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Exploring the Spatial Patterns of Ecological Footprints from the Perspective of Renewable and Non-Renewable Energy Use

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Abstract: *This study investigates the issue of energy dependency and its ecological impact in the context of the economic evolution of the 21st century. The research aims to strike a balance between economic growth and environmental protection by distinguishing between sustainable and non-sustainable energy use and exploring their spatial impact on the environment. To ensure statistical robustness, Principal Component Analysis (PCA) was applied to eliminate multicollinearity, and a Spatially Lagged X Model (SLX) was employed to identify the significant factors influencing a country's ecological footprint. The results of the SLX regression demonstrate that the Green Economic Development and Unsustainable Urbanization factors have a significant effect on a country's ecological footprint. An increase in the Green Economic Development factor indicates that countries with rapid economic growth tend to overuse natural resources. Conversely, the Unsustainable Urbanization factor emphasizes the significance of population density and consumption of traditional energy sources in addressing environmental degradation. Additionally, the spatial dependency analysis underscores the importance of taking into account a country's neighbors' policies and actions alongside its own. This finding emphasizes the need for regional and global cooperation in addressing environmental challenges and achieving sustainable development goals. Overall, the research findings offer valuable insights for shaping policies and initiatives aimed at advancing sustainable development and mitigating environmental degradation.*

Keywords: *Renewable Energy; Non-Renewable Energy; Ecological Footprint; Environment; Sustainability.*

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Introduction

The issue of pollution has become increasingly concerning in recent decades. Its impact on everyday life is becoming more visible, and the transition to clean energy is now a necessity rather than a desire. Our decisions and actions will determine whether, or not, we will be able to access modern forms of energy without compromising the systems that support life around the globe.

In the current economic context, the export of energy plays a major role, but human activities undertaken do not have a positive effect on the natural environment. Over the past century, the burning of fossil fuels such as coal and oil has increased the concentration of atmospheric carbon dioxide (CO_2) and to a lesser extent, deforestation for agriculture, industry, and other human activities have shared the same impact (IPCC, 2013).

Overall, the published evidence indicates that the damage from climate change is very likely to be significant and will only increase over time. Without prompt action to reduce emissions and limit its impact, renewable energy will not be sufficient to protect our own lives, livelihoods and the natural world on which humanity depends. The Earth's resources are depleting faster than they can be replenished, which makes it necessary to adopt and promote a sustainable way of life. An alternative to the use of classical energies is represented by the implementation of renewable energy sources and their expansion on a large scale. Renewable energy sources offer opportunities for social and economic development alongside climate change mitigation. Renewable energy is the most flexible form of energy, representing one of the essential infrastructure elements for socio-economic development (Dabboussi and Abid, 2022).

Globalization and urbanization are crucial factors to consider in promoting the use of renewable energy sources. As countries become more connected and urbanized, energy demands increase, resulting in increased carbon emissions. Therefore, implementing renewable energy in urban areas is an essential step toward sustainable development (Salim and Shafiei, 2014). Additionally, globalization provides opportunities for international cooperation in promoting renewable energy, as countries can collaborate to share resources, knowledge, and funding for renewable energy projects (Baloch et al., 2021).

Literature Review

The relationship between renewable energy consumption and economic development has been and continues to be a subject of significant interest among the scientific community. The economic benefits of renewable energy sources are multiple. According to Ohler and Fetters (2014), the implementation of alternative energy sources, represented by biomass, geothermal, hydroelectric, solar or wind energy, contributes in the long term to GDP growth. Radmehr et al. (2020) suggests that the economic benefits are not only limited to the implementing country, but also to neighboring countries, possibly even leading to trade development.

Li and Lee (2022) describe the relationship between economic growth and renewable energy consumption as bidirectional. Progress in the renewable energy sector can help stimulate economic growth and conversely, a strong economy can facilitate the development of renewable energy, requiring substantial investment, as they are more expensive than non-renewable resources. Considering all these benefits, it is not surprising that many developed and developing countries are making considerable efforts to replace conventional energy production with renewable sources (Ji et. al, 2021).

Empirical findings suggest that the use of renewable energy has a positive impact on per capita income (Padhan et. al, 2020). However, de Oliveira and Moutinho (2022) have noted that, contrary to expectations, modern energy consumption methods, including renewable sources, have a negative impact on national economies in some BRICS countries. As countries' economies expand and develop, so do their energy needs. Compared to developed economies, energy demand is growing fastest in emerging economies.

Sustainable economic growth is the main target of several countries around the world, so understanding the causal relationship between energy consumption and economic growth has been addressed in the study by Ohler and Fetters (2014), Padhan et. al. (2020), respectively by de Oliveira and Moutinho (2022). Additionally, Mounir and El-Houjjaji (2022) argue that, from an economic standpoint, prioritizing "clean" energy sources, such as renewable energy that produces no emissions and relies on energy-efficient practices, is crucial for achieving sustainable growth.

In the context of these efforts, the concept of ecological globalization has emerged as a means of expanding global networks to promote international collaboration on environmental practices. This involves coordinated efforts to increase connectivity and develop shared standards for sustainability across borders. The higher the level of globalization (from an economic, political or social perspective) the more the consumption of renewable energy is encouraged (Padhan et. al, 2020). Rahman (2020) and Baloch et al. (2021) claim that globalization has a significant negative impact on greenhouse gas emissions, which implies an improvement in environmental quality.

However, Miao et al. (2022) state that while increased income is closely related to high levels of output, it also leads to more emissions being produced. This will end once economic growth and incomes reach a certain point. Usman et al. (2022) found that non-renewable energy, economic development and natural resources have an increasing impact on the ecological footprint, while renewable energy and globalization reduce it. Most of the activities that endanger the regeneration and assimilation capacity of the environment can be closely related to the production of goods and services based on the depletion and refinement of natural resources.

The capacity for regeneration and assimilation is thus described as ecological footprint. Adekoya et al. (2022) argues that the use of non-renewable energy naturally leads to environmental degradation through carbon emissions, along with other harmful substances. For example, oil-importing countries are mainly more advanced, having a high level of energy efficiency compared to oil-exporting countries that develop to a large extent through the previously mentioned means. It is also observed that the use of energy from renewable sources does not have a significant impact on the ecological footprint of oil-producing countries (İnal et al., 2022).

