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Environmental performance, biocapacity, carbon & ecological footprint of nations: Drivers, trends and mitigation options

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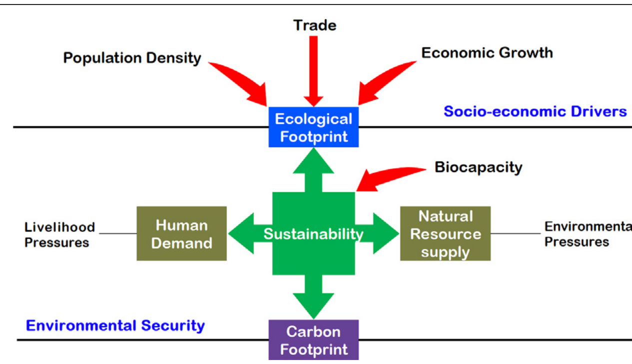
HIGHLIGHTS

- We assess ecological footprint, carbon footprint, biocapacity and ecological status of nations.
- We utilize both econometric and machine learning-based estimation methods.
- Top global ecological footprint hotspots include the US, China, Russia, India and Japan.
- Disparity in carbon and ecological footprint between income groups converge in the long-run.
- Trade-led carbon footprint confirms a potential transboundary carbon-embedded trade.

GRAPHICAL ABSTRACT



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ABSTRACT

The long-run effect of the synergy between natural resource consumption and environmental sustainability varies across countries depending on the economic structure. However, the transboundary effect of natural resource capital underscores the importance of environmental convergence. Here, we map ecological performance, biocapacity, and carbon footprint of nations. We assess the socio-economic drivers of environmental performance and convergence using novel cross-country time series techniques. We find that the expansion of biocapacity of nations has an ameliorating effect on ecological performance. The hotspot countries of environmental performance include Australia, Brazil, China, Germany, India, Japan, Russia, and the US. We confirm the existence of environmental convergence across nations — implying that the disparity in carbon and ecological footprint between higher-income and lower-income countries will converge in the long-run. This accentuates the need for global partnership towards achieving environmental sustainability.

1. Introduction

The question of environmental convergence between developed and developing countries remains inconclusive in the empirical literature. Uncertainties in achieving environmental sustainability arise in a globalized world where increasing demand for natural resource capital is key to sustaining economic development. Thus, from a policy perspective, can sustainability be achieved across nations with increasing population density, livelihood pressures and international trade?

The unprecedented increase in anthropogenic emissions and natural resource exploitation in developing countries underlines the necessity

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of environmental convergence, a situation that has implications on sustainability. A rapid increase in economic productivity triggers large demand for natural resources and contribute to waste generation, with greater consequences on the environment, leading to climate change (Panayotou, 1993). Such conventional and linear economic structure underpin natural resource exploitation and environmental pollution. The continual trajectory of this development model in developing countries will grow to eventually catch-up with developed countries and converge in the long run — if economic and productivity conditions are met (Abramovitz, 1986; Kuznets, 1955). Thus, environmental convergence reflects the economic convergence where economic development depends heavily on resource and pollution-intensive economic structure. The environmental convergence is in part captured in the environmental Kuznets curve hypothesis — where income level in developing economies increases with pollution levels but pollution declines after reaching a threshold of income level comparable to developed economies (Berkhout et al., 2017; Grossman and Krueger, 1991). Models of this nature are useful is assessing development pathways where there is a rapid transition to efficient natural resource extraction and low pollution levels.

Natural resource security and environmental sustainability are at stake amid growing material flow through trade and domestic material consumption to meet population demand (Wiedmann et al., 2015). The business-as-usual trend in natural resource extraction highlights a potential resource scarcity that has policy implications. Initial arguments on environmental sustainability in extant literature divulge that the triad relationship of social, economic and environmental indicators are essential to understanding the global status of sustainability (Sarkodie, 2020). Socio-economic and environmental indicators such as, inter alia, economic growth, population, and carbon footprint are always at the centre of several emission scenarios (Blanco et al., 2014). However, several theories such as ecological modernization, circular economy and environmental Kuznets curve suggest the importance of other factors such as trade, ecological footprint and biocapacity (Sauvé et al., 2016; York and Rosa, 2003). While tons of studies have utilized carbon dioxide emissions as a proxy for assessing environmental stress, very few studies have considered ecological footprint as a comprehensive proxy indicator for environmental degradation (Baabou et al., 2017; Lenzen and Murray, 2001; Wackernagel et al., 1999). This is true and representative as it stands, given the limitation of anthropogenic carbon dioxide emissions that account for atmospheric dynamics whereas ecological footprint covers the biosphere. Using ecological footprint rather than carbon dioxide emissions provides a true and inclusive perspective of assessing environmental deterioration. The ecological footprint accounts for built-up land, carbon emission levels, cropland, fishing grounds, forest land and grazing land (GFN, 2017), thus, capture all facets of environmental dynamics. This missing link in carbon dioxide emissions might have misled the assessment of environmental degradation across countries in extant literature.

Contrary to previous attempts, we for the first-time investigate the ecological footprint, carbon footprint, biocapacity and ecological status of nations using cross-sectional time series data over five decades in 188 countries and territories. To assess the ecological performance of nations, we used empirical methods to calculate ecological status from ecological footprint and biocapacity. We estimated the relative change of socio-economic and environmental indicators across nations and identified the hotspot countries. To understand the drivers of environmental performance, ecological footprint and carbon footprint of nations, we used two novel estimation techniques with characteristics of machine learning and econometrics. The panel kernel regularized least-squares algorithm and the dynamic panel bootstrap-corrected fixed-effects are consistent and robust, with the advantage in controlling for convergence, cross-section dependence, omitted variable bias, misspecification error, country-specific heterogeneity and non-additive effects.

2. Methods

2.1. Dataset

We gathered our cross-sectional time series data on ecological indicators from the global footprint network (GFN, 2017). The ecological indicators include ecological footprint, biocapacity, carbon footprint, and ecological status. Ecological footprint comprises built-up land, carbon levels, cropland, fishing grounds, forest land and grazing land, thus, captures all the environmental dynamics of the biosphere compared to the traditional carbon dioxide used as a proxy for environmental pollution. This infers that the ecological footprint is more inclusive and representative for assessing environmental stress. Biocapacity comprehensively captures the regenerative capacity of built-up land, cropland, fishing grounds, forest land and grazing land to meet livelihood demand. Carbon footprint measures fossil fuel-driven carbon dioxide emissions. The ecological status is calculated by deducting ecological footprint from biocapacity. In line with the definition of sustainability to meet present natural resource demand and still preserve the natural capital as a bequest for future generations, ecological status is for the first time used as an indicator to assess the ecological health or performance of nations. The socio-economic indicators namely economic growth, income level, trade and population are retrieved from the World Bank development database (World Bank, 2020). The data selection process stems from the concept of Sustainable Development and the assessment guidelines of the United Nations (DiSano, 2002). The data utilized for the choropleth maps have 245 countries and territories, however, for the empirical assessment — the unequal distribution and missing inputs led to a data-pruning. This resulted in a balanced panel data consisting of 188 countries and territories with a total of 10,528 observations spanning 1961–2016. Another set of ecological data captures the global and continental distribution— explicitly Africa, Asia, Australasia (Australia and New Zealand), Europe, North America and South America.

