PhD in Business // No. 99 - 2023

Compendium of Climate Change Econometrics

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ISBN: 978-82-92893-90-6
ISSN: 2464-4331

Print: Trykkeriet NORD

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This thesis is dedicated to my son—Supernatural Emmanuel Asumadu-Sarkodie.

ACKNOWLEDGMENTS

To everything there's a season, and a time for every purpose (Ecclesiastes 3:1 KJV). This second Ph.D. has been full of episodes, yet, we made it, Glory be to God. Thanks to Nord University, specifically, Business School and my Supervisor—Associate Professor Thomas Leirvik—for your support. Appreciation goes to all and sundry involved in this journey, I say thank you!

Finally, I end by paraphrasing Ecclesiastes 12:12 (NLT)——Be careful, for writing books is endless, and much study wears you out.

—— *SA Sarkodie, Ph.D.*

ABSTRACT

Climate change is topical yet, complex with several dynamics spanning different disciplines. The 21st-century development pathway is characterized by a roller coaster of climate change events—because of natural resource exploitation, fossil fuel utilization, energy intensity, population growth, and environmental pollution. Under this global environmental threat that development cooperation made several efforts to rally economies into sustainable policies that mitigate current and future threats. The Brundtland Report, "Our Common Future", outlines the importance of "*protecting the environment while meeting current demand without compromising available resources, but leaving the environment as a bequest for future generations"*. This infers the importance of achieving environmental sustainability through sustainable development, addressing institutional gaps, and developing policy measures that control for urban challenges, resource-dependent, energy-intensive industrial processes, fossil-driven energy portfolio, loss of biodiversity, ecosystem challenges, food security, population growth, and human resources. Climate change econometrics provides opportunities for assessing potential policy implications of historical alterations of climate events. Thus, understanding the various philosophical underpinnings of climate change and its impacts is useful in future policy development with mitigation effects. Here, we bring to the fore cyclical climate chain—a term coined to understand how climate change processes mimic typical "food chain". Philosophical perspectives of existing pollution theories including energy-growth, pollution halo/haven, environmental convergence, displacement effects, and environmental Kuznets curve hypotheses are examined using econometric techniques. This compendium contributes to the extant literature in both spirit and letters while criticizing, contrasting, and/or validating the status quo in climate change econometrics. We incorporate the concept of sustainability in the hypotheses and research design useful in developing conceptual tools for policy formulation while highlighting the policy implications of empirical results. Our empirical studies presented herein demonstrate the complexity of climate change, however, climate change mitigation and adaptation to climate impacts are possible through climate-resilience pathways—coping mechanisms of new and existing systems to modulate the harmful effects of climate change on sustainable development.

SAMMENDRAG

Klimaendringene er dagsaktuellt, men er et komplekst tema med dynamikker som spenner over flere ulike fagområder. Utviklingen i det 21. århundre er preget av en berg-og-dal-bane av hendelser relatert til klimaendringer – på grunn av utnyttelse av naturressurser, bruk av fossilt brensel, energiintensitet, befolkningsvekst og miljøforurensning. Under denne globale utfordringen for klima og miljø har det vært gjort mange forsøk på å utviklinge samarbeidet for å få verdens økonomier til å føre en bærekraftig politikk som reduserer nåværende og fremtidige trusler. Brundtland-rapporten, "Vår felles framtid", skisserer viktigheten av å "beskytte miljøet samtidig som vi møter dagens etterspørsel uten å gå på bekostning av tilgjengelige ressurser, men etterlater miljøet som en arv til fremtidige generasjoner". Dette innebærer at det er viktig å oppnå miljømessig bærekraft gjennom bærekraftig utvikling, tette institusjonelle hull og utvikle politiske tiltak som tar høyde for urbane utfordringer, ressursavhengige, energiintensive industriprosesser, fossildrevet energiportefølje, tap av biologisk mangfold, økosystemutfordringer, matsikkerhet, befolkningsvekst og menneskelige ressurser. Klimaøkonometri gir muligheter for å vurdere mulige politiske konsekvenser av historiske klimaendringer. Det er derfor nyttig å forstå de ulike filosofiske grunnlagene for klimaendringene og konsekvensene av dem for å kunne utforme en politikk som reduserer negative virkninger i fremtiden. Her setter vi søkelyset på den sykliske klimakjeden - et begrep som er skapt for å forstå hvordan klimaendringsprosessene etterligner en typisk "næringskjede". Filosofiske perspektiver på eksisterende forurensningsteorier, inkludert energi-vekst, forurensning glorie/havne, miljøkonvergens, fortrengningseffekter og miljømessige Kuznets-kurvehypoteser, undersøkes ved hjelp av økonometriske teknikker. Dette kompendiet bidrar til den eksisterende litteraturen i både ånd og bokstav, samtidig som det kritiserer, kontrasterer og/eller validerer status quo innen klimaesøkonometri. Vi inkorporerer begrepet bærekraft i hypotesene og forskningsdesignet som er nyttig for å utvikle konseptuelle verktøy for utforming av politikk, samtidig som vi fremhever de politiske implikasjonene av empiriske resultater. De empiriske studiene som presenteres her, viser hvor komplekse klimaendringene er, men at det er mulig å redusere klimaendringene og tilpasse seg klimakonsekvensene ved hjelp av klimatilpasningsmekanismer i nye og eksisterende systemer for å dempe de skadelige effektene av klimaendringene på bærekraftig utvikling.

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Chapter 1. Introduction

1.1 Overview

The rising level of anthropogenic emissions over the past decades has received global attention. The magnitude of extreme climate-related events and their impact on humanity and natural systems lead to increasing trends of extreme temperature (cold and warm), droughts, irregular precipitation levels, cyclones, floods, and wildfires—foreshadowing future risks and effects attributed to climate change (IPCC, 2014b; Sarkodie *et al.*, 2019a). The observed climate change and its causes have human and external attributes including carbon dioxide (CO_2) emissions from the combustion of fossil fuels, forestry, land use, cement production, and flaring (Pachauri *et al.*, 2014). Thus, the mitigation of climate change and its impact requires effective climate change management policies that reduce forcing and human influence on climate systems. The Sustainable Development Goals (SDGs) raise awareness of climate change mitigation through adaptation readiness, human and institutional capacity, and technological advancement among others—to assist in reducing global surface temperature to below 2°C (United Nations, 2015b). Future climate change uncertainties and their related risks have triggered scientific research from different disciplines. Several studies in energy and environmental economics have thus far examined the direct impact of immediate climate drivers (income level, population growth, carbon intensity, and energy intensity) on greenhouse gas (GHG) emissions (Apergis *et al.*, 2010; Asumadu *et al.*, 2016; Bekun *et al.*, 2019; Bouznit *et al.*, 2016; Ozturk *et al.*, 2010). Here, we present cyclical climate chain, theoretical framework, philosophical perspectives, viz. verification & falsification, and research design of climate change econometrics—useful in developing mitigation options for environmental pollution and degradation.

1.2 Cyclical Climate Chain

Cyclical Climate Chain is a term coined herein due to the complexity and mutual coupling of causal effects of climate change drivers. Climate change and its effects pose a long-term threat to humanity by altering the lithosphere, hydrosphere, and atmosphere. Anthropogenic GHG emissions involving CO_2, methane (CH_4), nitrous oxide (N_2O), sulfur hexafluoride (SF_6), perfluorocarbons, and hydrofluorocarbons underpin climate alterations (DiSano, 2002).

Global GHG emissions grew from 50.911 mmtCO_2eq in 2010 to approximately 53.523 mmtCO_2eq in 2012, however, global CO_2 emissions per economic productivity declined from 0.347 kg of CO_2 per constant 2010 US$ in 2010 to 0.320 kg of CO_2 per constant 2010 US$ in 2014 (UNEP, 2020). The immediate and underlying drivers of manmade-attributed climate change include economic productivity, livelihood demands, population growth, socio-political pressures, consumption, and lifestyle patterns. These manmade-attributed climate drivers distort both carbon and energy intensity, hence, contributing significantly to global emissions. While global GDP per capita declined from 3.03% in 2010 to 1.95% in 2011, a further decline was observed from 2.37% in 2018 to 1.71% in 2019. However, carbon intensity dropped from 1.20% in 2011 to -0.85% in 2019 whereas energy intensity dropped from 1.10% in 2010 to -1.43% in 2019. Similarly, global population fell from 1.22% in 2009 to 1.08% in 2019 (IMF, 2020).

While there are naturally occurring causes of climate change, manmade causation fast-tracks the deteriorating effect on the environment. The manmade causation includes direct determinants such as urban sprawl (Sarkodie, Owusu*, et al.*, 2020), transport (Chapman, 2007), buildings, energy production, and consumption (Bruckner T., 2015), industrialization, agriculture, forestry, and land use. Global urban population growth grew from 52.11% in 2011 to 56.19% of the total population in 2020 (UNTCD, 2020). Global urban population growth expanded the demand for electricity supply, increasing global urban access to electricity from 95.95% to 97.23% of the urban population in 2017 (SE4All, 2020). Global fossil fuel production (from oil, gas, and coal) and consumption from alternative energy sources (nuclear, hydro, bioenergy, wind, and solar) have increased significantly in the last decades (BP, 2020a). However, energy supply from renewables is inadequate to offset the growth in global fossil energy utilization despite a decline in both carbon and energy intensities (Blanco *et al.*, 2014). While the global area designated for agriculture and forestry has declined significantly in developing countries, forest plantation is increasing in developed countries (FAO, 2020b). This perhaps elucidates the role of agriculture and forestry practices in environmental sustainability. Agriculture and forestry play a crucial role in reducing atmospheric emissions through sequestration, however, its demand-side using crude methods to meet the growing population and economic productivity hampers environmental sustainability (Smith *et al.*, 2014). Food production and consumption contribute significantly to climate change and its impacts. Food consumption patterns alter the food balance sheet and increase demand for food supplies. For example, changes in dietary patterns increased the global food supply from 2,825 kcal/capita/day in 2008 to 2,927 kcal/capita/day in 2018. Specifically, fat supply quantity grew from 80.14 g/capita/day in 2008 to 86.17 g/capita/day whereas protein supply quantity grew from 78.73 g/capita/day in 2008 to 82.72 g/capita/day in 2018 (FAO, 2020a). Besides, socio-economic factors, urbanization, market and trade liberalization, income level, consumer attitude and lifestyle, and women's employment status underpin food consumption patterns (J, 2010).

In contrast, climate change impacts facilitate changes in weather patterns such as temperature, and precipitation—which lead to event occurrences including wildfire, heatwaves, droughts, floods, famine, earthquakes, and cyclones. Doubling of anthropogenic GHG concentrations escalates global temperature while changing pressure, rainfall, humidity, wind speed, dew-frost point, and cloudiness (Liu *et al.*, 2013; Rosenzweig *et al.*, 2008). The expected alterations in climatic patterns influence the variability of meteorological conditions that affect weather-related events. Likewise, alteration in weather frequencies affects aeroallergens and atmospheric pollutants including sulfur dioxide, methane, nitrous dioxide, carbon monoxide, ozone, and particulate matter (Reid *et al.*, 2009). Ambient intensities of air pollutants including black smoke suspended particulate matter, and volatile organic compounds are often high in urban areas reducing air quality (Hou *et al.*, 2016). Growth in concentrations of urban pollution can be attributed to energy utilization, infrastructure, overpopulation, transport-induced emissions, deforestation, carbon & energy-intensive industrial processes, and production & consumption patterns. The resultant effects of weather changes define health impacts, behavioral changes, food security, water security, energy security, land security, and ecosystem security (Patz *et al.*, 2006). Climate-driven weather-pollutant interaction, allergen-pollutant interaction, and weather-allergen interaction leads to allergic responses and affect respiratory health—leading to respiratory diseases and premature deaths (De Sario *et al.*, 2013; Wu *et al.*, 2016).

The conceptual framework presented in Figure 1 shows the cyclical climate chain outlining climate drivers, climate-driven weather changes & events, and climate effects. To the best of our knowledge, this thesis "Compendium of Climate Change Econometrics" is the first to introduce the concept of cyclical climate chain—which posits a mutualistic relationship between causal-effects of climate change and its impacts. This implies the understanding of climate chain is useful in the assessment of climate change vulnerabilities, climate adaptation mechanisms, and readiness to curb climate impacts.

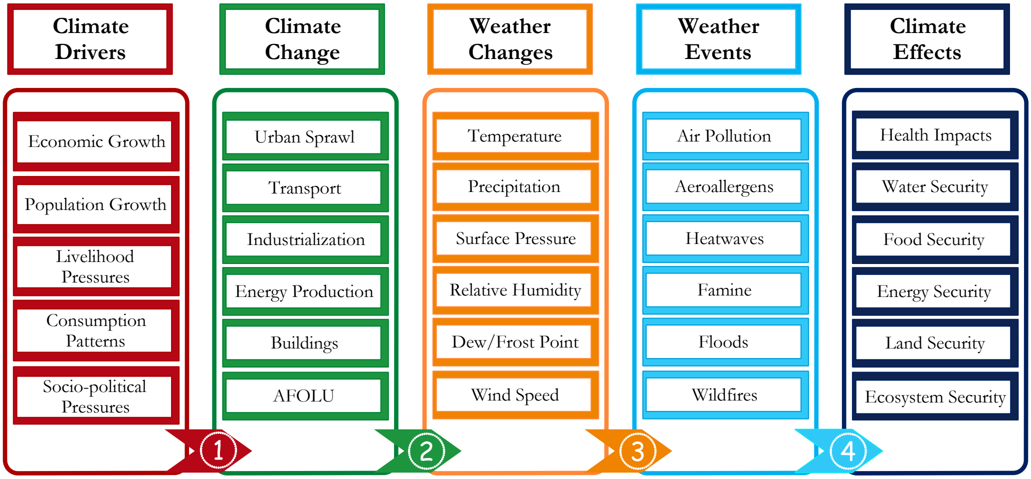

Figure 1. Conceptual framework depicting Cyclical Climate Chain.

1.3 Theoretical Framework

This section outlines the theoretical framework underpinning the selection of variables presented in the various compiled articles. Figure 2 presents the contribution of the economic sector to GHG emissions. The impact of land use, land-use change, and forestry sector on anthropogenic GHG emissions has declined by 6% since 2014, showing the positive development of land use and forestry-related policies namely conservation and management. Energy remains the crucial driver of economic development, however, its impact on environmental pollution is alarming. Figure 2 shows the role of energy supply as the main contributor to GHG emissions still prevails—intensifying global emissions by 28%. The transport sector contributes about 19% of global GHG emissions whereas industrial sector accounts for 18%. This justifies the role of sustainable industrial sector reforms in the sustainable development goal (SDG) 9. Other sectoral contributions to GHG emissions include agriculture, CO_2 emissions from biomass, residential & commercial buildings, waste management, international aviation, and navigation.

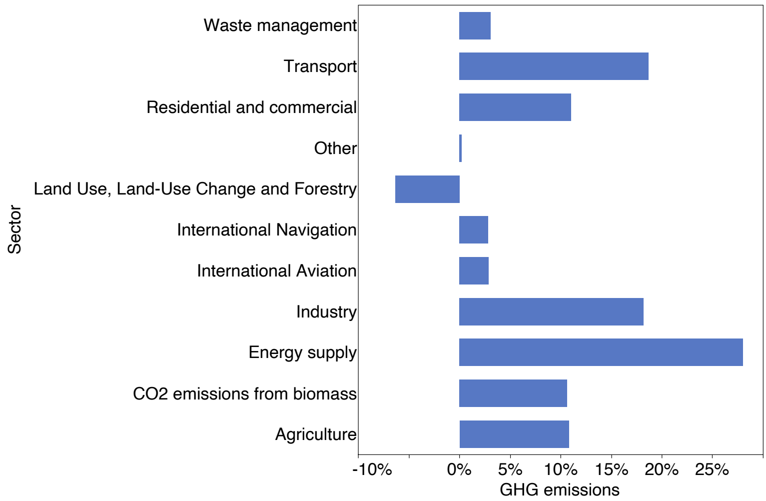

Figure 2. Economic sector contribution to GHG emissions. Data source: IPCC (2014a).

The theoretical framework presented in Figure 3 shows immediate drivers, underlying drivers, and policy and measures of GHG emissions. The immediate drivers of GHG emissions include population growth, GHG intensity, energy intensity, and income level. These indicators have direct impact on anthropogenic emissions caused by intensive human activities. Population growth increases the demand for food, water, and energy security, hence, expanding natural resource exploitation. Economic productivity increases the demand for energy services by promoting energy production and consumption. However, energy production increases GHG intensity only if the composition of the energy mix is dominated by fossil fuels. The underlying drivers include technology, governance, trade, resource availability, behavior & lifestyle, development, industrialization, infrastructure, and urbanization. In contrast, policy and measures of GHG emissions comprise planning, research & development, information provision, direct regulation, awareness creation, non-climate policies, and economic incentives. This theoretical framework implies no single cause of anthropogenic emissions, thus, underscoring the complexities of climate change and its impact.

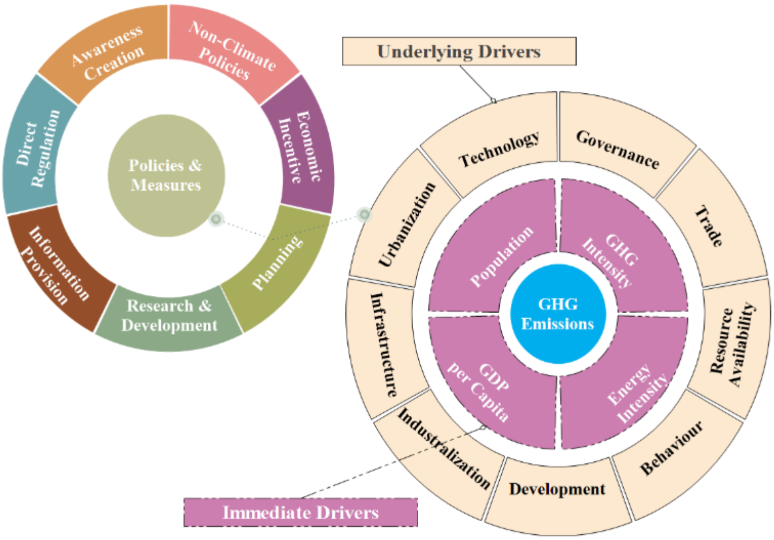

Figure 3. Theoretical Framework showing immediate drivers, underlying drivers, and policy and measures of GHG emissions. Source: Adapted from Blanco *et al.* (2014).

Several theories in the existing literature including environmental convergence, sustainability, environmental Kuznets curve (scale, composition, & technique effects), feedback, growth, conservation, neutrality, Pollution-Halo, and Pollution-Haven hypotheses underpin climate change economics and environmental sustainability. The theories presented herein are extracted from our published articles[1] during the candidature.

1.3.1 Pollution-Halo/Haven Hypothesis

The theoretical framework explaining the nexus between external funding [i.e., foreign direct investment (FDI)] and environmental pollution can be categorized as Pollution-Halo and Pollution-Haven hypotheses (Figure 4). The Pollution-Haven hypothesis suggests external funding, typically FDI spurs environmental pollution by expanding economic productivity through investment inflows and production efficiency (Adams, 2008). Besides, environmental policies & laws of recipient economies, viz. developing countries are often weak—in efforts to attract funding (external) from foreign investors (Walter & Ugelow, 1979). This scenario

[1] **Sarkodie, S. A.**, Adams, S., & Leirvik, T. (2020). Foreign direct investment and renewable energy in climate change mitigation: does governance matter?. *Journal of Cleaner Production*, *263*, 121262.; **Sarkodie, S. A.**, Ahmed, M. Y., & Leirvik, T. (2022). Trade volume affects bitcoin energy consumption and carbon footprint. *Finance Research Letters*, *48*, 102977.

shifts production from high-income economies to developing countries, and/or from high energy-intensive and carbonized economies to energy-efficient and decarbonized economies—promoting industrial development in developing economies. The Pollution Haven hypothesis is further explained by the "Heckscher-Ohlin" theory, where environmental indicators act as factors of production, hence, environmental policy stringency increases the production cost (Leontief, 1953). Economies with weak environmental laws will typically have a comparative advantage in attracting more external funding and financing—with the potential of increasing emissions. Similarly, if factors of production are readily mobile across frontiers, regulated industries from developed economies move to less regulated economies due to comparative advantage (McGuire, 1982). This implies carbon-intensive industries from high-income countries with stringent environmental laws, policy instruments and regulations will move to developing countries with lax environmental standards (Sarkodie, Adams*, et al.*, 2020). Thus, host economies of external funding become production hubs for pollution, viz. pollution haven. However, foreign contributors of pollution-based external funding often improve industrialization and economic development of recipient countries (Jiang *et al.*, 2018).

The Pollution-Halo hypothesis posits external funding that supports transfer of innovations, new green investment projects, and advanced technologies from developed economies to developing countries via knowledge spillover and value addition. The influx of external funding to developing economies encourages technological transfer and sustainable management practices with climate mitigating effects in developing economies (Zarsky, 1999). The cost of production and externalities of economic productivity may increase energy efficiency while improving environmental sustainability. Accordingly, the rate of external funding could motivate industrial competitiveness and sustainability in developing economies (Stavropoulos et al., 2018). This implies external funding could trigger the adoption of clean technology in developing economies through knowledge spillover from foreign-owned firms (Jiang *et al.*, 2015). Classic model specification to examine Pollution- Haven/Halo Hypothesis follow the linear relationship expressed as:

$$Y = f(Z, Z^2, X)$$

where Y denotes environmental indicators, viz. emissions, X represents control variables, Z and Z^2 denote external funding, viz. FDI inflows and quadratic (second-degree polynomial) FDI inflows. While pollution-haven hypothesis underpins natural resource seeking through external funding, pollution halo hypothesis promotes efficiency-seeking of existing natural resources through innovations, knowledge spillover, R&D, and abatement technologies (Sarkodie, 2021). Thus, the concept of pollution-halo involving green external funding is essential for developing economies to achieve sustainable development.

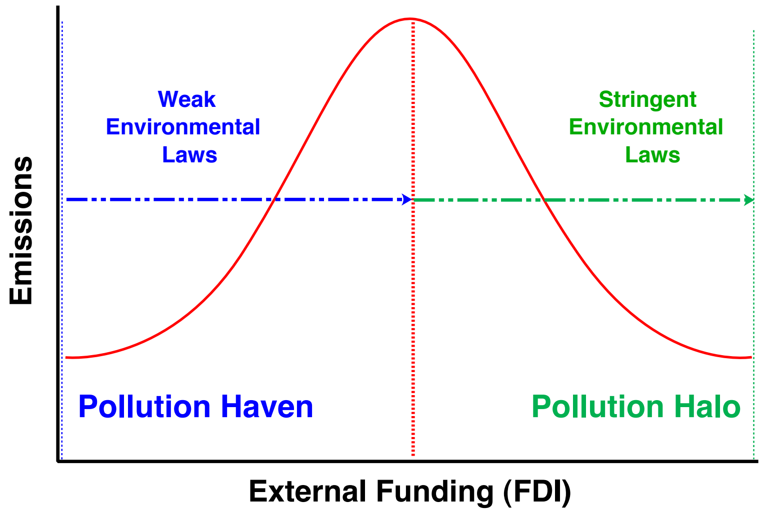

Figure 4. Representation of Pollution halo and haven hypotheses.

1.3.2 EKC Hypothesis

The environmental Kuznets curve (EKC) hypothesis is a widely known concept that postulates the "pollute now to get rich and clean later" ideology. This infers the effect of increasing levels of income determines environmental pollution and sustainability (Figure 5). The EKC hypothesis gained much attention following the seminal work of Grossman *et al.* (1991), which plays a crucial role in environmental policy formulation. The EKC hypothesis further argues that the initial stages of development (i.e., agrarian sector-driven economic productivity) are characterized by high pollution levels, resource exploitation, and waste generation (scale effects) but pollution declines after reaching a turning point in income level—due to paradigm shift to industrial and service sectors—with high income, knowledge spillover of environmental awareness, environmental sustainability, circular economy, investments in abatement technologies, and willingness to pay for cleaner environment (composition and technique effects) (Dinda, 2004; Panayotou, 1993; Sarkodie *et al.*, 2019b).

Three forms of transition effects presented in Figure 5 underpin the EKC hypothesis namely scale, composition, and technique (Copeland *et al.*, 1994, 2013; Vilas-Ghiso *et al.*, 2007). The scale effect posits rising levels of environmental degradation due to outgrowth in the exploitation of natural resources to meet human demand. Factors influencing the exploitation and consumption of productive assets of scale effect transitional pathway include trade openness, economic productivity, and FDI. The composition effect suggests an alteration in environmental degradation due to structural changes in economic productivity. This implies the level of environmental degradation depends on the composition of the economic structure, viz. either carbonized and energy-intensive economy (brown economy) or decarbonized and energy-efficient economy (green economy). In contrast, the technique effect hypothesizes environmental awareness, innovation, R&D, stringent environmental policies & regulations, and technological advancement with abatement technologies attributable to higher income. The traditional brown economy comprising the exploitation of natural resources, waste generation, and environmental pollution is shifted towards green economic development where sustainable development, specifically environmental sustainability is paramount. This implies using the EKC framework is useful in deriving policies across income groups. The linear relationship between emissions and income level connotes the EKC framework expressed as:

$$Y = f(U, U^2, X)$$

where Y and X are the dependent and control variables, U and U^2 represents income level and quadratic of income level. Thus, the EKC hypothesis can be assessed from the outlined equation if coefficient of U is positive whereas the estimated parameter of U^2 is negative—implying inverted U-shaped relationship between environmental indicator (emissions or degradation) and income level (see Figure 5).

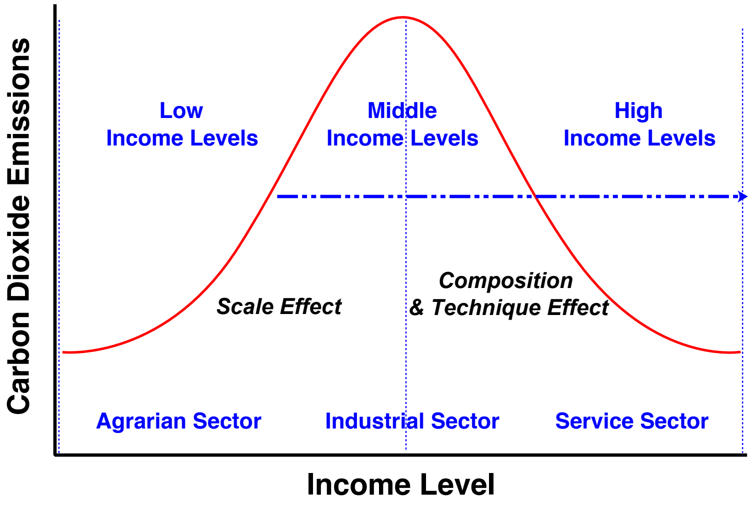

Figure 5. Representation of the EKC hypothesis.

1.3.3 Energy-Economic Growth

The dynamics in climate change are further driven by the role of energy-economic growth nexus and its effect on environmental pollution. The rate of pollution effects is determined by the mode of interaction between energy utilization and economic development existing in four hypotheses namely—feedback, conservation, growth, and neutrality (see Figure 6).

The feedback hypothesis postulates long-term mutualistic relationship between energy utilization and economic development. The coupling effect between energy and growth implies the institutionalization of environmentally friendly policies that decline energy intensity will affect sustained economic development and vice versa. In contrast, the coupling effect with limited green growth has implications on climate change and its impacts. Because of the feedback effect of energy consumption and economic development, energy production often increases to meet consumption demands triggered by economic activities. In the scenario where energy composition is dominated by fossil fuels, increasing level of energy intensity exacerbates pollution intensity—driving climate change due to increased concentrations of anthropogenic emissions. However, if the carbonized energy portfolio is replaced with clean and alternative energy sources while maintaining economic demand, the mitigation effects of clean energy technologies will decline long-term emissions attributed to economic activities. Thus, while decoupling energy from economic developments appears useful in energy-intensive and carbonized economies, the coupling effect of clean and alternative energy, and growth could be more practical to achieve sustainable economic development while fostering green energy.

The conservation hypothesis posits sustainable economic productivity driven by long-term energy utilization. This infers energy infrastructure determines the composition of economic pathway. Conservation hypothesis supports the notion of eco-sufficiency—where environmental footprint declines through sustainable production and utilization of energy and its services (Princen, 2005). Existing literature argues that the introduction and adoption of energy conservation and management options hinder sustainable economic development. In contrast to the notion, energy conservation may not always thwart economic productivity if energy portfolio is efficiently diversified with clean and renewable energy technologies. This implies that energy efficiency and eco-sufficiency can be achieved while meeting energy demand for economic activities. In this scenario, countries can shift from brown economic pathway to green economic growth.

In contrast, the growth hypothesis posits energy utilization driven by economic productivity. This hypothesis is useful in examining healthy economic pathways—by accounting for both energy intensity and energy efficiency. Energy intensity entails energy required per unit of economic productivity. High energy intensity represents inefficient growth-energy interaction where high energy cost is required for economic activity. However, low energy intensity represents efficient growth-energy interaction where low energy cost is needed for economic productivity. Thus, energy efficiency occurs when energy requirement per economic productivity declines due to enhanced energy infrastructures. Here, the composition of economic structure determines energy portfolio (fossil fuels vs. alternative sources), production, and consumption.

The neutrality hypothesis postulates no relationship between economic development and energy utilization. The decoupling effect between energy and growth implies effective measures and institutionalization of environmental policy stringency—from brown growth to green growth. From a policy perspective, the neutrality hypothesis infers that improving energy efficiency and environmental sustainability does not affect sustainable economic development and vice versa.

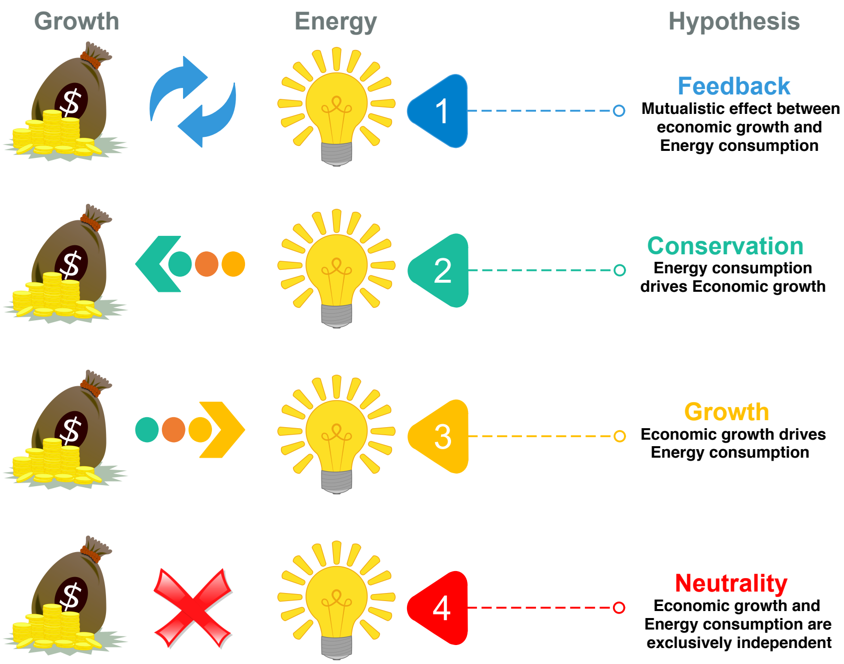

Figure 6. Representation of the Energy-Economic growth Nexus.

1.4 Philosophical Perspective

Climate change is topical yet complex with several dynamics spanning different disciplines. The 21st century development pathway is characterized by a roller coaster of climate change events—because of natural resource exploitation, fossil fuel utilization, energy intensity, population growth, and environmental pollution. Under this global environmental threat, development cooperation has made several efforts to rally economies into sustainable policies that mitigate current and future threats (United Nations, 2015a, 2015b, 2017; UNTC, 2015). The Brundtland Report, "*Our Common Future*", outlines the importance of protecting the environment while meeting current demand without compromising available resources, but leaving the environment as a bequest for future generations (Brundtland *et al.*, 1987). This explains the importance of achieving environmental sustainability through sustainable development, addressing institutional gaps, and developing policy measures that control for urban challenges, resource-dependent, and energy-intensive industrial processes, fossil-driven energy portfolio, loss of biodiversity, ecosystem challenges, food security, population growth, and human resources (Brundtland, 1987). Thus, understanding the various philosophical underpinnings of climate change and its impacts is useful in future policy development with mitigation effects.

1.4.1 Verification & Falsification

While several theories underpinning climate econometrics exist, several concerns are raised via the lenses of the logic of scientific discovery by Karl Popper (Popper, 2005). Accordingly, Karl Popper assumes provisional scientific knowledge that is finite and works best within a specific period. While there are positivist interpretations of climate change theories and econometric techniques, the empirical results from these theories and techniques are often subjected to several factors including data periodicity, location, data characteristics, and estimation methods used for the investigation. In this regard, induction reasoning becomes redundant while deductive reasoning is useful in verifying scientific theories. The deductive reasoning utilized herein comprises climate change theories, hypothesis testing, observation, and confirmation using econometric techniques. Hence, climate change theories can be verified using the falsification principle that involves testing hypotheses using econometric techniques to prove existing theories are false. By using the falsification principle, an attempt is made to disprove the EKC hypothesis, Pollution-halo/haven hypotheses, and energy-growth theories—rather than supporting the already established theory. While the existing literature confirms the outlined theories, we refute several of the climate theories using novel estimation methods including Romano-Wolf multiple hypotheses that control specification bias that rejects false null hypothesis (Clarke *et al.*, 2020).

1.5 Research Design

This thesis utilizes both qualitative and quantitative research design to conceptualize underlying drivers, immediate drivers, and policy implications of climate change. The qualitative part of the research design entails literature review through meta-analysis and bibliometric techniques. In contrast, the quantitative research design encompasses empirical assessment of causal relationships, and causalities using machine learning and econometric techniques. Several factors determine the adoption of estimation techniques including data structure (i.e., cross-sectional data, time series data, and panel data), data attribute (i.e., distribution, and quality), data properties (i.e., stationary, nonstationary, or mixed properties), *a priori* expectation, and proposition(s) of the study. In this research, data structure mainly focuses on both time series and panel data. The time series dataset comprises country-specific attributes with time dimensions, typically in annual frequency. Contrary, the panel data setting covers cross-sectional units (i.e., collection of countries utilized herein) with time dimensional attributes. Hence, the model specifications presented in the various articles are influenced by data characteristics, and pre-conditions underlying econometric techniques. We use both machine learning-inspired algorithms, time series, and panel-based econometric models.

1.5.1 Data

Data utilized herein are sourced from different verified and reliable databases with annual periodicity-based aggregated methods of either sum or weighted average. The selection of data was based on theoretical underpinnings, SDGs, variable importance, and selection techniques including Variable Importance of Projection and FreeViz explorative algorithm. Popular SDGs utilized herein include modern and clean energy (SDG 7), sustained economic development (SDG 8), industry, innovation and technology (SDG 9), sustainable cities (SDG 11), sustainable production and consumption (SDG 12), climate change mitigation (SDG 13), sustainable marine resources (SDG 14), sustainable land resources (SDG 15), institutional quality (SDG 16), and global partnership (SDG 17) (United Nations, 2015b).

Data series on ecological footprint, biocapacity, and carbon footprint were collected from the Global Footprint Network (GFN, 2017). Data on anthropogenic greenhouse gas (GHG) emissions, fossil emissions, and sectoral-based emissions were derived from Emissions Database for Global Atmospheric Research (Crippa *et al.*, 2021). Data on energy, environmental and socio-economic indicators namely energy utilization, electricity access, carbon dioxide emissions, income, population, foreign direct investment, trade, and sectoral economic growth (i.e., agriculture, industry, and services) were collated from the world development indicators of the World Bank (World Bank, 2020). Data on ambient air pollution, environmental policy stringency, human capital, environmental performance index, and green energy innovation (i.e., patent count on green technologies) were extracted from the OECD database (OECD, 2018). Data on energy production and consumption—fossil fuels, and clean and renewable energy technologies including nuclear, wind, and solar were derived from the International Energy Agency (IEA, 2019), and British Petroleum (BP, 2020b).

In the event of unevenly spaced data, several mechanisms were utilized to deal with such structural limitations. First, data trimming was employed to balance the data set. Second, we used existing data imputation algorithms such as missing-not-at-random and missing-completely-at-random (Sarkodie & Owusu, 2020b). Third, we employed econometric techniques that control for unevenly spaced and unbalanced data structures. Our sampled observations (cross-sections) consisted of 217 countries and territories for longitudinal design and country-specific observations for the time series design.

Estimation techniques often assume homoskedasticity of residuals—by assuming residuals have constant variance. However, this assumption is often violated, especially among cross-sectional time series data. To prevent heteroskedasticity (i.e., eliminate varying variance), the application of logarithmic transformation prior to model estimation provides residuals with a constant variance. To do this, the Jarque-Bera test with null hypothesis of normal distribution was utilized. Where the probability of the Jarque-Bera test statistics exceeds the 5% significance level, the variable is deemed as normally distributed, and vice versa.

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Chapter 2. Summary of Articles

This section presents a summary of the various articles, specifically 6 research articles based on panel model techniques and 1 paper centered on time series models collated herein. We present the objectives of the research articles and their contributions to the extant literature.

2.1 Contributions to Literature

2.1.1 Research Article 1

Studies have been conducted to advance the scientific understanding of climate vulnerability and adaptation, however, literature on sectoral assessment including food, health, water, ecosystem, infrastructure, and economic activities is sporadic. The existing literature focuses on immediate drivers and damages of emission effects, failing to account for underlying mechanisms occurring through the nexus between emission levels, economic, social, and governance adaptation readiness. Our study contributed to the existing literature on climate change mitigation and adaptation readiness by broadening the scope of previous attempts in assessing climate change vulnerability across several sectors through the selection of indicators in line with the methodologies and guidelines of the sustainable development goals. We examined the spatial-temporal severity of climate vulnerability across six sectors namely food, water, infrastructure, human habitat, health, and ecosystem services. Second, we assessed the geographical readiness to combat climate change and its impacts. Third, we investigated the long-term impact of climate change readiness and income expansion on sectoral-climate vulnerabilities. We simultaneously tested multiple hypotheses of climate vulnerabilities across sectors in 192 economies with the Romano-Wolf correction technique that controls the over-rejection of null hypotheses. Advantageously, the Romano-Wolf correction technique (Clarke *et al.*, 2020) accounts for the tendency of rejecting the estimated true null hypotheses in contrast to traditional testing techniques. Hence, produces robust and consistent p-values via bootstrap resampling of the original climate data—considering the dependence structure of the instrumental-variable-based single-equation test statistics. Our study found the stocks of periodic GHG emissions spur sectoral climate change vulnerability across countries—with much impact on developing countries. Outgrowth in income level and investment (i.e., economic, social, and governance adaptation readiness) declines investment costs by reducing long-term environmental damage. This implies income level and adaptation readiness play essential roles in mitigating climate change and its impacts. This study provides primary inputs for policymakers in decision-making towards a broader iterative cycle including planning, managing, designing, implementing, and monitoring resilient climate change vulnerability-based development actions. Empirical evidence from this study could be used to prioritize limited natural resources in addressing and managing adaptive actions of extreme climate change vulnerabilities.

2.1.2 Research Article 2

To date, no existing literature examines the progress of energy sustainability from pre-millennium development goals (MDGs), MDGs, and SDGs. This information is useful to assess the historical development of energy sustainability across countries, territories, and income groups, given the numerous ambitious global goals to promote sustainable development. This research developed and compared energy sustainability indicators using 11 targets and 15 indicators of the SDGs across 217 countries and territories from 1960-2019. Besides, we accounted for the coupling effect of several dimensions of sustainable development covering energy production and consumption, economic policy (i.e., adjusted savings, private sector and trade, external funding, and income), and national resource accounting (i.e., water and domestic materials, e.g., fossil fuels). The adoption of the SDG goals and indicators is based on their usefulness as tools for policy formulation (Taylor *et al.*, 2017). The existing literature assumes a global common shock and spillover effects for anthropogenic emissions, however, the notion appears inconsistent with energy sector dynamics. This implies that homogeneous behavior towards energy sustainability is erroneous, producing biased statistical inferences. Countries appear to have heterogeneous consumption patterns attributable to differences in economic structure, environmental priorities, and commitment to achieving sustainability. To compare countries from economic level, we further categorized countries into income groups per the existing income convergence of the World Bank. Using the constructed SDG indicators, we examined the winners and losers of energy sustainability while assessing global and country-specific spatial-temporal advancements toward achieving energy sustainability. Second, we evaluated the role of income convergence on energy diversity, economic development, and GHG emissions in developing and developed economies while controlling for income inequality. Our study finds significantly large heterogeneous characteristics of energy sustainability across income groups.

2.1.3 Research Article 3

Climate change vulnerability (i.e., exposure, climate sensitivity, and adaptive capacity) determines the magnitude of climate consequences across economies (Sarkodie *et al.*, 2022; Sarkodie *et al.*, 2019; Smit *et al.*, 2006). This demonstrates the importance of climate resilience including adaptation and mitigation in reducing the worst consequences of climate change effects (Smit *et al.*, 2006). Yet, empirical studies that examine drivers, adaptation, and co-benefits of climate change vulnerability through the lenses of diversified energy portfolios are limited. Several studies in the extant literature have assessed the energy-growth-emission nexus (see (Ozturk, 2010)). However, existing literature on the energy-growth-climate change nexus (Stern, 2011; Zheng *et al.*, 2020) assumes data exhibit a stochastic process—but, masqueraded as such due to poor conventional panel techniques to identify and solve dynamic systems. This implies existing techniques assume the causes of climate change are distinct from the effects (Sugihara *et al.*, 2012). However, there is a strong dynamic coupling between energy, economic growth, and climate change. Thus, we show that the coupling effect among energy, economic development, and climate change vulnerability exhibits dynamic systems that are driven by deterministic processes which cannot be modeled by existing traditional panel models. Here, we employed empirical dynamic modeling techniques, viz. convergent cross-mapping causality, and kernel regularized least-squares that go beyond equilibrium, linearity, and stability assumptions expounded in conventional panel models, yet control for heterogeneous and nonlinear effects. Our research evaluated the role of energy innovation, social, and governance adaptation readiness in offsetting global climate change vulnerability. Second, we investigated whether existing country-specific climate profiles and diversified energy portfolios show deterministic processes with policy implications. Third, we identified the winners and losers of sustainable development including energy sustainability, and human development. Fourth, we investigated whether alternative (renewables) and nuclear energy have displacement effects on fossil fuels. Our empirical models showed the interconnectedness (mostly mutual coupling) between energy portfolio, socio-economic drivers, adaptation readiness, and climate change vulnerability. From a policy perspective, our study suggests the complexity of decoupling the above-mentioned dependencies to achieve sustainable development.

2.1.4 Research Article 4

While the extant literature has reported spatial-temporal trends of ecological portfolio, and trade-embodied drivers of ecological resources (Hoang *et al.*, 2021), no study has assessed the symbiotic relationships existing between land-use intensity, demo-economics, and changes in emission levels. Understanding these dynamic relationships are crucial to unearthing historical trends useful for developing conceptual tools for climate change adaptation and mitigation of climate vulnerability. Second, country-specific, regional, and other global crises including the recent Covid-19 pandemic, and economic recessions affected business-as-usual which shifted production and consumption, leading to explosive behaviors across countries. These episodes of explosive behaviors that capture extremes are indicative of climate change and land-use intensity. Besides, this explains unusual events in emission patterns, resource, and biodiversity exploitation (deforestation, land degradation, ecological footprint, and domestic material consumption) that often contradict existing fundamental patterns. Yet, global multi-region input-output (MRIO) models may fail to capture explosive behaviors that are significant to tilt the balance between production and consumption. Here, we examined the drivers of global anthropogenic emissions and land-use intensity. We further assessed the feedback mechanisms, synergies, and trade-offs that underpin emission reduction from agricultural land, forestry, and land use. Using novel econometric techniques, viz. dynamic panel models that capture cross-section dependence, heterogeneity, nonlinearity, and chaotic functions—we examined the global symbiotic relationships and date-stamping explosive behaviors existing between land-use intensity, demo-economics, and changes in emissions——by capturing the complexities of climate change across countries and income groups. Our study identified episodes of explosive behavior highlighting country-specific events of influx or excesses in emissions, land-use intensity, urban sprawl, and income. We opine that these unusual periods of extremely low or high trends could have been triggered by country-specific economic structure and disparities in income distribution.

2.1.5 Research Article 5

Owing to limitations and sporadicity of existing literature on green energy, this study contributed to the global debate by exploring the effect of fossil-based CO_2 emissions in improving green energy innovation across 21 industrialized high-income countries. We used a novel convergence estimation method to classify industrialized high-income IEA member countries into similar emission, and energy transition pathways. We applied econometric and machine learning techniques to investigate the complexities of anthropogenic emissions and develop conceptual tools valuable for policy design. The employed novel techniques including panel-bootstrap bias-corrected fixed-effects, panel-kernel regularized least-squares, panel log-t regression-based convergence, panel threshold fixed-effects, and dynamic ARDL stochastic simulations. The selection of the estimation tools was useful in controlling for historical and inertial effects, transboundary correlation, heterogeneity, fixed-effects, omitted-variable, and misspecification bias. We investigated the heterogeneous effects of anthropogenic emissions, green energy innovation, energy intensity, energy research and development, and service-based industrial structure. We further estimated the forty-year trend of emissions and policy measures across countries and identified winners and losers of environmental sustainability through hotspot identification and ranking. We developed both aggregate emissions and economic sectoral fossil-based (buildings, power, industry, transport, and other sectors) models to explore the effects of immediate, underlying drivers, and policy measures. We predicted the counterfactual change in GHG emissions from 2014 to 2064 using the business-as-usual scenario of 1% growth in energy intensity across IEA member countries. Our study demonstrated that investment and integration of green energy innovation, energy research and development, and expansion of service-based industrial structures have mitigating effects on GHG emissions. The empirical analysis suggests countries with historical green energy orientation may invest over 58% more in achieving green growth through green innovation. Thus, higher GHG emission countries may improve green energy innovation in efforts toward achieving environmental sustainability while sustaining economic prosperity.

2.1.6 Research Article 6

While tons of studies have utilized CO_2 emissions as 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 *et al.*, 2001; Wackernagel *et al.*, 1999). Given the limitation of anthropogenic CO_2 emissions (atmospheric in nature), the ecological footprint covers the biosphere. Using ecological footprint rather than CO_2 emissions provides true and inclusive perspective for 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, capturing all facets of environmental dynamics. This missing link in CO_2 emissions might have misled the assessment of environmental degradation across countries in the extant literature. Contrary to previous attempts, we investigated 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 of controlling for convergence, cross-section dependence, omitted variable bias, misspecification error, country-specific heterogeneity, and non-additive effects. Our study estimated the overarching effect of economic development, population density, and international trade on ecological performance from a global perspective. The empirical results validated the scale effects hypothesis rather than the popular EKC hypothesis of nations. The scale effect hypothesis confirmed economic development is characterized by natural resource exploitation leading to environmental degradation, a situation that has global policy implications. Our study found that 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 long-run environmental convergence. This infers developing and harvesting renewable energy sources across nations declines the multiple emission-driven processes of fossil fuel extraction and consumption from cradle to grave. While fossil fuels are transportable and tradable across nations, renewable energy sources are localized, hence, eliminating the transboundary flow of emissions. Thus, 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 has long-term emission-reduction effects.

2.1.7 Research Article 7

The extant literature appears to focus on aggregate economic productivity and energy demand in assessing emission risks, however, such pathway provides very little knowledge for country-specific policies on environmental sustainability. In using disaggregate energy (namely fossil fuels, clean, and renewables) and economic growth (namely agriculture, industry, and services), several trends, policies, and measures became evident. For example, the magnitude of sectoral-based impact was quantified while identifying optimal resource investment that maximizes yield while reducing emissions. Second, the rebound effect is reported to affect both direct and indirect emission consequences. However, several studies failed to capture the importance of rebound effects evident in socio-economic and environmental factors. The rebound effects are reported to mediate the effectiveness of long-term energy and environmental-related policies and measures, specifically in emerging economies (Chakravarty *et al.*, 2013). Our study accounted for possible rebound effects of sectoral economic growth, energy utilization, and foreign direct investment. The impact of transboundary effects through global partnership was examined through FDI inflows. We assessed whether pollution trends that hamper environmental performance are domestically generated or induced by external funding. We employed innovative accounting techniques that graphically project minimum resource allocation while maximizing yield in one breath and maximum resource investment with limited gains. We further used stochastic simulation models to project the counterfactual change in environmental performance using the business-as-usual scenario with changes in FDI and environmental policy stringency. We observed the failure to account for economic sectoral inefficiencies by institutionalizing environmental policy stringency will disrupt environmental performance. The assessment of country-specific economic sectoral accounting highlights how linear economies can be shifted towards a circular economy by maximizing yield while reducing wastage, environmental pollution, and resource consumption. Our study demonstrated that the allocation of scarce resources should be based on long-term prospects rather than short-term gains. Contrary to the traditional EKC hypothesis, we showed that sectoral-based economic productivity is useful in understanding pollution-reduction policies.

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Chapter 3. Paper 1: Global adaptation readiness and income mitigate sectoral climate change vulnerabilities

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Author contribution

S.A.S designed the study, collected the data, performed the data analysis, coordinated and supervised the study. M.A.Y and P.A.O drafted the manuscript. All authors reviewed the manuscript and approved it for submission. Thus, S.A.S contributed 90% whereas M.A.Y and P.A.O contributed 5% each.

Global adaptation readiness and income mitigate sectoral climate change vulnerabilities [2]

Abstract

Climate change has become a global burden, requiring strong institutional quality and willingness to mitigate future impacts. Though emissions are transboundary and have the tendency of spreading from high emitting countries to low emitting countries, regional exposure, sensitivity, and adaptation readiness determine the extent of climate effects. The existing literature focuses on immediate drivers and damages of emission effects, failing to account for underlying mechanisms occurring via the nexus between emission levels, economic, social, and governance adaptation readiness. Here, this study broadens the scope of previous attempts and simultaneously examines climate change vulnerability across sectors including ecosystem services, food, health, human habitat, infrastructure, and water. We use the Romano-Wolf technique to test multiple hypotheses and present the spatial-temporal severity of climate vulnerability and readiness to combat climate change and its impacts. Besides, we assess the long-term impact of climate change readiness and income expansion on sectoral-climate vulnerabilities. We find that high-income economies with high social, governance, and economic readiness have low climate vulnerability whereas developing economies with low income have high climate change exposure and sensitivity. Our empirical evidence could be used to prioritize limited resources in addressing and managing adaptive actions of extreme climate change vulnerabilities.

3.1 Introduction

The global climatic condition is changing—as data collected over four decades show the earth is warming at an unprecedented level (IPCC, 2021). There is high probability that climate change will persist for decades and will continue to hamper humanity (IPCC, 2018). The majority of scientists associate the earth's warming trend with the greenhouse effect caused by greenhouse gas (GHG) emissions (Kerr, 1990; Wigley *et al.*, 1990). The main causes can be attributed to—the burning of fossil fuel such as crude oil, natural gas, and coal to meet the

[2] Published article: **Sarkodie, S.A.**, Ahmed, M.Y. & Owusu, P.A. Global adaptation readiness and income mitigate sectoral climate change vulnerabilities. *Humanit Soc Sci Commun* 9, 113 (2022). https://doi.org/10.1057/s41599-022-01130-7

increasing global energy demand—and intensive agricultural practices to meet the growing global food demand. Today, the world is experiencing climate change in the form of extreme weather and variations. For example, the average global temperature and sea level are estimated to rise between 1.8-4.0ºC and 0.09-0.88m by the end of the 21st century, respectively (SEEFCCA, 2012). Extreme climate events are threat to the considerable progress made on eradicating global hunger and malnutrition in the last decades. The global food market is already experiencing the effect of climate change particularly in rural areas where harvest crops have declined (Gitz *et al.*, 2016). The increase in food supply to meet demand is most often accompanied by deforestation (FAO, 2011). Persistent meteorological drought due to climate change affects water storage, reducing global water supply (Stagge *et al.*, 2015). Global studies indicate one in three people are already facing the threat of water security due to challenges with water shortage (IWMI, 2007; Vörösmarty *et al.*, 2010). Under current climate conditions, the availability of reliable surface water is estimated to decline due to rising variability in river flows triggered by increased variability in precipitation, and reduction in ice storage and snow (Kundzewicz *et al.*, 2009). Thus, climate change causes the global average sea level to rise by melting ice sheets and glaciers. Warming of the water from melting ice sheets and glaciers causes ocean volume to expand while declining the number of rivers, reservoirs, lakes, aquifers, and soil moisture (Lindsey, 2021). The degree and frequency of droughts are estimated to increase due to future climate change vulnerability, primarily due to regional decline in precipitation and rising levels in evapotranspiration driven by climate change variability (IPCC, 2013, 2021). Climate change vulnerability and environmental degradation induced human activities have affected the current habitat loss and fragmentation resulting in global biodiversity crisis (Hoffmann *et al.*, 2010).

The Kyoto protocol signed by developed countries in 1997 and Paris Agreement adopted in 2015 by 196 countries and territories with the sole commitment of reducing emissions is stalling, even though many countries are undertaking vigorous emission reduction policies. The GHG emissions emitted today will cause decades of climate change effects. Mitigating GHGs has been unsuccessful due to ineffective governance structures and institutions in creating effective climate policies, however, adaptation to climate change effects is possible (Denton *et al.*, 2014; SEEFCCA, 2012). The barriers to climate change adaptation include lack of human and institutional capacity, lack of awareness and communication, and financial constrain (Bergsma *et al.*, 2012; Stuart-Hill *et al.*, 2010). For example, the $100 billion broken promise of climate financing in developing could hamper trust and effort toward reducing emissions in developing economies (Timperley, 2021). In the last two decades, the world has witnessed extensive studies on the potential impacts of climate change on regional, national, and local development. The existing literature advances the scientific understanding of climate vulnerabilities across sectors including inter alia, economic, ecosystem, food, health, human habitat, infrastructure, and water. Climate change vulnerability can be classified as three interacting functions of exposure, sensitivity, and adaptive capacity (Smit *et al.*, 2006). Thus, climate vulnerability encompasses a range of methodologies drawn from multi-disciplinary fields offering valuable insights into reducing climate risks (USAID, 2014). Vulnerability to climate change assessment aims to provide insights on developmental policies that reduce the risk associated with the effects of climate change (Schneider *et al.*, 2001). The two primary response options to climate change effects involve mitigation and adaptation. While mitigation aims to reduce GHG emissions—thereby limiting the global climate change, adaptation refers to approaches that moderate adverse effects associated with climate change through a wide range of policies and responses targeted at vulnerable systems (Füssel *et al.*, 2006). Thus, climate change adaptation requires knowledge, awareness about exposure, viz. early warning signs, and adaptation options to deal with climate variabilities (Nunfam *et al.*, 2018). The extent of climate change vulnerability and its related risks are location-specific and depends majorly on the effectiveness of governance, quality public healthcare infrastructure, level of material resources, and timely access to critical weather threat information, viz. early warning signs (Mateeva, 2020).

Studies have been conducted to advance the scientific understanding of climate vulnerabilities and adaptation, however, literature on sectoral assessment including food, health, water, ecosystem, infrastructure, and economic activities is sporadic. The existing literature focuses on immediate drivers and damages of emission effects, failing to account for underlying mechanisms occurring via the nexus between emission levels, economic, social, and governance adaptation readiness. The proposed study contributes to the global debate on climate change mitigation and adaptation readiness through the selection of indicators in line with the methodologies and guidelines of the sustainable development goals. Here, we examine:

1. the spatial-temporal severity of climate vulnerability across six sectors namely food, water, infrastructure, human habitat, health, and ecosystem services.
2. the geographical readiness to combat climate change and its impacts.
3. the long-term impact of climate change readiness and income expansion on sectoral-climate vulnerabilities.

Thus, this study broadens the scope of previous attempts by assessing climate change vulnerability across several sectors. We simultaneously test multiple hypotheses of climate vulnerabilities across sectors in 192 economies with Romano-Wolf correction technique that controls the over-rejection of null hypotheses. Advantageously, Romano-Wolf correction technique (Clarke *et al.*, 2020) account for the tendency of rejecting the estimated true null hypotheses in contrast to traditional testing techniques. Hence, produces robust and consistent p-values via bootstrap resampling of the original climate data—considering the dependence structure of the instrumental-variable based single-equation test statistics. Because awareness creation is critical to enhancing the knowledge of early warning signs of climate change and its impact, this study proposes the engagement of policymakers and researchers to improve capacity building. Our results could be adopted by environmental agencies in defining the baseline of climate change exposure, sensitivity, and adaptive capacity, before implementing and monitoring adaptive actions.

The subsequent sections of this paper present the conceptual framework, data sources and characteristics, model estimation and validation, empirical results and discussion, summary of findings, and policy implications.

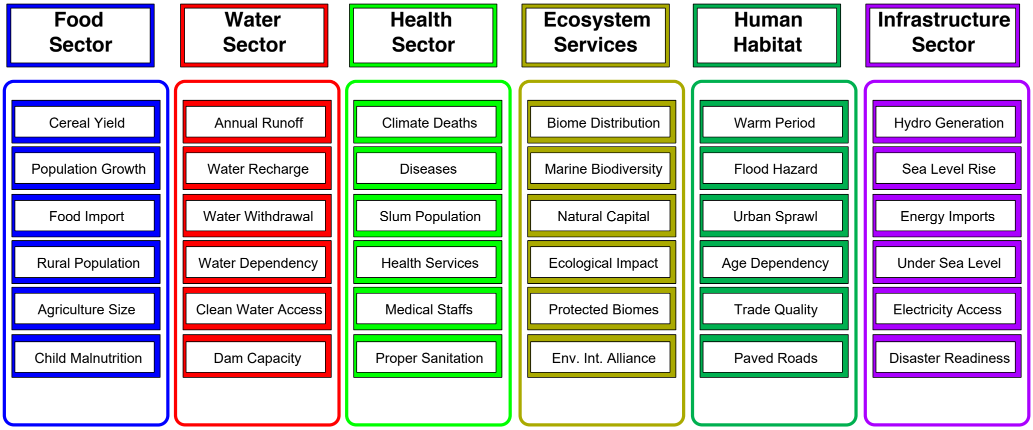

Figure 1. Conceptual framework of sectoral vulnerabilities to climate change and its impacts. Source: Author's construction based on ND-GAIN indicators. Legend: The first two rows of each column designate climate exposure, the third and fourth rows represents climate change sensitivity whereas the fifth and sixth rows denote adaptive capacity.

3.2 Methods

3.2.1 Conceptual Framework

The conceptual framework presented in Figure 1 provides an overview of climate vulnerabilities across sectors namely food, water, health, ecosystem services, human habitat, and infrastructure. Climate change vulnerability entails exposure, sensitivity, and adaptive capacity (Smit *et al.*, 2006), hence, the adoption of ND-GAIN (2018) indicators is crucial to assessing sectoral climate change vulnerabilities. For example, the sectoral exposure to climate change includes variations in cereal yield and population growth, variabilities in annual runoff and groundwater recharge, climate-related vector-borne morbidities and mortalities, modifications in biome and marine biodiversity, changes in temperature and flood hazards, and alterations in hydropower generation and sea-level rise (GFN, 2017; ND-GAIN, 2018; United Nations, 2015b; World Bank, 2020). In contrast, sectoral climate change adaptive capacity comprises agricultural production capacity, access to clean and reliable water supplies, access to clean and improved sanitation conditions, biomes protected, trade quality and transportation structure, access to electricity, and disaster readiness (GFN, 2017; ND-GAIN, 2018; United Nations, 2015b; World Bank, 2020).

3.2.1.1 Food Sector

Positive strides have been made to address the global impact of climate change in the past decades. For example, global food production (1986-2009) has increased by 121% in South America, 81% in Africa, 58% in Asia, and 57% in North America (D'Odorico *et al.*, 2014). However, based on the estimated 2050 population by United Nations and 2.5% global income growth, global crop production is projected to increase by 100-110% before 2050 (Tilman *et al.*, 2011). Agriculture is an important sector of the economy that provides livelihood to ~36% of the global workforce—particularly, 50% workforce in Asia and Pacific, and 66% of the working population in Sub-Saharan Africa (FAO, 2015). Extreme weather events due to climate change are reported to affect the agricultural sector in developing countries. The post-disaster events of 48 developing countries covering 10 years indicate 25% losses and damages caused by climate hazards such as floods, droughts, and storms (FAO, 2015). The climate change effect from 1981 to 2010 is found to decrease the global mean yield of corn, soybeans, and wheat relative to preindustrial climate (Iizumi *et al.*, 2018). The findings from existing literature suggest a growing strong relationship between crop yield and climate variables—inferring future increase in climate change may have severe impact on crop production (Mavromatis, 2015).

A recent study using the IPCC's highest climate change scenario shows global crop yields such as wheat, rice, and coarse grains will decline by 17% before 2050—given the scenario remains unchanged (FAO, 2015). The earth's landmass constitutes 40% dryland which is home to about 2.5 billion people (FAO, 2011). However, the dryland region particularly in developing countries, typically in Africa faces challenges with food security due to challenges to effectively manage and mitigate decreasing crop yield (Nellemann *et al.*, 2009). Climate variables including temperature above or below a certain threshold by a few days may damage cereal or fruit tree yield (Wheeler *et al.*, 2000). During the 2003 European heatwave, crops yield dropped drastically including 36% of maize harvest in Italy, and 25-30% of fruit and forage harvest in France (SEEFCCA, 2012). The impact of climate change affects the nutritional quality of food products including rice, maize, millet, and cassava—due to elevated CO_2 reducing the concentrated level of vitamins, minerals, or protein (FAO, 2015). The adverse effect of climate change may hamper agriculture production, particularly in developing countries (specifically in Asia and Africa) where the livelihood of rural folks depends majorly on farming, hence, may increase the vulnerability of food insecurity (Nellemann *et al.*, 2009).

