non-metallic minerals. Material footprint of consumption reports the amount of primary materials required to serve final demand of a country and can be interpreted as an

indicator of the material standard of living/level of capitalization of an economy. Per-capita MF describes the average material use for final demand.

The underlying footprint calculation uses the global Multi-Regional Input Output (MRIO) analysis, which compiles information from many countries national statistics to create a global multi-regional input-output table. The global estimation for MF is based on data available from different national and international datasets in the domain of material flow accounts, agriculture, forestry, fisheries, mining and energy statistics. International statistical sources for MF include the International Energy Agency, the United Nations Statistical Division, the United States Geological Survey, the Food and Agriculture Organization and COMTRADE databases. For global estimation, the International Resource Panel (IRP) Global Material Flows and Resource Productivity working group compiles the data from national and international databases. At the same time, country-provided indicators are collected through the Questionnaire on Economy Wide Material Flow Accounts for the Sustainable Development Goal (SDG) indicators 8.4.1/12.2.1 and 8.4.2/12.2.2.

Material footprint by type of raw material (tonnes) is calculated as:
$MF = DE + RMEIM - RMEEX$

Where:
MF – material footprint;
DE – domestic extraction of materials;
$RMEIM$* – raw material equivalent of imports;
$RMEEX$* – raw material equivalents of exports.

**Includes actual material flows and estimated flows based on import/export accounting values in currency*

For the attribution of the primary material needs of final demand a global MRIO framework is employed. The attribution method based on I-O analytical tools is described in detail in Wiedmann et al. 2015. It is based on the Eora MRIO framework developed by the University of Sydney, Australia (Lenzen, Dey, et al., 2013; Lenzen, Moran, et al., 2013; UNEP, 2025) which is an internationally well-established and the most detailed and reliable MRIO framework available to date.

Biomass: Biomass comprises organic non-fossil material of biological origin. The largest share of the extracted biomass is used as food for humans and feed for livestock. In these applications biomass is a non-substitutable resource. Biomass is further used to provide technical energy (e.g. fuelwood) or as raw materials (e.g. textiles, paper and construction wood) (Schandl, 2023).

Non-metallic minerals definition: The OECD officially defines non-metallic minerals as "[…] stone quarries and clay and sand pits; chemical and fertilizer mineral deposits; salt deposits; deposits of quartz, gypsum, natural gem stones, asphalt and bitumen, peat and other nonmetallic minerals other than coal and petroleum" (OECD 2001). These materials are widely available worldwide and are mostly domestically sourced. If accounted by mass, the vast majority of the materials of this category are sand, gravel, and clay used for construction, while the remainders are used either as decorative stones or for chemicals and fertilizers (Schandl, 2023).

Metal ores: Metals in their pure and unalloyed form are chemical elements. They are generally solids at room temperature (except mercury) and tend to be good conductors of electricity and heat, ductile and malleable, hard, and shiny. They account for around three quarters of the elements on the periodic table (Schandl, 2023).

Fossil fuels: materials formed from biomass in the geological past and comprise solid, liquid and gaseous materials. Petroleum resources are mainly used to provide energy, but they also serve as base materials for industrial processes (e.g. for the production of organic chemical compounds and synthetic materials or fibers) (Schandl, 2023).

Data Cleaning:
In order to aggregate to World Bank Income Groups, former Yugoslavian countries (Bosnia & Herzegovina, Croatia, North Macedonia, Serbia, Slovenia) and Sudan were removed; all removed countries fall into high- or upper-middle-income buckets except Sudan (only 60 entries). Data was combined with GDP and population datasets.

SO2 Emissions (1960 to 2022)
SO2 emissions primarily come from the burning of coal. Data comes from the Community Emissions Data System (CEDS) created by Hoesly et al. (2024) with major processing by Our World in Data. SO2 emissions are measured in metric tons produced by a given country. CEDS is an open, community-based emission inventory for different chemical compounds present in the atmosphere. The broad structure of emission estimation in CEDS follows a bottom-up (activity × emission factor) approach, often calibrated to country reported emissions, when reliable, as well as other external benchmarks. The bottom-up calculation yields a “prior” estimate; then scaling is performed to match known totals or adjust for systematic biases.

Data Cleaning:
No additional data manipulation needed beyond combining with GDP and population datasets.

CO2 Emissions (1990 to 2023)
National consumption-based CO2 emissions data from fossil fuels and industry come from the Global Carbon Budget with major processing performed by Our World in Data (Friedlingstein et al., 2023; OWID, 2024). This data does not include emissions from land use change, deforestation, soils, or vegetation. Emissions are measured in metric tons. Consumption-based emissions attribute the emissions generated in the production of goods and services according to where they were consumed, rather than where they were produced. The data is calculated by adjusting 'production-based' emissions (emissions produced domestically) for trade: Consumption-based emissions equal production-based emissions, minus emissions embedded in exports, plus emissions embedded in imports.

In Global Carbon Budget 2023, CO2 emissions are estimated using energy consumption data (coal, oil, gas) from sources like the BP statistical review and the International Energy Agency, multiplied by fuel-specific carbon emission factors that reflect carbon content and oxidation efficiency. Industrial process emissions (mainly from cement production, steel, and chemical processes) are calculated separately using production data and process-specific emission coefficients. Estimates are cross-checked and harmonized with national inventories and independent datasets. Where needed, temporal trends are extended to recent years using early-release data on energy production, trade, and consumption as well as short-term projections.

Data Cleaning:
In order to aggregate to World Bank Income Groups, Norway was removed from the dataset due to a significant amount of missing data across the time period. Linear interpolation was used to fill in missing values for Panama in 2006, 2008, and 2016. Data was combined with GDP and population datasets. Only 9 of 21 countries are represented in the low-income group (Burkina Faso, Ethiopia, Guinea, Madagascar, Malawi, Mozambique, Rwanda, Togo, and Uganda).

Primary Energy Consumption (1985 to 2024)
Primary energy consumption by type data comes from Energy Institute – Statistical Review of World Energy (2025) with major processing by Our World in Data (Energy Institute, 2025; OWID, 2025b). This data is reported in primary energy equivalent—kWh and separates sources into eight energy types: coal, oil, gas, nuclear, hydropower, wind, solar, and other renewables (which includes biofuels). Primary energy refers to energy in its natural, unconverted form. Primary energy equivalent is a standardized measure of the total amount of raw energy that would be needed to produce a given amount of energy, often electricity (i.e. fuels → thermal energy → mechanical energy → electricity; solar (PV) → electricity) and allows for comparison across different energy sources.

There are different methods for calculating the primary energy equivalent; the Energy Institute uses a physical energy content method, which calculates primary energy by measuring the energy content at the first point where an energy source has a practical, marketable use. Data on production, trade, transformation, and use of different energy types are collected from nations, international agencies, and industry reports. The data is aggregated into energy balances and converted into primary energy equivalents; non-combustible renewables (solar, wind, hydro) are counted at their gross electrical output. For technologies with a heat input (e.g. nuclear, geothermal, concentrated solar), their primary equivalent is estimated by back-calculating from assumed conversion efficiencies to derive the heat input needed. This approach better reflects the actual energy "supply" that a system must provide, including losses (Energy Institute, 2025).

Data Cleaning:
Data prior to 1985 were removed due to significant lack of data across countries for years prior. In order to aggregate to World Bank Income Groups, eight countries (Democratic Republic of Congo, low-income; Croatia, high-income; Madagascar, low-income; North Macedonia, upper-middle; Mozambique, low-income; Serbia, upper-middle; Slovenia, high-income; and Zambia, lower-middle) were removed due to lack of data during the time period from 1985 to 2023. Data was combined with GDP and population datasets. Only 2 of 21 countries are represented in the low-income group (Chad and Sudan).

Agricultural Land (1960 - 2023)
Agricultural land use data comes from HYDE (2023) with minor processing by Our World in Data (HYDE, 2023; OWID, 2023). Agricultural land use includes cropland and grazing land. Data are provided as 5-arc-minute (~85 km^2 at the equator) ESRI ASCII grids (raster data). For

land-use layers, the values are given as area in km^2 per grid cell with some products also offering cell fractions. Country and regional totals are produced by adding the km^2 per cell. HYDE combines national/subnational statistics (FAO post-1961; earlier censuses and historical sources) with time-varying spatial weighting maps (e.g., land-cover and suitability layers) to allocate totals onto the 5′ grid (HYDE, 2023).

Data Cleaning:
No additional data manipulation needed beyond combining with GDP and population datasets.

Fisheries (1950 - 2022)
World fisheries catch data by country comes from FAO (2023) and is measured in metric tons of live weight. Fish catch is defined as the quantity of fish, crustaceans, mollusks, and other aquatic animals taken from wild stocks for all purposes—commercial, industrial, recreational, and subsistence. Catch is compiled from national submissions (fisheries agencies) and, if unavailable, regional fishery organization data, scientific literature, and/or estimation procedures are used. Many countries do not report complete or timely catch statistics, or they underreport so estimation methods such as interpolation/extrapolation, scaling/expansion, stratified sampling + extrapolation, or benchmarking from stock assessments must be used (FAO, 2023).