2.2. Model structure

Cross-country time series models are affected by global common shocks like a pandemic, financial crisis, oil prices, among others, and transboundary spillover effects. In that scenario, the failure to account for cross-section dependence oftentimes render panel estimations spurious. The model estimation was initiated by examining the presence of cross-section dependence using a variable-based panel cross-section dependence test (Pesaran, 2004). Second, we investigated the stationarity properties of the sampled data series, another panel challenge that required attention. The necessity of the test stems from the random walk characteristic of certain series that could hinder the robustness and consistency of the estimated models, hence, affecting statistical inferences and policy implications. To avoid this possibility, we employed panel unit root tests from the second generational techniques. Third, to avoid misspecification errors, we proceeded to assess the heterogeneous effects of socio-economic and ecological indicators across nations. We used the novel panel bootstrap jackknife-bias-corrected estimation method to account for heterogeneous dynamics across countries. The preconditions of applying the heterogeneous technique require a stationary data series with Gaussian autoregressive-moving-average generated error term (Okui and Yanagi, 2019).

2.3. Model estimation

The pre-model estimation assessment provided leads to the selection of optimal cross-country time series techniques that are robust and produce consistent estimates. The linear representation of environmental performance and socio-economic nexus can be expressed as:

$$lnCARBON \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, \ln \Delta NECOPERM, lnGDP) \quad (1)$$

$$lnCARBON \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, \ln \Delta NECOPERM, lnGDPC, lnTRADE) \quad (2)$$

$$lnEFCONS \sim f(lnPOPDEN, lnENVSUS, lnGDP) \quad (3)$$

$$lnEFCONS \sim f(lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE) \quad (4)$$

$$\ln \Delta NECOPERM \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDP) \quad (5)$$

$$\ln \Delta NECOPERM \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE) \quad (6)$$

$$\ln \Delta NECOPERM \sim f\left(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, \ln GDPC^2, lnTRADE\right) \quad (7)$$

where, *ln* represents the logarithmic transformation of data series to achieve a constant variance; Δ is the first-dependence operator; *N* represents the normalization of the series to control for negative values before the application of logarithmic transformation; CARBON means Carbon Footprint measured in gha; ENVSUS is Biocapacity, measured in gha; EFCONS denotes Ecological Footprint, measured in gha, ECOPERM is the Ecological Status, measured in gha; GDPC indicates Income Level, a proxy for estimating wealth, measured in constant 2010 US$; GDP means Economic growth, measured in constant 2010 US$; POPDEN represents Population density, measured in people per sq. km of land area; and TRADE is Trade, measured as a % of GDP.

The baseline empirical specification of Eqs. (1)–(7) follows the novel panel kernel regularized least-squares algorithm. The application of the machine learning technique is expressed in pointwise partial derivatives of the target variables (CARBON, EFCONS and ECOPERM) and corresponding predictors expounded in Eqs. (1)–(7). For brevity, the generic panel kernel regularized least-squares pointwise partial derivatives $\frac{ln\delta\hat{y}}{ln\delta x_j^{(d)}}$ can be expressed as (Okui and Yanagi, 2019):

$$\frac{ln\delta\hat{y}}{ln\delta x_j^{(d)}} = \frac{-2}{\sigma^2} \sum_i c_i e^{\frac{-\|x_i - x_j\|^2}{\sigma^2}} \left(x_i^{(d)} - x_j^{(d)}\right) \quad (8)$$

where *y* denotes the partial derivative of the target variables related to variable *d*, $x^{(.)}$ represents the predictors with observation *j*, σ^2 is the kernel bandwidth, c_i is the weight of the predictor (choice coefficient), x_i is the input pattern, $i = 1, \ldots, N$, and $e^{(.)}$ is the exponential function. Though the panel kernel regularized least-squares algorithm is a simplified model that allows consistent and robust estimation of heterogeneous, non-additive and non-linear effects while reducing misspecification error, however, cannot be used to control country-specific fixed-effects and convergence. We further employed the dynamic panel bootstrap-corrected fixed-effects to account for the challenges in the baseline method expressed in a generic form as (De Vos et al., 2015):

$$lny_{i,t} = \delta * lny_{i,t-1} + \beta * lnx_{i,t} + \alpha_i + \varepsilon_{i,t}, i = 1, \ldots, N \text{ and } t = 1, \ldots, T \quad (9)$$

where $lny_{i,t}$ represents the logarithmic transformation of the target variables (*lnCARBON*, *lnEFCONS*, and *ln*Δ*NECOPERM*) for the model specification of Eqs. (1)–(7), *i* is the individual sampled countries, *t* is the period of the data spanning 1961–2016, δ is the AR parameter such that $|\delta| < 1$ to confirm a dynamic stable association between $lny_{i,t}$ and $lnx_{i,t}$, β represents the estimated coefficient of the regressors, $lnx_{i,t}$ denotes the regressors ($1 \times K$ vector), α_i is the country-specific unobserved heterogeneity or fixed-effects with zero mean and variance ($\sigma_\alpha^2 \geq 0$) and $\varepsilon_{i,t}$ is the unobserved idiosyncratic white noise with a zero mean and variance ($\sigma_\varepsilon^2 > 0$). The dynamic panel estimator assumes an equally uncorrelated whiter noise over the period and across countries. Second, it assumes that the country-specific unobserved heterogeneity or fixed-effects are exogeneous and uncorrelated. Third, it assumes that the regressors are strictly exogenous and preliminary conditions are either stationary or nonstationary and uncorrelated with the corresponding unobserved idiosyncratic white noise (Everaert and Pozzi, 2007).

