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RESEARCH ARTICLE

Spatial Econometric Analysis of the Ecological Footprint of European Countries

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ABSTRACT

This study explains the effects of various economic factors on the ecological footprint of 34 European countries in 2022 using spatial econometric techniques. Unlike previous studies on the ecological footprint, this study presents more comprehensive results by including spatial effects in the model using spatial econometric techniques for 34 countries for 2022. This study analyzes the lagged effects of per capita GDP growth, trade openness, and renewable energy use on the ecological footprint. The spatial Durbin Model was confirmed as the most appropriate through diagnostic tests and selection criteria. The results show that per capita GDP growth, trade openness, and renewable energy usage positively and significantly affect the ecological footprint. Additionally, the spatially lagged per capita GDP growth rate has a negative impact on the ecological footprint, while the spatially lagged trade openness has a positive impact, both of which are statistically significant. These findings underscore the importance of considering the environmental impacts of economic policies to achieve sustainable development. Furthermore, the identification of spatial effects in the spread of ecological footprints highlights the need to address environmental issues not only at the national level but also in relation to neighbouring countries.

Keywords: Ecological Footprint, Spatial Econometric Analysis, Spatial Durbin Model

JEL Classification: Q57, C21, O44

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1. Introduction

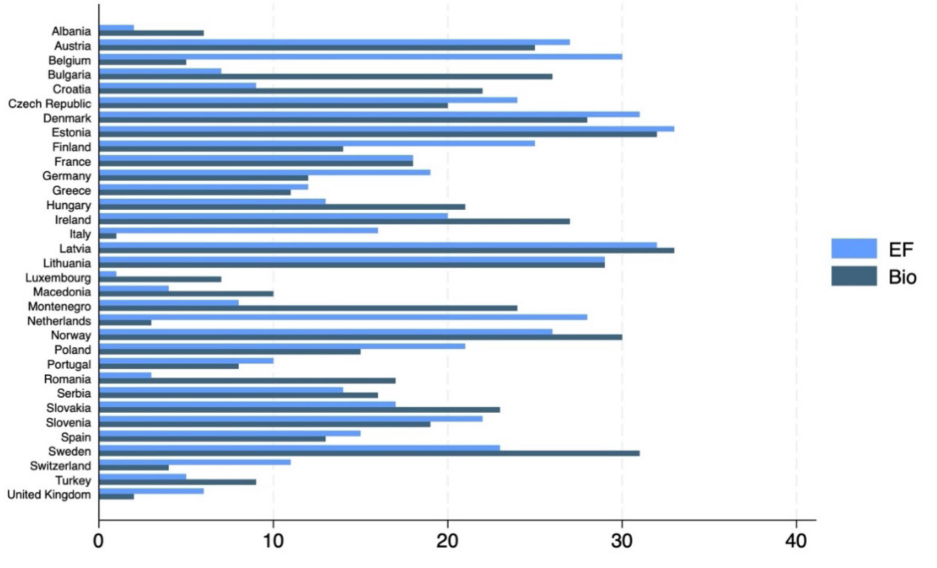
The key to sustainability lies in comprehending the considerable transformation in human spatial and material relationships with the rest of the environment, as urbanisation reflects ecological change despite seeming to indicate economic or demographic shifts (Rees and Wackernagel, 2008, p. 537). Given a specific level of technology, it is possible to determine the land or water area necessary to sustainably produce any resource or ecological service utilised by a population or economy, with most of the natural income originating from terrestrial and associated aquatic ecosystems. By calculating the total for all significant consumption categories, a cautious area-based approximation of the natural capital prerequisites for that population or economy can be obtained. This is the actual "ecological footprint" of the region's population (Rees and Wackernagel, 2008).

The ecological footprint (EF) measures how much biologically productive water or land is needed to generate the renewable resources that a population consumes sustainably and assimilate the waste generated using current technology. Biocapacity (BC) measures the biologically productive supply of a given area (e.g., cropland, pasture, forest, productive sea) available to meet this demand. Suppose the EF and the BC correspond to the economic supply and demand concepts. When employed jointly, they constitute the EF/BC accounting framework. EF is larger than BC; it leads to an ecological deficit in renewable resource accounting. When a nation has an ecological deficit, it can be offset by engaging in trade with countries possessing ecological reserves or depleting its ecological assets. Even nations with ecological reserves may face a local deficit. On the other hand, if the EF (ecological footprint) is smaller than the BC (biocapacity), it implies the existence of an ecological reserve. The ecological footprint is reduced in each area with lower consumption per capita, a smaller population size, and higher resource efficiency due to superior technology (Schaefer et al., 2006, p. 5).

The calculation of ecological footprints relies on two fundamental principles: Firstly, it is possible to monitor most resources we utilise and the waste we generate; secondly, the majority of these resources and waste streams can be converted into the biologically productive land area required to maintain these processes (Wackernagel et al., 1999, p. 377).

The graph below shows the Biocapacity and Ecological Footprint values for European countries in 2022, measured in global hectares(gha) per capita.