3.2.1.2 Water Sector

Global water resources are already under threat even without climate change. The rise in water scarcity is more pronounced in expanding cities around the globe. The estimated population growth in the next few decades is projected to double in size by an estimated 5 billion from 1995 to 2025 in urban areas (Vörösmarty *et al.*, 2000). It is estimated that climate change variability along with rampant extreme events including floods, drought, storms, and cyclones—will escalate the existing situation in countries already threatened with water insecurity whereas similar problems threaten areas that have not been severely affected (UN, 2020).

Irrigation remains the largest human water usage, accounting for 70% of annual water withdrawal—implying limited water supply is the bottleneck of sustainable agricultural production (Siebert *et al.*, 2010). However, some regions in the Middle East are reported to use water resources as a tool for political leverage (Cartier, 2021). Studies indicate that decrease in participation affects the availability of water resources (Gosling *et al.*, 2016; Hayashi *et al.*, 2010; Lionello *et al.*, 2018). Climate change is estimated to decrease global groundwater recharge, thus, affecting renewable groundwater resources (Kundzewicz *et al.*, 2009). For example, future water availability in the Maghreb and the Middle East while accounting for demand and supply will lead to a 12% decrease in water supply and a 50% increase in water demand (Droogers *et al.*, 2012). A rise in global temperature could increase permafrost degradation, and runoff from glaciers, affecting soil erosion and sediment loads in colder places (Lu *et al.*, 2010). The rise in temperature in the region is linked to a potential increase in evapotranspiration—which is mostly visible in late spring and early fall seasons—that are responsible for the decline in annual surface runoff (Schilling *et al.*, 2020). Infrastructure improvement and operation practices could help change the volume and timing of water supply systems (Connell-Buck *et al.*, 2011). Addressing the uncertainty associated with climate change variability would require, for example, water resource managers to move from the traditional approach, viz. "predict and provide" toward the adaptation of water resources management approach (Gersonius *et al.*, 2013; Short *et al.*, 2012).

3.2.1.3 Health Sector

The effects of climate change exposure on global health vary between countries. For instance, the loss of healthy life years in low-income countries in Asia and Africa is estimated to be 500 times more severe than that in Europe and the United States (McMichael *et al.*, 2008). The climate warming of 1.5ºC is considered hazardous to human lives, which is expected to exacerbate the physical and mental health of the vulnerable and poor population. Extreme poverty is reported to affect health outcomes (viz. morbidity and mortality) and health equity (Murray, 2006). Hence, individuals with lower economic status have higher risks of poor health (WHO, 2018b). Thus, climate change is considered an indicator of the poverty multiplier, which is estimated to force 100 million vulnerable populations into severe poverty by 2030 (WHO, 2018a). Evidence from literature is becoming increasingly clear that climate change variabilities have a severe impact on human health (WorldBank, 2018). An increase in warmer temperatures is associated with the rise in morbidity across countries (Campbell *et al.*, 2018). Prolonged exposure to heat may exacerbate pre-existing cardiovascular and chronic respiratory diseases among the aged and people with underlining health conditions (McGeehin *et al.*, 2001). Socioeconomic factors such as income, housing, education, and employment are highly sensitive to climate change vulnerability and exposure, which may result in uneven access and distribution of health facilities. For instance, the Chicago heatwave saw a vulnerable community experience high rate of heat-related deaths than community residents that felt secure and safe (Pasquini *et al.*, 2020). Large-scale environmental changes are reported to unlikely cause entirely new disease outbreaks, but rather alter the intensity, range, and seasonality of existing health diseases (McMichael *et al.*, 2008). Evidence shows the necessity of optimizing the health infrastructure, improving the know-how, and technical competence of health professionals to curb climate-induced health risks through treatment, and monitoring (Mateeva, 2020; McMichael *et al.*, 2008).

3.2.1.4 Ecosystem Services

Climate change affects individual species and how different organisms interact with others, hence, changing the structure and functioning of the ecosystem, benefits, and services provided to society (Weiskopf *et al.*, 2020). The periodic evaluation of the current and potential future impact of climate change on the ecosystem can allow society to better anticipate, plan, manage and adapt to the necessary changes (West *et al.*, 2009). The duration, degree, and frequency of extreme climate events including heatwaves, drought, flood, and forest fires are altered by long-term climate change (Hayhoe *et al.*, 2018). Recent studies indicate a 66% probability of increasing the impact of habitat loss and fragmentation in 18.5% of global ecoregions—with an estimated 54.1% of all known biodiversity including birds, mammals, reptiles, and terrestrial amphibians (Segan *et al.*, 2016).

Ecosystems and biodiversity provide vital regulation services including easing the impact of extreme events, soil and air quality maintenance, sequestering carbon, and controlling the spread of diseases. With the accelerated increase in climate change, carbon storage remains threatened. Given the increase in forest area in the last decades, it is still unclear whether the afforestation rate will continue to outweigh the rate of deforestation (Weiskopf *et al.*, 2020). The climate-driven threat to forestry production varies depending on forest type and may likely decrease in forests where soil water supply is limited in planting seasons (Halofsky *et al.*, 2020; Latta *et al.*, 2010). Existing studies remain unclear whether the use of fertilization is still effective as forest ages (Latta *et al.*, 2010). Additionally, human-induced climatic events enhance the introduction and spreading of non-native species—that capitalizes on the changing environment to colonize native species. The non-native species may dominate by reproduction, and in some cases lead to the extinction of native species (Schmitt *et al.*, 2019; Yeruham *et al.*, 2020). Climate change is predicted to exacerbate the impact of species invasion, with a global economic cost estimated at $1.4 trillion (Burgiel *et al.*, 2014).

Climate change adaptation and proactive techniques based on scientific methods to meet the emerging, anticipated, and extreme weather events are required to sustain the ecosystem and enhance biodiversity (Holsman *et al.*, 2019). For instance, the scientific-based data system employed by the US to capture and detect changes in fish productivity, catch, and abundance. This approach provides adequate information for decision-making and management of fisheries including seasonality, annual quota, stock rebuilding policies, and spatial closures (Weiskopf *et al.*, 2020). In creating adaptive climate change strategies, institutional managers could determine relative risks exposure, sensitivity, and adaptability through climate change vulnerability assessment of species, and exposure to non-climate stressors (Glick *et al.*, 2011; Spencer *et al.*, 2019).

3.2.1.5 *Human Habitat*

Drought and heat waves are significant climate events that increase risks associated with wildfire. The destructive wildfire that occurred in California in 2017-2018 is reportedly caused by extreme summertime forest fire (Williams *et al.*, 2019). Similarly, Macedonia in the summer of 2007 experienced wildfire which destroyed an estimated 40,000 acres of forest whereas severe drought in 2003 caused an economic loss of $330 million in Croatia (SEEFCCA, 2012). Climate change exposure such as flooding has become a global phenomenon with varying degrees. For instance, long heavy rain that occurred in early 2000 caused the Nzoia river to flood western Kenya, affecting over 800,000 people, killing 237 people, and destroying properties (Cartier, 2021). The climate change effect extended beyond Africa, with heavy floods in the Middle East that ruined farmlands, particularly in Iran, affecting crop yield (Cartier, 2021).

Global Urbanization is one of the 21st-century megatrends which cannot be stopped or adjusted. Urbanization is considered one of the most sensitive sectors to climate change vulnerability. The 55% of the world's population constituting 4.2 billion (i.e., est. 2018) of the total 7.6 billion lives in urban cities. The estimate of urban settlement in the future reveals 60%, and 66.4% of the total world's population of 8.6 billion by 2030 and 9.8 billion by 2050, respectively (UN, 2020). The majority of urban dweller population growth is estimated to occur in developing countries within East Asia, South Asia, and Sub-Saharan Africa (UNDESA, 2019). Urban sprawl is expected to increase, affecting the already limited resources such as energy, water, sanitation, and waste management—that can further spur climate change effects (Sarkodie, Owusu*, et al.*, 2020). Unstable and rapid urbanization with slums proliferation and overcrowding often exposes people to related health risks due to lack of clean and safe water, poor sanitary conditions, among others. Thus, population growth and economic development are dominant contributing factors influencing the increase in the number of people affected by coastal and river floods (PBLNEAA, 2014).

3.2.1.6 *Infrastructure Sector*

It is reported that 8 of the world's largest top 10 cities are located near coastal areas. In the US alone, about 40% of the population lives in density-populated coastal provinces prone to rising sea levels—leading to shoreline erosion, flooding, and storms (Lindsey, 2021). The rising sea level has a direct impact on humanity by increasing sea floods and coastal erosions unless costly climate change adaptation including sea defense and relocation of communities is undertaken. The sea level has risen at a rate averaging 0.11-0.14 inches yearly since 2013—which is relatively twice faster than the projected long-term trend (EPA, 2016a). For instance, significant coastal areas sensitive to climate change vulnerability in European countries (including Denmark, England, Germany, The Netherlands, and Italy) are already below normal high tide levels and prone to flooding from storm surges (McCarthy *et al.*, 2001). A projected 9% of all European coastal zones are below 5m elevation, particularly in The Netherlands and Belgium where 85% of the coastal areas are below the 5m elevation level. These areas below the 5m elevation level are potentially vulnerable to sea-level rise and inundations (EEA, 2005). The effect of rising sea level on groundwater may result in a short-term and long-term decrease in terrestrial water resources, ecosystem, and infrastructure (Kirwan *et al.*, 2019; Knott *et al.*, 2018; Nicholls *et al.*, 2011).

Climate change effect is certain, but adverse impacts or exposure on the water sector are uncertain. The energy sector is estimated to take 10% of the world's freshwater (IEA, 2016b). The dependence of industry and energy sectors on global freshwater is predicted to grow to 24% by the end of 2050, specifically in Europe and Asia (UN, 2020). The global freshwater withdrawal for energy sectors is projected to grow more than 2% by 2040, with a 60% increment in consumption (IEA, 2016b). The global plan to accelerate the agenda towards switching from fossil fuel consumption to renewable energy is critical to climate change mitigation. The global installed renewable power generation capacity is dominated by 70% hydropower resources (Trace, 2019). While hydropower is considered a sustainable, clean, and low-carbon source of renewable energy, climate change variability threatens the future of hydropower. Extreme climate change events including high recorded temperature and drought could have exacerbated the already threatened arid and semi-arid areas in Africa (IPCC, 2007). For instance, the impact of climate change is estimated to decline hydropower generating capacity from the Zambezi river basin over the next 60 years (Yamba *et al.*, 2011). Similarly, the increase in temperature is reducing the Nile river basin, which is projected to negatively affect the Aswan dam (Beyene *et al.*, 2010). Besides the impact of climate change variability, the expansion of hydropower reservoirs has a potential threat to the indigenous settlement, loss of habitat and fragmentation, and transboundary conflicts (Ferreira *et al.*, 2014; Zarfl *et al.*, 2015).

Existing studies showed the impact of extreme climate change on energy demand (Bradshaw, 2010; Sailor, 2001). For instance, extreme temperature affects the daily peak of energy demand in Eastern European countries, due to the intensive use of air condition during the summer season, and this trend is expected to continue (EEA, 2004). For climate change vulnerability adaptive strategy of an engineering-based solution, existing literature suggests an expansion of hydropower dams, management of wetland ecosystems and floodplains with improved coordinated policies and legislations (Watts *et al.*, 2011). Other effective adaptation strategies in reducing the vulnerability of hydropower include increasing power plant efficiency, cohesive management of dams, and renewable energy diversification such as wind, solar, and bioenergy (Guerra *et al.*, 2019; Owusu *et al.*, 2016). Climate change uncertainty could be considered in planning hydropower projects including location, dam type, integrated energy development, and water management policies (Cole *et al.*, 2014).

3.2.2 Data

This study employs time-frequency data spanning 1995-2017 from the Emission Database for global atmospheric research (EDGAR, 2020), development indicators database of the World Bank (World Bank, 2020), and Notre Dame global adaptation index (ND-GAIN, 2018). The selection of data series for subsequent empirical assessment incorporates the concept and indicators of the sustainable development goals into our hypotheses. Our data include: greenhouse gas emissions per capita (ton CO_2eq/cap)—used as a proxy for climate change while accounting for population dynamics, GDP per capita (US$)—used to examine the role of income level in climate change, climate change readiness (measured in scores)—consist of economic, social and governance investment for climate change mitigation and adaptation mechanisms, and climate change vulnerability (measured in scores)—comprising of ecosystem services, food sector, health sector, human habitat, infrastructure sector, and water sector (ND-GAIN, 2018). Economic readiness involves easiness of doing business—a form of climate financing, whereas governance readiness incorporates political stability, corruption control, regulatory quality, and rule of law. In contrast, social readiness includes social inequality, innovation, ICT, and education (World Bank, 2020). Based on the ND-GAIN pre-defined indicators (Figure 1), the six categories of climate change vulnerability consist score generated aggregated inputs of two adaptive capacity indicators for each category (6×2), two sensitivity indicators for each category (6×2), and two exposure indicators for each category (6×2). Thus, each of the six categories of climate change vulnerability consists of 6 input indicators (6×6).

3.2.3 Model Estimation

The empirical procedure presented herein follows a linear panel regression model with 6 target variables regressed on several individual regressors separately in multiple models. For brevity, the model specification can be expressed as (Clarke *et al.*, 2020):

$$y_{i,t}^{a} = \beta_0^{a} + \beta_1^{a} x_{i,t} + \varepsilon_{i,t}^{a} \tag{1}$$

where, $y_{i,t}^{a}$ denotes the multiple target variables $a = 1, \dots, 6$ namely ecosystem services, food sector, human habitat, health sector, infrastructure sector, and water sector across countries $i = 1, \dots, 192$, in annual period $t = 1995, \dots, 2017$; β_0^{a} represents the constant across multiple target variables, $x_{i,t}$ represents the regressors including economic readiness, governance readiness, social readiness, income level, and GHG emissions as control variable; β_1^{a} is the estimated parameter of regressors across the 6 target variables, and $\varepsilon_{i,t}^{a}$ denotes 6 stochastic white noise from a normal distribution with multivariate specification. To examine the long-term relationship between climate change vulnerabilities and readiness to combat climate change and its impacts, we test several multiple hypotheses. The Romano-Wolf correction technique is employed to investigate the multiple hypotheses using the baseline model specification (equation 1) — following the instrumental-variable based single-equation via two-stage least squares estimator, expressed as:

$$Ecosystem\ services_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$Food\ sector_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$Human\ habitat_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \tag{4}$$

$$Health\ sector_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \tag{5}$$

$$Infrastructure\ sector_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \tag{6}$$

$$Water\ sector_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \tag{7}$$

where $Ecosystem\ services_{i,t}$ (Sector 1), $Food\ sector_{i,t}$ (Sector 2), $Human\ habitat_{i,t}$ (Sector 3), $Health\ sector_{i,t}$ (Sector 4), $Infrastructure\ sector_{i,t}$ (Sector 5), and $Water\ sector_{i,t}$ (Sector 6) denote the outcome variables, Z represents the regressors, viz. economic readiness, governance readiness, and social readiness, respectively. Equations 2-7 are run simultaneously with income level as endogenous variable used as instruments alongside country-specific resampling clusters, $GHG_{i,t}$ denotes greenhouse gas emissions—implemented as control variable.

$$Ecosystem\ services_{i,t} = \beta_0 + \beta_1 Income\ level_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \quad (8)$$

$$Food\ sector_{i,t} = \beta_0 + \beta_1 Income\ level_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \quad (9)$$

$$Human\ habitat_{i,t} = \beta_0 + \beta_1 Income\ level_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \quad (10)$$

$$Health\ sector_{i,t} = \beta_0 + \beta_1 Income\ level_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \quad (11)$$

$$Infrastructure\ sector_{i,t} = \beta_0 + \beta_1 Income\ level_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \quad (12)$$

$$Water\ sector_{i,t} = \beta_0 + \beta_1 Income\ level_{i,t} + \lambda GHG_{i,t} + \varepsilon_{i,t} \quad (13)$$

where $income\ level$ denotes income level across country i and time t, whereas $\varepsilon_{i,t}$ is the white noise. Similarly, equations 8-13 are run simultaneously with economic readiness, governance readiness, and social readiness as treatment variables used as instruments beside country-specific resampling clusters. The Romano-Wolf multiple-hypothesis testing procedure incorporates model specifications in equations 2-13 as baseline models whereas λ is the estimated parameter for control variable $GHG_{i,t}$, with country-specific resampling clusters based on bootstrapping technique for null distributions.

3.2.4 Model Validation

The 24 estimated baseline models are validated graphically using the Romano-Wolf multiple-hypothesis correction expressed as (Clarke *et al.*, 2020):

$$max_{t,j}^{*,k} := max\{t_{(j)}^{*,k}, \dots, t_{(A)}^{*,k}\} \text{ for } j = 1, \dots, A \text{ and } k = 1, \dots, K \quad (14)$$

where, $max_{t,j}^{*,k}$ is the max value of vector $\{t_{(j)}^{*,k}, \dots, t_{(A)}^{*,k}\}$. Here, we test 6 hypotheses H_a (i.e., $a = 1, \dots, A$) each for the specified equations 2-7, and 8-13. Each of the 6 hypotheses has corresponding coefficient of interest ∂_a, an estimator of $\hat{\partial}_a$ with standard error $\hat{\sigma}_a$. The alternative hypothesis using the instrumental-variable-based single-equation via two-stage least squares estimator is based on two-sided tests expressed as: H'_a: $\partial_a \neq 0$ assuming $\partial_a^0 = 0$, for $a = 1, \dots, A$. Studentization of the test statistic based on data (D) resampling using bootstrapping technique can be expressed as (Clarke *et al.*, 2020):

$$c_a^{*,k} := \frac{\hat{\partial}_a^{*,k} - \hat{\partial}_a}{\hat{\sigma}_a^{*,k}} \tag{15}$$

where, $c_a^{*,k}$ is the test statistics centered around zero assuming the resampled estimate $\hat{\partial}_a^{*,k}$ minus the baseline (original) estimate $\hat{\partial}_a$, k denotes each resample of the original data for each H_a, and $\hat{\sigma}_a^{*,k}$ represents the standard errors of resampled estimates. Thus, each null hypothesis is rejected if the multiple-testing adjusting probability value is less than 5% significance level.

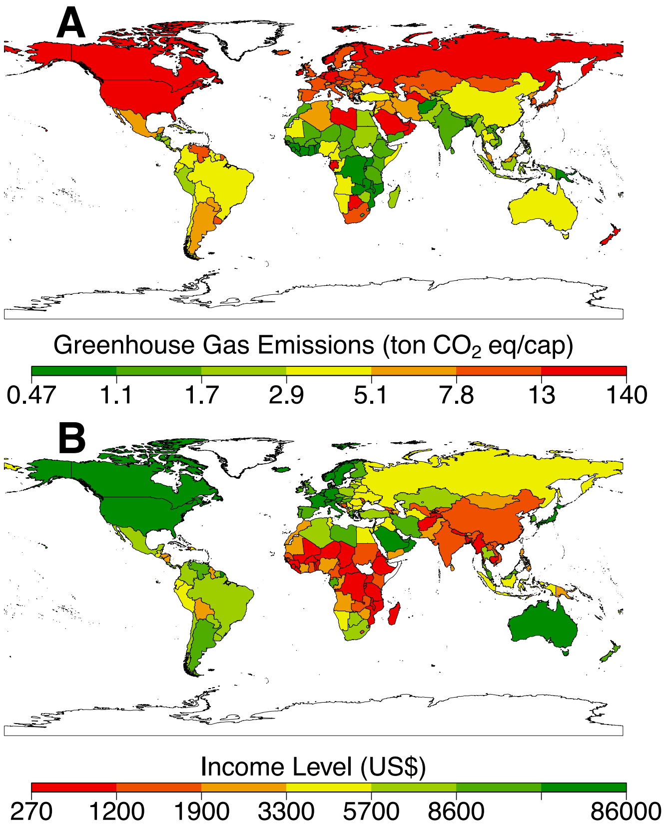

Figure 2. Geographical distribution of (A) GHG Emissions (B) Income Level. Legend: From green to red in Fig. 2A denotes low to high GHG emissions, whereas from red to green in Fig. 2B denotes low to high-income level. The method of country-level data categorization was based on quantiles, used to capture continuous intervals with uniform distribution. *Fig. 2A—mean: 7.95, minimum: 0.49, and maximum: 105.58, (N = 192); measured in ton CO_2eq/cap. Fig. 2B—mean: 14423, minimum: 616, and maximum: 106471, (N = 183); measured in US$.*

3.3 Results

3.3.1 Geographical trends

The spillover effect of GHG emissions is undeniable, however, varies in concentrations across global economies as depicted in Figure 2A (i.e., N = 192, mean = 7.95, median = 4.01, min = 0.49, and max = 105.58, measured based on average in tonCO_2eq/cap). The geographical distribution of GHG emissions presented in Figure 2A accounts for country-specific population growth dynamics, identifying Palau (105.58 tonCO_2eq/cap) as the highest emitter of GHG emissions whereas DR Congo (0.49 tonCO_2eq/cap) is the lowest GHG emitter. It is noteworthy that while Palau is a high-income country in the East Asia & Pacific region, DR Congo is classified as low-income country in Sub-Saharan Africa. The other top 5 GHG emitters include Qatar (79.23 tonCO_2eq/cap), Falkland Islands (58.28 tonCO_2eq/cap), Curaçao (43.18 tonCO_2eq/cap), Kuwait (79.23 tonCO_2eq/cap), and Botswana (79.23 tonCO_2eq/cap). In contrast, other 5 low emitters aside DR Congo includes Burundi (0.49 tonCO_2eq/cap), Malawi (0.53 tonCO_2eq/cap), Rwanda (0.54 tonCO_2eq/cap), Faroes (0.57 tonCO_2eq/cap), and Solomon Islands (0.65 tonCO_2eq/cap). Aside from both GHG concentration limits (i.e., min: 0.49 tonCO_2eq/cap, and max: 105.58 tonCO_2eq/cap), the average global GHG emissions is pegged at 7.95 tonCO_2eq/cap—of which 60 economies exceed the average while 132 economies are below average. Thus, economies with considerably low GHG emissions are concentrated in Sub-Saharan Africa and Southern Asia whereas high emitting countries are found in North America, Europe, Central Asia, Middle East & North Africa, and Central Asia (see Figure 2A).

The environmental Kuznets curve (eKc) hypothesis underscores the importance of income level in assessing emission concentrations across economies. The geographical disparities of income distribution are evident in Figure 2B (i.e., N = 183, mean = 14423, min = 616, and max = 106471, measured based on average in US$). The top 5 countries with high average income levels comprise Qatar, Brunei Darussalam, Luxembourg, United Arab Emirates, and Kuwait. It is evident that majority of low-income economies are geographically located in Sub-Saharan Africa, Eastern Asia, and Southern Asia—however, DR Congo, Burundi, Central African Republic, Mozambique, and Niger are 5 hotspot countries with low-income distribution (Figure 2B).

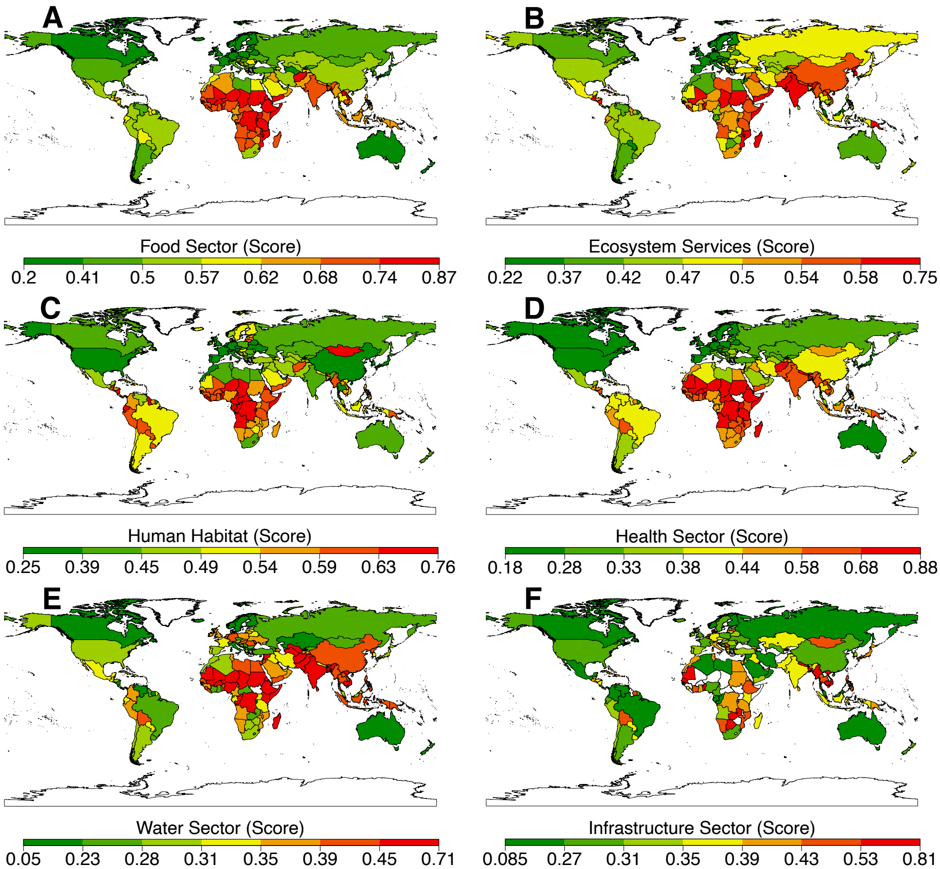

Figure 3. Vulnerability of (A) Food Sector (B) Ecosystem Services (C) Human Habitat (D) Health Sector (E) Water Sector (F) Infrastructure Sector—to climate change and its impacts. Legend: From green to red denotes low to high vulnerability. The method of country-level data categorization was based on quantiles, used to capture continuous intervals with uniform distribution. *Fig. 3A— mean: 0.57, minimum: 0.20, and maximum: 0.84, (N = 188); measured in scores, dimensionless. Fig. 3B— mean: 0.47, minimum: 0.22, and maximum: 0.74, (N = 181); measured in scores, dimensionless. Fig. 3C— mean: 0.50, minimum: 0.26, maximum: 0.75, (N = 178); measured in scores, dimensionless. Fig. 3D— mean: 0.46, minimum: 0.18, maximum: 0.84, (N = 188); measured in scores, dimensionless. Fig. 3E— mean: 0.33, minimum: 0.05, maximum: 0.69, (N = 177); measured in scores, dimensionless. Fig. 3F— mean: 0.37, minimum: 0.08, maximum: 0.79, (N = 152); measured in scores, dimensionless.*

The climate change vulnerability presented herein indicates the tendency of economies to experience the negative impacts of climate risks. We examined the geographical risk distribution of sectoral climate vulnerabilities across economies presented in Figure 3. As shown in Figure 3, countries with high-risk sectoral climate vulnerabilities are mostly located in Sub-Saharan Africa, Southern Asia, Eastern Asia, and South-East Asia. The top 5 countries with high-risk food sector vulnerability (i.e., *N* = 188, mean = 0.57, min = 0.20, and max = 0.84, measured in scores—dimensionless) include Niger, Timor-Leste, Burkina Faso, Chad, and Eritrea—whereas Denmark, United Kingdom, Germany, Iceland, and Luxembourg represent 5 principal economies with low-risk food sector climate vulnerability (Figure 3A). Figure 3B (i.e., *N* = 181, mean = 0.47, min = 0.22, and max = 0.74, measured in scores—dimensionless) shows that while Spain, Germany, Hungary, Switzerland, and Denmark are 5 leading countries with low-risk ecosystem service vulnerability, Kiribati, North Korea, Sudan, Tonga, and Solomon Islands are the top 5 countries with high-risk ecosystem service vulnerability. In terms of human habitat climate vulnerability (i.e., *N* = 178, mean = 0.50, min = 0.26, and max = 0.75, measured in scores—dimensionless), Congo, Solomon Islands, Gabon, Timor-Leste, and Central African Republic are the top 5 countries with high-risk whereas Spain, Switzerland, Barbados, United Arab Emirates, and Germany are low-risk countries (Figure 3C). The principal 5 countries with high-risk health sector vulnerability (i.e., *N* = 188, mean = 0.46, min = 0.18, and max = 0.84, measured in scores—dimensionless) include Somalia, Ethiopia, Guinea-Bissau, Tanzania, and Chad whereas Monaco, Denmark, Netherlands, Iceland, and Switzerland are low-risk economies (Figure 3D). Figure 3E (i.e., *N* = 177, mean = 0.33, min = 0.05, and max = 0.69, measured in scores—dimensionless) shows that while Niger, Sudan, Pakistan, Somalia, and Turkmenistan are high-risk countries with water vulnerability, Suriname, Dominica, Saint Vincent, and the Grenadines, Djibouti, and Bahamas are low-risk economies. The top 5 countries with high-risk infrastructure sector vulnerability (i.e., *N* = 152, mean = 0.37, min = 0.08, max = 0.79, measured in scores—dimensionless) include Niger, Timor-Leste, Burkina Faso, Chad, and Eritrea—whereas Denmark, United Kingdom, Germany, Iceland, and Luxembourg are 5 major economies with low-risk food sector climate vulnerability (Figure 3F).

Climate change readiness underpins long-term climate change mitigation and impact reduction strategies across global economies. The geographical distribution of the three forms of readiness viz. governance (i.e., *N* = 188, mean = 0.50, min = 0.08, and max = 0.88, measured in scores—dimensionless), economic (i.e., *N* = 178, mean = 0.39, min = 0.03, max = 0.81, measured in scores—dimensionless) and social (i.e., *N* = 180, mean = 0.31, min = 0.09, max = 0.74, measured in scores—dimensionless) are presented in Figure 4. The top 5 economies with high governance readiness comprise Finland, New Zealand, Denmark, Switzerland, and Sweden whereas Myanmar, Sudan, Iraq, Afghanistan, and Somalia are countries with very low governance readiness (Figure 4A). Governance readiness entails stable investment and institutional environment that reassures investors of growth and sustained invested capital devoid of governance and institutional disruptions—hence, stimulating climate adaptation actions (Chen *et al.*, 2015). Countries with low governance have similar characteristics of political instability, high perceived levels of public corruption, low regulatory quality, and lack of rule of law (TI, 2022). Poor governance, social unrest, and terrorism are found to have a negative impact on economic development and vice versa (McGowan, 2006). Evidence from Figure 4B shows the top 5 countries with high economic readiness include Norway, Singapore, New Zealand, United States, and Iceland while 5 hotspot countries with low economic readiness comprise Myanmar, Chad, Central African Republic, Eritrea, and DR Congo. Economic readiness involves the investment environment that makes it easy to do business and facilitates private sector capital mobilization for climate adaptation strategies (Chen *et al.*, 2015). Countries with high economic readiness have similar characteristics of good governance, high regulatory quality, political stability, and rule of law, hence, creating a conducive environment for investment and ease of doing business. The top 5 economies with high social readiness comprise South Korea, Finland, Denmark, Norway, and New Zealand, however, countries with low social readiness include Lesotho, Equatorial Guinea, Samoa, Eritrea, and Zimbabwe (Figure 4C). Social readiness captures societal conditions that enable the effectiveness, equitable use, and profitability of investments that facilitate climate change adaptation (Chen *et al.*, 2015). Hence, countries with low social readiness have either high social inequality, low literacy rates, or low innovation/ICT integration.

3.3.2 Empirical relationships

The nexus between sectoral climate vulnerabilities and climatic drivers are examined and reported in Table 1. Because GHG emissions, specifically CO_2 have transboundary effects, the empirical assessment presented herein accounted for spillover effects and heterogeneity across 192 countries and territories. We used novel panel estimation techniques capable of solving the complexities of emissions and cross-country time series data. Following standard econometric standards, we validated the estimated parameters using error metrics and multiple hypotheses testing via Romano-Wolf technique (see Methods). The resampled p-values and Romano-Wolf p-values in Figure 5 confirm the null hypothesis of the estimated p-values of multiple models, hence, validating the instrumental-variable-based single-equation model via two-stage least squares. This implies the model specifications and estimated parameters are robust to make unbiased statistical inferences.

We observe differing effects of anthropogenic GHG emissions, income, and climate change readiness on health sector, food sector, human habitat, ecosystem services, infrastructure sector, and water sector (Table 1). The empirical results presented in Table 1 show improvements in economic, governance, and social readiness across countries decline sectoral climate vulnerability of ecosystem services by 0.28-1.48%. However, the mitigation effect of social readiness across sectors is relatively high compared to governance and economic readiness. Similarly, rise in income level mitigates sectoral climate vulnerability by 0.02-0.15%. The empirical assessment is confirmed by the linear relationship between income and climate change vulnerability presented in Figure 6. In accounting for income convergence, vulnerability falloff as countries move up the ranks from low income→lower middle income→upper middle income to high income. For example, low-income countries, predominantly in Sub-Saharan Africa, comprising Niger, Sierra Leone, Eritrea, Madagascar, Burkina Faso, Ethiopia, Uganda, Chad, Rwanda, Guinea, and Mali have high climate vulnerability whereas developed economies namely Luxembourg, Denmark, Sweden, Finland, Norway, the US, Iceland, Austria, Singapore, Qatar, UAE, and New Zealand exhibit low climate vulnerability (Figure 6). Thus, as income level increases across economies in long term, climate change vulnerability declines. In contrast, rising levels of anthropogenic GHG emissions intensify climate vulnerability across sectors. Among various sectors, the climate reduction effect of readiness and income is fairly high in health services compared to water services. Thus, the climate reduction effect is in the order health> food> habitat> ecosystem services> infrastructure> water. This infers high-income level, social, governance, and economic readiness minimizes climate change exposure and sensitivity but improves adaptive capacity across vulnerable sectors, predominantly in climate-prone regions. For example, long-term climate readiness and sustainable income improve the health sector by reducing climate-related deaths and diseases caused by warm periods and flood hazards. Sustainable economic readiness reduces dependency on foreign aids for health service delivery, especially in developing countries but strengthens domestic capacity to lessen climate-related sensitivity in the health sector. Thus, strengthening adaptive capacity of the health sector involves improving health and sanitation facilities, increasing the quantity and quality of medical staff, and healthcare access for slum and poor population.

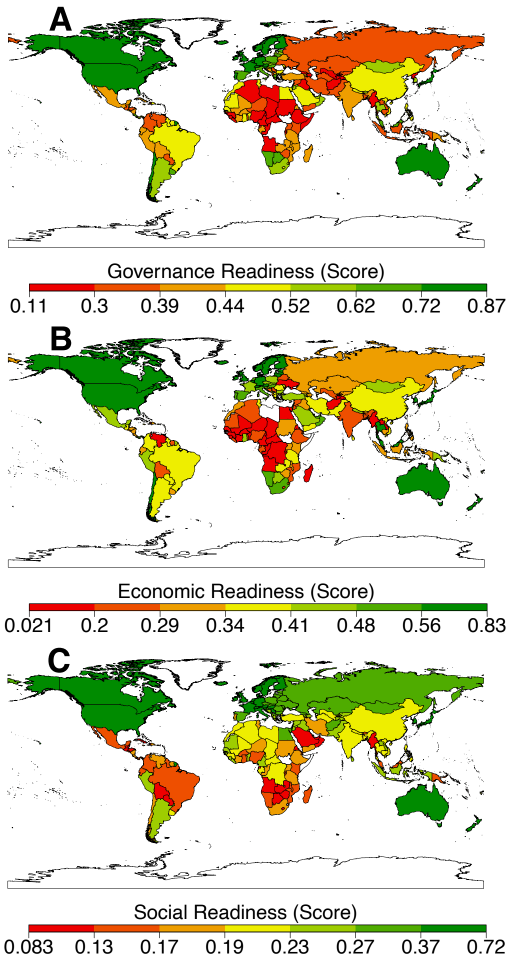

Figure 4. Mitigation of climate change (A) Governance Readiness (B) Economic Readiness (C) Social Readiness. Legend: From red to green denotes low to high readiness. The method of country-level data categorization was based on quantiles, used to capture continuous intervals with uniform distribution. *Fig. 4A— mean: 0.50, minimum: 0.08, and maximum: 0.88, (N = 188); measured in scores, dimensionless. Fig. 4B— mean: 0.39, minimum: 0.03, maximum: 0.81, (N = 178); measured in scores, dimensionless. Fig. 4C—mean: 0.31, minimum: 0.09, maximum: 0.74, (N = 180); measured in scores, dimensionless.*

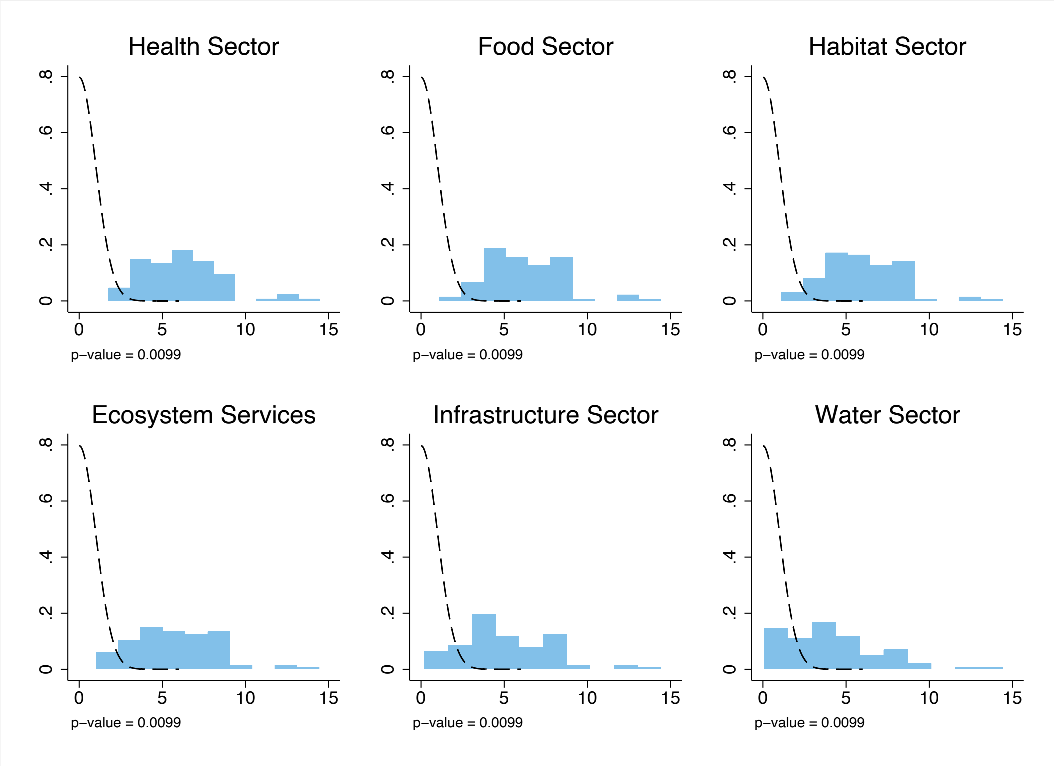

Figure 5. Multiple-hypotheses testing and model validation for sectoral vulnerability vs. economic readiness using Romano-Wolf *p-value*.

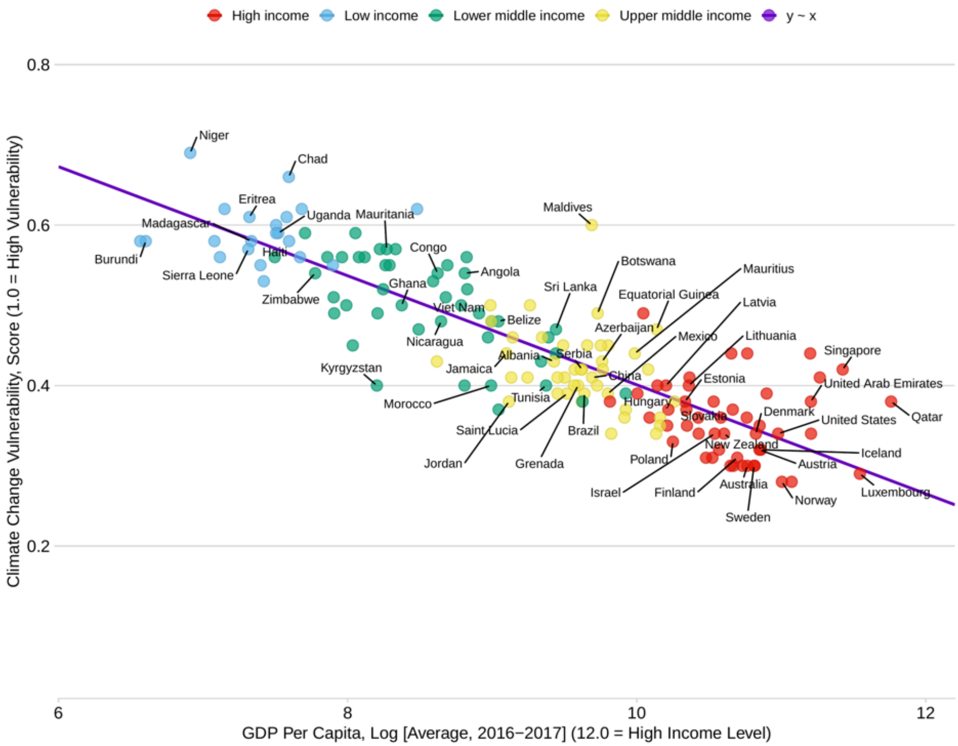

Figure 6. Linear relationship between GDP per capita and climate change vulnerability. This plot captures income convergence (i.e., High income, Low income, Lower middle income, and Upper middle income) of sampled economies based on average annual frequency.

3.3.3 Country-specific linking of climate drivers

As presented in Figures 7-11, we graphically investigated country-specific effects of climate and its related drivers by accounting for either income or regional convergence. Figure 7 reveals the nexus between anthropogenic GHG emissions and income across income groups. We observe a positive monotonic relationship with lower emission levels for low-income countries, typically Sub-Saharan Africa, and high emission levels for high-income economies, predominantly North America, Europe, and Central Asia. While the eKc hypothesis highlights decline in environmental pollution due to stringent environmental regulations after achieving high-income status (Dasgupta *et al.*, 2002), our empirical assessment contradicts the theory to some extent, even in the era of the SDGs. Using average data spanning 2016-2017 to examine GHG-income relationship, it is evident that agrarian economies in Sub-Saharan Africa namely inter alia, Comoros, Rwanda, Burundi, Niger, and Benin emit less anthropogenic emissions whereas service sector countries like the US, Australia, Russia, Japan, and Germany produce more emissions, violating the tenets of eKc hypothesis. In contrast, some high-income countries including Palau, Saint Kitts & Nevis, Antigua & Barbuda, Malta, Bahamas, Iceland, Barbados, Cyprus, Latvia, and Luxembourg have reduced emissions with sustained income levels, validating the eKc hypothesis (Figure 7). The common denominator across these countries is the small population size (below 2 million, World Bank est. 2020), implying that neither do economic growth alone declines anthropogenic emissions, especially in high income but changes in population composition and other unobserved factors are crucial to achieving environmental quality (Menz *et al.*, 2011).

The regional and country-specific relationship between climate change readiness and climate change vulnerability is presented in Figure 8. Similarly, the nexus between climate vulnerability and disaggregate climate readiness namely social, governance, and economic readiness are depicted in Figures 9-11. We observe a negative relationship between climate change readiness and climate change vulnerability. Countries with high readiness, primarily high-income economies including Norway, Finland, Switzerland, Iceland, Australia, Austria, and the US have low vulnerability. While this hypothesis is largely true, recent occurrences show high-income does not protect against extreme weather events such as hurricanes, storms, wildfires, and droughts (Geiger *et al.*, 2016). In contrast, low-income countries from Sub-Saharan Africa namely Niger, Somalia, Chad, Guinea-Bissau, Mali, Sudan, Liberia, Eritrea, Burkina Faso, Benin, Uganda, Ethiopia, DR Congo, Burundi, and Central African Republic with low climate readiness exhibit high climate change vulnerability (Figure 8). Besides, economies in East Asia & Pacific, North America, and Europe & Central Asia with high social, governance, and economic readiness have low climate change vulnerability compared to developing economies (Figures 9-11). In contrast, the high climate vulnerability across sectors in developing countries can be attributed to low social readiness (Figure 9), poor governance readiness (Figure 10), reduced income level, and low economic readiness (Figure 11). Second, developing countries typically have high climate exposure and sensitivity but often fail to take precautionary measures due to limited social, governance, and economic resources, hence, becoming highly vulnerable to climate change and its impacts. The income convergence depicted in Figure 11 reveals the importance of income in reducing climate change vulnerability in climate-exposed and sensitive regions with high poverty rates. While high-income countries have the financial muscle to take economic precautions against future climatic events, low-income countries with low or no financial capabilities are often caught unaware of future climate consequences.

Table 1. Parameter estimates

Parameters	Economics	Governance	Social	Income
Ecosystem	-0.5026***	-0.5135***	-0.5429***	-0.0658***
	[0.0152]	[0.0140]	[0.0151]	[0.0017]
Food	-0.7834***	-0.7885***	-0.9902***	-0.1180***
	[0.0166]	[0.0183]	[0.0214]	[0.0021]
Habitat	-0.5985***	-0.5963***	-0.6492***	-0.0815***
	[0.0169]	[0.0182]	[0.0180]	[0.0002]
Health	-1.1857***	-1.2079***	-1.4752***	-0.1510***
	[0.0211]	[0.0246]	[0.0329]	[0.0021]
Infrastructure	-0.3467***	-0.3898***	-0.4218***	-0.0211***
	[0.0195]	[0.0213]	[0.0226]	[0.0027]
Water	-0.2801***	-0.2798***	-0.3073***	-0.0338***
	[0.0158]	[0.0156]	[0.0188]	[0.0023]
GHG→Ecosystem	0.0013***	0.0015***	-0.0002	0.0032***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]
GHG→Food	-0.0004**	-0.0001	-0.0012***	0.0025***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]
GHG→Habitat	0.0002	0.0003	-0.0019***	0.0025***
	[0.0002]	[0.0003]	[0.0002]	[0.0025]
GHG→Health	0.0005***	0.0012***	-0.0008***	0.0033***
	[0.0002]	[0.0003]	[0.0003]	[0.0002]
GHG→Infrastructure	0.0007***	0.0010***	0.0003*	0.0005**
	[0.0002]	[0.0002]	[0.0002]	[0.0002]
GHG→Water	0.0008***	0.0011***	-0.0001	0.0014***
	[0.0002]	[0.0002]	[0.0002]	[0.0003]
Constant→Ecosystem	0.6497***	0.7070***	0.6262***	1.0206***
	[0.0055]	[0.0064]	[0.0044]	[0.0143]

Constant→Food	0.8749***	0.9553***	0.8688***	1.5893***
	[0.0063]	[0.0087]	[0.0065]	[0.0180]
Constant→Habitat	0.7242***	0.7839***	0.7020***	1.1966***
	[0.0060]	[0.0082]	[0.0053]	[0.0178]
Constant→Health	0.9130***	1.0441***	0.9058***	1.7686***
	[0.0081]	[0.0118]	[0.0099]	[0.0178]
Constant→Infrastructure	0.5013***	0.5579***	0.4943***	0.5511***
	[0.0079]	[0.0106]	[0.0072]	[0.0233]
Constant→Water	0.4286***	0.4561***	0.4231***	0.6167***
	[0.0057]	[0.0071]	[0.0056]	[0.0195]
Obs (*N*)[1]	3,676	3,697	3,676	3,550
Obs (*N*)[2]	3,739	3,760	3,697	3,571
Obs (*N*)[3]	3,634	3,655	3,655	3,529
Obs (*N*)[4]	3,739	3,760	3,697	3,571
Obs (*N*)[5]	3,088	3,088	3,109	3,004
Obs (*N*)[6]	3,592	3,613	3,592	3,466
p-value[1]	0.0000***	0.0000***	0.0000***	0.0000***
p-value[2]	0.0000***	0.0000***	0.0000***	0.0000***
p-value[3]	0.0000***	0.0000***	0.0000***	0.0000***
p-value[4]	0.0000***	0.0000***	0.0000***	0.0000***
p-value[5]	0.0000***	0.0000***	0.0000***	0.0000***
p-value[6]	0.0000***	0.0000***	0.0000***	0.0000***
R-square[1]	—	0.1412	0.1154	0.3749
R-square[2]	0.3228	0.2081	0.2755	0.4747
R-square[3]	0.1603	0.0449	0.2212	0.4000
R-square[4]	0.2980	0.0779	—	0.6741
R-square[5]	—	—	—	0.0914
R-square[6]	0.0680	0.0948	—	0.0922

Notes: ***, **, * denote statistical significance at 1, 5, 10%; [1], …, [6] represent Sector 1, …., Sector 6; [.] denotes standard errors, and → represents the causal effect relationship across 192 countries and territories.

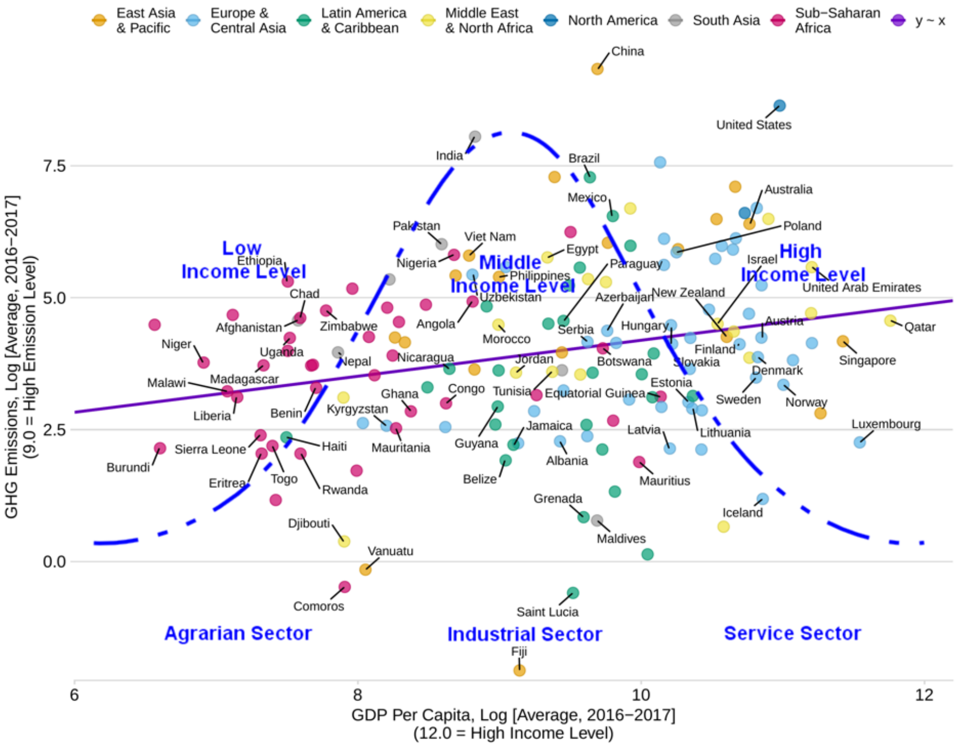

Figure 7. Nexus between anthropogenic GHG emissions and income level across income groups. Using average data spanning 2016-2017 helps to account for the inception and impact of the SDGs, specifically the 13th target of climate change mitigation. This plot captures regional convergence (i.e., East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa) of sampled economies.

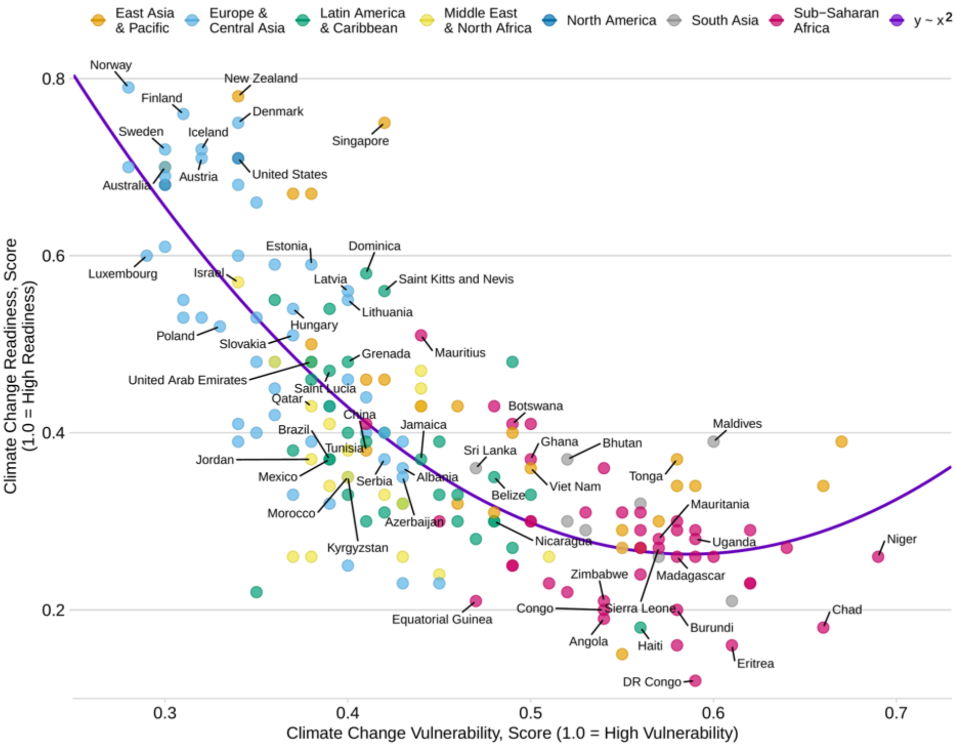

Figure 8. Relationship between climate change readiness and climate change vulnerability. This plot captures regional convergence (i.e., East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa) of sampled economies based on average annual frequency.

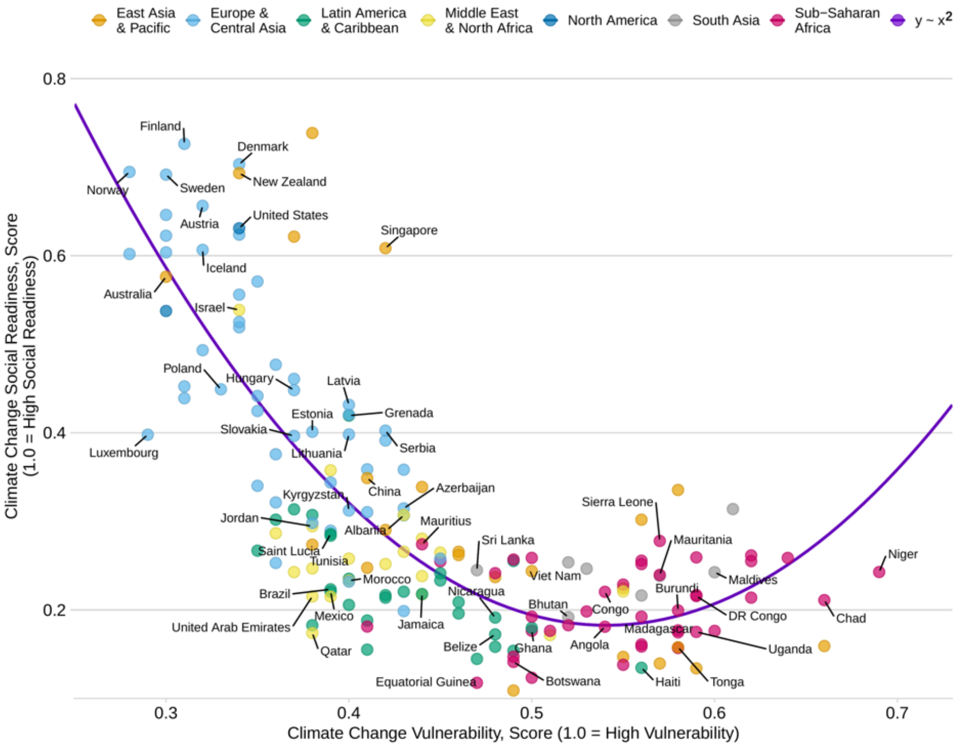

Figure 9. Relationship between climate change social readiness and climate change vulnerability. This plot captures regional convergence (i.e., East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa) of sampled economies based on average annual frequency.

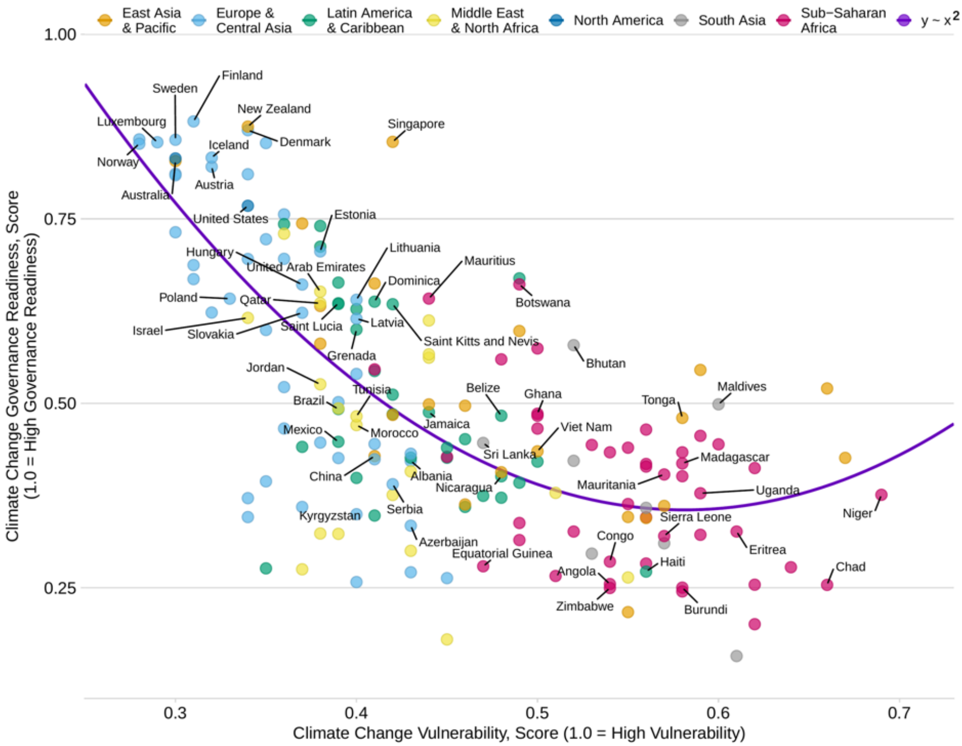

Figure 10. Relationship between climate change governance readiness and climate change vulnerability**.** This plot captures regional convergence (i.e., East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa) of sampled economies based on average annual frequency.

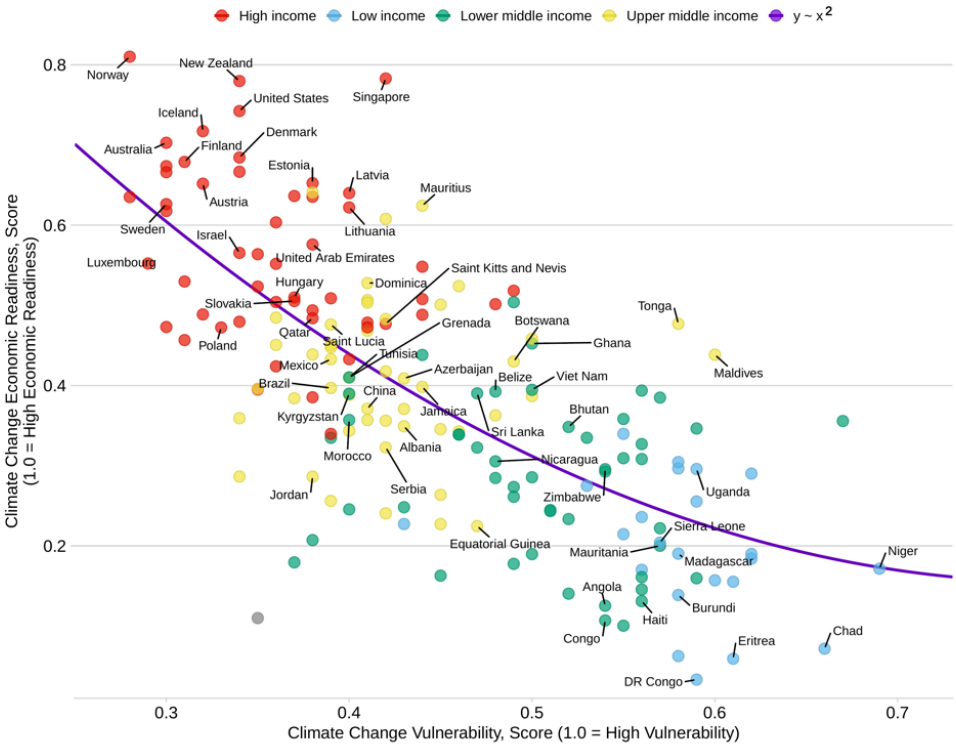

Figure 11. Relationship between climate change economic readiness and climate change vulnerability. This plot captures income convergence (i.e., High income, Low income, Lower middle income, and Upper middle income) of sampled economies based on average annual frequency.