3. Results

The choropleth maps (Figs. 1–2) identify the geographical distribution of ecological footprint, carbon footprint, biocapacity, and ecological status. The constructed geographical maps are based on the mean distribution spanning 1961–2016 across 245 countries and territories. The ecological footprint measures a country's land and water resources that are biologically productive for economic consumption and absorption of waste generation using resource management technologies and practices (Global Footprint Network, 2017). On this note, higher ecological footprint due to consumption of available natural resources is not beneficial for environmental sustainability. Top global ecological footprint hotspots include the US (~2.41 billion gha), China (~2.24 billion gha), Russia (~1.12 billion gha), India (~0.73 billion gha), and Japan (~0.58 billion gha) [see Fig. 1]. Carbon footprint measures carbon dioxide emissions attributed to fossil fuel consumption. Here, carbon footprint denotes the corresponding biologically productive resources required to absorb carbon dioxide. Thus, higher levels of carbon dioxide emissions in the atmosphere signify an expansion of the ecological debt. The carbon footprint hotspots across countries include the US (~1.75 billion gha), China (~1.23 billion gha), Japan (~0.38 billion gha), Germany (~0.32 billion gha), and India (~0.27 billion gha) [see Fig. 1]. These countries tally with the ranking on carbon dioxide emissions from fossil fuel combustion reported in Global Energy Statistical Yearbook 2019 (Enerdata, 2019). Which appears that ecological and carbon footprint correlate with domestic material consumption (fossil fuel, biomass, metal and nonmetal ores). Biocapacity measures the regenerative and waste absorptive capacity of the ecosystem following natural resources exploitation to meet population demand. Thus, a higher level of biocapacity compared to ecological footprint is key to achieving environmental sustainability. Top tier countries with the highest biocapacity include Brazil (~1.77 billion gha), Russia (~1.09 billion gha), the US (~1.04 billion gha), China (~1.00 billion gha), and Canada (~0.52 billion gha) [see Fig. 2]. These countries coincidentally correspond to the global ranking of countries by landmass (Worldometers, 2020). Ecological status of nations was calculated using the difference between the regenerative capacity of the ecosystem and consumption of natural resources. Thus, ecological status occurs in two forms namely ecological deficit and ecological reserve. Ecological deficit occurs when a country's natural resource exploitation exceeds its regenerative capacity, whereas ecological reserve occurs when the regenerative capacity of a country's natural resources exceeds consumption. This implies that countries with ecological deficit import resources from other countries endowed with reserves. Top ecological deficit hotspots include the US (−1.37 billion gha), China (−1.25 billion gha), Japan (−0.49 billion gha), India (−0.35 billion gha), and Germany (−0.34 billion gha) [see Fig. 2]. However, top five countries with ecological reserve comprise Brazil (~1.36 billion gha), Canada (~0.28 billion gha), Australia (~0.18 billion gha), Congo (Kinshasa) (~0.18 billion gha), and Bolivia (~0.17 billion gha) [see Fig. 2]. Based on the ecological status of nations, we mapped the continental and global status of ecological performance presented in Fig. 3. While Asia, Europe and North America have an ecological deficit, Australia & New Zealand, South America and Africa (except Morocco, Nigeria, Niger, Algeria, Libya, Egypt, Ethiopia, South Sudan, Uganda, South Africa, Malawi, Kenya, and Togo) have an ecological reserve. The global total shows ecological deficit with potential future consequences on environmental sustainability (Fig. 3).

To determine the 56-year comparative growth trajectory of environmental performance reported in the choropleth maps, we estimated the mean relative change of 8 hotspot countries plus the global average (Fig. 4). The 56-year mean trend for biocapacity reveals that India, Germany, and the US are above the global average of 0.429% whereas

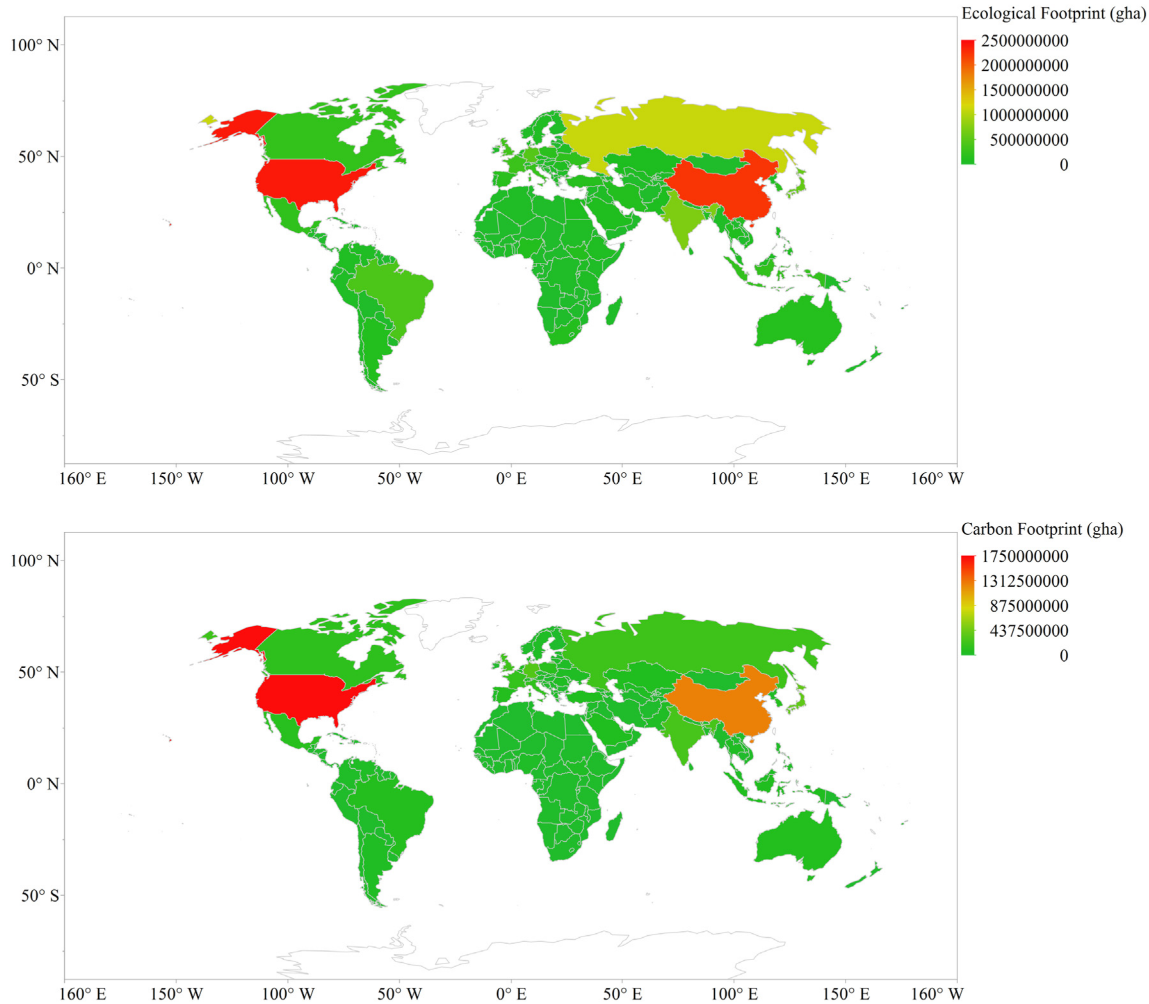


Fig. 1. Geographical mapping of ecological and carbon footprint (gha).

