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Research article

Assessing the spillover effects of various forms of energy on CO_2 emissions — An empirical study based on dynamic spatial Durbin model

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A R T I C L E I N F O

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A B S T R A C T

Previous studies ignored the geospatial dynamics spillover effects of energy consumption on CO_2 emissions while assessing such impacts in developed and developing countries. Moreover, most studies wrongfully assess spillover effects in its aggregated format rather than decomposing by its components. This is important as not all energy sources share the same characteristics. We fill these gaps in the literature by investigating the spillover effects of various forms of energy, including fossil fuels, renewable energy, and nuclear power, on CO_2 emissions in 135 developed and developing countries from 2000 to 2019. We used the Dynamic Spatial Durbin Model (DSDM) to better understand the results. A series of indicative tests confirmed using the DSDM model and including spatial interaction of CO_2 emissions in the analysis. Our findings show evidence of indirect spillover effects of the various energy sources on CO_2 emissions. Further considering the spillover effects of the energy sources of neighbouring countries, the paper finds that the driving increase in CO_2 emissions mainly came from the energy consumption of the country itself and neighbouring countries' energy consumption. Nevertheless, the results indicate that the direct effects of energy consumption often exceed its indirect effects. The results also confirm that total and fossil energy consumption harms the environment, whereas adopting renewable and nuclear energy sources reduces CO_2 emissions. Lastly, we find nuclear energy is the most environmentally sustainable energy source. The study concludes that the Dynamic Spatial Durbin Model is paramount in estimating the environmental impact of energy consumption in our sample. The practical policy implications drawn from this study could be used to promote increased collaboration to hasten the energy transition process and address global warming and climate change.

1. Introduction

According to the National Research Council (2020), the observed rise in temperature over the past five decades has been primarily attributed to the heightened levels of carbon dioxide and other greenhouse gases in the atmosphere [1]. Scientists have investigated the role of greenhouse gas emissions in aggravating global warming since the 19th century. Indeed, Svante Arrhenius, a Swedish scientist often referred to as the father of climate change, was the first to inquire about the impact of greenhouse gas emissions on the

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atmospheric temperature in 1894. As a result, atmospheric carbon dioxide is 50 % higher than pre-industrial levels, reaching a historical level of 417.06 parts per million in 2022 [2]. In addition, as per the report by the Intergovernmental Panel on Climate Change (2019), failure to decrease net non-CO_2 emissions can lead to a lower probability of achieving the goal of limiting global warming to 1.5 °C [3]. Therefore, mitigating global warming and climate change is contingent upon reducing greenhouse gas emissions, specifically carbon dioxide. Accordingly, several studies have investigated the causes and effects of CO_2 emissions on the environment. Research has found that many factors contribute to CO_2 emissions, such as the initial levels and conditions of CO_2 emissions [4], the level of financial development ([5–8]), foreign direct investment flows ([9,10]), the use of fossil fuels ([11]), globalization in economic, social, and political spheres [12], international tourism [13], demographic changes such as age structure and urbanization trends [14], the quality of institutions [15], energy consumption and economic growth [16], government ideology [17], electoral systems and political representation [18], political corruption and media [19], religious and social values [20], and gender equality [21]. Estimates of the Global Carbon Project (2022) show that fossil fuel CO_2 emissions increased from 10.9 billion tons in the 1960s to 36.6 billion tons annually in 2022, the highest ever [22]. Coal handled 46 % of fossil CO_2 emissions, followed by oil at 35 % and natural gas at 15 %. A recent study by Ref. [23] explored the determinants of CO_2 emissions in 92 developed and developing countries using the Bayesian Model, Averaging those accounts for model uncertainty. The analysis suggests that fossil fuel consumption is the most robust and common determinant of CO_2 emissions in developed and developing countries. There has been a boom in empirical research analyzing the effects of energy consumption on environmental quality. However, the findings show that the environmental effects of energy depend on the energy source. Fossil fuel energy sources, including coal, oil, and natural gas, have been shown to harm the environment and deteriorate the ecosystem ([24–27]). In contrast, renewable energy sources, such as wind, solar, and hydropower, are emission-free clean energy sources that help to safeguard the environment ([28–31]). The potential environmental impacts of nuclear energy have yet to be thoroughly examined, and a definitive consensus has not been established ([32,33]).

According to the literature, methodological approaches in the analysis of CO_2 emissions have been witnessed by using econometric models such as the STIRPAT model ([34–44]). Most STIRPAT studies analyze CO_2 emissions in the industrial/service sectors. Additionally, industry participation in total GDP is often used to represent technology. These studies often encompass regions with thriving industries, such as China. However, most existing studies have extensively explored the linear relationship between the factors and CO_2 emissions, thus overlooking the spatial correlation of CO_2 emissions that can arise among economies [45]. Arguably, spatial dependence on CO_2 emissions can occur due to two reasons. Firstly, countries may intentionally manipulate environmental standards either to attract capital or for trade purposes. Secondly, there may be a geographical interdependence in the technologies used to produce goods and services across different countries ([46,47]).

Although existing studies have widely and deeply discussed the linear relationship between financial development and CO_2 emissions, potential nonlinear relations have not been systematically analyzed [5]. Therefore, given the inappropriateness of traditional IPAT and SPIRAT models, to estimate the effects of CO2 emissions on the environment, substantive studies have developed spatial econometric models considering spatial CO_2 distribution and interaction and the influencing factors' spatial role. Khezri et al. (2021) examine the spatial effects of financial development on CO_2 emission by applying spatial econometric techniques [48]. Doing so, the authors have found that as demand and financial growth in neighbouring countries increase, CO_2 emissions decrease. Mahmood et al. (2020) studied the effects of income, trade, energy consumption, and FDI on CO_2 emissions in five North African countries from 1990 to 2014 [49]. Their results indicate evidence of the negative effect of exports on CO_2 emissions, while their spillover effects on the neighbouring countries are positive. Moreover, the effects of imports and total trade openness are positive on local economies, and their spillovers are negative. Their results also show that FDI does not affect CO_2 emissions. Balado-Naves et al. (2018) analyze the relationship between economic growth and CO_2 emissions [50]. The authors employ a panel data set composed of 173 countries for the 1990–2014 period to analyze the existence of a spatial EKC for CO_2 emissions. Their findings indicate that (i) most regions follow the EKC, (ii) neighbouring per capita income has an inverted U-shaped relationship with national per capita emissions in Europe, Asia, and globally, (iii) neighbouring energy intensity increases national per capita emissions, and (iv) economic growth will accelerate climate change. Wang et al. (2022) used a spatial fixed effects model to analyze the impact of renewable energy on CO2 emissions in 36 European countries from 2000 to 2018 [41]. Their main results show that CO2 emissions were positively affected by GDP per capita, foreign direct investment, urbanization, and energy intensity.