The rapid increase in population density due to economic development and urbanization places significant stress on the local environment, especially in developing economies. This can result in a greater exodus of population from rural areas to larger cities, leading to the expansion of smaller cities and increased concentration of economic activity. As urbanization accelerates, there is a shift from less energy-intensive agriculture to more energy-intensive manufacturing, fuel switching, and increased mobility. This leads to greater demand for transportation and travel, resulting in increased energy consumption and a larger ecological footprint. As a result, urbanization can have a significant negative impact on the environment, especially in terms of greenhouse gas emissions and the overall ecological footprint (Fang et al., 2022).

Shafiei and Salim (2014) researched renewable and non-renewable energy consumption in OECD countries, along with CO_2 emissions and the empirical results of the comparative analysis state the fact that classic types of consumption amplify carbon dioxide emissions, contrary to renewable ones which minimize them.

On the contrary, Apergis et. al (2010) argue that renewable energy does not contribute significantly to the process of reducing polluting emissions. This effect is explained by the inefficiency of energy storage technologies available at the time of the study.

The study by Al-Mulali et al. (2015) investigates the environmental Kuznets curve by focusing its attention on the ecological footprint as an indicator of environmental degradation. Including a ninety-three countries examination, the study finds that the environmental performance of those countries is related to their income. Using panel data, the research is focusing its attention on how the ecological footprint and the environmental damage that the country is causing are directly proportional. The amplification of environmental degradation using non-renewable energy is explained by the fact that the continuous extraction of natural resources leads to their significant decrease. On the other hand, financial development has a negative effect on the ecological footprint, which indicates that financial development reduces environmental damage in these countries.

Likewise, the study by Balsalobre-Lorente et al. (2022) examines the environmental Kuznets curve and the pollution haven hypothesis in PIIGS countries (Portugal, Ireland, Italy, Greece, and Spain). The study finds that the environmental performance of PIIGS countries is related to their economic complexity. It also finds that some PIIGS countries may act as pollution havens, attracting polluting industries due to weaker environmental regulations. Using the dynamic OLS estimator, it was observed that the initial stage of economic development generates a high level of environmental pollution, represented by CO_2 emissions.

The research conducted by Doğan et al. (2020) examines the relationship between economic complexity, renewable energy consumption, and carbon emissions in the 28 selected OECD countries over the period of 1990-2014. Using alternative panel data techniques like AMG (Averaging Group Means), ARDL (Autoregressive Distributed Lag) and DOLS (Dynamic OLS), the research is focused on the OECD countries due to their high level of energy consumption and the fact that their energy mix is still dominated by non-renewable sources, which contributes to sustainable development issues. It finds that economic complexity has a negative impact on carbon emissions and that the technological change and economic complexity can reduce environmental externalities. This study is suggesting that economic complexity can help mitigate environmental degradation and OECD countries should focus on producing more complex products related to air quality. On the other hand it sustains the idea that the use of renewable energy sources helps to reduce the environmental impact.

The study conducted by Zambrano-Monserrate et al. (2020) aimed to identify the spatial correlation and the direct, indirect, and total spatial effects of biocapacity, GDP, and trade openness on the ecological footprint of 158 countries in the short and long run. Using a dynamic spatial Durbin model (SDM) with spatial fixed effects, the authors found significant impacts of spatial interdependence. Specifically, they observed that biocapacity, trade openness, and GDP contribute to an increase in the ecological footprint of countries. However, the effects of biocapacity and trade openness are mostly indirect, affecting the ecological footprint in both short- and long-term horizons, while the effect of GDP is mainly direct. Taken together, these effects explain a substantial portion of the variation in the ecological footprint.

Ramezani et al. (2022) analyzed the ecological footprint (EF) and its determinants in MENA countries, with a focus on exploring spatial relationships using the Spatial Durbin Model (SDM). They found that significant spatial dependence existed in both the EF and its determinants, indicating that environmental performance and economic conditions in one country affect the environmental quality of neighboring countries.

Wang et al. (2013) proposed a spatial econometric approach to investigate the relationship between economic growth and environmental impact, using ecological footprint as an indicator. The study reveals significant spatial autocorrelation in the dataset of 150 countries' ecological footprint, indicating the need for a different model specification than traditional methods. The findings do not support the inverted U-shape Environmental Kuznets Curve (EKC) hypothesis for ecological footprint, and highlight that domestic ecological footprint is influenced by neighboring countries' ecological footprint, income, and biocapacity.

Moreover, Kassouri (2021) conducted the first empirical investigation on the spatial spillover effects of urbanization on family footprints in 28 Sub-Saharan African (SSA) countries from 2000 to 2017. Using a spatial panel model based on the STIRPAT framework, the study analyzed the impacts of urbanization on these footprint indicators across different countries. The findings revealed significant positive spatial correlations between footprint indicators in the SSA region, highlighting the need for coordinated environmental and biodiversity policies for sustainable development. The study also found that while urbanization increases human-related pressures on water and land, it reduces pressures on ecosystems, emphasizing the need for sustainable resource utilization policies during rapid urbanization.

Ke et al. (2021) conducted a case study on 280 Chinese cities from 2012 to 2018 and found a statistically significant positive spatial correlation among ecological footprints of cities in China's eastern and central regions but not in the western regions. The study underlines the need to promote clean energy use in industrial transfer and cross-regional trade to reduce dependence on traditional resources and improve the overall ecological environment quality in China.

While prior research has explored the relationship between renewable energy consumption, economic development, and their ecological impact, it has often overlooked the multidimensional nature of economic complexity and energy efficiency. Existing studies frequently focus on isolated dimensions rather than a comprehensive view of these interactions. This study aims to contribute to the existing literature by adopting a multidimensional approach to explore the intricate relationship between economic complexity and energy efficiency. Recognizing the multifaceted nature of these factors, Principal Component Analysis (PCA) will be employed as a robust method to ensure the independence of the newly created variables.

Moreover, the study seeks to spatially visualize the spillover effects to determine the relevance of neighboring policies and uncover global patterns. While local insights obtained from higher granularity data are valuable, the global perspective can significantly shape higher-level policy-making and foster a deeper understanding of the intricate relationships between nations.