Canada, Brazil, Russia, China and Japan are below the global mean biocapacity. India ranks on top of the 8 hotspot countries to expand its biocapacity by 1.77% within 56 years whereas Japan is the worst performer in improving biocapacity with a decline of 0.427%. India, Brazil and China have increased their ecological footprint within 56 years by 3.14%, 2.22% and 2.19% respectively above the global average of 1.98%. Canada, Japan, Russia and Germany have intensified its ecological footprint but below the global average, however, the US has declined its ecological footprint within the same period by 0.825%. Similarly, India ranks high in terms of the relative change in carbon footprint within 56 years by 5.46% compared to the global average (2.56%) — followed by China (4.30%), Brazil (4.24%), Russia (3.14%) and Japan (2.72%). Canada and Germany are below the global average of carbon footprint by 2.17% and 0.772% respectively, however, the US has declined its carbon footprint by 0.691% within 56 years. We observe from the ecological status of hotspot countries that only China has expanded its ecological deficit (20.2%) above the global average of 10.8%. However, countries such as India, Japan and Germany have increased their ecological deficit but below the global average. In contrast, Russia, the US, Brazil and Canada have improved their ecological reserve by 26%, 1.39%, 0.388% and 0.382%, respectively. Concurrently, population density relatively increased by 0.21%, 0.32%, 1.03%, 1.35%, 1.53%, 1.87% and 1.94% from 1961 to 2016 in Germany, Russia, the US, China, Australia, Brazil and India, respectively. Trade experienced a mean change of 0.84%, 2.42%, 2.93%, 3.73%, 4.13%, 15.72%, and 17.62% in Australia, Brazil, India, China, the US, Germany and Russia within the 56 years. Income level has witnessed a tremendous change from 1961 to 2016 in Germany and Russia by 170.33% and 352.78%, respectively. Besides, income level saw a gradual growth in Australia, the US, Brazil, India and China by 1.94%, 2.02%, 2.09%, 3.22%, and 7.44%. Similarly, Germany and Russia experienced a mean change in economic growth from 1961 to 2016 by 1190.04% and 3513.11%, respectively. Economic growth grew by 3.08%, 3.51%, 4.00%, 5.22% and 8.89% in the US, Australia, Brazil, India and China (Supplementary 1).

We find from the assessment of environmental indicators that natural resources extraction and carbon footprint are critical to environmental consequences. To understand the dynamics of the immediate and underlying causes of the ecological performance of nations, we developed conceptual tools using socio-economic variables namely economic development (GDP/GDPC), population density (POPDEN) and trade (TRADE). The selection of the data series is based on the IPCC 5th Assessment report and Sustainable Development Goals (SDGs). The IPCC report classifies GDP/GDPC and POPDEN as immediate drivers of GHG emissions whereas TRADE is considered as an underlying driver (Blanco et al., 2014). We used socio-economic inputs which incorporate the concept of SDGs as explanatory variables defined as:

- Economic development: Economic growth and GDP per capita denote aggregate productivity and individual income levels, a proxy for estimating wealth across countries. This input is essential to investigate

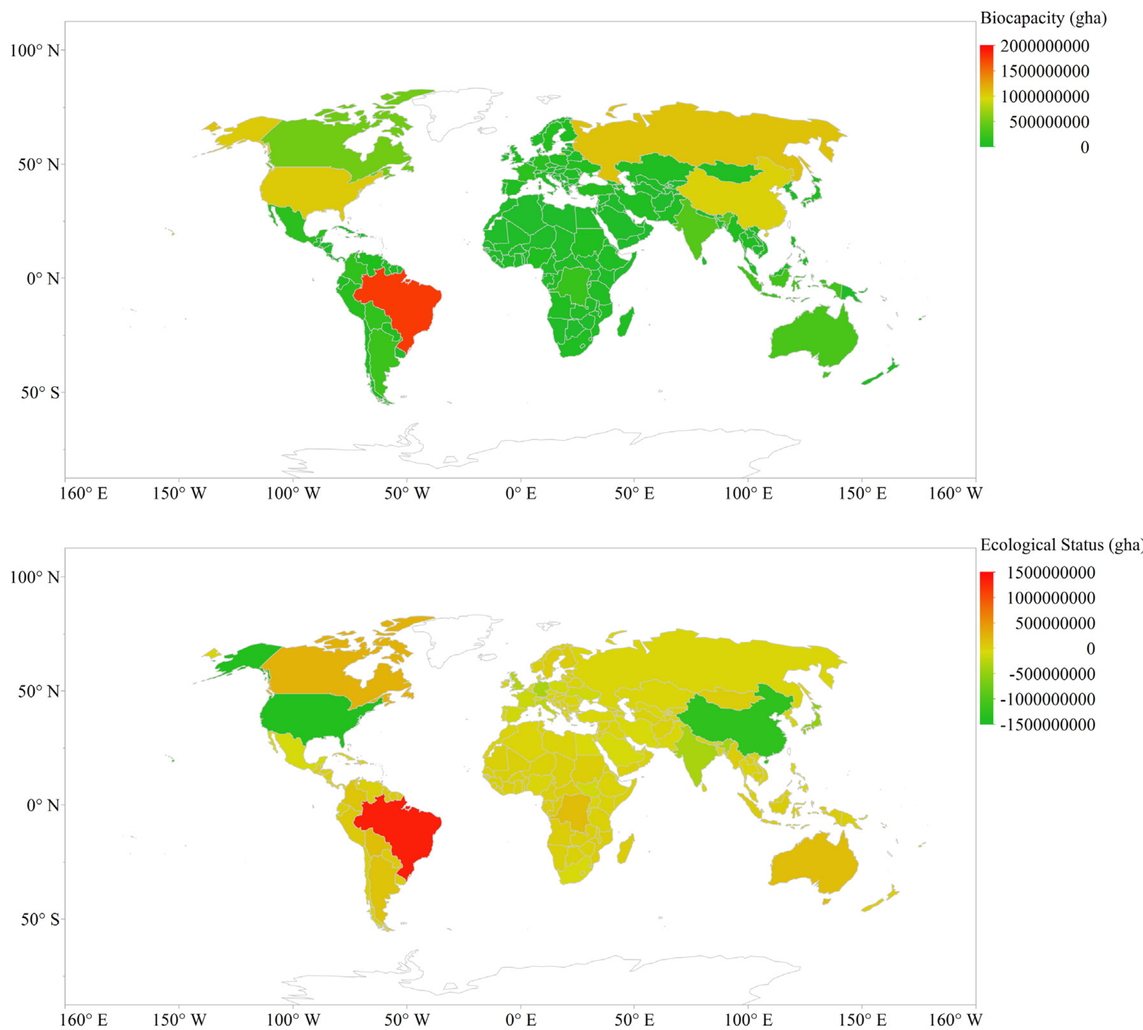


Fig. 2. Geographical mapping of biocapacity and ecological status (gha).

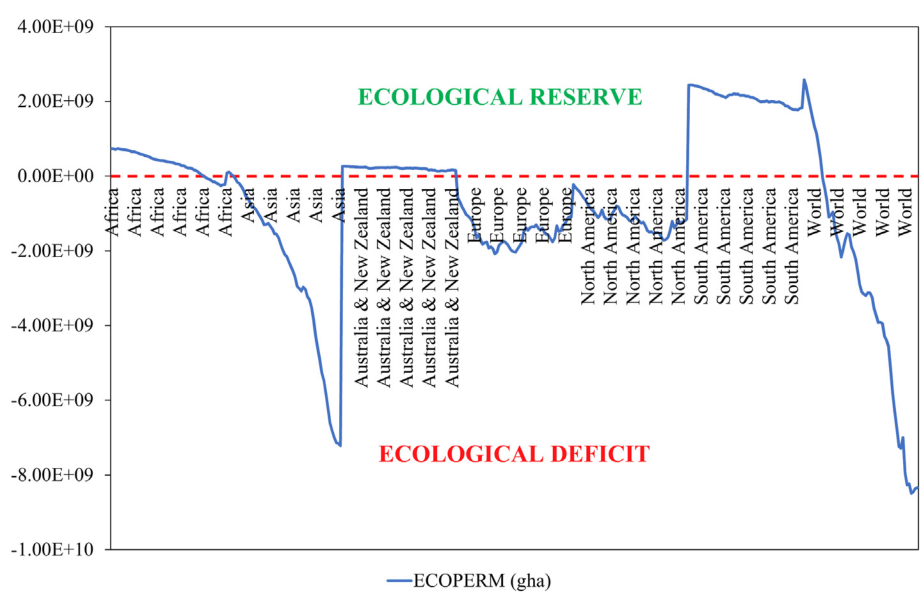


Fig. 3. Continental and global status of ecological performance (gha).