3.4 Discussion

Although climate change impact cannot be overemphasized, significant evidence shows the magnitude of the response differs across the globe as a function of relative vulnerability due to disparities in terms of exposure, sensitivity, and adaptability (Foden *et al.*, 2016; Kovach *et al.*, 2019; Sarkodie *et al.*, 2019a). We find that high governance readiness coupled with high social and economic climate readiness decline climate change vulnerability in developed countries. This implies high governance readiness with reduced corruption, political instability, and violence while upholding rule of law and institutional quality enables effective investments into climate change adaptation options that have long-term effects on environmental sustainability (Hope Sr, 2020). Second, the ease of doing business trigger both domestic and foreign investments that could facilitate climate financing and assist sustainable development, especially in developing economies. Third, reduced social inequality, improved education, innovation, and modern ICT infrastructures promote high social readiness—which has the potential of accelerating the agenda towards achieving clean and sustainable environment.

The empirical results show increasing levels of anthropogenic GHG emissions exacerbate the vulnerability of ecosystem services, typically in sub-Saharan Africa, Eastern and Southern Asia. Human-induced climate change is likely to exacerbate habitat loss, which is the greatest threat to biodiversity and ecosystems. Existing studies indicate climate effects on the Arctic marine environment increase temperature, ocean acidification, and changes in sea ice cover, thereby hampering the survival and existence of marine habitat (EPA, 2016; Weiskopf *et al.*, 2020). The direct impact of habitat loss and fragmentation is predicted to continue and exacerbate the pressure on ecosystems and species in decades (Segan *et al.*, 2016). Increasing occurrence and intensity of extreme events triggered by climate change variabilities may diminish the already threatened population by habitat loss and fragmentation (McKechnie *et al.*, 2010).

The lingering effect of anthropogenic GHG emissions if not curtailed with sustained economic development, exacerbate the vulnerability of human habitat to climate change and its impacts. Yet, we observe the limiting effect of economic, governance, and social readiness on the vulnerability of human habitats to climate change. Likewise, upsurge in income level lessens the exposure and sensitivity of human habitat to climate change effects. The degree and occurrence of drought are estimated to increase due to future climate vulnerability, predominantly due to regional decline in precipitation and rising levels in evapotranspiration (IPCC, 2013).

Long-term food sector vulnerability declines with increasing levels of economic, governance, and social readiness. The mitigation effect of economic readiness is reinforced by the impact of income growth on the exposure and sensitivity of the food sector to climate change vulnerability. However, the escalation of GHG emissions amidst weak income levels strengthens the food sector's vulnerability to climate change and its impacts. Climate change vulnerability will likely contribute to food price fluctuation due to its sensitivity that may stall access to the global market, especially among the poorest countries with low purchasing power (Schilling *et al.*, 2012). High market price of food is usually associated with inadequate supply whereas persistent increase in food prices can force low-income people to reduce consumption levels required to meet the standard for healthy and good life—which may result in social uprising and food riot (FAO, 2008; Schmidhuber *et al.*, 2007). The rise in global population in the past decades coupled with urban sprawl, dietary changes, and the rising effect of climate change has enormous pressure on food production (Sahay, 2000). The global population is estimated to increase by 2.5 billion in 2050 (i.e., 9.1 billion), thus, increasing food demand (Carvalho, 2006). Therefore, producing higher yields per unit of input such as land, plant, nutrient, and water—is essential to meet future food demands (FAO, 2008).

Continues increase in anthropogenic GHG emissions bolsters the vulnerability of health sector to climatic shocks. Nevertheless, the effect of income outgrowth, economic, governance, and social readiness in reducing exposure and sensitivity of health sector dynamics is evident in its mitigation of climate change vulnerability across countries. Evidence from literature is becoming increasingly clear that climate change variabilities have severe impact on human health (WorldBank, 2018). Climate change variability such as heatwaves, floods, cold spells, and ultraviolet radiation directly affects human health, leading to morbidities including stroke, cancer, stress-related disorder, respiratory diseases, neurological diseases, and water-borne, food-borne, and vector-borne diseases (Cissé, 2019; Mateeva, 2020). Extreme climate change events including heat waves spur annual death toll than other extreme weather events combined (Luber *et al.*, 2008). Studies show strong relationship between extreme temperature, ambient air pollution, and all-cause mortality rate (Owusu *et al.*, 2020; Scovronick *et al.*, 2018; Wu *et al.*, 2014).

The rising level in income and improvements in economic, governance, and social readiness hamper the vulnerability of infrastructure sector to climate change effects—by reducing exposure and sensitivity to climatic events. However, increasing levels of GHG emissions strengthen infrastructure sector vulnerability to climate exposure and its consequences. With the many impacts of climate change, the rising sea level is considered more threatening to sustainable infrastructure, economic development, and longevity (Nicholls *et al.*, 2010). Sea level rise may significantly contribute to estimated hundreds of million people displaced settlement globally—resulting from extreme climate change event over the next century (Nicholls *et al.*, 2011). For instance, prior studies indicate climate change-induced overland flooding could threaten more than 600,000 people and infrastructure expansion of $15 billion across urbanized coastal cities in California (Befus *et al.*, 2020).

The persistent effect of GHG emissions spurs the vulnerability of water sector to climate change—by increasing climatic exposures and sensitivities. Conversely, increasing levels of income and advancement in economic, governance, and social readiness decline water sector vulnerability to climate change effects. Currently, 2.2 billion people around the globe do not have access to clean drinking water (UN, 2020). Hence, climate change effects could hinder the achievement of sustainable development goal 7 of ensuring access to safe drinking water for all by 2030 (UN, 2020). Besides, several studies have established a relationship between the future decline in groundwater recharge and decline in surface runoff over the past decades (Benabdallah *et al.*, 2018; Schilling *et al.*, 2020). About 8% of the global population is reported to experience severe decline in water resources resulting from ~20% reduction in annual runoff—with 1% increase in global mean temperature (Schewe *et al.*, 2014). Climate change effects alter rainfall patterns, hence, affect water availability for food and livestock production. However, water harvesting adaptation policies undertaken in vulnerable regions can improve and sustain agricultural production across seasons (Bunclark *et al.*, 2018).

Because the effect of climate change is not country-specific but transboundary, climate change adaptation could be undertaken on cross-border cooperation to enhance collaboration across countries. The adaptation to climate change vulnerability requires strong cooperation at regional and international levels to facilitate the exchange of research findings, vulnerability risk assessment, adaptation options, and transboundary pest and disease control and prevention (FAO, 2015). Besides, investment in climate-smart agriculture, provision of timely weather warning forecasts, and appropriate adaptation measures can limit long-term climatic effects at the farm level (Kogo *et al.*, 2020). Adaptation measures involve improving policy and governance, moderating demand, reducing food waste, and increasing food production where needed (Godfray *et al.*, 2010). This implies adaptation technologies improve the food system to be resistant to climate change, and improve crop yield to feed the growing world population (Mbow *et al.*, 2014). Thus, drastic measures are required at both the local and national levels through climate change adaptation policies that strengthen the global agriculture sector and food production to meet the growing population.

3.5 Conclusion

Motivated by the 2030 agenda, this study modeled the mitigation effect of adaptation readiness on climate change from economic, social, and governance perspectives. Besides, we assessed the spatial-temporal severity of climate vulnerability across sectors in 192 global economies. Second, we examined the geographical readiness (i.e., social, governance, and economic) to combat climate change and its impacts. Third, we investigated the long-term impact of climate change readiness and income expansion on sectoral-climate vulnerabilities.

The empirical procedure presented herein denotes first-best solution to mitigate climate change vulnerabilities across sectors including ecosystem services, food, health, human habitat, infrastructure, and water. We examined global common shocks and spillover effects using the cross-section dependence test and further assessed heterogeneity, for which heterogeneous effects across 192 countries were accounted for using the novel Romano-Wolf estimation technique. Besides, both noncooperative business-as-usual scenarios and dynamic games were indirectly accounted for—by assuming countries emit too much periodically. Climate change readiness denotes investments in abatement technologies, and among other sustainable options—to limit climate change vulnerability. In contrast, the business-as-usual scenario examines the historical effects of anthropogenic GHG emissions on different sectors presented herein. The study found the stocks of periodic GHG emissions spur sectoral climate change vulnerability across countries—with much impact on developing countries. Outgrowth in income level and investment (i.e., economic, social, and governance adaptation readiness) decline investment cost by reducing long-term environmental damage. This implies income level and adaptation readiness play essential role in mitigating climate change and its impacts. As a limitation, our study fails to account for discount factors and punishment essential to examine the sustainable first-best solution to climate change effects. This infers future studies could consider these limitations and investigate how countries could achieve environmental sustainability through stringent or rewarding climate reduction measures.

From a policy perspective, this study provides primary inputs for policymakers and government in decision making towards a broader iterative cycle including planning, managing, designing, implementing, and monitoring resilient climate change vulnerability-based development actions. Empirical evidence from this study could be used to determine the strength and weaknesses of vulnerability reduction and prioritize limited natural resources in addressing and managing adaptive actions of extreme climate change vulnerabilities. Interested third parties may use our results to monitor and assess country-specific vulnerability exposure, sensitivity, and adaptation.

Data availability

All data analyzed are publicly available (see Methods).

Competing interests

The authors declare no competing interests.

Ethical approval

Not applicable.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Acknowledgment

Open access funding provided by Nord University.

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Chapter 4. Paper 2: Winners and losers of energy sustainability—Global assessment of the Sustainable Development Goals

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Author contribution

S.A.S designed the study, collected the data, performed the data analysis, coordinated & supervised the study, and drafted the manuscript—thus, contributing 100%.

Winners and losers of energy sustainability—Global assessment of the Sustainable Development Goals [3]

Abstract

Energy sustainability plays a crucial role in achieving environmental sustainability, hence, underpins climate change mitigation. Yet, studies assessing the overarching effect of existing sustainability frameworks on energy production and consumption are limited. Here, we provide comprehensive assessment of energy sustainability across 217 countries and territories spanning 1960-2019. Using 11 targets and 15 indicators of the Sustainable Development Goals (SDGs), we present winners and losers of energy sustainability by accounting for pre-millennium development goals (MDGs), MDGs, and SDGs across income groups. While the inception of the 2030 agenda has improved energy and environmental performance across economies, low-income countries are still struggling to meet several of the SDGs. We find that sustained economic growth with reduced income inequality improves energy sustainability in developing economies. However, sustainable climate policies that reduce trade-offs between energy resources and environmental threats are highly recommended in climate-prone regions that depend heavily on water resources to boost power generation capacity.

4.1 Introduction

The concept of sustainability has enhanced global efforts toward mitigating climate change and its impacts (Blanco *et al.*, 2014). The Brundtland report titled, “our common future” highlights the significance of developmental options that meet present demand without compromising the environment for the sake of future generations (Brundtland, 1987). In this regard, several global goals have been formulated to address and guide present demands while attaining environmental sustainability. However, such ideal developmental pathway appears problematic, owing to the trade-off between energy sustainability and sustained economic development. Energy production and consumption are critical for economic

[3] Published article: **Sarkodie, S. A.** (2022). Winners and losers of energy sustainability—Global assessment of the Sustainable Development Goals. *Science of The Total Environment*, 154945. https://doi.org/10.1016/j.scitotenv.2022.154945

development, hence, remain the major driver of anthropogenic GHG emissions that underpin climate change (Edenhofer *et al.*, 2011). This implies the extraction, composition, and adoption of energy resources to meet “present demand” and “future supply” is crucial to achieving sustainable development. In contrast, economic development (i.e., income level and income inequality) is reported to affect a country’s energy production and consumption patterns (Fouquet, 2016). Despite the significant policy implications, existing literature merely examines the drivers of energy consumption, emissions, and economic development—ignoring the progress towards attaining energy sustainability targets. The only existing literature examines the trade-offs between Sustainable Development Goals (SDGs) and energy services, however, calls for extensive energy research that links targets and goals to country-specific and global energy-related issues (Nerini *et al.*, 2018). To date, no existing literature examines the progress of energy sustainability from pre-millennium development goals (MDGs), MDGs, and SDGs. This information is useful to assess the historical development of energy sustainability across countries, territories, and income groups, given the numerous ambitious global goals to promote sustainable development.

Here, we develop and compare energy sustainability indicators using 11 targets and 15 indicators of the SDGs across 217 countries and territories (Supplementary Table 1) from 1960-2019. Besides, we account for the coupling effect of several dimensions of sustainable development covering energy production and consumption, economic policy (i.e., adjusted savings, private sector and trade, external funding and income), and national resource accounting (i.e., water and domestic materials, e.g., fossil fuels). The quantifiable metrics include SDG 6.4 (increasing H_2O efficiency across sectors by ensuring sustainable H_2O withdrawals & addressing scarcity in freshwater supplies), SDG 7.1 (ensuring availability and accessibility to modern energy and its services), SDG 7.2 (increasing renewable energy penetration), SDG 7.3 (improving global energy efficiency), SDG 7.4 (enhancing clean energy technologies), SDG 7.5 (infrastructural expansion of sustainable energy), SDG 8.1 (sustained economic growth), SDG 8.4 (decoupling growth from pollution), SDG 9.4 (expansion in resource-efficient and clean technologies that ensure sustainable production and consumption in infrastructures and industries), SDG 12.2 (sustainable and efficient use of natural resources in production and consumption), and SDG 13 (mitigating climate change and its impacts). The adoption of the goals and indicators is based on their usefulness as tools for policy formulation (Taylor *et al.*, 2017). The existing literature assumes a global common shock and spillover effects for anthropogenic emissions, however, the notion appears inconsistent with energy sector dynamics. This implies assuming homogeneous behavior towards energy sustainability will be erroneous, hence, producing biased statistical inferences. Countries appear to have heterogeneous consumption patterns attributable to differences in economic structure, environmental priorities, and commitment towards achieving sustainability. To compare countries from economic level, we further categorized countries into income groups per the existing income convergence of the World Bank. Using the constructed SDG indicators, we address the following research questions: first, are SDG indicators homogeneous or heterogeneous across income groups while accounting for pre-MDGs, MDGs, and SDGs? Second, who are the winners and losers of energy sustainability? Third, what are the global and country-specific spatial-temporal advancements toward achieving energy sustainability? Fourth, how does income convergence affect energy diversity, economic development, and GHG emissions in developing and developed economies? Fifth, what is the impact of income level on energy sustainability indicators while controlling for income inequality? The research questions are addressed by employing statistical techniques to compute the weighted average of indicator-specific effect estimates across income groups classified based on income convergence. Due to differences in economic structure across economies, we use normalization technique to develop scores for the SDG indicators to examine energy sustainability performance. We utilize meta-analysis to assess similar pre-MDG, MDG, and SDG indicators across income groups, while comparing them to global pre-MDGs, MDGs, and SDGs. The adoption of income group-specific fixed-effects in the statistical model controls for heterogeneous effects. Historical changes of energy and its related services are captured and compared from pre-MDGs, MDGs, and SDGs periods. A graphical comparison of performance across economies is presented using linear regression technique that controls for country-specific effects. We find significantly large heterogeneous characteristics of energy sustainability across income groups.

4.2 Methods

4.2.1 Data

We employed data from world development indicators—a World Bank database (World Bank, 2020) with collection of reliable data sources including International Monetary Fund (IMF), International Financial Statistics (IFS), and Balance of Payments (BOPs) databases, International Debt Statistics, OECD, Sustainable Energy for All (SE4ALL) database from WHO Global Household Energy database, SE4ALL Global Tracking Framework, IEA Statistics, Food, and Agriculture Organization (FAO), AQUASTAT data, Carbon Dioxide Information Analysis Centre, Environmental Sciences Division—Oak Ridge National Laboratory in the US, Private Participation in Infrastructure Project Database, European Commission, Joint Research Centre—Netherlands Environmental Assessment Agency (PBL), and Emission Database for Global Atmospheric Research (EDGAR). We used weighted average annual frequency data spanning 1960-2019 across 217 countries and territories (Supplementary Table 1). We further used aggregated data at the global level (WLD), and across income groups namely low-income countries (LIC), lower-middle-income countries (LMC), low- & middle-income countries (LMY), middle-income countries (MIC), upper-middle-income countries (UMC), and high-income countries (HIC) (World Bank, 1978). Using over six decades of data across several topics, country-specific and income group dynamics provide broader coverage to capture historical changes in energy sustainability from pre-MDGs (1961-1999), MDGs (2000-2015), and SDGs (2016-2019) epochs.

Table 1| SDG targets, & indicators for energy sustainability assessment

№	SDG targets	SDG indicators	Our series
1	6.4 Increasing H_2O efficiency across sectors by ensuring sustainable H_2O withdrawals & addressing scarcity in freshwater supplies	6.4.1 Periodic changes in H_2O consumption efficiency 6.4.2 Dynamics of water stress: factors affecting freshwater withdrawals and regeneration of H_2O resources	Total water productivity (constant 2010 US$ GDP/m^3 of total freshwater withdrawal) Annual freshwater withdrawals for industrial use (% of total freshwater withdrawal) Total renewable internal freshwater resources (billion m^3)
2	7.1 Ensuring availability and accessibility to modern energy and its services	7.1.1 Share of population with access to electricity	Access to electricity (% of population) Rural access to electricity (% of rural population) Urban access to electricity (% of urban population)
		7.1.2 1 Share of population relying on clean technologies	Access to clean fuels and technologies for cooking (% of population)
3	7.2 Increasing renewable energy penetration in global energy portfolio	7.2.1 Share of renewables in final energy utilization	Renewable energy consumption (% of total final energy consumption)
4	7.3 Improving global energy efficiency	7.3.1 Energy intensity comprising primary energy and economic growth	Energy intensity level of primary energy (MJ/$2011 PPP GDP)
5	7.a Enhancing clean energy technologies and cleaner fossil fuel technologies	7.a.1 Support of clean and renewable energy production through R&D	Alternative and nuclear energy (% of total energy use) Combustible renewables and waste (% of total energy)
6	7.b Infrastructural expansion of sustainable energy and its related services from external funding	7.b.1 Foreign direct investments in energy efficiency and technologies to achieve sustainable development	Investment in energy with private participation (current US$) Foreign direct investment inflows (% of GDP)
7	8.1 Sustained economic growth	8.1.1 Annual growth rate of GDP per capita	GDP per capita (constant 2010 US$)

8	8.4 Decoupling growth from pollution by ensuring natural resource efficiency in production and consumption	8.4.1 Material footprint 8.4.2 Domestic material consumption	Adjusted savings: energy depletion (% of GNI) Fossil fuel energy consumption (% of total) Net energy imports (% of energy use)
9	9.4 Expansion in resource-efficient and clean technologies that ensure sustainable production and consumption in infrastructures and industries	9.4.1 Industrial-based emissions	CO_2 emissions from electricity and heat production (% of total fuel combustion) CO_2 emissions from gaseous fuel consumption (% of total) CO_2 emissions from liquid fuel consumption (% of total) CO_2 emissions from solid fuel consumption (% of total) Energy related methane emissions (% of total) Nitrous oxide emissions in energy sector (% of total)
10	12.2 Sustainable and efficient use of natural resources in production and consumption	12.2.1 Reducing material footprint 12.2.2 Sustainable domestic material consumption	Adjusted savings: energy depletion (% of GNI) Fossil fuel energy consumption (% of total) Net energy imports (% of energy use)
11	13.0 Mitigating climate change and its impacts	13.3.1 Impact reduction of climate change	Total greenhouse gas emissions (kt of CO_2 equivalent)

Notes: The SDG targets and indicators presented are based on the Sustainable Development Goals (United Nations, 2015b). Our series denote global data variables used as proxy to assess the various indicators and classify countries meeting the target.

4.2.2 *Proxy SDG Indicators*

The energy sector is not standalone but depends on other sectors, thus, our SDG targets and indicators for assessing energy sustainability account for natural resource efficiency, environmental pollution, and economic dynamics. The 11 SDG targets presented herein (Table 1) are adopted from the SDG framework by the United Nations. Owing to the difficulty in retrieving data on exact SDG targets/indicators, we utilized proxy data options. For example, to account for SDG 8.4, "Decoupling growth from pollution by ensuring natural resource efficiency in production and consumption", we utilized adjusted savings: energy depletion, fossil fuel energy consumption, and net energy imports. Adjusted savings: energy depletion denotes the ratio of the rate of coal, crude oil, and natural gas energy resource supply to the unexpended reserve lifetime (World Bank, 2020). Fossil fuel energy consumption entails the utilization of coal, oil, natural gas, and petroleum products whereas net energy imports cover energy utilization less production. Hence, these indicators are used to capture both material footprint and domestic material consumption. Second, SDG 13.0, "Mitigating climate change and its impacts" is assessed and reported using the total greenhouse gas emissions (i.e., include carbon dioxide, methane, nitrous oxide, and Fluorinated gases) as proxy to capture the impact of climate change. In this way, our variable selection is based on several factors including—data availability, and data series that explicitly capture SDG indicators or function as proxy indicators.

4.2.3 *Periodic Assessment*

To capture and compare historical changes of energy and its related services from pre-MDGs, MDGs, and SDGs periods. We calculate the arithmetic mean of the yearly data across countries and territories expressed as:

$$Y_i = \frac{1}{n}\sum_{x=1}^{n} z_x \tag{1}$$

where Y denotes the calculated arithmetic mean of the data across countries, or territories i, n represents the periods spanning 1961-1999 for pre-MDGs, 2000-2015 for MDGs, and 2016-2019 for SDGs, and z_x denotes the sum of data series under consideration for epoch n. Similarly, we estimate the standard deviation of the data using the expression:

$$S_i = \sqrt{\frac{\sum(z_x - \bar{z})^2}{n-1}} \quad (2)$$

where S represents the estimated standard deviation of the sampled series across countries and territories i, while accounting for pre-MDGs, MDGs, and SDGs. $\bar{z}$ denotes the mean of data series z_x for period n.

4.2.4 Settings for Meta-analysis

Using the expressions in equations 1-2, we derive the mean and standard deviation of both experimental and control groups. From here, we compute the effect size of income groups and global measurements—by designating income groups namely LIC, LMC, LMY, MIC, UMC, and HIC as experimental groups whereas the global measurements, viz. WLD represents the control group. The effect sizes for pre-MDGs and MDGs are computed using Hedges' *g* statistic (Hedges, 1981) with approximate bias correction to control for upward bias in computing for standardized mean difference whereas Cohen's *d* statistic (Cohen, 2013) is used to control for small sample bias due to small data sample for computing standardized mean difference for the SDG epoch. The specification for the meta-analysis comprises the number of observations, mean, and standard deviation of both experimental and control groups, income group-specific fixed-effects model to capture heterogeneous effects using the inverse-variance estimation technique (Cooper *et al.*, 2019). Existing studies adopt meta-analysis (Glass, 1976) as statistical technique to analyze results from existing studies with related research questions, however, we utilized this technique to assess similar pre-MDG, MDG, and SDG indicators across income groups, by comparing them with the global pre-MDGs, MDGs, and SDGs. In this scenario, we compute the weighted average of indicator-specific effect estimates to validate the possibility of substantial variations across income groups. Thus, using the estimated effect of interest, we can draw useful conclusions to ascertain the causes of variations in energy sustainability across income groups.

4.2.5 Empirical Estimation

Following the Brundtland report titled, "our common future" (Brundtland, 1987), we define energy sustainability as meeting energy demand without compromising the environment and depleting energy resources for the sake of future generations (Tester *et al.*, 2012). Our empirical estimation accounts for three pillars of energy sustainability namely energy demand (i.e., energy access and utilization), energy supply (i.e., energy availability, and affordability), and energy footprint (i.e., energy intensity vs. energy efficiency, and energy eco-capacity). For energy footprint, we investigate energy resource exploitation and utilization by assessing characteristics including renewable (infinite) vs. non-renewable (finite), and sustainable (efficient) vs. unsustainable (inefficient). The energy footprint across countries and territories is examined using the composition of the energy portfolio, level of energy (in)dependence, and rate of environmental degradation (i.e., waste generation, resource depletion, and emissions). Consistent with SDG 6.4 of ensuring H_2O efficiency and sustainable H_2O withdrawals, we estimated H_2O stress dynamics by assessing the role of energy sector production in changing H_2O consumption efficiency and regeneration of H_2O resources. The energy-water stress EWS across country i, is expressed as:

$$EWS_i = f_N \left[{\mu WP_i}/_{(AWE_i * \mu RFR_i)} \right], AWE_i = (\mu AWI_i * 0.6475) \quad (3)$$

where μ represents the population mean, WP denotes water productivity (i.e., estimated as gross domestic product in 2010 US$ prices divided by annual total H_2O withdrawals), AWE is the annual freshwater withdrawals for energy production, AWI is the annual freshwater withdrawals for industrial use and RFR represents total renewable internal freshwater resources. According to UNESCO, industrial water utilization accounts for ~20% of freshwater withdrawals—of which an average of 63% is used for hydro and nuclear power generation, 1.75% (on average) for energy generation via thermal power plants, and the remaining for industrial processes (UNESCO, 2021). Using these approximations, the annual freshwater withdrawals for energy production is calculated by multiplying the annual freshwater withdrawals for industrial use by 0.6475. Though there are variations in water use for energy production, however, due to country-specific data limitations, we assume the global energy-driven water withdrawal value (i.e., 0.6475) is fixed for all countries and territories. The SDG 12.2 was evaluated to assess the progress of sustainable and efficient use of natural resources in production and consumption. We accounted for material footprint by estimating the sustainability of domestic material consumption expressed as:

$$FS_i = f_N\left({}^{\mu FFE_i}/_{\mu AED_i}\right) \tag{4}$$

where FS represents fossil stress, calculated using fossil fuel energy consumption FFE divided by adjusted savings of energy depletion AED. Fossil fuel encompasses coal, natural gas, oil and petroleum products while energy depletion accounts for the stock of coal, crude oil, and natural gas energy resources compared to its lifetime of remaining reserves. To examine the long-term impact of energy resource exploitation on future generations (i.e., energy security), we quantify for both energy deficit and energy reserve using our estimated benefit-cost formulation expressed as:

$$BC_i = f_N(\delta_i - \gamma_i) \tag{5}$$

$$\delta_i = \sum(CLN_i, ACC_i, CLE_i, INV_i) \tag{6}$$

$$\gamma_i = \sum(FS_i, EWS_i, EMI_i, IMP_i, INT_i) \tag{7}$$

where *BC* is the benefit-cost assessment to classify countries and territories into winners and losers of energy sustainability, δ_i represents the summation of SDG indicator scores with positive effects on energy sustainability whereas γ_i denotes score summation of SDG indicators with poor energy sustainability performance. The best energy sustainability performance indicators include access to clean fuels and technologies for cooking CLN, access to electricity ACC, consumption of nuclear energy, renewable energy, and combustible renewables and waste CLE, and investment in energy with private participation INV. In contrast, the poor energy sustainability performance indicators comprise fossil stress, energy-water stress, CO_2 emissions from fuel consumption, electricity and heat production, energy related CH_4 emissions, and N_2O emissions in energy sector EMI, energy imports IMP, and energy intensity INT. From equation 5, countries can be categorized under either energy deficit—if energy cost exceeds benefits or energy reserve—if energy benefits exceed energy cost. Due to differences in economic structure, production, consumption, and population dynamics across countries and territories, using a comparable metric, viz. normalization technique is critical for assessing SDG targets (Xu *et al.*, 2020). The function f_N in equations 3-5 denotes the normalization function for scoring a specific SDG indicator y' expressed as:

$$f_N \approx y' = 100(y - y_{min})/(y_{max} - y_{min}) \tag{8}$$

where y' represents the score of SDG indicator y via the normalization technique with scores ranging from 0-100 across countries over time. Thus, the lower bound (i.e., score 0) represents poor performance whereas the upper bound (i.e., score 100) represents best performance. Countries with score above 50 denotes transformation towards achieving best performance. Using this ratio, countries are ranked accordingly from pre-MDGs, MDGs, and SDGs periods––to ascertain the winners and losers of energy sustainability.

4.2.6 Country-specific effects

Here we use cross-country linear regression technique that controls for country-specific effects. The estimation technique has been used to investigate several within and between effects of economic dynamics on energy sector portfolio across several countries over specified periods (Hsiang, 2010). Contrary to historical periods used in existing literature, we adopt the periodic mean of sampled variables for the ease of graphical comparison across economies. The linear specification of the model can be expressed as:

$$\bar{y}_i = \bar{x}_i + \bar{z}_i \tag{9}$$

where $\bar{y}_i$ denotes the mean target variables [i.e., energy sustainability target (pros & cons), benefit-cost, energy intensity, access to electricity, access to clean technologies, composition of clean energy technologies, and energy-related GHG emissions] across economies i, $\bar{x}$ represents the independent variable, namely income level whereas $\bar{z}$ denotes income inequality, the effect size of the regression. The empirical scenario in equation (9) allows the assessment of the nexus between the dynamics of energy sustainability and average income level while accounting for the effect of income inequality across countries and territories.

4.2.7 *Income convergence*

Income homogeneity occurs in economies with similar economic structure, technology, and factors of production, hence, the likelihood of achieving economic convergence if growth in poor economies is faster than in wealthy economies (Tamura, 1991). This implies income level and technology spillover play a substantial role in achieving energy sustainability (Nordhaus, 2010). Using the updated version (2020-2021) of World Bank's country and lending group, 217 sampled economies are classified into similar income groups (World Bank, 2021b). Thus, using the atlas conversion factor, countries and territories are classified based on gross national income (GNI) per capita. The atlas conversion factor helps to control for domestic and international inflation-driven changes to a country's exchange rate (World Bank, 2021a). The income group classification entails—27 lower-income economies (≤$1045), 55 lower-middle-income economies ($1046-$4095), 55 upper-middle-income economies ($4096-$12695), and 80 high-income economies (≥$12696). Aside from country-specific rankings, the income convergence allows the assessment of energy sustainability across income groups compared to global ratings. The generic assessment of energy diversity, economic development, and GHG emissions across income groups can be expressed as:

$$g_j^R = \bar{k}_j^R \tag{10}$$

where g_j^R is the output proportion of SDG indicators R namely—energy use, global GHG emissions, rural access to electricity, urban access to electricity, GDP per capita, foreign direct investment (FDI) inflows, FDI outflows, renewable energy and fossil fuel energy consumption––across income groups and global ratings j (i.e., LIC, LMC, LMY, MIC, UMC, HIC, and WLD). $\bar{k}$ denotes the mean of input of SDG indicators used to calculate income group-specific output proportions.

4.3 Results

4.3.1 *Comparing pre-MDGs, MDGs, and SDGs*

To ascertain the progress towards achieving sustainable development, we compared energy sustainability dynamics from pre-MDG (1961-1999), MDG (2000-2015), and SDG (2016-2019) periods. Because past events foreshadow present and future occurrences, employing these assessment criteria and conceptualization are useful tools for policy formulation. Using meta-analytic statistical technique, we analyzed 20 data series (Supplementary Table 2) by comparing income-specific groups to global ratings. We find that access to electricity (i.e., rural and urban access) has increased substantially across income groups throughout the SDG era compared to both pre-MDG and MDGs (see Supplementary Figs. 1-6). In contrast, energy depletion (i.e., ratio of the stock of energy resources versus lifetime reserves) declined significantly during the SDG period compared to pre-MDG and MDGs. Among income groups, the SDG policies benefited low-income countries more than high-income countries, hence, improving lifetime reserves of energy resources. Failure of the MDGs to clearly highlight energy sustainability in the global policies may have worsened energy depletion, energy sector-related N_2O emissions, energy-related CH_4 emissions, and CO_2 emissions from electricity and heat production during the MDG era compared to pre-MDG periods (see Supplementary Figs. 1-6). To rule out the notion of global common shocks and equality (i.e., cross-section dependence and homogeneity) of energy indicators across income groups, we require energy indicators to be inconsistent across income economies—implying a high level of heterogeneity. In this way, the independence of SDG indicators can be properly examined. To achieve this, we used the inverse-variance estimation technique that captures income group-specific fixed-effects, thus, accounting for heterogeneity (see Methods). The forest plots showing the estimated results were constructed based on means of both experimental and control groups, effect sizes, corresponding confidence intervals, and percentage of overall weight for each data series (Supplementary Figs. 1-6). The test for θ denotes the overall effect sizes—expressed as the weighted average of variable-specific effect sizes with corresponding significance test of $H_0: \theta = 0$ reported as *p-value<0.01*. This implies the overall effect sizes of the sampled energy indicators are statistically and significantly different from zero. The homogeneity test between variables, $H_0: \theta_i = \theta_j$ is statistically significant at *p-value<0.01*, confirming heterogeneous effects (I^2) across variables. This infers sampled variables for energy sustainability across income groups have large heterogeneous (i.e., I^2>75%) characteristics (Higgins *et al.*, 2003). This confirms the expectation of a reverse output compared to standard empirical results. Thus, >90% variations in effect size estimation can be attributed to between-variable heterogeneity.

4.3.2 Assessing energy sustainability indicators

Unlike the MDGs, the SDGs (i.e., SDG 7) explicitly highlights the importance of achieving energy sustainability, which mainly comprises a combination of the energy portfolio, economics, and emissions. Using six decades of energy sustainability indicators, we observe the average share of renewables in the energy portfolio is higher in low-income countries (i.e., 68.7%) compared to the global average of 17.5%. However, the penetration of renewables in high-income countries (i.e., 8%) is lower than the global average (see Fig. 1a). Thus, LIC>LMC>LMY>MIC>UMC>WLD>HIC — implying developing countries have higher renewable energy adoption compared to developed countries (Fig. 2b). In contrast, the energy portfolio in high-income countries is dominated by fossil fuel energy (i.e., 87.5%), slightly higher than the global average of 83.6%. This order (i.e., HIC>WLD>UMC>MIC>LMY>LMC>LIC) infers that developed economies consume fossil fuels compared to developing economies (see Fig. 1b). Urban-rural access to electrification (i.e., 60% & 21.4%) is much lower in low-income economies compared to the global average of 95.5% (urban) and 71.7% (rural) [see Fig. 1d]. Lack of electricity access in low-income countries (Fig. 2c) may have mirrored the low level of income (<$650, Fig. 1c), low energy use (<400 kgoe, Fig. 1f), but high foreign direct investment inflows (Fig. 1e). The high-income level (Fig. 1c) and FDI outflows (Fig. 1e) in high-income economies could have been driven by access to electricity (Fig. 1d), high energy use (Fig. 1f), and dominance of fossil fuels (Fig. 1b) in the energy mix. Yet, the proportion of global GHG emissions is higher in low- & middle-income countries (27.6%) and middle-income (24.7%) countries compared to high-income countries (20%) but lower in low income (3%) and lower-middle-income countries (6.7%) [see Fig. 1g]. The score of population with access to clean fuels and technologies for cooking in high-income countries (score=98.80) far exceeds low-income countries by 8.5 times (score=11.60) [see Fig. 2a].

However, energy investment participation by the private sector is more visible in low- & middle-income countries (score=100) than in high-income countries (see Fig. 2d). Due to dependence on fossil fuels for economic activities, fossil energy stress is relatively high in developed economies than in developing economies (Fig. 2e). Energy-water stress is visibly high in low-income economies that depend on hydropower resources for energy generation (Fig. 2f). The benefit-to-cost ratio of energy sustainability across income groups is in the order MIC>LMY>UMC>HIC>LMC>WLD>LIC, implying the overall scores of energy sustainability is fairly high in middle-income countries compared to low-income economies (see Supplementary Fig. 7d,e,f).

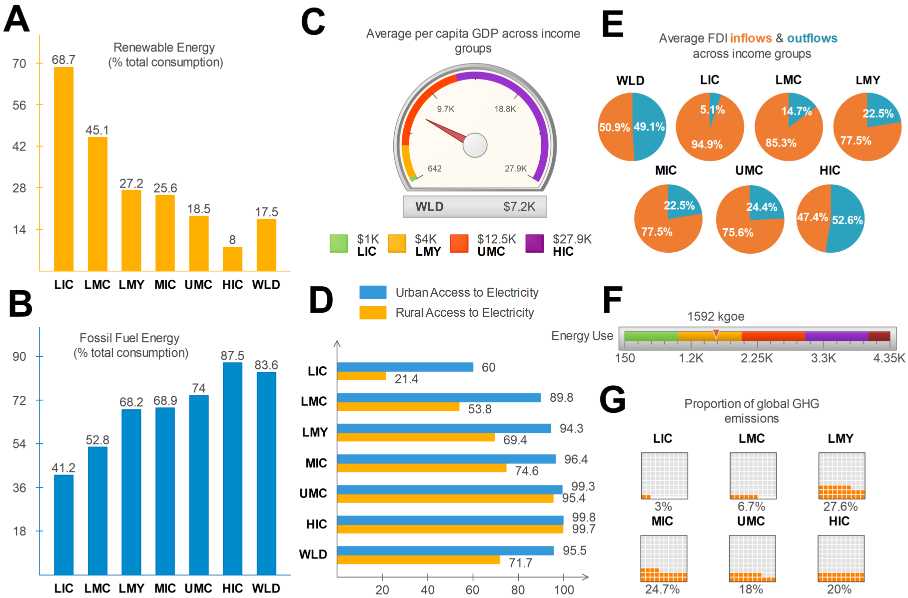


Fig. 1| Trends of energy diversity, economic development, and GHG emissions across income groups. (A) Renewable energy (B) Fossil fuel energy (C) Average income level (D) Access to electricity (E) FDI inflows and outflows (F) Energy utilization (G) Global GHG emissions. The estimates presented across income groups were computed using the mean from 1961-2019. *Income group abbreviations— global average (WLD), low-income countries (LIC), lower-middle-income countries (LMC), low- & middle-income countries (LMY), middle-income countries (MIC), upper-middle-income countries (UMC), and high-income countries (HIC).*

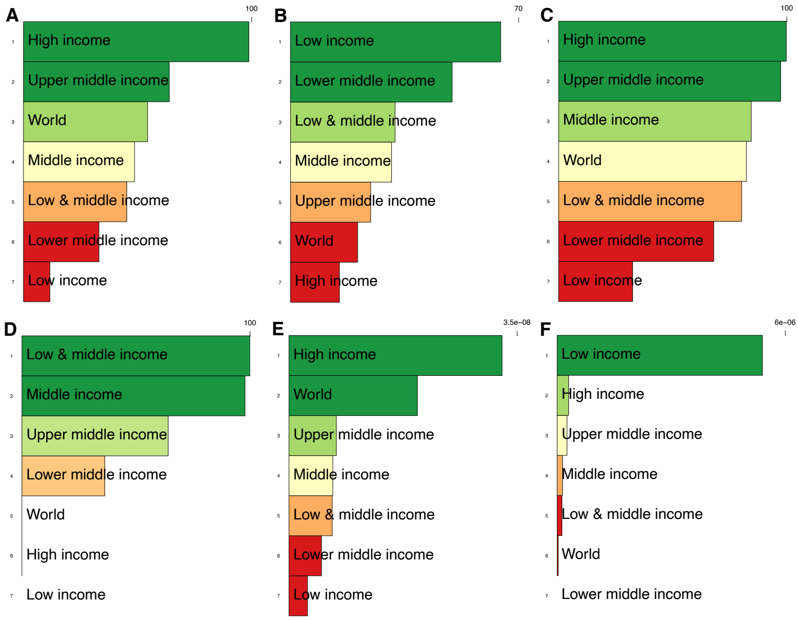


Fig. 2| Sustainability assessment of energy and its services across income groups (A) Access to clean fuels and technologies (B) Clean energy technologies (C) Access to electricity (D) Energy Investment (E) Fossil energy stress (F) Energy-Water stress. Legend: The indicators are estimated using the empirical procedure presented in the methods. Colors ranging from dark-green, lime-green, yellow, orange, and red represent the magnitude of estimated indicators in descending order. Missing filled-rectangular shape with white background (D and F) denotes missing data.

4.3.3 Spatial-temporal changes of SDG indicators

Using the country-specific estimated scores from 1961-2019, we spatially map the SDG indicators to capture energy sustainability performance. In assessing the level of clean fuels and technologies for cooking, we find developed countries have the best performance (score≥92) than most developing countries (Fig. 3a). Contrary, developing countries (i.e., DR Congo, Nepal, Ethiopia, Mozambique, Tanzania, Zambia, Nigeria, Cameroon, Niger, Myanmar, Paraguay, Haiti, Tajikistan, Kenya, Benin, Togo, Gabon, Cambodia, and Zimbabwe) have better performance (score≥73) in the adoption and utilization of clean energy technologies (i.e., renewable energy, nuclear energy, combustible renewables, and waste) compared to developed countries excluding Iceland, and Norway (Fig. 3b). However, access to electricity is fairly high (score=100) in high-income economies compared to low-income countries (Fig. 3c). Private participation in energy investment is limited to few countries including Brazil, India, Turkey, China, Russia, Indonesia, Lao, Mexico, South Africa, Morocco, Argentina, Thailand, Pakistan, Philippines, Romania, Vietnam, Algeria, Malaysia, Belarus, Peru, Bulgaria, Benin, Jordan, Egypt, Colombia, Ghana, Serbia, Zambia, Ukraine, and Nigeria (Fig. 3d). The over six decades of data used to assess fossil stress and energy-water stress show bad and worse performance across all countries and territories—a situation that has energy policy implications (Supplementary Fig. 9). We observe relatively high energy-related emissions (score≥73) in Bahrain, Kuwait, Qatar, Russia, Brunei Darussalam, Trinidad & Tobago, Poland, Saudi Arabia, Estonia, Oman, Libya, UAE, Equatorial Guinea, Hong Kong, Singapore, Kazakhstan, Czech Republic, and Bosnia and Herzegovina (Fig. 4a). The fairly high scores in Fig. 4b reveal the high energy required to produce one unit of output in Somalia (score=100), Liberia (score=77.50), Mozambique (score=74), and Ethiopia (score=70.10) — whereas the remaining countries and territories have scores below 69.

It is evident in Fig. 4c that 117 countries and territories are highly energy-dependent (score≥92), which infers energy importation to supplement domestic generation capacity. The highest energy importers (score=100) include Singapore, Malta, Hong Kong, Gibraltar, and Curacao (Fig. 4c). Using the sampled SDG indicators, we accounted for both pros (Fig. 4d) and cons (Fig. 4e) of energy sustainability targets before deriving the overall sustainability index, viz. benefit-cost (Fig. 4f). The pros element comprises factors that drive the agenda toward energy sustainability whereas the cons element derails the progress. Evidence from Fig. 4d shows 3 best-performing countries (Iceland, Norway, and Sweden), 54 better-performing economies, and 88 good-performing economies with SDG indicators that favor energy sustainability. In contrast, 142 economies are good performers (score≥44) of SDG indicators that disrupt the agenda toward energy sustainability (Fig. 4e). The overall sustainability index that examines the pros and cons of energy sustainability targets from 1961-2019 shows 13 good-performing economies, 73 bad-performing economies, and 131 worse-performing economies. For example, the winners making progress towards achieving energy sustainability include *inter alia*, Bahamas, Belize, Monaco, Norway, and San Marino whereas the losers of energy sustainability comprise *inter alia*, North Korea, Mozambique, Liberia, Hong Kong, and South Sudan (Fig. 4f). We corroborate the robustness of the constructed energy sustainability indicator using between-group visualization with statistical features (Patil, 2021). The output statistics in Fig. 5 show significant ($p\text{-}value<0.01$) mean differences in energy sustainability between income groups. The mean score of energy sustainability increases across income groups (Fig. 5). For example, the average scores in low-income, lower-middle-income, upper-middle-income, and high-income economies are 27.04, 39.52, 48.82, and 55.32. This implies growth in income and/or economic development increases energy sustainability.

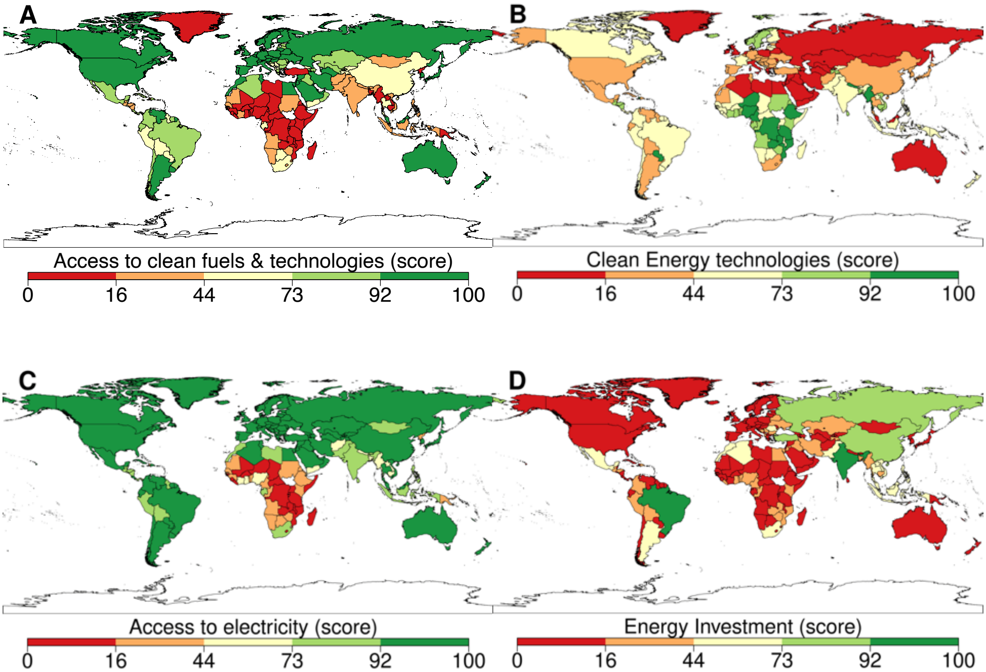


Fig. 3| Global sustainability indicators of energy and its services (A) Access to clean fuels and technologies (B) Clean energy technologies (C) Access to electricity (D) Energy Investment (E) Fossil energy stress (F) Energy-Water stress. Legend: The indicators are estimated using the empirical procedure presented in the methods. Colors ranging from red, orange, yellow, lime-green and dark-green represent the estimated indicators in ratio from 0-15.9 (worse), 16-43.9 (bad), 44-72.9 (good), 73-91.9 (better), and 92-100 (best), respectively.

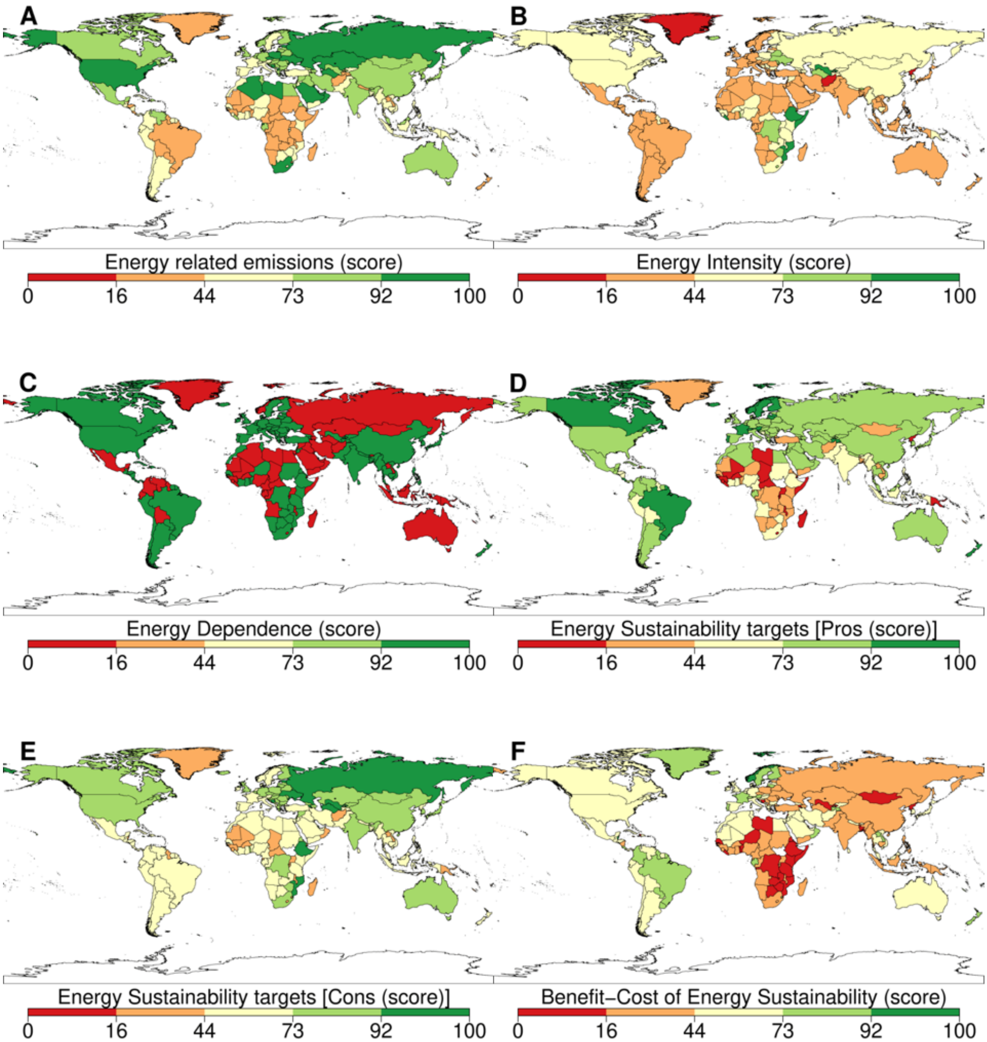


Fig. 4| Global sustainability indicators of energy and its services (A) Energy-related emissions (B) Energy intensity (C) Energy dependence (D) Pros of energy sustainability target (E) Cons of energy sustainability target (F) Benefit-cost of energy sustainability target. Legend: The indicators are estimated using the empirical procedure presented in the methods. Colors ranging from red, orange, yellow, lime-green, and dark-green represent the estimated indicators in ratio from 0-15.9, 16-43.9, 44-72.9, 73-91.9, and 92-100, respectively.

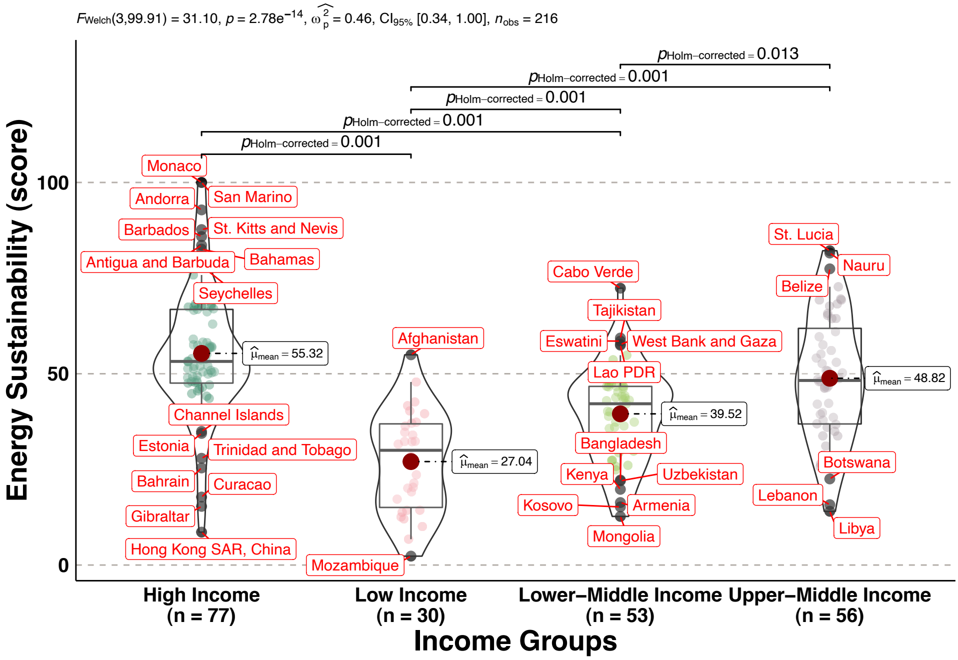
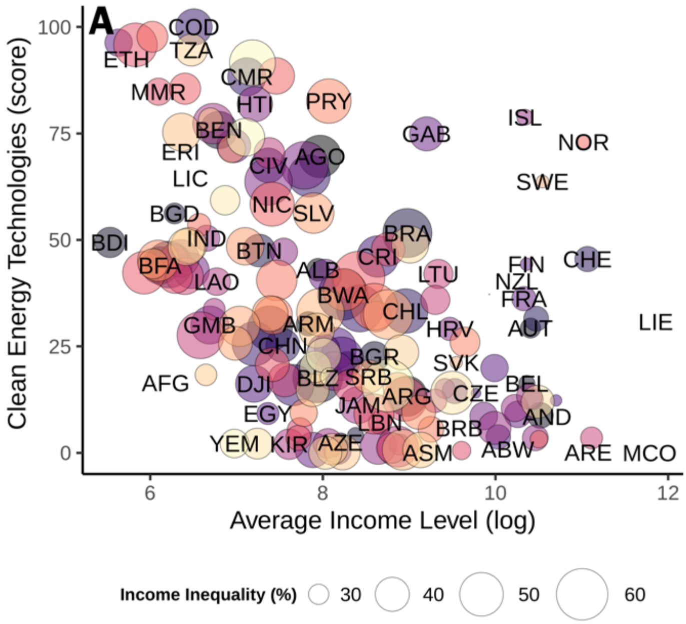


Fig. 5| Comparison of energy sustainability across income groups. The output statistics show significant (*p-value<0.01*) mean differences in energy sustainability between income groups.

4.3.4 Factors affecting energy sustainability

In line with SDG 8 and 10, we assessed the role of sustained economic development (i.e., income level and income inequality) in achieving energy resource efficiency across global economies. We find a negative monotonic relationship between energy intensity and average income level (Fig. 6a). Developing economies with high-income inequality, typically sub-Saharan Africa (i.e., *inter alia*, Ethiopia, Liberia, DR Congo, Burundi, and Zimbabwe) and Asian countries (i.e., *inter alia*, Uzbekistan, Bhutan, and Turkmenistan) have high energy intensity with corresponding low-income level. Contrary, developed economies (i.e., *inter alia*, Australia, United Arab Emirates, Bermuda, Japan, Liechtenstein, and Canada) with high-income levels and reduced income inequality have low energy intensity (Fig. 6a). The Z-shape relation in Fig. 6b shows income level and income inequality have little impact on SDG indicators that disrupt energy sustainability. However, a positive monotonic relationship can be observed between: income level vs. SDG indicators that promote energy sustainability (Fig.

7a); and income level vs. overall sustainability index (Fig. 7b). Low-income level and extreme inequality in developing economies namely *inter alia*, Mozambique, South Sudan, Burundi, Burkina Faso, Central African Republic, Liberia, Ethiopia, DR Congo, and The Gambia hamper efforts towards attaining energy resource efficiency, hence, affecting energy sustainability (see Supplementary Fig. 9b,c). Conversely, high-income countries with reduced inequality (i.e., *inter alia*, Israel, Norway, Switzerland, Finland, and Austria) have high readiness in fulfilling the SDG targets (Fig. 7a) while achieving energy sustainability (Fig. 7b).



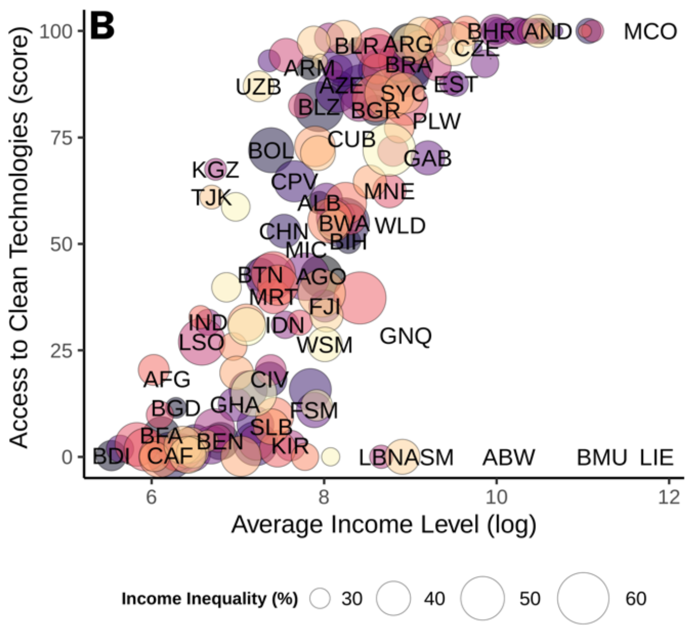


Fig. 6| Global nexus of sustainability indicators of energy and its services in income function while controlling for income inequality (A) Energy intensity (B) Cons of energy sustainability target. Legend: The trend indicates the relationship between sustainability indicators of energy and its services and average income level whereas the white filled-circles with black outline denotes the magnitude of income inequality. *See Supplementary Table 1 for interpretation of ISO 3166-1 aplha-3 country codes.*

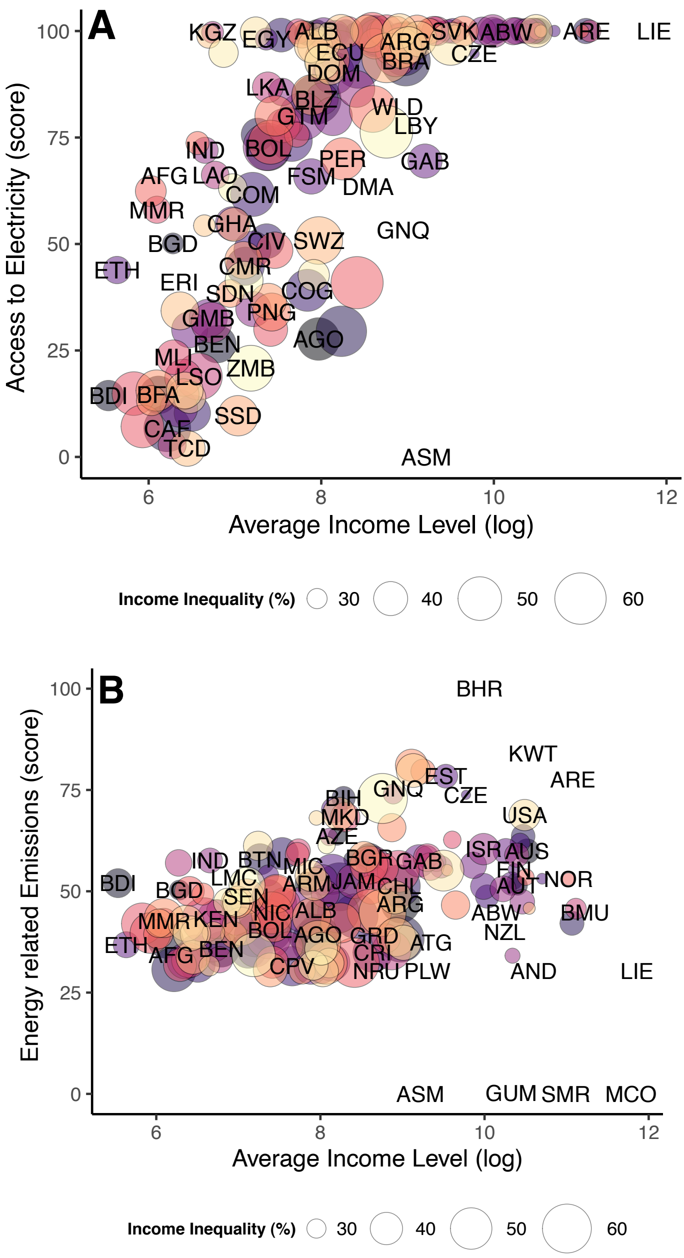


Fig. 7| Global nexus of sustainability indicators of energy and its services in income function while controlling for income inequality (A) Pros of energy sustainability target (B) Benefit-cost of energy sustainability target. Legend: The trend indicates the relationship between sustainability indicators of energy and its services and average income level whereas the white filled-circles with black outline denotes the magnitude of income inequality. *See Supplementary Table 1 for interpretation of ISO 3166-1 aplha-3 country codes.*

4.4 Discussion & conclusion

While it appears premature to elucidate winners and losers of energy sustainability, investigating the past, and present state of affairs serves as a key performance indicator for assessing progress towards attaining the SDG targets of the 2030 agenda. Though the MDGs failed to explicitly highlight energy sustainability, yet, energy played a crucial role in the achievement of several goals (Sovacool, 2012). Since the inclusion of energy and its services as the central theme of the 2030 agenda, mitigating climate change and its impacts through energy sustainability has become eminent. Experts argue that the complexity between energy and sustainable development entails systemic, demand, and supply-side management (Grubler *et al.*, 2018). Thus, assessing the complex global energy sector dynamics unveils the energy-SDG synergies and trade-offs. Contrary to the extant qualitative-based literature on SDGs (Nerini *et al.*, 2018), we provide an empirical-based assessment that examines the progress of energy sustainability from pre-MDG, MDG, and SDG periods.

There are over 2.6 billion people globally that depend on either kerosene, solid biomass (i.e., charcoal and fuelwood) or coal for heating and cooking purposes (IEA, 2020b). Evidentially, our empirical assessment shows access to clean fuels and technologies for cooking in developing countries is still limited. The estimated 11.6% population in low-income economies with access to clean cooking technologies is below the global adoption, averaging 54.5%. This implies attaining universal access to clean cooking by 2030 requires significant climate policy interventions including shielding poor households from the distributional burden of carbon taxation (Cameron *et al.*, 2016) and cost-effectiveness in switching from solid and carbon-intensive fuels to modern cooking fuels. Consistent with existing literature (Yadav *et al.*, 2021), improving income, access to reliable power supply, and reducing income inequality enhance the adoption of clean cooking options. Global access to electricity in both rural and urban areas has increased significantly on average from 75.3% to 84.7% since the inception of the SDGs. However, electricity access remains relatively low in low-income countries, specifically in rural areas of sub-Saharan Africa, which has affected electricity consumption, hence, leading to energy poverty. Consistent with our empirical findings, the lack of electricity in rural areas is attributable to income and inequality (i.e., sparse population density, high upfront cost, and lack of energy infrastructure like grid extension) (Szabó *et al.*, 2016). This implies the achievement of universal access to electricity, particularly in low-income economies requires both internal and external interventions including political will and commitment, external funding through FDI and technology spillover, and private sector investment (Sachs *et al.*, 2019). Private sector energy investment participation comprising generation, transmission, and distribution is quite evidential in low- & middle-income economies than in high-income countries. However, significant energy investments are still required in developing countries to improve infrastructures, boost power supply and increase access to attain SDG-7 (Foster *et al.*, 2010).