Data Cleaning:
Elven countries (Bosnia and Herzegovina, upper-middle; Croatia, high-income; Eswatini, lower-middle; Luxembourg, high-income; Mongolia, lower-middle; Montenegro, upper-middle; North Macedonia, upper-middle; Palestine, lower-middle; Serbia, upper-middle; Slovenia, high-income; United Arab Emirates, high-income) had too much missing data and were cut in order to allow for World Bank income group aggregation. Data was combined with GDP and population datasets.

Nitrogen & Phosphorus (1961 - 2022)
Nitrogen and phosphorus data come from FAO (2025) and are measured in metric tons. Their use as an inorganic fertilizer (agricultural use) is collected from national submissions (annual fertilizer usage questionnaires), national agricultural ministries, published national statistics, international organizations, and industry associations. FAO also applies several methods to estimate missing values or adjust data for consistency, methods include: mass balance/supply-use identity (i.e. production + imports = exports + agricultural use + other uses), interpolation/trend extrapolation, and expert judgement.

Data Cleaning:
No additional data manipulation needed beyond combining with GDP and population datasets.

Animal Abundance (1961 - 2022)
The animal abundance metric is based on the Live Planet Index (LPI) created by World Wildlife Fund with processing by Our World in Data (OWID, 2022; WWF, 2024). The LPI is a measure of the state of biodiversity in each world region (i.e. Africa, Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, North America, and Fresh Water) based on population trends of vertebrate species from around the world. The index value is measured relative to

species' populations in 1970 (i.e. 1970 = 1 or 100%). The index represents 34,836 populations of 5,495 species.

All indices are weighted by species richness, giving species-rich taxonomic groups in terrestrial, marine and freshwater systems more weight than groups with fewer species. Using a method developed by ZSL and WWF, these species population trends are aggregated to produce indices of the state of biodiversity. To calculate an LPI, a generalized additive modelling framework is used to determine the underlying trend in each population time-series. Average rates of change are then calculated and aggregated to the species level (WWF, 2024).

Data Cleaning:
In order to combine LPI's regional values with the country level GDP and population datasets, GDP and population data for each country were put into the regional bucket they fell within and aggregated from there. The WWF bases LPI numbers on 210 countries while we have GDP and population data for 144 countries. The regional aggregates (GDP, population, income shares) are based solely on those 144 countries, not on all 210 possible countries or the full global economy. The regional LPI values still correspond to the full regional biodiversity dataset. But the regional GDP and population totals are underestimates of the true regional totals.

Table S2. LPI Countries within a Given Geographic Region

Region		**Number of Countries in Region**
Africa		55
Asia and Pacific		63
Europe and Central Asia		56
Latin America		34
North America		2
Total		**210**

Production-Based CO_2 Emissions (1972-2024)
These data are based on territorial emissions from fossil fuels and industry, meaning the emissions produced within a country's borders, but not those from imported goods. For example, emissions from imported steel are counted in the country where the steel is produced. Land-use change emissions are not included. Data comes from Our World in Data and Global Carbon Budget (OWID, 2025a).

Data Cleaning:
Production-based CO_2 emissions data was combined with GDP and population datasets. One high-income country (Puerto Rico) was missing from the dataset and three countries were cut due to insufficient data: Namibia (upper-middle), Lesotho (lower-middle), and Palestine (lower-middle).

Shared Socioeconomic Pathways Data
The Shared Socioeconomic Pathways database is a standardized global scenario framework used to explore how different future socioeconomic developments—like population growth, economic trends, technology, and inequality—could influence climate change and society's ability to

mitigate or adapt (Riahi et al., 2017). We use GDP, population, agricultural land use, CO2 production-based emissions, and primary energy use projections from SSP1-26 and SSP4-34.

Data Cleaning:
SSP data were combined with the historical data for GDP, population, agricultural land, CO2 emissions, and primary energy use. Data were aggregated by SSP region with several countries cut due to inconsistencies across datasets.

Table S3. Countries present in the SSP region mapping but missing from each dataset

SSP Region (total entities)	**Agricultural land**	**CO_2 Emissions**	**Energy**
OECD (75 countries)	41	38	47
Asia (45 countries)	27	26	31
Latin America (46 countries)	23	23	37
Middle East & Africa (69 countries)	10	9	47
Reforming Economies (12 countries)	11	11	11

Most of the missing entities across all regions are overseas territories, microstates, or special administrative regions that are included in SSP regional mappings for completeness but are not modeled individually in sectoral datasets such as energy, emissions, or agricultural land use. As a result, the apparent coverage gaps—especially in the OECD and Middle East & Africa regions—reflect modeling scope and data aggregation choices, not systematic exclusion of large or economically significant countries.

S.2 Approximation of Final Energy Consumption from Primary Energy by Fuel Type

Conversion framework

Final energy FE was estimated separately for each energy type and then summed. For fossil fuels, primary energy was partitioned between electricity generation and direct final use using average high-income allocation shares. Electricity generation inputs were converted to delivered electricity using average generation efficiencies and transmission and distribution (T&D) loss factors; direct fuel use was adjusted for processing and refining losses.

For each fossil fuel $i \in$ {coal, oil, gas}, final energy was calculated as:

$$FE_i = PE_i[s_{i\to elec} \cdot \eta_{i,gen} \cdot (1 - L_{T\&D}) + (1 - s_{i\to elec}) \cdot (1 - L_{i,dir})]$$

where:

- PE_i is primary energy consumption,
- $s_{i\to elec}$ is the share of fuel used for electricity and combined heat and power,
- $\eta_{i,gen}$ is average electricity generation efficiency,
- $L_{T\&D}$ is the electricity transmission and distribution loss fraction,
- $L_{i,dir}$ is the loss fraction associated with direct fuel processing or refining.

Treatment of non-combustible energy sources

Consistent with the physical energy content method:

- Hydropower, wind, and solar energy were treated as **1:1 primary-to-final**, since primary energy is reported at gross electricity output.
- Nuclear energy was converted from reported primary thermal input to final electricity using a standard average thermal efficiency of 33%.

Assumptions and parameter values

The following parameter values were used, chosen to reflect **typical high-income/OECD averages** and to err conservatively where uncertainty exists:

Parameter	Value	Description
$s_{\text{coal}\to elec}$	0.75	Coal primarily used for electricity
$s_{\text{gas}\to elec}$	0.45	Gas split between power and direct use
$s_{\text{oil}\to elec}$	0.07	Oil predominantly used in transport
η_{coal}	0.37	Coal-fired electricity efficiency
η_{gas}	0.50	Gas-fired electricity efficiency
η_{oil}	0.37	Oil-fired electricity efficiency
η_{nuclear}	0.33	Nuclear thermal-to-electric efficiency
$L_{T\&D}$	0.06	Electricity transmission & distribution losses
$L_{\text{oil,dir}}$	0.05	Refining & processing losses
$L_{\text{gas,dir}}$	0.03	Processing losses
$L_{\text{coal,dir}}$	0.00	Assumed negligible

Final energy totals were converted to per-capita values and expressed in gigajoules using:

$$1\ \text{kWh} = 0.0036\ \text{GJ}$$

References:

Electricity generation efficiencies
OECD (2009). *Energy Efficiency Indicators for Public Electricity Production from Fossil Fuels*.
IEA (2022). *Electricity Information*.
Fuel allocation patterns
IEA (2023). *World Energy Balances*.
IEA (2021). *Key World Energy Statistics*.
Transmission and distribution losses
World Bank (2023). *Electric power transmission and distribution losses (% of output)*.
Nuclear efficiency conventions
IEA (2021). *World Energy Balances: Definitions and Methodology*.
IPCC (2014). *AR5 Working Group III, Annex II: Metrics & Methodological Issues*.

S.3 SO_2 Emissions Collapse in Democratic Republic of Congo

During the early 1990s, Gécamines—the state-owned mining and smelting company—experienced dramatic production contraction due to political instability and violence in the Katanga region and a major mine collapse, substantially reducing emissions from sulfur-intensive copper processing (Bauer et al., 2015). Although the contraction also reduced national GDP, the proportional decline in emissions was substantially larger, producing a sharp reduction in emissions intensity for the group. Following sectoral reforms and foreign investment, mining production recovered, and post-recovery operations increasingly incorporated hydrometallurgical processing, which produces substantially lower SO_2 emissions compared to the pyrometallurgical smelting it replaced (World Bank, 2008; Yager, 2015).

S.4 Additional Methods Information

To systematically identify absolute decoupling between EMs and economic growth, we developed a multi-criteria framework that employs locally estimated scatterplot smoothing (LOESS) regression combined with five decision rules. The purpose of this approach is to detect instances where environmental impact has peaked and subsequently declined while GDP continues to grow, potentially representing a transition towards absolute decoupling.