Furthermore, recognizing the significance of spatial modeling, this study intends to go beyond a single approach. By utilizing multiple spatial models, the aim is to gain a comprehensive understanding of the spatial patterns and the ways in which economic complexity and energy efficiency interact within different contexts.

Methodology

The research aims to draw attention to a topic of major interest, namely energy dependence and its ecological impact, at a global level.

In order to achieve the research objective, it is desired to highlight global patterns regarding the consumption of non-renewable and renewable energy, as well as greenhouse gas emissions, through principal component analysis. This involves reducing the complexity of the dataset while also creating new independent variables to address multicollinearity and improve the interpretability of the results.

Principal Component Analysis (PCA) is a widely used technique in data preprocessing that helps to obtain a compact representation of a dataset. Instead of using the original many variables, PCA allows expressing the dataset in terms of a reduced set of principal components (Bro and Smilde, 2014). After determining the optimal number of principal components, it is common to perform a rotation of the retained components to facilitate their interpretation in PCA analysis. This process involves applying a linear transformation to the original set of components, resulting in a new set of rotated components. The primary goal of rotation is to obtain a more interpretable and meaningful representation of the data by aligning the axes of the rotated components with the underlying structure or patterns in the data (Abdi and Williams, 2010).

Varimax rotation is a specific type of orthomax rotation that focuses on maximizing the sums of squares of the coefficients within each of the resultant vectors, as opposed to Quartimax rotation, which aims to maximize the sums of squares of the coefficients across the vectors for each of the original variables. Each rotated component is expected to be characterized by high loadings for a small subset of variables, while having low or near-zero loadings for the remaining variables. By maximizing the variance of the squared loadings within each rotated component, Varimax rotation aims to achieve a sparser and more structured representation of the data (Jackson, 2005).

Further, this research aims to develop a spatial regression model, which highlights the dependence of the ecological footprint on non-renewable and renewable energy factors, at a global level. In order to accomplish the purpose of the study, several spatial regression models are estimated, including the Spatial Lagged X Model (SLX), Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Error Model (SDEM), Spatial Durbin Model (SDM), and Spatial Autoregressive with additional autoregressive error structure (SARAR) Model.

Spatial autocorrelation is a statistical measure used to assess the similarity or dissimilarity between attribute values that are close to each other in geographical space. Positive spatial autocorrelation indicates that high or low attribute values tend to cluster together in space, while negative spatial autocorrelation suggests that neighboring locations exhibit contrasting attribute values. There are several indices available for quantifying spatial autocorrelation, with Moran's I statistic being widely used (Moran, 1948). Moran's I measures the strength of the linear association between an attribute (y) at a specific location and the weighted average of the same attribute at its neighboring locations (Wy) and can be interpreted as the regression slope of (y) on (Wy).

The *SLX* model incorporates a spatial lag term that captures the spatial dependence of the dependent variable on exogenous variables and facilitates the parametrization of the spatial weights matrix, enabling the application of established econometric methods to assess the presence of endogenous explanatory variables (Halleck Vega and Elhorst, 2015).

$$Y = \alpha + X\beta + WX\theta + \varepsilon \tag{1}$$

where α is the constant term, X denotes a matrix of exogenous explanatory variables, WXθ represents the exogenous interaction effects and ε is a vector of disturbance terms.

Meanwhile, the Spatial Autoregressive Model (*SAR*) model includes a spatial lag term for the dependent variable itself. The usage of spatially lagged explanatory variables provides a distinct approach to capture spatial dependence and interrelatedness among neighboring observations. By including lagged values of explanatory variables, the model accounts for the potential impact of nearby observations on the dependent variable, which may not be captured by traditional regression models that solely rely on contemporaneous values (Drukker et al., 2013).

$$Y = \rho WY + \alpha + X\beta + \varepsilon \tag{2}$$

where ρWY is the endogenous interaction effect, α is the constant term, X denotes a matrix of exogenous explanatory variables and ε is a vector of disturbance terms.

In the case of the Spatial Error Model (*SEM*), it accounts for spatial dependence in the error term through a spatial error term. They use an error term (u) and its spatially lagged counterpart (Wu) to model spatial autocorrelation. The error term (u) captures unobserved spatially correlated factors affecting the dependent variable, while the spatially lagged error term (Wu) measures the impact of neighboring errors on the error term of a particular observation (Chi and Zhu, 2008).

$$Y = \alpha + X\beta + u, \text{with } u = \lambda Wu + \varepsilon \tag{3}$$

where α is the constant term, X denotes a matrix of exogenous explanatory variables, λWu represents the interaction effect among error terms and ε is a vector of disturbance terms.

The spatial Durbin Error Model (**SDEM**) is an extension of the spatial lagged X (SLX) model that incorporates a spatially autocorrelated error structure. In the spatial Durbin error model, the error term is modeled as a combination of a spatial lag of the dependent variable and a spatial lag of the error term, allowing for the inclusion of spatial dependence in the error structure. This augmented SLX model accounts for the potential spatial autocorrelation in the error term, which may arise from spatially correlated factors that affect the dependent variable but are not included in the model (Lacombe et al., 2014).

$$Y = \alpha + X\beta + WX\theta + u, \text{with } u = \lambda Wu + \varepsilon \tag{4}$$

where α is the constant term, X denotes a matrix of exogenous explanatory variables, WXθ represents the exogenous interaction effects, λWu represents the interaction effect among error terms and ε is a vector of disturbance terms.

Regarding the Spatial Durbin Model (**SDM**), it includes a spatially lagged dependent and explanatory variables (Halleck Vega and Elhorst, 2015).

$$Y = \rho WY + \alpha + X\beta + WX\theta + \varepsilon \tag{5}$$

where ρWY is the endogenous interaction effect, α is the constant term, X denotes a matrix of exogenous explanatory variables, WXθ represents the exogenous interaction effects and ε is a vector of disturbance terms.