Figure 1: Biocapacity (Bio) and Ecological Footprint (EF) for European Countries (gha per capita)



Countries whose biocapacity is greater or equal to their ecological footprint paint a more positive picture regarding sustainability. Estonia, Finland, Latvia, Norway, and Sweden are among these countries. Italy has the lowest biocapacity, while Latvia has the highest. Luxembourg has the lowest ecological footprint, and Estonia the highest.

The primary goal of this research is to demonstrate the spatial effect on the ecological footprint of European countries and to reveal the factors influencing the ecological footprint of European countries using spatial econometric techniques. To this end, the literature section of the study includes ecological footprint studies conducted in European countries and studies explaining ecological footprints through spatial econometric techniques. Following this, the paper discusses the methodology and econometric analysis and presents the results.

2. Literature Review

2.1. Ecological Footprint Literature of the European Countries

Destek, Ulucak and Doğan, (2018) used panel data from 1980 to 2013 to investigate the determinants of the ecological footprint. The study conducted in EU countries discovered a U-shaped relationship between real income and the ecological footprint. Renewable energy and trade openness negatively influence the degradation of the environment in the EU countries, whereas non-renewable energy has a beneficial impact.

Saint Akadiri et al., (2019) analysed the determinants of the ecological footprint using a balanced panel dataset covering 16 EU countries from 1997 to 2014. The PMG-ARDL analysis revealed that non-renewable energy consumption has a negative effect on environmental quality, whereas renewable energy consumption has a positive effect on environmental sustainability. Rahman et al. (2019) employed the ecological footprint as a comprehensive measure to evaluate environmental quality. Their research on Central and Eastern European countries (CEE) indicated that economic growth's influence on the ecological footprint is not consistent, showing a lack of consistency. Additionally, the study identified an N-shaped relationship between per capita income and the ecological footprint when expressed in cubic functional form. The results also showed that financial development and a significant negative impact are associated with energy use on environmental degradation. Renewable energy significantly contributes positively by decreasing the ecological footprint and enhancing the environmental quality. Causality tests identified a two-way causal relationship between the ecological footprint and energy consumption, financial development, per capita GDP, biocapacity, and human capital. Furthermore, there was a one-way causality relationship between renewable energy and the ecological footprint. Saqib and Benhmad (2021) investigated 22 European countries from 1995 to 2015. Their research showed a quadratic relationship between income growth and the ecological footprint, supporting the Environmental Kuznets Curve's (EKC) validity. While energy consumption has a positive impact on the ecological footprint, the study found no significant influence of population growth on the environmental quality. The study analysed causality and found a unidirectional causality relationship between the gross domestic product (GDP) and the ecological footprint. Additionally, there was a bidirectional causality relationship between energy consumption and the ecological footprint. Researchers conducted a robustness analysis to validate the long-term estimation. Furthermore, the study concluded that population growth in Europe poses less of a challenge to environmental sustainability compared to the impact of intensive energy consumption.

Adedoyin, Alola and Bekun, (2020) study used balanced panel data from 16 European Union countries between 1997 and 2014. The study identified a cointegration among the ecological footprint, economic growth, research and development (R&D) expenditures, and renewable and non-renewable energy consumption. The findings revealed a significant negative relationship between R&D expenditures and the ecological footprint over time, implying that R&D expenditures have a notable effect on the environmental sustainability of the countries. The study additionally confirmed that employing renewable energy contributes to the reduction of the ecological footprint. Conversely, carbon emissions escalate due to the consumption of non-renewable energy and economic growth. The panel causality test identified the mutual causal relationships between the ecological footprint, R&D expenditures, and energy consumption, alongside the bidirectional causality between the ecological footprint and economic growth. Furthermore, the findings validated the Environmental Kuznets Curve (EKC) hypothesis for the analysed EU countries. Addai, Serener and Kirikkaleli (2022) explained the ecological footprint using quarterly time series data from 9 Eastern European countries between 1998 and 2017. Their findings indicated a negative relationship between urbanisation, economic growth, and the ecological footprint.

Saqib et al. (2023) investigated the presence of the environmental Kuznets curve and the pollution haven hypothesis across 16 European countries from 1990 to 2020. The findings revealed that the pollution haven hypothesis is valid, with foreign direct investment (FDI) having a negative impact on ecological footprints. The EKC hypothesis was confirmed when the GNP and ecological footprint relationship followed a reversed U-shaped curve. The study also discovered that the ecological footprint negatively correlated with renewable energy but a positive correlation with the energy structure. Furthermore, panel causality tests revealed a two-way causality between the GNI and the ecological footprint. In contrast, a one-way causality was observed between FDI, renewable energy, energy structure, and the ecological footprint on human capital. Wang et al., (2023) evaluated the impact of several factors on the ecological footprints of 14 developing European Union economies between 1995 and 2020 using panel data. According to the study, renewable energy and technological innovation are positively affect the environmental sustainability, as they decrease environmental degradation. Conversely, financial development, non-renewable energy consumption, and foreign direct investment (FDI) have a negative impact on environmental sustainability as they increase environmental degradation.