For each country-environmental indicator pair, a LOESS curve was fitted with environmental impact as the response variable and GDP as the predictor (EM ~ GDP), with observations ordered chronologically. LOESS was selected for its ability to capture non-linear relationships without imposing a predetermined functional form, making it well-suited to detect a decoupling pattern where one might exist. For each EPI, we analyzed a LOESS-smoothed (degree = 2, span = 0.7 for country level data; degree = 2, span = 0.4 for aggregated World Bank income groups) version of its relationship with GDP to isolate underlying trends and reduce chances of mistaking temporary fluctuations for true decoupling. We used a smaller span for the World Bank income groups because smoothing already occurred through aggregation reducing noise. LOESS regression offers advantages over parametric approaches (e.g., polynomial or logarithmic fits) by allowing the data to determine the shape of the relationship rather than constraining it to a specific functional form. Four complementary rules were implemented to classify countries as exhibiting absolute decoupling, each addressing a specific aspect of the decoupling phenomenon.

Decision Rules for Absolute Decoupling Computational Analysis:

1. Temporal precedence—the fitted EM peak must occur before the GDP peak in the time series. This rule ensures that the decline in environmental pressure is not simply an artifact of economic contraction or stagnation. True absolute decoupling requires sustained economic growth following the environmental peak.
2. Substantive Decline Magnitude—the decline from peak fitted EM to the subsequent minimum must exceed one standard deviation of the LOESS residuals (decline_k = 1.0 × SD_{resid}). This criterion distinguishes genuine structural declines from statistical noise or minor fluctuations inherent in environmental and economic data. By scaling the threshold to the residual variance of each country-indicator model, the rule adapts to varying data quality and measurement precision across datasets.
3. Sustained Downward Trajectory—post-peak decline must satisfy all of the below conditions. These criteria prevent misclassification of temporary dips followed by resumed growth. Part a. ensures the overall trend direction is downward or stable, while Part b. guards against cases where a few large negative changes dominate the average, but most years show increases. The 55% threshold represents a majority requirement while allowing for year-to-year variability. Part c. ensures the change is persistent.
    a. Average year-to-year slope ≤ 0.0001 (essentially non-positive)
    b. At least 55% of year-to-year changes must be negative
    c. Minimum duration of 3 consecutive years of non-positive slope after the peak (avg. slope <= 0)
4. Rebound Constraint—following the post-peak environmental metric minimum, any subsequent increase must not exceed 30% of the initial decline plus small allowances (0.25 × SD of residuals + floor value of 1×10^{-10}). This rule addresses the critical concern of temporary versus sustained decoupling. Many apparent decoupling cases represent short-term reductions followed by renewed increases (rebounds), undermining claims of fundamental structural change. By capping allowable rebounds at 30% of the decline, this rule ensures that detected decoupling represents durable environmental improvement rather than transient fluctuations.

Countries were classified as exhibiting absolute decoupling only if all four rules were satisfied simultaneously. This conservative approach prioritizes specificity over sensitivity, reducing false positives at the potential cost of overlooking borderline or emerging cases. The conjunction of multiple criteria provides robust protection against misclassification due to data anomalies, measurement error, or temporary fluctuations. This approach aligns with the high evidentiary standard appropriate for claims of absolute decoupling, which have important theoretical and policy implications. Countries determined to be decoupling were then visually inspected to determine if they were decoupling or stagnant.

Relative Decoupling Computational Analysis
To formally test for relative decoupling across income groups, we regressed EPI intensity (EPI/GDP) against year using ordinary least squares (OLS) for each combination of World Bank income group and environmental metric. For each group, we required a minimum of three non-missing observations spanning at least two distinct years. We report the OLS slope, standard error, t-statistic, p-value, 95% confidence interval, and R^2 for each regression. An income group was classified as exhibiting relative decoupling if the slope was negative and statistically significant at the $\alpha = 0.05$ level (two-tailed). For the Living Planet Index, the criterion was reversed: a significantly positive slope indicated relative decoupling (i.e., biodiversity recovering faster than GDP grows). This procedure was applied consistently across all nine environmental metrics and all income groups.

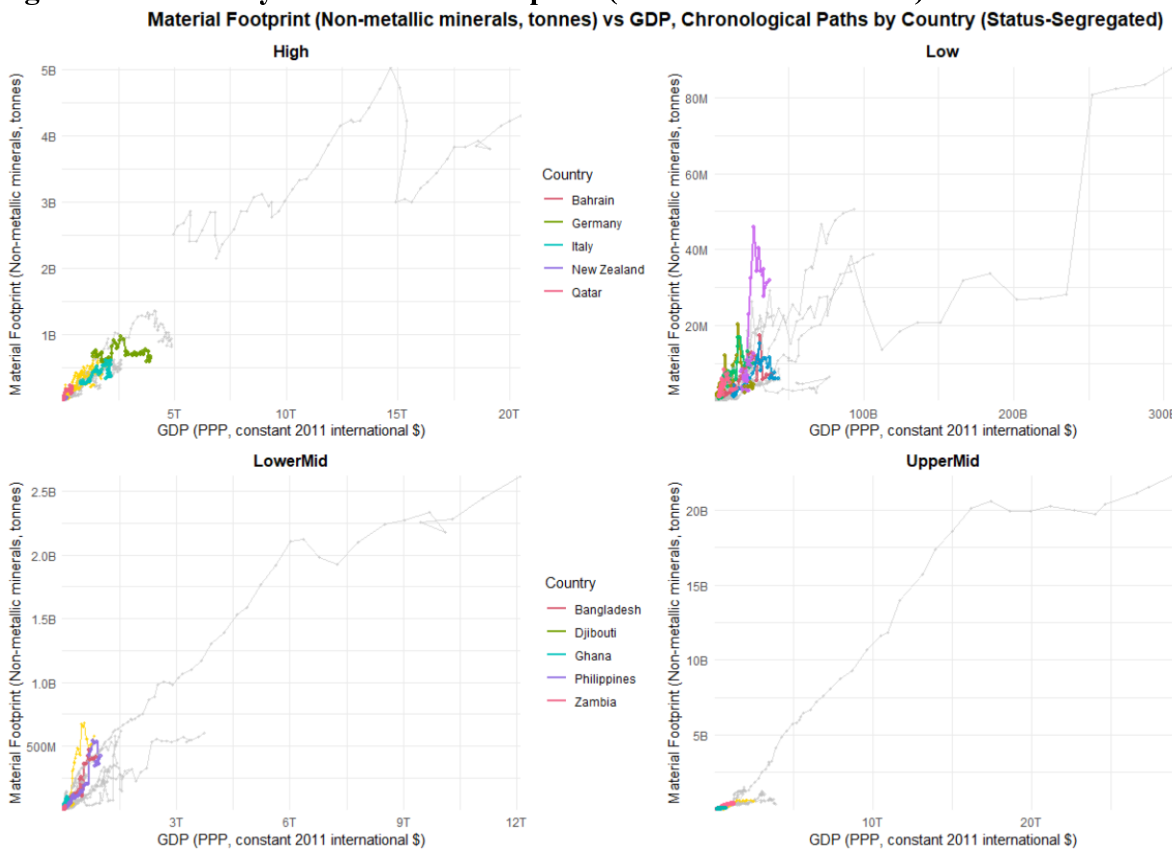
Limitations
This analysis was subject to several limitations related to data availability, quality, and methodological design. Several of the environmental datasets used in this study were derived had varying degrees of quality and coverage. In some cases—such as agricultural land coverage derived from satellite imagery—measurement uncertainty and differences in classification methods may have introduced noise or small apparent changes that reflected estimation error rather than actual shifts in land use. Similarly, biodiversity and fisheries data often relied on indirect or model-based estimates, which may have obscured localized declines or masked recovery in under-sampled regions. The material footprint indicator, which depends on complex global input–output modeling, was also limited by its dependence on underlying trade and extraction data of uneven quality across countries.

Methodologically, the use of LOESS regression required sufficient data density and GDP variation to produce stable estimates, leading to the exclusion of countries with sparse time series. Because LOESS smoothing can be sensitive at data boundaries, the method may have been less reliable in detecting very recent or emerging decoupling trends. Additionally, several parameter and threshold choices—such as the LOESS span, decline magnitude, and rebound tolerance—were based on informed judgment rather than theoretical derivation. Although these parameters were designed to balance sensitivity and specificity, alternative specifications could have yielded slightly different classifications of absolute decoupling.

While the multi-criteria framework identified sustained declines relative to GDP, it does not determine whether such patterns are likely to persist under future economic or policy conditions. Overall, these limitations suggest that the results should be interpreted as indicative rather than definitive evidence of absolute decoupling.