On the topic of the Spatial Autoregressive with additional autoregressive error structure (**SARAR**) model, it is known to incorporate spatial autoregressive and autoregressive terms for both the dependent variable and the error term (Okunlola et al., 2021). The specification takes the following form:

$$Y = \rho WY + \alpha + X\beta + u, \text{with } u = \lambda Wu + \varepsilon \tag{6}$$

where ρWY is the endogenous interaction effect, α is the constant term, X denotes a matrix of exogenous explanatory variables, λWu represents the interaction effect among error terms and ε is a vector of disturbance terms.

The spatial weights matrix, which captures the spatial relationships between the geographic units, is carefully constructed based on appropriate criteria, such as contiguity, distance, or other relevant measures. The weights are standardized to ensure comparability across units, and sensitivity analysis is conducted to assess the robustness of the results to different weighting schemes. The spatial weights matrix is used in the estimation of SLX, SAR, SDEM, SDM, and SARAR models.

The Queen matrix, also known as the Queen Contiguity matrix, establishes the spatial relationships between neighboring areas based on the criterion that two areas are considered neighbors if they share a common boundary or a common vertex (corner). In other words, in the queen matrix, two areas are considered to be neighbors if they are directly adjacent to each other, either through a shared boundary or a shared corner (Anselin and Rey, 2014).

The endogenous factor, Ecological Footprint was introduced into the model in order to observe to what extent existing resources can support human behavior. The Ecological Footprint is a method of comparing the sustainability of resource use among populations. It measures the effect of human consumption on cultivated land, forest, built-up land and the ocean, along with the degree to which these surfaces can support the indefinite existence of human communities (Ahmed et al., 2019). Thus, unsustainable populations are those with an ecological footprint larger than available land.

To analyze the differences and similarities between the two energy categories, a series of variables representative of the study were used, which are available for 75 countries, in 2018. Also, to investigate the impact on the environment, an additional variable, Number of earths, was introduced into the analysis. This represents the number of planets necessary for survival conditioned by the fact that the total population of the Globe adopts the same behavior.

The Number of earths indicator (which is defined in Table 1) was chosen as the dependent variable because it offers an element of novelty and is an indicator that is currently of great interest to researchers, while also being an important reference point in the transition to sustainability. The independent variables chosen include population density, urban population, and various energy consumption measures such as natural gas, coal, solar, wind, hydroelectricity, geothermal, biomass, and others, covering the main factors regarding the energy sector that represented the subject of research interest.

Table 1. Variables included in analysis

Variable	Description	Source
Number of earths	Every individual and country's Ecological Footprint have a corresponding planet equivalent, or the number of Earths it would take to support humanity's Footprint if everyone lived like that individual or residents of a given country. The ratio of a country's per capita footprint to the available per capita biological capacity on Earth ("Glossary - Global Footprint Network")	Global Footprint Network
Greenhouse gases	Carbon Dioxide (CO2), Methane (CH4), Nitrous Oxide (N2O) and Fluorinated Gases (F-Gas) emissions in MtCO2e	Climate Watch
KOFGI	KOF Globalisation Index	KOF Swiss Economic Institute
GDP per capita	GDP per capita (current US$)	World Bank
Population density	Population density (people per km2 of land area)	World Bank
Urban population	Urban population (% of total population)	World Bank
Natural gas	Total natural gas consumption (GJ per capita)	bp Statistical Review of World Energy
Oil	Total oil consumption (GJ per capita)	bp Statistical Review of World Energy
Coal	Total coal consumption (GJ per capita)	bp Statistical Review of World Energy
Solar	Total solar energy consumption (GJ per capita)	bp Statistical Review of World Energy
Wind	Total wind energy consumption (GJ per capita)	bp Statistical Review of World Energy
Hydroelectricity	Total hydroelectricity consumption (GJ per capita)	bp Statistical Review of World Energy
Geothermal, Biomass and other	Total geothermal, biomass and other energy consumption (GJ per capita)	bp Statistical Review of World Energy

Source: Created by authors.

To obtain conclusive and comprehensive results, we deliberately selected a diverse range of countries spanning six continents to include in our analysis. Specifically, our dataset comprised of the following countries:

- *North America*: Canada, Mexico, and the United States;
- *South America*: Argentina, Brazil, Chile, Colombia, Ecuador, Peru, and Trinidad and Tobago;
- *Europe*: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, and the United Kingdom;
- *Asia*: Azerbaijan, Belarus, China, India, Indonesia, Iran, Iraq, Israel, Japan, Kazakhstan, Kuwait, Malaysia, Oman, Pakistan, Philippines, Qatar, Russian Federation, Saudi Arabia, Singapore, South Korea, Sri Lanka, Thailand, Turkmenistan, United Arab Emirates, Uzbekistan, and Vietnam;
- *Africa*: Algeria, Egypt and Morocco;
- *Australia*: Australia and New Zealand.

We applied a selection criterion that primarily focused on the availability of data, while also considering a broad range of economic, cultural, and geographic factors. This diverse and extensive dataset enabled us to capture a comprehensive understanding of the global context and yielded robust results.

A first step in the analysis of variables is to visualize their distributions, in order to notice extreme values or erroneous records. The verification of the homogeneity of the variables is conducted by the coefficient of variation calculated according to the formula

$$v = \frac{s}{\bar{x}} \tag{7}$$

where s represents the standard deviation, and $\bar{x}$ the mean of the values. It is known that a coefficient value above 35% signals the absence of homogeneity. The coefficient of variation is often favored as a statistical tool because it allows for the comparison of variables without being influenced by differences in scale, as it is a dimensionless measure (Brown, 2012).

To ensure comparability between heterogeneous variables with varying units of measurement, standardization becomes essential. One commonly used method is the Z-score, which rescales the data values according to the formula

$$Z = \frac{x - \bar{x}}{s} \tag{8}$$

The utilization of the Z-score enables the standardization of parameter ranges, facilitating meaningful comparisons and harmonizing their scales. This statistical procedure is typically considered a necessary preliminary step prior to conducting Principal Component Analysis known also as PCA (Jang et al., 2018).

Findings

The majority of the studied variables were found to be heterogeneous, except for the KOF Globalisation Index and urban population, which exhibited coefficient of variation values of approximately 0.16 and 0.24, respectively. Additionally, the distributions of the researched variables demonstrated non-normality, with outliers present and different units of measurement. Therefore, to ensure comparability, the Z-score method was employed to standardize the variables. To determine if Principal Component Analysis (PCA) was a suitable technique for the study, the correlation matrix was analyzed (Figure 1).