According to the foregoing, previous studies ignore the geospatial dynamic spillover effects. Further, most studies wrongfully use spillover effects in their aggregated format rather than decomposing spillover by its components (direct and indirect effects). Therefore, this research aims to contribute to the expanding body of literature on the assessment of spillover effects of energy consumption on environmental quality as spatial spillover may unveil the indirect spillover effects of energy consumption and avoid underestimating or overestimating its environmental effects. Moreover, there seems to be little research in the literature on the spillover (direct/indirect) effects of various forms of energy consumption on CO2 emissions in a geospatial context analysis. In this regard, using a non-spatial analysis approach leads to the omission of relevant spatial dependence in the data, which in turn is of relevance in the econometric analysis as it could lead to bias/inconsistent and inefficient estimates ([51–53]).

To fill the above academic gaps, this study investigates the effects of various forms of energy on CO_2 emissions in 135 developed and developing countries from 2000 to 2019. The research uses, therefore, Explanatory Spatial Data Analysis (ESDA) techniques to explore the relationship between variables, followed by spatial econometric models to better understand the results. Therefore, compared with the analyses considered in the previous empirical literature, this study makes several novel contributions to literature. The econometric modelling framework employed here has several advantages concerning the previous analysis, which only considers spillover effects in its aggregated format rather than decomposing spillover by its components (direct and indirect effects). First, this study rigorously assesses the spatial spillover effects over a more extensive set of environmental quality determinants and various forms of energy. These covariates can be grouped into human, economic globalization, and financial development. Second, this study considers spatial spillover effects that may occur modelling CO2 emissions, which the economic and financial interconnections between countries can support. Therefore, incorporating spatial spillovers resolves misspecification problems [50], and excluding spatial terms can lead to flawed estimates [51]. Third, the empirical investigation is also based on two spatial weights matrices used to determine the area's neighbourhood. Following this, ESDA techniques are used to identify spatial autocorrelation that may exist between data [54]. Fourth, this study compares the impacts of different energy sources on CO2 emissions, including total, fossil fuel, renewable, and nuclear energy. This may extend our understanding of the determinants of CO2 emissions.

Altogether, the suitable econometric framework proposed in this research effectively provides a systematic example for determining significant drivers of carbon emissions within 135 developed and developing economies. Therefore, policymakers should fully consider these results when constructing long-term strategies for reducing CO2.

The main objective of this research is to determine the spillover effects of energy consumption on carbon dioxide emissions for 135 developed and developing countries between 2000 and 2019. To achieve this, the study investigated the environmental impact of various energy sources, such as fossil fuels, renewable energy, and nuclear power, on CO2 emissions. Additionally, the study considered the spatial dependencies among CO2 emissions across different units of study while applying a spatial dynamic model. This model was used to argue the significance of using such an approach in accurately estimating and comparing the effects of different energy sources on CO2 emissions. This approach is crucial in comprehending the shared effects of direct and indirect sources, which were previously disregarded in other studies.

The rest of the paper is ordered as follows: Section 2 encompasses the research methodology. Results from decomposition and empirical analysis have been discussed in section 3, and the study is concluded with relevant policy suggestions in section 4.

2. Methodology and data

2.1. Study area

This study examines the impact of various energy sources on environmental quality in both developed and emerging countries. The scope of the study includes Argentina, the Association of Southeast Asian Nations (ASEAN), Australia, Brazil, Canada, China, the European Union (EU), India, Japan, Mexico, the Russian Federation, Saudi Arabia, South Africa, Turkey, the United Kingdom (UK), and the United States (US). In terms of geography, the selection of the countries is based solely on data availability that can reasonably be used over a long period of time and is not related to any specific regional characteristics. The study focuses on developed and developing countries, where we believe developing countries' responsibilities for CO_2 emissions are more extensive and growing faster than developed countries. In fact, from 1995 to 2015, developing countries were accountable for 43.2 % of the cumulative global CO_2 emissions, whereas developed countries were responsible for 56.8 % [79]. Considerable differences in CO_2 emissions have been found within the study countries (i.e., country-based CO_2 emissions ranging from 0 to 96.79 in developing countries and from 0.5 to 0.9 in developed countries). These differences are attributed to variations in economic status, level of industrialization, and spatial associations among countries. Therefore, the study emphasizes the need to incorporate spatial dependence relationships between countries into the methodological application to ensure accurate assessments.

2.2. Spatial dependence test

Before estimating the spatial spillover effects, examining the presence of spatial dependence is essential. To this end, we perform the Moran's I statistic and the Moran's scatter. Moran's, I test is based on the null hypothesis that the dependent variable (CO_2 emissions) associated with different countries is spatially independent. In the case of negative Moran statistics values, spatial dispersion characterizes the data. In contrast, positive values of Moran statistics indicate positive spatial autocorrelation and spatial concentration. The following equation defines the global Moran's I index:

$$I_t = n/_{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_{it}-\mu_t)(x_{jt}-\mu_t)}{\sum_{i=1}^{n}(x_{it}-\mu_t)^2} \tag{1}$$

where x_{it} is the interest variable (CO_2 emissions), μ_t is the average of x in year t. w_{ij} denote the spatial weight matrix (W_d or W_c) between two countries i and j. n is the number of countries, while S_0 is a scalar equal to the sum of all w_{ij}.

Similarly, the local Moran's I index is used to identify the nature and magnitude of the externality. The index takes the following form:

$$I_{it} = \frac{\left(z_{ij} - m_{t)} \sum_{j=1;j\neq i}^{n} w_{ij}(m_{ij} - z_t)\right.}{S_i^2} \tag{2}$$

$$S_i^2 = \frac{\sum_{j=1;j\neq i}^{n} w_{ij}(z_{jt} - m_t)^2}{n-1} - m_t^2 \tag{3}$$

where z_{it} is the variable subject to spatial autocorrelation, m_t denotes the mean of z at year t. w_{ij} represents the weights matrix between the two countries i and j, n is the number of countries.

2.3. Spatial weighting matrix

Specifying the spatial weighting matrix is fundamental in spatial econometric models, as different matrices capture different spillover channels [55]. Two diagonal weight matrices are employed in this study to assess the robustness of the findings. The first matrix, specified as W_d, is based on the inverse distance of dimension $n * n$, where n is the number of countries considered in the analysis. This matrix can be written as follows:

$$W_d = \begin{cases} d_{ij}^{-1}, if\ i \neq j \\ 0, if\ i = j \end{cases} \tag{4}$$

where d_{ij} is the geographical distance between two countries i and j.