2.2. Ecological Footprint Literature with Spatial Econometric Analysis

Zambrano-Monserrate et al. (2020) applied a dynamic spatial panel data model from 2007 to 2016 in 158 countries. Their findings indicate that GDP, incapacity, and trade openness all positively affect countries' ecological footprints, with incapacity and trade openness having strong indirect effects in both cross sections, while GDP shows significant direct effects. Abdo et al. (2022**)** used spatial panel data analysis from 1992 to 2018 to study 57 Belt and Road Initiative countries. The analysis demonstrated GDP, urbanisation, and FDI positively impact the consumption of ecology, carbon, and non-carbon footprint. In contrast, globalisation and total natural resource rent have a negative impact. Furthermore, regarding spillover effects, GDP increases ecological, carbon, and non-carbon footprint consumption; foreign direct investment increases ecological and carbon footprint consumption. In contrast, globalisation and total natural resource rent decrease the consumption-based ecological footprint and non-carbon footprint consumption, respectively.

Using spatial econometric methods, Kassouri and Alola (2022) investigated factors influencing the ecological footprint of 28 sub-Saharan African countries between 2000 and 2017. The study revealed that biological capacity plays a significant role in reducing the ecological footprint. However, globalisation and urbanisation exert pressure on the environment, making it challenging to decrease the ecological footprint. Additionally, the research confirmed the hypothesis of the EKC, indicating a curvilinear relationship between the per capita ecological footprint and the per capita gross domestic product (GDP). Ramirez (2014) used forest cover, water coverage, and literacy variables to explain Colombia's 2010 ecological footprint. The research revealed a positive correlation between forest cover and the ecological footprint but a negative correlation involving water coverage and literacy with the ecological footprint. In a study on Middle East and North African countries from 2000 to 2016, Ramezani et al. (2022) examined factors influencing environmental degradation, focusing on per capita GDP, trade openness and financial development. The study revealed that using renewable energy, urbanisation, and democratic quality negatively affect the ecological footprint. In contrast, per capita GDP, trade openness, and financial development have a significant positive effect.

The concept of the ecological footprint was developed through studies conducted in the 1990s. In recent years, as the importance of sustainability has been recognised, the number of studies on this topic has increased, especially those aiming to explain the factors affecting the ecological footprint. Spatial econometric techniques were employed in this study to enhance our understanding of the ecological footprint in the European region, making a valuable contribution to the existing literature. Spatial perception needs to be incorporated into studies investigating ecological footprints in Europe. This study not only analysed ecological footprints across European nations but also integrated spatial effects into the model. The findings revealed that the spatial effect was statistically significant. The presence of spatial impact was tested using the Moran I, Lagrange multiplier, and likelihood ratio tests. The model selection criteria were used to determine the appropriate model. After model estimation, tests were conducted for heteroskedasticity, specification error, and normality assumptions to determine the final model.

3. Methodology

Jean Paelinck, introduced the term “spatial econometrics” in 1970s to describe a subset of regional science research that focuses on the challenges of estimating and testing multi-regional econometric models. Spatial effects, which allow spatial econometrics to be treated as a separate branch of science, are examined at two points: spatial autocorrelation (dependence) and spatial heterogeneity (Anselin, 1988, pp. 7–11).

Anselin (1988) and LeSage and Pace (2009) addressed the construction and application of spatial weight matrices in spatial econometrics. Spatial weight matrices(W) serve the purpose of delineating spatial relationships among observations. Specifically, they assign a value of 1 to indicate adjacency between observations and 0 otherwise. This approach is fundamental in quantifying spatial interactions within econometric models, facilitating the analysis of spatial patterns and dependencies.

According to this, “spatial heterogeneity” refers to the variability of relationships across different points in space. In the broadest sense, anticipate that a distinct relationship may exist for each point in space (LeSage, 1999, p. 7). Spatial autocorrelation can be defined as the covariance and correlation of a variable with its neighbours. If there is a similar relationship in the same direction between neighbouring observation values, it is referred to as a positive spatial autocorrelation. If there is no spatial relationship between the observed values, there is no spatial autocorrelation (Fischer and Wang, 2011, pp. 7–22). A field X(s), (where $s \in S$ is given:

$$\gamma(s_i, s_j) = E\left[\left(X(s_i) - \mu(s_i)\right)\left(X(s_j) - \mu(s_j)\right)\right] \; s_i, s_j \in R^2 \tag{1}$$

The function presented in Equation 2, often referred to as the spatial autocovariance function of the field, is defined. Moreover, the standardised form is given as follows:

$$Q(s_1,s_2) = \frac{\gamma(s_1,s_2)}{\sqrt{\gamma(s_1)\gamma(s_2)}} \quad s_i,s_j \in R^2 \tag{2}$$

The spatial autocorrelation function of the field is defined. For every pair of random variables $X(s_1)$ and $X(s_2)$ within the random field $\{X(s), (\text{where } s \in S)\}$ (Arbia, 2006, p. 41).