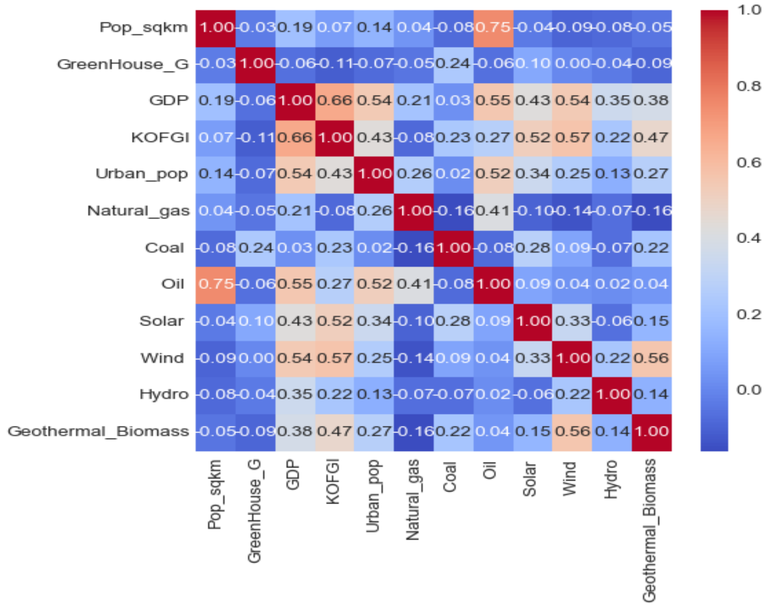

Fig. 1. Correlation matrix

Source: Created by authors using Python.

Several variables exhibited strong positive correlations, such as oil consumption and population density (0.75), and the KOF Globalisation Index and GDP per capita (0.66). Hence, it was concluded that the application of PCA was effective in identifying new synthetic variables.

After analyzing the eigenvalue matrix (Table 2), it is advised to retain four principal components, as eigenvalues greater than or equal to 1 are usually selected. The first component appears to replace approximately 4 variables and explains 29.37% of the total variance, while the second component appears to replace about 2 variables and accounts for 17.84% of the variance. The third and fourth components explain around 8% of the variance each, with each component possibly reflecting a single variable, which raises concerns about their interpretability and usefulness in practice. However, the scree plot (Figure 2) suggests keeping only three principal components, as they account for a total of 58.56% of the variance and retain a significant portion of the initial information (Samuels, 2017). Therefore, we will proceed with further analysis using these three components.

Table 2. Matrix of eigenvalues

	Eigenvalue	Proportion	Cumulative Proportion
1	3.5250	0.2937	0.2937
2	2.1429	0.1786	0.4723
3	1.3581	0.1132	0.5855
4	1.0498	0.0875	0.6730
5	0.9723	0.0810	0.7540
6	0.7972	0.0664	0.8204

Source: Created by authors using Python

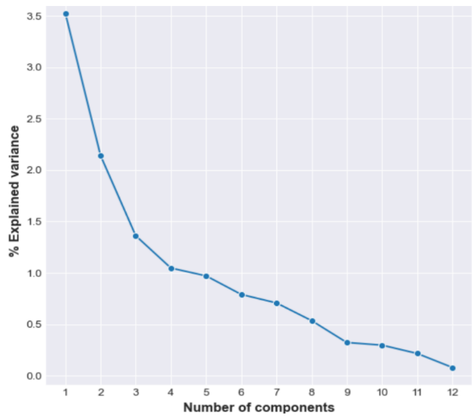

Fig 2. Scree Plot

Source: Created by authors using Python.

The results presented in Table 3 indicate that the first principal component is positively influenced by greenhouse gas emissions, the KOF Globalisation Index, and energy consumption from wind, geothermal and biomass sources, with coefficients having average values. Similarly, the second principal component is positively influenced by GDP per capita, the percentage of urban population, and consumption of hydroelectricity, but negatively influenced by coal consumption, with coefficients also having average values. Finally, the third principal component is positively influenced by population density, as well as oil and solar energy consumption.

Table 3. Eigenvectors and structure of principal components

	Eigenvectors			Factor Pattern		
	PC1	PC2	PC3	Factor1	Factor2	Factor3
Pop_sqft	0.122445	0.458014	0.210691	0.122445	.	0.467398
GreenHouse_G	-0.04191	-0.11686	0.509307	0.458014	-0.11686	.
GDP	0.467398	0.093149	-0.09097	0.210691	0.509307	.
KOFGI	0.443228	-0.14615	0.001221	0.599821	-0.16964	-0.10684
Urban_pop	0.365796	0.188758	0.016472	.	0.657103	0.136259
Natural_gas	0.046251	0.407292	-0.03802	.	-0.43558	.
Coal	0.11154	-0.27967	0.518171	.	-0.12757	0.236523
Oil	0.288154	0.527899	0.135283	.	-0.11944	-0.10423
Solar	0.299232	-0.17491	0.363993	0.146719	-0.19524	.
Wind	0.35767	-0.28249	-0.16047	-0.29547	.	0.742359
Hydro	0.156796	-0.08598	-0.47279	-0.49436	.	-0.32527
Geothermal_Biomass	0.308004	-0.26521	-0.13282	0.122445	.	0.467398

Source: Created by authors using Python.

The absolute values of the coefficients for the three principal components are mostly within the range of 0.1 to 0.5, making it difficult to identify which variables contribute significantly to the creation of the components. To improve interpretability, an axis system rotation will be conducted (Table 4) using the Varimax orthogonal rotation method. Since the three components exhibit average correlations, this method will help simplify the relationships between the original variables and the new components.

Table 4. Rotated factors pattern

	Factor1	Factor2	Factor3
Pop_sqkm	.	0.742842	.
GreenHouse_G	.	.	0.611458
GDP	0.773939	0.440558	.
KOFGI	0.842016	.	.
Urban_pop	0.528429	0.518701	.
Natural_gas	.	0.558384	.
Coal	.	.	0.701004
Oil	.	0.936562	.
Solar	0.542596	.	0.510167
Wind	0.795966	.	.
Hydro	0.402269	.	-0.480229
Geothermal_Biomass	0.696069	.	.