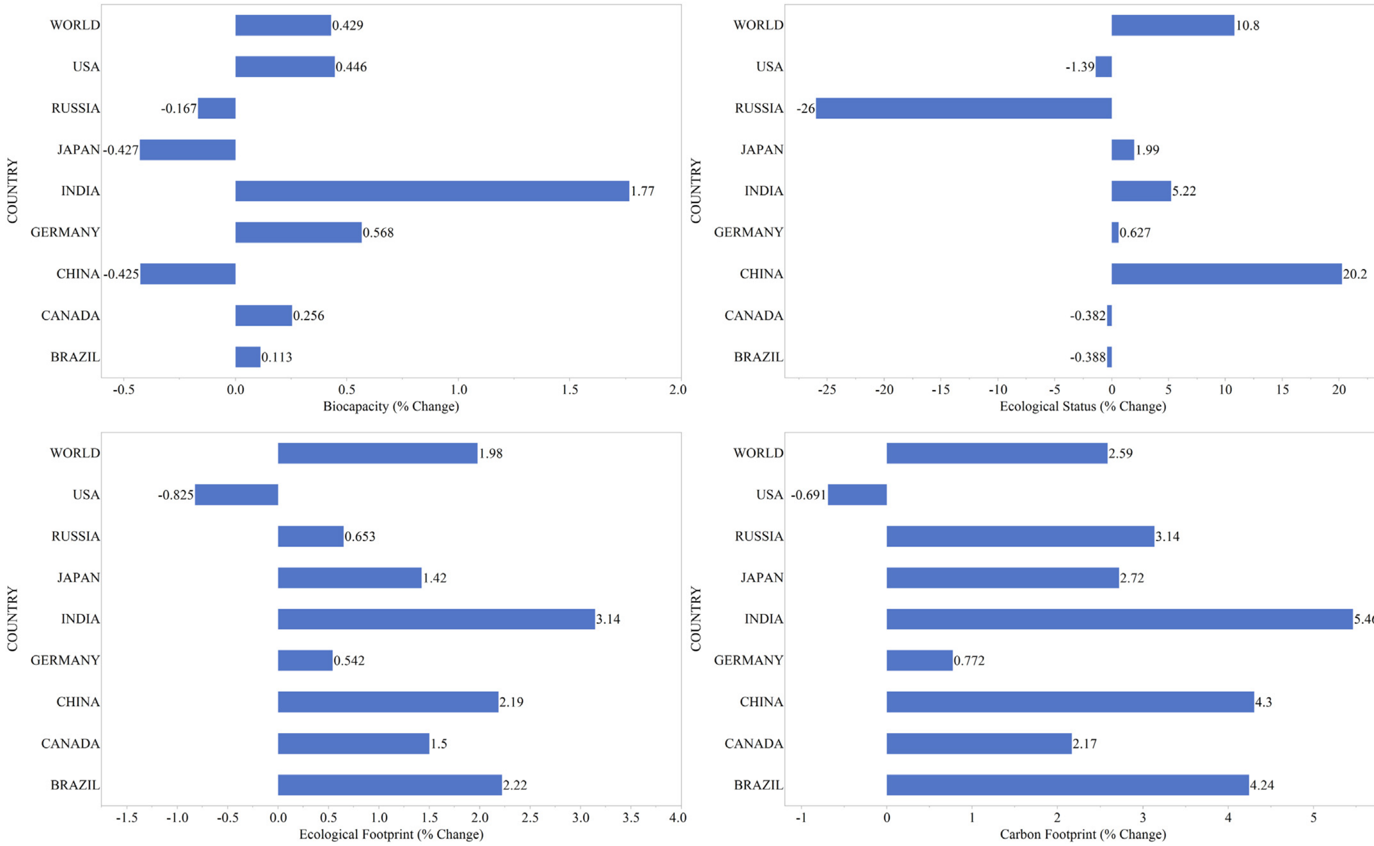


Fig. 4. Mean relative change (%) in biocapacity, ecological footprint, ecological status and carbon footprint of the US, Russia, Japan, India, Germany, China, Canada and the World.

the nexus between wealth and economic performance, thus, a useful indicator to examine SDG-8 of sustained economic growth.

- Population density: Population expansion intensifies natural resource consumption either through extraction or importation to meet the growing demand (Sarkodie et al., 2020). Thus, importation can only materialize in countries where population demand for biologically productive resources exceeds the regenerative capacity due to the levels of carbon footprint attributable to economic productivity. Population density plays enormous roles in achieving many of the SDGs (United Nations, 2015) namely reduced inequality (SDG-10), sustainable cities (SDG-11), sustainable production and consumption (SDG-12), climate change mitigation (SDG-13), and sustainable life below water and land (SDG-14 &15).
- Trade: International trade is a conduit of globalization that is critical to achieving economic productivity (SDG-8), industrialization, innovation and technology (SDG-9), climate change mitigation (SDG-13), and global partnership (SDG-17). Thus, trade navigates domestic material consumption and environmental sustainability.

The elasticities of the socio-economic inputs were computed using multiple cross-country time series estimation techniques and a machine learning algorithm for panel data modelling. Stationarity, omitted-variable bias, heterogeneity, misspecification, and cross-section dependence are challenges associated with cross-country time series models. Here, we used a battery of novel estimation techniques that control for the outlined issues. First, cross-sectional units of panel data models may suffer from global common shocks, which ignoring it will lead to another challenge related to the error term known as endogeneity, hence, produces inconsistent model estimates. We examined the variable- cross-section dependence with corresponding results presented in Table 1. We find that the null hypothesis of cross-section independence is rejected at 1% significance level, confirming the presence of cross-section dependence in the data series. This supports the estimation of stationarity using CIPS and CADF second generational unit root tests. We find that all series are stationary at level except ecological status which is difference stationary. To examine heterogeneity across countries, we used the novel kernel-smoothing technique with half-panel jackknife (type of split-panel jackknife) bias correction for estimating densities (Okui and Yanagi, 2020). This in effect controls for nonlinearity and incidental parameter bias. The non-parametric panel kernel density estimation for testing the degree of heterogeneous dynamics across countries assumes heterogeneous stationary time series for initial input variables, panel autoregressive moving average and Gaussian white noise (Okui and Yanagi, 2019). The estimated kernel densities show a persistent long-run heterogeneity (*p-value* < 0.05) of income level, economic growth, population density, trade, biocapacity, carbon footprint, ecological footprint, and ecological status (Fig. 5). We observe that while population density, trade, biocapacity, carbon footprint, and ecological footprint exhibit a unimodal distribution — income level, economic growth, and ecological status appear to show a bimodal distribution. The structural estimation confirms a significant and strong degree of heterogeneous dynamics across countries.