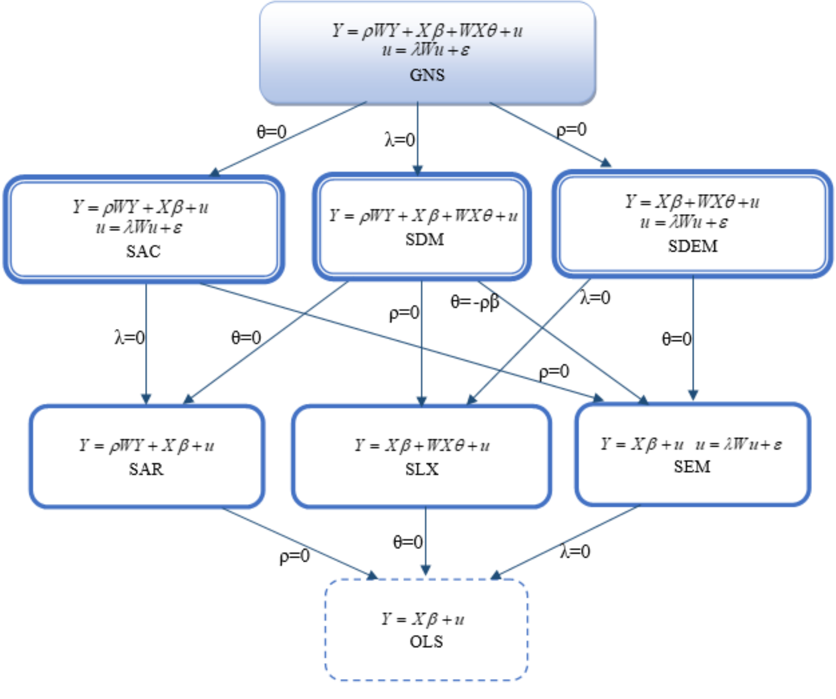
The most common test to test the significance of spatial autocorrelation is the Moran I test (Cliff and Ord (1972) and Hordijk (1974)). The Moran I statistic for a z variable can be calculated as follows:

$$I = \frac{n}{W_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(z_i-\bar{z})(z_j-\bar{z})}{\sum_{j=1}^{n}(z_j-\bar{z})^2} \tag{3}$$

The Moran I statistic, denoted by I, is calculated as shown in Equation 3 and takes values between -1 and +1. As the value approaches -1, it indicates a negative spatial autocorrelation, and as it approaches +1, it indicates a positive spatial autocorrelation. In addition, in Equation 3, i and j represent different locations, w_{ij} is the spatial weight matrix, n is the number of observations, w_0 is the standardisation vector, and z_i and z_j represent the variable's value at locations i and j, respectively (Cliff and Ord, 1981, p. 17; Fischer and Wang, 2011, p.23).

In spatial econometrics, models are constructed based on the presence or absence of spatial error or lag for dependent and independent variables, together or separately. As seen in Figure 2; the Spatial Error Model (SEM) involves a spatial autoregressive error term, whereas the spatial autoregressive combined model (SAC) includes a spatial lagged dependent variable along with a spatial autoregressive error term. The spatial Durbin error model (SDEM) includes both a spatial lagged independent variable and a spatial autoregressive error term. The spatial Autoregressive Model (SAR) only consists of the spatially lagged dependent variable, the Spatial Lag of X Model (SLX) includes only the spatially lagged independent variable, the General Nesting Spatial Model (GNS) includes all spatial effects, and the OLS model has no spatial effects. The likelihood ratio (LR) and Lagrange Multiplier (LM) type tests decide the valid model.

Figure 2: Spatial Econometric Models



Source: Yerdelen Tatoğlu F., Spatial Econometrics: Stata Applied, Beta, 2022, Istanbul, p. 58.

Burridge (1980) and Anselin (1988) proposed the LM test. Equations 4 and 5 provide the LM test statistic and the robust LM test statistic, respectively, used to detect the spatial error.

$$LM_\lambda = \frac{\left(\frac{\hat{u}'\left(\left(\iota_T \otimes w\right)\hat{u}\right.}{\hat{\sigma}_u^2}\right)^2}{tr\left(WW + W'W\right)} \sim X^2(1) \qquad (4)$$

$$LM_{\lambda}^{*} = \frac{\left(\frac{\hat{u}'(I_T \otimes W)\hat{u}}{\hat{\sigma}_u^2}\right) - \left(\frac{\hat{u}'W_y}{\hat{\sigma}_u^2}\right)B^{-1}tr(WW + W'W)}{tr(WW + W'W)(1 - Btr(WW + W'W))} \sim X^2(1) \tag{5}$$

$\hat{u}$: Estimated residuals from a spatial regression model. ι_T : Identity matrix of size T × T, where T is the number of observations. *W*: Spatial weights matrix representing the spatial structure of the data. $\hat{\sigma}_u^2$: Estimated variance of the error term in the spatial regression model. tr(): Trace operator, representing the sum of the diagonal elements of a matrix. $X^2(1)$: Chi-squared distribution with 1 degree of freedom, indicating the distribution of the test statistic under the null hypothesis. Specifically for Equation (5): W_y: A matrix representing the spatially lagged-dependent variable. *B*: A coefficient matrix or parameter related to the spatially lagged-dependent variable.