SDG-7 is not a magic bullet to achieving energy sustainability but depends on other SDGs with environmental and economic concerns (Taylor *et al.*, 2017). We find that low-income countries, typically sub-Saharan Africa have the highest renewable energy penetration (68.7%) with corresponding low fossil fuel consumption (41.2%) and low GHG emissions (3%), yet, far below (US$642) the global average income level (i.e., US$7,200). Though renewable energy sources are useful haven technologies for market price volatility, environmental and health impacts of climate change (Owusu *et al.*, 2016), however, experts argue of the challenges of renewables including the risk of resource competition, viz. land and water use intensity (Evans *et al.*, 2009). Decarbonization pathways that rely on nuclear power, concentrating solar power (CSP) deployment, carbon capture, and biofuel production may escalate water stress without robust water-saving and harvesting technologies (IEA, 2016a). It is estimated that about ~63% of industrial water utilization (i.e., freshwater withdrawals) is used for hydro and nuclear power generation, whereas 1.75% is used for energy generation via thermal power plants (UNESCO, 2021). While water consumption for renewable energy generation (particularly wind and solar PV) is considerably lower than fossil fuel-based power plants, land-use footprint (i.e., ~1.31-809.74 km^2/TWhr) is typically higher for renewables (Sarkodie & Owusu, 2020a; Trainor *et al.*, 2016). Africa produces less emissions but its energy portfolio is more vulnerable to climate change sensitivity and exposure, hence, faces challenging water legacies (i.e., "*hydrological variability and multiplicity of transboundary river basins*") that impede economic development (Foster *et al.*, 2010).

Our empirical analyses underscore the importance of addressing energy system - climate vulnerability that reduces pressure and trade-off between natural resources (i.e., domestic material, food, water, and land resources) and environmental threats (biodiversity loss, transboundary and domestic pollution) (Conway *et al.*, 2015). Though the SDG indicators assessed herein are mere tools and not a finality in itself, yet, provide a snapshot of progress towards attaining sustainable development from energy and environmental perspective—which has long-term policy implications.

Additional information

Supplementary information. Supplementary material available.

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Chapter 6. Paper 4: Global land-use intensity and anthropogenic emissions exhibit symbiotic and explosive behavior

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Author contribution

S.A.S designed the study, collected the data, performed the data analysis, coordinated and supervised the study. S.A.S and P.A.O drafted the manuscript. All authors reviewed the manuscript and approved it for submission. Thus, S.A.S contributed 90% whereas P.A.O contributed 10%.

Global land-use intensity and anthropogenic emissions exhibit symbiotic and explosive behavior [5]

Summary

The intensification of land-use is accelerating and remains a threat towards achieving environmental sustainability. While prior literature identifies unsustainable demand for resources as crucial to ecosystem vitality, here we highlight explosive behavior and entangled indicators associated with changing global land-use intensity and anthropogenic GHG emissions. We assess emission footprints, forestry, and agricultural land-use intensity across income groups using econometric models and data spanning 27 years (1990-2016). We find that long-term income growth above US$1005 per capita has mitigation effects on emissions whereas anthropogenic emissions stimulate the global expansion of land-use for agricultural and forestry activities. Urban expansion has a diminishing return on agricultural lands in developed countries, which may alter future agricultural production and food consumption. The top 5 countries with high deforestation rates (0.9-2.39%) include Mali, Uganda, Nigeria, Algeria, and Pakistan whereas hotspots of agricultural expansion include Vietnam, Niger, Mali, Indonesia, and Myanmar. The heterogeneous effects across countries demonstrate the need for domestic context, including cultural and historical factors, in assessing forest decline, agricultural expansion, and land-use intensity. The co-benefits of Reducing Emissions from Deforestation and Forest Degradation (REDD+) in developing economies are crucial to mitigating emissions while improving the livelihoods of forest-dependent populations.

6.1 Introduction

Global land-use intensity is a crucial driver of land degradation, which may pose threat to ecosystem vitality, leading to loss of natural habitat and changes in landscape (DiSano, 2002). Unsustainable land-use affects ecological composition including productive lands for forestry and agriculture, which has long-term impacts on biodiversity and emissions. While the global forest cover is improving compared to historical trends decades ago, agricultural expansion,

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[5] Published article: **Sarkodie, S.A.,** & Owusu, P. A. (2022). Global land-use intensity and anthropogenic emissions exhibit symbiotic and explosive behavior. *IScience*, 25(8), 104741. https://doi.org/10.1016/j.isci.2022.104741

deforestation, and land degradation remain a threat to land conservation in developing countries, especially low-income economies. For example, the global forest area declined from 32.5% to 30.8% (i.e., 178 million ha) between the periods 1990-2020 due to human-induced changes such as agricultural expansion (FAO, 2020). While South America observed an unprecedented decline in forest area spanning 1990-2010, Africa witnessed the highest net loss of forest area between 2010-2020, whereas the highest net gain between 2010-2020 occurred in Asia (FAO, 2020). However, climate change mitigation and adaptation in agriculture, forestry, and land-use are intertwined via feedback mechanisms, synergies, and trade-offs (Krystal Crumpler *et al.*, 2021; Smith *et al.*, 2010). This implies sustainable land-use management (agroforestry, land-based mitigation options, and integrated landscape approach) is a key adaptation measure to reduce anthropogenic emissions and climate change vulnerability (Hosonuma *et al.*, 2012; Rosenzweig *et al.*, 2007; Verchot *et al.*, 2007). However, a trilemma exists between agricultural land expansion, forestry, and GHG emissions, which are driven by population growth, economic development, and urbanization. The global population is increasing with increasing demand for food and resources for economic benefit, yet conservation practices require sustainable forest management to limit the rising levels of emissions. The complex nexus between climate change, socio-economic and ecological systems require attention due to the threat of climate change and its impacts on sustainable development (Denton *et al.*, 2014).

While the extant literature has reported spatial-temporal trends of ecological portfolio, and trade-embodied drivers of ecological resources (Hoang *et al.*, 2021), no study comprehensively assessed the symbiotic relationships existing between land-use intensity, demo-economics, and changes in emission levels. Understanding these dynamic relationships are crucial to unearth historical trends useful to develop conceptual tools for climate change adaptation and mitigation of climate vulnerability. Second, country-specific, regional, and other global crises including the recent Covid-19 pandemic, and economic recessions affected business-as-usual which shifted production and consumption, leading to explosive behaviors across countries. These episodes of explosive behaviors that capture extremes are indicative of climate change and land-use intensity. Besides, this explains unusual events in emission patterns, resource and biodiversity exploitation (deforestation, land degradation, ecological footprint, and domestic material consumption) that often contradict existing fundamental patterns. Yet, global multi-region input-output (MRIO) models may fail to capture explosive behaviors that are significant to tilt the balance between production and consumption. Here, we ask the following research questions using 27-years of data: (a) what are the drivers of global anthropogenic emissions and land-use intensity? (b) what are the feedback mechanisms, synergies, and trade-offs that underpin emission reduction from agricultural land, forestry, land-use? (c) What are the current trends of ecosystem dynamics across countries (identifying winners and losers)? We use novel econometric techniques to examine global symbiotic relationships, and date-stamping explosive behaviors existing between land-use intensity, demo-economics, and changes in emissions. Using dynamic panel models that capture cross-section dependence, heterogeneity, nonlinearity, and chaotic functions allow to capture the complexities of climate change across countries and income groups. Our study identified episodes of explosive behavior highlighting country-specific events of influx or excesses in emissions, land-use intensity, urban sprawl, and income. We opine that these unusual periods of extremely low or high trends could have been triggered by country-specific economic structure and disparities in income distribution.

6.2 Results

6.2.1 Current trends of ecosystem dynamics

To assess performance, we use a normalization scale [0, 100] to develop country-specific scores from average changes of sampled variables over the 27-year period. For comparison, we categorize performance scores of countries based on income groups (Fig. 1). While average income level improved (between 0.13-2.25%) in all economies regardless of income group, Iraq, an upper-middle-income country in Middle East and North Africa observed the highest gain in income by 2.25% whereas Niger, a low-income country in Sub-Saharan Africa observed the lowest increase by 0.13%. GHG emissions witnessed an increase in developing countries typically low-income economies—Niger, Pakistan, Afghanistan, Ethiopia, and Mozambique are identified as the top 5 hotspot countries with rising anthropogenic emissions by 1-1.97% (score=70.10-100). In contrast, China, India, DR Congo, Germany, and Cameroon saw an average decline in yearly GHG emissions by 0.49-0.97% (score=0-16.05). The yearly expansion in agricultural land-use by 0.24-0.72% (score=52.92-100) can be observed in low-income and lower-middle-income economies in East Asia & Pacific, and Sub-Saharan Africa. The top 5 gainers in agricultural land include Vietnam, Niger, Mali, Indonesia, and Myanmar whereas the top 5 losers (i.e., declined by 0.15-0.30%) include Canada, Australia, Poland, Italy, and Iran. The yearly average urban population grew in almost all countries except Russia, and Poland with stabilized growth (0%), whereas Ukraine, and Romania declined by 0.02-0.04%. Conspicuously, the rate of urban population growth was higher in Sub-Saharan Africa, occupying the top 5 hotspots (i.e., Uganda, Burkina Faso, Angola, Mali, and Tanzania), and 7-15 countries. Yet, countries with low urban population growth are located in North America, Europe, and Central Asia, and are predictably high-income economies. Top 5 countries that saw potential deforestation, viz. decline in forest area by 0.9-2.39% include Mali, Uganda, Nigeria, Algeria, and Pakistan whereas Niger, Syria, Vietnam, China, and Iran observed yearly average improvement/expansion in forest area by 0.34-61.09% (Extended Data Fig. 1). Niger is singled out in Extended Data Fig. 1 due to potential explosive behavior observed over the time period. While historical trends show a decline in forest area, average yearly change reports otherwise, due to unusual decline in 2005 by 106% and sudden rebound effect by 1,780.7% increase in 2006, hence, showing a conspicuous behavior requiring attention. The high rate of deforestation (i.e., a decline in forest area) in low-income economies is driven by poverty, high demand for forestry products and resources to meet energy demands for cooking and heating purposes (Koop *et al.*, 2001). Fuelwood charcoal and timber logging are reported as the main determinants of forest degradation in Africa whereas timber logging is the primary driver of forest degradation in subtropical Asia and Latin America (Hosonuma *et al.*, 2012). Besides, agrarian economies often exploit forest resources through legal or illegal trade to improve economic productivity, especially among poor communities whose livelihood depends on. For example, illegal logging of wood, specifically extinction species such as rosewood has become popular in sub-Saharan Africa due to its high price value and demand in international markets (Barrett *et al.*, 2010). Thus, these activities serve as a conduit for spillover of emissions and deforestation embodied trade (Hoang *et al.*, 2021). In contrast, high-income countries are mostly high-tech and service-based economies, hence, depend less on environmental capital including forestry products (Ewers, 2006).

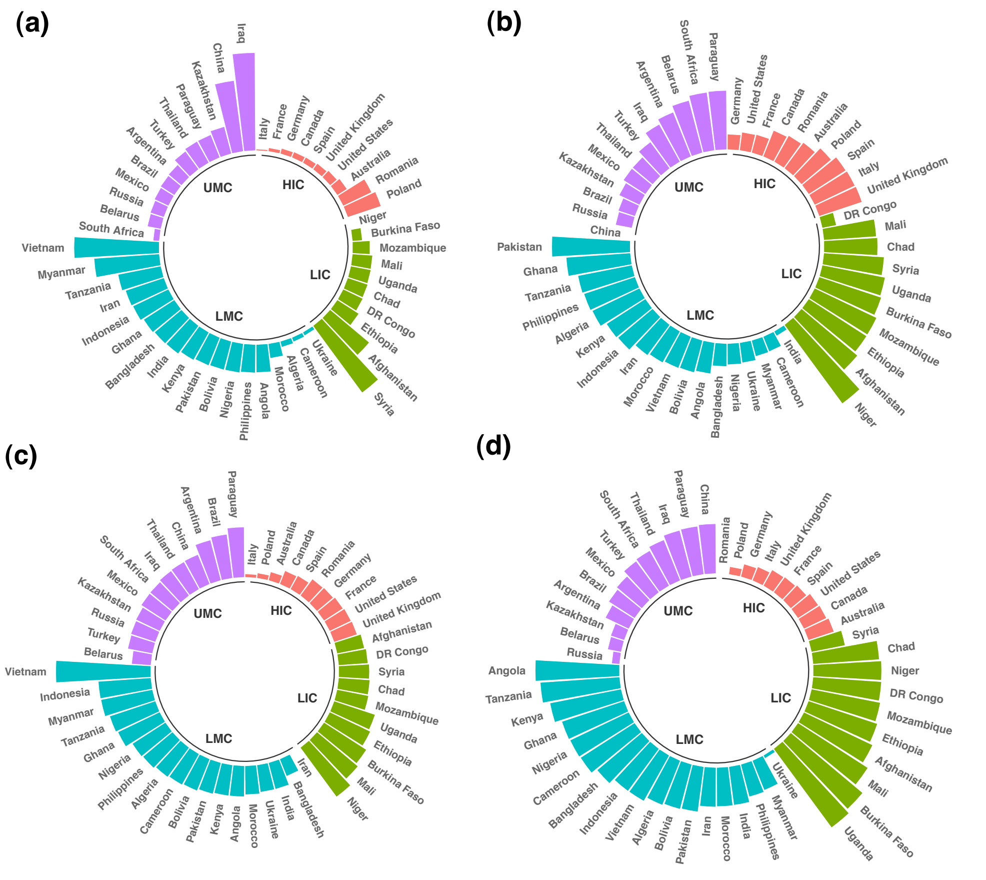


Fig. 1| Country-specific average change from 1990-2016 (a) income (b) GHG emissions (c) Agricultural land-use (d) urbanization. LIC, LMC, UMC, and HIC represent low-income countries, lower-middle-income countries, upper-middle-income countries, and high-income countries. We use a normalization scale [0, 100] to develop country-specific scores from average changes over the sampled time period.

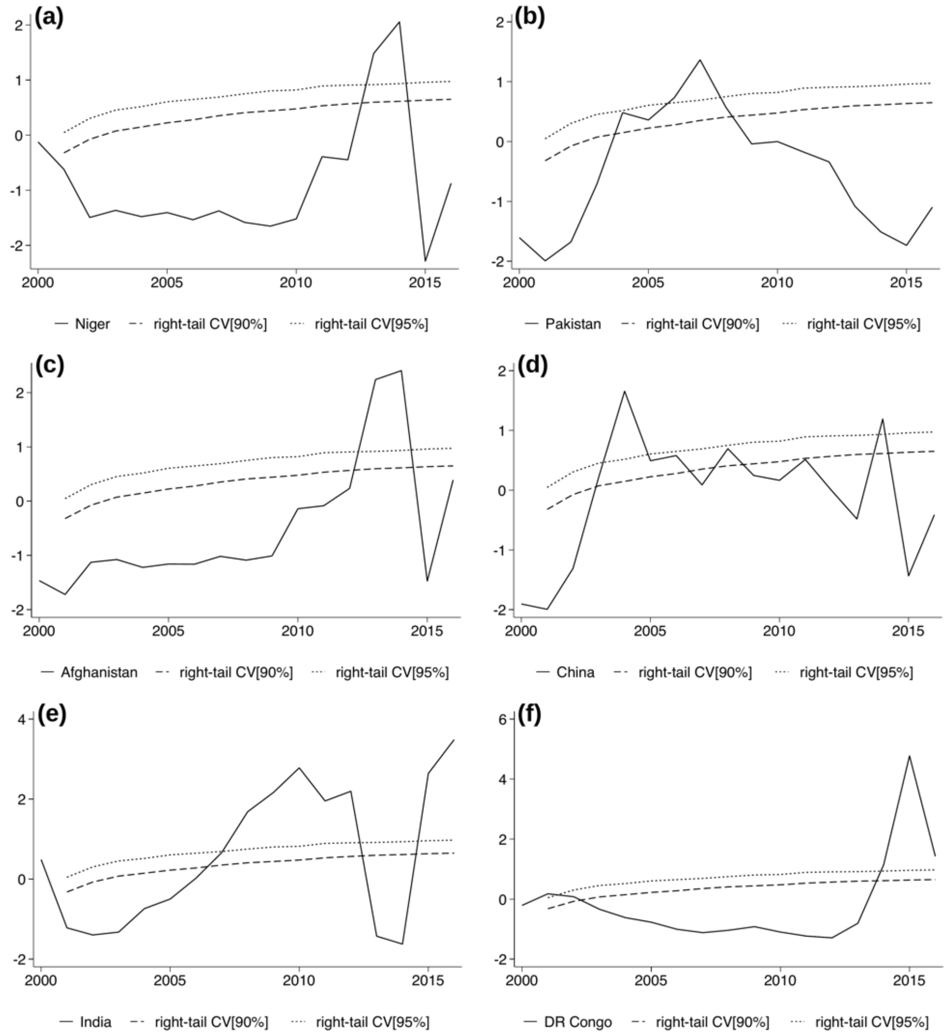


Fig. 2| Date-stamping explosive behavior of GHG emissions in top 3 low-performing and high-performing countries using BSADF test (a) Niger (b) Pakistan (c) Afghanistan (d) China (e) India (f) DR Congo. Episodes of explosive behavior occur in 2013-2014 (Niger), 2006-2007 (Pakistan), 2013-2014 (Afghanistan), 2004, 2014 (China), 2008-2012, 2015-2016 (India), and 2001, 2014-2016 (DR Congo). Explosive behaviors are assessed using backward supremum ADF (BSADF) test based on recursive window widths for data-stamping of episodes.

6.2.2 Date-stamping explosive behavior

The unusual trend observed among variables across time periods reveals the existence of dynamic properties requiring further estimation. Explosive behavior of economic indicators often trickle-down to socio-demographic and environmental variables during distress or crises. Thus, explosive behavior may cause sampled variables to deviate from their fundamentals leading to “bubbles”. To account for this unusual behavior, we use the novel backward supremum right-tail augmented Dickey-Fuller unit root technique based on recursive window widths for data-stamping of episodes (Baum *et al.*, 2021; Phillips *et al.*, 2011). The estimation technique is applied to the top 3 low-performing and high-performing countries of sampled variables (i.e., GHG emissions, forest, and agricultural land) to examine for potential explosive behaviors (Fig. 2, Extended Data Fig. 2, Extended Data Fig. 3). We observe a rejection of the null hypothesis of unit root corresponding to the right-tail 90-95% confidence interval, implying the existence of varying periods of explosive behavior across sampled countries. In Fig. 2, one episode of explosive behavior in GHG emissions is observed in Niger (2013-2014), Pakistan (2006-2007), and Afghanistan (2013-2014) whereas two episodes are detected in China (2004, 2014), India (2008-2012, 2015-2016), and DR Congo (2001, 2014-2016). The unusual rebound effect of forest expansion detected in Niger is corroborated with two episodes of explosive behavior occurring in 2001, 2009-2016 (Extended Data Fig. 2). However, no evidence of explosive behavior is found for Nigeria and Syria in the forest model (Extended Data Fig. 2) and Iran in agricultural land model (Extended Data Fig. 3). Similar episodes of explosive behavior are confirmed among sampled variables using the US as a benchmark (Extended Data Fig. 4). The validation of explosive behavior of sampled variables across the top 3 low-performing and high-performing countries is suggestive of heterogeneous and/or nonlinear behavior driven by unobserved factors. This infers the adoption of business-as-usual estimation techniques for variables exhibiting sensitive behaviors may be erroneous. The identified episodes of explosive behavior highlight country-specific events of influx or excesses in emissions, land-use intensity, urban sprawl, and income. These unusual periods of extremely low or high trends could have been triggered by country-specific or global financial crises.

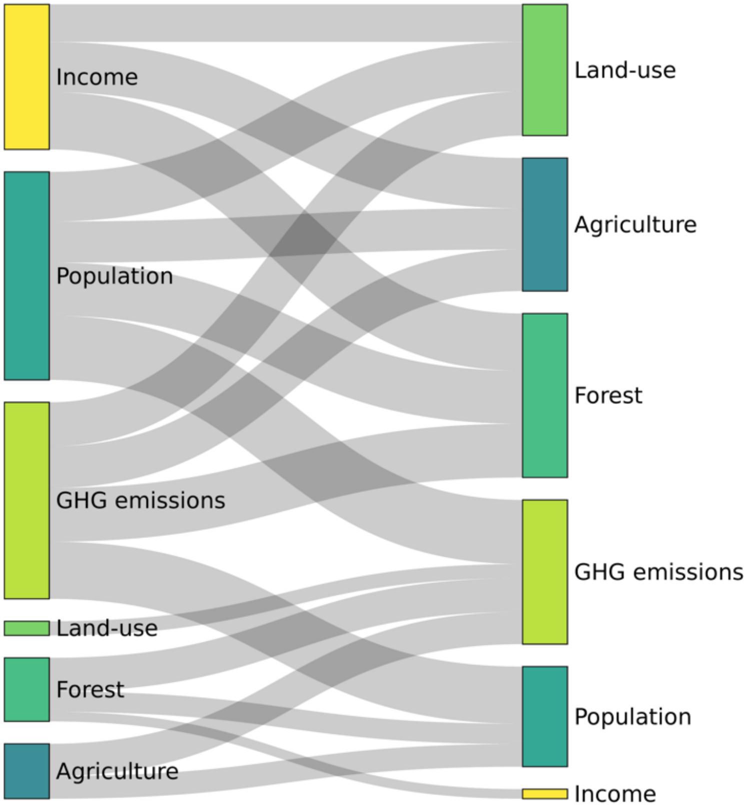


Fig. 3| Symbiotic relationship among sampled variables across countries**.** The parameters were estimated using convergent cross-mapping technique to examine causal-effects. The Sankey diagram presented shows the predictor (left) to target (right) causal relationship. We only presented causal effect relationships that are statistically significant. The arrow represents the causal links with width proportionate to the weight/coefficient of the flow whereas the rectangles with corresponding texts are the nodes.

6.2.3 Assessment of symbiotic relationships

Due to limitations of standard empirical techniques to examine dynamic systems with complex, nonlinear, and chaotic functions, we employ the nonparametric convergent cross-mapping (CCM) algorithm (Li *et al.*, 2021) to assess causality by mimicking biological symbiotic relationships. Contrary to standard econometric techniques that predict outcomes using causes, the CCM algorithm employs the reverse—arguing that the search for causes, in reality, begins with an outcome to ascertain whether its dynamic structure is embedded with the signature of a cause (Schiff *et al.*, 1996). Additionally, we control for transitivity and external forcing of non-coupled series that exists in ecological systems. Thus, the CCM models presented herein account for complexities that are problematic in the literature that examine causations (Sugihara *et al.*, 2012). The validation of causality infers the paired variables share information about a common dynamic system that underpins the direction of causality (Sugihara *et al.*, 2012). The Sankey diagram presented in Fig. 3 shows statistically significant causal networks among sampled variables. The unidirectional coupling observed from income to land-use, income to agriculture, and population to land-use shows commensal or amensal relationships that have policy implications. This confirms the effect of urban population on land-use, and the influence of income on land-use, and agriculture. In contrast, bidirectional coupling is validated between GHG emissions and land-use, GHG emissions and forest, GHG emissions and urban population, GHG emissions and agricultural land, agricultural land and urban population, income and forest, and forest and population. These mutualistic relationships validate known feedback mechanisms in biological systems where organisms are mutually dependent on each other.

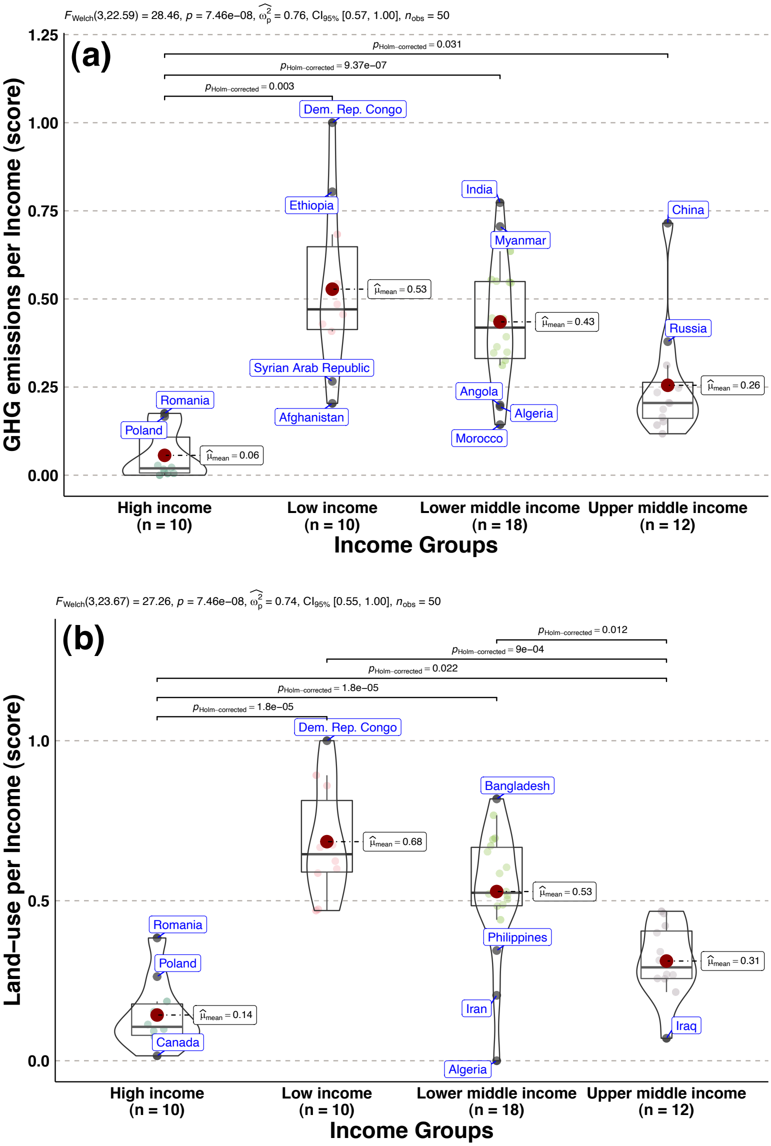


Fig. 4| Distribution of across income groups (a) GHG emissions per Income (b) Land-use intensity per Income. The pairwise test using Games-Howell technique shows only statistically significant comparisons. (•) represents the within mean across income groups. The output of the frequentist analysis F_{welch} (.) = #, p = #, $\widehat{\omega_p^2}$ = #, $CI_{95\%}$ [#, #], n_{obs} = # denote the parameter test statistic, significance of the p-value, estimate of the effect size, confidence interval, and number of observations.

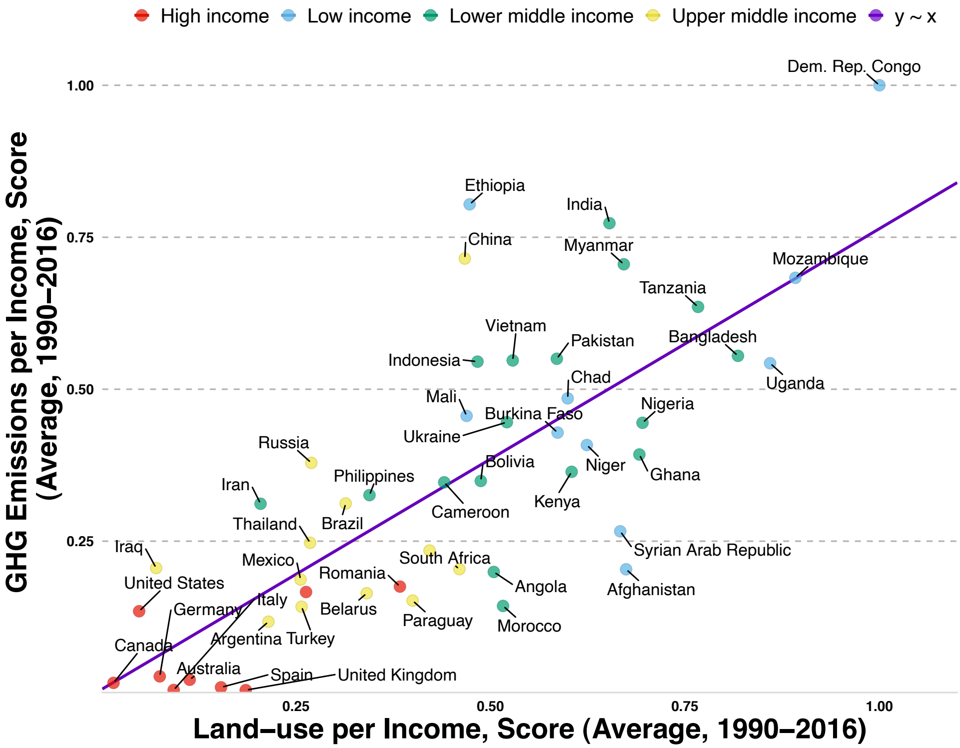


Fig. 5| Relationship between GHG emissions per Income and land-use intensity per Income across income groups. Both population and income dynamics are accounted for in both variables, hence, showing a positive monotonic relationship that validates the feedback coupling mechanism of GHG emissions and land-use in the convergent cross-mapping causality.

6.2.4 Predictors of changes in land-use

Accounting for decadal effects of income level on land-use intensity and anthropogenic GHG emissions using Games-Howell pairwise test (Patil, 2021) across income groups provides statistically significant between-group comparisons. Based on Welch's parametric one-way ANOVA hypothesis testing, several country-specific means are compared without restrictions on equal sample variances (Welch, 1951). In the output distribution plots, we use outlier tagging to detect extremely high and low performance across income groups. A visual inspection of Fig. 4 confirms the statistical evidence showing the ranking: low-income>lower-middle-income>upper-middle-income>high-income. This infers the within-mean of low-income countries is higher than their counterparts in both emissions and land-use models.

Another observation is that economies with low-income levels have higher GHG emissions and land-use intensity whereas high-income countries exhibit low emissions and land-use intensity. For example, DR Congo produces higher GHG emissions per income whereas Afghanistan is the lowest emitter per income in low-income countries (Fig. 4a). Countries with low-income levels often depend on vintage technologies for agriculture, forestry, and land-use, with little or no sustainable practices and environmental consciousness—which coincides with pollution-driven growth trajectory at early stages of economic development (Sarkodie *et al.*, 2019). In contrast, Romania exhibits the highest land-use intensity per income whereas Canada is the lowest land-use per income economy in high-income countries (Fig. 4b). To further strengthen the argument, Fig. 5 examines the relationship between GHG emissions and land-use by accounting for both population and income dynamics. The resultant nexus shows a positive monotonic relationship that validates the distribution plot and feedback coupling mechanism of GHG emissions and land-use in the convergent cross-mapping causality. In a similar ranking, while high-income economies are associated with low emissions and land-use intensity, low-income economies including inter alia, DR Congo, Mozambique, and Uganda have close linkage with high land-use intensity and GHG emissions (Fig. 5). In another scenario (Extended Data Fig. 5), the effect of urban population on land-use intensity is glaring, showing that income group with high urban population has lower land-use intensity whereas countries with low urban population rate have higher land-use intensity. A similar study found little impact of urban expansion on land-use intensity, viz. forest degradation in Africa and Latin America, yet, the impact is high as anticipated in Asia (Hosonuma *et al.*, 2012). Noticeably, the lowest change in agricultural land in low-income countries far exceeds the highest agricultural land change in high-income economies. This describes a potential diminishing return of agricultural land in developed countries, altering agricultural production.

6.2.5 Drivers of anthropogenic emissions and land-use

To examine relationships that identify determinants of GHG emissions, agriculture, forestry, and land-use, we adopt panel dynamic estimation techniques that investigate global common shocks, spillover effects, heterogeneous effects, and controls for both endogeneity and omitted-variable bias. We use the panel bootstrap corrected fixed-effects regression based on cross-section dependence resampling and analytical heterogeneous initialization to achieve convergence (De Vos *et al.*, 2015). We observe significant (*P-value*<0.01) inertia effects in historical anthropogenic emissions that predict future rise in GHGs (Fig. 6, Extended Data Fig. 6). This explains why 60% (30/50) of the sampled countries including 11 of 15 Sub-Saharan Africa economies show positive yearly average in emission levels. Due to the absorptive capacity of forests and crops, rising levels of anthropogenic GHG emissions significantly (*P-value*<0.05) trigger global expansion of land-use for agricultural and forestry activities (Extended Data Fig. 7). We find evidence of global shift from forestry to agricultural land-use, which may have been triggered by the increasing global demand for food to control threats of food insecurity—that permeates many low-income economies. Our model provides statistically significant (*P-value*<0.05) evidence supporting the escalation effect of urban population on GHG emissions, land-use (Extended Data Fig. 7), and agricultural land (Extended Data Fig. 8a), but has mitigating effects on forest land-use (Extended Data Fig. 8b). While urbanization is a threat to future land allocation, we identify opportunities for reducing forest loss with improved innovation and technology. The yearly fixed-effects predict (*P-value*<0.01) future forest expansion as innovation increases over time (Extended Data Fig. 9b), evidenced in several countries excluding Kazakhstan and Niger (Extended Data Fig. 9a). Such predicted threat of forest loss, aside from low forest cover in Kazakhstan may be linked to the failure to address climate change in forest policies (Sehring, 2012). The biological diversity loss of forest in Niger can be associated with degradation due to agricultural expansion, inadequate forest management, immature harvesting of forest products, and climate change driven desertification and wildfires (WA BiCC, 2020). Growth in income level exhibits insignificant positive effect on forest, but insignificant negative effect on land-use intensity. Contrary, income growth significantly (*P-value*<0.01) spur GHG emissions and agricultural land-use, however, the coefficient (*P-value*<0.01) on the quadratic of income is negative in both emissions and agricultural land-use models. This implies that income level exhibits a parabolic shape, hence, has diminishing effects on GHG emissions and agricultural land-use. From the estimated slope relationship, 1% growth in income exacerbates GHG emissions by 0.74% and agricultural land-use by 0.12%. Using the approximation [$\widehat{\beta_1 GD}P/-2\widehat{\beta_2 GD}P^2$], the turning points for both models are calculated as 6.912 (in log) for GHG model and 7.333 (in log) for agricultural land-use model. This infers the return to income level becomes zero at ~US$1005 per capita in GHG model and ~US$1530 per capita for agricultural land-use model. This has policy implications as the income data shows about 64% of countries have average income levels above the turning point in the GHG model whereas 52% of economies are beyond the extremum point in the agricultural land-use model. Our model reveals the possibility of income level increasing anthropogenic GHG emissions until it reaches an extremum point of U$1005 per capita and declines thereafter. While the seemingly low turning points may have been influenced by the dominance of low- and lower-middle-income countries sampled in the model, many of these countries are still below the extremum point. This describes extreme income inequality where a large population in low-income countries are poor, hence, averaging income level affect the few wealthy population. Countries with average income below the turning point in the GHG model include Nigeria, Afghanistan, Pakistan, India, Ghana, Kenya, Vietnam, Bangladesh, Myanmar, Mali, Chad, Tanzania, Burkina Faso, Uganda, Mozambique, Niger, DR Congo, and Ethiopia. Similarly, income growth escalates agricultural land-use intensity until a turning point of U$1530 per capita before declining. Other countries below the extremum point in the agricultural land-use model including the listed economies in the GHG model comprise Indonesia, Philippines, Angola, Syria, Bolivia, and Cameroon.

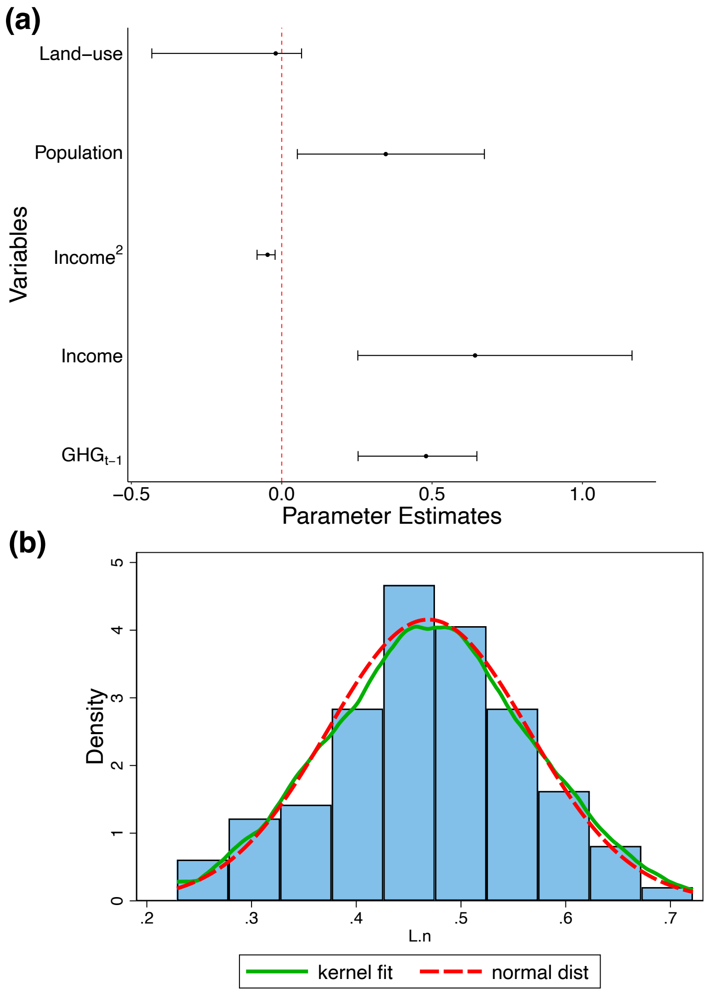
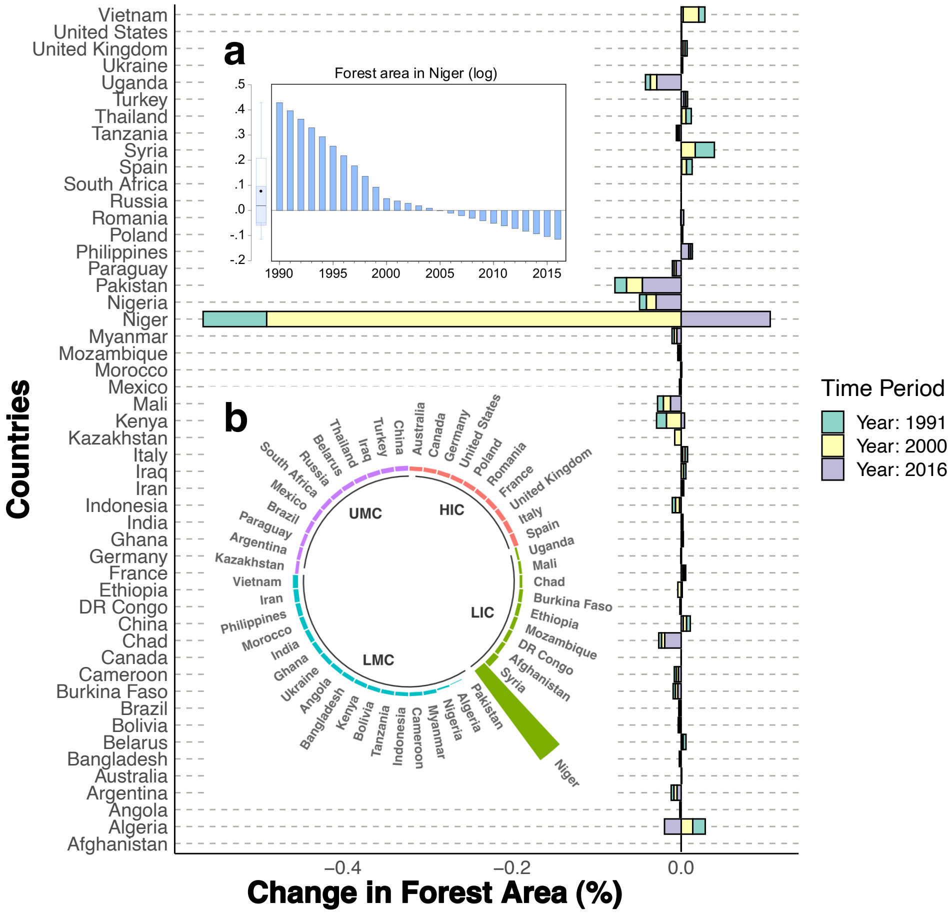
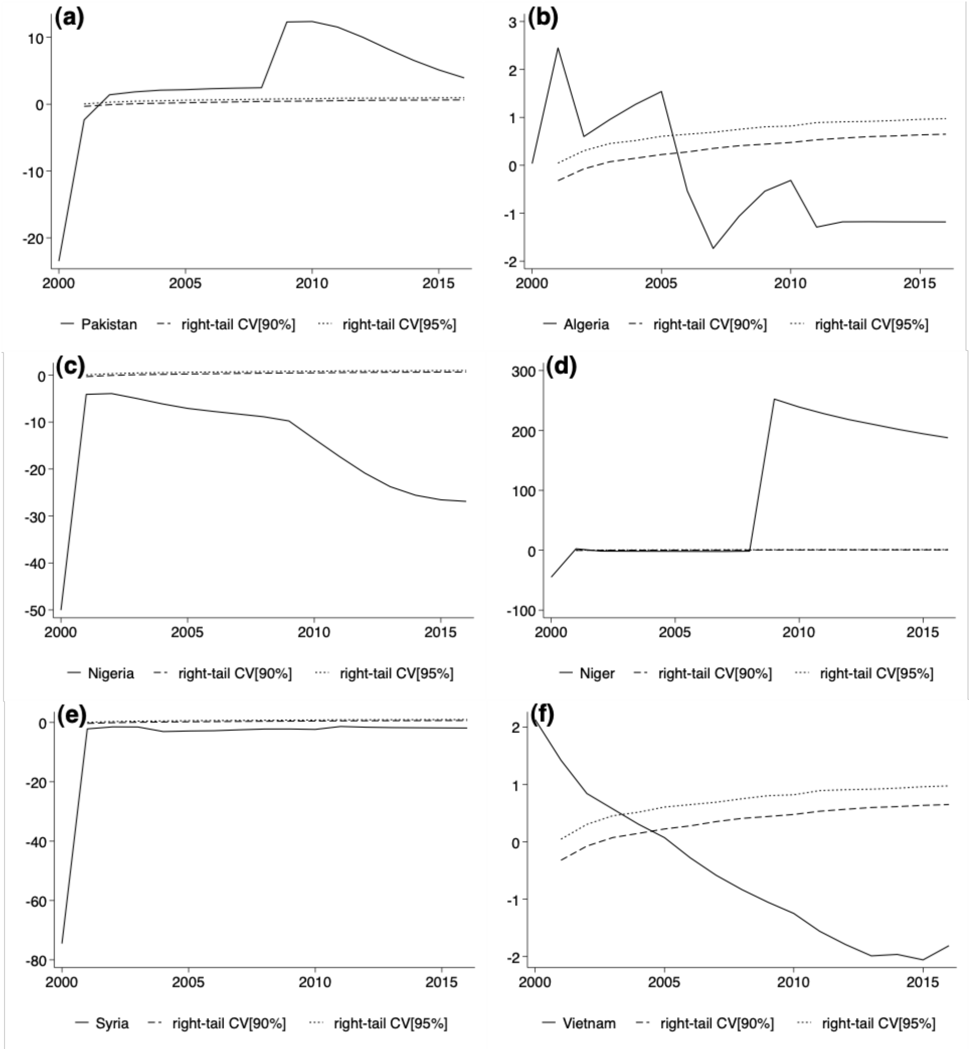


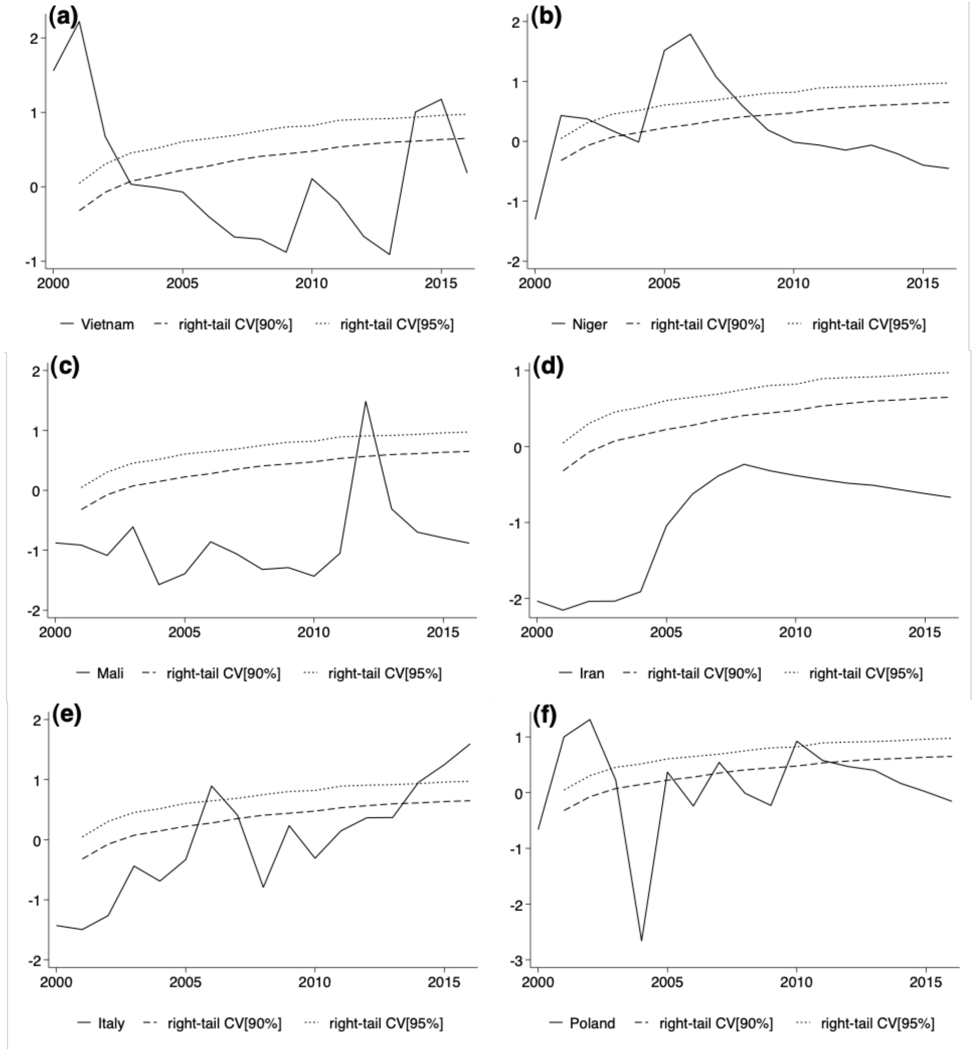
Fig. 6| Parameter estimation (a) GHG emissions, income, and land-use (b) Model validation using bootstrap distribution for all autoregressive coefficients. A visual inspection of the histogram shows that the bootstrap-simulated distribution is normally distributed, which is informative for investigating residual stationarity. The parameter estimates of all variables excluding land-use are statistically significant at *P-value*<0.05. The heterogeneous slope testing—Standard delta test $\tilde{\Delta}$ (9.030, *p<0.01*), adjusted delta test $\tilde{\Delta}_{adj}$ (10.240, *p<0.01*), and HAC robust delta test $\tilde{\Delta}_{HAC}$ (3.664, *p<0.01*), confirms heterogeneous effects across countries. Bootstrap corrected dynamic fixed-effects regression (n = 1300) based on cross-section dependence resampling and analytical heterogeneous initialization to achieve convergence. The estimated model has bootstrapped standard errors, bootstrap 95% (percentile-based) confidence intervals, and statistical inferences performed with non-parametric bootstrap. Residual diagnostics: CD-test (-0.23) & *p-value* (0.821); Pesaran's CADF test (-1.375) & *p-value* (0.998).



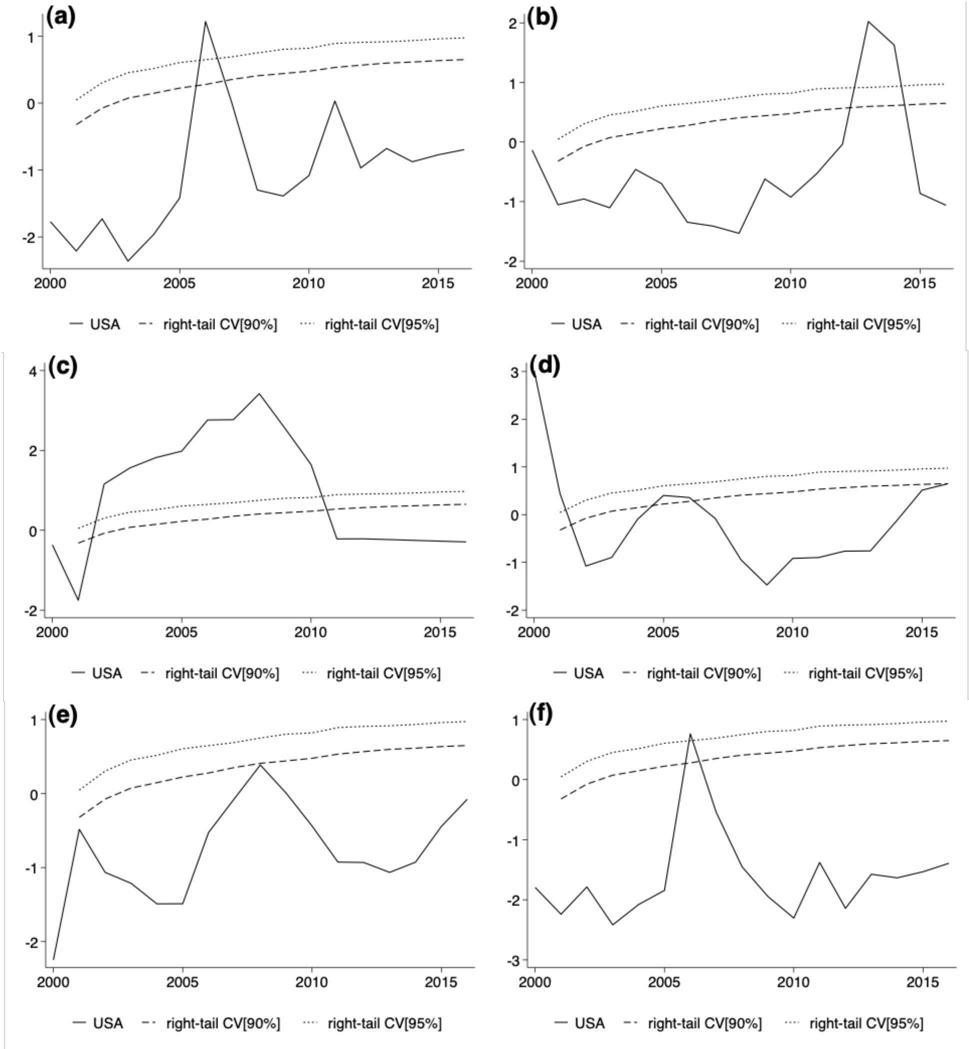
Extended Data Fig. 1| Percentage change in forest area by comparing 1991, 2000, and 2016 time periods. The inside plot (a) represents the log historical trend of forest area in Niger (b) denotes country-specific average change in forest area from 1990-2016. LIC, LMC, UMC, and HIC represent low-income countries, lower-middle-income countries, upper-middle-income countries, and high-income countries. Niger is singled out due to potential explosive behavior observed over time. While historical trends show decline in forest area, average yearly change reports otherwise, due to unusual decline in 2005 by 106% and sudden rebound effect by 1,780.7% in 2006, hence, showing a conspicuous behavior requiring attention.



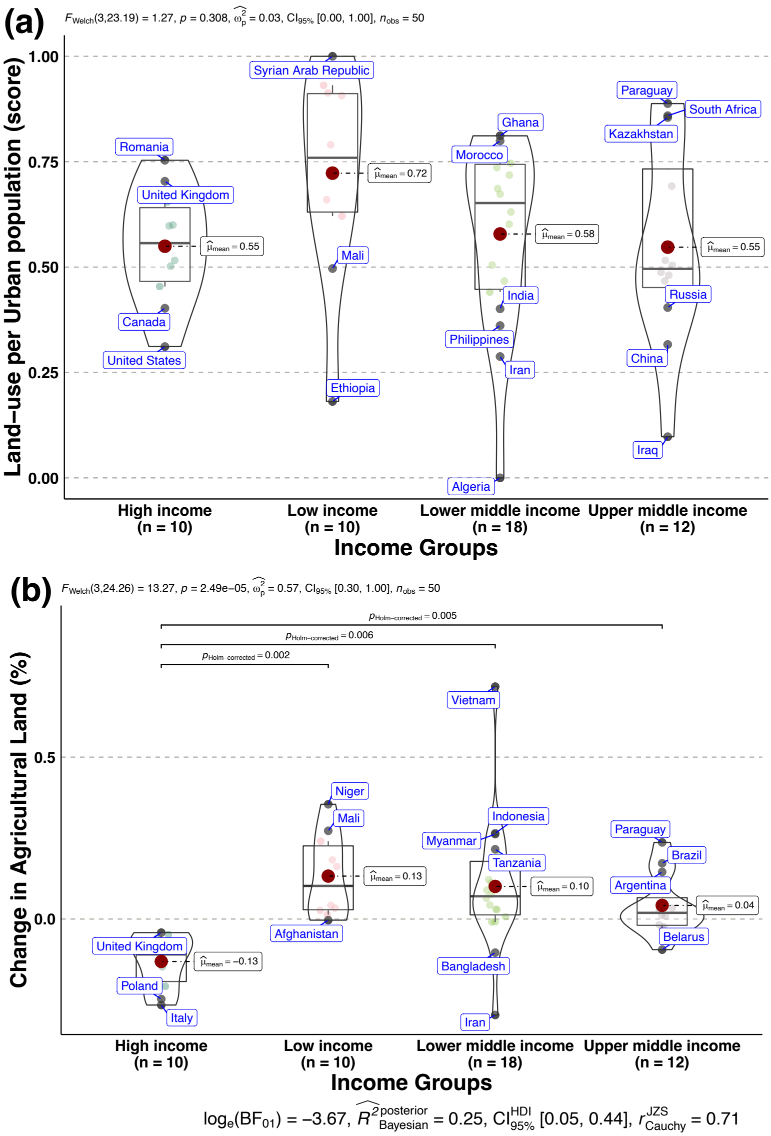
Extended Data Fig. 2| Date-stamping explosive behavior of forest land-use in top 3 low-performing and high-performing countries using BSADF test (a) Pakistan (b) Algeria (c) Nigeria (d) Niger (e) Syria (f) Vietnam. Episodes of explosive behavior occur in 2002-2016 (Pakistan), 2001-2005 (Algeria), 2001, 2009-2016 (Niger), and 2001-2003 (Vietnam) whereas no episodes of explosive behavior occur in Nigeria and Syria, since the estimated test is insignificant.



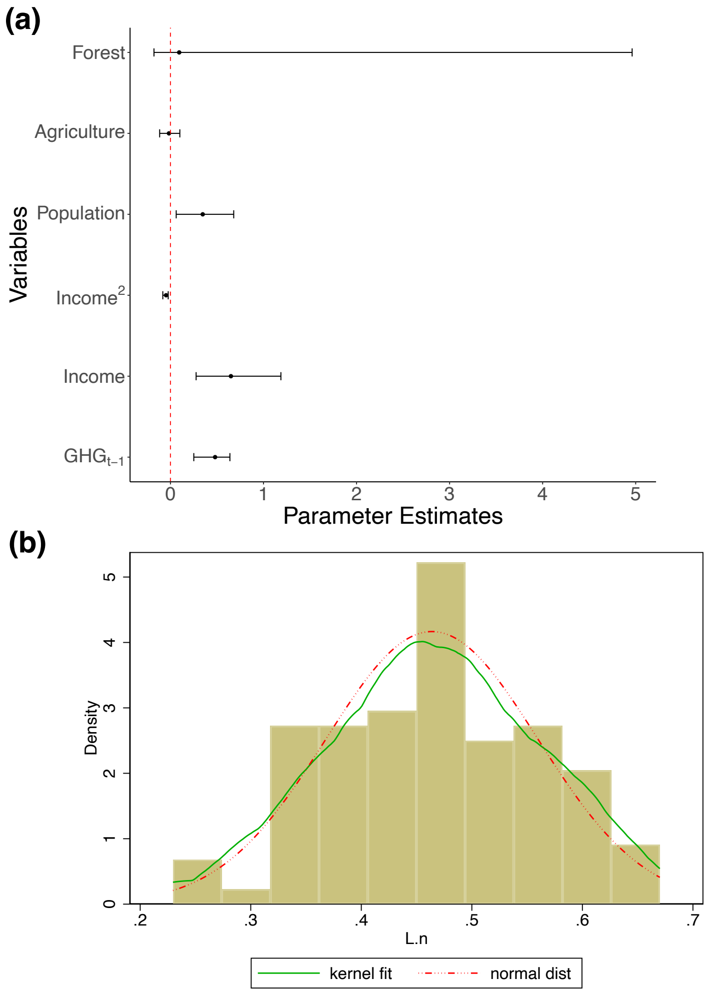
Extended Data Fig. 3| Date-stamping explosive behavior of agricultural land-use in top 3 high-performing and low-performing countries using BSADF test (a) Vietnam (b) Niger (c) Mali (d) Iran (e) Italy (f) Poland. Episodes of explosive behavior occur in 2001-2002, 2014-2015 (Vietnam), 2001-2002, 2005-2007 (Niger), 2012 (Mali), 2006, 2014-2016 (Italy), and 2001-2002, 2010 (Poland) whereas no episodes of explosive behavior occur in Iran, since the estimated test is insignificant.



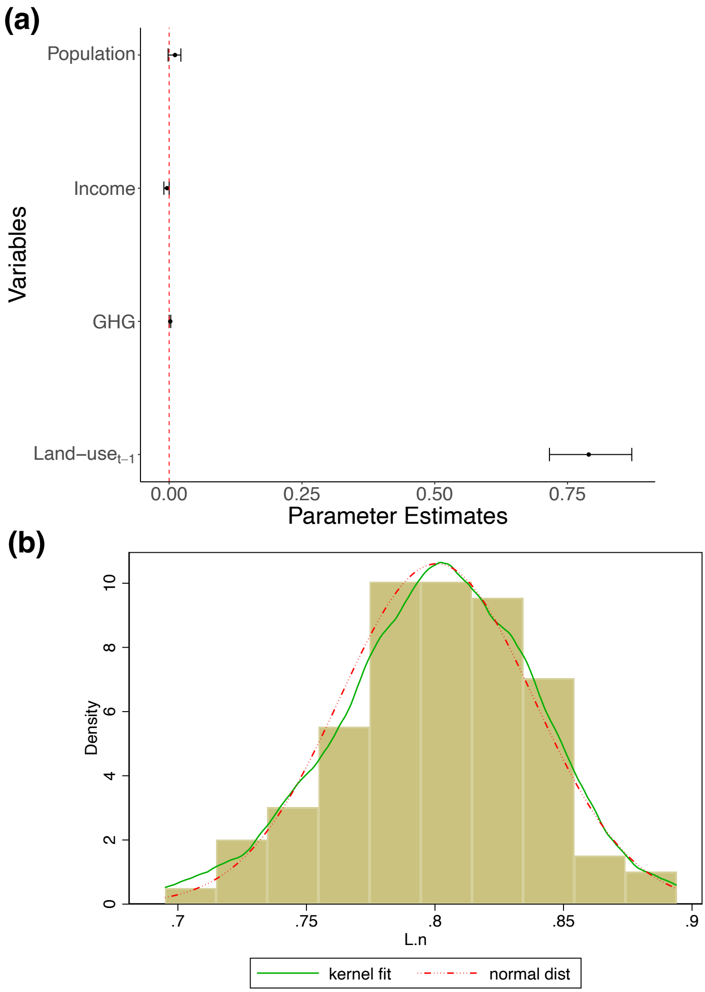
Extended Data Fig. 4| Date-stamping explosive behavior of sampled variables in USA using BSADF test (a) Agricultural land (b) GHG emissions (c) Forest (d) Income (e) Urban population (f) Land-use. Episodes of explosive behavior occur in 2006 (Agriculture), 2013-2014 (GHG), 2002-2010 (Forest), 2001 (Income), and 2006 (Land-use) whereas no episodes of explosive behavior occur for urban population, since the estimated test is insignificant.