Note: Lower values than 0.4 are not shown

Source: Created by authors using Python.

The analysis revealed that the first factor, named *Green Economic Development*, is primarily determined by GDP per capita, KOF Globalisation Index, and energy consumption from solar, wind, geothermal, and biomass sources. The second factor, referred to as **U***nsustainable Urbanization*, is mainly determined by population density, urban population percentage, natural gas, and oil consumption. The third factor, named *Polluting Fossil Fuels*, is primarily determined by greenhouse gases emissions and coal consumption.

To facilitate the interpretation of the results, a scatterplot (Figure 3) was created to visualize the relationship between the Green Economic Development and Unsustainable Urbanization factors. The 75 countries included in the analysis were color-coded based on their Polluting Fossil Fuels factor values.

After performing the Varimax orthogonal axis rotation, some outliers were observed in the dataset. Notably, Singapore and Qatar were identified as having high values for demographics and non-renewable energy consumption but comparatively low or moderate greenhouse gas emissions. The high population density of Singapore could be a contributing factor to its energy consumption patterns. `Our observation that Qatar exhibits high values for energy consumption and moderate greenhouse gas emissions is in line with the findings of Conde (2014), who notes that Qatar is one of the largest oil-producing countries with high levels of energy consumption per capita and CO_2 emissions per Km^2.

In contrast, Denmark, Sweden, Finland, and Norway emerged as developed countries with high consumption of renewable energy sources and low greenhouse gas emissions, which aligns with their economic and globalization aspects. This highlights the significance of policy decisions and investment in renewable energy sources in mitigating greenhouse gas emissions. These findings align with those of Irandoust (2016), who suggests in his paper that the Nordic countries exhibit low energy intensities and high energy efficiencies. Furthermore, China, a high-tech user country, was not an outlier concerning the first two synthetic variables, but it had notably high greenhouse gas emissions, which were highlighted in red in the scatterplot. This observation could be due to China's status as a major producer and consumer of energy, as well as its reliance on coal and other polluting fossil fuels.

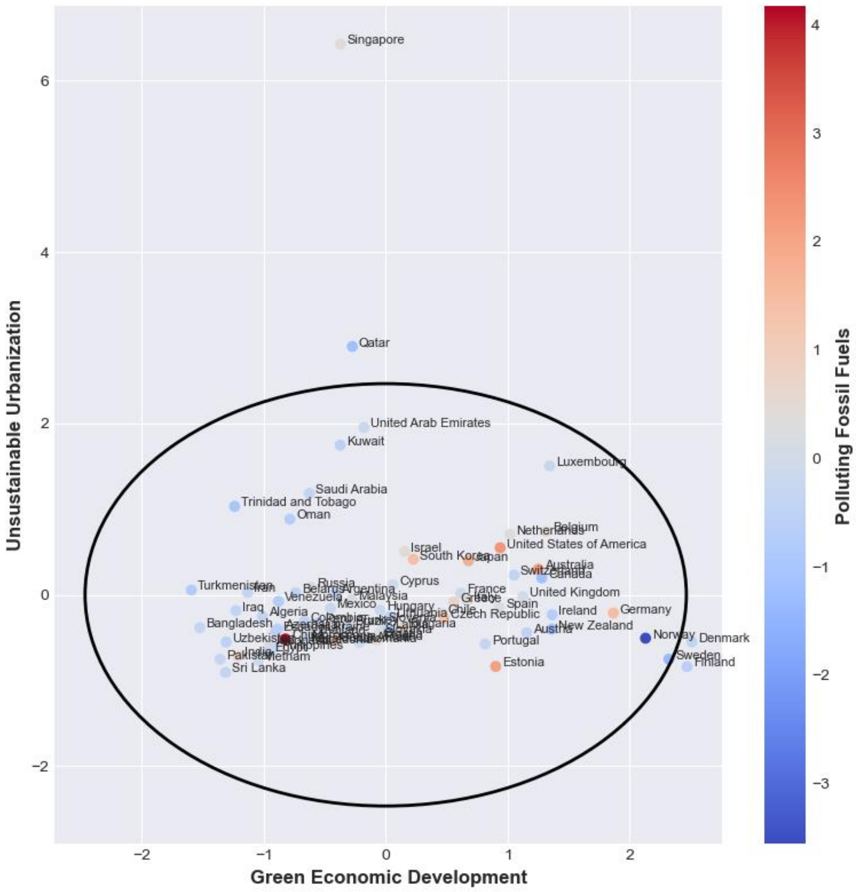

Fig 3. Factor Scores (95% Prediction Ellipse)

Source: Created by authors using Python

The spatial distribution of the ecological footprint in Figure 4 reveals that smaller, less economically developed countries with low population and surface area generally have a smaller ecological footprint (color-coded in blue), except for outliers Qatar and Luxembourg with ecological footprints equivalent to approximately 9 and 8 earths, respectively. In contrast, larger and more economically developed countries such as Canada, the United States, and Russia exhibit a larger ecological footprint, denoted by shades of red. This pattern is also observed in the Nordic countries previously mentioned. These findings suggest that as a country becomes more developed, its natural resource consumption increases, resulting in greater environmental pollution. Additionally, the clustering of neighboring countries based on their ecological footprint may indicate the influence of geographic proximity on natural resource consumption.