To correct the panel heterogeneous effects exhibited across countries, we employed panel kernel regularized least squares and dynamic bootstrap-corrected fixed-effects panel approach. The panel kernel regularized least-squares technique is applied by fitting the functions with Gaussian kernels and regularizing the less complex functions that reduce squared loss to control over-fitting (Hainmueller and Hazlett, 2014). The machine learning-based cross-country time series technique provides unbiased and consistent estimated coefficients due to the automatic selection of optimal kernel bandwidth and regularization parameter for the proposed model. The panel dynamic bootstrap-corrected fixed-effects is applied to the proposed model to correct the small time-bias (Everaert and Pozzi, 2007). We accounted for cross-section dependence and heterogeneous effects by utilizing the Monte Carlo

Table 1
Model estimation results.

Variable	Drivers of carbon footprint				Drivers of the ecological footprint				Drivers of ecological performance		
	Model 1[a]	Model 1[b]	Model 2[a]	Model 2[b]	Model 3[a]	Model 3[b]	Model 4[a]	Model 4[b]	Model 5[a]	Model 6[a]	Model 7[a]
CARBON†	–	0.108***	–	0.110***	–	–	–	–	–	–	–
		[0.032]		[0.033]							
EFCONS†	0.533***	0.582***	0.648***	0.572***	–	0.619***	–	0.615***	−0.003***	−0.003***	−0.003***
	[0.034]	[0.107]	[0.029]	[0.108]		[0.064]		[0.065]	[0.000]	[0.000]	[0.000]
ENVSUS†	−0.044	−0.108	0.032	−0.093	0.656***	0.430***	0.778***	0.429***	0.002***	0.003***	0.003***
	[0.028]	[0.176]	[0.029]	[0.173]	[0.006]	[0.118]	[0.006]	[0.117]	[0.000]	[0.000]	[0.000]
Δ*NECOPERM*†	18.725	−3.018	11.511	−2.987	–	–	–	–	–	–	–
	[11.756]	[3.492]	[10.013]	[3.519]							
GDPC†	–	–	0.362***	0.030	–	–	0.134***	0.006	–	0.001***	0.001**
			[0.018]	[0.024]			[0.008]	[0.010]		[0.000]	[0.000]
GDPC^{2}†	–	–	–	–	–	–	–	–	–	–	0.000***
											[0.000]
GDP†	0.280***	0.077***	–	–	0.171***	−0.004	–	–	0.001***	–	–
	[0.015]	[0.025]			[0.005]	[0.006]			[0.002]		
POPDEN†	0.169***	0.307**	0.256***	0.327**	0.463***	0.235***	0.525***	0.231***	0.001**	0.001***	0.001***
	[0 0.024]	[0.127]	[0.024]	[0.135]	[0.008]	[0.068]	[0.008]	[0.068]	[0.003]	[0.000]	[0.000]
TRADE†	–	–	0.231***	0.088*	–	–	−0.067***	0.016	–	−0.001*	−0.001*
			[0.038]	[0.048]			[0.016]	[0.013]		[0.000]	[0.000]
Eff. df	105.5	–	161.5	–	73.43	–	133.7	–	97.25	158.7	154.6
R^2	0.594	–	0.612	–	0.907	–	0.905	–	0.243	0.261	0.253
Looloss	7679	–	7467	–	1476	–	1534	–	144.9	144	145.7
Convergence	–	YES	–	YES	–	YES	–	YES	–	–	–

Notes: † represents the rejection of the null hypothesis of homogeneity using Pesaran CD test; I(0) means a stationary series at level whereas I(1) represents first-difference stationary series; *,**,*** denotes statistical significance at *p-value* < 0.10, *p-value* < 0.05 and *p-value* < 0.01; [.] is the standard error; *N* signifies normalization [0,100], Δ means the first-difference; [a], [b] represent panel estimation using kernel regularized least squares and panel bootstrap-corrected fixed-effects. Model 1 - lnCARBON ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnΔ*NECOPERM*, lnGDP); Model 2 - lnCARBON ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnΔ*NECOPERM*, lnGDPC, lnTRADE); Model 3 - lnEFCONS ~ f(lnPOPDEN, lnENVSUS, lnGDP); Model 4 - lnEFCONS ~ f(lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE); Model 5 - lnΔ*NECOPERM* ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDP); Model 6 - lnΔ*NECOPERM* ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE); Model 7 - lnΔ*NECOPERM* ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnGDPC^2, lnTRADE). Legend: GDPC - Income Level, GDP - Economic growth, POPDEN - Population density, TRADE - Trade, ENVSUS - Biocapacity, CARBON - Carbon Footprint, EFCONS - Ecological Footprint, NECOPERM - Ecological Status.

heteroskedastic bootstrap error resampling scheme to generate samples and analytical heterogeneous initialization to generate preliminary conditions of the resampling process (De Vos et al., 2015). We also used multivariate normal distribution to sample the preliminary conditions. To control for omitted variable bias, we incorporated the lagged-dependent variable of ecological status, carbon and ecological footprint. We plugged-in country-specific fixed-effects to mitigate unobserved effects across sampled countries. We validated the estimated parameters using a baseline and actual model for which the actual model captures the inertia effects of target variables. In comparison, both models produce similar signs and statistical significance of desirable parameters. The panel kernel regularized least-squares technique reveals the goodness of fit (R-squared) between 24 and 91% and partial derivatives that are robust and consistent. The panel dynamic bootstrap-corrected fixed-effects model finds a positive coefficient for the lagged-dependent variables that is less than 1, fulfilling the assumption of consistent model estimates. The inferences procedure further shows a bootstrapped histogram distribution with a characteristic of a bell-shape (Fig. 6). This is validated by the superimposed kernel fit and normal distribution line, confirming the residual independence of the estimated models.