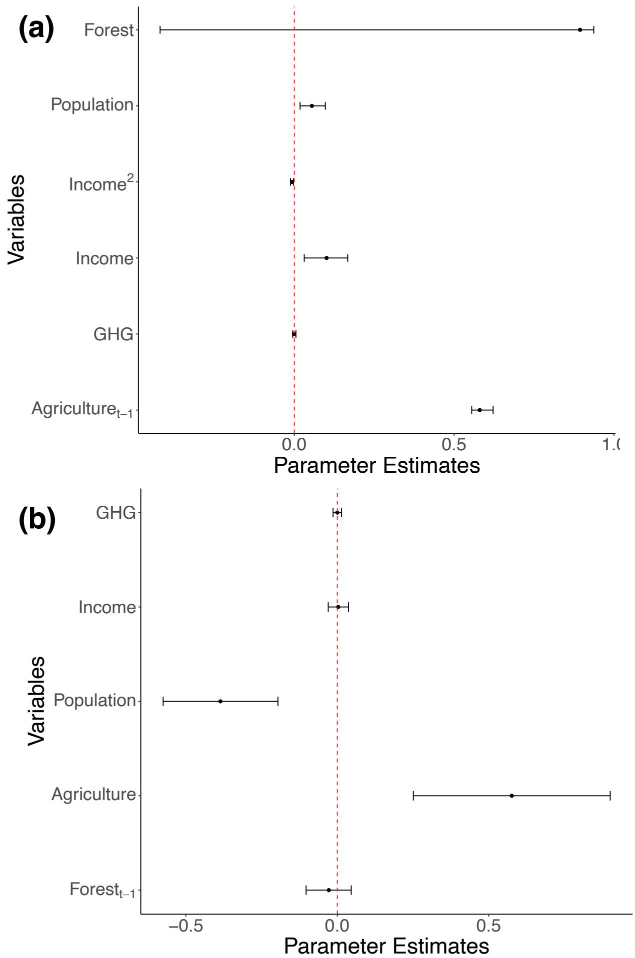
Extended Data Fig. 5| Distribution of across income groups (a) Land-use intensity per urban population (b) Change in Agricultural land. Pairwise test using Games-Howell test showing only statistically significant comparisons. (•) represents the within mean across income groups. The output of the frequentist analysis $F_{welch}(.) = \#$, $p = \#$, $\widehat{\omega_p^2} = \#$, $CI_{95\%}$ [#, #], $n_{obs} = \#$, denote the parameter test statistic, significance of the *p*-value, estimate of the effect size, confidence interval, and number of observations. The output of the Bayesian analysis $log_e(.) = \#$, $\widehat{R^2}^{posterior}_{Bayesian} = \#$, $CI^{HDI}_{95\%}$ [#, #], $r^{JZS}_{Cauchy} = \#$, represents the logarithm of Bayes Factor to test evidence in favor of the null hypothesis over the alternative, R^2 estimate of posterior Bayesian, and prior value.



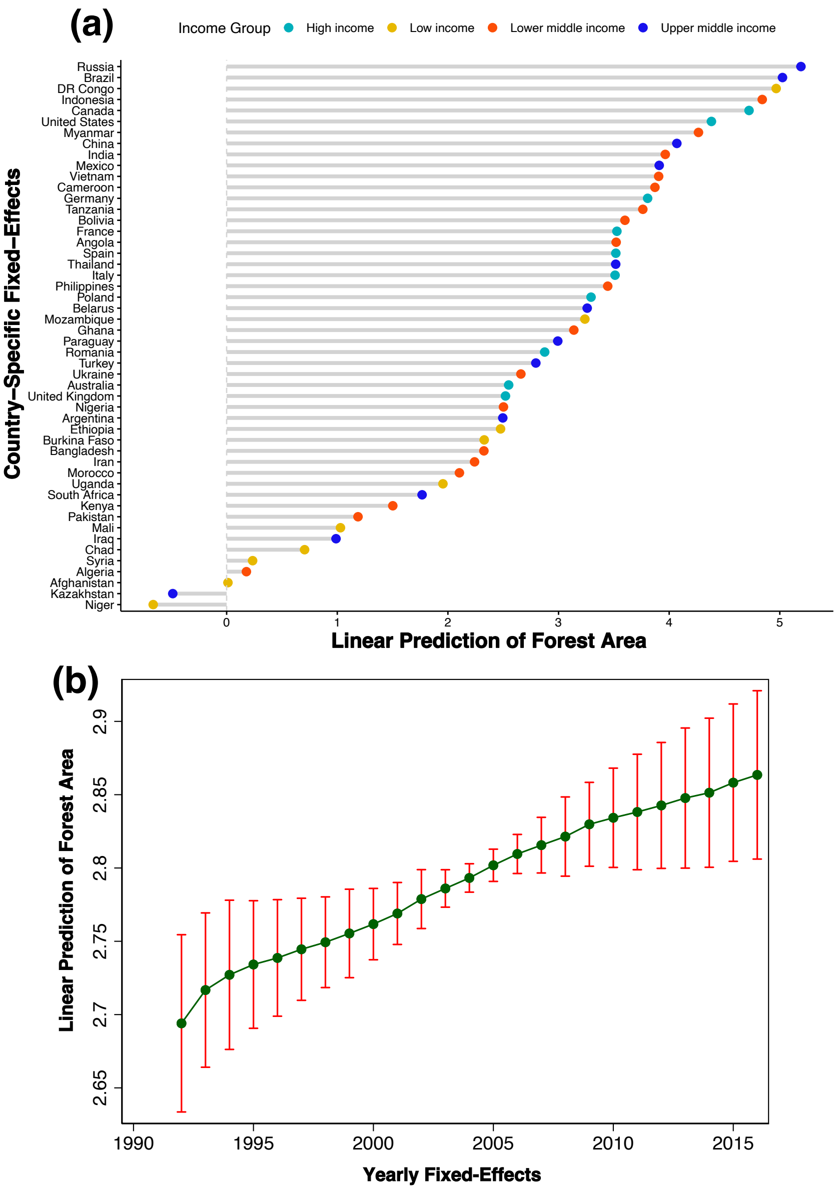
Extended Data Fig. 6| Parameter estimation (a) GHG emissions, income, agriculture, and forest nexus (b) Model validation using bootstrap distribution for all autoregressive coefficients. The parameter estimates of all variables excluding agricultural and forest land-use are statistically significant at *P-value*<0.05. Bootstrap corrected dynamic FE regression (n = 1300) based on Cross-section dependence resampling and analytical heterogeneous initialization to achieve convergence. The estimated model has bootstrapped standard errors, bootstrap 95% (percentile-based) confidence intervals, and statistical inferences performed with non-parametric bootstrap. Residual diagnostics: CD-test (-0.21) & *p-value* (0.836); Pesaran's CADF test (-1.382) & *p-value* (0.997).



Extended Data Fig. 7| Parameter estimation (a) Land-use, GHG emissions, income, and urbanization (b) Model validation using bootstrap distribution for all autoregressive coefficients. The parameter estimates of all variables excluding income level are statistically significant at *P-value*<0.05. Heterogeneous slope testing—Standard delta test $\tilde{\Delta}$ (23.728, *p<0.01*), adjusted delta test $\tilde{\Delta}_{adj}$ (26.286, *p<0.01*), and HAC robust delta test $\tilde{\Delta}_{HAC}$ (-3.209, *p<0.01*). Bootstrap corrected dynamic FE regression (n = 1300) based on cross-section dependence resampling and analytical heterogeneous initialization to achieve convergence. The estimated model has bootstrapped standard errors, bootstrap 95% (percentile-based) confidence intervals, and statistical inferences performed with non-parametric bootstrap. Residual diagnostics: CD-test (7.24); Pesaran's CADF test (-1.079) & *p-value* (1.000).



Extended Data Fig. 8| Parameter estimation for the nexus between (a) Agricultural land-EKC hypothesis (b) Forest, agriculture, urbanization, income, and GHG emissions. The parameter estimates of all variables in (a) excluding GHG emissions are statistically significant at *P-value*<0.05 whereas estimates of all variables in (b) excluding agricultural land-use, income and GHG emissions are statistically significant at *P-value*<0.01. Model validation for (a) was executed using bootstrap distribution for all autoregressive coefficients. Bootstrap corrected dynamic FE regression (n = 1300) based on Cross-section dependence resampling and burn-in initialization to achieve convergence. The estimated model has bootstrapped standard errors, bootstrap 95% (percentile-based) confidence intervals, and statistical inferences performed with non-parametric bootstrap. Residual diagnostics: CD-test (7.67) & *p-value* (0.000); Pesaran's CADF test (-1.305) & *p-value* (0.999). In contrast, (b) entails heterogeneous slope testing—Standard delta test $\tilde{\Delta}$ (35.882, *p<0.01*), adjusted delta test $\tilde{\Delta}_{adj}$ (40.687, *p<0.01*), and HAC robust delta test $\tilde{\Delta}_{HAC}$ (-6.775, *p<0.01*). Test of endogeneity using robust regression: F(1,49) = 3.690 [verdict: The test for endogeneity confirms the validity of adopting instrumental-variables estimator for the forest model], & *p<0.1*. Residual diagnostics: CD-test (27.52); Pesaran's CADF test (-0.607), & *p-value* (1.000).



Extended Data Fig. 9| Predictive margins of (a) Country-Specific-Fixed Effects on Forest Area (b) Yearly-Fixed Effects on Forest Area. The red vertical-bars represent 95% confidence intervals whereas the green dots are the linear predictions.

6.3 Discussion

This study examines ecosystem dynamics to better understand historical trends and performance of nations. We further date-stamped episodes of analyzed explosive behavior for unusual trends observed among sampled variables. The convergent cross-mapping for causations showed both unidirectional and bidirectional coupling among network of variables. The validation of potential spillover effects across countries implies GHG emissions have transboundary tendencies through trade in agricultural and forestry products that affect land-use intensity, especially in low-income countries. However, the magnitude of anthropogenic emissions, forestry, and agricultural land-use appears heterogeneous across income groups. While economic productivity has improved across countries, there is evidence of outgrowth in anthropogenic GHG emissions in developing countries, specifically in low-income economies. The turning point of income in both quadratic models shows GHG emissions and agricultural land-use intensity across high-income and upper-middle-income countries have lessened at some point but somewhat unclear if this decline occurred around US$1005-1530 per capita. Nevertheless, we still found structural evidence confirming countries with low average income characterized by high GHG emissions and high land-use intensity whereas emissions and land-use intensity diminishes as income increases. This parabolic shape confirms the existence of the environmental Kuznets curve hypothesis, which posits income outgrowth characterized by extensive resource utilization, pollution, and waste intensity at developmental stages in weakly regulated countries. However, emissions levels, waste, and resource intensity decline after realizing a specific turning point of income in stringent and regulated countries with environmental awareness (Dasgupta *et al.*, 2002; Sarkodie *et al.*, 2019). While income growth is not an exclusive determinant of anthropogenic emissions and land-use intensity, the fundamental difference between income groups in terms of production and consumption patterns is determined by income distribution. Similarly, income level underpins the dynamics of agriculture, forestry, and land-use intensity (FAO, 2022).

Our date-stamping technique shows explosive behavior for forest lands, with many countries observing a structural decline in forest areas. Deforestation is reportedly increasing and becoming a global threat due to the decline in forest areas embodied in global supply chains (Hoang *et al.*, 2021). The historical changes in forest area can be attributed to deforestation due to increase in commodity demand, a shift from forestry to agriculture—

especially when food security is a threat, urbanization-driven infrastructure expansion, and wildfires (Curtis *et al.*, 2018). Expansion of agricultural land remains the primary driver of forest degradation and deforestation, yet the resilience of food production systems and their adaptive capacity to future changes depend on forest biological diversity (FAO, 2022). Agricultural expansion is evident in countries, typically developing economies that depend heavily on agriculture to meet economic targets. For example, while subsistence agriculture is the main driver of deforestation in Africa and subtropical Asia, large-scale commercial agriculture is the primary determinant of deforestation in Latin America (Hosonuma *et al.*, 2012). The concept of scale effect applies here, given the expansion in agricultural land resources for productive use to meet the growing population and global demand for food and domestic material resources for global supply chains. This explains why anomalies identified in forest land-use and agricultural land expansion are mostly located in low-income countries with extreme poverty (FAO, 2022). While wealthy nations are reported to conserve disappearing forest and embark on further afforestation, low-income nations with little forest cover are reported to likely consume the remaining resources at faster rates than low-income economies with huge forest resources (Ewers, 2006). The presence of heterogeneous effects across countries demonstrates the need for domestic context, viz. cultural and historical factors in assessing agricultural expansion, forest decline, and land-use intensity (FAO, 2022). The interaction between local forces (i.e., cultural values, access to resources, corruption, markets), regional policies (i.e., trade and environmental policies, institutional quality, commodity markets), and global processes (i.e., subsidies, global commodity markets, international agreements) underpin local resources and responses that could determine conservation and management outcomes (Giller *et al.*, 2008). Thus, achieving sustainable development requires tailoring global readiness, adaptation, and mitigation options to the local context and identifying opportunities that decline vulnerabilities and effects of climate change.

6.3.1 Limitation of the study

Our empirical estimation has limitations that may have affected statistical inferences. First, the land-use indicator consists of arable land, forests, permanent cropland, and pasture but excludes built-up areas and others, which may affect the ability to capture changes in land distribution, especially in urbanized countries. However, the adoption of a novel panel heterogeneous technique allows controlling for unobserved heterogeneity and omitted-variable bias. Second, our model doesn't assess the equilibrium relationship between country-specific supply and demand as in the case of production-side assessment in input-output models, yet, we use econometric models that examine historical patterns and drivers of inputs and outputs useful for policy formulation. Such information is useful to mitigate land-use and emission threats and prevent irreversible damage to natural resources. Besides, we identify opportunities for sustainable land management and land-use planning strategies. For example, we observe that most developing countries are more likely to address the ecological and economic benefits of land-use rather than climate change effects. This tradeoff highlights the role of Reducing Emissions from Deforestation and Forest Degradation (REDD+) in developing economies that has co-benefits in mitigating anthropogenic emissions while improving income and social equity of those whose livelihood depends on forestry (Denton *et al.*, 2014). Extending the forest carbon partnership to include more developing countries would help in building REDD+ readiness, hence, has long-term impact on forest carbon stock conservation, sustainable forest management, and emission reduction from forest degradation and deforestation (FCPC, 2022).

6.4 Star★Methods

RESOURCE AVAILABILITY

Materials availability

This study did not generate new unique reagents.

Data and code availability

Data: This paper analyses existing, publicly available data. These accession numbers for the datasets are listed in the key resources table.

Code: This paper does not report original code.

Additional Information: Any additional information required to reanalyse the data reported in this paper is available from the lead contact upon request.

6.4.1 *Method details*

Data. The empirical assessment is based on over decadal (1990-2016) data derived from the World Bank database (World Bank, 2020) consisting of 50 countries in 7 regions [i.e., East Asia & Pacific (7 economies), Europe & Central Asia (12 economies), Latin America & Caribbean (5 economies), Middle East & North Africa (5 economies), North America (2 economies), South Asia (4 economies), and Sub-Saharan Africa (15 economies)]. The sampled data comprises anthropogenic GHG emissions, income level, urban population, agricultural land, and forest area (used as proxy for forest land-use). The adoption of GHG emissions as indicator for environmental vitality enables the assessment of the direct effect of global emission status on climate change. While GDP per capita is used as indicator of income level, urban population is used to examine the role of urbanization on changes in land resources. Agricultural land used in this study captures cropland, arable land, and permanent pasture whereas forest area is the proportion of land covered by forests. The indicator used to comprehensively assess changes in land-use (LU) is constructed using the weights (W_A, W_F) of both agricultural land (A) and forest area (F) expressed as:

$$LU = (A * W_A + F * W_F)/2, W_A = \frac{A}{A + F} \text{ and } W_F = \frac{F}{A + F} \quad (1)$$

Multiple data transformations and quantifications including logarithm, normalization, first-difference, and means were used to capture specific data features in the models. We quantified low- and high-performing countries across income groups using the average percentage change in sampled variables over time. The graphical relationship between GHG emissions and land-use intensity was investigated across income groups while accounting for both population and income dynamics (Fig. 6). Both variables were divided by income level and subsequently averaged over the sample period before being normalized to generate country-specific scores using the expression: score (0,1) = [V_i-V_{min}]/[V_{max}-V_{min}], where V_{min} represents the minimum data point whereas V_{max} denotes maximum data point.

Model estimation. To visualize the distribution across income groups, we used the Games-Howell test (i.e., parametric technique with no equal variance but normally distributed residuals) for between-group pairwise comparison (Pohlert, 2014). The visualization produces detailed statistical inferences (Patil, 2021) based on Welch's one-way ANOVA (parametric technique) hypothesis testing procedure with parametric effect size estimation (Welch, 1951). Assessing unexplained characteristics of historical data across countries is a useful step in econometric modeling. Thus, the unusual characteristics observed among variables across time periods reveal the presence of dynamic properties among sampled variables requiring attention. Explosive behaviors in economic indicators have a trickle-down effect on demographic and ecological markers during crises. From a policy perspective, explosive behaviors may cause historical trends to deviate from their fundamentals leading to unusual and unexplained scenarios. Our empirical analysis accounted for such unusual behaviors in demo-economic and ecological variables using the backward supremum right-tail augmented Dickey-Fuller unit root technique based on recursive window widths for data-stamping of episodes (Baum *et al.*, 2021; Phillips *et al.*, 2011). The date-stamping explosive behaviors of demo-economic and ecological variables were examined for the top 3 low-performing and high-performing countries namely Niger, Pakistan, Afghanistan, China, India, and DR Congo. We further used the dataset of the US to validate the estimated behaviors over the time period.

Global partnerships between countries and across income groups may stimulate spillover effects, pollution-embodied in trade, deforestation-embodied in trade, and land-degradation-embodied in international trade. Besides, economies are prone to global common shocks such as the recent Covid-19 pandemic and other historical global economic recessions. Yet, the impact may be heterogeneous across economies depending on the economic structure and ecological status. Beyond the challenges of traditional panel data models, income groups exhibit economic diversification, income disparities between population structures, varying pollution levels, and diverse environmental policies that affect the specification of ecological models. To account for this, we examined panel cross-section dependence (CD) and heterogeneous effects using the Pesaran-CD test (Pesaran, 2004) for both variable and residual diagnostics and standardized Swamey-tests (i.e., Standard delta test $\tilde{\Delta}$, adjusted delta test $\tilde{\Delta}_{adj}$, and HAC robust delta test $\tilde{\Delta}_{HAC}$) (Pesaran *et al.*, 2008) for panel slope homogeneity (i.e., a violation of the test implies heterogeneous effects). After confirming panel cross-section dependence and heterogeneous effects, we used the panel unit root test (i.e., CADF is a 2nd generational panel unit root test for heterogeneous panels) to examine stationary properties of sampled variables (Lewandowski, 2006). This technique curtails the possibility of spurious regression while improving model specification. We observed level stationary characteristics for almost all sampled series.

Subsequently, we assessed symbiotic relationships using the convergent cross-mapping technique while accounting for complexities, and dynamics among variables. Contrary to standard panel techniques that fail to report true causality in non-linear dynamic systems, the empirical dynamic modeling technique, viz. convergent cross-mapping solves the challenges of traditional panel methods by predicting causality amidst variables that exhibit nonlinearities, explosive behaviors, and complexities (Li *et al.*, 2021). The convergent cross-mapping is a non-parametric technique where manifolds are reconstructed with one-to-one mapping if, for example, both *GHG* and *Income* variables occur within the same dynamic system with manifold $\boldsymbol{M}$ (Sugihara *et al.*, 2012). Thus, causality (*GHG* $\rightarrow$ *Income*) exists if the reconstructed manifold ($\boldsymbol{M}_{Income}$) cross-maps *GHG* with accuracy in prediction for $GHG|\boldsymbol{M}_{Income}$.

After assessing the causal associations using the convergent cross-mapping method, we proceeded to estimate the determinants of anthropogenic emissions and land-use using bootstrap-corrected dynamic fixed-effects regression. For brevity, the generic dynamic panel model can be expressed as (De Vos *et al.*, 2015; Everaert *et al.*, 2007):

$$y_{i,t} = \alpha_1 y_{i,t-1} + .. + \alpha_q y_{i,t-q} + \beta x_{i,t} + u_i + \epsilon_{i,t} \qquad (2)$$

where y denotes the dependent variable across countries i in time period t, β is estimated parameters (coefficient vector) of exogenous variables x, $\alpha_1 - \alpha_q$ represent autoregressive coefficients of lagged-dependent variables, u_i denotes the fixed-effect across countries, and $\epsilon_{i,t}$ is the observation-specific error across countries over the time period. Using the model specification in equation 2, we developed four models where the EKC hypothesis is examined using income, quadratic of income, urban population, and land-use in GHG emission function (Fig. 6). Second, we validate the EKC hypothesis using income, quadratic of income, urban population, disaggregated land-use, i.e., forestry and agricultural land in GHG emission function (Extended Data Fig. 6). Third, we assessed the effect of GHG emissions, income, and urban population on land-use intensity (Extended Data Fig. 7). Finally, we examined the impact of GHG emissions, income, quadratic income, urban population, and forestry on agricultural land (Extended Data Fig. 8a). Advantageously, the bootstrap-corrected dynamic fixed-effects estimator controls for panel cross-sectional dependence and heteroskedasticity patterns that undermine standard correction techniques (Everaert *et al.*, 2007). The bootstrap-corrected dynamic fixed-effects regression (n = 1300) is improved to incorporate cross-sectional dependence resampling and analytical heterogeneous initialization to achieve convergence (De Vos *et al.*, 2015; Sarkodie *et al.*, 2020). The cross-sectional dependence resampling enforces cross-section-specific error terms but with identical time indices across countries. Besides, the analytical heterogeneous initialization technique is utilized to generate the initial conditions, i.e., multi-variate normal distribution sample with country-specific means and variance-covariance matrices in the resampling procedure (De Vos *et al.*, 2015; Everaert *et al.*, 2007). The estimated model has bootstrapped standard errors, bootstrap 95% (percentile-based) confidence intervals, and statistical inferences performed with non-parametric bootstrap. The estimated models are further diagnosed for residual independence using bootstrap distribution for all autoregressive coefficients, residual cross-sectional dependence (CD-test), and residual panel stationarity tests (Pesaran's CADF test).

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

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Chapter 7. Paper 5: Escalation effect of Fossil-based CO_2 emissions improves Green Energy Innovation

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Author contribution

S.A.S designed the study, collected the data, performed the data analysis, coordinated and supervised the study. P.A.O drafted the manuscript. All authors reviewed the manuscript and approved it for submission. Thus, S.A.S contributed 95% whereas P.A.O contributed 5%.

Escalation effect of Fossil-based CO_2 emissions improves Green Energy Innovation [6]

Abstract

The 21st-century development pathway is facing a challenge between climate change mitigation, sustained economic prosperity, and energy security. While extant literature focuses on drivers of anthropogenic emissions, the role of policy measures including green energy innovation, and energy research and development are limited in scope. Here we develop conceptual tools across IEA member countries with four decades of data that demonstrate the role of green energy innovation, and research and development in reducing emissions. Our assessment reveals that sectoral fossil-based CO_2 contributes directly to GHG emissions by 29.7-40.6% from transport, 24.6-32% from industry, 18.6-19.5% from buildings, 15-18.4% from other sectors, and 0.5-1.1% from power. We highlight that industrialized high-income countries converge on green energy innovation but diverge on emissions. The empirical evidence shows that achieving green growth is possible through green energy innovation amidst climate change and its impact.

7.1 Introduction

Climate change has become a global concern due to its longstanding impact on the biosphere. Adverse effects of climate change include variability in weather patterns leading to extreme conditions and events such as flooding, hunger, earthquake, tsunamis, wildfires, drought, and sea-level rise (Bowman *et al.*, 2020; Bronselaer *et al.*, 2020; Fujimori *et al.*, 2019; Trnka *et al.*, 2014). However, climate change is inevitable owing to natural occurrences, increasing population, urban sprawl, growing energy, food, and water demands (Meehl *et al.*, 2007). Nevertheless, the rate of biospheric deterioration driven by human activities can be curtailed through emission-reduction strategies (Meckling *et al.*, 2020; Meckling *et al.*, 2017).

[6] Published article: **Sarkodie, S. A.**, & Owusu, P. A. (2021). Escalation effect of fossil-based CO2 emissions improves green energy innovation. *Science of the Total Environment*, 785, 147257. https://doi.org/10.1016/j.scitotenv.2021.147257

Energy intensity and fossil fuels are fundamental drivers of anthropogenic emissions, hence, mitigating climate change entails structural adjustment in energy systems—where renewables and new technologies can improve energy efficiency (IEA, 2020a). Majority of emissions come from sectors including buildings, industry, other sectors, power industry, and transport—with limited technological advancement. Decarbonization of these sectors requires technological advancement and innovation that improve sectoral efficiency while reducing energy intensity and emissions (Rockström *et al.*, 2017). Efficient end-use technologies—where energy conversion drives economic development—are reported to contribute largely to emission reduction compared to energy-supply technologies. Similarly, end-use technologies provide relatively high social benefits, viz. environmental, economic, and energy security returns on technological investment compared to energy-supply technologies (Wilson *et al.*, 2012).

While there is no single pathway towards achieving net-zero emissions, adoption of green energy innovation can accelerate the agenda towards environmental sustainability (IEA, 2020a). Global energy research and development spending increased by 3% (i.e., US$ 30 billion) in 2019 with 80% of the budget allocated to low-carbon and clean energy technologies (IEA, 2020a). While several countries allocate high budgets for research and development, very little is known about the effect of research and development on green energy innovation, and sectoral-fossil-based GHG emissions. The existing studies have explored the immediate driving forces of anthropogenic emissions (Le Quéré *et al.*, 2019; Rosa *et al.*, 2012; Schmidt *et al.*, 2017), however, very few studies have assessed underlying drivers of emissions—whereas studies on policy-drivers of GHG emissions are limited. Policy drivers including green energy innovation and energy research and development act as abatement strategies of global emissions (Meng *et al.*, 2020; Sarkodie *et al.*, 2021). In a century of carbon and energy-intensive economic growth trajectory, studies on green energy innovation are useful in achieving decarbonized and energy-efficient growth while mitigating GHG emissions and its impacts (D'Alessandro *et al.*, 2020; Wilson *et al.*, 2012).

Owing to limitations and sporadicity of existing literature on green energy, this study contributes to the global debate by exploring the effect of fossil-based CO_2 emissions in improving green energy innovation in 21 industrialized high-income countries using annual occurrence data from 1975-2014. We use a novel convergence estimation method to classify industrialized high-income IEA member countries into similar emission, and energy transition pathways. We apply both econometric and machine learning techniques to investigate the complexities of anthropogenic emissions and develop conceptual tools valuable for policy design. The novel techniques include panel-bootstrap bias-corrected fixed-effects, panel-kernel regularized least-squares, panel log-t regression-based convergence, panel threshold fixed-effects, and dynamic ARDL stochastic simulations. The selection of the estimation tools is useful in controlling for historical and inertial effects, transboundary correlation, heterogeneity, fixed-effects, omitted-variable, and misspecification bias. We examine the heterogeneous effects of anthropogenic emissions, green energy innovation, energy intensity, energy research and development, and service-based industrial structure. We estimate the forty-year trend of emissions and policy measures across countries and identify winners and losers of environmental sustainability through hotspot identification and ranking. We develop both aggregate emissions and economic sectoral fossil-based (buildings, power, industry, transport, and other sectors) models to explore the effects of immediate, underlying drivers, and policy measures. We predict the counterfactual change in GHG emissions from 2014-2064 using the business-as-usual scenario of 1% growth in energy intensity across IEA member countries. Our study demonstrates that investment and integration of green energy innovation, energy research and development, and expansion of service-based industrial structure have mitigating effects on GHG emissions. Our prediction model reveals that 1% shock in energy intensity will increase GHG emissions by over 5.56% in 2064. Further evidence shows that fossil CO_2 emissions from IEA member countries with high GHG emission levels have a positive relationship with green energy innovation. The empirical analysis suggests that countries with historical green energy orientation may invest over 58% more in achieving green growth through green innovation. Thus, higher GHG emission countries like the US may perhaps improve green energy innovation in efforts toward achieving environmental sustainability while sustaining economic prosperity.

7.2 Methods

Our cross-country time series estimation modeling was based on data spanning 1975-2014—retrieved from IEA, OECD, World Bank, and EDGAR databases. Due to periodic data limitations and completeness, our data comprises 21 industrialized high-income countries from the 30 IEA member blocs. The selected countries in ISO 31661—alpha-3 code include AUS, AUT, BEL, CAN, CHE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, JPN, NLD, NOR, NZL, PRT, SWE, and

USA. The sustainable development agenda underpins the numerous indicators selected for this study. From energy and environmental policy perspective, the utilization of aggregated fossil fuel-based CO_2 limits the specificity of sectoral contributions toward anthropogenic emissions, hence, hamper climate control frameworks. We adopt disaggregate fossil-based CO_2 namely industry, power, buildings, transport, and other sectors (agriculture and waste) (Crippa *et al.*, 2019). Data on energy research and development are adopted via a perpetual system of stock inventory (Chakraborty *et al.*, 2020). Total patent counts from OECD-categorized GHG abatement technologies (carbon capture, storage, and sequestration) and service-based gross domestic product are used as surrogates for assessing green energy innovation and industrial structure following the extant literature (Popp *et al.*, 2011). Green energy innovation is defined herein as energy-based innovations, technologies, and practices with emission reduction effect. The selection of service-based GDP as indicator for industrial structure stems from the popular environmental Kuznets curve hypothesis. It is assumed that the economic structure of the sampled countries shifts towards energy efficiency and environmental sustainability (Sarkodie *et al.*, 2019b). In this regard, our *a priori* expects a negative parameter as a sign towards emission reduction. Second, the inclusion of services is essential to curtail omitted-variable bias—as other economic sectoral indices namely agriculture and industry are accounted for. Our empirical assessment includes several empirics, metrics, and structural adjustments including averages, minimum, maximum, aggregate, disaggregate, ranking, weighted, accounting, machine learning algorithm, and econometric modeling techniques. To achieve a constant variance of sampled variables across countries regardless of population and economic structure, we applied log transformation. To estimate the compound annual growth rate of sectoral-based fossil CO_2 emissions, we use the mathematical expression:

$$FCO_{2,i}(t_0, t_T) = \left(\frac{SFCO_{2,j}\,(t_T)}{SFCO_{2,j}\,(t_0)}\right)^{\frac{1}{t_T - t_0}} - 1 \qquad (1)$$

where FCO_2 is the compound annual growth rate of fossil-based CO_2 across countries i and sectoral emissions j, t_0 and t_T are the initial and final years of emission trends considered, $SFCO_{2,j}\,(t_T)$ is the final input of sectoral fossil-based CO_2 whereas $SFCO_{2,j}\,(t_0)$ is the initial input of sectoral fossil-based CO_2 emissions. Using the specified mathematical expression allows circumventing periodical volatilities that affect arithmetic comparisons between countries and sectoral emissions using means (Chan, 2009).

Traditional cross-country time series estimation techniques used in empirical assessment fail to account for global common shocks, spillover, and heterogeneous effects across countries. Failure to observe such comprehensive empirical procedure renders statistical inferences spurious. The Covid-19 pandemic accentuates the importance of accounting for global events with long-term transboundary effects. We implement robust cross-section dependence and homogeneity tests to examine potential transboundary correlation and heterogeneous effects (Ditzen *et al.*, 2020; Pesaran, Ullah*, et al.*, 2008). Several indicators used in empirical assessment often suffer from random-walk properties, hence, exhibit highly persistent characteristic that leads to estimation bias. To control this amidst cross-country dependence and heterogeneity, we examine stationarity across sampled indicators using panel-based unit root test from the second generation (Pesaran, 2007). In this regard, data series integrated of order one is first-differenced before model estimation to eliminate potential spurious regression.

7.2.1 Empirical Procedure

We first test convergence using traditional methods to examine the stationarity and cointegration properties of the cross-sectional time series data. However, such estimation procedures are limited in detecting asymptotic long-term relationships (Phillips *et al.*, 2007). We initiate the novel estimation approach that examines convergence built on time-varying factor with nonlinear effect. The empirical *log-t* test procedure outweighs conventional techniques by controlling for heterogeneous and evolutional effects without imposing assumptions of stationarity (Phillips *et al.*, 2007). The convergence theory posits that all economies of similar industrial and economic structures converge in the long run. The categorization of countries into income groups underpins several emission scenarios, energy, and environmental policies. However, such scenario remains in doubt owing to the heterogeneous distribution and unobserved factors across countries. Thus, rather than using traditional classification of countries to assume potential convergence of industrialized high-income IEA countries, we test for convergence using the empirical procedure expressed as (Du, 2017):

$$TP_{i,t} = \frac{1}{N}\sum_{i=1}^{N}\left(tp_{i,t} - 1\right)^2 \rightarrow 0 \; if \lim_{t\to\infty} \psi_{i,t} = \psi, for \; i \tag{2}$$

where $TP_{i,t}$ is the cross-country variance of the comparative transitional pathway parameter $tp_{i,t}$— quantifying the coefficient of the panel means across transitional pathway of countries i at time t. The transitional pathway parameter is estimated by the imposition of restrictions on the time-varying component $\psi_{i,t}$ that calculates the distance between the input variable and stochastic term derived from the decomposition of input variable. The null hypothesis of convergence is rejected if the *T*-statistic from the *log-t* test is less than -1.65 after discarding 33.3% of the data fraction before regression (Phillips *et al.*, 2007). Next, we employ panel heterogeneous causality in a bivariate model as a general-to-specific test to examine the predictive power of the sampled series. This procedure is essential to identify the direction of causal influence across divergent countries confirmed from the convergence test (Supplementary Table 1). The novel procedure accounts for both cross-section dependence and heterogeneity, a scenario evident in this study. We apply a panel-based causality estimator using the expression (Dumitrescu *et al.*, 2012):

$$D_{i,t} = \delta_i + \sum_{k=1}^{K} \lambda_i^{(k)} D_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} I_{i,t-k} + \varepsilon_{i,t} \tag{3}$$

where $D_{i,t}$ is the target variable, $I_{i,t}$ denotes the predictor variable, K is the lag order, δ_i is the country-specific (i) effects fixed over time t, $\lambda_i^{(k)}$and $\beta_i^{(k)}$signify the autoregressive constraints and slope coefficients of the regression. Using the predictive components, we assess the determinants of sectoral-based fossil fuel CO_2 expressed as:

$$\Delta lnBuildings_{i,t} = \delta_i + \lambda\Delta lnBuildings_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t} \tag{4}$$

$$\Delta lnIndustry_{i,t} = \delta_i + \lambda\Delta lnIndustry_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2\Delta lnGHG\ Emissions_{i,t} + \gamma_3\Delta Energy\ Intensity_{i,t} + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5\Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t} \tag{5}$$

$$\Delta lnOther_{i,t} = \delta_i + \lambda \Delta lnOther_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2 \Delta lnGHG\ Emissions_{i,t} + \gamma_3 \Delta Energy\ Intensity_{i,t} + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5 \Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t} \tag{6}$$

$$\Delta lnTransport_{i,t} = \delta_i + \lambda \Delta lnTransport_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2 \Delta lnGHG\ Emissions_{i,t} + \gamma_3 \Delta Energy\ Intensity_{i,t} + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5 \Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t} \tag{7}$$

$$lnPower_{i,t} = \delta_i + \lambda lnPower_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2 \Delta lnGHG\ Emissions_{i,t} + \gamma_3 \Delta Energy\ Intensity_{i,t} + \gamma_4 lnEnergy\ R\&D_{i,t} + \gamma_5 \Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t} \tag{8}$$

where Δ and ln denote first-difference and logarithmic transformation, δ_i represents heterogeneous effects, that account for unobserved transboundary effects, λ is the estimated parameter of the lagged-dependent variable—which is typically <1—signifying dynamic stability of the relationship. $\gamma_{(..)}$ denotes unknown coefficients of green innovation, GHG emissions, energy intensity, energy R&D, and industrial structure to be estimated. $\varepsilon_{i,t}$ is the unobserved error term with *i.i.d.* characteristics, thus, jointly uncorrelated across countries $i = 1, \ldots, 21$ over time $t = 2, \ldots, 40$. While power, green innovation, and energy R&D are level stationary series, buildings, industry, other sectors, transport, GHG emissions, energy intensity, and industrial structure are first-difference stationary series (Table 1). This explains the estimation of equations 4-8 with level and first-difference variables. Because emissions have past occurrences that influence current trends, the inclusion of $\Delta lnBuildings_{i,t-1}$ in equation 4, $\Delta lnIndustry_{i,t-1}$ in equation 5, $\Delta lnOther_{i,t-1}$ in equation 6, $\Delta lnTransport_{i,t-1}$ in equation 7, and $lnPower_{i,t-1}$ in equation 8 is used as a proxy variable to control for omitted variable bias, and account for unobserved historical factors. The sign of the corresponding coefficient results in two scenarios, i.e., permanent or transitory behavior of sectoral CO_2. Thus, incorporating lagged-dependent sectoral CO_2 helps to capture inertia effects across IEA member countries (Wooldridge, 2016). We further develop a comprehensive model that incorporates all sectoral-based fossil CO_2, green innovation, energy intensity, energy R&D, and industrial structure in GHG emissions function, expressed as:

$$\Delta lnGHG\ Emissions_{i,t} = \delta_i + \lambda \Delta lnGHG\ Emissions_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2 \Delta Energy\ Intensity_{i,t} + \gamma_3 lnEnergy\ R\&D_{i,t} + \gamma_4 \Delta lnIndustrial\ Structure_{i,t} + \gamma_5 \Delta lnBuildings_{i,t} + \gamma_6 \Delta lnIndustry_{i,t} + \gamma_7 \Delta lnOther_{i,t} + \gamma_8 \Delta lnTransport_{i,t} + \gamma_9 lnPower_{i,t} + \varepsilon_{i,t} \quad (9)$$

Using the resultant parameters of individual sector-based fossil CO_2, we estimate observed and unobserved economic sectoral contributions to GHG emissions in IEA member countries using ranking. In this scenario, we can strictly assess the impact of disaggregate fossil CO_2 emissions on GHG emissions for policy purposes based on *ceteris paribus* assumption. The green energy innovation model specification is constructed using the following expression:

$$Green\ Innovation_{i,t} = \delta_i + \lambda Green\ Innovation_{i,t-1} + \gamma_1 \Delta Energy\ Intensity_{i,t} + \gamma_2 lnEnergy\ R\&D_{i,t} + \gamma_3 \Delta lnIndustrial\ Structure_{i,t} + \varepsilon_{i,t} \quad (10)$$

This model exclusively assesses the role of energy and its services and industrial structure in expanding green energy innovation amidst increasing levels of energy intensity. The dynamic model specifications expressed in equations 4-10 are estimated with panel biased-corrected fixed-effects estimator using bootstrapping for estimation and statistical inferences. In equations 4-9, we utilize the cross-sectional dependence scheme for the resampling pattern of the error terms and analytical heterogeneous method for generating the initialization conditions. In contrast, equation 10 applies four different resampling error schemes namely cross-sectional dependence, cross-sectional heteroskedasticity, wild bootstrap, and cross-sectional heteroskedasticity based on Monte Carlo error sampling. Similarly, equation 10 applies three methods for initialization conditions namely burn-in, analytical heterogeneous, and deterministic (De Vos *et al.*, 2015; Everaert *et al.*, 2007). The choice of optimal resampling scheme and initialization method depends largely on the stationary properties, cross-section dependence, and heterogeneous characteristics of the data series and the model specification. For model specifications in equations 4-10, we derive the corresponding standard errors using non-parametric bootstrap distribution of the dynamic panel estimator (Sarkodie & Owusu, 2020b). The estimated models are validated using the panel biased-corrected fixed-effects distribution of the autoregressive coefficients expressed in histogram (Supplementary Figures 1-7).

To improve the consistency of the estimated model, we mimic the econometric-based model specification with panel Kernel-based regularized least squares. This machine learning-based estimator eliminates linearity and controls for heterogeneity in lieu of misspecification bias, hence, produces consistent pointwise parameter estimates and marginal effects (Hainmueller *et al.*, 2014). Contrary to the manual model specification using panel biased-corrected fixed-effects estimator, the Gaussian-kernel based regularized least-squares automatically selects an optimal functional form by learning the data dynamics. For brevity, the panel Kernel-based regularized least squares can be expressed in a generic form as:

$$f(I) = \sum_{i=1}^{N} c_i k(I, I_i), \qquad D = f(I) \tag{11}$$

where D is the target variable, I denotes the predictors, c_i represents the weight of the predictors, and $k(I, I_i)$ pulls similarity evidence from the observations. The estimator automatically selects an optimal kernel bandwidth and regularization parameter. Thus, the pointwise derivatives of the target variables ($\Delta lnBuildings_{i,t}$, $\Delta lnIndustry_{i,t}$, $\Delta lnOther_{i,t}$, $\Delta lnTransport_{i,t}$, $lnPower_{i,t}$, and $\Delta lnGHG\ Emissions_{i,t}$) and predictors can be estimated to explore the pointwise marginal effects using the estimator expressed as (Hainmueller *et al.*, 2014):

$$E_N\left[\widehat{\frac{\partial D}{\partial I_j^{(d)}}}\right] = \frac{-2}{\sigma^2 N} \sum_j \sum_i c_i e^{-\|I_i - I_j\|^2} k\left(I_i^{(d)} - I_j^{(d)}\right) \tag{12}$$

where $\widehat{\frac{\partial D}{\partial I_j^{(d)}}}$ is the partial derivative of the target variables to the predictors, σ^2 is kernel bandwidth. The effect of regime-dependent fossil-based CO_2 emissions on green energy innovation is modeled using the novel panel threshold fixed-effects expressed as (Wang, 2015):

$$Green\ Innovation_{i,t} = \mu + X_{i,t}\,(\delta_{i,t} < \gamma_1) * \beta_1 + X_{i,t}\,(\gamma_1 \le \delta_{i,t} < \gamma_2) * \beta_2 + X_{i,t}\,(\delta_{i,t} \ge \gamma_2) * \beta_3 + u_i + \varepsilon_{i,t} \tag{13}$$

where u_i is the country-specific effects, and $\varepsilon_{i,t}$ is the white noise. $X_{i,t}$ denote the covariates $\Delta Energy\ Intensity_{i,t}$, $lnEnergy\ R\&D_{i,t}$ and $\Delta lnIndustrial\ Structure_{i,t}$. $\delta_{i,t}$ and γ

represent the threshold variable and parameter splitting the panel equation into four regimes with corresponding coefficients β_1, …, β_3. Finally, we re-estimate equation 9 using dynamic autoregressive distributed lag model with stochastic simulations expressed as (Jordan *et al.*, 2018):

$$\Delta lnGHG\ Emissions_{i,t} = constant + \Delta lnGHG\ Emissions_{i,t-1} + \gamma_1 Green\ Innovation_{i,t} + \gamma_2 Green\ Innovation_{i,t-1} + \gamma_3 \Delta Energy\ Intensity_{i,t} + \gamma_4 \Delta Energy\ Intensity_{i,t-1} + \gamma_5 lnEnergy\ R\&D_{i,t} + \gamma_6 lnEnergy\ R\&D_{i,t-1} + \gamma_7 \Delta lnIndustrial\ Structure_{i,t} + \gamma_8 \Delta lnIndustrial\ Structure_{i,t-1} + \gamma_9 \Delta lnBuildings_{i,t} + \gamma_{10} \Delta lnBuildings_{i,t-1} + \gamma_{11} \Delta lnIndustry_{i,t} + \gamma_{12} \Delta lnIndustry_{i,t-1} + \gamma_{13} \Delta lnOther_{i,t} + \gamma_{14} \Delta lnOther_{i,t-1} + \gamma_{15} \Delta lnTransport_{i,t} + \gamma_{16} \Delta lnTransport_{i,t-1} + \gamma_{17} lnPower_{i,t} + \gamma_{18} lnPower_{i,t-2} + \varepsilon_{i,t} \quad (14)$$

We use equation 14 to examine both long and short-term impacts of sectoral fossil-CO_2, green energy innovation, energy intensity, energy research and development, and industrial structure. The proposed estimator is used to stochastically simulate the long-term GHG effects of a counterfactual change in energy intensity from 2014-2064 based on *ceteris paribus* assumption. The 50-year prediction is essential to test the business-as-usual scenario where there is 1% increase in energy-intensive based economic development.

7.3 Results

7.3.1 Forty-year trend estimation in IEA member countries

The hotspot ranking of indicators identifies the minimum, mean and maximum activities of countries over 40 years. Using a lollipop plot presented in Fig. 1, we show that Finland and Portugal have the lowest (0.12) and highest (0.56) level of green energy innovation, respectively. This implies that Portugal has more CO_2 abatement innovations compared to other IEA member countries. In connection with energy intensity, Switzerland records the lowest average (0.08) over 40 years whereas Canada ranks first (0.24). Higher energy intensity signifies lower energy efficiency due to higher levels of energy utilization per GDP. Greece ranks 21st (2.71) in terms of contribution towards energy research development and demonstration whereas the UK ranks 1st (11.28). Both France and the US (4.27) have the largest industrial structure compared to Ireland (4.09). The US has the highest level of both fossil fuel-based CO_2 and GHG emissions whereas Switzerland and New Zealand have the lowest emissions (Fig. 1). We examine the annual change of over decadal sectoral-based fossil CO_2 using the compound annual growth rate formulation (Fig. 2). Using this expression enables easy comparison of persistent rate of reoccurrences of CO_2 across sectors of the same component. In this way, we can base our judgment on the business as usual scenario of the RCP 8.5 assuming sectoral-based fossil CO_2 grows at the same rate annually (van Vuuren *et al.*, 2011). The sectoral-based fossil CO_2 includes Buildings, Industry, Other Sectors, Power Industry, and Transport. The highest compound annual growth rate of fossil CO_2 occurs in the power industry of Norway, New Zealand, Portugal, Australia, and Greece by 7.95%, 5.07%, 4.32%, 2.51%, and 2.45%, respectively. While GHG emissions declined in Norway, Australia, and Greece after 2009, historical high of GHG emissions is dominate from 1975-2009. Other sectors including agriculture, waste, indirect, and industrial activity emissions increased by 3.19%, 1.16%, 1.02%, 1.01%, and 0.72% compound annual growth rate in New Zealand, Australia, Canada, Netherlands, and Portugal. Top five hotspot countries like Greece, Ireland, Portugal, Australia, and Spain saw transport-based fossil CO_2 grow by 3.02%, 3.01%, 2.81%, 2.13%, and 2.11%, respectively. Buildings-based fossil CO_2 grew by 1.55%, 1.45% 1.17%, 0.59%, and 0.22% compound annual growth rate in Spain, Australia, Portugal, Ireland, and New Zealand. Besides, industry-based fossil CO_2 grew by 1.33%, 1.10%, 0.98%, 0.75%, and 0.36% in New Zealand, Norway, Canada, Australia, and Portugal. In contrast, Buildings-based fossil CO_2 saw the highest decline by 7.11%, 3.93%, 2.55%, 1.65%, and 1.37% compound annual growth rate in Sweden, Denmark, Finland, Germany, and Norway. Power industry-based fossil CO_2 dropped by 2.77%, 1.40%, 1.09%, 0.39%, and 0.17% in France, Belgium, the UK, Denmark, and Germany. Further assessment from historical data shows several EU countries saw a decline in GHG emissions from the power sector after the 2009 EU Renewables directive. Likewise, industry-based fossil CO_2 declined by 2.53%, 2.29%, 2.29%, 2.28%, and 2.24% in Sweden, France, the UK, Germany, and Italy, respectively. Other sector-based fossil CO_2 fell by 1.56%, 1.29%, 1.10%, 1.02%, and 0.98% in the UK, Italy, France, Norway, and Germany. It is important to note that transport is the only sector across IEA member countries that saw no decline (compound annual growth rate) in fossil CO_2 (see Fig. 2).

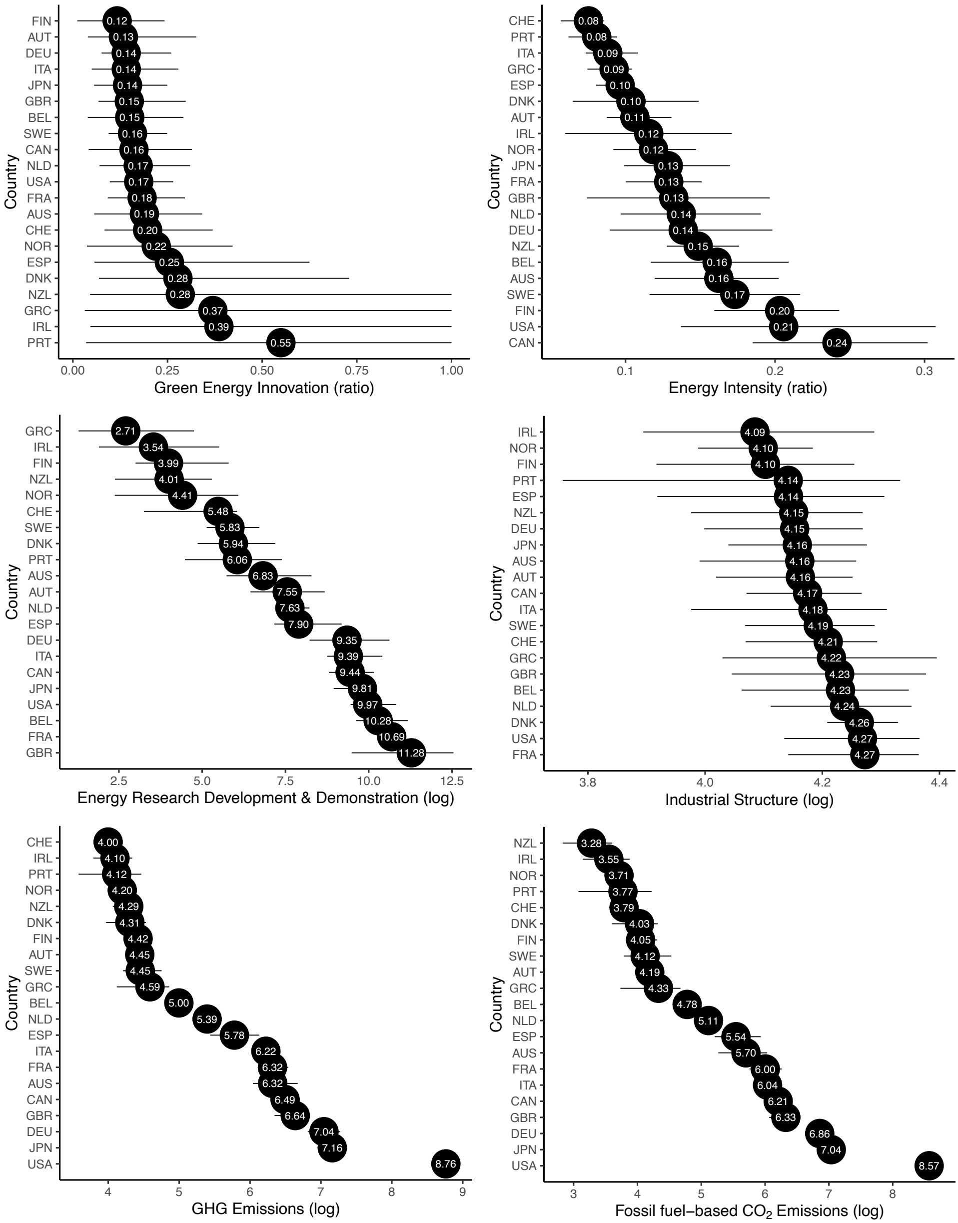

Fig. 1| 40-year cross-country trend of (a) Green energy innovation (b) Energy intensity (c) Energy Research and Development (d) Industrial Structure (e) GHG emissions (f) Fossil fuel-based CO_2 emissions. The lollipop plot shows horizontal line from left to right—representing minimum and maximum whereas the black dot signifies the mean with overlayed text in descending order.

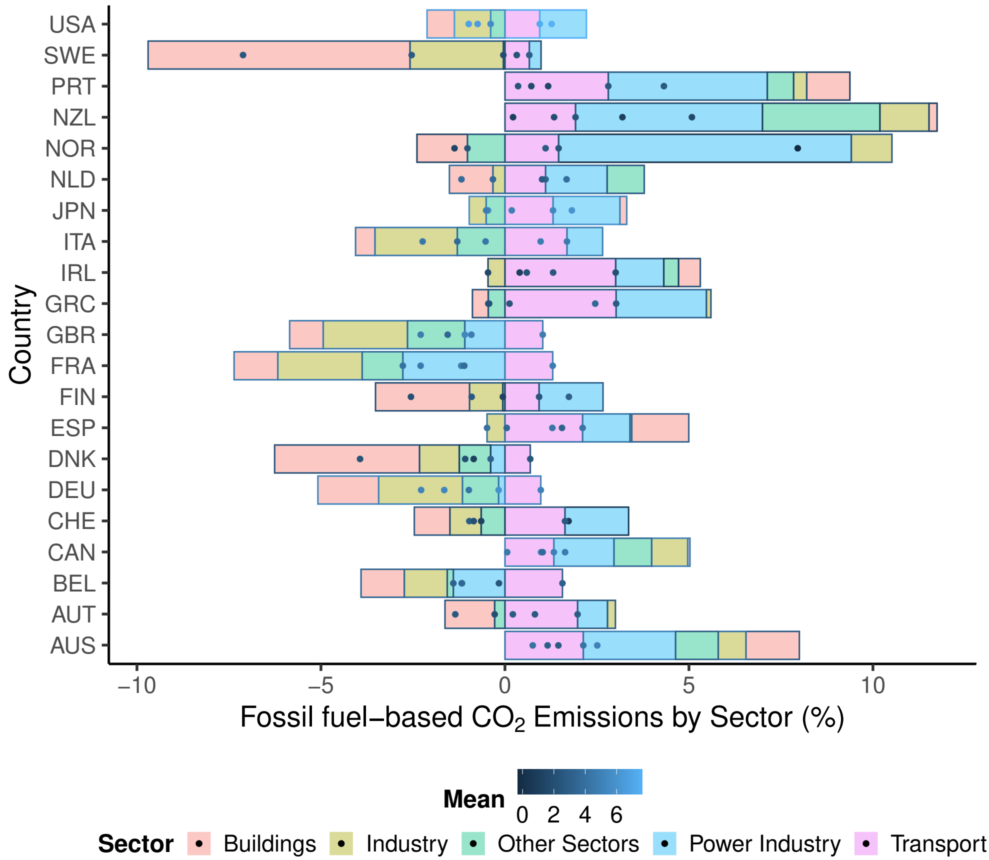

Fig. 2| Sectoral compound growth rate accounting of fossil-based CO_2 emissions. This figure shows the estimated compound annual growth rate (%) of sectoral-based fossil CO_2 on the x-axis and Cross-countries on the y-axis. The filled bars denote sectoral growth rates and colored dots are 40-year mean across IEA member countries.

7.3.2 Convergence & heterogeneous causal effects

This theory posits that countries with similar economic structure converge over time (Quah, 1996). While convergence may hold in terms of economic productivity, it may fail in terms of environmental sustainability. Meanwhile, the environmental Kuznets curve theory postulates in part that higher-income countries become sophisticated with technology and environmental awareness, hence, decline emissions over time (Panayotou, 1993). The decline of emissions can be attributed to environmental policy stringency and a shift from carbon and energy-intensive economy to decarbonized and energy-efficient economic structure. Thus, high-income countries are expected to converge on anthropogenic emissions. To test this hypothesis, we first generate trend components of the data series using panel-based Hodrick-Prescott smoothing filter method (Hodrick *et al.*, 1997). This data filtering technique is necessary to estimate the long-term behavior of the indicators. We apply the proposed log-t regression test to examine the overall null hypothesis of convergence across countries (Phillips *et al.*, 2007). Subsequently, we undertake sub-group formation into club membership and club merging for clubs satisfying the joint hypothesis of convergence (Du, 2017). We observe in Supplementary Table 1 that the overall log-t test statistic for all data series is less than < -1.65 (i.e., rejecting H_0: of convergence) except green energy innovation. This implies that industrialized high-income countries converge on green energy innovation but divergent on GHG emissions, energy intensity, energy R&D, industrial structure, and sectoral-based fossil CO_2. To examine heterogeneous effects across IEA member countries, we first examine both cross-section dependence (CD) and stationarity using Breusch-Pagan LM (LM), bias-adjusted LM (LM_{adj}), CD (LM_{CD}), and CADF tests. We observe from Table 1 column 2 all the data series are first-difference stationary except for power industry, green energy innovation, and energy R&D. Besides, we confirm the presence of panel correlation across countries for the proposed models, rejecting H_0: of cross-section independence. This infers that IEA member countries are susceptible to global common shock including Covid-19 pandemic, oil shocks, market volatility, and spillover effects. Subsequently, we apply panel slope homogeneity test after validating the preconditions. In this test, we examine whether slope parameters are equal across countries (Pesaran & Yamagata, 2008). The estimated slope parameters (Δ, Δ_{adj}) reject H_0: of identical slope coefficients at *p-value<0.01*, confirming slope heterogeneity. Now, we estimate the panel heterogeneous causal effects as general-to-specific approach for our proposed model (Fig. 3). The panel heterogeneous Granger-causality is useful in assessing the predictive components of data series. We notice a rejection of the null hypothesis of no causality for all countries in Figs. 3-4. Thus, there is causality from transport, green energy innovation, energy intensity, energy R&D, industrial structure, industry, other sectors, and power industry to GHG emissions for at least one country (Fig. 3a). The country-specific causality shows that green energy innovation predicts GHG emissions in Belgium, Italy, Netherlands, Spain, and the US. Additionally, energy intensity predicts GHG emissions in Australia, Belgium, Canada, Denmark, Germany, Italy, Norway, and Spain. Besides, the power industry predicts GHG emissions in Australia, France, Germany, Greece, Ireland, Italy, New

Zealand, Spain, and Switzerland (Supplementary Table 2). Similarly, we observe panel causality from transport, GHG emissions, energy intensity, energy R&D, industrial structure, industry, buildings, and power industry to green energy innovation (Fig. 3b). Besides, there is causality from transport, GHG emissions, energy intensity, industry, other sectors, green energy innovation, buildings, and power industry to energy research and development for at least one country (Fig. 4a). Likewise, causal relationship is observed from transport, GHG emissions, other sectors, energy R&D, industrial sector, industry, buildings, and power industry to energy intensity for at least one country (Fig. 4b). The country-pooled causality reveals that GHG emissions predict green energy innovation in Denmark, Finland, Netherlands, Norway, and Portugal. Energy R&D predicts green energy innovation in Denmark, Finland, Germany, Italy, Portugal, and Switzerland (Supplementary Table 4). The variations of empirical evidence across IEA member countries underpin our earlier findings of heterogeneous and divergence effect, highlighting the importance of using more sophisticated techniques to control these challenges.

Table 1| Assessment of fossil-based anthropogenic emissions

	Δf	GHG		Buildings		Industry		Other		Transport		Power	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
GHG_{t-1}	–	−0.063*	−0.002**	–	–	–	–	–	–	–	–	–	–
		[0.035]	[0.001]										
$Buildings_{t-1}$	–	–	–	−0.064	−0.056***	–	–	–	–	–	–	–	–
				[0.045]	[0.025]								
$Industry_{t-1}$	–	–	–	–	–	−0.095***	−0.059**	–	–	–	–	–	–
						[0.040]	[0.028]						
$Other_{t-1}$	–	–	–	–	–	–	–	−0.064	−0.067**	–	–	–	–
								[0.052]	[0.032]				
$Transport_{t-1}$	–	–	–	–	–	–	–	–	–	0.272***	0.204***	–	–
										[0.056]	[0.030]		
$Power_{t-1}$	–	–	–	–	–	–	–	–	–	–	–	0.944***	0.774***
												[0.016]	[0.007]
GHG	−13.149***	–	–	0.620***	0.557***	0.760***	0.656***	0.654***	0.597***	0.364***	0.251***	1.861***	1.712***
				[0.181]	[0.061]	[0.164]	[0.051]	[0.155]	[0.057]	[0.066]	[0.032]	[0.239]	[0.354]
Buildings	−13.703***	0.116**	0.085***	–	–	–	–	–	–	–	–	–	–
		[0.018]	[0.008]										
Industry	−12.245***	0.154***	0.139***	–	–	–	–	–	–	–	–	–	–
		[0.028]	[0.011]										
Other	−12.909***	0.094***	0.080***	–	–	–	–	–	–	–	–	–	–
		[0.019]	[0.011]										
Transport	−9.864***	0.254***	0.129***	–	–	–	–	–	–	–	–	–	–
		[0.031]	[0.017]										
Power	−2.380[a]***	0.007**	0.002***	–	–	–	–	–	–	–	–	–	–
		[0.003]	[0.000]										
Green energy innovation	−3.207[a]***	−0.001	−0.010*	−0.028*	0.024	0.005	−0.005	−0.012	0.009	−0.018*	−0.036***	0.035	0.152
		[0.013]	[0.006]	[0.016]	[0.022]	[0.019]	[0.019]	[0.017]	[0.021]	[0.011]	[0.011]	[0.043]	[0.123]
Energy intensity	−12.793***	2.231***	1.493***	4.002***	4.925***	0.277	0.227	−0.980*	−1.868***	−0.622	−0.242	2.132	−2.366
		[0.580]	[0.140]	[1.375]	[0.475]	[0.596]	[0.405]	[0.533]	[0.450]	[0.400]	[0.237]	[1.681]	[2.765]
Energy R&D	−3.178[a]***	−0.001	−0.001***	−0.002	0.001	−0.005**	−0.001*	−0.001	−0.001	−0.003	−0.001**	−0.003	0.014**
		[0.002]	[0.000]	[0.005]	[0.001]	[0.002]	[0.001]	[0.004]	[0.001]	[0.005]	[0.000]	[0.006]	[0.006]
Industrial structure	−11.443***	−0.111	−0.132***	0.511***	0.541***	−0.222	−0.612**	−0.755***	−0.609***	−0.015	−0.061	0.998*	1.123
		[0.069]	[0.046]	[0.154]	[0.158]	[0.272]	[0.135]	[0.164]	[0.153]	[0.108]	[0.081]	[0.577]	[0.914]
Convergence	–	Y	–	Y	–	Y	–	Y	–	Y	–	Y	–
Resample	–	CSD	–	CSD	–	CSD	–	CSD	–	CSD	–	CSD	–
Initialization	–	AHE	–	AHE	–	AHE	–	AHE	–	AHE	–	AHE	–
LM	–	244.1*	244.1*	454.9***	454.9***	226.5	226.5	273.7***	273.7***	359.5***	359.5***	1087***	1087***
LM^{b}_{adj}	–	2.354**	2.354**	35.89***	35.89***	0.867	0.867	8.187***	8.187***	21.33***	21.33***	133.4***	133.4***
LM^{b}_{CD}	–	1.244	1.244	5.061***	5.061***	4.589***	4.589***	4.892***	4.892***	9.048***	9.048***	20.31***	20.31***
Δ	–	7.733***	7.733***	7.903***	7.903***	4.204***	4.204***	4.087***	4.087***	6.669***	6.669***	14.281***	14.281***
Δ_{adj}	–	9.126***	9.126***	8.725***	8.725***	4.641***	4.641***	4.512***	4.512***	7.363***	7.363***	15.766***	15.766***
Cointegration	–	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-K	Y-W	Y-W
Countries	–	21	21	21	21	21	21	21	21	21	21	21	21
Obs	–	798	819	798	798	798	798	798	798	798	798	819	819
R^2	–	–	0.825	–	0.597	–	0.569	–	0.516	–	0.552	–	0.977

Notes: [a] level stationary series, [b] LM test based on two-sided biased-adjusted estimation test, Y-(K/W) validation of long-term relationship with Kao (K) and Westerlund (W) cointegration tests, CSD means cross-section dependence, AHE denotes analytical heterogeneous, LM, LM_{adj}, and LM_{CD} represent Breusch-Pagan LM, Biased-adjusted LM and CD tests. Δƒ represents rejection of the null hypothesis of unit root. **(1)** Estimated using cross-sectional time series biased-corrected fixed-effects; **(2)** Estimated using panel-kernel based regularized least-squares. *, **, *** signify statistical significance at 99, 95, 90% Confidence Interval.