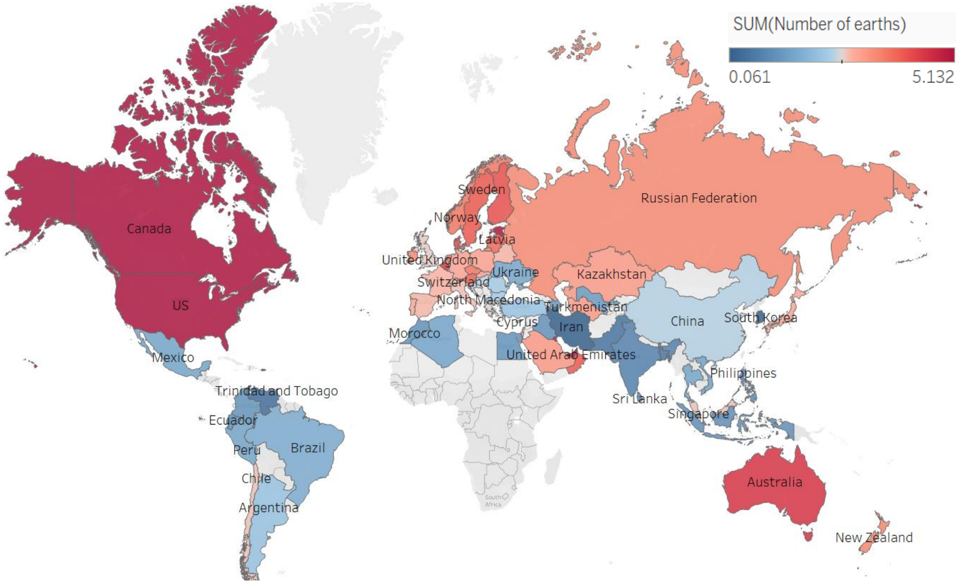

Fig 4. Spatial distribution of ecological footprint

Source: Created by authors in Tableau.

To investigate the potential presence of spatial clustering in a dataset, a diagnostic check was performed using OLS regression. Moran's I coefficient was then applied to the residuals obtained from the fitted OLS regression. The Moran's I coefficient's positive value suggested that neighboring countries had similar environmental approaches and that spatial autocorrelation was present in the dataset. This finding implies that environmental policies and resource consumption patterns may be influenced by geographic proximity, highlighting the importance of considering spatial effects in modeling and analysis.

The study utilizes six spatial regression models evaluated through AIC information criterion to examine the dynamic effects of renewable and non-renewable energy consumption, greenhouse gas emissions, economic growth, and demographic indicators on ecological footprint (Table 5). The models included spatial lagged X (SLX), spatial autoregressive (SAR), spatial error (SEM), spatial Durbin error (SDEM), spatial Durbin (SDM) and spatial Autoregressive with additional autoregressive error structure (SARAR).

Table 5. Informational Criteria – Spatial Models

Independent variables	**SLX**	**SAR**	**SEM**	**SDEM**	**SDM**	**SARAR**
Green_Economic_Development	1.014092 ***	0.746223 ***	0.843530 ***	1.004983 ***	1.00164316 ***	0.669468 ***
Unsustainable_Urbanization	0.621337 ***	0.752864 ***	0.744796 ***	0.646153 ***	0.62580231 ***	0.741486***
Polluting_Fossil_Fuels	-0.002913	-0.018593	-0.014219	-0.013671	-0.00089975	-0.033199
Lag.Green_Economic_Development	-0.265065			-0.255574	0.50359847 *	
Lag.Unsustainable_Urbanization	0.635096 **			0.618842 **	0.618842 **	
Lag.Polluting_Fossil_Fuels	-0.228975			-0.247353	-0.24100951	
Model selection criteria						
AIC	241.15	243.15	243.86	242.43	242.18	244.96

* p < 0.10, ** p < 0.05, *** p < 0.01

Source: Created by authors using R Studio.

Upon analyzing the results, it was observed that the SLX and SDEM models had similar estimates in terms of sign and significance. However, they differed from the SDM estimates in terms of significance. Additionally, the coefficients for the Green Economic Development factor were smaller in the SAR, SEM, and SARAR models, while the coefficients for the Unsustainable Urbanization factor were higher in these models compared to the three previously mentioned models. Based on the AIC criteria, the SLX model was found to be the most suitable for the dataset.

After applying the Spatial Lagged X model (Table 6), it was found that the variables that significantly impact the ecological footprint are the Green Economic Development factor, as well as the Unsustainable Urbanization factor and its spatial lag. However, the Polluting Fossil Fuels factor did not show any significant impact. The analysis of the regression model suggests that the Green Economic Development factor, which is affected by factors such as GDP per capita, KOF Globalisation Index, and the use of solar, wind, geothermal, and biomass energy, has a positive influence on the ecological footprint. Likewise, the Unsustainable Urbanization factor, which is influenced by factors such as population density, percentage of urban population, and consumption of natural gas and oil, also contributes to an increase in the ecological footprint.

Table 6. SLX model estimates

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	2.846196	0.137686	20.672	< 2e-16 ***
Green_Economic_Development	1.014092	0.262806	3.859	0.000256 ***
Unsustainable_Urbanization	0.621337	0.142577	4.358	0.0000455 ***
Polluting_Fossil_Fuels	-0.002913	0.140182	-0.021	0.983480
lag.Green_Economic_Development	-0.265065	0.320401	-0.827	0.410965
lag.Unsustainable_Urbanization	0.635096	0.279633	2.271	0.026306 *
lag.Polluting_Fossil_Fuels	-0.228975	0.162940	-1.405	0.164493

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Created by authors using R Studio.

The spatial dependency analysis (Table 7) indicates that the Green Economic Development factor has a significant impact on the number of earths only through its direct effect, indicating that a country's own policies and actions towards economic growth and use of modern energy sources influence its ecological footprint. In contrast, the Unsustainable Urbanization factor has both direct and indirect impacts on the ecological footprint, suggesting that a country's ecological footprint is affected by both its own demographic patterns and consumption of traditional energy sources as well as those of its neighboring countries. Specifically, an increase of one unit in the Green Economic Development factor leads to a corresponding increase of 1.01 units in the ecological footprint, while an increase of one unit in the Unsustainable Urbanization factor results in a 0.62-unit increase in the ecological footprint. Additionally, the significant coefficient of the lagged factor highlights that a one-unit increase in a country's neighbors' consumption of non-renewable energy leads to a 0.64-unit increase in its own ecological footprint.