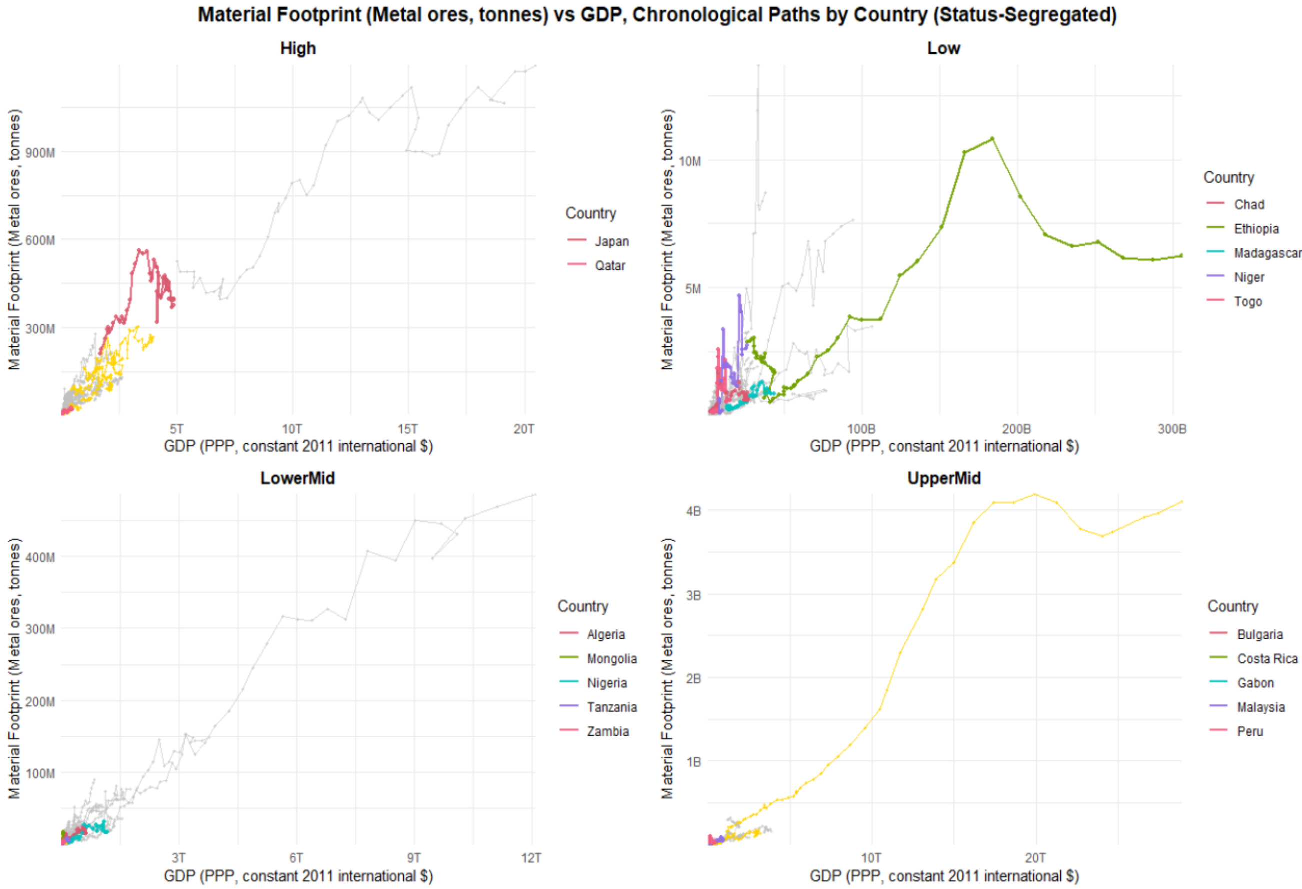
S.5 Additional Figures

Figure S5.1 Country level material footprint (non-metallic minerals) v.s. GDP



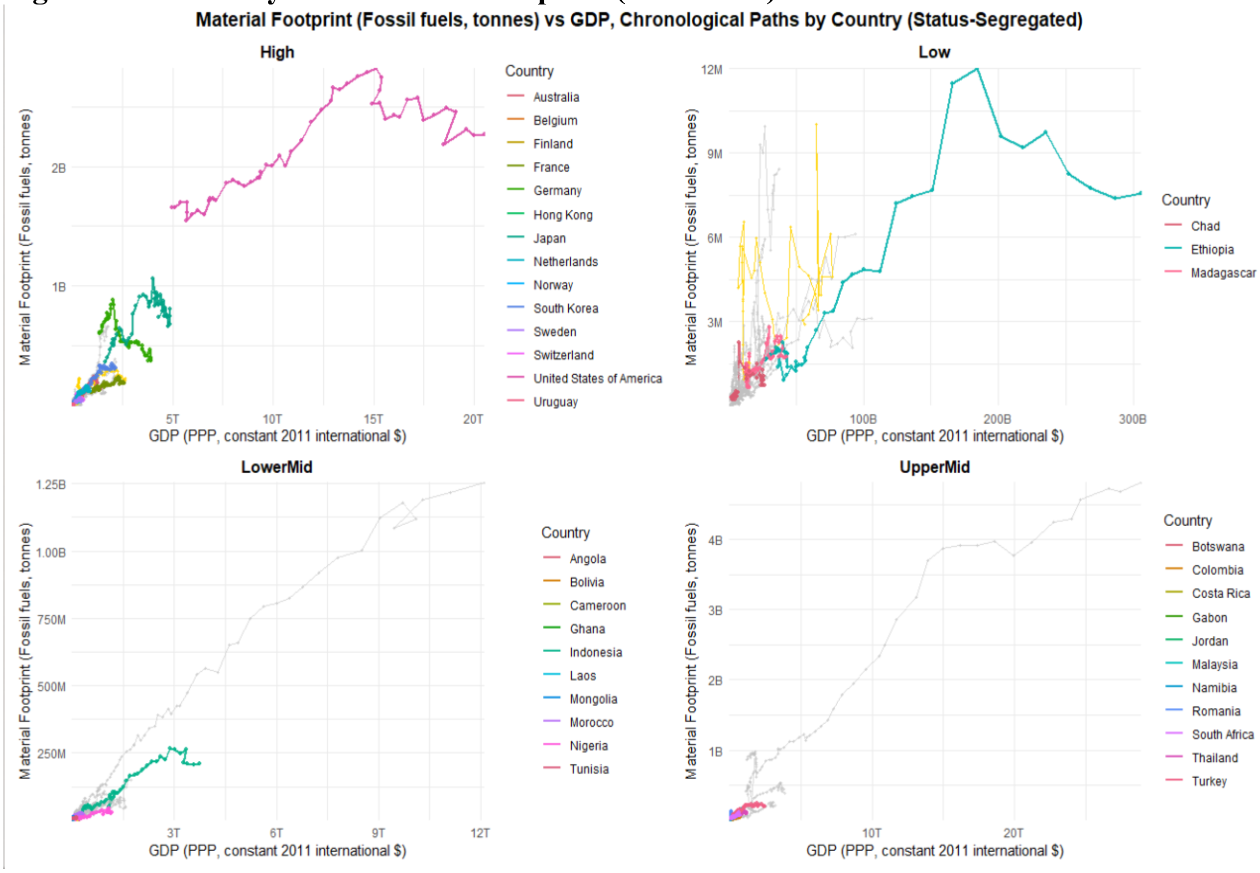
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.2 Country level material footprint (metal ores) vs. GDP



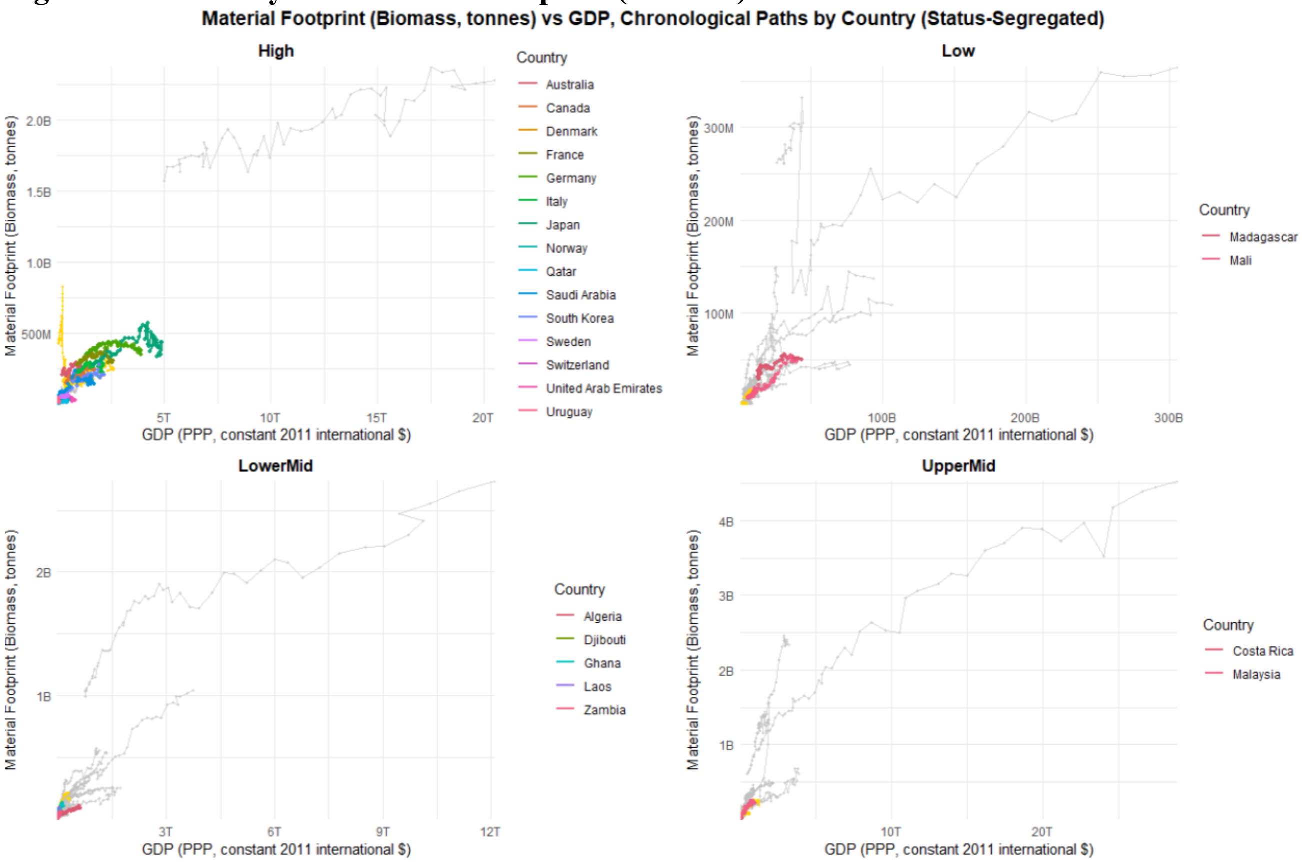
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.3 Country level material footprint (fossil fuels) vs. GDP