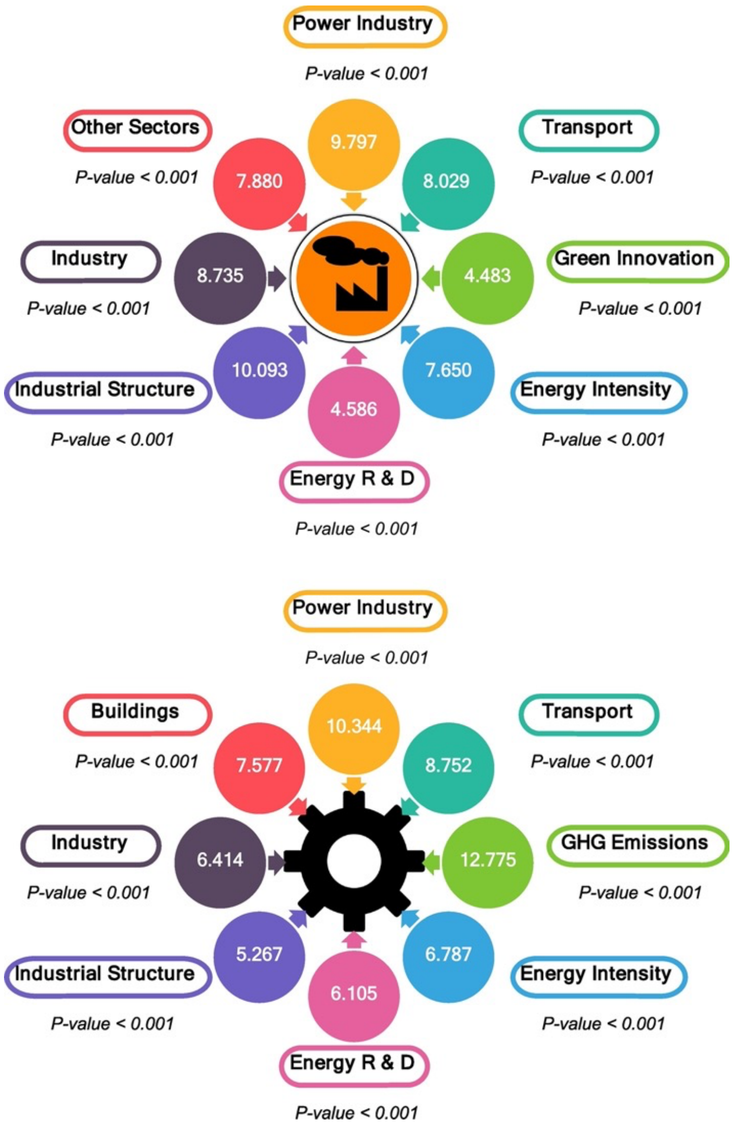

Fig. 3| Heterogeneous causal effect of (a) sectoral-based fossil-driven CO_2 and energy services on GHG emissions (b) sectoral-based anthropogenic emissions and energy services on green energy innovation. Estimated based on heterogeneous panel Granger non-causality test. The arrows depict the direction of causality whereas the *p-values* denote the rejection of the null hypothesis of non-causality.

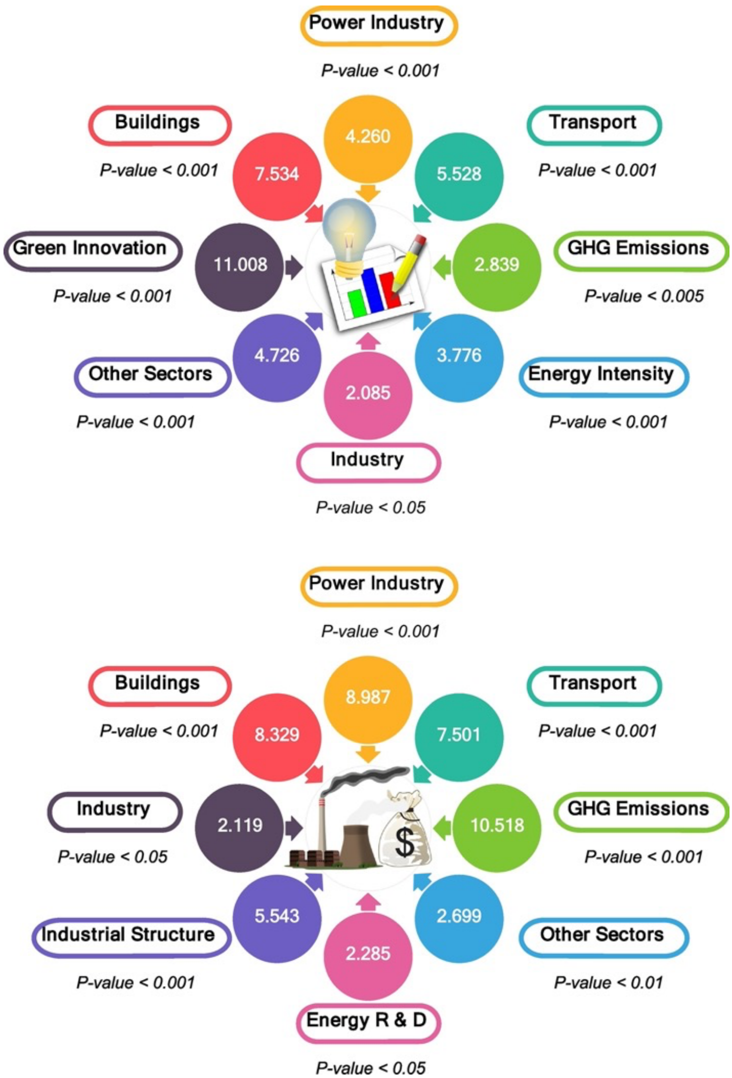

Fig. 4| Heterogeneous causal effect of (a) sectoral-based anthropogenic emissions and energy services on Energy R&D (b) sectoral-based anthropogenic emissions and energy services on Energy Intensity. Estimated based on heterogeneous panel Granger non-causality test. The arrows depict the direction of causality whereas the *p-values* denote the rejection of the null hypothesis of non-causality.

7.3.3 *Assessment of fossil-based anthropogenic emissions*

We assess the drivers of GHG emissions and sectoral-based fossil CO_2 using both panel-bootstrap bias-corrected fixed-effects and panel-kernel regularized least-squares. While the former is our choice econometric approach for estimation, the latter technique based on machine learning is used to validate the parameter estimates. Using these sophisticated estimation techniques allows accounting for omitted-variable and misspecification bias, cross-section dependence, additivity, heterogeneity, and country-specific fixed-effects (Owusu *et al.*, 2020). The overall models show statistical significance at 1% level, with corresponding R^2 between 0.52-0.98 and residual independence (Supplementary Figs. 1-7). Thus, the regressors explain 52-98% of variations in anthropogenic emissions (Table 1). The GHG model shows a negative and significant GHG_{t-1}, signifying the recovery effect of historical GHG emissions. We find a positive and statistically significant parameter of sectoral-based fossil CO_2, implying that emissions from buildings, industry, other sectors (agriculture, waste, indirect emissions), transport, and power industry escalates GHG emissions in the long-term. Similarly, historical increase in energy intensity exacerbates GHG emissions by 1.49-2.23%. In contrast, improving green energy innovation, increasing energy research and development, and expanding industrial structure have mitigating effects on GHG emissions. To corroborate the findings, we examine the relationship between green energy innovation and GHG emissions while accounting for industrial structure. We observe in Fig. 5 that countries with high green energy innovation and medium-high industrial structure have lower GHG emissions and vice versa. For example, Portugal, Ireland, Greece, New Zealand, Denmark, Norway, and Switzerland have lower levels of GHG emissions whereas the US, Germany, Italy, Australia, and Canada with low-medium green energy innovation but high industrial structure emit more GHG. This implies that diversification of energy portfolio with green energy innovation has GHG emission-reduction effect. In the sectoral-based fossil CO_2 models, the coefficient on $Buildings_{t-1}$, $Industry_{t-1}$, and $Other_{t-1}$ is negative and significant—inferring that historical emission factors from buildings, industry and other sectors correct anomalies with time. Contrary, the parameter on $Transport_{t-1}$ and $Power_{t-1}$ are significantly positive with a large magnitude, especially power—implying that past emissions influence current levels of emissions from transport and power. Unobserved factors may explain the inertial effect of historical emissions from transport and power industry. Increasing levels (1%) of GHG emissions—the main cause of climate change—increase fossil CO_2 emissions from buildings (0.56-0.62%), industry (0.66-0.76%), other sectors (0.60-0.65%), transport (0.25-0.36%), and power industry (1.71-1.86%). Growth in energy intensity by 1% spur CO_2 emissions by 4.0-4.93% from buildings but declines other sector-based fossil CO_2 emissions by 0.98-1.87%. Expansion of industrial structure by 1% increases buildings-based fossil CO_2 emissions by 0.51-0.54% but declines industry and other sector-based fossil CO_2 emissions by 0.61% and 0.61-0.76%. Improving energy research and development by 1% decreases industry and transport-based fossil CO_2 emissions. Besides, accelerating green energy innovation declines long-term buildings and transport-based fossil CO_2 emissions. In summary, the impact of long-term economic sectoral-based fossil CO_2 on GHG emissions depicted in Fig. 6 can be expressed as –– transport>industry>buildings>others>power. Empirically, power, and heat generation contribute 0.46-1.12% of GHG emissions. Other sectors including agriculture, waste, and indirect emissions contribute 15.04-18.39% of GHG emissions. The building sector is ranked as the third contributor to long-term GHG emissions by 18.56-19.54%. The industrial sector including manufacturing and fuel production is ranked 2nd determinant of GHG emissions, contributing about 24.64-31.95%. Transportation is identified as the main contributor to long-term GHG emissions in a fossil-based CO_2 regime, contributing about 29.66-40.64%. This corroborates our earlier findings of persistent transport-based fossil CO_2 emissions across all countries depicted in Fig. 2. We examine the counterfactual change in GHG emissions from 2014-2064 using dynamic ARDL stochastic simulations. Using the business-as-usual scenario of the RCP 8.5, we assume energy intensity will grow at the same rate (1%) annually based on the compound annual growth rate estimation. We observe in Fig. 7 that 1% shock in energy intensity will increase GHG emissions by over 5.56% in 2064.

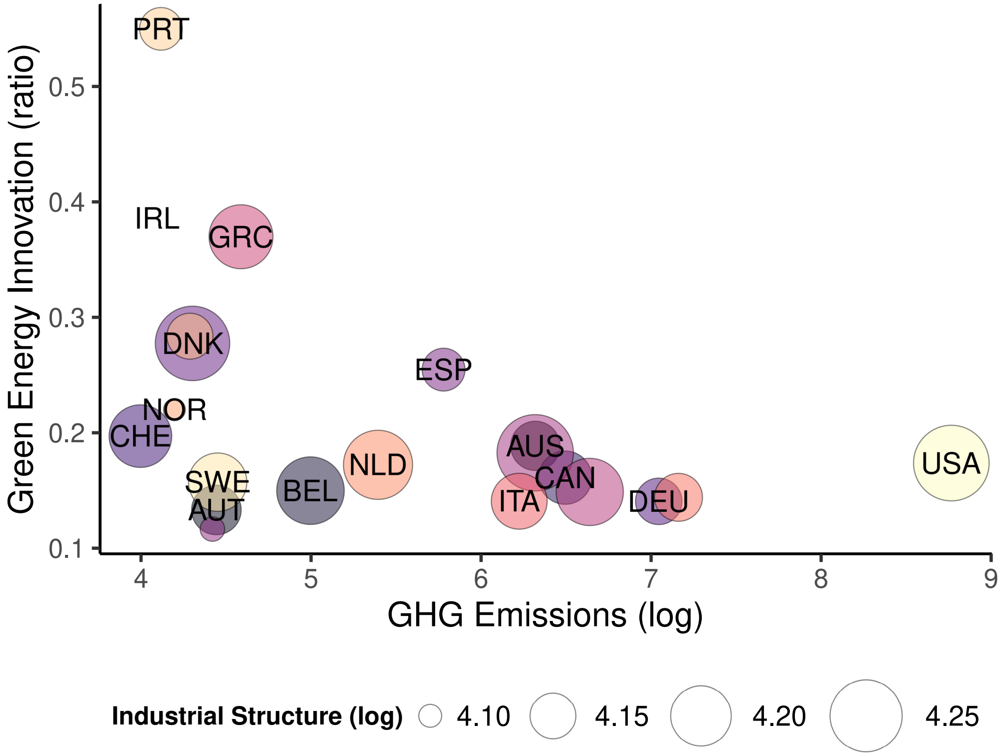

Fig. 5| Relationship between green energy innovation and GHG emissions while accounting for industrial structure.

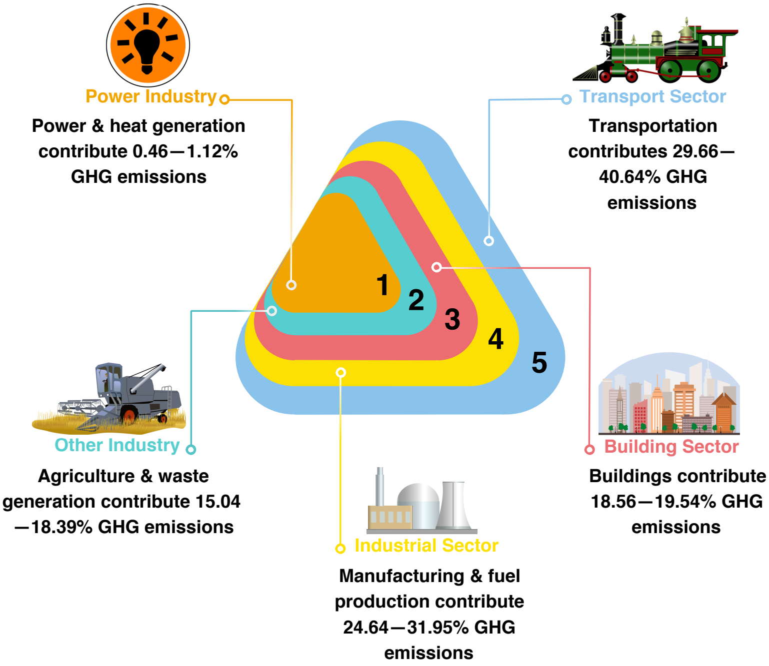

Fig. 6| Long-term contribution of sectoral-based fossil CO_2 to GHG emissions. Percentages calculated from the estimated parameters based on *ceteris paribus* assumption—using both panel-based kernel regularized least-squares and panel bootstrap bias-correction fixed-effects. The numbering system ranks sectoral-fossil CO_2 from lowest to highest.

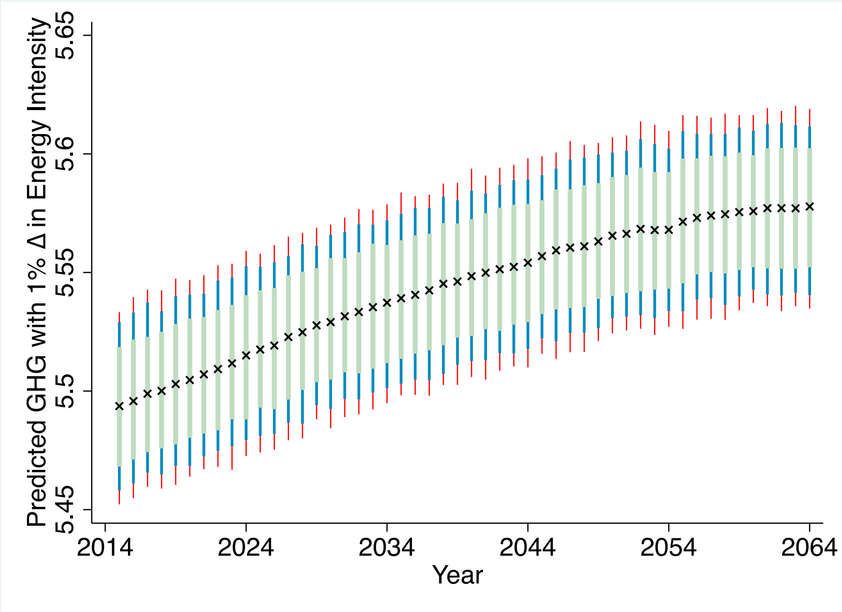

Fig. 7| Counterfactual change in GHG emissions with 1% Δ in Energy Intensity (%). The forecasting is executed based on the dynamic ARDL stochastic simulations. Olive teal, light blue and red spikes denote 75, 90, 95% Confidence Interval.

7.3.4 Regime-based fossil CO_2 effects on green energy innovation

We used panel-bootstrap bias-corrected fixed-effects to estimate Models 1-6 whereas Model 7 is estimated with panel threshold fixed-effects. The lagged-green energy innovation (λ) is positive and significant for all six models (Models 1-6) in Table 2. This suggests that countries with historical green energy orientation may invest ~58% more in achieving green growth through green innovation. Countries that have improved historical green energy innovation include Portugal, Ireland, Greece, New Zealand, Denmark, and Spain (Fig. 1a). This perhaps corroborates the findings in Table 1, explaining why countries with high investment in green energy innovation have low levels of GHG emissions (Fig. 5). Comparably, 1% investment increase in energy research and development expands green energy innovation by 0.01-0.02%. Investment in energy research and development across industrialized high-income countries may shift towards other energy technologies that expand economic productivity with limited green energy innovation. This may justify why techno-economic giants like the UK, France, Belgium, the US, Japan, Canada, Italy, and Germany have huge investments for energy research development and demonstration but limited green energy innovation (Fig. 1c). In contrast, 1% growth in energy intensity and industrial structure expansion decline green energy innovation by ~0.78% and ~0.25%, respectively. In model 7, we validate the green energy innovation model by incorporating fossil CO_2 emissions as regime-dependent variable and GHG emissions as the threshold variable. The model specification is useful in assessing multiple thresholds of GHG emissions—exogeneous indicator of green energy innovation in a fossil regime. Evidence from model 7 validates the estimated parameters of energy intensity, energy R&D, and industrial structure. We observe that fossil CO_2 emissions from IEA member countries with very low and low-medium GHG emissions are significant and negatively related to green energy innovation. Contrary, fossil CO_2 emissions from IEA member countries with high GHG emission levels have positive relationship with green energy innovation. Thus, strengthening the theory of divergent GHG emissions across industrialized high-income countries. This implies the likelihood of IEA countries with lower economic productivity expanding their fossil-driven industrial structure by lowering green energy innovation standards. In contrast, higher GHG emission countries like the US may perhaps improve green energy innovation towards environmental sustainability.

Table 2| Effect of regime-dependent fossil-based CO_2 emissions on green energy innovation

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
λ	0.574*** (0.433–0.707) [0.072]	0.576*** (0.419–0.735) [0.079]	0.577*** (0.447–0.692) [0.064]	0.564*** (0.428–0.729) [0.070]	0.566*** (0.437–0.696) [0.067]	0.566*** (0.434–0.666) [0.064]	–
Energy intensity	−0.741** (−1.727 to −0.246) [0.368]	−0.734** (−1.672 to −0.141) [0.360]	−0.761** (−1.464 to −0.115) [0.341]	−0.755** (−1.378 to −0.164) [0.326]	−0.776** (−1.433 to −0.231) [0.329]	−0.772** (−1.587 to −0.245) [0.362]	−1.534*** (−1.961 to −1.117) [0.215]
Energy R&D	0.014* (0.002–0.030) [0.008]	0.014* (0.000–0.030) [0.007]	0.013* (0.001–0.031) [0.007]	0.014* (0.002–0.033) [0.008]	0.015* (0.001–0.037) [0.009]	0.014* (0.002–0.034) [0.008]	0.037*** (0.024–0.051) [0.007]
Industrial structure	−0.233** (−0.477 to −0.025) [0.118]	−0.236** (−0.442 to −0.025) [0.113]	−0.242** (−0.420 to −0.037) [0.110]	−0.240** (−0.488 to −0.012) [0.116]	−0.248** (−0.435 to −0.053) [0.106]	−0.250** (−0.442 to −0.042) [0.119]	−0.527*** (−0.645 to −0.410) [0.060]
Constant	–	–	–	–	–	–	2.320*** (1.754–2.887) [0.289]
Regime#Fossil							
Very low	–	–	–	–	–	–	−0.528*** (−0.833 to −0.222) [0.156]
Low-medium	–	–	–	–	–	–	−9.552*** (−15.226 to −3.878) [2.891]
High	–	–	–	–	–	–	0.297** (−0.002–0.596) [0.152]
Threshold							
Single	–	–	–	–	–	–	13.430**
Double	–	–	–	–	–	–	8.640*
Triple	–	–	–	–	–	–	7.830
R-sq(within)	–	–	–	–	–	–	0.190
Observations	819	819	819	819	819	819	819
No. of countries	21	21	21	21	21	21	21
Resampling	CSD	WBOOT	CSD	CSHET	MCHE	MCHE	–
Initialization	Burn-in	AHE	AHE	Burn-in	AHE	DET	–
Convergence	Yes	Yes	Yes	Yes	Yes	Yes	–

Notes: λ is the lagged-dependent variable (Green Energy Innovation); *,**,*** represents statistical significance at 10, 5 and 1% level; CSD denotes Cross-section dependence; WBOOT denotes Wild bootstrap, AHE denotes Analytical heterogeneous; CSHET denotes Cross-section heteroscedastic; MCHE denotes Monte Carlo heterogeneous; DET denotes Deterministic; (..) represents 95% Conf. Interval; [..] is the standard error. LM (819.3, *p-value <0.01*), LM_{adj} (96.85, *p-value <0.01*), LM_{CD} (19.07, *p-value <0.01*), Δ (19.343, *p-value <0.01*), and Δ_{adj} (20.679, *p-value <0.01*).

7.4 Discussion

This study investigates the impact of energy intensity and economic-sectoral-based fossil CO_2 emissions including buildings, industry, transport, power, and other sectors spanning 1975-2014 across 21 IEA member countries. We caution that unobserved factors may affect GHG emissions and green energy innovations not addressed in this research, however, our empirical assessment is robust to estimation and misspecification bias. We further explore GHG mitigation effects of green energy innovation, energy research development and demonstration, and industrial structure. While existing literature largely focuses on the immediate drivers of aggregate anthropogenic emissions (Feng *et al.*, 2015; Liang *et al.*, 2016;

Rosa *et al.*, 2012), this research examines both aggregate and disaggregate sectoral emissions, immediate and underlying drivers, and policy measures useful for policy formulation. Our study shows that IEA member countries converge on green energy innovation—accentuating the potential of achieving clean energy through green growth. Contrary, achieving environmental sustainability through emission reduction, energy efficiency, energy R&D, and service-driven industrial structure remain divergent. This implies that country-specific policies on environmental sustainability will yield better results for mitigating anthropogenic emissions. Second, green energy innovation and energy R&D decline long-term GHG emissions by reducing negative environmental externalities. Investment and integration of energy R&D are reported to increase clean energy transition through sustainable electricity supply that is cost-effective and low in CO_2 emissions (Kittner *et al.*, 2017). Additionally, green energy innovation hampers CO_2 emissions from buildings, implying that a transition towards green buildings improves both indoor and outdoor emissions (Nykamp, 2017). The variability in climatic patterns affects heating and cooling degree days, hence, affecting energy demand. If the energy requirement for these seasons is replaced with green energy technologies, energy consumption declines while reducing energy cost and indoor pollution (Castleton *et al.*, 2010). We find that transport sector is the most persistent source of over-decadal CO_2 emissions—contributing about 29.66-40.64% of GHG emissions across IEA member countries. However, replacing fossils in the transport sector with green energy innovation-based alternative energy declines emissions by reducing transport footprint (van Vuuren *et al.*, 2018). Besides, we find that fossil emissions increase green energy innovations in countries with high GHG emissions. This infers that IEA member countries in a fossil-based CO_2 regime are more likely to invest and adopt green energy innovations and pursue environmental sustainability after achieving economic prosperity. Increasing investment in energy research development and demonstration is critical for green energy innovations and facilitates the transition towards clean energy and emission reduction.

7.5 Conclusion

Reducing climate change and its related impacts remain critical to achieving environmental sustainability. However, growing population demand for energy and sustained economic productivity appears a hurdle for the mitigation target. While the extant literature has explored the determinants of anthropogenic GHG emissions, studies on the role of policy drivers including green energy innovation and energy research and development are limited. These green growth drivers act as abatement strategies of global emissions in carbonized and energy-intensive economies. To advance global and policy discussions, we examined how fossil emissions appear advantageous to green energy innovations, and energy R&D across industrialized high-income IEA countries.

The forty-year trend estimation showed power sector-driven GHG emissions declined substantially after 2009, coinciding with the 2009 renewables directive (Directive 2009/28/EC) by the EU. This perhaps prompted several EU member countries to develop national goals for renewables—that declined the share of fossil fuels in the energy portfolio—leading to a decline in GHG emissions. The incorporation of green energy innovation amidst sectoral emissions showed 1% increase in energy intensity could spur GHG emissions from 5.47% in 2014 to over 5.56% in 2064. While there is potential increase in GHG emissions from 2014-2064, the rate of increase is relatively low. This infers green energy innovation is useful in energy diversification and decarbonization of economic productivity. Besides, we observed low concentration of GHG emissions from IEA countries including, inter alia, Portugal, Denmark, Sweden, Norway, Switzerland, and Austria—with high adoption of green energy innovation. Our empirical results support the European Green Deal agenda—of reducing emissions and preserving environmental quality through investment and adoption of green energy innovation. However, while our analysis showed evidence of convergence in green energy innovations, IEA member countries appear to diverge in GHG emissions. While IEA member countries are industrialized and developed economies, their economic structure and composition are different, hence, similar emission targets may hamper sustained economic development. This implies caution in the integration of green energy innovation in high carbonized economies—to avoid potential tradeoff between sustained economic growth, and environmental sustainability. Nevertheless, our study showed green growth strategies are useful in achieving decarbonized and energy-efficient growth while mitigating emissions.
Because of limitation in acquiring extensive data for the sampled series, our data periodicity spans from 1975-2014—thus, this implies our data capture exactly 2 years after the inception of the sustainable development goals (SDGs). Future research could adopt dataset that captures more years of the SDGs and several income groups—to assess the effect and limitations of income status on green energy innovation and green growth.

Data Availability

Data utilized in this study are available on public repositories and can be acquired from IEA, OECD, World Bank, and EDGAR databases.

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Chapter 8. Paper 6: Environmental performance, biocapacity, carbon & ecological footprint of nations: drivers, trends, and mitigation options

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S.A.S designed the study, collected the data, performed the data analysis, coordinated and supervised the study, and drafted the manuscript—thus, contributing 100%.

Environmental performance, biocapacity, carbon & ecological footprint of nations: drivers, trends, and mitigation options [7]

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.

8.1 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 of environmental convergence, a situation that has implications on sustainability. A rapid increase in economic productivity

[7] Published article: **Sarkodie, S. A.** (2021). Environmental performance, biocapacity, carbon & ecological footprint of nations: Drivers, trends and mitigation options. *Science of The Total Environment*, 141912. https://doi.org/10.1016/j.scitotenv.2020.141912

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 to the atmosphere 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.

8.2 Methods

8.2.1 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 and South America.

8.2.2 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).

8.2.3 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:

$$lnCARBON \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, ln\Delta NECOPERM, lnGDP) \quad (1)$$
$$lnCARBON \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, ln\Delta NECOPERM, lnGDPC, lnTRADE) \quad (2)$$
$$lnEFCONS \sim f(lnPOPDEN, lnENVSUS, lnGDP) \quad (3)$$
$$lnEFCONS \sim f(lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE) \quad (4)$$
$$ln\Delta NECOPERM \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDP) \quad (5)$$
$$ln\Delta NECOPERM \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE) \quad (6)$$
$$ln\Delta NECOPERM \sim f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnGDPC^2, lnTRADE) \quad (7)$$

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 Equations 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 Equations 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):

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

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):

$$lny_{i,t} = \delta * lny_{i,t-1} + \beta * lnx_{i,t} + \alpha_i + \varepsilon_{i,t}, \;\; i = 1, \ldots, N \; and \; t = 1, \ldots, T \tag{9}$$

where $lny_{i,t}$ represents the logarithmic transformation of the target variables ($lnCARBON$, $lnEFCONS$, and $ln\Delta NECOPERM$) for the model specification of equation 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).

8.3 Results

The choropleth maps (Figures 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 Figure 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 Figure 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 Figure 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 Figure 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 Figure 2]. Based on the ecological status of nations, we mapped the continental and global status of ecological performance presented in Figure 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 (Figure 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 (Figure 4). The 56-year mean trend for biocapacity reveals that India, Germany, and the US are above the global average of 0.429% whereas 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 1961-2016 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 1961-2016 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 1961-2016 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).

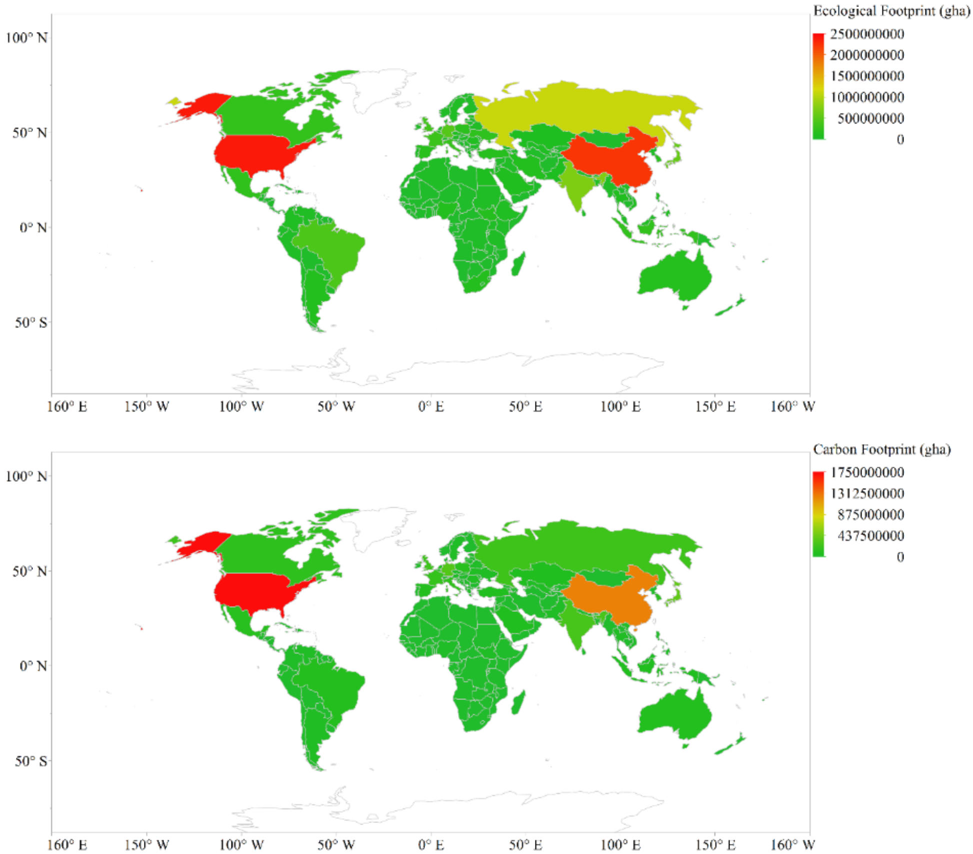

Figure 1| Geographical mapping of ecological and carbon footprint (gha).

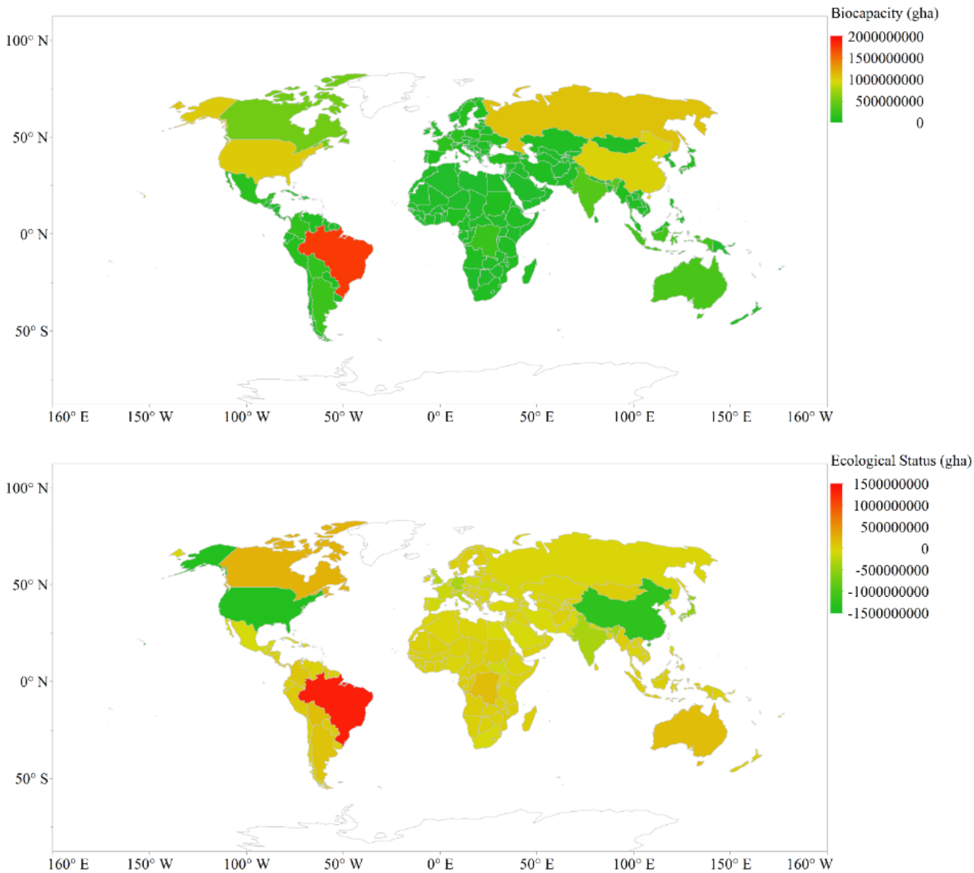

Figure 2| Geographical mapping of biocapacity and ecological status (gha).

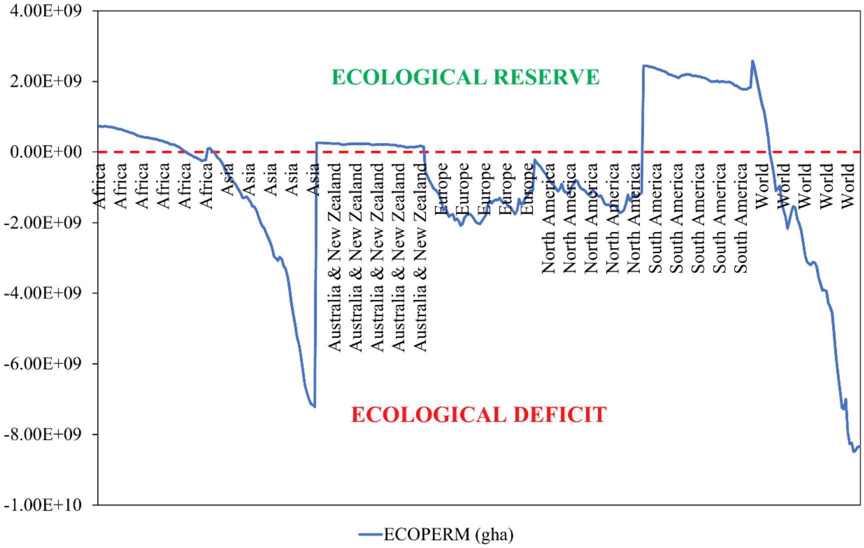

Figure 3| Continental and global status of ecological performance (gha).

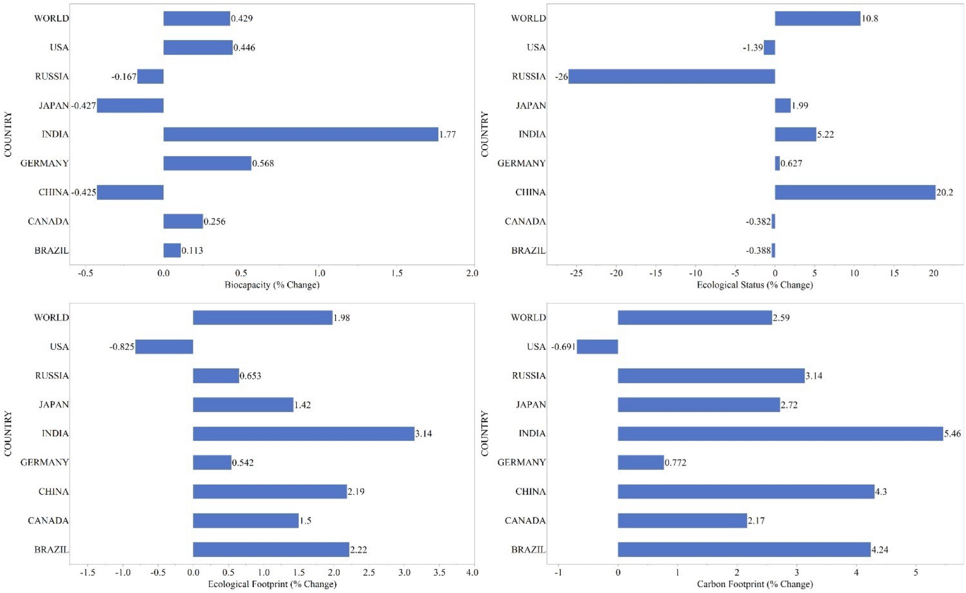

Figure 4| Mean relative change (%) in biocapacity, ecological footprint, ecological status and carbon footprint of the US, Russia, Japan, India, Germany, China, Canada and the World.

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 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 (Figure 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 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 24-91% 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 (Figure 6). This is validated by the superimposed kernel fit and normal distribution line, confirming the residual independence of the estimated models.

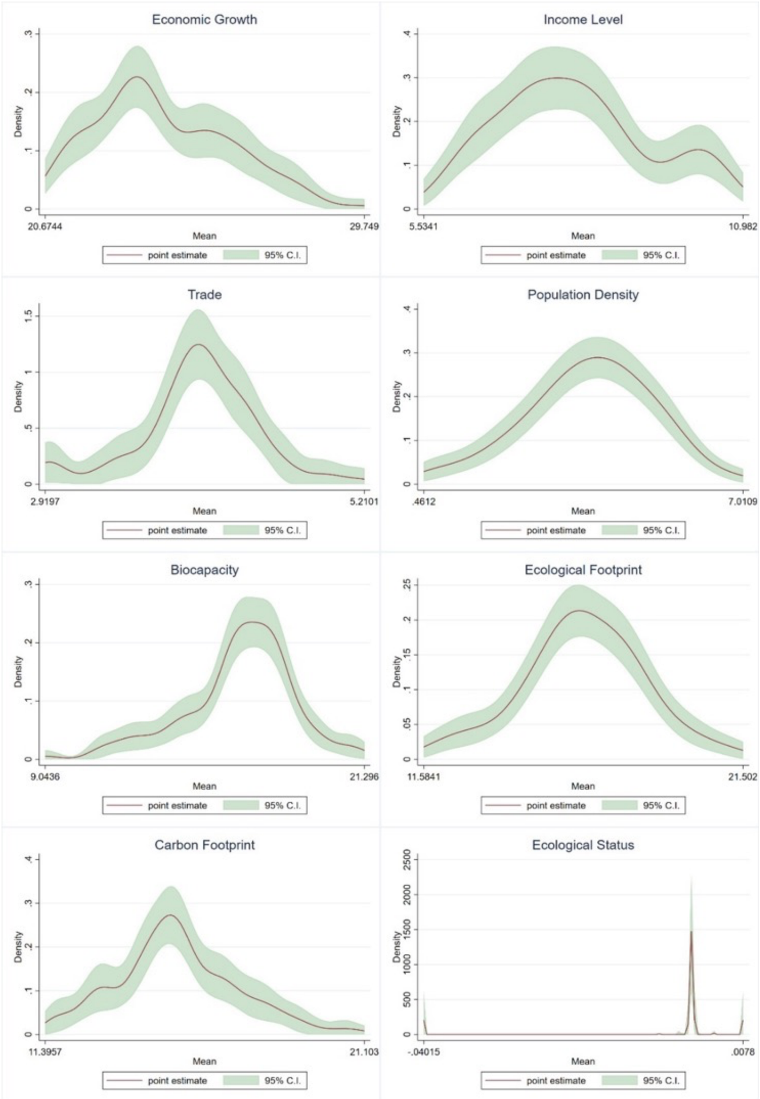

Figure 5| Panel heterogeneous distribution of socio-economic and environmental performance indicators. Legend: The 95% confidence interval (C.I) denotes the rejection of the null hypothesis that the distribution is identical (homogeneous) across the 188 countries.

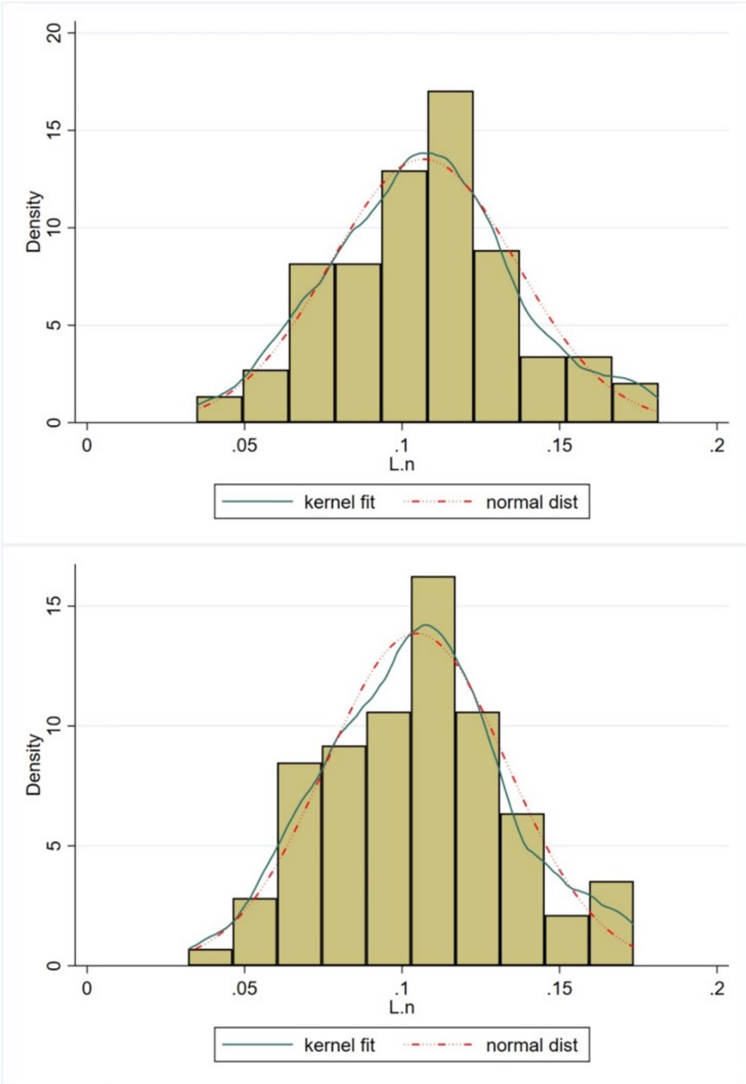

Figure 6| Model Validation of the panel bootstrap-corrected fixed-effects estimation models using histogram distribution — overlaid by kernel fit and normal distribution.

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]
ΔNECOPERM†	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, lnΔNECOPERM, lnGDP); Model 2 - lnCARBON ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnΔNECOPERM, lnGDPC, lnTRADE); Model 3 - lnEFCONS ~ f(lnPOPDEN, lnENVSUS, lnGDP); Model 4 - lnEFCONS ~ f(lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE); Model 5 - lnΔNECOPERM ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDP); Model 6 - lnΔNECOPERM ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnTRADE); Model 7 - lnΔNECOPERM ~ f(lnEFCONS, lnPOPDEN, lnENVSUS, lnGDPC, lnGDPC2, lnTRADE). Legend: GDPC - Income Level, GDP - Economic growth, POPDEN - Population density, TRADE - Trade, ENVSUS - Biocapacity, CARBON - Carbon Footprint, EFCONS - Ecological Footprint, NECOPERM - Ecological Status.

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.

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. Analogous 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.

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 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*).

8.4 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 implications 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-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.

8.5 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.

Acknowledgement

Open Access funding provided by Nord University.

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Chapter 9. Paper 7: Failure to control economic sectoral inefficiencies through policy stringency disrupts environmental performance

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Author contribution

S.A.S designed the study, collected the data, performed the data analysis, coordinated and supervised the study, and drafted the manuscript—thus, contributing 100%.

Failure to control economic sectoral inefficiencies through policy stringency disrupts environmental performance [8]

Abstract

The developmental agenda of emerging countries often depend heavily on natural resource exploitation — a situation that hampers environmental performance. Hence, maximizing economic sectoral yield while reducing overdependence on fossil fuels and resources is essential to reducing wastage. Here, we assess the economic sectoral impact on emissions while controlling for foreign direct investment and energy utilization from 1990-2018. Besides, we investigate the role of environmental policy stringency in ameliorating environmental performance in a carbonized and energy-intensive economy where fossil fuels outweigh renewables. Agrarian, industrial, and energy sector dynamics are found to offshoot CO_2 emissions by 0.12%, 0.14%, and 0.20% whereas service sector productivity decline CO_2 emissions by 0.34%. We observe fossil fuel dominated energy portfolio with limited clean and renewable energy diversification that hinders long-term environmental performance. The validation of the pollution halo hypothesis implies that FDI inflows are possibly embedded with green and abatement technologies that reduce emissions while improving environmental performance. Thus, a comprehensive masterplan on climate change mitigation will comprise sectoral-specific resource investment that maximizes productivity while reducing natural resource exploitation, energy, and carbon-intensity.

9.1 Introduction

The traditional linear economy poses great danger to achieving environmental sustainability through climate change mitigation. While efforts have been made to shift from linear economy (Sauvé *et al.*, 2016) to sustainable production and consumption—accentuated in the twelfth Sustainable Development Goal (United Nations, 2015), several existing factors limit the global emission reduction efforts. The immediate and underlying determinants of global emissions are reported to include population growth, energy intensity, economic growth,

[8] Published article: **Sarkodie, S. A.** (2021). Failure to control economic sectoral inefficiencies through policy stringency disrupts environmental performance. *Science of The Total Environment*, 145603. https://doi.org/10.1016/j.scitotenv.2021.145603

trade, urbanization, industrialization, governance, technology, infrastructure, development, behavior, and resource availability (Blanco *et al.*, 2014; Rosa *et al.*, 2012). Besides, economic sectors such as energy, industry, agriculture, forestry, and land use account for ~79.6% of the 49 Gt CO_2 equivalent direct greenhouse gas emissions driven by economic activities (IPCC, 2016). The trilemma between environmental sustainability, economic development, and resource-energy utilization highlights the importance of resource allocation and economic structural adjustment.

While the environmental Kuznets curve (EKC) hypothesis assumes carbonized-economic productivity driven by intense energy and resource utilization in developing economies, decarbonized-economy with energy efficiency through technological innovation (Jordaan *et al.*, 2017) is reported to decline emissions in developed economies (Panayotou, 1993). However, failure to account for economic sectoral and disaggregate energy contribution to global emissions render environmental policies weak. It is acknowledged that no single country operates in one specific economic sector but multiple (agriculture, industry, and services). Hence, using aggregate growth in assessing the popular EKC hypothesis may limit country-specific policy formulation. This implies that the assessment of the various sectoral effects on emissions helps in resource allocation with limited carbon and energy intensity (UNEP, 2011). However, previous studies (Arce *et al.*, 2016; López *et al.*, 2018; Steinberger *et al.*, 2012) fail to address these structural adjustments in both economic and energy sector portfolios.

Though several studies assess the effects of domestically generated emissions, very few have examined the impact of transboundary attributed emissions generated through trade (Arce *et al.*, 2016; López *et al.*, 2018; Steinberger *et al.*, 2012). Yet, the role of external funding such as foreign direct investment (FDI) — which underpins both pollution haven and halo hypotheses has not been extensively assessed. Pollution haven hypothesis is characterized by natural resource seeking—access and exploitation-based FDI inducing emissions whereas pollution halo is characterized by efficiency-seeking based FDI—boosting technology transfer, innovation, research, and development—hence, declining long-term emission concentrations (Dunning, 1980). Aside immediate and underlying drivers of GHG emissions, several policies, and measures through institutional quality underpin long-term emission standards (Le Quéré *et al.*, 2019). In this regard, proper institutional quality can be assessed by the level of stringency on environmental policies. This also implies that the nature of foreign investment is determined by environmental policy stringency.

Contrary to existing literature, our study presents novel concepts in both spirit and letters. Extant literature appears to focus on aggregate economic productivity and energy demand in assessing emission risks, however, such pathway provides very little knowledge for country-specific policies on environmental sustainability. In considering disaggregate energy namely fossil fuels, clean and renewables—disaggregate economic growth namely agriculture, industry, and services—rather than the usual aggregates — several trends, policies, and measures become evident. In using disaggregates, the magnitude of sectoral-based impact can be quantified and assist in optimal resource investment that maximizes yield while reducing emissions. Second, the rebound effect is reported to affect both direct and indirect emission consequences. However, several studies fail to capture the importance of rebound effects that is evident with socio-economic and environmental factors. The rebound effects are reported to mediate the effectiveness of long-term energy and environmental-related policies and measures. Thus, rebound effects are relatively high in emerging economies (Chakravarty *et al.*, 2013) and require attention — especially with emission reduction modeling in developing countries. We account for possible rebound effects of sectoral economic growth, energy utilization, and foreign direct investment. The impact of transboundary effect through global partnership is examined through foreign direct investment inflows. We assess whether pollution trends that hamper environmental performance are domestically generated or induced by external funding. Here, we model the nonlinear effects of sectoral economic growth, foreign direct investment, and energy utilization. We use innovative accounting technique that graphically projects minimum resource allocation while maximizing yield in one breath and maximum resource investment with limited gains. The different kinds of nonlinear projections demonstrate the importance of considering sectoral economic accounting in environmental policies. We further use stochastic simulation models to project the counterfactual change in environmental performance using the business-as-usual scenario with changes in FDI and environmental policy stringency.

9.2 Materials & Method

The assessment of the proposed hypotheses begins with data identification, selection, and preprocessing. The choice of data series presented in Table 1 for further processing stems from the Sustainable Development indicators and IPCC 5th assessment report on climate change (Blanco *et al.*, 2014; DiSano, 2002). To account for Sustainable Development Goal (SDG) 7 of sustained economic development, we employ both aggregate GDP and sectoral economic contribution namely agrarian, industry, and services. Similarly, to account for clean energy, sustainable industrial productivity, innovation, and responsible production and consumption expounded in SDGs 7, 9, and 12, we employ aggregate energy and disaggregate energy that encompasses both fossil fuels and renewables. To develop conceptual tools for climate change mitigation entailed in SDG 12, we use both carbon dioxide emissions and environmental performance index as target variables (Alhassan *et al.*, 2020). We incorporate environmental policy stringency to account for institutional quality explained in SDG 16. To assess the role of global partnership (SDG 17), we utilize foreign direct investment net inflows as indicator for achieving Sustainable development in developing countries. To control for unevenly spaced data, we utilize the imputation technique presented in Owusu *et al.* (2020). Our comprehensive model uses South Africa as a case study with data spanning 1990-2018. South Africa ranks fifth (192 Mt) in terms of global coal consumption (Enerdata, 2019) and the only African country with different economic structure compared to the others in the sub-region. The country has a characteristic of an emerging economy with overdependence on fossil fuels and very little attention to clean environment. While foreign direct investment flows to Africa increased by 11% (~US$46 Billion) with slow growth in African countries, South Africa over-doubled its inflows from US$2 Billion to US$5.3 Billion due to resource-seeking investments (UNCTAD, 2019). The over 165.8% growth in FDI flows to South Africa is alarming and requires attention, owing to the interest of foreign investors in exploiting available natural resources. Hence, South Africa is the only African country among the top 10 FDI (ranks 7th) stock economies after France, Netherlands, the US, UK, China, and Italy.

Table 1. Data Description

Abbreviation	Variable	Unit
AGRARIAN	Agriculture	% of GDP
CO_2	CO_2 emissions	kg per 2010 US$ of GDP
ENERGY	Energy use	kg of oil equivalent per capita
ENVPER	Environmental Performance Index	index
ENVPS	Environmental Policy Stringency	index
FDI	Foreign direct investment net inflows	BoP, current US$
FOSSIL	Fossil fuel energy consumption	% of total final energy consumption
GDP	Economic growth	current US$
INDUSTRY	Industry	% of GDP
RENCONS	Renewable energy consumption	% of total final energy consumption
SERVICES	Services	% of GDP

9.2.1 Hypothesization

We utilize the FreeViz explorative analysis technique to construct optimal research hypotheses through the nexus pattern of variables depicted in Figure 1. The FreeViz technique employed herein is used to develop hypotheses based on evidential relationships revealed between classes and characteristics, interactions, and intra-class information of similarities between important variables. Contrary to the principal component analysis that creates projections, the FreeViz algorithm improves linear projections via gradient optimization technique that classifies variables based on relationships and patterns using visualizations (Demšar *et al.*, 2007). Hence, the FreeViz algorithm is a useful explorative analysis tool for hypothesization of highly dimensional data series. It can be observed from the initial position of multivariate visualization that higher levels of CO_2 emissions (indicated by yellow colored-square legend) have strong association with energy, industry, services, and agrarian [Figure 1 (a)]. In contrast, FDI, environmental policy stringency and environmental performance index have relatively weak correlation with CO_2 emissions (indicated by blue colored-square legend). While we find almost all the hypotheses of the FreeViz explorative analysis corroborating existing theories, the linkage between average levels of CO_2 emissions and the neutrality between GDP, renewable energy consumption, fossil fuels call for more vigorous analysis. Hence, we apply the random optimization procedure to improve the initial position of the sampled variables. Subsequently, we find a strong correlation between high levels of CO_2 emissions, fossil fuels, industry, and agrarian whereas lower levels of CO_2 emissions are attributed to energy, GDP, and environmental policy stringency [Figure 1 (b)]. Besides, a negative or neutral effect is observed running from FDI, renewable energy, services, and environmental performance index to CO_2 emissions. The questions emanating from the explorative analysis include:

(1) What is the sectoral contribution to CO_2 emissions while accounting for inflows, economic development, and energy consumption? (Hypothesized from Appendix B)

(2) What accounts for the strong affinity between renewables and CO_2 emissions while controlling for the dominance of fossil fuel and sustained economic growth? (Hypothesized from Appendix C)

(3) How does the interplay of disaggregate energy mix and economic development affect environmental performance? (Hypothesized from Appendix D)

(4) Does environmental policy stringency ameliorate environmental performance in a carbonized and energy-intensive economy where fossil fuels outweigh renewables? (Hypothesized from Appendix E)

Thus, the questions distilled from FreeViz multivariate visualization of CO_2 emissions and environmental performance require answers that form our *a priori* expectations for further empirical assessment.

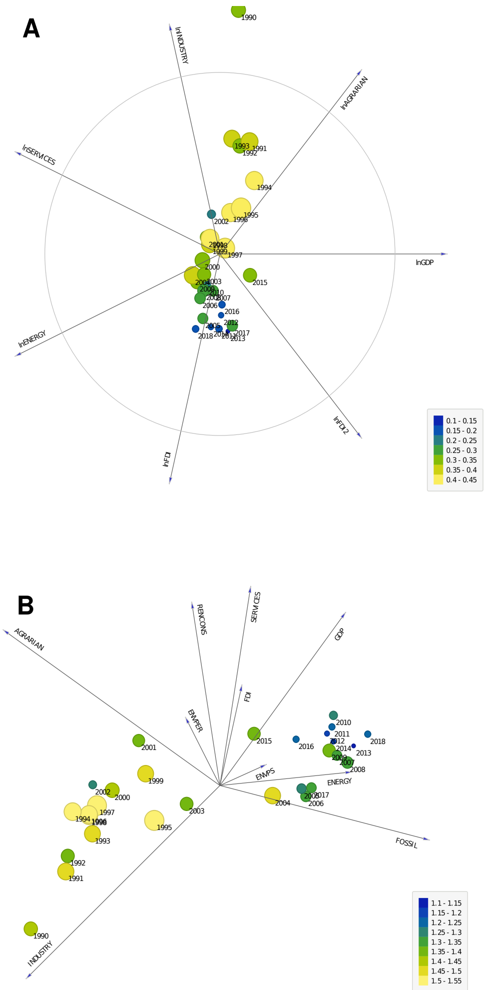

Figure 1. Multivariate visualization of CO_2 emissions (indicated by legend) versus socio-economic and environmental indicators: (a) Before FreeViz (b) After the application of FreeViz algorithm. Legend: Yellow colored-square indicates high levels of CO_2 emissions whereas blue colored-square represents low levels of CO_2 emissions.

9.2.2 Model Construction

Following the FreeViz explorative analysis technique, we use the novel Kernel Regularized Least Squares (KRLS) estimation method to investigate the hypothesis of the study. KRLS is a machine learning algorithm drawn from an independent identically distributed data with Gaussian kernel — i.e. partly positive definite and symmetric function of inputs mapped onto actual-valued output, hence, measures the resemblance between two input patterns (Ferwerda *et al.*, 2017). The target (CO_2 emissions and environmental performance) functions are fitted with Gaussian kernels, where each input pattern is centered, corresponding weight scaled and summed up. Next, regularization is applied to optimize the tradeoff between fit approximation and complexities of the model by the imposition of a penalty (Tihonov, 1963). To avoid over-parametrization, an optimal regularization boundary is automatically selected by the minimization of leave-one-out errors of the sum of squares (Hastie *et al.*, 2009). The pointwise partial derivatives of CO_2 emissions and environmental performance are derived from the input variables namely agriculture, energy use, environmental policy stringency, FDI inflows, fossil fuels, economic growth, industry, renewables, and services—to examine the pointwise marginal effects of the input variables.

The KRLS estimator is used to derive hypothesis testing, pointwise average marginal effect, and average marginal effects, formation of confidence interval, choose an optimal bandwidth automatically for the Gaussian kernel—leading to unbiased, consistent, and normally distributed fitted values with asymptotic characteristics (Hainmueller *et al.*, 2014). To improve the complexity of the estimated model — i.e., nonlinearity and interactive effects, we paired the estimated pointwise marginal effects with the independent variables to assess potential statistical significance for inclusion in subsequent analysis. For instance, a statistically significant nexus between pointwise marginal effect of a regressor and target variable signifies nonlinearity whereas a strong relationship between pointwise marginal effect of a regressor and another regressor denotes interaction. In such a situation, re-estimation of the machine-based learning algorithm is executed to include the newly identified additional variables to improve the model's complexity.

To examine the counterfactual change in environmental performance over the next 30 years while accounting for FDI and environmental policy stringency. We predict environmental performance using the average change in growth of FDI (2.12%) and environmental policy stringency (0.07%) based on ceteris paribus analysis using dynamic ARDL simulations algorithm. To apply the dynamic ARDL simulations, several pre-conditions were examined and requirements met. First, data series were first-difference stationary — tested using Phillips-Perron (Phillips *et al.*, 1988) and Augmented-Dickey fuller (Dickey *et al.*, 1979) unit root. Second, we adopted an optimal lag structure based on first difference via useful information criteria. Third, the nexus between environmental performance, FDI, and environmental policy stringency was cointegrated with long-run effect — validated using the Pesaran-Shin-Smith bounds test based on surface regression with critical and approximate probability values. A confirmation of the long-run nexus between the sampled series led to the adoption of error correction-based ARDL estimation technique. Thereafter, we applied the dynamic ARDL (Jordan *et al.*, 2018) stochastic simulations approach with the selected optimal lag in first-difference. Besides, we utilized a single shock regressor for counterfactual impulse analysis using the specified ± change (%) along the 20-length scenario at 10-year scenario time for impulse to occur along the horizon based on error correction technique with 5,000 stochastic simulations. The parameters stimulated based on the business-as-usual scenario are used in predicting future changes in environmental performance over the time period via stochastic improbability drawn from a zero-mean and variance attributed multivariate-normal distribution. The simulated values are automatically averaged to produce predicted parameters, confidence intervals, and stochastic uncertainties presented in spiked plots.