3.1. What are the drivers of carbon footprint?

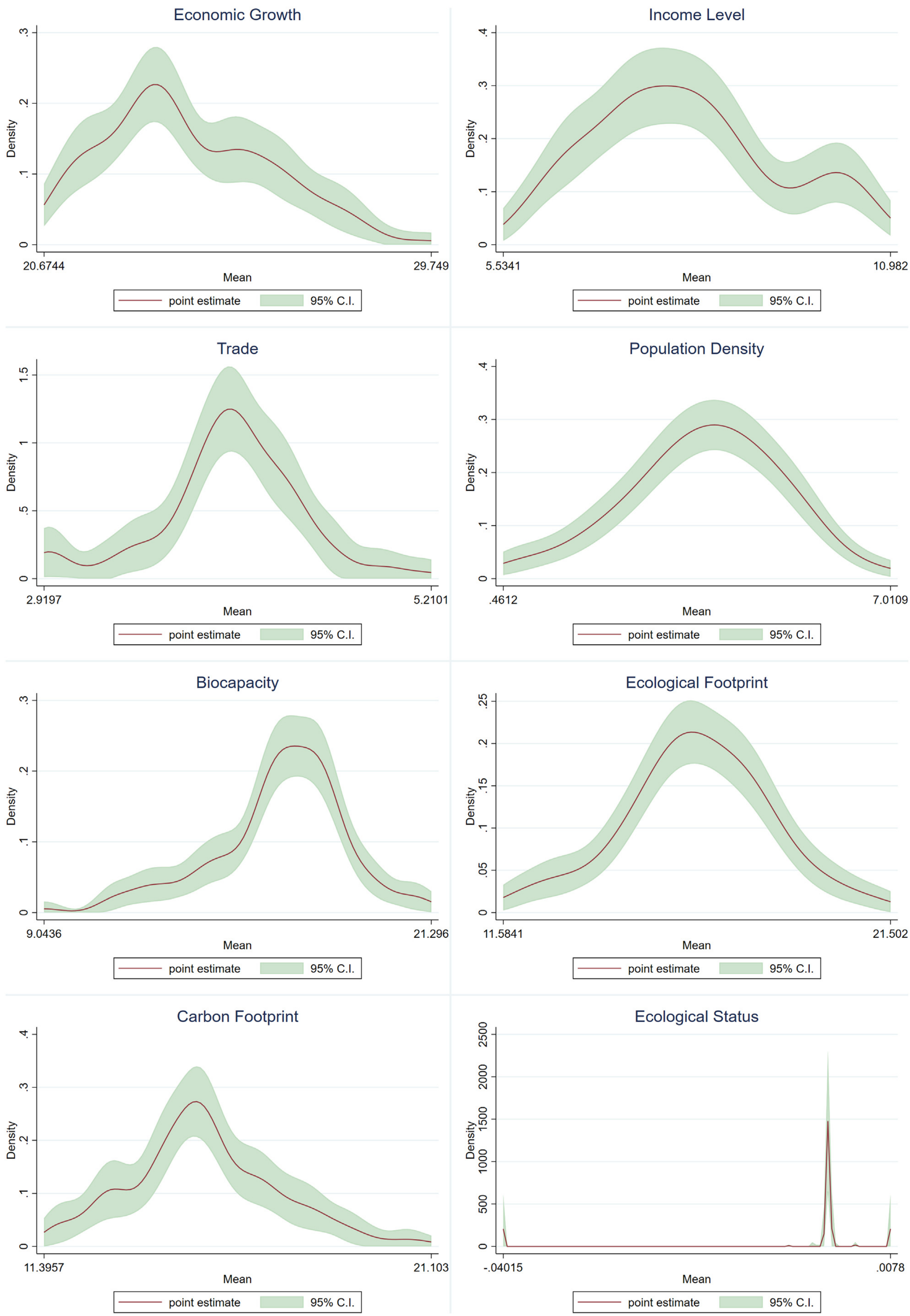
The lagged-carbon footprint estimate is positive and significant (*p-value* < 0.01), hence, confirming the inertial effects of carbon footprint. This entails that the current and historical levels of carbon footprint are triggered by unobserved common factors across nations. The estimated model achieves convergence, hence, validating the carbon footprint convergence hypothesis (Table 1). We accounted for national-level income in model 1 whereas individual income, an indicator for wealth was used in model 2. The empirical results find that a systemic change in both aggregates and per capita income exacerbate carbon footprint. We note that the escalation effect of economic development drives carbon footprint by 28–36%. Consequently, a dynamic change in international trade spur carbon footprint, confirming a potential transboundary carbon-embedded trade. Population density is reported to increase the population demand for natural resource-attributed goods and services and waste generation which hamper the environmental quality. Our estimated model confirms that an increase in population density intensifies carbon footprint.

3.2. What factors account for changes in ecological footprint?

The significant (*p-value* < 0.01) positive coefficient of lagged-ecological footprint confirms unobserved factor-attributed high current and past trends of ecological footprint of nations. Evidence from Table 1 reveals that the ecological footprint of nations achieves convergence at a faster pace compared to carbon footprint. Though environmental sustainability requires the expansion of biocapacity to serve as a bequest for future generations. However, our empirical results show that an expansion of ecological reserves triggers resource extraction, hence, affecting ecological footprint. This is confirmed by the strong effect of population density on ecological footprint. Similarly to carbon footprint, population density facilitates resources extraction and consumption of the available natural capital to meet livelihood pressures. The pointwise estimate highlights that an average impact of economic growth and income level across countries have escalation effect on ecological footprint. Here, we find global economic development and international trade driven by excessive extraction and consumption of natural resources.

3.3. What drives the environmental performance of nations?

While the expansion of biocapacity improves economic performance, growth in ecological footprint and international trade hamper the ecological performance of nations. This results further strengthen our position on carbon and natural resource-embedded trade effects across countries. In contrast, population density deviates from the initial position on carbon and ecological footprint. We find that growth in population density increases ecological performance. We further capture the environmental Kuznets curve (EKC) hypothesis to examine the


Economic Growth
Density
0
.1
.2
.3
20.6744
29.749
Mean
point estimate
95% C.I.
Income Level
Density
0
.1
.2
.3
.4
5.5341
10.982
Mean
point estimate
95% C.I.
Trade
Density
0
.5
1
1.5
2.9197
5.2101
Mean
point estimate
95% C.I.
Population Density
Density
0
.1
.2
.3
.4
.4612
7.0109
Mean
point estimate
95% C.I.
Biocapacity
Density
0
.1
.2
.3
9.0436
21.296
Mean
point estimate
95% C.I.
Ecological Footprint
Density
0
.05
.1
.15
.2
.25
11.5841
21.502
Mean
point estimate
95% C.I.
Carbon Footprint
Density
0
.1
.2
.3
.4
11.3957
21.103
Mean
point estimate
95% C.I.
Ecological Status
Density
0
500
1000
1500
2000
2500
-.04015
.0078
Mean
point estimate
95% C.I.