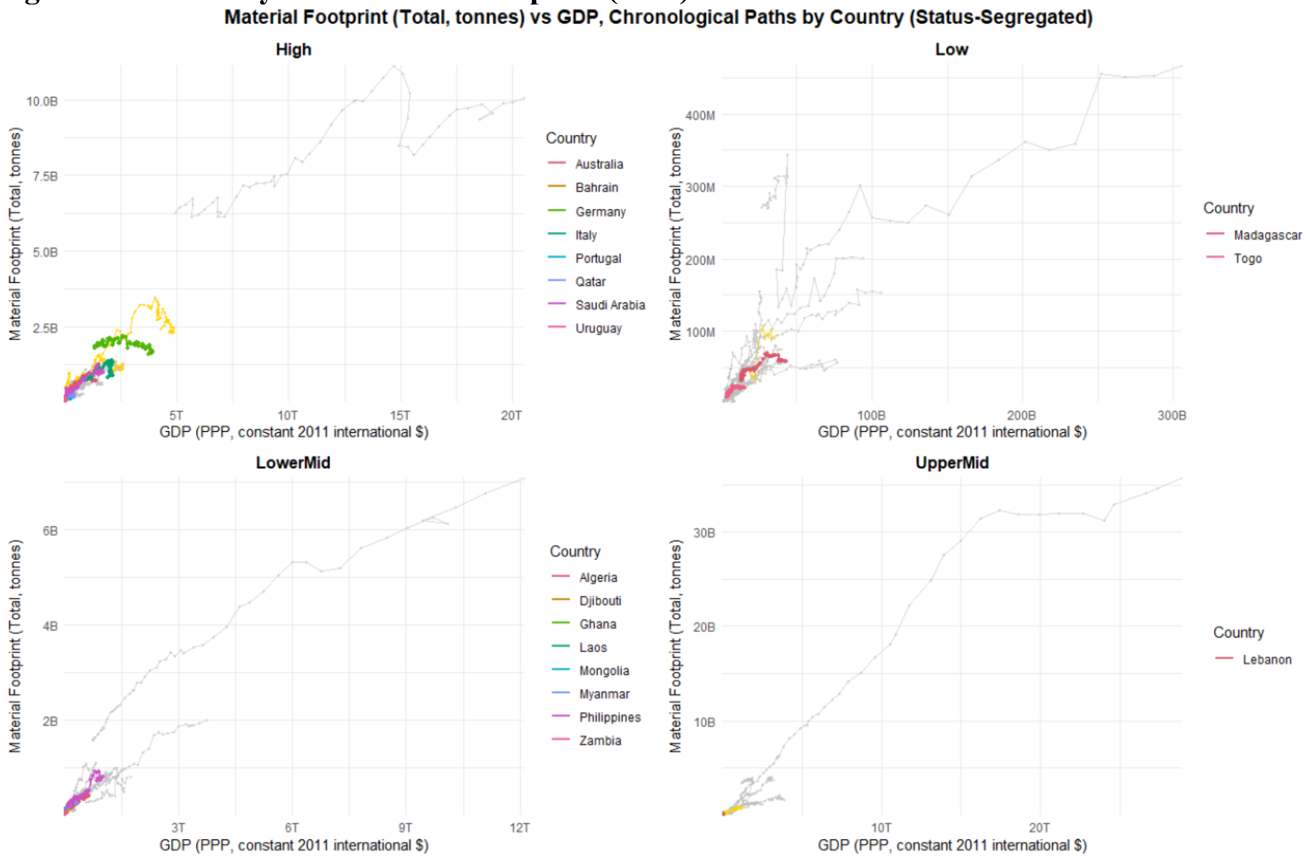
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.4 Country level material footprint (biomass) vs. GDP



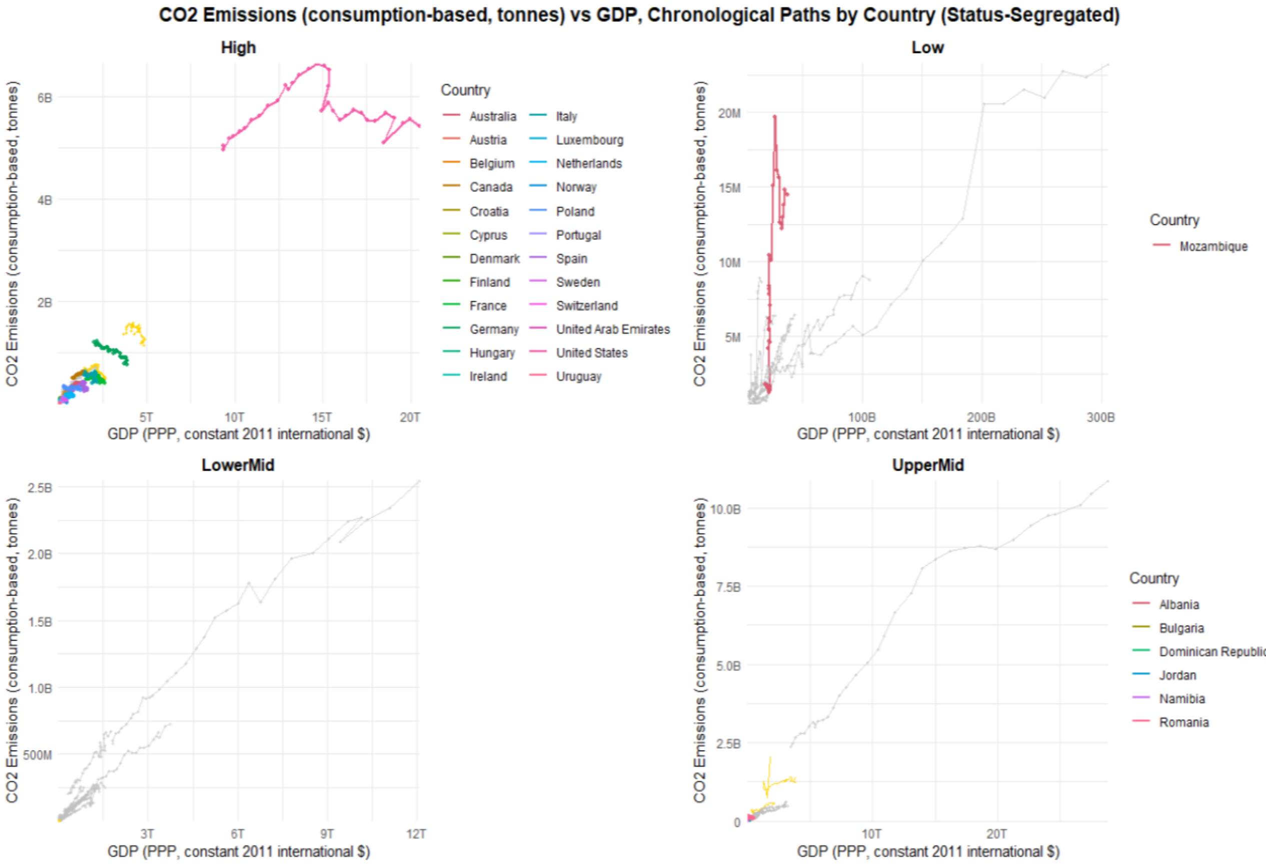
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.5 Country level material footprint (total) vs. GDP