Table 7. SLX impact measures

	Direct	**Indirect**	**Total**
Green_Economic_Development	1.014091833	-0.2650655	0.7490263
Unsustainable_Urbanization	0.621336728	0.6350957	1.2564325
Polluting_Fossil_Fuels	-0.002913243	-0.2289745	-0.2318878
p-values			
Green_Economic_Development	0.00011399	0.408071	0.0000032347
Unsustainable_Urbanization	0.000013132	0.023136	0.0000019944
Polluting_Fossil_Fuels	0.98341963	0.159941	0.22167

Source: Created by authors using R Studio

Similar to our results, according to Rüstemoğlu's (2022) study on the drivers of CO_2 emissions and ecological footprint growth in Australia, CO_2 emissions were not found to have a significant impact on ecological footprint. Instead, population and real income were more dominant factors in changes of ecological footprint. The study highlights the importance of considering multiple factors in analyzing environmental degradation and suggests the need for further research to explore the complex relationships between ecological footprint, CO_2 emissions, and their determinants. The study conducted by Alola et al. (2019) on European countries concludes that the adoption of renewable energy sources has a significant positive effect on environmental quality. The study estimates that in the long run, a 1% increase in the proportion of renewable energy in total energy consumption leads to approximately a 0.04% increase in environmental deterioration. The study by Pata et al. (2021) highlights the importance of researching China's pollution levels, as they have significant implications for the country's economy and the global environment. The findings suggest that relying solely on increasing the use of renewable energy sources may not be sufficient to improve environmental quality as long as the consumption of fossil fuels continues to rise. Additionally, the empirical study conducted by Amin (2016), which investigates a sample of 48 sub-Saharan countries over the 1990-2009 period using the SLX model, also suggests that countries are influenced by their contiguous neighbors in environmental policymaking. Similarly, Zambrano-Monserrate et al. (2020) explore the factors that determine the Ecological Footprint of 158 countries over the period of 2007-2016, taking into account the influence of neighboring countries. Using a dynamic spatial Durbin model, the researchers analyze the direct, indirect, and total effects of biocapacity, trade openness, and GDP on the Ecological Footprint in the short- and long-term. The findings indicate that biocapacity, trade openness, and GDP are all positively associated with the Ecological Footprint, but with varying degrees of direct and indirect effects.

Contrary to our findings, a study by Huang et al. (2022), which analyzes panel data from 1995 to 2018 in E-7 and G-7 countries, shows that renewable energy use can indeed help preserve environmental quality in both panels by reducing the ecological footprint. However, the magnitude of the coefficient differs between the two panels. The study recommends that countries should adopt strategies that promote innovative resolution-based renewable and green energy technologies to reduce their ecological footprint.

Conclusions

This study provides a comprehensive analysis of the impact of renewable energy consumption compared to conventional energy use on a country's ecological footprint. The research identifies three new variables that highlight the relationship between energy consumption, globalization, urbanization, economic development, and their impact on the environment. The study finds that high population density countries may have greater energy consumption needs, while Nordic countries have high consumption of renewable energy sources and low greenhouse gas emissions. However, countries relying on non-renewable energy sources produce significantly more greenhouse gas emissions than those using modern sources.

The spatial patterns analysis shows that the Green Economic Development and Unsustainable Urbanization factors have a significant impact on a country's ecological footprint. An increase in the Green Economic Development factor leads to a corresponding increase in the ecological footprint, suggesting a possible excessive use of natural resources in countries with rapid economic development. The Unsustainable Urbanization factor also contributes to an increase in the ecological footprint, indicating that population density and consumption of traditional energy sources are important factors to consider in addressing environmental degradation.

The analysis of spatial dependency highlights the importance of considering a country's neighbors' policies and actions in addition to its own. This highlights the need for regional and global cooperation in addressing environmental challenges and achieving sustainable development goals.

Overall, the study's findings can inform policy decisions and actions aimed at promoting sustainable development and reducing environmental degradation. The study suggests that countries with high population density and substantial urban populations should reduce their consumption of non-renewables while incorporating sustainable energy on a larger scale to ensure a more environmentally friendly future. Additionally, developed nations should invest in adopting more efficient, modern, and resource-efficient energy technologies in order to achieve a more sustainable environment.

Transitioning from non-renewable to renewable energy sources offers a multitude of potential benefits, fundamentally reshaping the utilization of natural resources. Unlike their conventional passive role, natural resources acquire an active purpose through energy production, promoting sustainability. This shift can help mitigate ecological footprints and reduce environmental degradation, largely due to the lower emissions associated with renewable energy generation.

The renewable nature of these sources further magnifies their positive impact, as they are not depleted over time like non-renewables. By harnessing energy from sources such as wind, solar, hydrological and geothermal, communities can not only meet their energy needs but also contribute to the restoration and preservation of natural ecosystems.

Additionally, transitioning to renewable energy sources contributes to the diversification of energy supply. Reducing reliance on imported fossil fuels enhances energy security and reduces vulnerability to international fuel market fluctuations. This can positively impact economic stability and national security. The renewable energy transition is not just a technological advancement but also aligns with a forward-looking approach that values long-term sustainability over short-term gains. Adopting renewable energy sources at a global scale is a transformative approach that holds the potential to reshape the energy landscape, enhance global sustainability efforts, and create a more secure and resilient future.

Renewable energy stands as the most cost-effective global energy option. Renewable technology prices are plummeting; solar costs decreased by 85% from 2010 to 2020, while onshore and offshore wind expenses dropped by 56% and 48%, respectively. This price decline heightens the appeal of renewables overall, particularly for low- and middle-income countries witnessing a surge in electricity demand. The prospect of substantial low-carbon energy production emerges, decarbonizing 90% of the energy sector by 2050, significantly mitigating climate change. This perspective draws from the core diagnostic report titled "Country Climate and Development Report (2023)", developed by the World Bank.

Alongside the implementation of the green economy, improvements extend to the health sector. The World Health Organization (WHO) reports that almost all of the global population breathes polluted air, attributing millions of yearly deaths to preventable environmental factors, like air pollution. The burning of fossil fuels predominantly generates detrimental pollutants. In 2018, fossil fuel-related air pollution incurred billions in economic and health expenses. Embracing clean energy sources such as solar and wind concurrently addresses climate change while enhancing air quality and public health.

However, the study acknowledges several limitations. Future research should consider more countries over a longer period, along with regional variations and the influence of political and cultural factors. Additionally, technological advancements and innovations should also be taken into account in future research. Two other notable limitations of the study are the temporal constraint of using data exclusively from 2018, which may impact the generalizability of the findings, and the potential lack of significant novelty in the research outcomes, which may limit the originality and innovation of the study.

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