The second matrix implemented in this research is the contiguity matrix, written as follows:

$$W_c = \begin{cases} 1 \text{ if country } i \text{ is adjecent to country } j \\ \qquad\qquad 0 \text{ otherwise} \end{cases} \tag{5}$$

Moran's scatter plot technique identified specific spatial configurations for CO2 emissions, including high-high or hot spots, low-low or cold spots, high-low or potential spatial outliers, and low-high or potential spatial outliers.

2.4. Spatial econometric model

Historically, researchers have long investigated the factors contributing to CO_2 emissions through the Environmental Kuznets Curve (EKC) hypothesis, which examines the relationship between pollution and income and follows an inverted U-shape [56]. The findings on this hypothesis have been inconclusive. As a result, in 1971, Erlich and Holdren developed the IPAT model as a way to study environmental impacts (I) [57]. It involves analyzing the factors of population (P), affluence (A), and technology (T). However, this model has faced criticism for not analyzing the three variables simultaneously. To address this concern, Dietz and Rosa (1997) reformulated the IPAT model into a Stochastic Impact by Regression on Population, Affluence, and Technology (SPIRAT) [58]. This new model allowed for the analysis of multiple factors at once, specifically examining the influences of population, industrialization level, affluence, technology, and urbanization level on the environment. In this regard, our research examines the environmental impact of various energy sources on CO_2 emissions. For this purpose, we mostly rely on the STIRPAT econometric model. However, we encountered challenges when applying this model in a spatial econometric context. It appears that the STIRPAT model was not suitable for our purpose due to several reasons. Firstly, the model in its current form cannot reflect the spatial correlation among countries' carbon emissions, which might affect the correlation results. Secondly, the model cannot account for different concepts of cross-country interactions and spillover effects on CO_2 emissions. Lastly, we considered the effect of time lag, space lag, and time lag on current country carbon emissions, and hence, a spatial panel model should be used in this study.

A dynamic spatial model was, therefore, proposed to extend our understanding of the determinants of CO_2 emissions. Various types of dynamic spatial measurement models exist. These models include the dynamic spatial lag model (DSLM), dynamic spatial error model (DSEM), and dynamic spatial Durbin model (DSDM). Each of these models has different focuses and implications for the economy. However, the DSDM combines the advantages of both the DSEM and DSLM. It considers the spatial dependence of both explained variables and explanatory variables, as well as the spatial spillover effects of random shocks at the same time. Its functional form is as follows:

$$\begin{aligned} lnCO2_{i,t} = {} & b_0 + \lambda lnCO2_{i,t-1} + \theta WlnCO2_{i,t} + \varphi WlnCO2_{i,t-1} + \alpha_1\ ln\ GDP_{i,t} + \alpha_2 \left(ln\ GDP_{i,t}\right)^2 + \alpha_3\ ln\ EI_{i,t} + \alpha_4\ ln\ POP_{i,t} + \alpha_5\ ln\ HC_{i,t} \\ & + \alpha_6\ ln\ KOF_{i,t} + \alpha_7\ ln\ FD_{i,t} + \alpha_8\ ln\ EC_{i,t} + \theta_1 WlnGDP_{i,t} + \theta_2 W\left(ln\ GDP_{i,t}\right)^2 + \theta_3 WlnEI_{i,t} + \theta_4 WlnPOP_{i,t} + \theta_5 WlnHC_{i,t} \\ & + \theta_6 WlnKOF_{i,t} + \theta_7 WlnFD_{i,t} + \theta_8 WlnEC_{i,t} + \upsilon_i + \mu_{i,t} \end{aligned} \tag{6}$$

Where λ refers to the coefficient used to assess the presence of dynamics of CO_2 emissions while θ represents the coefficient measuring the structure of the spatial diffusion of CO_2 emissions. φ refers to the coefficient of the spatial autocorrelation of CO_2 emissions (spatial lag coefficient). α_K refers to coefficients of the independent variables to be estimated. θ_k stands for the spatial coefficient for independent variables. W denotes the spatial weighting matrix (W_c or W_d), υ denotes the country-specific effect, b_0 the constant, and finally $\mu_{i,t}$ the error term.

Model (6) used several variables to reflect their impact on CO2 emissions. These variables include Real GDP (measured in 2017 US $), Energy intensity (measured in Btu/2015$ GDP PPP), Population, Human index, KOF economic globalization index, Financial Development Index, Total energy consumption (measured in a million Btu), Fossil energy consumption (measured in a million Btu), Renewable energy consumption (measured in a million Btu), and nuclear energy consumption (measured in a million Btu). Below, each variable is explained in more detail, along with its definition and sources.

2.5. Data sources

The empirical analysis aims to estimate the spatial effects of different energy sources on environmental quality for 135 developed and developing economies from 2000 to 2019. CO_2 emissions from the U.S. Energy Information Administration measure environmental quality. The selection of CO_2 emissions depends on their availability for a large sample of countries over a long period. Regarding the interest variable, we consider different energy sources: total energy consumption, fossil energy consumption, renewable energy consumption and nuclear energy consumption. Data regarding energy consumption are also extracted from the U.S. Energy Information Administration. Furthermore, a wide range of control variables that could affect CO_2 emissions has been included in the specification. It is worth noting that the empirical study is based on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) proposed by Dietz and Rosa (1997). According to the model, environmental degradation is affected by three factors: population (*P*), affluence (*A*) and technology (*T*). This study measures P by the total population, A by GDP per capita, and T by energy intensity [59]. The specification also includes GDP squared to verify the validity of the Environmental Kuznets Curve hypothesis. Finally, the specification also incorporates three variables that have received renewed attention as potential drivers of environmental quality: human capital, economic globalization, and financial development. The human capital index from the Penn World Table is measured by the human capital index, which is based on years of schooling and returns to education [60]. Economic globalization is measured by the KOF economic globalization index computed by Ref. [61] and provided by the KOF Swiss Economic Institute. Finally, the financial development index, recently developed by the International Monetary Fund, is used as a proxy for financial development. The index has the advantage of considering various financial development aspects of financial institutions and financial markets. Further definitions and sources of the variables are reported in Table 1.