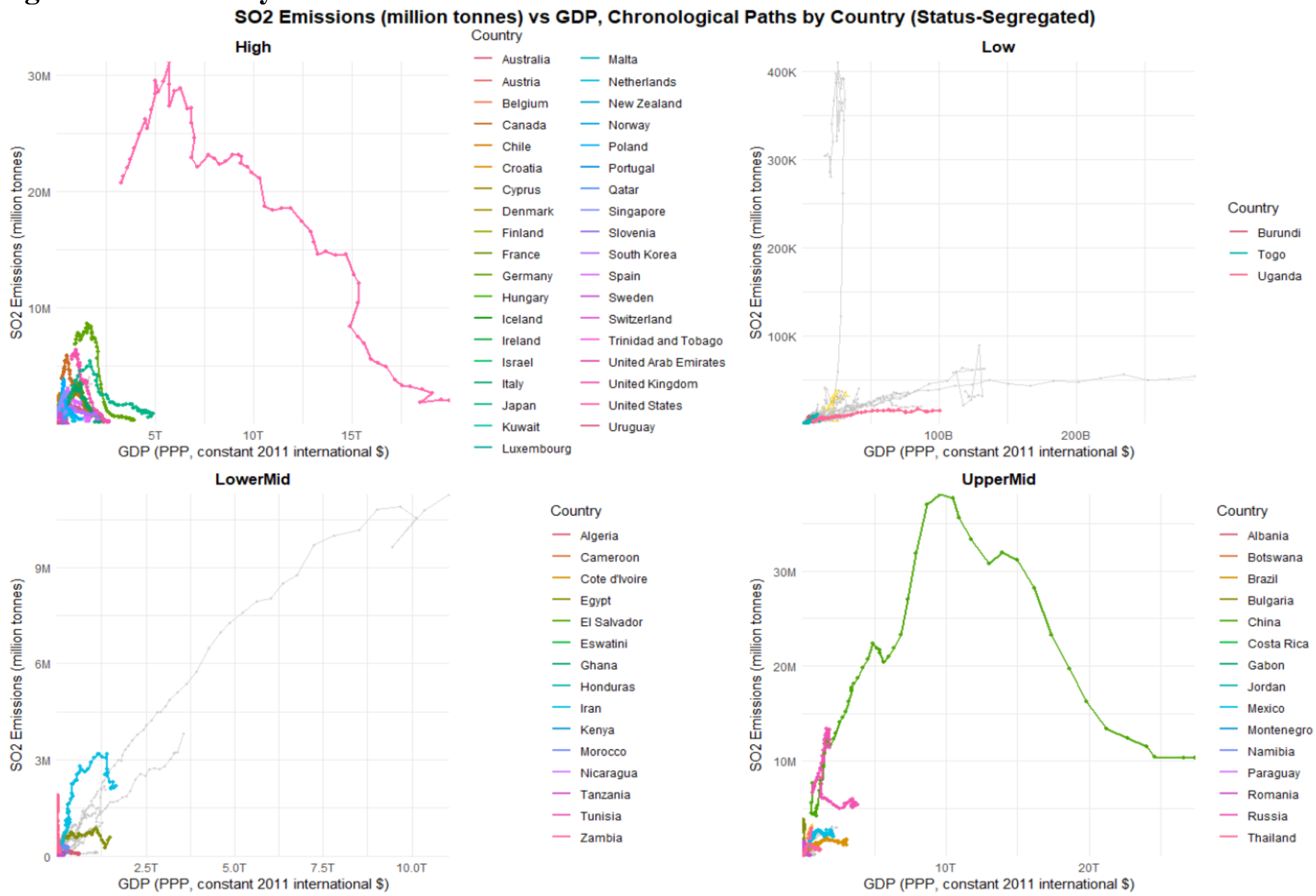
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.6 Country level CO2 emissions vs. GDP



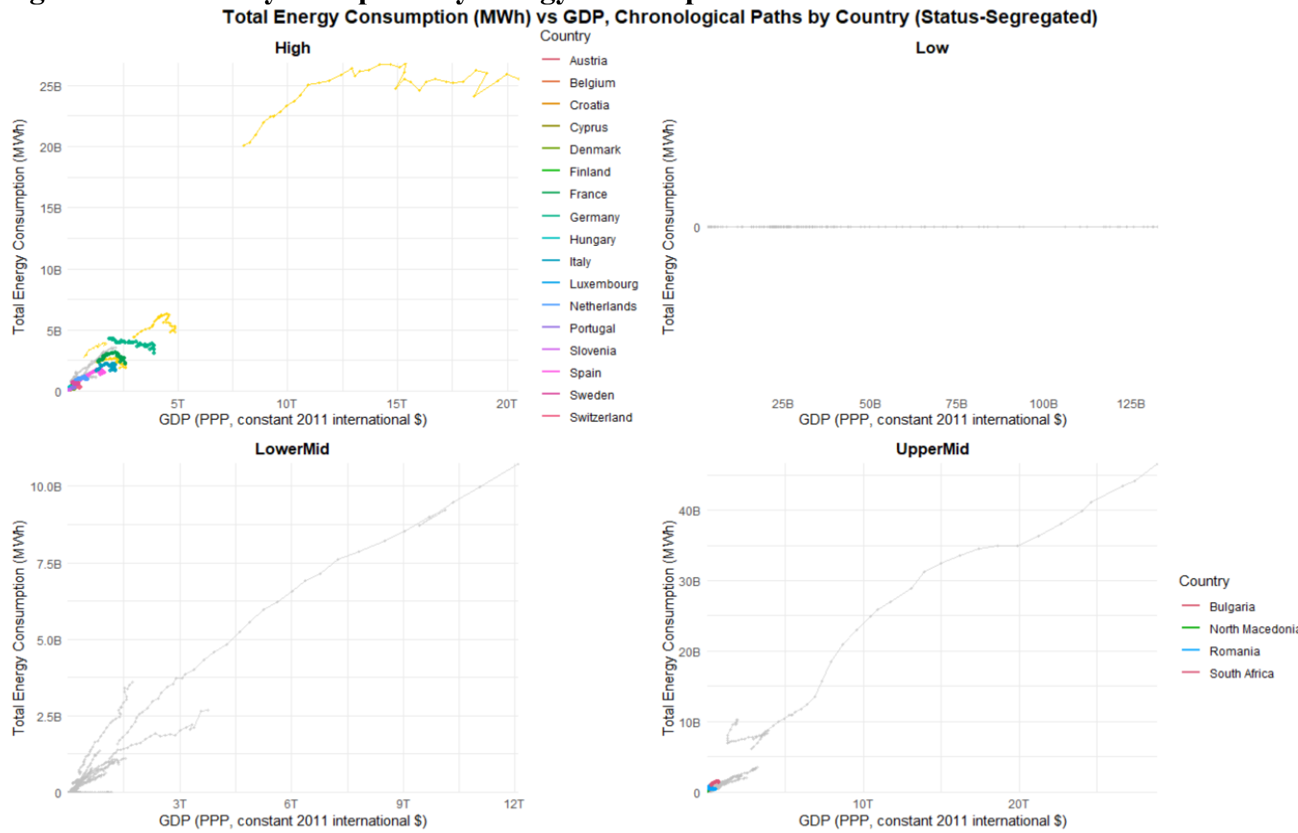
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.7 Country level SO2 emissions vs. GDP



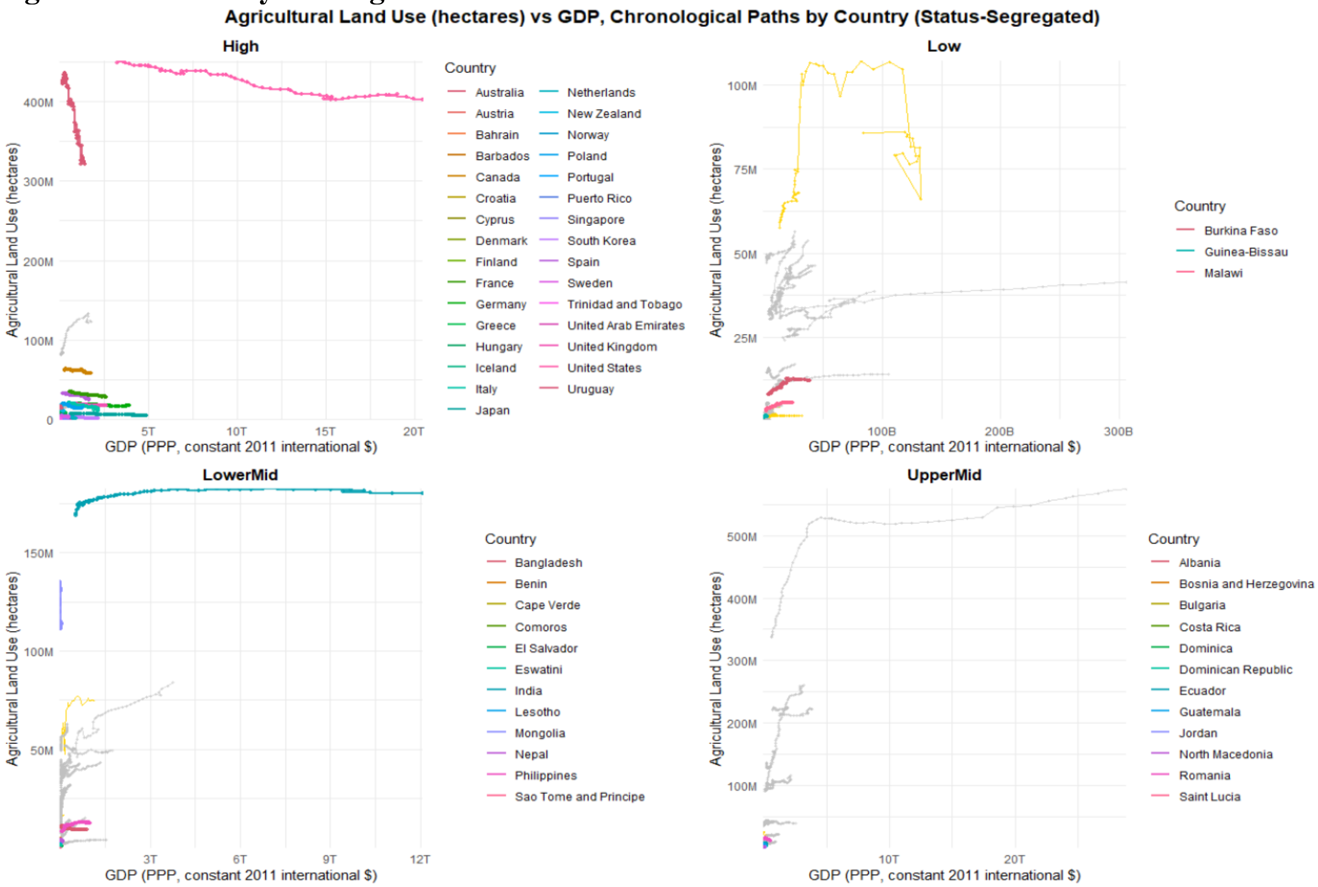
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.8 Country level primary energy consumption vs. GDP