Model Validation. Contrary to traditional linear regression that is extremely vulnerable to misspecification bias, the KRLS estimator is less vulnerable due to an initial flexibility modeling of conditional expectation function and subsequent reporting of parameters as mean derivative of the enhanced fitted model. Second, the optimization of the fitted model with a penalty-attributed to optimal regularization function helps prevent over-fitting. Third, the KRLS estimator controls for complex models with non-additivity, non-linearities, and interaction effects (Hainmueller *et al.*, 2014). The marginal effects of the estimated models were examined for heterogeneous effects using the pointwise derivatives expressed in percentiles. We observe that all the covariates in the estimated models from 1-99 percentiles lack uniform distribution of the marginal effects. Hence, failure to examine heterogeneous effects and account for conditional distribution across percentiles leads to biased-statistical inferences and policy formulation. This called for the adoption of average marginal effects rather than the traditional estimation procedure. To confirm the parameter stability of the estimated coefficients of covariates over the period, we adopted the recursive cumulative sum test presented in Figure 2. We observe that the estimated parameters of covariates are within the 95% confidence band, hence, confirming the time-specific constancy and stability of the models.

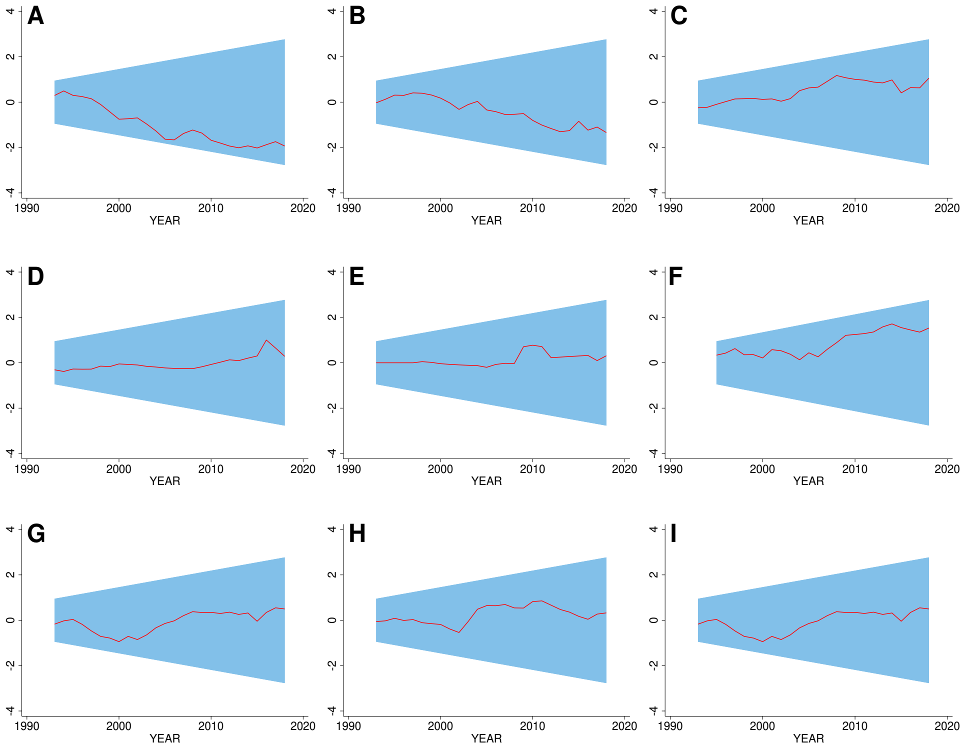

Figure 2. Recursive CUSUM for stability test: (A) Agrarian Sector (B) CO_2 Emissions (C) Energy Utilization (D) Environmental Performance Index (E) ENVPS (F) FDI (G) Fossil Energy Utilization (H) GDP (I) Industrial Sector

9.3 Results & Discussion

We discern from Table 2 that FDI inflows observed the highest growth by 2.12% within the 28-year data sample, followed by environmental policy stringency (0.07%), economic growth (0.05%), services (0.01%), energy (0.01%), and disaggregate energy (fossil fuels and renewables) at par with 0.001% change. In contrast, agrarian sector experienced the highest decline in 28 years by 0.02% and trailed closely by industrial sector (0.01%), CO_2 emissions (0.003%), and environmental performance (0.001%). In terms of sectoral contribution to economic growth, we find that services dominate on average by 58.74%, followed by industry (28.93%) and agrarian (2.97%).

Table 2. Descriptive statistics of sampled indicators

Statistic	AGRARIAN	CO_2	ENERGY	ENVPER	ENVPS	FDI	FOSSIL	GDP	INDUSTRY	RENCONS	SERVICES
%Δ	-0.0198	-0.0031	0.0066	-0.0005	0.0724	2.1155	0.0005	0.0502	-0.0119	0.0005	0.0069
Mean	2.9664	1.3605	2570.9870	51.5607	0.6401	3.06E+09	86.3254	2.35E+11	28.9259	17.2006	58.7428
Median	2.8595	1.3811	2518.3330	50.4600	0.4792	1.52E+09	86.5753	2.29E+11	28.0077	17.1072	60.0857
Maximum	4.2150	1.5569	2950.1540	70.5200	1.7500	9.89E+09	88.1487	4.16E+11	36.4069	19.1214	61.3893
Minimum	2.0888	1.1484	2290.6670	44.7300	0.3958	-75722412	84.2434	1.15E+11	25.8535	15.5703	50.4671
Std. Dev.	0.7041	0.1196	168.1998	4.4623	0.3684	2.94E+09	1.1119	1.03E+11	2.8775	0.9405	2.7957
Skewness	0.3580	-0.0808	0.4327	2.4048	2.2950	0.7550	-0.3462	0.2807	1.0606	0.2918	-1.3743
Kurtosis	1.8164	1.8735	2.4845	12.6793	6.9182	2.2827	1.9415	1.5117	3.2113	2.1397	4.2948
Jarque-Bera	2.3123	1.5651	1.2261	141.1568	44.0076	3.3767	1.9333	3.0576	5.4905	1.3058	11.1539
Probability	0.3147	0.4572	0.5417	0.0000	0.0000	0.1848	0.3804	0.2168	0.0642	0.5205	0.0038
AGRARIAN	1										
CO_2	0.7834*	1									
ENERGY	-0.4854*	-0.4124*	1								
ENVPER	-0.1564	-0.1791	-0.0992	1							
ENVPS	-0.4199*	-0.3871*	0.4496*	0.1916	1						
FDI	-0.5213*	-0.5351*	0.7037*	-0.059	0.3012	1					
FOSSIL	-0.4917*	-0.5016*	0.7616*	-0.0529	0.3731*	0.5199*	1				
GDP	-0.8803*	-0.7707*	0.6331*	0.0806	0.6076*	0.5528*	0.6873*	1			
INDUSTRY	0.9162*	0.6208*	-0.4955*	-0.0598	-0.3344	-0.5026*	-0.3926*	-0.7678*	1		
RENCONS	0.5581*	0.4456*	-0.7454*	-0.0394	-0.3087	-0.5386*	-0.6659*	-0.6837*	0.4961*	1	
SERVICES	-0.9059*	-0.6041*	0.4490*	0.0544	0.3864*	0.4940*	0.33	0.7454*	-0.9838*	-0.4184*	1

Notes: %Δ denotes the mean relative change from 1990-2018 (elaborated in Appendix A). Pearson correlation of sampled indicators based on a 2-tailed test of significance is used; * Pearson correlation is significant at 5% level.

How does sectoral-based economy affect CO_2 emissions? To answer this question, we adapted the theoretical support of the traditional EKC hypothesis and substituted it with sectoral economic growth namely agrarian, industry, and services (Figure 3). The EKC hypothesis posits that initial agrarian-based economic development of low-income countries emboldens environmental consequences due to excessive resource extraction and waste generation — a process termed as the scale effect (Panayotou, 1997; Sarkodie *et al.*, 2019). However, it is assumed that as low-income countries migrate to middle-income status catalyzed by a shift from agrarian to industrial economy, increasing level of income to a specific threshold engenders environmental awareness. This leads to environmentally friendly policies that change the composition of the economic structure, resulting in a gradual decline of emissions — a process termed as the composition effect. In contrast, high-income countries are characterized by services, modern technologies, innovation, and environmental policy stringency, ensuing in transfer of polluting industries to developing economies. This in effect declines environmental consequences compared to industry sector — a process termed as the technique effect.

While the EKC hypothesis assumes a specific sector across income groups, all three sectoral-based economies practically exist in a country's economic structure but with varying contributions to economic development. Thus, assessment of all sectoral-based economic growth with environmental consequences appears more policy-oriented compared to the traditional framework of the EKC hypothesis. In Figure 3(A-C), we show that disaggregate economic growth versus CO_2 emissions achieves similar trend as the so-called inverted-U-shaped curve aka EKC hypothesis. On this note, we empirically test the hypothesis with CO_2 emissions as target variable whereas agrarian, industry, and services are regressors while controlling for energy, FDI, and squared of FDI.

We used the general-to-specific reasoning to improve the complexity of the estimated model via KRLS pointwise partial derivatives. Using partial derivatives of covariates generated from economic sectoral accounting, we substituted the derivatives of each covariate in place of CO_2 emissions for subsequent analysis. Regressors that proved significant against specified derivatives qualified for either interaction or nonlinearity. Though the goodness fit test in Table 4 is 79% compared to 81% in Table 3, however, the resulting complex model in Table 4 produces same sign and significance but shows more robust and consistent results. The estimated average marginal effects in Table 3 show that expansion in agrarian, industrial, and energy sector dynamics offshoot CO_2 emissions by 0.12%, 0.14%, and 0.20% —whereas service sector productivity and growth in FDI reduce CO_2 emissions by 0.34% and 0.01%, respectively. Besides, both linear and second-degree polynomials of FDI are negative and statistically significant at *p-value<0.01*, thus, confirming the validity of the pollution halo hypothesis (see Table 3). This infers that contrary to arguments of pollution-embedded FDI inflows transferred to developing economies, our empirical analysis shows that the type of FDI inflows to South Africa supports green growth. Meaning that the external funding is possibly embedded with green and abatement technologies such as renewables and clean energy, and green knowledge spillover that underpins circular and green economic growth.

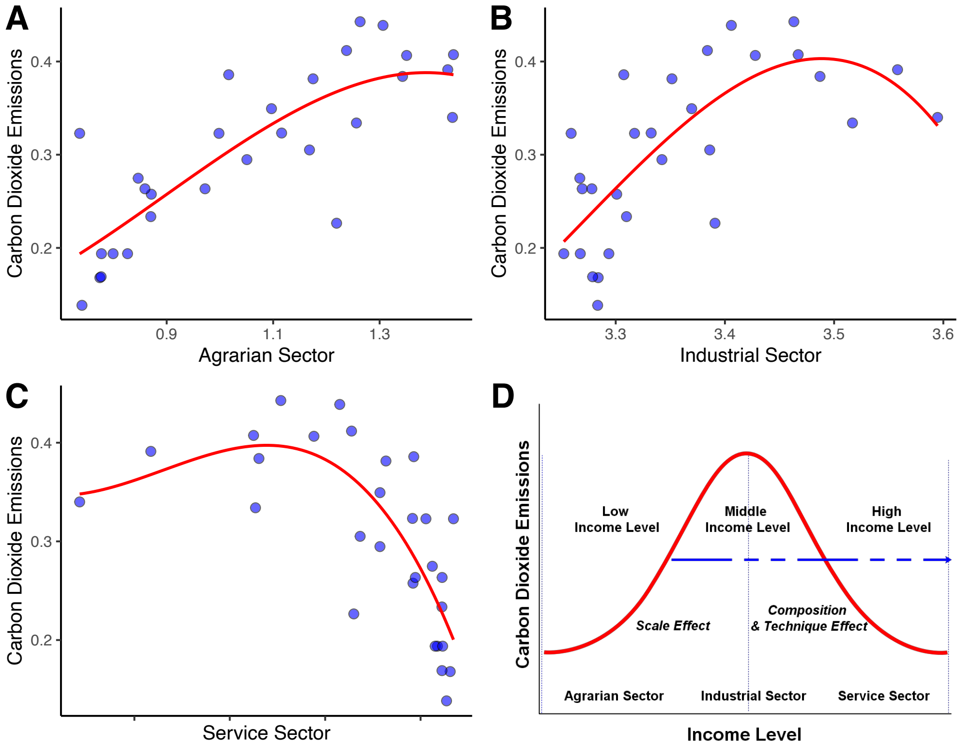

Figure 3. Schematic representation (A) Trend of CO_2 emissions versus Agrarian sectoral-based economic development (B) Trend of CO_2 emissions versus Industrial sectoral-based economic development (C) Trend of CO_2 emissions versus Service sectoral-based economic development (D) EKC hypothesis showing Income level in CO_2 emissions function.

Table 3. Estimated Parameters & Pointwise Derivatives — Economic Sectoral Accounting

Percentiles	AGRARIAN	INDUSTRY	SERVICES	ENERGY	FDI	FDI^2
Avg.	0.1207***	0.1367***	-0.3407***	0.1982**	-0.0062***	-0.0002***
	[0.0200]	[0.0477]	[0.0837]	[0.0837]	[0.0020]	[0.0001]
1%	-0.0448***	-0.1854***	-0.7002***	-0.4920**	-0.0159***	-0.0004***
5%	-0.0246***	-0.0476***	-0.6173***	-0.3245**	-0.0154***	-0.0004***
10%	0.0017***	-0.0448***	-0.6092***	-0.2331**	-0.0150***	-0.0004***
25%	0.0652***	0.0604***	-0.5146***	0.0199**	-0.0095***	-0.0003***
50%	0.1372***	0.1649***	-0.3915***	0.2604**	-0.0066***	-0.0002***
75%	0.1730***	0.2264***	-0.2437***	0.4154**	-0.0034***	-0.0001***
90%	0.2369***	0.2807***	0.0171***	0.5191**	0.0015***	0.0000***
95%	0.2375***	0.2853***	0.0296***	0.5236**	0.0061***	0.0001***
99%	0.2597***	0.3112***	0.5541***	0.6306**	0.0074***	0.0002***
Diagnostics	—	—	—	—	—	—
Mean	0.1207	0.1367	-0.3407	0.1982	-0.0062	-0.0002
Std. Dev.	0.0848	0.1205	0.2706	0.2735	0.0056	0.0002
Variance	0.0072	0.0145	0.0732	0.0748	0.0000	0.0000
Skewness	-0.2887	-0.7662	1.4137	-0.7174	0.5617	0.3572
Kurtosis	2.1445	3.0862	5.3290	2.9535	3.2905	2.9220
Lambda	0.8000	—	—	—	—	—
R-square	0.8141	—	—	—	—	—
Looloss	0.8198	—	—	—	—	—
Sigma	6.0000	—	—	—	—	—
Eff. Df	7.3250	—	—	—	—	—
Cointegration	YES[a]	—	—	—	—	—

Notes: [a]The null hypothesis of no cointegration is rejected at 5% significance level by Johansen maximum eigenvalue and Boswijk test for cointegration; [.] represents the standard errors while **, *** denote statistical significance at 5% and 1% level.

The pointwise derivatives of nonlinear and interactive effects in Table 4 show a negative and significant effect of maximum service productivity ($SERVICES^2$) on CO_2 emissions. This reveals that long-term maximization of the service sector yield has a mitigation effect on CO_2 emissions by 0.012%. We observe that the interaction between energy and agrarian sector (ENERGY×AGRARIAN) — energy and industrial sector (ENERGY×INDUSTRY) escalates CO_2 emissions by ~0.01%, however, the statistical insignificant interaction effect of energy and services (ENERGY×SERVICES) decline CO_2 emissions. This suggests that energy-intensive agricultural and industrial production exacerbates CO_2 emissions whereas service sector driven energy utilization has no effect on emissions. Similarly, the interaction between agrarian and services — agrarian and industrial sector spurs CO_2 emissions by ~0.01%, however, the interaction effect of FDI and services — FDI and industrial sector declines emissions. This corroborates the existence of pollution halo hypothesis — implying that FDI inflows are possibly embedded with green growth, hence, has CO_2 emissions reduction effect.

Table 4. Pointwise Derivatives of Nonlinear and Interactive effects — Economic Sectoral Accounting

CO_2	Avg.	S.E.	t	P>t	P 5	P 50	P 95
ENERGY^2	0.0048	0.0036	1.3220	0.2050	-0.0172	0.0032	0.0198
SERVICES^2	-*0.0115*	0.0045	-2.5730	*0.0200***	-0.0216	-0.0138	0.0004
ENERGY×AGRARIAN	*0.0064*	0.0010	6.1550	*0.0000****	-0.0011	0.0069	0.0122
ENERGY×SERVICES	-0.0016	0.0035	-0.4440	0.6630	-0.0200	-0.0004	0.0142
AGRARIAN×SERVICES	*0.0125*	0.0021	5.9910	*0.0000****	-0.0017	0.0137	0.0245
AGRARIAN×INDUSTRY	*0.0111*	0.0017	6.6550	*0.0000****	-0.0026	0.0117	0.0218
ENERGY×INDUSTRY	*0.0066*	0.0035	1.8830	*0.0780**	-0.0134	0.0086	0.0195
SERVICES×INDUSTRY	0.0031	0.0130	0.2370	0.8160	-0.0262	0.0072	0.0287
FDI×INDUSTRY	-*0.0004*	0.0002	-2.4000	*0.0290***	-0.0008	-0.0006	0.0005
FDI×SERVICES	-*0.0004*	0.0001	-2.7990	*0.0130***	-0.0007	-0.0005	0.0004
Diagnostics							
Lambda	*0.8000*	**Eff. df**	*6.5390*	**R^2**	*0.7859*	**Looloss**	*0.8465*

Notes: For brevity, individual variables in Table 3 are not reported in this Table to avoid repetition. SE denotes standard error, P 5 is the 5th percentile, P 50 is the 50th percentile, and P 95 is the 95th percentile; S.E. represents the standard errors while *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Next, we graphically estimated the pointwise marginal effect of derivatives from the optimal and significant candidates (interaction and nonlinearity in Table 4) presented in Figure 4 with long term policy implications. We observe an inverted-U shape relationship between the marginal effect of industry and agrarian sector—an initial positive sectoral change in industry from low to medium level agrarian productivity and decreases thereafter, reaching the point of maximum agrarian sector yield. This implies that the industrial sector has long-term decreasing marginal returns for high investment in agricultural sector but short-term increasing industrial marginal returns until medium-level agrarian investment. Similarly, the marginal effect of FDI increases with increasing service sector investment but declines to negative after medium to high levels of service sector investment. This indicates that high levels of service sector investment improve internal financing and domestic development but declines external financing, foreign innovation, development assistance, and spillover effects of knowledge, technology, and labor.

The marginal effect of energy rises from negative to positive with corresponding low to high levels of agrarian investment. This implies that long-term agrarian investment increases energy consumption. We observe a U-shaped relationship between the marginal effect of services and agrarian sector. Decreasing marginal return of the service sector is evident between low to medium agrarian investments, however, experiences upturn after reaching the point of minimum agrarian sector yield. This infers that the service sector has long-term positive returns for high investment in the agricultural sector. Next, we examine the long-term association between the marginal effect of services and service sector dynamics. There is evidence of N-shaped relationship, which confirms two different turning points of both maximum and minimum service sector yield — revealing both productive and negative marginal returns. This in effect implies that allocation of resources or investments in only service sector is unhealthy for long-term economic development.

The relationship between the marginal effect of energy and energy consumption reveals a bimodal shape aka M-shape, however, the fit reveals N-shape. We observe two maxima energy sector yields showing increasing marginal returns at two individual points and zero-depression point with decreasing marginal returns. The M-shaped relationship probably reveals the dynamics of disaggregated energy (i.e., fossil fuel and renewable energy) — accentuating the importance of diversification in the energy portfolio. The nexus between the marginal effect of services and industrial sector validates an inversed-N-shaped relationship — revealing an initial negative marginal return (minimum industrial sector yield) before long-term increasing service productivity. Thus, investment in industrial sector has initial recession effects on service sector efficiency but provides long-term opportunities leading to expansion of the service sector.

We confirm an inversed-U-shaped relationship between the marginal effect of energy consumption and the industrial sector. This implies that energy utilization increases at the initial stages of industrial sector production until maximum industrial sector yield is achieved before energy utilization declines with increasing industrial productivity. The relationship between the marginal effect of FDI and industrial sector confirms an elongated uphill-shaped relationship — showing an increasing level of FDI inflows with industrial sector expansion until maximum industrial sector yield is reached before reduction sets in. This further implies that countries with high industrial sector production attract more foreign direct investment inflows. This in effect explains why countries like China, India, among others have high levels of FDI inflows (World Bank, 2020). Concurrently, the nature of FDI namely pollution-halo or pollution-haven is determined by the composition of the industrial sector.

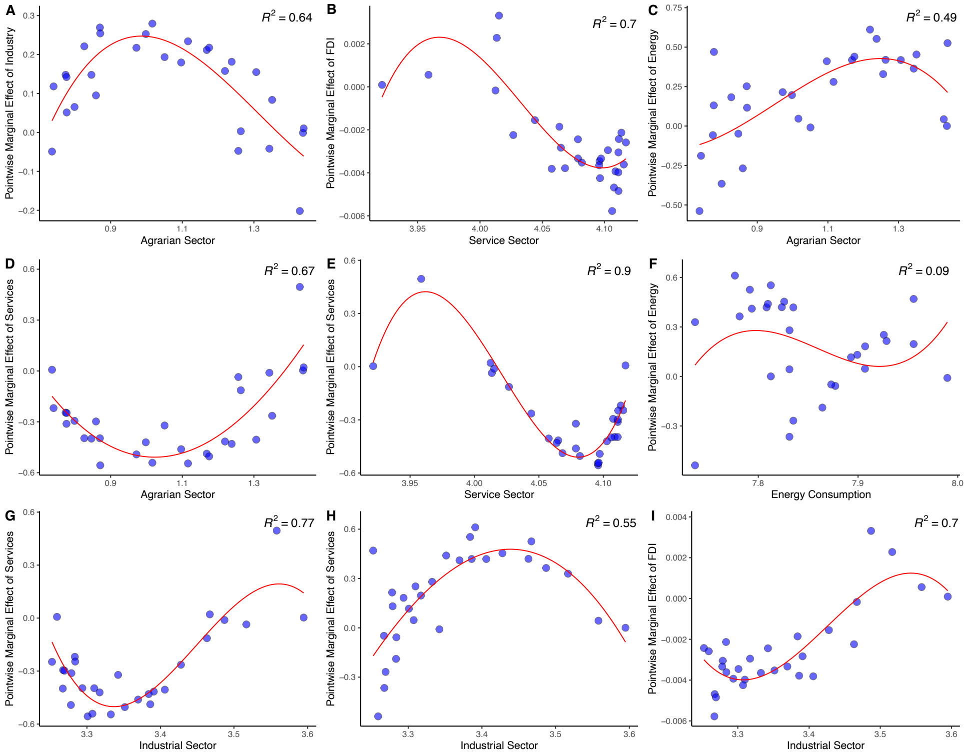

Figure 4. Pointwise marginal effect of (A) Industry ~ Agrarian sector (B) FDI ~ Service sector (C) Energy ~ Agrarian sector (D) Services ~ Agrarian sector (E) Services ~ Service sector (F) Energy ~ Energy Consumption (G) Services ~ Industrial sector (H) Energy ~ Industrial sector (I) FDI ~ Industrial sector.

Does growth in GDP, renewables, and fossil fuels affect CO_2 emissions and environmental performance? From a policy viewpoint, accounting for disaggregated energy utilization and economic development is reported to provide useful insights for energy-driven economic policy formulation. We estimated the effect of disaggregate energy utilization and aggregate economic growth on CO_2 emissions and environmental performance. The goodness of fit test for both models is 0.996 and 0.908 — implying that the regressors explain 99.6% of CO_2 emissions and 90.8% of environmental performance. The average marginal effect parameters presented in Table 5 reveal an increase in fossil fuel consumption and economic growth increases CO_2 emissions by 4.13% and 0.13% whereas renewable-based energy consumption declines CO_2 emissions by 0.28%. In contrast, an increase in the average marginal effect of fossil fuels and economic growth declines environmental performance by 6.54% and 0.13% whereas increasing the share of renewables improves environmental performance by 1.51%. This equally reflects the composition and share of fossil fuels and renewables in South Africa's energy portfolio. As of 2019, domestic utilization of coal, oil, natural gas, nuclear energy, and renewables stood at 85.98 Mtoe, 25.26 Mtoe, 0.42 Mtoe, 2.51Mtoe, and 2.80 Mtoe, respectively (BP, 2019). This infers that the share of clean energy technologies (i.e., renewables and nuclear energy) accounts for a mere 4.54% of domestic consumption, hence, corroborating the empirical results. Besides, it amplifies carbon and energy-intensive economic development driven by fossil fuel utilization. Thus, fossil fuel-dominated energy mix with limited diversification from clean and renewable energy technologies is a threat to environmental performance (Sarkodie, Adams*, et al.*, 2020).

Table 5. Estimated Parameters of Emissions & Environmental Performance

Percentiles	FOSSIL	RENCONS	GDP
Avg. CO_2[a]	4.1261***[a]	-0.2760***[a]	0.1262***[a]
	[0.3140][a]	[0.0669][a]	[0.0144][a]
Avg. ENVPER[b]	-6.5374***[b]	1.5055***[b]	-0.1295**[b]
	[1.3019][b]	[0.2773][b]	[0.0597][b]
1%	-27.2626[a]	-4.8144[a]	-0.6518[a]
	-26.1362[b]	-3.7482[b]	-1.1681[b]
5%	-11.8789[a]	-2.5872[a]	-0.4615[a]
	-23.7009[b]	-3.6690[b]	-0.9142[b]
10%	-11.3494[a]	-2.5002[a]	-0.4374[a]
	-21.5267[b]	-3.6073[b]	-0.8176[b]
25%	-0.9686[a]	-0.7759[a]	-0.1601[a]
	-15.1635[b]	-1.4949[b]	-0.5021[b]
50%	6.7879[a]	-0.0395[a]	0.0092[a]
	-3.9549[b]	1.2234[b]	-0.0908[b]
75%	9.9579[a]	0.7130[a]	0.4991[a]
	1.9348[b]	3.8137[b]	0.2281[b]
90%	15.9668[a]	1.5730[a]	0.7254[a]
	5.1049[b]	5.7474[b]	0.5389[b]
95%	17.1760[a]	2.0191[a]	0.7336[a]
	10.7233[b]	7.4852[b]	0.5768[b]
99%	19.1097[a]	2.6240[a]	0.8075[a]
	21.6801[b]	12.0052[b]	0.7226[b]

Diagnostics			
Mean	4.1260[a]	-0.2760[a]	0.1262[a]
	-6.5374[b]	1.5055[b]	-0.1295[b]
Std. Dev.	9.7136[a]	1.6063[a]	0.4271[a]
	11.5228[b]	3.6869[b]	0.4893[b]
Variance	94.3539[a]	2.5801[a]	0.1824[a]
	132.7753[b]	13.5929[b]	0.2394[b]
Skewness	-1.2110[a]	-0.7749[a]	0.0771[a]
	0.2465[b]	0.6848[b]	-0.2700[b]
Kurtosis	5.0804[a]	3.6476[a]	1.8230[a]
	2.5145[b]	3.5128[b]	2.1674[b]
Lambda	0.0010[a/b]	—	—
R-square	0.9956[a]	—	—
	0.9079[b]		
Looloss	1.5330[a]	—	—
	4.7440[b]		
Sigma	3.0000[a/b]	—	—
Eff. df	25.3900[a/b]	—	—
Cointegration	YES[a/b]	—	—

Notes: [a] The null hypothesis of no cointegration is rejected at 5% significance level by Johansen maximum eigenvalue, Banerjee, and Boswijk test for cointegration. [b] Engle-Granger, Johansen, Banerjee and Boswijk test for cointegration reject the null hypothesis of no cointegration at $p<0.05$; [.] represents the standard errors while **, *** denote statistical significance at 5% and 1% level.

Does environmental policy stringency ameliorate environmental performance? Environmental policy stringency plays an essential role in FDI inflows from high-income countries to developing countries, albeit key to environmental sustainability. The composition of the economic sector, energy portfolio, production and consumption, and environmental performance depends on environmental policies and measures. Here, we examined the impact of environmental policy stringency — as a policy measure in enhancing environmental performance in a carbon-embedded and energy-intensive economy where fossil fuel utilization outweighs renewables and clean energy. The estimated model with parameters presented in Table 6 reveals that the regressors explain 99.7% variations in the target variable. Hence, confirming the predictability of disaggregate energy, GDP, environmental policy stringency, and CO_2 emissions in explaining the dynamics of environmental performance. We observe from the average marginal effect that CO_2 emissions, fossil fuel utilization, and economic growth contribute significantly to reducing environmental performance by 1.16%, 0.71%, and 0.25%, respectively. According to the IPCC 5th Assessment report (Blanco *et al.*, 2014), carbon intensity, economic growth, and energy utilization are the immediate drivers of greenhouse gas emissions — implying that these limiting factors disrupt environmental performance, hence, thwarts efforts toward attaining environmental sustainability. Besides, carbon dioxide is the main contributory factor of anthropogenic GHG emissions that hampers environmental sustainability through its long-term degradation effect. In contrast, the expansion of renewable energy and environmental policy stringency improves environmental performance significantly by 1.27% and 0.17%, respectively. Though the adoption of renewable energy technologies is reportedly affected by policy instruments, technological innovation attributable cost, and market failure, however, its climate mitigation, environmental, and health impact reduction effects cannot be underrated (Owusu *et al.*, 2016). Likewise, diversification of the energy mix with renewable energy technologies is reported to provide opportunities for achieving energy access, energy security, human development, and socio-economic development (Edenhofer *et al.*, 2011; Owusu *et al.*, 2016; Sarkodie & Adams, 2020). Increasing levels of environmental policy stringency serve two purposes in developed economies — first, it may stimulate emission-reduction technologies, innovation, and research and development, or second, shift polluting industries to developing countries with lax environmental regulations. Environmental policy stringency navigates industrial production efficiency, hence, an important determinant of fossil fuel utilization and pollutant emissions (Johnstone *et al.*, 2017). This explains why the introduction of stringent environmental policies, viz. environmental regulations are reported to escalate industrial and technological innovations, hence, lower pollution abatement costs due to a reduction in emission intensities (Milani, 2017). In contrast, pollution-embedded external financial support — in the form of FDI inflows underscores knowledge spillover, technology, and human capital attributed emissions from foreign countries — which underpins the pollution haven hypothesis. However, our empirical analysis contradicts pollution haven in support of pollution halo hypothesis.

To further validate the hypothesis on environmental performance, we plugged in the individualistic and interactive effects of FDI inflows, and environmental policy stringency using the dynamic ARDL simulations and further predicted future shocks in regressors using the average change over the 28-year period. We observe a potential long-run association evidenced in the bounds test cointegration results in Appendix F. To examine the response of environmental performance to counterfactual shocks in FDI inflows and environmental policy stringency, we utilized the mean change of historical trends — 2.12% and 0.07%, respectively, and assumed a constancy over the predicted 20-year (2018-2038) horizon. Our predicted parameters are within the 95, 90 and 75% confidence interval represented by cranberry, sand, teal colored-spikes. Using the ceteris paribus analysis, we observe in Figure 5 (a) that 2.12% shock in FDI inflows will increase environmental performance after the 2nd year by ~0.39% and stabilize thereafter. In contrast, -2.12% shock in FDI inflows declines environmental performance by ~0.39% after the 2nd horizon [Figure 5 (b)]. Thus, confirming our initial results in Table 4 that validate the pollution-halo hypothesis. We further observe very little change in the response of environmental performance to ±0.07% shock in environmental policy stringency [Figure 5 (c-d)]. The lagged (2)-interaction between FDI inflows and stringency (Appendix F) corroborates the position of pollution-halo hypothesis. This implies that the current state of agrarian and industrial-based emissions and poor environmental performance are not imported but domestically generated, hence, environmental policy stringency and FDI inflows are not linked to polluting industries.

Table 6. Determinants of Environmental Performance – Stringency Nexus

Percentiles	FOSSIL	RENCONS	GDP	ENVPS	CO_2
Avg.	-0.7055**	1.2734***	-0.2482***	0.1706**	-1.1590***
	[0.2861]	[0.0503]	[0.0072]	[0.0120]	[0.0382]
1%	-15.6870**	-3.3078***	-0.6940***	-0.4986**	-7.0334***
5%	-15.3372**	-3.1941***	-0.6402***	-0.4628**	-6.1806***
10%	-7.7055**	-2.3021***	-0.6074***	-0.4547**	-6.0261***
25%	-3.4926**	-1.7096***	-0.4223***	-0.0634**	-1.5521***
50%	0.7298**	0.0726***	-0.2418***	0.2725**	-0.4399***
75%	2.6944**	2.8625***	-0.0464***	0.4111**	0.4333***
90%	4.2148**	9.1763***	0.0743***	0.5679**	1.1827***
95%	4.3682**	9.1873***	0.1798***	0.6544**	1.2164***
99%	4.3850**	9.7176***	0.2686***	0.7349**	2.1911***
Diagnostics	—	—	—	—	—
Mean	-0.7055	1.2734	-0.2482	0.1706	-1.1590
Std. Dev.	5.1857	3.9436	0.2517	0.3600	2.4823
Variance	26.8915	15.5521	0.0633	0.1296	6.1620
Skewness	-1.6271	0.9757	0.0676	-0.5721	-1.1651
Kurtosis	5.2798	2.7248	2.2480	2.1903	3.2518
Lambda	0.0010	—	—	—	—
R-square	0.9970	—	—	—	—
Looloss	5.5240	—	—	—	—
Sigma	5.0000	—	—	—	—
Eff. Df	28.16	—	—	—	—

Notes: [.] represents the standard errors while **, *** denote statistical significance at 5% and 1% level.

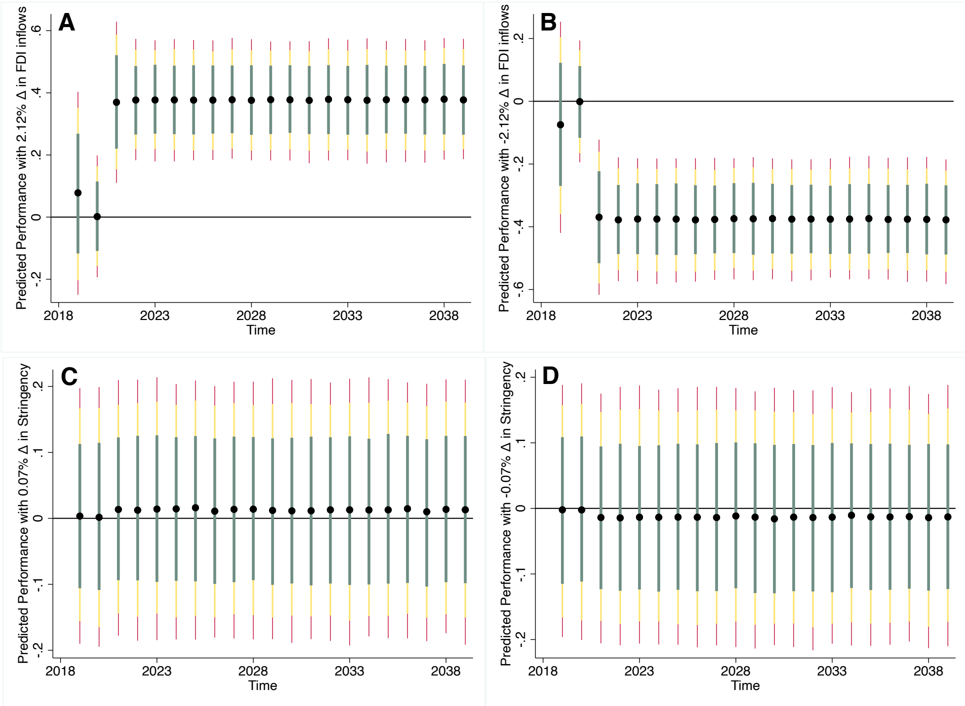

Figure 5. Predicted Environmental Performance with (A) 2.12% change in FDI inflows (B) -2.12% change in FDI inflows (C) 0.07% change in Environmental Policy Stringency (D) -0.07% change in Environmental Policy Stringency. Legend: cranberry, sand, teal colored-spikes represent 95, 90, and 75% confidence interval.

9.4 Conclusion

We investigated the determinants of environmental performance – environmental policy stringency nexus while controlling for economic sectoral dynamics. In summary, we observed that the failure to account for economic sectoral inefficiencies by the institutionalization of environmental policy stringency will disrupt environmental performance. Our case scenario of the assessment of economic-driven emissions revealed that using aggregate economic growth rather than individual economic sectoral input provides little and vague overview for environmental policy formulation, especially in resource allocation. Hence, the assessment of country-specific economic sectoral accounting highlights how linear economy can be shifted towards circular economy by maximizing yield while reducing wastage, environmental pollution, and resource consumption. Our study demonstrated that the allocation of scarce resources should be based on long-term prospects rather than short-term gains. Contrary to the traditional EKC hypothesis, we showed that sectoral-based economic productivity is useful in understanding pollution-reduction policies. Besides, our empirical analysis reveals *when* and *where* to allocate limited natural resources for sustainable economic development while reducing production shortfalls. Thus, at the point of diminishing returns in the service sector, it is advisable to invest, combine, or substitute resources from both agrarian and industrial sectors. Implying that a combination of other sectors like agrarian and industry has long-term productivity. We showed that diversification of the energy portfolio is essential to sustain long-term economic development. Our study revealed that the overdependence on fossil fuels has long-term environmental costs that hinder progress towards the mitigation of climate change and its impacts. The introduction of energy efficiency and decarbonization of economic policies could begin with disaggregation of economic growth rather than the traditional aggregated GDP. This provides opportunity to examine both efficiency and deficiency of the economic structure and incorporate the appropriate policy. Long-term industrial sector production is observed to increase energy efficiency while short-term industrial sector productivity increases energy intensity. This implies that industrial sector production has both escalation and mitigation effects, hence, the introduction of energy conservation and management policies will hamper short-term industrial sector productivity. Our empirical estimation confirmed that foreign direct investment inflows are driven by industrial sector production. Thus, the industrial structure determines the level of external funding, environmental performance, knowledge, and technological spillover. From a policy perspective, increasing the share of renewables while reducing fossil fuels in the energy portfolio declines CO_2 emissions while increasing environmental performance. Political will through the enactment of stringent environmental policies is critical to improving long-term environmental performance.

Acknowledgment

Open Access funding provided by Nord University.

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Supplementary Information

Appendices for Chapter 4

Winners and losers of energy sustainability—global assessment

Table 1. List of countries, territories, and income groups

No.	Country Name	ISO3
1	Afghanistan	AFG
2	Albania	ALB
3	Algeria	DZA
4	American Samoa	ASM
5	Andorra	AND
6	Angola	AGO
7	Antigua and Barbuda	ATG
8	Argentina	ARG
9	Armenia	ARM
10	Aruba	ABW
11	Australia	AUS
12	Austria	AUT
13	Azerbaijan	AZE
14	Bahamas, The	BHS
15	Bahrain	BHR
16	Bangladesh	BGD
17	Barbados	BRB
18	Belarus	BLR
19	Belgium	BEL
20	Belize	BLZ
21	Benin	BEN
22	Bermuda	BMU
23	Bhutan	BTN
24	Bolivia	BOL
25	Bosnia and Herzegovina	BIH
26	Botswana	BWA
27	Brazil	BRA
28	British Virgin Islands	VGB
29	Brunei Darussalam	BRN
30	Bulgaria	BGR
31	Burkina Faso	BFA

32	Burundi	BDI
33	Cabo Verde	CPV
34	Cambodia	KHM
35	Cameroon	CMR
36	Canada	CAN
37	Cayman Islands	CYM
38	Central African Republic	CAF
39	Chad	TCD
40	Channel Islands	CHI
41	Chile	CHL
42	China	CHN
43	Colombia	COL
44	Comoros	COM
45	Congo, Dem. Rep.	COD
46	Congo, Rep.	COG
47	Costa Rica	CRI
48	Cote d'Ivoire	CIV
49	Croatia	HRV
50	Cuba	CUB
51	Curacao	CUW
52	Cyprus	CYP
53	Czech Republic	CZE
54	Denmark	DNK
55	Djibouti	DJI
56	Dominica	DMA
57	Dominican Republic	DOM
58	Ecuador	ECU
59	Egypt, Arab Rep.	EGY
60	El Salvador	SLV
61	Equatorial Guinea	GNQ
62	Eritrea	ERI
63	Estonia	EST
64	Ethiopia	ETH
65	Faroe Islands	FRO
66	Fiji	FJI
67	Finland	FIN
68	France	FRA
69	French Polynesia	PYF
70	Gabon	GAB
71	Gambia, The	GMB
72	Georgia	GEO
73	Germany	DEU
74	Ghana	GHA
75	Gibraltar	GIB
76	Greece	GRC

77	Greenland	GRL
78	Grenada	GRD
79	Guam	GUM
80	Guatemala	GTM
81	Guinea	GIN
82	Guinea-Bissau	GNB
83	Guyana	GUY
84	Haiti	HTI
85	Honduras	HND
86	Hong Kong SAR, China	HKG
87	Hungary	HUN
88	Iceland	ISL
89	India	IND
90	Indonesia	IDN
91	Iran, Islamic Rep.	IRN
92	Iraq	IRQ
93	Ireland	IRL
94	Isle of Man	IMN
95	Israel	ISR
96	Italy	ITA
97	Jamaica	JAM
98	Japan	JPN
99	Jordan	JOR
100	Kazakhstan	KAZ
101	Kenya	KEN
102	Kiribati	KIR
103	Korea, Dem. People's Rep.	PRK
104	Korea, Rep.	KOR
105	Kosovo	XKX
106	Kuwait	KWT
107	Kyrgyz Republic	KGZ
108	Lao PDR	LAO
109	Latvia	LVA
110	Lebanon	LBN
111	Lesotho	LSO
112	Liberia	LBR
113	Libya	LBY
114	Liechtenstein	LIE
115	Lithuania	LTU
116	Luxembourg	LUX
117	Macao SAR, China	MAC
118	North Macedonia	MKD
119	Madagascar	MDG
120	Malawi	MWI
121	Malaysia	MYS

122	Maldives	MDV
123	Mali	MLI
124	Malta	MLT
125	Marshall Islands	MHL
126	Mauritania	MRT
127	Mauritius	MUS
128	Mexico	MEX
129	Micronesia, Fed. Sts.	FSM
130	Moldova	MDA
131	Monaco	MCO
132	Mongolia	MNG
133	Montenegro	MNE
134	Morocco	MAR
135	Mozambique	MOZ
136	Myanmar	MMR
137	Namibia	NAM
138	Nauru	NRU
139	Nepal	NPL
140	Netherlands	NLD
141	New Caledonia	NCL
142	New Zealand	NZL
143	Nicaragua	NIC
144	Niger	NER
145	Nigeria	NGA
146	Northern Mariana Islands	MNP
147	Norway	NOR
148	Oman	OMN
149	Pakistan	PAK
150	Palau	PLW
151	Panama	PAN
152	Papua New Guinea	PNG
153	Paraguay	PRY
154	Peru	PER
155	Philippines	PHL
156	Poland	POL
157	Portugal	PRT
158	Puerto Rico	PRI
159	Qatar	QAT
160	Romania	ROU
161	Russian Federation	RUS
162	Rwanda	RWA
163	Samoa	WSM
164	San Marino	SMR
165	Sao Tome and Principe	STP
166	Saudi Arabia	SAU

167	Senegal	SEN
168	Serbia	SRB
169	Seychelles	SYC
170	Sierra Leone	SLE
171	Singapore	SGP
172	Sint Maarten (Dutch part)	SXM
173	Slovak Republic	SVK
174	Slovenia	SVN
175	Solomon Islands	SLB
176	Somalia	SOM
177	South Africa	ZAF
178	South Sudan	SSD
179	Spain	ESP
180	Sri Lanka	LKA
181	St. Kitts and Nevis	KNA
182	St. Lucia	LCA
183	St. Martin (French part)	MAF
184	St. Vincent and the Grenadines	VCT
185	Sudan	SDN
186	Suriname	SUR
187	Eswatini	SWZ
188	Sweden	SWE
189	Switzerland	CHE
190	Syrian Arab Republic	SYR
191	Tajikistan	TJK
192	Tanzania	TZA
193	Thailand	THA
194	Timor-Leste	TLS
195	Togo	TGO
196	Tonga	TON
197	Trinidad and Tobago	TTO
198	Tunisia	TUN
199	Turkey	TUR
200	Turkmenistan	TKM
201	Turks and Caicos Islands	TCA
202	Tuvalu	TUV
203	Uganda	UGA
204	Ukraine	UKR
205	United Arab Emirates	ARE
206	United Kingdom	GBR
207	United States	USA
208	Uruguay	URY
209	Uzbekistan	UZB
210	Vanuatu	VUT
211	Venezuela, RB	VEN

212	Vietnam	VNM
213	Virgin Islands (U.S.)	VIR
214	West Bank and Gaza	PSE
215	Yemen, Rep.	YEM
216	Zambia	ZMB
217	Zimbabwe	ZWE
218	World	WLD
219	High income	HIC
220	Low & middle income	LMY
221	Lower middle income	LMC
222	Middle income	MIC
223	Upper middle income	UMC
224	Low income	LIC

Table 2. Variable description

Data Series	Abbrev
Access to clean fuels and technologies for cooking (% of population)	CLEAN
Access to electricity (% of population)	ACCESS
Access to electricity, rural (% of rural population)	ACCESSR
Access to electricity, urban (% of urban population)	ACCESSU
Adjusted savings: energy depletion (% of GNI)	ADJUST
Alternative and nuclear energy (% of total energy use)	ALTNUC
CO_2 emissions from electricity and heat production, total (% of total fuel combustion)	CO2ELECTHEAT
CO_2 emissions from gaseous fuel consumption (% of total)	CO2GASF
CO_2 emissions from liquid fuel consumption (% of total)	CO2LFUEL
CO_2 emissions from solid fuel consumption (% of total)	CO2SFUEL
Combustible renewables and waste (% of total energy)	CRENWAS
Energy imports, net (% of energy use)	ENIMPORT
Energy related methane emissions (% of total)	ENECH4
Energy use (kg of oil equivalent per capita)	EUSE
Fossil fuel energy consumption (% of total)	FOSSIL
Nitrous oxide emissions in energy sector (% of total)	ENNOX
Renewable energy consumption (% of total final energy consumption)	RENCON
Renewable internal freshwater resources, total (billion m^3)	RENH2O
Total GHG emissions (kt of CO_2 equivalent)	GHG
Water productivity, total (constant 2010 US$ GDP/m^3 of total freshwater withdrawal)	H2OPROD

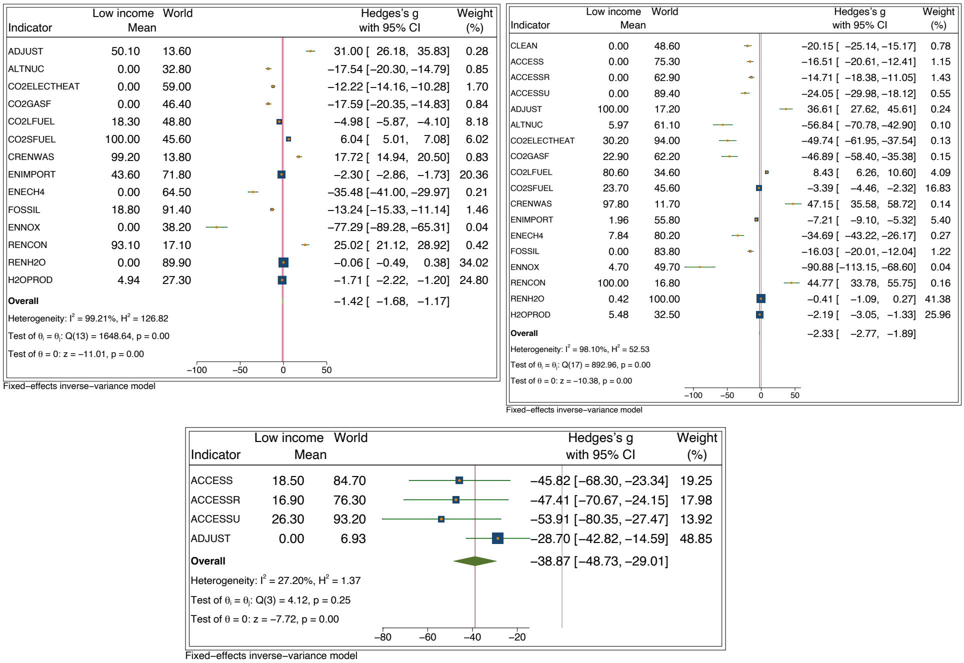


Fig. 1. Energy sustainability indicator assessment for low-income vs. world (A) Pre-MDGs [1961-1999] (B) MDGs [2000-2015] (C) SDGs [2016-2019]. Legend: The indicators presented are estimated using the meta-analysis procedure presented in the methods (see Supplementary Table 2 for variable description). Data used in the estimated are divided into three categories namely 1961-1999, 2000-2015, and 2016-2019—that capture Pre-MDGs, MDGs, and SDGs. The horizontal line denotes 95% confidence interval (i.e., wider horizonal line denotes smaller variable observations and vice versa) whereas the dark-blue filled box represents the point estimate (i.e., the size of the box explains the number of observations). In this study, we expect a high heterogeneity (I^2 = >90%), thus, a rejection of the slope equality at *p-value<0.01*—denotes the expected heterogeneous distribution of varied energy indicators across diverse countries. The left-side of the line of null effect (i.e., zero vertical line—denoting no difference between experimental and control groups) favors the global measurements whereas the right-side favors the income groups.

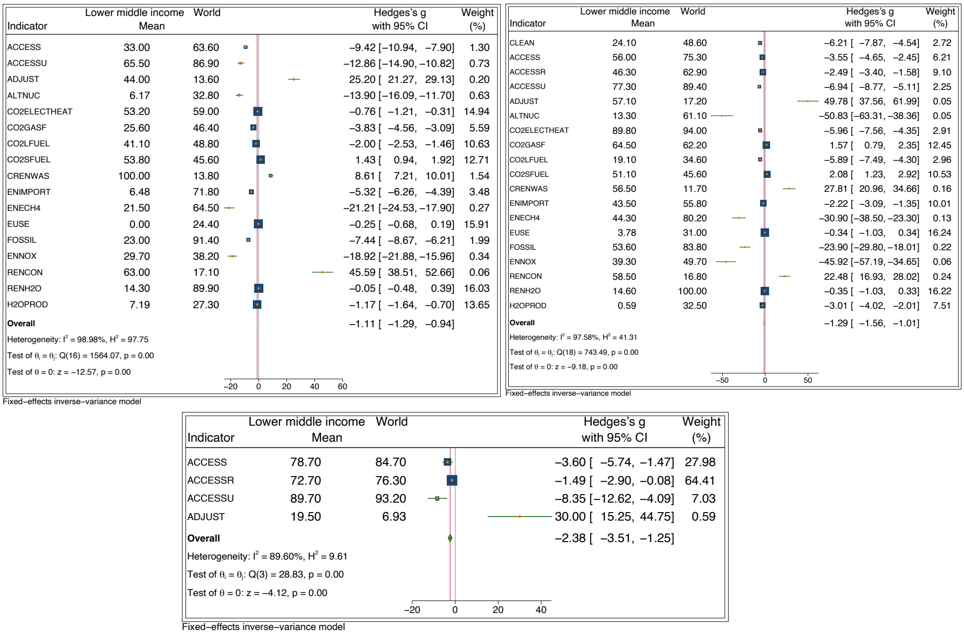


Fig. 2. Energy sustainability indicator assessment for lower middle-income vs. world (A) Pre-MDGs [1961-1999] (B) MDGs [2000-2015] (C) SDGs [2016-2019]. Legend: The indicators presented are estimated using the meta-analysis procedure presented in the methods (see Supplementary Table 2 for variable description). Data used in the estimated are divided into three categories namely 1961-1999, 2000-2015, and 2016-2019—that capture Pre-MDGs, MDGs, and SDGs. The horizontal line denotes 95% confidence interval (i.e., wider horizonal line denotes smaller variable observations and vice versa) whereas the dark-blue filled box represents the point estimate (i.e., the size of the box explains the number of observations). In this study, we expect a high heterogeneity (I^2 = >90%), thus, a rejection of the slope equality at *p-value<0.01*—denotes the expected heterogeneous distribution of varied energy indicators across diverse countries. The left-side of the line of null effect (i.e., zero vertical line—denoting no difference between experimental and control groups) favors the global measurements whereas the right-side favors the income groups.

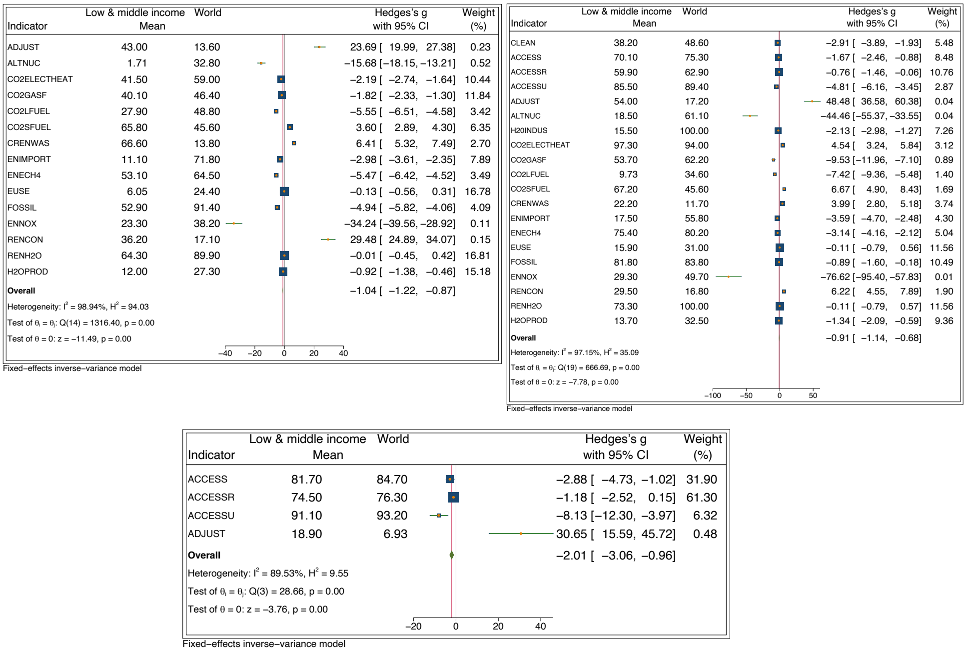


Fig. 3. Energy sustainability indicator assessment for low & middle-income vs. world (A) Pre-MDGs [1961-1999] (B) MDGs [2000-2015] (C) SDGs [2016-2019]. Legend: The indicators presented are estimated using the meta-analysis procedure presented in the methods (see Supplementary Table 2 for variable description). Data used in the estimated are divided into three categories namely 1961-1999, 2000-2015, and 2016-2019—that capture Pre-MDGs, MDGs, and SDGs. The horizontal line denotes 95% confidence interval (i.e., wider horizonal line denotes smaller variable observations and vice versa) whereas the dark-blue filled box represents the point estimate (i.e., the size of the box explains the number of observations). In this study, we expect a high heterogeneity (I^2 = >90%), thus, a rejection of the slope equality at *p-value<0.01*—denotes the expected heterogeneous distribution of varied energy indicators across diverse countries. The left-side of the line of null effect (i.e., zero vertical line—denoting no difference between experimental and control groups) favors the global measurements whereas the right-side favors the income groups.

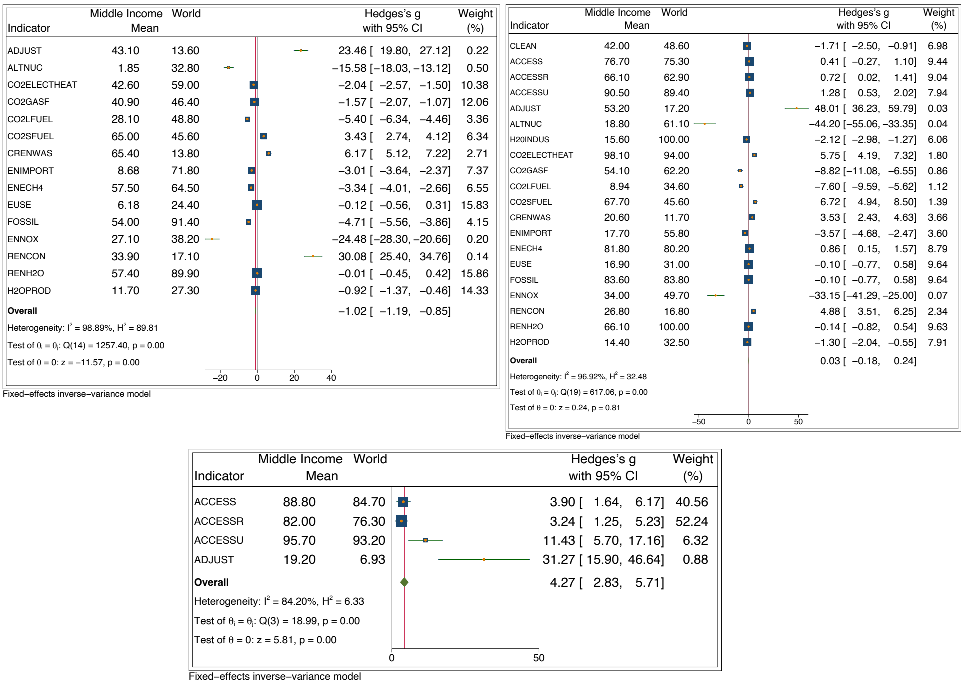


Fig. 4. Energy sustainability indicator assessment for middle-income vs. world (A) Pre-MDGs [1961-1999] (B) MDGs [2000-2015] (C) SDGs [2016-2019]. Legend: The indicators presented are estimated using the meta-analysis procedure presented in the methods (see Supplementary Table 2 for variable description). Data used in the estimated are divided into three categories namely 1961-1999, 2000-2015, and 2016-2019—that capture Pre-MDGs, MDGs, and SDGs. The horizontal line denotes 95% confidence interval (i.e., wider horizonal line denotes smaller variable observations and vice versa) whereas the dark-blue filled box represents the point estimate (i.e., the size of the box explains the number of observations). In this study, we expect a high heterogeneity (I^2 = >90%), thus, a rejection of the slope equality at *p-value<0.01*—denotes the expected heterogeneous distribution of varied energy indicators across diverse countries. The left-side of the line of null effect (i.e., zero vertical line—denoting no difference between experimental and control groups) favors the global measurements whereas the right-side favors the income groups.

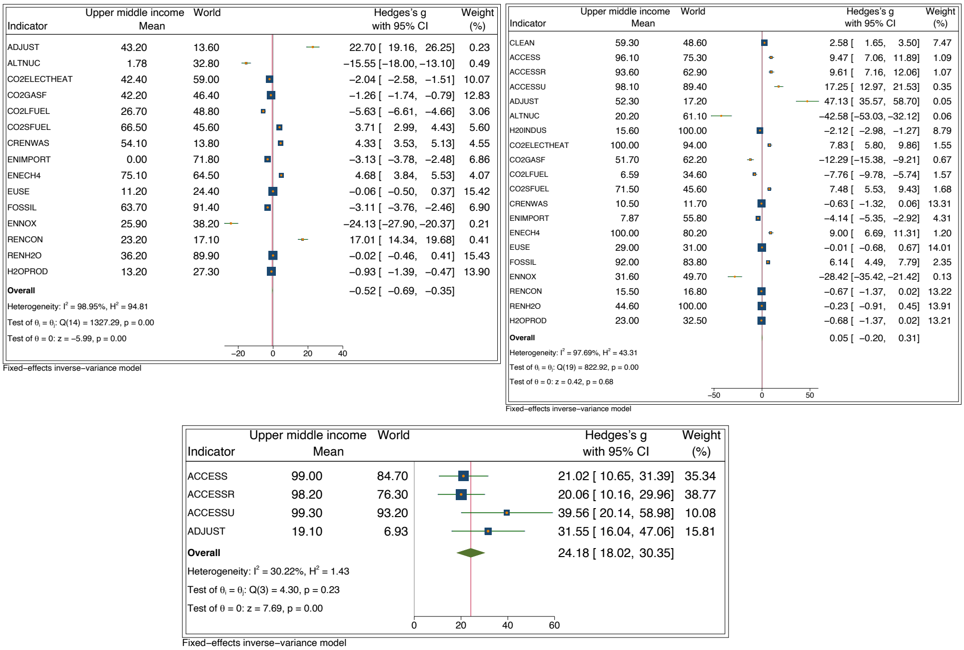


Fig. 5. Energy sustainability indicator assessment for upper middle-income vs. world (A) Pre-MDGs [1961-1999] (B) MDGs [2000-2015] (C) SDGs [2016-2019]. Legend: The indicators presented are estimated using the meta-analysis procedure presented in the methods (see Supplementary Table 2 for variable description). Data used in the estimated are divided into three categories namely 1961-1999, 2000-2015, and 2016-2019—that capture Pre-MDGs, MDGs, and SDGs. The horizontal line denotes 95% confidence interval (i.e., wider horizonal line denotes smaller variable observations and vice versa) whereas the dark-blue filled box represents the point estimate (i.e., the size of the box explains the number of observations). In this study, we expect a high heterogeneity (I^2 = >90%), thus, a rejection of the slope equality at *p-value<0.01*—denotes the expected heterogeneous distribution of varied energy indicators across diverse countries. The left-side of the line of null effect (i.e., zero vertical line—denoting no difference between experimental and control groups) favors the global measurements whereas the right-side favors the income groups.