The Lagrange Multiplier (LM) test and the robust LM test, which are conducted to test the presence of spatial lag, have statistics given in equations 6 and 7, respectively (Anselin et al., 1996, pp. 83–84):

$$LM_{\rho} = \frac{\left(\frac{\hat{u}'WY}{\hat{\sigma}_u^2}\right)^2}{B} \sim X^2(1) \tag{6}$$

$$LM_{\rho}^{*} = \frac{\left(\left(\frac{\hat{u}'Wy}{\hat{\sigma}_u^2}\right) - \left(\frac{\hat{u}'(I_T \otimes W)\hat{u}}{\hat{\sigma}_u^2}\right)\right)^2}{B - tr(WW + W'W)} \sim X^2(1) \tag{7}$$

The likelihood ratio test was also used to assess spatial error, spatial lag, a combination of spatial error and spatial lag, as well as spatially independent variables. The following equations give the test:

$$LR_{\lambda} = -2[\hat{L} - \tilde{L}] \tag{8}$$

$$LR_{\rho} = -2[\hat{L} - \tilde{L}] \tag{9}$$

$$LR_{\lambda,\rho} = -2[\hat{L} - \tilde{L}] \tag{10}$$

$$LR_{\theta} = -2[\hat{L} - \tilde{L}] \quad (11)$$

$\hat{L}$ is the likelihood function of the restricted model, i.e., the model without the spatial effect. The log-likelihood function of the spatial error model (SEM) is presented in $\tilde{L}$ (8), while $\tilde{L}$ (9) provides the log-likelihood function of the spatial lag model (SAR). The log-likelihood function of the unconstrained model (SAC with spatial error and lag) is shown in $\tilde{L}$ (10), and $\tilde{L}$ (11) presents the log-likelihood function of the unconstrained model (SDM with spatial lagged independent variables) (Burridge, 1980 pp. 107-108; Yerdelen Tatoğlu, 2022, pp. 139–150).

After selecting the appropriate spatial econometric model, basic assumptions deviation such as heteroskedasticity, non-normal distribution, and specification error should be tested.

4. Data and Analysis Results

This study employs a spatial econometrics methodology to evaluate how certain economic factors will impact the ecological footprint of 34 European countries in 2022. A spatial weight matrix is used to include the spatial effect in the model. This matrix can be created according to the border neighbourhood. In this direction, a study was conducted in 34 countries. In this study, the ecological footprint in 2022 is examined in relation to the lagged effects of trade openness, renewable energy use, and GDP growth rate per capita.

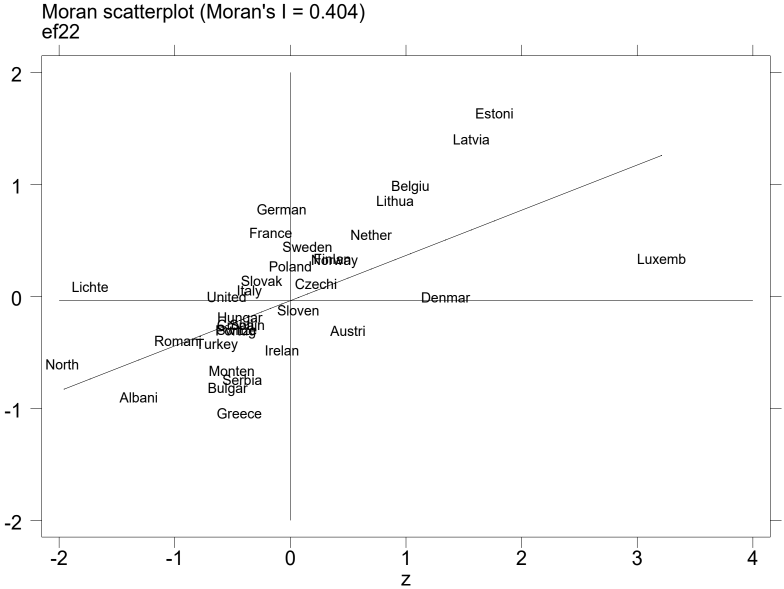
Table 1: Variable Names and Descriptions

Variable Name	Description	Year	Source
GRW	Annual Gross Domestic Product Growth Rate per Capita	2021	World Bank
TRD	Trade Openness	2021	World Bank
REC	Share of primary energy consumption from renewable sources	2021	Our World in Data
FOOTP	The footprint of Consumption (global hectares per capita)	2022	Global Footprint Network

The map below shows the ecological footprint distribution in 2022. The blue colour is used and scaled into four levels, with the highest footprint in the darkest colour. Spatial clustering is evident among different countries. This map shows that the ecological footprint variable has a spatial feature.

Figure 3: Spatial Distribution Map of the FOOTP Variable

Figure 4: FOOTP Variable Moran I Scatter Diagram



In the Moran I scatter diagram, the upper left is low high, the upper right is high high, the lower left is low low, and the lower right is high low. If the observations fall mostly in the low-low and high-high regions, it indicates a positive autocorrelation. If they fall mostly in the low-high or high-low regions, there is a negative autocorrelation. If the Moran I value is positive (if there is positive autocorrelation), it corresponds to a positive slope; otherwise, it will have a negative slope. When the Moran I scatter diagram is examined, it is seen that most of the observations fall in the high high and low low regions. For this reason, the global Moran I value at the top is positive. There is positive Spatial autocorrelation in the ecological footprint. The spatial autocorrelations shown in the scatterplot above can only be interpreted if they are statistically significant. Countries with significant spatial correlation appear in colour in Figure 5.