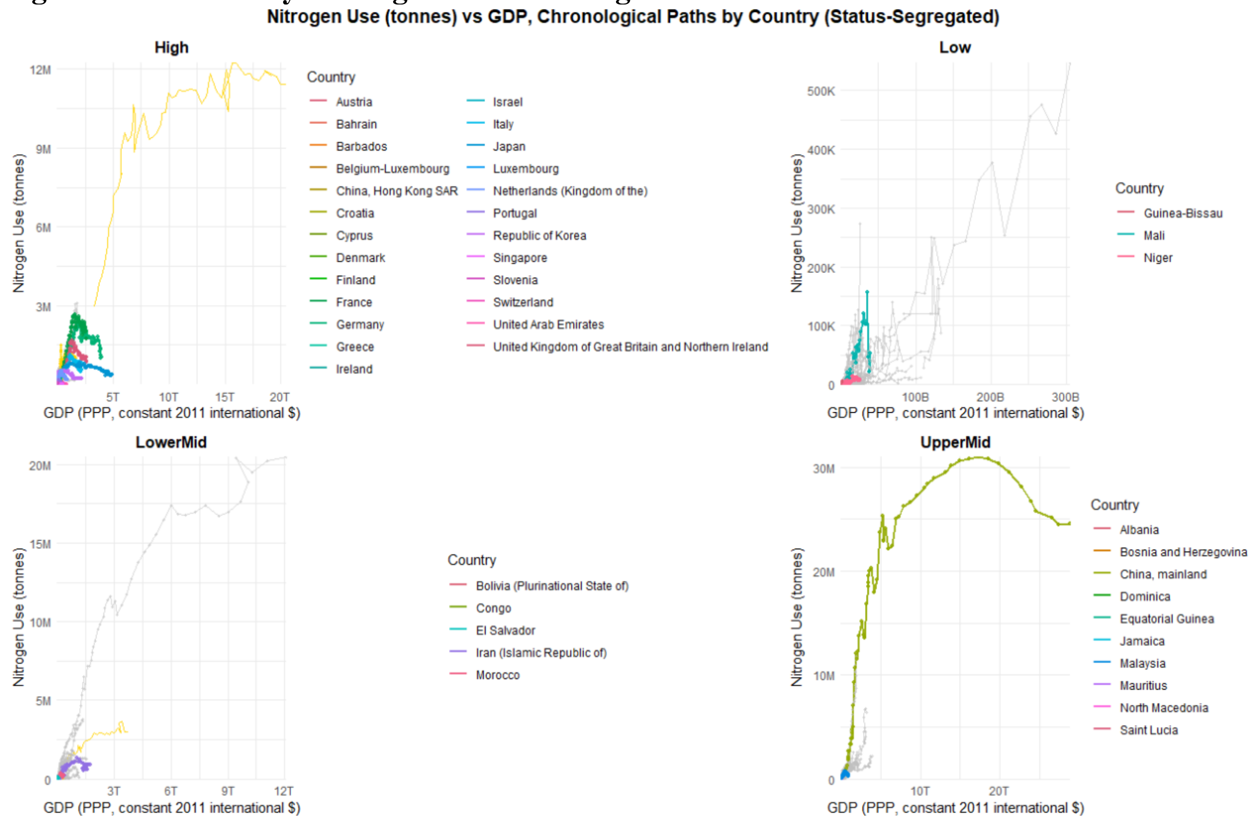
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.9 Country level agricultural land use vs. GDP



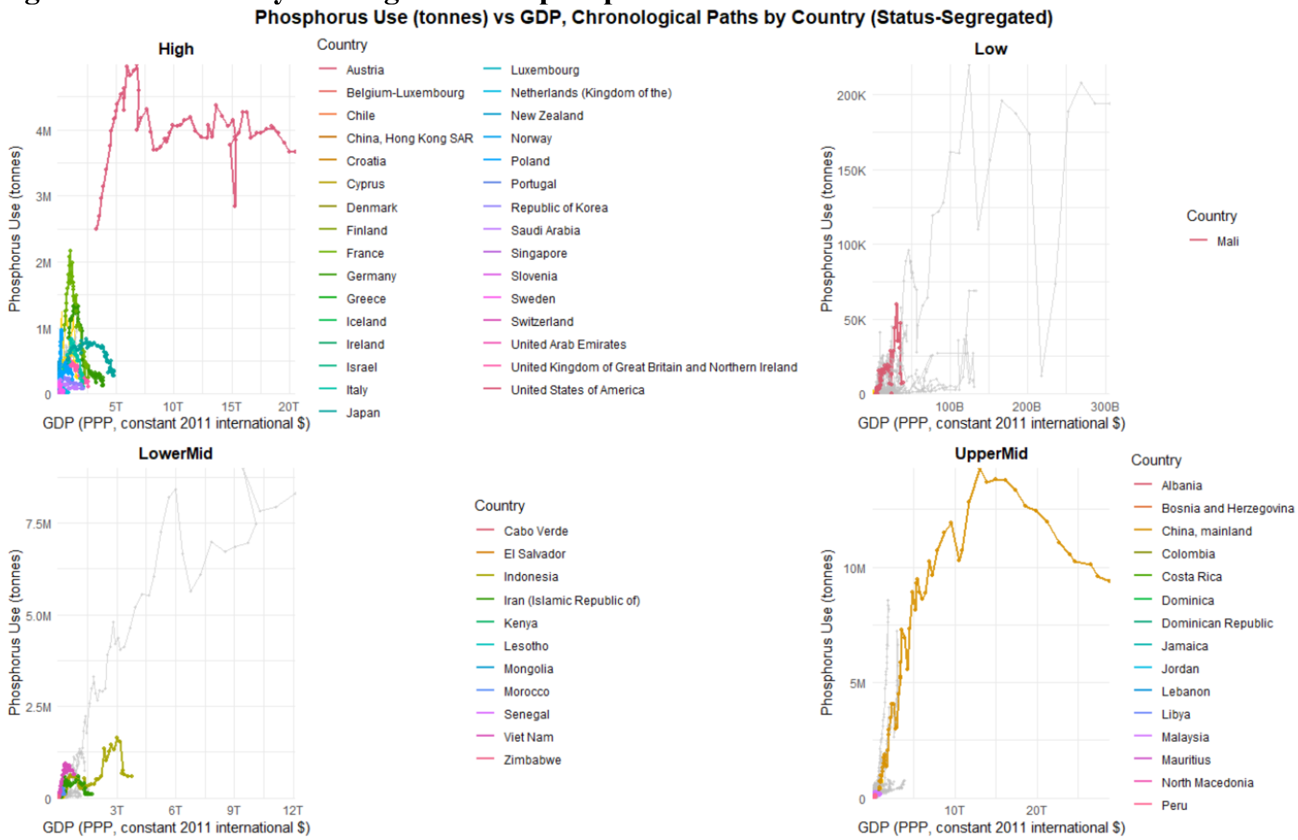
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.10 Country level agricultural nitrogen use vs. GDP