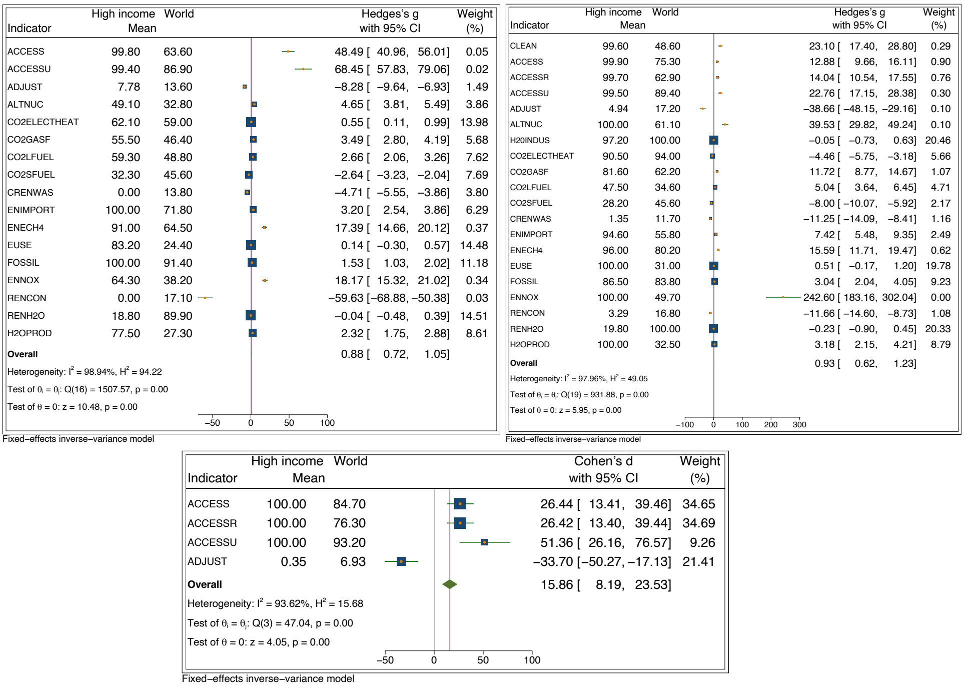


Fig. 6. Energy sustainability indicator assessment for high-income vs. world (A) Pre-MDGs [1961-1999] (B) MDGs [2000-2015] (C) SDGs [2016-2019]. Legend: The indicators presented are estimated using the meta-analysis procedure presented in the methods (see Supplementary Table 2 for variable description). Data used in the estimated are divided into three categories namely 1961-1999, 2000-2015, and 2016-2019—that capture Pre-MDGs, MDGs, and SDGs. The horizontal line denotes 95% confidence interval (i.e., wider horizonal line denotes smaller variable observations and vice versa) whereas the dark-blue filled box represents the point estimate (i.e., the size of the box explains the number of observations). In this study, we expect a high heterogeneity (I^2 = >90%), thus, a rejection of the slope equality at *p-value<0.01*—denotes the expected heterogeneous distribution of varied energy indicators across diverse countries. The left-side of the line of null effect (i.e., zero vertical line—denoting no difference between experimental and control groups) favors the global measurements whereas the right-side favors the income groups.

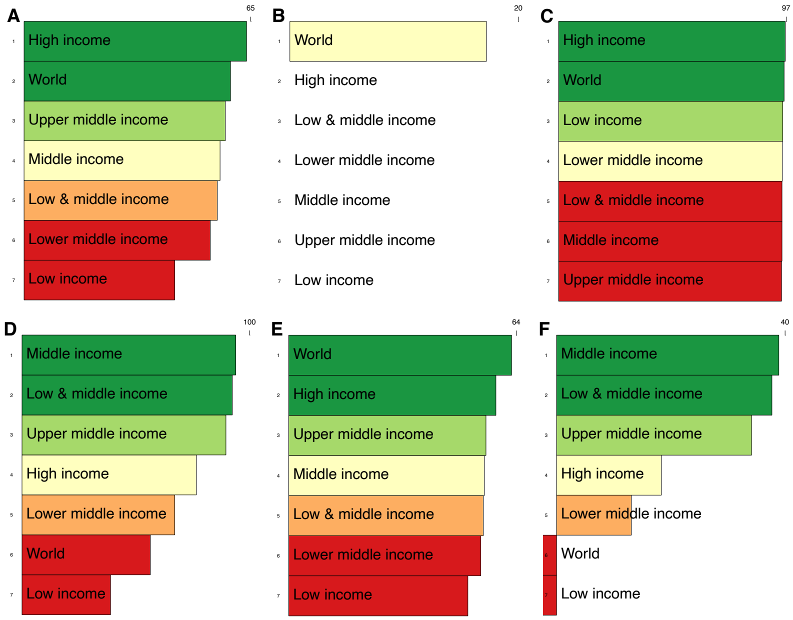


Fig. 7. Sustainability assessment of energy and its services across income groups (A) Energy related emissions (B) Energy intensity (C) Energy dependence (D) Pros of energy sustainability target (E) Cons of energy sustainability target (F) Benefit-cost of energy sustainability target. Legend: The indicators are estimated using the empirical procedure presented in the methods. Colors ranging from dark-green, lime-green, yellow, orange, and red represent the magnitude of estimated indicators in descending order. Missing filled-rectangular shape with white background (B) denotes missing data.

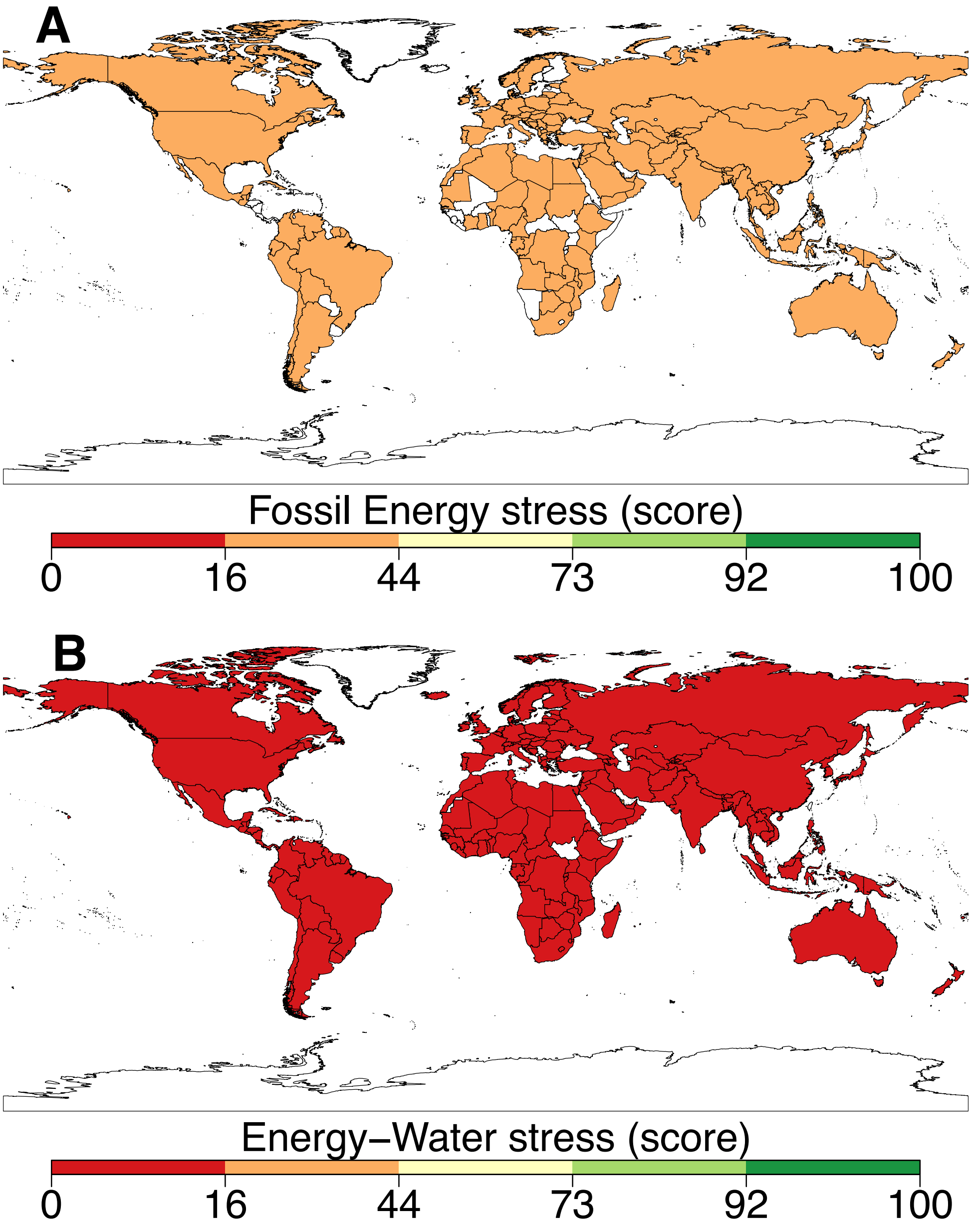


Fig. 8. Global sustainability indicators of energy and its services (A) Fossil energy stress (B) Energy-Water stress**.** Legend: The indicators are estimated using the empirical procedure presented in the methods. Colors ranging from red, orange, yellow, lime-green and dark-green represent the estimated indicators in ratio from 0-15.9 (worse), 16-43.9 (bad), 44-72.9 (good), 73-91.9 (better), and 92-100 (best), respectively.

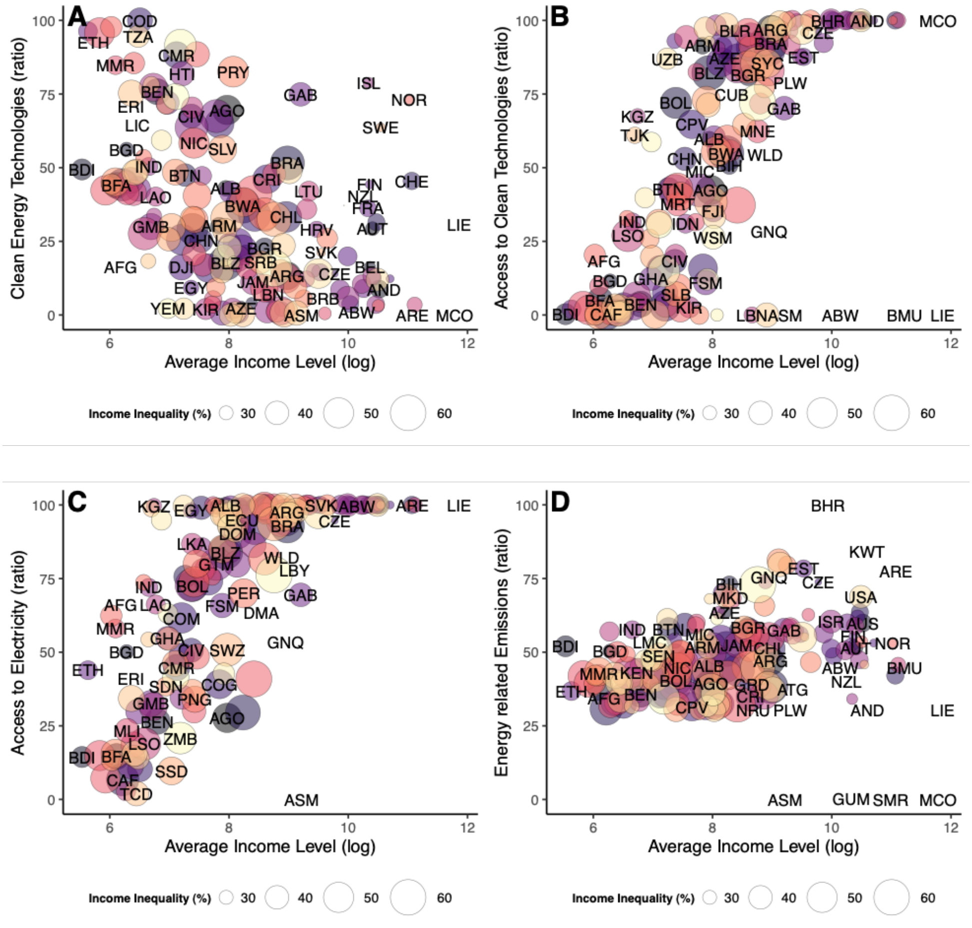
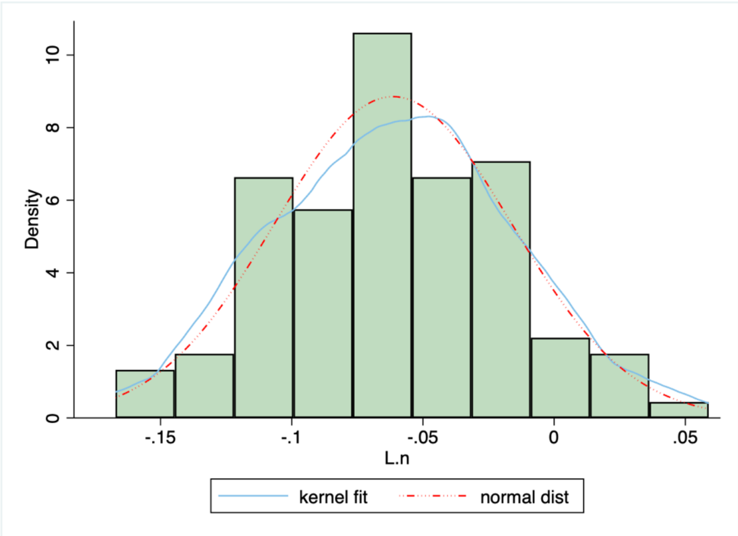


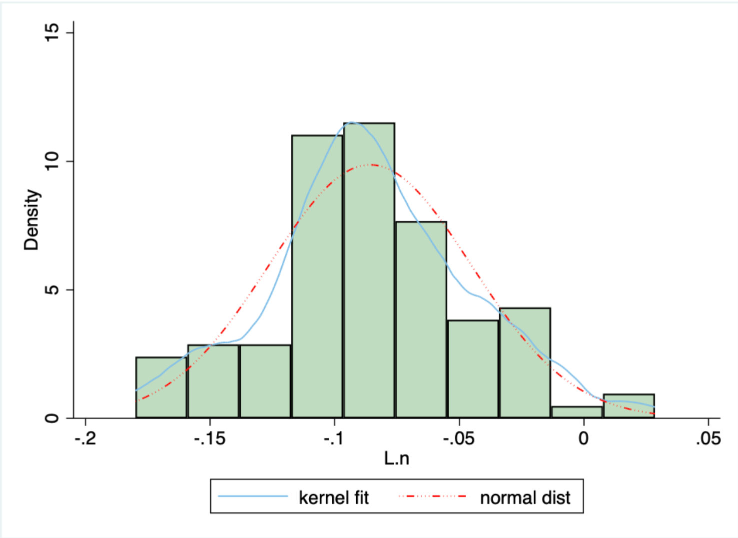
Fig. 9. Global nexus of sustainability indicators of energy and its services in income function while controlling for income inequality (A) Access to clean fuels and technologies (B) Clean energy technologies (C) Access to electricity (D) Energy related emissions. Legend: The trend indicates the relationship between sustainability indicators of energy and its services and average income level whereas the white filled-circles with black outline denotes the magnitude of income inequality.

Appendices for Chapter 7

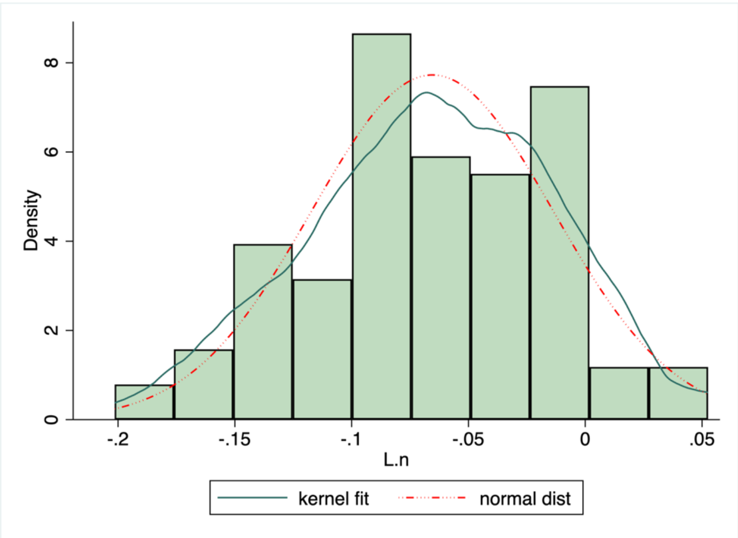
Escalation effect of Fossil-based CO_2 emissions improves Green Energy Innovation



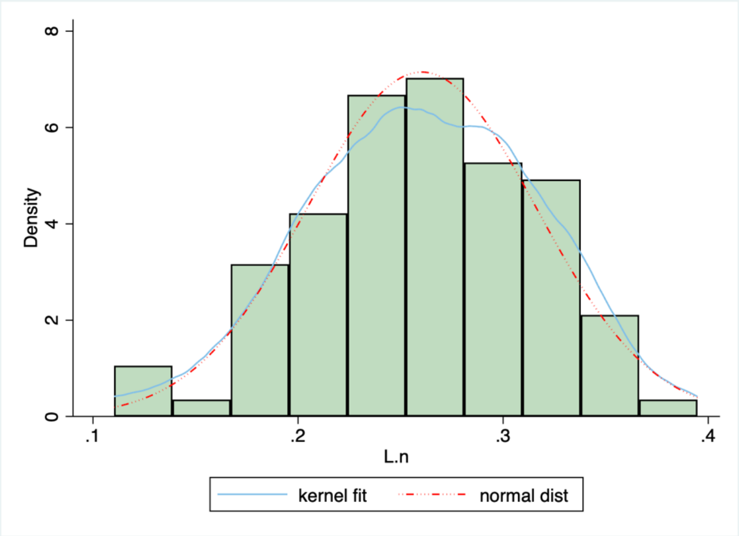
Supplementary Figure 1. Validation of Buildings model



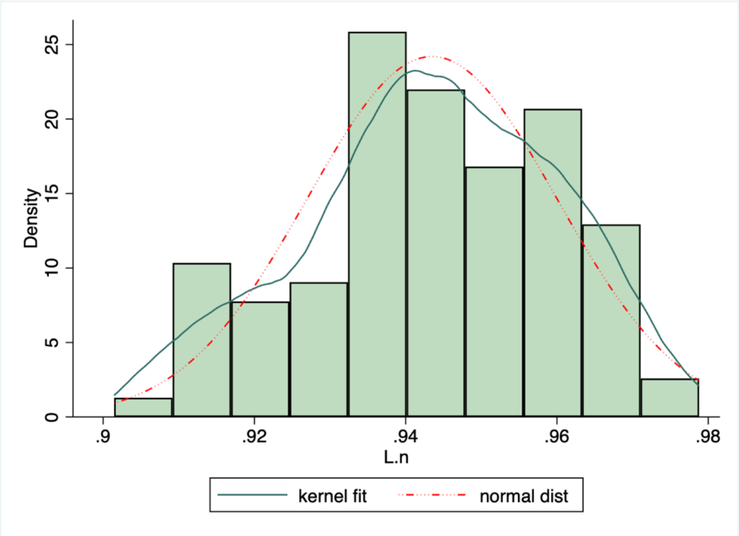
Supplementary Figure 2. Validation of Industry model



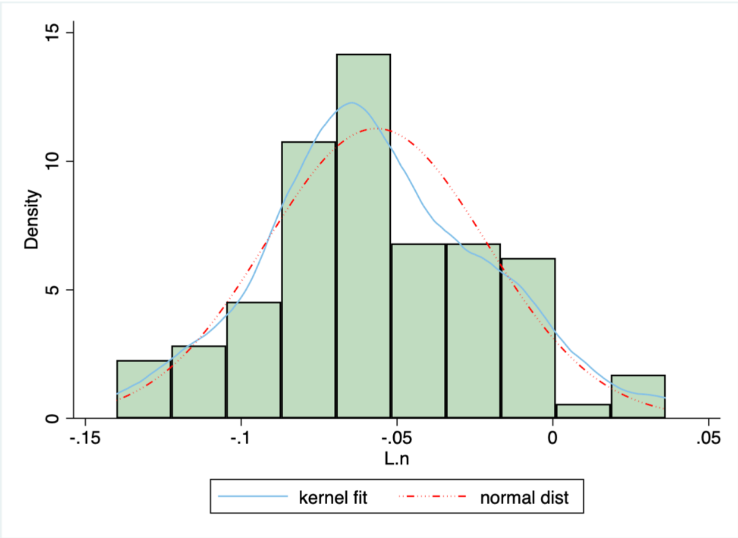
Supplementary Figure 3. Validation of Other Sector model



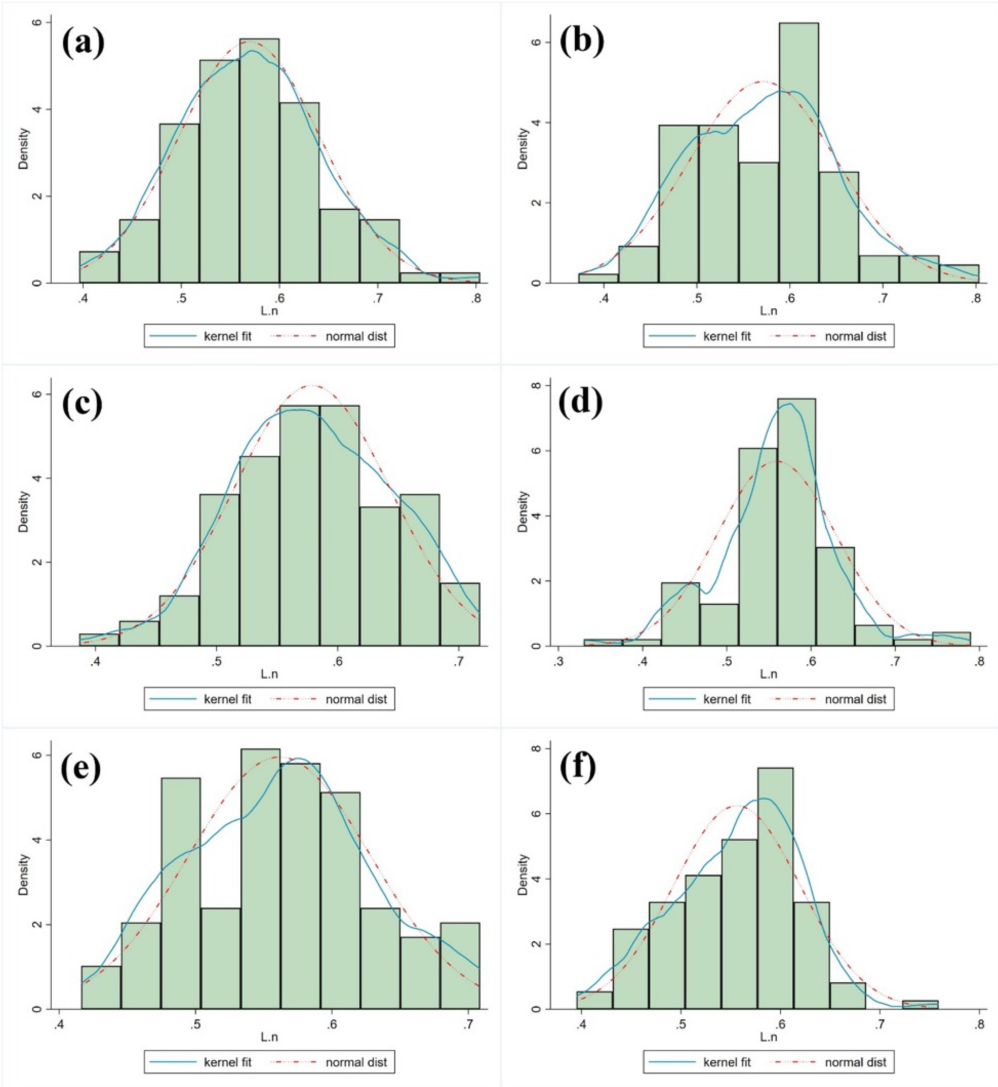
Supplementary Figure 4. Validation of Transport model



Supplementary Figure 5. Validation of Power model



Supplementary Figure 6. Validation of GHG emissions model



Supplementary Figure 7. Green energy innovation model. Diagnostics of parameter estimates in Table 2 (a) Model 1 (b) Model 2 (c) Model 3 (d) Model 4 (e) Model 5 (f) Model 6

Supplementary Table 1. Convergence and club clustering across IEA member countries

Models	Log(t)*	Countries
GHG	-53.496	All
Club 1	3.775	| AUS | CAN | DEU | ITA | ESP | GBR |
Club 2	18.440	| AUT | BEL | FIN | GRC | IRL | NZL | NOR | PRT |
Club 3	9.462	| DNK | SWE | CHE |
Group 4	-442.576	| FRA | JPN | NLD | USA |
Club 1+2	-29.928	
Club 2+3	-37.766	
Club 3 + Group 4	-129.221	
Energy Intensity	-46.063	All
Club 1	8.901	| AUS | AUT | BEL | FRA | GRC | ITA | JPN | NLD | NZL | NOR | PRT | ESP | SWE | USA | DNK | CHE | GBR |
Group 2	-183.523	| CAN | FIN | DEU | IRL |
Energy Research	-7.105	All
Club 1	0.687	| AUS | AUT | BEL | CAN | DNK | FIN | FRA | DEU | IRL | ITA | JPN | NLD | NZL | NOR | SWE | GBR | USA |
Club 2	0.448	| PRT | CHE |
Group 3	-27.132	| GRC | ESP |
Industrial Structure	-16.803	All
Club 1	6.359	| BEL | DNK | FRA | GRC | IRL | ITA | JPN | NLD | PRT | ESP | CHE | GBR | USA |
Club 2	1.781	| AUS | AUT | FIN | DEU | NZL | SWE |
Group 3	-41.997	| CAN | NOR |
Club 1+2	-28.685	
Club 2 + Group 3	-15.479	
Fossil-CO_2	-39.925	All
Club 1	5.462	| AUS | CAN | FRA | DEU | ITA | ESP | GBR |
Club 2	21.687	| AUT | BEL | GRC | NZL | PRT |
Club 3	13.729	| DNK | FIN | IRL | NOR | SWE | CHE |
Group 4	-198.789	| JPN | NLD | USA |
Club 1+2	-16.925	
Club 2+3	-3.866	
Club 3 + Group 4	-56.073	

Buildings	-30.337	All
Club 1	4.297	| AUS | CAN | FRA | DEU | ITA | JPN | ESP | GBR |
Club 2	7.563	| AUT | GRC | IRL | NZL | PRT | CHE |
Club 3	7.298	| DNK | FIN | NOR |
Group 4	-46.055	| BEL | NLD | SWE | USA |
Club 1+2	-13.190	
Club 2+3	-17.618	
Club 3 + Group 4	-54.565	
Industry	-39.684	All
Club 1	-1.340	| AUS | CAN | JPN | USA |
Club 2	3.799	| AUT | FRA | DEU | ITA | NOR | ESP | GBR |
Club 3	2.388	| DNK | FIN | GRC | NZL | PRT | SWE |
Group 4	-46.495	| BEL | IRL | NLD | CHE |
Club 1+2	-22.382	
Club 2+3	-33.123	
Club 3 + Group 4	-18.451	
Other Sectors	-34.589	All
Club 1	-1.224	| AUS | BEL | CAN | FRA | DEU | JPN | NZL | ESP |
Club 2	0.265	| ITA | NLD | NOR | SWE | GBR |
Club 3	11.720	| AUT | GRC | PRT |
Club 4	-0.468	| IRL | CHE |
Group 5	-53.324	| DNK | FIN | USA |
Club 1+2	-12.793	
Club 2+3	-23.651	
Club 3+4	-45.900	
Club 4 + Group 5	-45.646	
Power	-20.828	All
Club 1	-0.822	| AUS | CAN | DEU | ITA | JPN | NOR | ESP | GBR |
Club 2	9.008	| FIN | FRA | GRC | NZL | PRT | CHE |
Club 3	13.732	| AUT | BEL | DNK | IRL |
Group 4	-110.529	| NLD | SWE | USA |
Club 1+2	-3.938	
Club 2+3	7.304	
Club 3 + Group 4	-46.012	

Transport	-40.132	All
Club 1	7.099	| AUS | CAN | IRL | JPN | ESP |
Club 2	6.406	| AUT | FRA | DEU | ITA | PRT | GBR |
Club 3	4.323	| DNK | FIN | GRC | NZL | NOR | SWE | CHE |
Group 4	-69.721	| BEL | NLD | USA |
Club 1+2	6.202	
Club 2+3	-24.221	
Club 3 + Group 4	-57.807	
Green Innovation	24.002	All
Club 1		| AUS | AUT | BEL | CAN | DNK | FIN | FRA | DEU | GRC | IRL | ITA | JPN | NLD | NZL | NOR | PRT | ESP | SWE | CHE | GBR | USA |

Notes: *T-statistics <-1.65 denotes a rejection of the null hypothesis of convergence at 5% significance level.

Supplementary Table 2. Country-specific panel heterogeneous causality in GHG function

	Transport–GHG		Green Innovation–GHG		Energy Intensity–GHG		Energy R&D–GHG		Industrial Structure–GHG		Industry–GHG		Other Sector–GHG		Power Industry–GHG	
Country	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob
AUS	6.767	0.013	0.103	0.750	6.564	0.015	0.022	0.883	6.859	0.013	1.897	0.177	5.933	0.020	7.741	0.009
AUT	4.821	0.035	0.196	0.660	2.595	0.116	2.126	0.153	1.029	0.317	0.264	0.611	1.600	0.214	0.684	0.414
BEL	0.779	0.383	9.027	0.005	5.277	0.028	0.330	0.569	3.670	0.063	2.730	0.107	1.815	0.186	0.100	0.754
CAN	0.008	0.927	0.363	0.550	3.295	0.078	0.001	0.976	6.642	0.014	0.001	0.971	0.000	0.988	0.045	0.834
DNK	3.097	0.087	2.428	0.128	3.231	0.081	5.350	0.027	6.369	0.016	2.033	0.162	3.457	0.071	2.047	0.161
FIN	2.413	0.129	0.204	0.654	1.412	0.243	1.800	0.188	1.363	0.251	1.545	0.222	3.673	0.063	1.999	0.166
FRA	0.021	0.887	1.686	0.202	1.539	0.223	2.414	0.129	2.358	0.133	8.775	0.005	0.157	0.694	3.394	0.074
DEU	5.444	0.025	2.146	0.152	18.936	0.000	1.966	0.169	8.009	0.008	8.678	0.006	0.414	0.524	4.195	0.048
GRC	12.060	0.001	0.254	0.617	2.302	0.138	0.036	0.850	22.863	0.000	11.545	0.002	15.080	0.000	17.189	0.000
IRL	4.704	0.037	1.014	0.321	0.435	0.514	14.616	0.001	3.621	0.065	0.514	0.478	2.007	0.165	13.090	0.001
ITA	2.159	0.150	12.419	0.001	3.752	0.061	0.223	0.639	4.803	0.035	8.576	0.006	2.970	0.093	13.326	0.001
JPN	1.346	0.254	1.702	0.200	2.556	0.119	0.036	0.850	2.760	0.105	0.650	0.425	6.594	0.015	0.037	0.848
NLD	0.290	0.594	7.811	0.008	1.476	0.232	0.250	0.620	0.800	0.377	0.267	0.609	0.022	0.884	0.663	0.421
NZL	3.592	0.066	0.325	0.572	0.766	0.387	1.680	0.203	0.461	0.501	2.327	0.136	13.966	0.001	6.322	0.017
NOR	3.030	0.090	1.686	0.202	3.950	0.055	0.766	0.387	1.031	0.317	0.696	0.410	1.387	0.247	0.052	0.821
PRT	2.918	0.096	1.208	0.279	0.536	0.469	0.049	0.826	0.595	0.446	6.547	0.015	2.187	0.148	2.216	0.145
ESP	3.851	0.057	3.136	0.085	5.250	0.028	12.726	0.001	1.009	0.322	0.496	0.486	5.753	0.022	3.920	0.055
SWE	0.362	0.551	0.561	0.459	2.373	0.132	1.705	0.200	1.099	0.301	5.097	0.030	1.654	0.207	0.216	0.645
CHE	7.174	0.011	0.076	0.785	1.169	0.287	0.069	0.794	4.664	0.038	7.146	0.011	1.662	0.206	4.016	0.053
GBR	0.293	0.591	0.149	0.702	2.236	0.144	0.004	0.952	0.798	0.378	0.774	0.385	1.524	0.225	1.301	0.262
USA	7.903	0.008	3.558	0.067	0.924	0.343	4.551	0.040	5.604	0.023	7.052	0.012	0.215	0.645	1.940	0.172

Supplementary Table 3. Country-specific panel heterogeneous causality in Energy Intensity function

	Transport–Energy Intensity		GHG–Energy Intensity		Other Sectors–Energy Intensity		Energy R&D–Energy Intensity		Industrial Structure–Energy Intensity		Industry–Energy Intensity		Power Industry–Energy Intensity		Buildings–Energy Intensity	
Country	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob
AUS	12.887	0.001	5.181	0.029	2.061	0.160	6.933	0.012	1.731	0.197	0.026	0.874	3.784	0.060	5.016	0.031
AUT	3.037	0.090	4.091	0.051	0.000	0.997	0.590	0.447	10.046	0.003	0.508	0.481	0.030	0.864	5.360	0.026
BEL	1.500	0.229	9.355	0.004	7.851	0.008	0.200	0.657	4.604	0.039	0.366	0.549	7.520	0.009	1.876	0.179
CAN	7.473	0.010	6.685	0.014	1.061	0.310	0.274	0.604	1.542	0.222	1.504	0.228	2.362	0.133	0.917	0.345
DNK	1.096	0.302	3.200	0.082	0.010	0.919	1.345	0.254	3.483	0.070	0.045	0.834	0.425	0.518	2.926	0.096
FIN	6.412	0.016	10.819	0.002	2.380	0.132	5.868	0.021	1.943	0.172	0.079	0.780	5.287	0.027	8.738	0.005
FRA	1.016	0.320	0.009	0.923	0.366	0.549	0.304	0.585	6.024	0.019	0.494	0.486	1.068	0.308	0.028	0.868
DEU	1.706	0.200	6.960	0.012	1.461	0.235	0.098	0.757	0.006	0.938	0.020	0.890	3.086	0.087	7.573	0.009
GRC	0.169	0.684	0.323	0.574	0.065	0.801	0.404	0.529	0.504	0.482	0.984	0.328	1.469	0.233	0.634	0.431
IRL	0.000	0.982	4.622	0.038	0.816	0.372	0.362	0.551	2.526	0.121	0.186	0.669	6.323	0.017	3.537	0.068
ITA	0.591	0.447	0.971	0.331	1.428	0.240	0.706	0.406	0.091	0.764	6.174	0.018	5.226	0.028	0.047	0.829
JPN	1.263	0.269	0.029	0.866	0.508	0.481	0.570	0.455	0.980	0.329	0.066	0.799	0.843	0.365	0.807	0.375
NLD	3.229	0.081	8.950	0.005	2.982	0.093	2.172	0.149	4.395	0.043	4.305	0.045	5.211	0.028	6.875	0.013
NZL	4.443	0.042	5.569	0.024	4.428	0.042	4.218	0.047	1.584	0.216	2.226	0.144	11.658	0.002	8.156	0.007
NOR	9.677	0.004	3.456	0.071	1.133	0.294	4.580	0.039	0.011	0.918	4.005	0.053	1.316	0.259	3.848	0.058
PRT	0.073	0.789	1.068	0.308	2.331	0.136	0.105	0.748	0.150	0.701	7.182	0.011	0.030	0.864	0.011	0.919
ESP	4.515	0.041	6.858	0.013	3.553	0.068	0.822	0.371	4.771	0.036	1.659	0.206	6.467	0.015	12.104	0.001
SWE	5.963	0.020	0.011	0.918	0.179	0.675	0.780	0.383	5.969	0.020	0.359	0.553	0.928	0.342	6.929	0.012
CHE	4.307	0.045	9.487	0.004	2.966	0.094	2.604	0.115	4.898	0.033	0.907	0.347	1.714	0.199	2.489	0.123
GBR	0.039	0.845	0.080	0.779	1.941	0.172	0.001	0.974	0.230	0.634	0.644	0.427	10.191	0.003	0.339	0.564
USA	0.216	0.645	1.440	0.238	0.973	0.331	2.872	0.099	1.431	0.239	2.993	0.092	0.041	0.840	1.032	0.316

Supplementary Table 4. Country-specific panel heterogeneous causality in Green Energy Innovation function

	GHG–Green Innovation		Transport–Green Innovation		Energy Intensity–Green Innovation		Energy R&D–Green Innovation		Industrial Structure–Green Innovation		Industry–Green Innovation		Buildings–Green Innovation		Power Industry–Green Innovation	
Country	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob
AUS	0.934	0.340	1.737	0.196	0.317	0.577	0.411	0.526	0.474	0.496	2.161	0.150	3.206	0.082	1.709	0.199
AUT	1.080	0.306	0.781	0.383	0.266	0.609	0.927	0.342	0.052	0.821	6.441	0.016	2.543	0.120	0.450	0.507
BEL	0.000	0.995	2.259	0.142	0.000	0.988	1.827	0.185	0.002	0.965	0.187	0.668	0.122	0.729	2.219	0.145
CAN	1.233	0.274	1.249	0.271	0.788	0.381	0.019	0.890	0.068	0.795	3.306	0.077	3.162	0.084	0.772	0.386
DNK	3.353	0.075	5.461	0.025	2.900	0.097	5.426	0.026	2.629	0.114	1.214	0.278	1.138	0.293	3.680	0.063
FIN	4.099	0.050	2.788	0.104	5.016	0.031	15.623	0.000	7.717	0.009	6.405	0.016	6.189	0.018	2.996	0.092
FRA	0.004	0.949	0.529	0.472	0.569	0.456	1.645	0.208	0.383	0.540	0.083	0.775	2.789	0.104	2.912	0.097
DEU	0.369	0.547	3.059	0.089	1.717	0.198	3.336	0.076	2.074	0.158	1.548	0.221	2.267	0.141	3.756	0.060
GRC	0.780	0.383	1.114	0.298	2.211	0.146	2.286	0.139	0.735	0.397	0.268	0.608	1.081	0.305	1.522	0.225
IRL	1.965	0.170	6.711	0.014	4.454	0.042	0.100	0.753	4.535	0.040	0.517	0.477	1.986	0.167	11.010	0.002
ITA	0.180	0.674	2.158	0.151	2.968	0.093	3.878	0.057	0.003	0.959	0.686	0.413	14.242	0.001	0.820	0.371
JPN	0.291	0.593	0.022	0.883	0.103	0.750	0.019	0.891	0.910	0.346	0.810	0.374	1.284	0.265	0.150	0.701
NLD	3.330	0.076	0.816	0.372	0.462	0.501	0.893	0.351	1.517	0.226	0.403	0.530	0.029	0.866	1.820	0.186
NZL	1.875	0.179	3.506	0.069	0.673	0.417	0.378	0.542	2.584	0.117	6.959	0.012	0.048	0.827	1.000	0.324
NOR	14.239	0.001	19.060	0.000	6.791	0.013	1.464	0.234	2.929	0.096	9.420	0.004	1.591	0.215	3.557	0.067
PRT	38.602	0.000	41.770	0.000	27.043	0.000	17.149	0.000	22.921	0.000	11.665	0.002	20.624	0.000	44.883	0.000
ESP	1.065	0.309	0.830	0.368	1.956	0.171	0.014	0.905	0.001	0.972	4.890	0.033	1.340	0.255	0.770	0.386
SWE	0.727	0.400	6.220	0.017	0.628	0.433	0.002	0.967	1.523	0.225	3.287	0.078	3.128	0.085	0.244	0.624
CHE	0.394	0.534	0.253	0.618	2.765	0.105	3.468	0.071	0.471	0.497	0.625	0.434	0.273	0.605	2.892	0.098
GBR	2.501	0.123	1.791	0.189	3.330	0.076	1.697	0.201	3.604	0.066	1.493	0.230	2.438	0.127	0.001	0.982
USA	0.698	0.409	1.676	0.204	0.026	0.874	0.003	0.956	0.000	0.987	0.198	0.659	0.624	0.435	0.879	0.355

Supplementary Table 5. Country-specific panel heterogeneous causality in Energy R&D function

	Transport–Energy R&D		GHG–Energy R&D		Energy Intensity–Energy R&D		Industry–Energy R&D		Other Sectors–Energy R&D		Green Innovation–Energy R&D		Buildings–Energy R&D		Power Industry–Energy R&D	
Country	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob	W	Prob
AUS	5.085	0.030	3.875	0.057	1.929	0.173	2.867	0.099	6.668	0.014	1.713	0.199	3.963	0.054	5.054	0.031
AUT	3.924	0.055	2.745	0.106	2.685	0.110	5.803	0.021	1.124	0.296	3.248	0.080	5.439	0.025	3.020	0.091
BEL	0.147	0.704	0.691	0.411	0.105	0.748	0.131	0.719	6.026	0.019	4.336	0.044	0.459	0.502	0.213	0.647
CAN	0.578	0.452	0.094	0.762	0.141	0.709	1.358	0.251	0.641	0.429	8.092	0.007	6.064	0.019	0.049	0.827
DNK	4.844	0.034	1.096	0.302	1.426	0.240	1.436	0.239	0.707	0.406	8.076	0.007	1.390	0.246	0.001	0.976
FIN	4.034	0.052	4.491	0.041	6.083	0.019	7.768	0.008	0.687	0.413	2.726	0.107	3.040	0.090	4.284	0.046
FRA	0.280	0.600	0.001	0.976	2.237	0.143	0.152	0.699	0.036	0.850	0.186	0.668	0.335	0.566	0.289	0.594
DEU	6.858	0.013	1.269	0.267	0.278	0.601	0.044	0.836	0.198	0.659	7.493	0.010	1.569	0.218	0.866	0.358
GRC	1.250	0.271	0.387	0.538	0.477	0.494	3.325	0.077	5.487	0.025	0.688	0.412	0.078	0.782	1.184	0.284
IRL	5.525	0.024	2.098	0.156	2.390	0.131	0.017	0.898	0.420	0.521	0.040	0.842	1.036	0.316	1.477	0.232
ITA	4.070	0.051	2.357	0.133	2.675	0.111	0.287	0.595	0.087	0.769	7.273	0.011	1.025	0.318	2.198	0.147
JPN	1.815	0.186	0.955	0.335	0.288	0.595	0.160	0.691	0.140	0.711	1.220	0.277	3.707	0.062	0.098	0.756
NLD	9.267	0.004	3.939	0.055	8.896	0.005	1.077	0.306	8.427	0.006	0.196	0.661	3.111	0.086	15.149	0.000
NZL	0.806	0.375	0.548	0.464	0.733	0.398	0.812	0.374	0.933	0.340	1.112	0.299	15.304	0.000	1.567	0.219
NOR	2.295	0.139	2.103	0.156	0.013	0.908	0.441	0.511	1.840	0.183	18.505	0.000	0.003	0.953	3.425	0.072
PRT	4.967	0.032	7.333	0.010	10.499	0.003	5.584	0.024	12.722	0.001	2.677	0.111	14.625	0.001	5.941	0.020
ESP	0.445	0.509	0.796	0.378	2.233	0.144	0.008	0.928	0.137	0.714	1.909	0.176	0.319	0.576	1.118	0.297
SWE	0.469	0.498	1.082	0.305	0.431	0.516	0.489	0.489	3.766	0.060	3.431	0.072	1.130	0.295	1.789	0.189
CHE	0.006	0.940	1.348	0.253	0.487	0.490	0.376	0.544	0.265	0.610	1.932	0.173	0.582	0.451	0.027	0.870
GBR	0.038	0.847	1.237	0.273	1.010	0.322	0.137	0.713	1.304	0.261	8.474	0.006	1.635	0.209	0.836	0.367
USA	0.127	0.724	0.957	0.334	0.452	0.505	2.238	0.143	0.012	0.912	9.009	0.005	5.012	0.031	0.021	0.885

Supplementary Table 6. Test for threshold effects

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	10.477	0.013	13.430	0.023**	9.381	11.336	15.833
Double	10.362	0.013	8.640	0.080*	8.202	10.237	14.243
Triple	10.259	0.013	7.830	0.327	14.869	20.150	25.160

Note: Rejection of the null hypothesis of no threshold at 5 and 10% significance level. This model suggests subsequent double threshold analysis.

Supplementary Table 7. Dynamic stochastic simulated ARDL

Parameter	Estimate	Stderr	t	*P-value*	Min 95	Max 95
GHG emissions$_{t-1}$	-0.019	0.005	-3.890	0.000	-0.028	-0.009
ΔBuildings	0.120	0.011	10.940	0.000	0.099	0.142
ΔIndustry	0.151	0.013	11.432	0.000	0.125	0.177
ΔOther	0.092	0.013	7.231	0.000	0.067	0.117
ΔTransport	0.182	0.023	7.950	0.000	0.137	0.227
ΔPower	0.118	0.006	19.259	0.000	0.106	0.130
ΔGreen innovation	-0.008	0.008	-0.965	0.335	-0.024	0.008
ΔEnergy Intensity	1.221	0.190	6.425	0.000	0.848	1.594
ΔEnergy R&D	0.001	0.003	0.241	0.810	-0.004	0.006
ΔIndustrial Structure	-0.248	0.050	-4.979	0.000	-0.345	-0.150
Buildings$_{t-1}$	0.000	0.001	0.132	0.895	-0.003	0.003
Industry$_{t-1}$	0.005	0.005	0.988	0.323	-0.005	0.015
Other$_{t-1}$	-0.001	0.004	-0.177	0.860	-0.008	0.006
Transport$_{t-1}$	0.010	0.004	2.894	0.004	0.003	0.017
Power$_{t-2}$	0.004	0.001	4.196	0.000	0.002	0.006
Green innovation$_{t-1}$	0.003	0.006	0.526	0.599	-0.009	0.015
Energy Intensity$_{t-1}$	0.024	0.024	0.993	0.321	-0.024	0.072
Energy R&D$_{t-1}$	-0.001	0.001	-1.364	0.173	-0.002	0.000
Industrial Structure$_{t-1}$	-0.029	0.012	-2.301	0.022	-0.053	-0.004
Constant	0.157	0.055	2.863	0.004	0.049	0.264

Appendices for Chapter 8

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

Supplementary 1. Relative change (%) of socio-economic and environmental indicators from 1961-2016

Country	POPDEN (% Δ)	TRADE (%Δ)	GDPC (%Δ)	GDP (%Δ)	ENVSUS (%Δ)	EFCONS (%Δ)	ECOPERM (%Δ)	CARBON (%Δ)
Afghanistan	2.52	37.34	176.86	1559.36	0.65	1.68	-67.67	6.74
Albania	1.02	7.65	170.12	1011.27	0.27	1.35	6.19	2.73
Algeria	2.35	0.12	1.76	4.15	1.02	5.05	9.14	
Angola	3.05	21.16	212.92	11986.51	0.11	3.94	1.66	11.26
Argentina	1.35	2.84	1.16	2.53	0.63	1.41	0.42	2.47
Australia	1.53	0.84	1.94	3.51	-0.01	1.62	-0.74	2.45
Austria	0.38	5.33	2.34	2.73	0.19	1.44	5.61	2.12
Barbados	0.38	17.99	188.38	301.43	-0.72	2.38	2.82	4.09
Belgium	228.56	10.55	2.25	2.65	0.29	-1.13	-1.33	-0.90
Benin	2.74	3.38	0.88	3.64	0.39	2.96	0.24	7.41
Bermuda	0.64	50.69	7.27	28401.43	0.03	2.00	2.06	
Bolivia	1.99	1.08	1.65	3.67	-0.23	2.78	-0.56	8.40
Botswana	2.65	0.76	5.57	8.39	0.44	17.28	-62.85	2718.52
Brazil	1.87	2.42	2.09	4.00	0.11	2.22	-0.39	4.24
Bulgaria	-0.16	21.80	55.71	617.24	0.98	0.70	95.32	
Burkina Faso	2.46	2.80	1.87	4.38	1.46	1.96	-556.49	5.44
Burundi	2.40	1.27	0.48	2.90	1.23	1.69	3.32	4.75
Cambodia	1.75	19.14	220.31	1334.59	1.13	1.69	2.76	
Cameroon	1.82	21.46	391.78	2286.57	0.42	2.84	-2.10	5.73
Canada	2.78	5.33	0.94	3.75	0.26	1.50	-0.38	2.17
Cape Verde	1.25	1.21	2.05	3.33	0.30	4.61	0.21	
Central African Republic	2.00	0.16	-0.75	1.25	-0.02	2.23	-0.24	9.06
Chad	2.88	3.27	0.73	3.65	0.27	2.32	-2.04	8.38
Chile	1.44	1.78	2.64	4.12	0.40	2.97	-14.25	4.51
China	1.35	3.73	7.44	8.89	-0.42	2.19	20.25	4.30
Colombia	1.96	0.79	2.16	4.16	-0.03	1.86	-1.10	3.63
Comoros	2.60	3.87	315.34	401.31	1.59	4.62	15.59	
Congo	2.98	20.90	-1.27	1.67	-0.06	3.40	-0.24	7.48
Congo (Kinshasa)	2.88	1.74	1.27	4.19	-0.21	0.75	-0.04	2.36
Costa Rica	2.33	0.95	2.25	4.63	-0.18	2.90	-4.01	6.28
Cote d'Ivoire	3.48	0.31	0.44	3.94	1.00	3.21	-0.25	6.40

Cuba	0.87	2.28	113.48	111.09	0.66	1.30	2.37	1.48
Cyprus	1.30	6.51	92.97	459.46	2.00	3.02	4.15	
Czech Republic	0.18	34.00	514.40	1320.29	-0.06	-1.75	-2.77	-4.02
Denmark	0.41	3.67	1.95	2.35	0.34	0.84	2.63	0.69
Djibouti	4.41	81.80	949.34	4353.30	0.90	5.18	-202.87	
Dominica	0.29	11.18	63.80	1734.95	0.37	3.02	70.58	
Dominican Republic	2.05	1.71	3.30	5.42	1.03	3.32	-3.16	5.46
Ecuador	2.53	1.84	1.54	3.90	-0.14	3.18	10.58	
Egypt	2.28	0.62	2.87	5.22	2.47	3.93	5.08	
El Salvador	1.49	6.67	154.46	30.51	0.27	2.73	8.10	5.28
Ethiopia	2.80	25.30	158.56	3264.69	0.71	-0.26	-41.02	4.85
Fiji	1.40	65.59	1.78	3.20	0.17	3.79	-5.31	5.23
Finland	0.38	4.32	2.40	2.79	0.12	0.61	0.28	
France	0.63	1.68	2.15	2.80	0.78	0.80	1.01	1.15
French Polynesia	2.26	36.00	727.47	1282.21	925.74	6190.09	-44.54	741.49
Gabon	2.54	0.98	1.59	4.16	-0.01	6.58	-0.18	
Gambia	3.24	4.19	0.79	358.38	0.21	3.70	-11.58	7.71
Germany	0.21	15.72	170.33	1190.04	0.57	0.54	0.63	0.77
Ghana	2.63	2.59	0.90	3.55	1.19	3.76	-0.74	5.36
Greece	0.46	2.04	2.25	2.72	0.87	2.26	4.61	3.69
Guatemala	2.47	1.66	1.38	3.88	0.89	3.20	6.52	
Guinea	2.20	20.36	275.39	3544.25	0.17	2.23	-1.92	5.35
Guinea-Bissau	1.93	4.65	39.23	18.73	128.07	28.49	-87.79	30.67
Guyana	0.49	0.75	1.56	2.07	-0.22	1.88	-0.27	6.30
Haiti	1.86	15.86	-0.40	1.45	1.25	2.02	3.52	4.80
Honduras	2.74	1.89	1.26	4.03	-0.27	1.68	975.98	
Hungary	-0.05	27.04	243.69	686.76	1.41	0.74	0.60	
India	1.94	2.93	3.22	5.22	1.77	3.14	5.22	5.46
Indonesia	1.96	5.05	3.23	5.25	0.55	2.26	-10.76	7.10
Iran	2.33	1.75	1.77	4.12	1.07	4.96	161.10	
Ireland	0.95	7.78	32.13	160.67	8.19	218.83	305.18	30.93
Israel	2.51	3.38	2.39	4.96	2.13	4.08	4.45	4.76
Italy	0.33	2.88	2.02	2.36	0.20	1.59	2.33	2.23
Jamaica	1.03	1.10	19.76	36.72	0.34	1.80	2.83	
Japan	0.54	2.42	3.04	3.60	-0.43	1.42	1.99	2.72
Jordan	4.24	10.19	91.48	6874.35	5.31	5.54	7.43	7.36
Kenya	3.27	-0.44	1.65	4.97	0.85	2.31	12.32	4.95
North Korea	1.42	32.48	508.88	8598.03	-0.02	1.28	30.42	1.67
South Korea	1.24	3.21	6.17	7.52	0.00	5.29	4.63	7.09
Lao	2.11	13.25	499.05	31852.27	0.88	2.54	-0.43	6.28
Lebanon	2.37	13.17	265.49	1199.96	1.51	3.61	4.15	4.66
Lesotho	1.64	35.69	3.32	5.00	276.50	85.66	9.08	-2.85
Liberia	2.58	246.77	639.87	7999.85	-0.14	2.75	-1.04	
Luxembourg	279.59	32.71	2.59	3.73	-0.55	6.24	7.16	4.69
Madagascar	2.88	2.10	-0.90	1.96	0.13	1.50	-0.39	5.56

Malawi	2.82	2.03	1.41	4.25	120.50	-0.46	39.91	2.53
Malaysia	2.38	0.83	3.90	6.37	0.57	4.68	6.97	53.35
Mali	2.24	10.88	2.26	398.04	0.90	2.71	-6.48	6.33
Malta	0.62	19.69	22.37	162.90	0.13	3.06	4.03	
Mauritania	2.88	2.66	0.86	3.77	-0.05	2.32	-1.19	
Mauritius	1.13	6.47	59.99	1824.71	0.00	3.85	-15.89	
Mexico	2.12	3.03	1.78	3.94	0.19	3.19	-10.18	5.44
Morocco	1.87	1.40	7.48	173.75	3.02	3.84	-54.04	
Mozambique	2.46	51.50	137.33	2294.02	0.07	2.52	-0.76	5.46
Myanmar	1.60	604.10	4.30	5.95	0.89	3.66	-2.26	4.76
Namibia	2.37	13.10	218.69	923.77	-0.07	6.42	-0.74	515.29
Nepal	1.79	1.29	1.88	3.71	0.00	26.10	5.18	10.19
Netherlands	0.70	5.12	2.19	2.90	-0.04	-0.31	-0.15	-0.38
New Zealand	1.22	7.40	95.98	1199.57	-0.06	0.29	0.98	
Nicaragua	2.28	3.79	0.54	2.82	-0.61	1.12	1.25	3.74
Niger	3.30	2.61	-0.68	2.60	2.51	4.14	62.41	6.71
Nigeria	2.57	3.50	1.35	3.96	1.78	1.35	-0.13	5.82
Norway	0.68	3.14	2.42	3.11	0.15	0.45	-1.98	2.15
Pakistan	2.74	0.18	2.36	5.16	2.17	1.68	5.58	3.32
Panama	2.28	0.15	2.99	5.34	-0.49	12.26	-99.10	28.15
Papua New Guinea	2.36	1.67	1.65	4.04	0.22	2.76	0.12	-87.57
Paraguay	2.29	1.88	2.41	4.75	-0.45	2.80	-1.17	4.35
Peru	2.00	0.74	1.61	3.63	0.07	0.62	0.78	3.94
Philippines	2.47	2.08	1.75	4.26	1.44	3.04	17865.60	5.64
Poland	0.43	23.65	1319.93	806.83	0.40	-0.88	-1.42	-1.02
Portugal	0.27	8.05	2.96	3.22	0.43	-0.33	0.01	2.23
Romania	0.11	15.06	387.00	8451.55	0.88	-1.02	12.47	-0.82
Russia	0.32	17.62	352.78	3513.11	-0.17	0.65	-25.99	3.14
Rwanda	2.54	4.09	2.20	4.82	2.04	205.10	507.49	1373.19
Saint Lucia	1.01	24.32	433.84	550.50	-0.57	2.23	4.01	3.31
Samoa	2.11	16.39	649.86	969.11	0.61	130.11	337.48	
Sao Tome & Principe	2.79	1.29	0.15	2.95	-0.17	164.06	310.60	
Senegal	2.09	5.78	0.60	2.73	0.21	1.52	-118.94	-94.92
Sierra Leone	3.02	13.97	896.89	4711.49	0.75	1.24	-26.22	9.72
Somalia	2.14	0.60	0.88	3.04	-0.08	5.67	33.32	2.62
South Africa	0.76	1.93	2.52	3.29	0.17	1.39	11.69	-81.94
Spain	1.36	0.12	3.47	4.86	1.42	0.15	0.42	1.00
Sri Lanka	1.25	9.07	63.49	1029.40	1.27	2.67	4.62	4.38
Sudan	843.05	1.49	1.57	4.03	-0.12	64.11	-11.73	22.57
Swaziland	2.17	0.78	76.03	2.16	573.93	109.42	266.33	451.30
Sweden	0.52	1.51	2.03	2.55	-0.05	-0.32	4.08	0.05
Switzerland	0.79	7.02	316.09	2989.27	0.30	-0.74	-0.97	-0.33
Syria	2.43	1.90	701.10	1802.36	3.49	3.30	-5.27	3.78
Tanzania	3.02	14.75	190.94	900.25	15.16	104.70	-28.37	2.87

Thailand	1.64	2.59	4.35	6.07	0.98	1.97	-84.96	5.98
Timor-Leste	1.70	20.93	319.36	22507.68	-0.04	7.56	-3.13	42.18
Togo	2.86	1.69	1.06	3.94	1.05	0.55	9.90	9.40
Tonga	0.85	15.53	116.11	1758.40	0.68	5.04	13.52	
Trinidad & Tobago	0.85	27.80	2.43	3.29	-0.18	6.37	7.97	-86.52
Tunisia	1.80	2.49	2.40	58.50	2.40	5.29	28.67	6.48
Turkey	1.91	3.69	2.84	4.81	0.82	1.75	-29.89	4.12
Uganda	3.20	1.34	489.49	523.55	1.00	40.08	76.47	5.75
United Kingdom	0.40	3.05	2.04	2.44	0.61	-0.43	-0.65	-1.94
USA	1.03	4.13	2.02	3.08	0.45	-0.83	-1.39	-0.69
Uruguay	0.52	1.77	1.81	2.34	0.18	12.99	-1.49	
Venezuela	2.33	1.76	-0.06	2.27	0.14	1.86	101.04	2.91
Viet Nam	1.97	13.76	125.25	1768.40	1.58	2.74	-48.16	5.26
Yemen	2.99	441.78	404.87	3703.63	-0.03	2.39	-6.16	7.34
Zambia	3.03	20.43	0.32	3.36	2.33	3.73	-1510.06	22.54
Zimbabwe	2.36	5.80	0.59	2.98	0.47	0.17	-71.97	1.46
Global Average	11.73	18.80	109.18	1369.99	15.62	56.58	134.14	51.38

“Never expect different results maintaining the status quo.”

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Compendium of Climate Change Econometrics

Climate change is topical yet, complex with several dynamics spanning different disciplines. The 21st-century development pathway is characterized by a roller coaster of climate change events––because of natural resource exploitation, fossil fuel utilization, energy intensity, population growth, and environmental pollution. Under this global environmental threat, development cooperation made several efforts to rally economies into sustainable policies that mitigate current and future threats. The Brundtland Report, "Our Common Future", outlines the importance of *"protecting the environment while meeting current demand without compromising available resources, but leaving the environment as a bequest for future generations"*. This infers the importance of achieving environmental sustainability through sustainable development, addressing institutional gaps, and developing policy measures that control urban challenges, resource-dependent, energy-intensive industrial processes, fossil-driven energy portfolio, biodiversity loss, ecosystem challenges, food security, population growth, and human resources. Climate change econometrics provides opportunities for assessing potential policy implications of historical alterations of climate events. Thus, understanding the various philosophical underpinnings of climate change and its impacts is useful in future policy development with mitigation effects. Here, we bring to the fore cyclical climate chain—a term coined to understand how climate change processes mimic typical "food chain". Philosophical perspectives of existing pollution theories including energy-growth, pollution halo/haven, environmental convergence, displacement effects, and environmental Kuznets curve hypotheses are examined using econometric techniques. This compendium contributes to the extant literature in both spirit and letters while criticizing, contrasting, and/or validating the status quo in climate change econometrics. We incorporate the concept of sustainability in the hypotheses and research design useful in developing conceptual tools for policy formulation while highlighting the policy implications of empirical results. Our empirical studies presented herein demonstrate the complexity of climate change, however, climate change mitigation and adaptation to climate impacts are possible through climate-resilience pathways––coping mechanisms of new and existing systems to modulate the harmful effects of climate change on sustainable development.

NORD University

ISBN: 978-82-92893-90-6
ISSN: 2464-4331
Trykk: Trykkeriet, Nord universitet
www.nord.no