Figure 5: Spatial Distribution Map of the FOOTP Variable

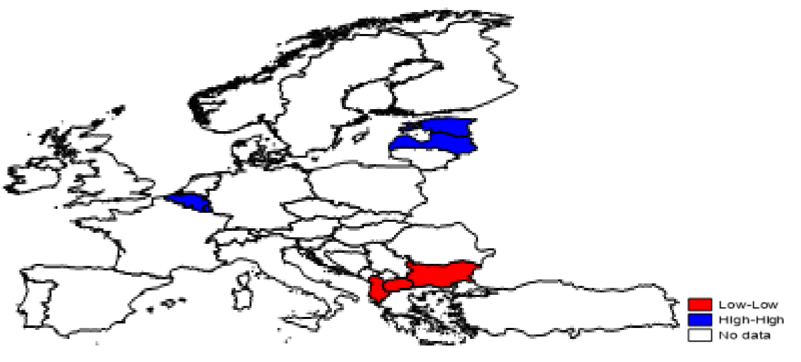


Figure 5 shows the clustering for countries with significant spatial correlation. The red areas (North Macedonia, Albania, Bulgaria) are those with low-low spatial autocorrelation, and the blue areas (Estonia, Latvia, Belgium) are those with high-high spatial autocorrelation. This spatial autocorrelation map, which shows significant movements of the ecological footprint with neighbouring countries, can a priori indicate that models that include spatial lags among spatial econometric models may be meaningful. However, it is still necessary to support this result with tests.

When working with spatial econometric models, LM and LR tests can be performed to separately test the existence of spatial error or spatial lag. The LR test can also test the existence of spatial lag and error together, as well as the spatial effect on the independent variable. After investigating the existence of spatial error, spatial lag, and spatial effect in the independent variable with diagnostic tests, the appropriate model will be estimated, and the assumptions will be tested. Table 2 includes the LM and LR tests to test the presence and type of spatial effects.

Table 2: Diagnostic Test Results

Test	Coefficient	P- value
1. Moran I	2.951	0.003**
2.LM_ρ (H_0: ρ=0)	10.926	0.001**
3.LM_λ (H_0: λ=0)	5.643	0.018**
4.Robust LM_ρ (H_0: ρ=0)	7.048	0.008**
5.Robust LM_λ (H_0: λ=0)	1.765	0.184
6.LR_ρ (H_0:ρ=0)	25.8615	0.000***
7.LR_λ (H_0: λ=0)	0.6389	0.424
8.$LR_{\rho,\lambda}$ (H_0: ρ=λ=0)	34.8695	0.000***
9.LR_θ (H_0:θ=0)	6.5102	0.089*

Note: *, ** and *** indicate the 10%, 5% and 1% significance levels, respectively.

The table presents diagnostic test results for spatial dependence, including tests for spatial lag (ρ) and spatial error (λ) dependence. According to the Moran I (1), LM_ρ (2) tests and LM_λ (3), H_0 is rejected for tests at a significance level of 5%. This indicates that there is spatial lag and spatial autocorrelation. According to the robust LM tests (4 and 5), there is no spatial error, but there is a spatial lag. The LM test results showed that the spatial lagged (SAR) model was more appropriate.

The Spatial Autoregressive Combined (SAC) model output includes tests for spatial lag and spatial error. LR test results (8) indicate the presence of either spatial error or spatial lag. LR test results (6 and 7): For spatial error, H_0 is not rejected. There is no spatial error, but there is a spatial lag at a 1% significance level. The test for the spatial independent variable is included in the SDM model output. According to the test result (9), the spatially lagged independent variables are significant.

Consequently, the test results support the existence of the SDM model. To support the results, the estimations of all the spatial models and the model selection criteria are below.

Table 3: Results of the Model Selection Criteria

Criteria	SAC	SEM	SAR	SDEM	SDM(1)	SDM(2)
$\bar{R}^2$	0.534	0.3648	0.5156	0.6055	**0.6443**	0.6399
AIC	2.0778	2.8322	2.1599	1.8958	**1.7092**	**1.6898**
SC	2.4865	3.3894	2.5848	2.5951	**2.3403**	**1.8524**
HQ	2.2090	3.0111	2.2963	2.1097	**1.9026**	**1.8524**
RICE	2.1475	2.9272	2.2323	2.1345	**1.9249**	**1.8349**
Shibata	2.0286	2.7651	2.1087	1.7726	**1.5986**	1.6064

According to the model selection criteria, the model with the highest $\bar{R}^2$ and lowest information criteria is the appropriate model. The model with the highest $\bar{R}^2$ and the lowest Akaike information criteria (AIC), Schwarz (SC), Hannan Quin (HQ), RICE and Shibata information criteria is the Spatial Durbin Model (SDM). However, in the SDM, the spatially lagged renewable energy use variable was statistically insignificant, so the variable was removed and re-estimated (SDM(2)). This model is also suitable according to the criteria.