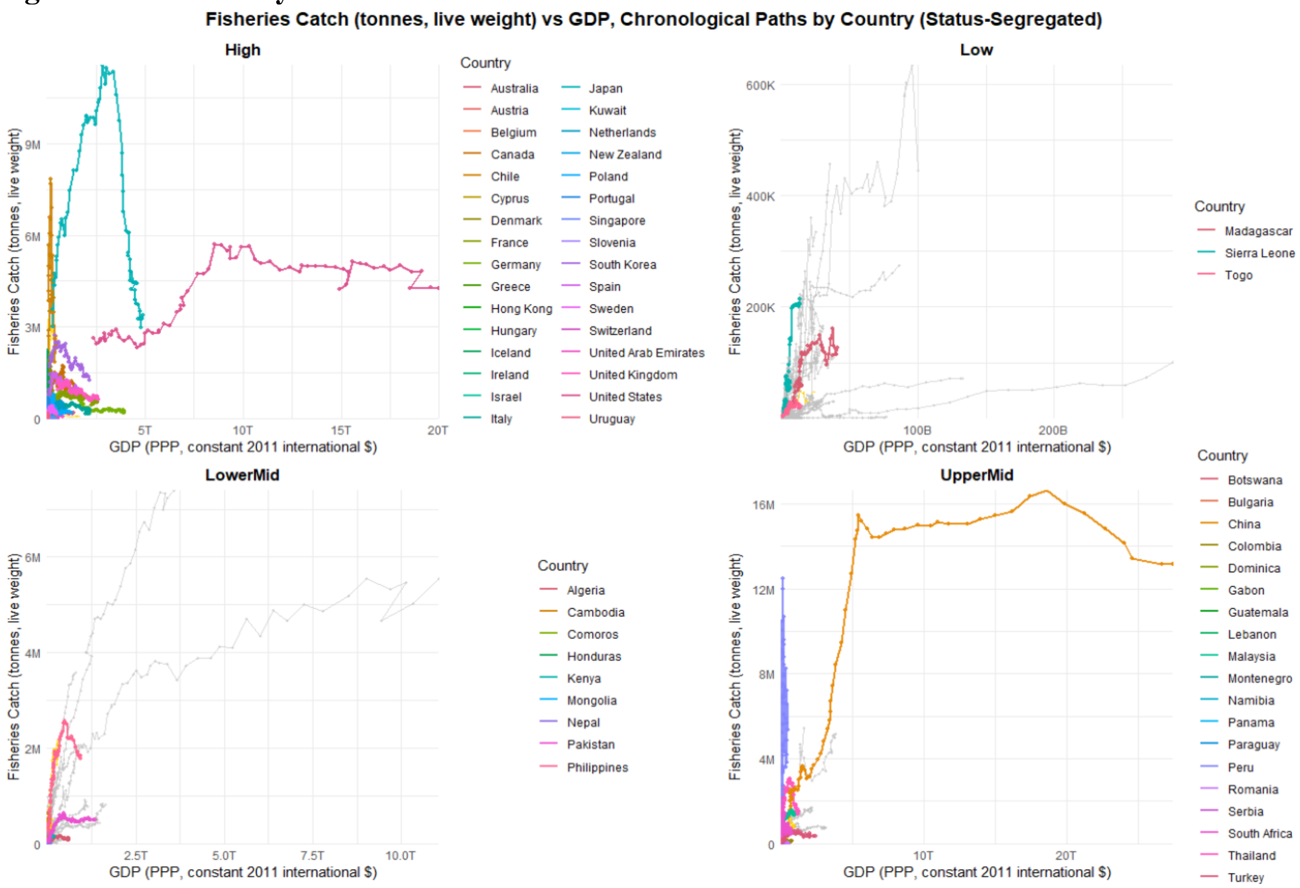
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.11 Country level agricultural phosphorus use vs. GDP



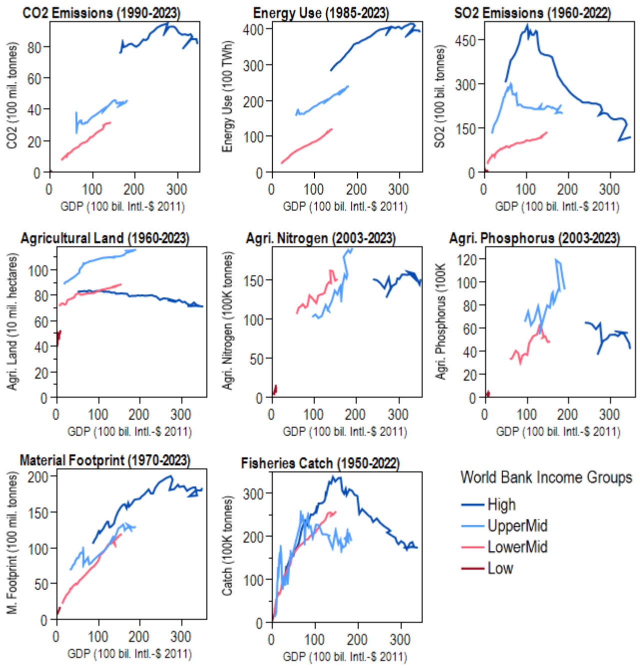
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.12 Country level fisheries catch vs. GDP



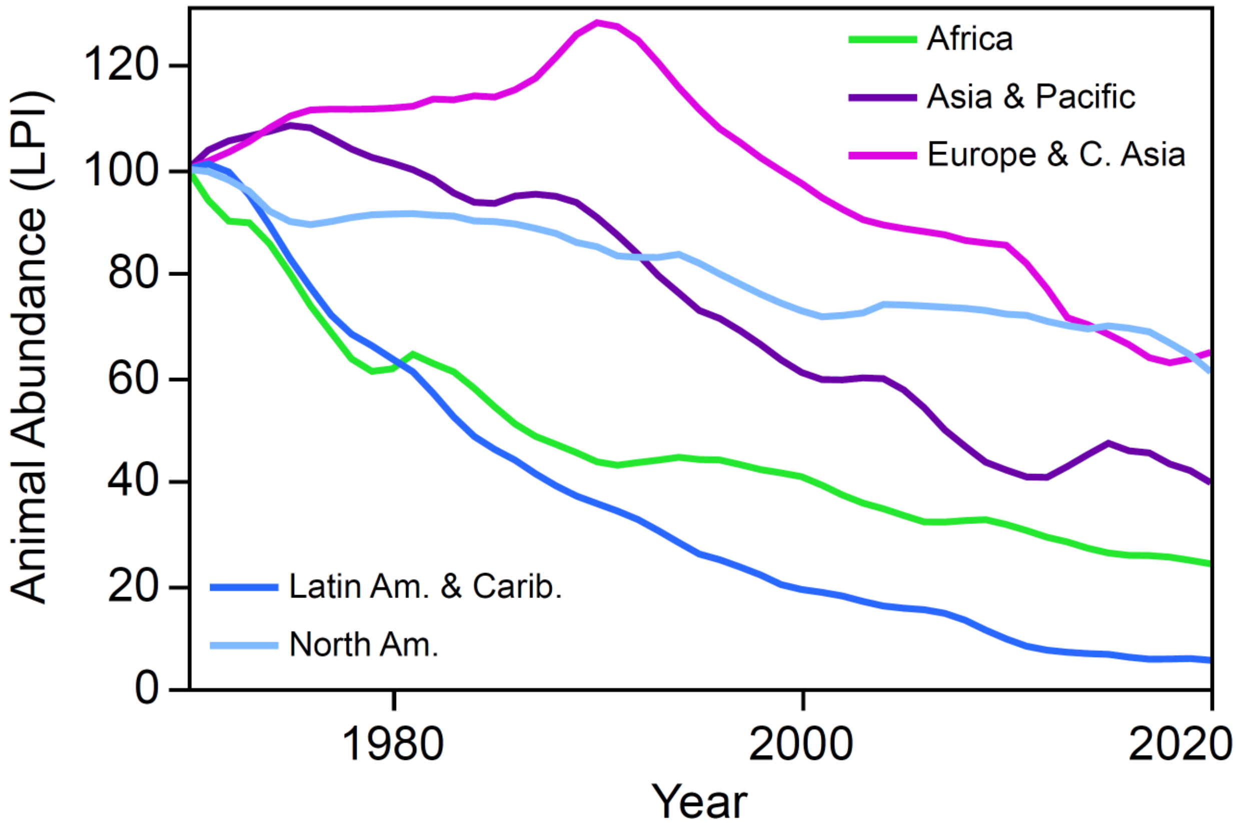
Note: Figure displays colored lines for countries that are identified as meeting the decoupling criteria (also listed in legend), greyed out countries did not meet decoupling criteria, and yellow countries did not meet criteria but are plateauing or have rebounded. Figure can be recreated using R code provided on Zenodo.

Figure S5.13 Environmental impact/pressures totals without USA, China, and India



Note: Figure shows environmental pressure or impact relative to GDP. Values are displayed in chronological order and are grouped by world bank income groups with the USA (high-income group), China (upper-middle-income group), and India (lower-middle-income group) excluded.

Figure S5.14 World Region Animal Abundance through time



Note: Figure shows animal abundance (LPI) through time. Values are grouped by world region. The Living Planet Index (LPI) estimates vertebrate abundance based on population trends of species from around the world, with index values measured relative to species' populations in 1970 (1970 = 100%). Besides a brief increase in Europe and Central Asia---likely due to agricultural land abandonment and forest recovery as the Soviet Union collapsed---the Living Planet Index consistently fell through time as populations of vertebrate species continued to decline globally, with the greatest losses occurring in Latin America and the Caribbean (Estel et al., 2015; Kamp et al., 2011; Kuemmerle et al., 2011).

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