3. Empirical findings

3.1. Data analysis

Before estimating the dynamic spatial regression, it is essential to check the stationary properties of variables. Since we are conducting a panel data analysis, cross-section dependence between the variables may arise. Indeed, cross-section dependence may occur due to standard economic and financial shocks affecting the economy. Checking the presence of cross-section dependence is essential because it allows the selection and implementation of the appropriate unit root tests. Indeed, first-generation panel unit root tests are no longer valid in cross-section dependence, and second-generation tests should be employed. Findings of the cross-section dependence test developed by Ref. [62] are reported in Table 2. The CD test suggests rejecting the null hypothesis for all variables except nuclear energy consumption. Consequently, one could confirm the presence of cross-section dependence for most countries, which implies the invalidity of first-generation panel unit root tests.

The present study assesses the order of integration of all variables considered in the analysis using the cross-sectionally augmented Dickey-Fuller (CADF) test proposed by Ref. [63]. The findings for variables at levels and first differences are summarized in Table 3. The results strongly confirm that one cannot reject the null hypothesis of a unit root for all variables. However, when considering the first differences, variables become stationary at the 1 and 5 % statistical levels. Therefore, all variables are integrated into order 1.

Before estimating the dynamic spatial model, it is imperative to perform a spatial autocorrelation test to check whether there has been spatial autocorrelation. To do that, we compute the global Moran's I index for CO_2 emissions and energy consumption using the inverse distance weighting matrix and the contiguity weighting matrix. The global Moran's I index results of CO_2 emissions are reported in Table 4.

The findings show that the Moran 'I index is positive and statistically significant at 1 %, with the highest magnitude observed when the contiguity matrix is employed. One could also observe that Moran's I index values are positive but have a downward trend over time. This suggests the presence of positive spatial autocorrelation between CO_2 emissions in the different countries. These results strongly support the presence of significant spatial autocorrelation for CO_2 emissions and confirm the appropriateness of the dynamic spatial model to estimate the effects of energy consumption on CO_2 emissions. To further assess the presence of spatial autocorrelation, we conduct the Moran 'I index for the different energy consumption series. The findings summarized in Table 5 indicate that Moran's I

Table 1
Definitions and sources of variables.

Abbreviation	Definition	Source
CO_2	CO_2 Emissions (metric tons of carbon dioxide)	U.S. Energy Information Administration
GDP	Real GDP (2017 US$)	Penn World Table 10.0
EI	Energy intensity (Btu/2015$ GDP PPP)	U.S. Energy Information Administration
POP	Population	Penn World Table 10.0
HC	Human capital index	Penn World Table 10.0
KOF	KOF economic globalization index	Gygli et al. (2019)
FD	Financial development Index	International Monetary Fund
TEC	Total energy consumption (million Btu)	U.S. Energy Information Administration
FEC	Fossil energy consumption (million Btu)	U.S. Energy Information Administration
REC	Renewable energy consumption (million Btu)	U.S. Energy Information Administration
NEC	Nuclear energy consumption (million Btu)	U.S. Energy Information Administration

Table 2
Cross-sectional dependence test results.

Variables	CD statistics	p-value
CO_2 emissions	83.714[a]	0.000
GDP	348.445[a]	0.000
Energy intensity	77.208[a]	0.000
Population	247.776[a]	0.000
Human capital	347.931[a]	0.000
Economic globalization	44.591[a]	0.000
Financial development	144.893[a]	0.000
Total energy consumption	130.753[a]	0.000
Fossil energy consumption	103.303[a]	0.000
Renewable energy consumption	162.540[a]	0.000
Nuclear energy consumption	0.719	0.472

[a] Denote rejecting the null hypothesis of no cross-section dependence at the 1 % level.

Table 3
CADF Panel unit root test.

Variables	level		1st. difference	
	statistics	p-value	statistics	p-value
CO_2 emissions	−1.576	0.969	−3.079***	0.000
GDP	−1.831	1.000	−2.441**	0.042
Energy intensity	−1.990	1.000	−3.193***	0.000
Population	−1.822	1.000	−4.376***	0.000
Human capital	−1.231	1.000	−24.765***	0.000
Economic globalization	−2.073	0.994	−2.471**	0.019
Financial development	−1.890	1.000	−2.966***	0.000
Total energy consumption	−1.701	1.000	−4.033***	0.000
Fossil energy consumption	−1.538	0.989	−2.900***	0.000
Renewable energy consumption	−2.228	0.764	−2.699***	0.000
Nuclear energy consumption	0.765	1.000	−17.000***	0.000

Notes: *** and ** denote the rejection of the null hypothesis at the 1 and 5 % levels.

Table 4
Moran's, I index of CO_2 emissions.

Year	W_c		W_d	
	Moran's I	p-value	Moran's I	p-value
2000	0.371[a]	0.000	0.137[a]	0.000
2001	0.368[a]	0.000	0.137[a]	0.000
2002	0.368[a]	0.000	0.138[a]	0.000
2003	0.364[a]	0.000	0.138[a]	0.000
2004	0.356[a]	0.000	0.137[a]	0.000
2005	0.353[a]	0.000	0.136[a]	0.000
2006	0.350[a]	0.000	0.136[a]	0.000
2007	0.348[a]	0.000	0.134[a]	0.000
2008	0.343[a]	0.000	0.134[a]	0.000
2009	0.322[a]	0.000	0.130[a]	0.000
2010	0.326[a]	0.000	0.129[a]	0.000
2011	0.303[a]	0.000	0.123[a]	0.000
2012	0.301[a]	0.000	0.123[a]	0.000
2013	0.289[a]	0.000	0.119[a]	0.000
2014	0.278[a]	0.000	0.116[a]	0.000
2015	0.264[a]	0.000	0.112[a]	0.000
2016	0.269[a]	0.000	0.113[a]	0.000
2017	0.275[a]	0.000	0.115[a]	0.000
2018	0.275[a]	0.000	0.115[a]	0.000
2019	0.274[a]	0.000	0.115[a]	0.000

[a] Denotes the rejection of the null hypothesis on no spatial autocorrelation at the 1 % level.

index is significant at the 1 % level for all energy sources and under the two spatial weighting matrices.

Moreover, using the contiguity weighting matrix, the highest Moran's I index is observed for renewable energy consumption. In contrast, fossil energy consumption has the highest Moran's I index when using the inverse distance weighting matrix. Finally, nuclear energy consumption exhibits the lowest Moran's I index. Another critical remark is that the index is positive in all cases, suggesting the

Table 5
The Moran's I index of energy consumption.