Table 4: SDM Model Results

Variable	Coefficient	Standard Error	z
GRW	0.149*	0.083	1.8
TRD	0.018***	0.000	5.67
REC	0.026*	0.014	1.77
wGRW	-0.270**	0.128	-2.11
wTRD	0.012*	0.007	1.66
cons	0.575	0.847	0.68
ρ	0.462**	0.155	2.98
σ	1.020***	0.128	7.97
Wald	60.4706	p-value	0.000
F	12.0941	p-value	0.000
R^2	0.6835		

Test	Statistic	p-value
White Test (H_0:σ_1^2=σ_2^2)	3.6164	0.605
Jarque-Bera LM Test (H_0: S=0, K=3)	0.577	0.749
Ramsey RESET F	3.563	0.069

Note: *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

According to the White test result, H_0 cannot be rejected, and there is no heteroscedasticity. The Jarque-Bera LM test results show that H_0, which means the normal distribution of the error terms, cannot be rejected. According to the Ramsey RESET test result, H_0 (no specification error) cannot be rejected, so there is no specification error in the model.

Because of the Wald and F Test statistics, the model is significant, the model's independent variables explain 68% of the variability in the ecological footprint. It was determined that the variables of GDP growth rate, trade openness, and renewable energy use positively and significantly affected the ecological footprint.

The findings highlight the importance of accounting for spatial effects in understanding the determinants of the ecological footprint. The negative effect of the spatially lagged GDP growth rate (wGRW) regional economic policies promoting sustainable growth can have cross-border environmental benefits. Conversely, the positive effect of spatially lagged trade openness (wTRD) indicates the potential for trade activities to amplify ecological footprints through spillover effects. Moreover, the significant spatial autocorrelation coefficient (ρ = 0.462) underscores the interdependence of the countries' environmental outcomes, emphasising the need for coordinated regional environmental policies. These results provide valuable insights for policymakers aiming to balance economic growth and environmental sustainability in a globally interconnected context.

5. Conclusion

The findings of this research confirm a significant spatial effect on the ecological footprint among European countries. Specifically, the Moran I scatter plot indicated positive spatial autocorrelation. There is a positive spatial autocorrelation in the ecological footprint variable. According to the diagnostic test results used to determine the correct model, the Spatial Durbin Model (SDM) is the correct model. The spatial Durbin Model revealed that the GDP growth rate, trade openness, and renewable energy use significantly impact the ecological footprint. Additionally, the spatially lagged GDP variable negatively affected the ecological footprint, whereas the spatially lagged trade openness variable had a positive and statistically significant effect.

The ecological footprint increases with the rise in the trade ratio of goods and services to GDP. However, the study notes that trade enables more efficient resource allocation among countries, making the regulation of trade necessary to reduce the ecological footprint. Based on these findings, policies should focus on increasing renewable energy sources, liberalising trade, and sustaining economic growth. Countries must adjust their trade policies with sustainability in mind. Policy recommendations for European countries should include investing in renewable energy, reducing the carbon intensity of goods and services trade, and implementing sustainable growth strategies that consider the environmental impact of economic growth.

The research highlights the necessity of sustainable economic growth. Consequently, countries should reshape their economic growth strategies to prioritise environmental protection and sustainability. Economic growth should be aligned with the sustainable development goals.

In addition, since it was determined in the study that the ecological footprint spreads with spatial effects, efforts should be made to reduce the ecological footprint not only on a country basis but also regionally, including neighbouring countries. These policy recommendations can help reduce differences in the ecological footprint among countries and take steps towards a sustainable future.

Peer-review: Externally peer-reviewed.
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References

Abdo, A. B., Bin, L., Zhang, X., Saeed, M., Qahtan, A. S. A., & Ghallab, H. M. H. (2022). Spatial analysis of financial development's effect on the ecological footprint of belt and road initiative countries: Mitigation options through renewable energy consumption and institutional quality. *Journal of Cleaner Production*, *366*, 132696.

Addai, K., Serener, B., & Kirikkaleli, D. (2022). Empirical analysis of the relationship among urbanization, economic growth and ecological footprint: evidence from Eastern Europe. *Environmental Science and Pollution Research*, *29*(19), 27749-27760.

Adedoyin, F. F., Alola, A. A., & Bekun, F. V. (2020). An assessment of environmental sustainability corridor: the role of economic expansion and research and development in EU countries. *Science of the total environment, 713,* 136726.

Anselin, L. (1988). Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical analysis*, *20*(1), 1-17.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional science and urban economics*, *26*(1), 77-104.

Arbia, G. (2006). Spatial Econometrics: Statistical foundations and applications to regional convergence. Springer Science & Business Media.

Burridge, P. (1980). On the Cliff-Ord test for spatial correlation. *Journal of the Royal Statistical Society: Series B (Methodological)*, *42*(1), 107-108.

Cliff, A., & Ord, K. (1972). Testing for spatial autocorrelation among regression residuals. *Geographical analysis*, *4*(3), 267-284.