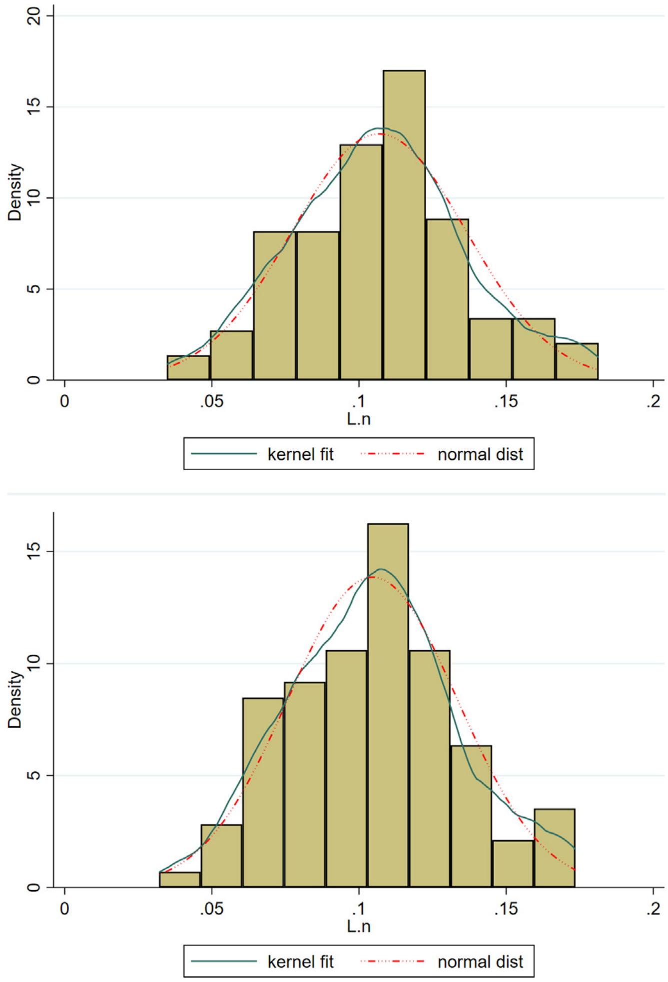


Fig. 6. Model Validation of the panel bootstrap-corrected fixed-effects estimation models using histogram distribution — overlaid by kernel fit and normal distribution.

nexus between environmental performance and wealth. We find that the EKC hypothesis is not valid but rather the scale effect hypothesis. This is because both the first- and second- degree polynomial of income level is positive and statistically significant (*p-value* < 0.05).

4. Discussion

The long-run relationship between socio-economic drivers and environmental indicators reveals that carbon footprint, ecological footprint and ecological performance may deviate from its equilibrium at any time period. But the deviation is a temporary transition with the tendency of returning to equilibrium through sustainable policies and measures. This implies that the factors of production across 188 countries can be altered through structural change in economic development. For example, energy and carbon-intensive economic structure can be altered at the production level by shifting from fossil fuels to cleaner and sustainable alternative energy technologies (Owusu and Asumadu, 2016). Energy transformation in the form of replacing fossil fuels with clean energy technologies is reported to have multiple mplications on investment, import, export and trade of natural resources, and other co-benefits (Jakob and Steckel, 2016; Mayrhofer and Gupta, 2016).

Expansion in environmental performance is beneficial to environmental sustainability whereas a decline in environmental performance signifies environmental damage, which spurs climate change and its impact. Our study confirms that increasing levels of ecological footprint and trade across nations obstruct environmental quality. Expansion of ecological constraints due to the exploitation of available natural resources is reported to increase climatic debt (Bertrand et al., 2016). Rather than the excessive exploitation of natural resources, advancing on artificial alternatives that can replace the natural capital as inputs at the production level will improve environmental sustainability through the expansion of biocapacity.

Livelihood pressures underpin excessive natural resources extraction and waste generation, especially in developing countries (Biggs et al., 2015). It is reported that 2.5 million of the world's population depends on traditional biomass such as charcoal, and fuelwood for cooking and heating purposes (IEA, 2017). The notion of the scale and EKC hypotheses provide support for our empirical interpretations. While the scale effect posits environmental degradation based economic development at pre-industrial level (agrarian economy), the EKC hypothesis has similar connotation but with the hope that pollution declines at a threshold of income level when environmental awareness becomes a priority. The failure to validate the existence of the EKC hypothesis solely relies on the choice of expansive and detailed environmental indicator compared to the usual emission indicators in extant literature (Dinda, 2004; Sarkodie and Strezov, 2019).

Validation of the scale effect hypothesis between ecological status and income level underscores the deteriorating state of ecological performance across nations due to the tendency of potential competitive advantage. The issue of competitive advantage may arise when Nation "*A*" institutes environmental stringency policy that hampers production size and efficiency, but Nation "*B*" employs lax policies that expand the size and efficiency of production. The production level of Nation "*B*" will translate into lower cost and higher profit than Nation "*A*", hence, offer Nation "*B*" a competitive advantage. This may be one of the several factors hampering the achievement of the multiple global targets on climate change mitigation.

Though growth in both national and individual income is reported to facilitate environmental sustainability, however, our study emphasizes on escalation effect. Expectations are that higher-income trigger environmental awareness, however, there appears to be a missing link between the production level where there is heavy-dependence on natural resource utilization and green economic growth. This means that a mere advancement in economic development cannot mitigate the escalation effect but a structural change through diversification of production will facilitate the agenda towards achieving sustainable production and consumption.

International trade facilitates the transboundary effect of localized natural capital and carbon-embedded goods and services. Major economic sectors such as manufacturing, agriculture and transportation depend majorly on conventional energy sources to power productivity, hence, countries with limited or lack fossil fuel resources import fossil fuels from producing countries. This means that environmental degradation can directly or indirectly be transferred between income groups of nations. Hence, validating the presence of convergence — where environmental deterioration will reach the same level across nations under similar conditions regardless of income group.

The validity of environmental convergence hypothesis through carbon and ecological footprint has policy implications for achieving the global emission targets. The presence of environmental convergence might have been possible due to global common shocks and transboundary effects of carbon and natural resource-depletion embedded in trade and globalization. Affluence and population growth are reported to drive the displacement of emissions from high levels of income to lower-income, hence, affecting environmental stress (Dietz et al., 2015). This means that country-specific resource-

Fig. 5. Panel heterogeneous distribution of socio-economic and environmental performance indicators. Legend: The 95% confidence interval (C·I) denotes the rejection of the null hypothesis that the distribution is identical (homogeneous) across the 188 countries.

attributable emissions are no longer localized but transferrable through international trade. Thus, the existence of environmental convergence implies that though the level of economic development across nations is not equal in terms of production function and growth characteristics, however, the disparities in carbon and ecological footprint are bound to exhibit similar features in the long run.

5. Conclusion

We estimated the overarching effect of economic development, population density and international trade on ecological performance from a global perspective. Using a battery of novel estimation methods, we accounted for omitted variable bias, heterogeneous effects across countries and misspecification errors. The empirical results validated the scale effects hypothesis rather than the popular environmental Kuznets curve hypothesis of nations. The scale effect confirms that economic development is characterized by natural resource exploitation leading to environmental degradation, a situation that has global policy implications. We identified the US, China, India, Russia, Germany, Brazil, Japan and Australia as the hotspot countries for environmental performance. Our study highlights that the diversification of the economic structure by replacing fossil fuels will decline the international trade capacities of carbon-embedded resources transferred from countries with higher carbon concentrations to countries with lower carbon concentrations. This then explains the possibility of environmental convergence in the long run. Meaning that developing and harvesting the flow of renewable energy sources across nations decline the multiple emission-driven processes of fossil fuel extraction and consumption from cradle-to-grave. While fossil fuels are transportable and internationally tradable across nations, renewable energy sources are localized, hence, eliminates the transboundary flow of emissions. Thus, has policy implications in understanding the drivers of environmental degradation through natural resource depletion. This calls for global adoption of renewable energy technologies, increased efficiency of renewables to compete with fossil fuels, reduction in the price of renewables and strong political will for clean and modern energy.

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CRediT authorship contribution statement

Samuel Asumadu Sarkodie: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Software, Validation, Visualization, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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