Year	Total energy consumption				Fossil energy consumption			
	W_c		W_d		W_c		W_d	
	Moran's I	*p*-value	Moran's I	*p*-value	Moran's I	*p*-value	Moran's I	*p*-value
2000	0.386***	0.000	0.138***	0.000	0.378***	0.000	0.138***	0.000
2001	0.378***	0.000	0.137***	0.000	0.373***	0.000	0.138***	0.000
2002	0.377***	0.000	0.137***	0.000	0.370***	0.000	0.138***	0.000
2003	0.377***	0.000	0.138***	0.000	0.669***	0.000	0.139***	0.000
2004	0.374***	0.000	0.138***	0.000	0.367***	0.000	0.139***	0.000
2005	0.370***	0.000	0.137***	0.000	0.361***	0.000	0.139***	0.000
2006	0.368***	0.000	0.137***	0.000	0.356***	0.000	0.138***	0.000
2007	0.362***	0.000	0.135***	0.000	0.347***	0.000	0.134***	0.000
2008	0.356***	0.000	0.133***	0.000	0.343***	0.000	0.133***	0.000
2009	0.351***	0.000	0.130***	0.000	0.337***	0.000	0.130***	0.000
2010	0.338***	0.000	0.121***	0.000	0.325***	0.000	0.128***	0.000
2011	0.320***	0.000	0.123***	0.000	0.304***	0.000	0.122***	0.000
2012	0.318***	0.000	0.123***	0.000	0.304***	0.000	0.121***	0.000
2013	0.313***	0.000	0.120***	0.000	0.292***	0.000	0.118***	0.000
2014	0.304***	0.000	0.118***	0.000	0.282***	0.000	0.116***	0.000
2015	0.294***	0.000	0.115***	0.000	0.269***	0.000	0.112***	0.000
2016	0.298***	0.000	0.116***	0.000	0.275***	0.000	0.114***	0.000
2017	0.302***	0.000	0.117***	0.000	0.282***	0.000	0.115***	0.000
2018	0.303***	0.000	0.118***	0.000	0.282***	0.000	0.115***	0.000
2019	0.300***	0.000	0.116***	0.000	0.279***	0.000	0.114***	0.000
Year	**Renewable energy consumption**				**Nuclear energy consumption**			
	W_c		W_d		W_c		W_d	
	Moran's I	*p*-value	Moran's I	*p*-value	Moran's I	*p*-value	Moran's I	*p*-value
2000	0.453***	0.000	0.101***	0.000	0.192***	0.000	0.085***	0.000
2001	0.452***	0.000	0.101***	0.000	0.189***	0.000	0.084***	0.000
2002	0.437***	0.000	0.097***	0.000	0.189***	0.000	0.084***	0.000
2003	0.435***	0.000	0.096***	0.000	0.187***	0.000	0.083***	0.000
2004	0.430***	0.000	0.095***	0.000	0.188***	0.000	0.083***	0.000
2005	0.226***	0.000	0.053***	0.000	0.189***	0.000	0.083***	0.000
2006	0.501***	0.000	0.078***	0.000	0.189***	0.000	0.083***	0.000
2007	0.503***	0.000	0.075***	0.000	0.189***	0.000	0.083***	0.000
2008	0.489***	0.000	0.065***	0.000	0.190***	0.000	0.083***	0.000
2009	0.516***	0.000	0.071***	0.000	0.189***	0.000	0.083***	0.000
2010	0.503***	0.000	0.075***	0.000	0.190***	0.000	0.077***	0.000
2011	0.457***	0.000	0.066***	0.000	0.225***	0.000	0.075***	0.000
2012	0.342***	0.000	0.082***	0.000	0.231***	0.000	0.075***	0.000
2013	0.357***	0.000	0.084***	0.000	0.231***	0.000	0.074***	0.000
2014	0.374***	0.000	0.090***	0.000	0.240***	0.000	0.073***	0.000
2015	0.368***	0.000	0.096***	0.000	0.232***	0.000	0.074***	0.000
2016	0.346***	0.000	0.093***	0.000	0.230***	0.000	0.073***	0.000
2017	0.355***	0.000	0.098***	0.000	0.230***	0.000	0.073***	0.000
2018	0.344***	0.000	0.093***	0.000	0.229***	0.000	0.073***	0.000
2019	0.333***	0.000	0.094***	0.000	0.238***	0.000	0.073***	0.000

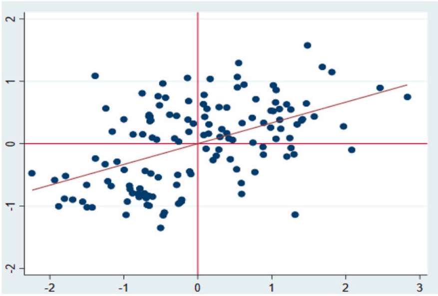
*** denotes the rejection of the null hypothesis on no spatial autocorrelation at the 1 % level.

presence of significant positive spatial autocorrelation exists between units considered in the analysis.

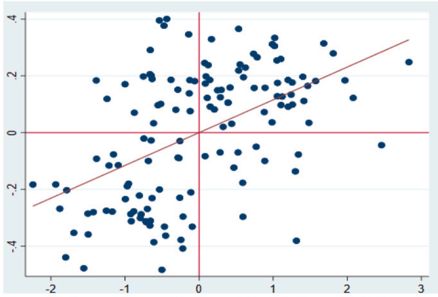
The local Moran's I test results are shown in Fig. 1 under W_c and W_d. There is evidence of significant spatial autocorrelation for CO_2 emissions, where most countries are concentrated in positive clustering (High-High/Low-Low). There is also evidence of spatial autocorrelation for energy consumption. This finding is valid for total, fossil, and renewable energy consumption. Results relative to nuclear energy consumption are comparable to those of Table 5 and suggest the presence of relatively low spatial autocorrelation. In conclusion, the previous analysis provides strong evidence that CO_2 emissions and energy consumption exhibit significant positive correlations. In this case, one could estimate the dynamic spatial model.

3.2. Results and discussion

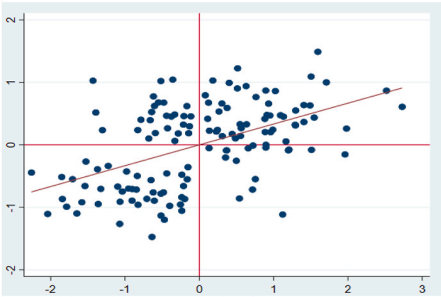
Before estimating the dynamic spatial model, one should select the appropriate spatial model. To do so, we performed the Wald test to identify whether the DSAR, DSEM, or DSDM would be fit for our estimations. The results of the Wald test are reported at the bottom of Tables 6 and 7. The Wald statistics are significant at the 1 % level in all cases, suggesting that the DSDM model is more appropriate for our estimation than the DSAR and DSEM models. The superiority of the DSDM model is observed for both weighting matrices. It is worth noting that the DSDM model allows considering the spatial interaction at the levels of the dependent variable and the different explanatory variables.