Cliff, A. D., & Ord, J. K. (1981). Spatial processes: models & applications.

Destek, M. A., Ulucak, R., & Dogan, E. (2018). Analyzing the environmental Kuznets curve for the EU countries: the role of ecological footprint. *Environmental Science and Pollution Research, 25*(29), 29387-29396.

Fischer, M. M., & Wang, J. (2011). *Spatial data analysis: models, methods and techniques*. Springer Science & Business Media.

Global Footprint Network (2024). *https://www.footprintnetwork.org/*

Hordijk, L. (1974). Spatial correlation in the disturbances of a linear interregional model. *Regional and Urban Economics*, *4*(2), 117–140. https://doi.org/10.1016/0034-3331(74)90025-6

Kassouri, Y., & Alola, A. A. (2022). Towards unlocking sustainable land consumption in sub-Saharan Africa: Analysing spatio-temporal variation of built-up land footprint and its determinants. *Land Use Policy*, *120*, 106291.

LeSage, J. P. (1999). The theory and practice of spatial econometrics. *University of Toledo. Toledo, Ohio*, *28*(11), 1-39.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC.

Our World in Data (2024). *https://ourworldindata.org/*

Paelinck, J. (1978). Spatial econometrics. *Economics Letters*, *1*(1), 59-63.

Rahman, S., Chen, S., Saud, S., Saleem, N., & Bari, M. W. (2019). Nexus between financial development, energy consumption, income level, and ecological footprint in CEE countries: do human capital and biocapacity matter?. *Environmental Science and Pollution Research*, *26*, 31856-31872.

Ramezani, M., Abolhassani, L., Shahnoushi Foroushani, N., Burgess, D., & Aminizadeh, M. (2022). Ecological footprint and its determinants in MENA countries: a spatial econometric approach. *Sustainability*, *14*(18), 11708.

Ramirez, Y. N. (2014, September). Spatial econometric model of the Ecological Footprint. In *Proceedings of the METMA VII and GRASPA14 Conference. Torino (IT), Università degli studi di Bergamo, Bergamo, Italy* (pp. 10-12).

Rees, W., & Wackernagel, M. (2008). Urban ecological footprints: why cities cannot be sustainable—and why they are a key to sustainability. *Urban ecology: an international perspective on the interaction between humans and nature*, 537-555.

Saint Akadiri, S., Alola, A. A., Akadiri, A. C., & Alola, U. V. (2019). Renewable energy consumption in EU-28 countries: policy toward pollution mitigation and economic sustainability. *Energy Policy*, *132*, 803-810.

Saqib, M., & Benhmad, F. (2021). Does ecological footprint matter for the shape of the environmental Kuznets curve? Evidence from European countries. *Environmental Science and Pollution Research*, *28*(11), 13634-13648.

Saqib, N., Ozturk, I., Usman, M., Sharif, A., & Razzaq, A. (2023). Pollution haven or halo? How European countries leverage FDI, energy, and human capital to alleviate their ecological footprint. *Gondwana Research*, *116*, 136-148.

Schaefer, F., Luksch, U., Steinbach, N., Cabeça, J., & Hanauer, J. (2006). Ecological footprint and biocapacity: the world's ability to regenerate resources and absorb waste in a limited time period. *Office for Official Publications of the European Communities: Luxembourg.*

Wackernagel, M., Onisto, L., Bello, P., Linares, A. C., Falfán, I. S. L., García, J. M., ... & Guerrero, M. G. S. (1999). National natural capital accounting with the ecological footprint concept. *Ecological economics*, *29*(3), 375-390.

Wang, R., Usman, M., Radulescu, M., Cifuentes-Faura, J., & Balsalobre-Lorente, D. (2023). Achieving ecological sustainability through technological innovations, financial development, foreign direct investment, and energy consumption in developing European countries. *Gondwana Research*, *119*, 138-15.

World Bank (2024). *https://databank.worldbank.org/*

Yerdelen Tatoğlu, F. (2022). *Mekansal Ekonometri Stata Uygulamalı.* Beta Basım Yayım Dağıtım AŞ, İstanbul.

Zakari, A., & Toplak, J. (2021). Investigation into the social behavioural effects on a country's ecological footprint: Evidence from Central Europe. *Technological Forecasting and Social Change*, *170*, 120891.

Zambrano-Monserrate, M. A., Ruano, M. A., Ruano, M. A., Ormeño-Candelario, V., & Sanchez-Loor, D. A. (2020). Global ecological footprint and spatial dependence between countries. *Journal of environmental management*, *272*, 111069.

Appendices: Countries Included in the Study

COUNTRIES			
Bulgaria	Italy	Greece	Poland
Switzerland	Lichtenstein	Spain	Portugal
Albania	Lithuania	Finland	Romania
Czechia	Luxembourg	Croatia	Serbia
Belgium	Latvia	France	Sweden
Austria	Montenegro	Hungary	Slovenia
Germany	North Macedonia	Ireland	Slovakia
Denmark	Netherlands	United Kingdom	Turkey
Estonia	Norway		