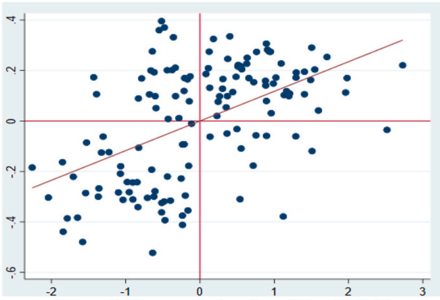
Moran's I scatter plot for CO2 with Wc



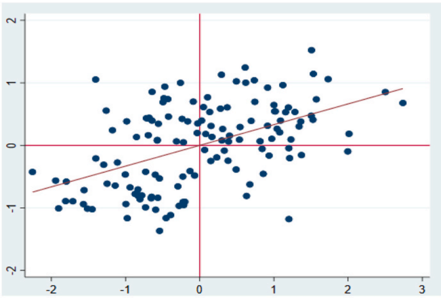
Moran's I scatter plot for CO2 with Wd



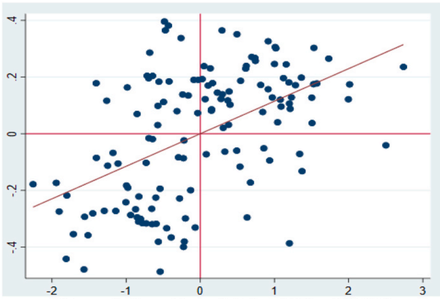
Moran's I scatter plot for TEC with Wc



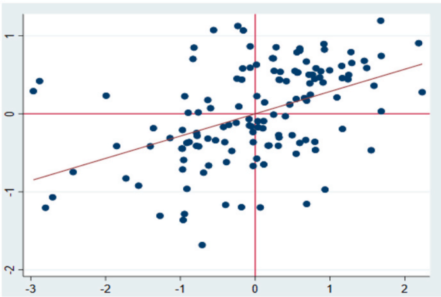
Moran's I scatter plot for TEC with Wd



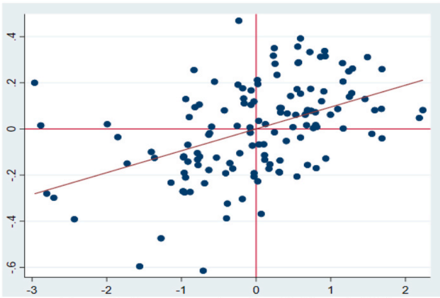
Moran's I scatter plot for FEC with Wc



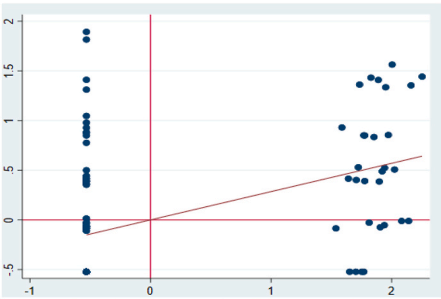
Moran's I scatter plot for FEC with Wd



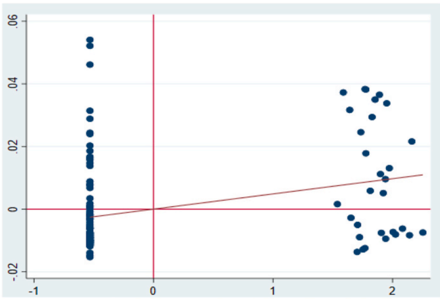
Moran's I scatter plot for REC with Wc



Moran's I scatter plot for REC with Wd



Moran's I scatter plot for NEC with Wc



Moran's I scatter plot for NEC with Wd

(caption on next page)

Fig. 1. Scatter plots of Moran's I index.

The DSDM model is estimated for total energy consumption and the different energy sources (fossil, renewable and nuclear). Tables 6 and 7 summarize the total and disaggregated energy consumption results under the weighting matrices W_c and W_d, respectively. The impact of energy intensity is positive and statistically significant. In addition, we also found its spatial spillover effect to be significantly positive. These findings show that local energy intensity increases CO_2 emissions in the same country. In addition, the rise in energy intensity in neighbouring countries also increases local CO_2 emissions.

The impact of human capital is negative and significant. Its spatial spillover effect is significantly positive. When the inverse distance weighting matrix is used, the externality effect is higher than the local effect. This result suggests that enhancing human capital can have a positive impact on a country's environmental performance. By improving human capital, better energy efficiency can be achieved, which in turn reduces carbon emissions [64]. Consequently, if a country's carbon emissions are steadily decreasing, this can lead to a reduction in environmental degradation not only within the country itself but also in neighbouring countries. Therefore, investing in education and other forms of human capital can help build knowledgeable and skilled human capital, leading to a reduction in carbon emissions in the long term, which benefits both the country and its neighbours [65]. It is worth noting that the relationship between financial development and CO_2 emissions has been unclear so far. On the one hand, studies conducted by Refs. [6,7,37], and [66] suggest that financial development can effectively reduce CO_2 emissions. On the other hand, financial development may also promote economic growth, leading to an increase in CO_2 emissions, as suggested by Refs. [67,68], and [69]. According to the empirical results in Table 7, the direct and spillover effects of financial development were significantly adverse. The significantly negative direct effect indicated that a one-unit increase in financial development decreased CO_2 emissions by 0.05 % (total direct effect). This finding is consistent with that of [70] but is inconsistent with [71,72]. On the other hand, the significant negative spillover effect suggests that a one-unit increase in the financial development of neighbouring countries would decrease CO_2 emissions by 1.7 % (total spillover effect) in the local country. More importantly, we observed that the spillover effect of financial development was much greater than the direct effect, resulting in a negative total effect of financial development. Therefore, neighbouring countries that have higher levels of financial development can boost the spillover of advanced technological diffusion, knowledge sharing, improved

Table 6
The estimation results of the DSDM under ***Wc***.

	(1)		(2)		(3)		(4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Lagged CO_2 emissions	0.657***	(0.005)	0.613***	(0.008)	0.660***	(0.005)	0.693***	(0.005)
GDP	0.174***	(0.055)	0.132***	(0.040)	−0.154***	(0.046)	0.062	(0.052)
Squared GDP	0.003***	(0.001)	0.0039***	(0.000)	0.0051***	(0.000)	0.0067***	(0.001)
Energy intensity	0.023	(0.021)	0.108***	(0.022)	0.133***	(0.008)	0.122***	(0.007)
Population	0.007	(0.006)	0.043***	(0.008)	0.008***	(0.002)	0.029***	(0.007)
Human capital	−0.078***	(0.010)	−0.130***	(0.009)	−0.038***	(0.007)	−0.161***	(0.009)
Economic globalization	−0.001***	(0.000)	−0.0001	(0.000)	−0.0011***	(0.000)	−0.0002	(0.000)
Financial development	−0.001***	(0.000)	−0.001***	(0.000)	−0.0005***	(0.000)	−0.0005***	(0.000)
Total energy consumption	0.129***	(0.020)	–		–		–	
Fossil energy consumption	–		0.297***	(0.017)	–		–	
Renewable energy consumption	–		–		−0.001***	(0.000)		
Nuclear energy consumption	–		–		–		−0.010***	(0.001)
W_c × CO_2 emissions	0.021***	(0.005)	0.077***	(0.008)	0.082***	(0.008)	0.087***	(0.007)
W_c× lagged CO_2 emissions	−0.490***	(0.005)	−0.470***	(0.007)	−0.467***	(0.005)	−0.533***	(0.005)
W_c× GDP	0.037***	(0.008)	0.039***	(0.007)	0.015**	(0.007)	0.025***	(0.008)
W_c× squared GDP	−0.001	(0.000)	−0.0026***	(0.000)	−0.001***	(0.000)	−0.0001	(0.000)
W_c× energy intensity	0.145***	(0.047)	0.298***	(0.023)	0.153***	(0.008)	0.119***	(0.013)
W_c× Population	0.020***	(0.005)	0.020***	(0.004)	0.047***	(0.006)	0.024***	(0.005)
W_c× human capital	−0.056***	(0.005)	−0.029***	(0.005)	−0.015	(0.011)	−0.052***	(0.007)
W_c× economic globalization	−1.65e-05	(0.000)	−0.0006***	(9.87e-05)	−0.0005***	(0.000)	2.81e-05	(0.000)
W_c× financial development	−0.005***	(0.000)	−0.004***	(0.000)	−0.005***	(0.000)	−0.004***	(0.000)
W_c× x total energy consumption	0.052***	(0.005)	–	–	–		–	
W_c× fossil energy consumption	–		0.217***	(0.023)	–		–	
W_c× renewable energy consumption	–		–		−0.003***	(0.000)	–	
W_c× nuclear energy consumption	–		–		–		−0.025***	(0.002)
VIF	8.51		8.25		5.40		5.02	
Wald 1 (p-value)	126.88 (0.000)		178.23 (0.000)		165.55 (0.000)		147.02 (0.000)	
Wald 2 (p-value)	120.23(0.000)		122.75 (0.000)		126.72 (0.000)		125.33 (0.000)	
LL	3464.1817		3468.3737		3481.6708		3633.0193	
R-squared	0.98		0.98		0.98		0.98	

Notes: ***, **, and * denote the significance at the 1 %, 5 %, and 10 % levels. Values in ( ) denote the standard error (SE). W is the spatial weight matrix. W x X stands for the product of W and the variable X, representing the spillover effect of the variable X on CO_2 emissions. The Wald test is applied to determine whether DSAR, DSEM, or DSDM would be fit for our estimations. VIF is used to check whether multiple mutual linear problems exist. LL is the log-likelihood.

Table 7
The estimation results the DSDM under W_d.

	(1)		**(2)**		**(3)**		**(4)**	
	Coeff.	SE.	Coeff.	SE	Coeff.	SE	Coeff.	SE
Lagged CO_2 emissions	0.883***	(0.002)	0.852***	(0.002)	0.880***	(0.001)	0.888***	(0.002)
GDP	0.325***	(0.047)	0.280***	(0.040)	0.250***	(0.030)	0.199***	(0.032)
Squared GDP	−0.171***	(0.000)	−0.166***	(0.000)	−0.180***	(0.000)	−0.163***	(0.001)
Energy intensity	0.005	(0.021)	0.028***	(0.007)	0.138***	(0.003)	0.092***	(0.003)
Population	0.013***	(0.004)	0.019***	(0.004)	0.014***	(0.005)	0.032***	(0.005)
Human capital	−0.067***	(0.009)	−0.027***	(0.007)	−0.046***	(0.009)	−0.051***	(0.010)
Economic globalization	−0.0003***	(9.91^{e}-05)	−0.0002***	(5.99^{e}-05)	−0.0005***	(0.000)	−0.0003***	(9.08^{e}-05)
Financial development	−0.0005***	(0.000)	−0.0005***	(8.36^{e}-05)	−0.0005***	(0.000)	−0.0003***	(0.000)
Total energy consumption	0.123***	(0.019)	–	–	–	–	–	–
Fossil energy consumption	–	–	0.120***	(0.006)	–	–	–	–
Renewable energy consumption	–	–	–	–	−0.001***	(0.000)	–	–
Nuclear energy consumption	–	–	–	–	–	–	−0.0004***	(0.000)
W_d × CO_2 emissions	0.344***	(0.008)	0.222***	(0.007)	0.394***	(0.007)	0.450***	(0.008)
W_d× lagged CO_2 emissions	−0.743***	(0.002)	−0.721***	(0.002)	−0.740***	(0.002)	−0.759***	(0.001)
W_d× GDP	0.370**	(0.149)	0.312**	(0.141)	0.340**	(0.165)	0.351***	(0.130)
W_d× squared GDP	−0.095	(0.003)	−0.072***	(0.002)	−0.072***	(0.003)	−0.074***	(0.002)
W_d× energy intensity	0.233***	(0.054)	0.179***	(0.031)	0.150***	(0.013)	0.119***	(0.016)
W_d× Population	0.139***	(0.023)	0.091***	(0.022)	0.201***	(0.020)	0.104***	(0.022)
W_d× human capital	−0.207***	(0.022)	−0.220***	(0.015)	−0.272***	(0.024)	−0.526***	(0.023)
W_d× economic globalization	−0.006***	(0.000)	−0.006***	(0.000)	−0.005***	(0.000)	−0.005***	(0.000)
W_d× financial development	−0.017***	(0.000)	−0.016***	(0.000)	−0.013***	(0.000)	−0.008***	(0.000)
W_d× total energy consumption	0.096***	(0.006)	–		–		–	
W_d× fossil energy consumption	–		0.487***	(0.020)	–		–	
W_d× renewable energy consumption	–		–		−0.004***	(0.000)	–	
W_d× nuclear energy consumption	–		–		–		−0.083***	(0.002)
VIF	8.51		8.25		5.40		5.02	
Wald 1 (p-value)	182.33 (0.000)		185.27 (0.000)		185.72 (0.000)		192.92 (0.000)	
Wald 2 (p-value)	130.43 (0.000)		134.29 (0.000)		146.89 (0.000)		155.86 (0.000)	
LL	5004.8957		5029.3644		5099.2042		5325.9842	
R-squared	0.98		0.98		0.98		0.98	

Notes: ***, **, and * denote the significance at the 1 %, 5 %, and 10 % levels. Values in ( ) denote the standard error (SE). *W* is the spatial weight matrix. *WX* stands for the product of *W* and the variable *X*, representing the spillover effect of the variable *X* on CO_2 emissions. The Wald test is applied to determine whether DSAR, DSEM, or DSDM would be fit for our estimations. VIF is used to check whether multiple mutual linear problems exist. LL is the log-likelihood.

governance, stable policies, and the transfer of skills. This can greatly help to reduce CO_2 emissions in the local country. This conclusion differs from previous studies that concluded that financial development reduced local CO_2 emissions ([7,73]). Based on the spatial relationship between financial development and CO_2 emissions, this study infers that financial development, through spillover effects, reduces CO_2 emissions. The environmental effects of economic globalization are also found to be negative and statistically significant. Notably, the coefficients exhibit a relatively low magnitude, showing that economic globalization has a limited effect on reducing CO_2 emissions. In addition, the spatial environmental effect is weaker than the direct effect of economic globalization. As for financial development, the weak effect of economic globalization (trade and financial flows) on the environment may be because of two competing effects. According to Ref. [74], introducing new production techniques and speeding up economic activity through international trade may negatively impact the environment. Free international trade may improve the environment by facilitating the import of new green technologies. However, foreign direct investments also have conflicting effects. They could improve the environmental quality (Pollution Halo Hypothesis) or deteriorate it (Pollution Haven Hypothesis).

Our research yielded significant results regarding the spatial impact of energy consumption on CO_2 emissions. The local impact of total energy consumption is positive and statistically significant using both weighting matrices. Similar findings are observed for the spatial spillover effect of total energy consumption, which has a positive externality. Increasing the total energy consumption of neighbours increases local CO_2 emissions. A similar result is obtained for fossil energy consumption since the associated coefficient is positive and statistically significant. This finding supports [75] conclusion that burning fossil fuels increases CO2 emissions. The local hike in fossil energy consumption increases CO_2 emissions, while an increase in fossil energy consumption in neighbouring countries further deteriorates the environmental quality and increases local CO_2 emissions. However, it should be mentioned that the local and spillover adverse effects of fossil energy consumption are higher than those of total energy consumption. The potential explanation of this result could be attributed to total energy, encompassing fossil, renewable, and nuclear energy sources, each of which may have different environmental implications. In contrast, the coefficients of renewable energy consumption and nuclear energy consumption are found to be negative and statistically significant. This result is consistent with the findings of [76], who discovered that the use of renewable energy leads to a significant decrease in CO2 emissions. The local increase of these two categories of energy sources decreases CO_2 emissions. The results, also, show that the local impact of nuclear energy consumption is much higher than that of renewable energy. Similarly, the increase in nuclear and renewable energy consumption in neighbouring countries decreases local CO_2

emissions. The magnitude spillover impact of nuclear energy consumption is also higher than the effect of renewable energy consumption. These findings imply that using clean energy sources (renewable and nuclear) allows countries to reduce their CO_2 and CO_2 emissions in their neighbouring countries.

3.3. Computing the marginal effects of energy consumption

According to Ref. [51], one could compute the cumulative marginal effects. Therefore, the final stage of the dynamic spatial analysis comprises computing the direct, indirect (spillover) and total cumulative marginal effects of the variables under study, particularly energy consumption. The effects mentioned above are computed for specifications of the different energy sources using the two weighting matrices and are based on estimation regression in Tables 6 and 7 The findings are reported in Table 8.

The findings reveal that the direct and indirect effects of the gross domestic product are positive and statistically significant under the two spatial weight matrices, W_c and W_d. This result shows that economic growth in a country positively and significantly affects CO_2 emissions. Similarly, neighbouring countries' GDP has an adverse and significant impact on the CO_2 emissions of other countries. However, the direct effect of GDP on CO_2 emissions is always higher than the indirect spillover effect. The sum of the two effects ranges from 0.08 to 0.21 under W_c and 0.55 to 0.69 under W_d. The findings also suggest that the energy intensity band population have direct and indirect detrimental effects on environmental quality. The table shows that both variables have positive and statistically significant direct and indirect effects. Furthermore, it can be observed that the indirect effects exceed the direct effect in almost all cases. These findings confirm that energy intensity and population in a country deteriorate the environment in the same country and their neighbouring countries. The table also shows that human capital, economic globalization, and financial development have adverse direct, indirect, and total effects on CO_2 emissions [64]. Indeed, the most important outcome here is the existence of a spillover effect for both variables. These results confirm that human capital, economic globalization, and financial development in a specific country reduce CO_2 emissions in the same country and their neighbours. However, human capital has the highest indirect and total effects on CO_2 emissions.

Regarding total energy consumption, the results indicate that the direct impact is positive and significant. The indirect effect is also positive and significant. This indicates that an increase in total energy consumption in a particular country significantly affects its CO_2 emissions. Similarly, the increase in total energy consumption in neighbouring countries has a detrimental and significant impact on the environment of the host country. It is worth noting that the direct adverse effect of total energy consumption is higher than the indirect adverse effect. The total marginal impact also appears significant (0.181 under W_c and 0.22 under W_d). Similarly, the same result is obtained for fossil energy consumption, with significant direct and indirect impacts. This result reveals that an increase in fossil energy consumption in all neighbouring countries leads to more significant pollution in local countries. The cumulative marginal impact is 0.51 and 0.60 when W_c and W_d are used, respectively. One could note here that the total environmental effect of fossil energy consumption is higher than that of total energy consumption. Unlike fossil energy sources, renewable energy consumption has significant negative direct and indirect effects. Thus, reducing pollutant emissions in a specific country may be caused by renewable energy consumption in the country under consideration and in its neighbouring countries. The cumulative marginal impact was negative and significant. The cumulative marginal impact is equal to -0.005 when W_c and W_d are used. t is noteworthy to acknowledge that the direct, indirect, and total effects are relatively low compared to the adverse effects of fossil energy consumption. In other words, while renewable energy consumption has been shown to have positive environmental impacts, it is insufficient in offsetting the adverse impacts of fossil fuel consumption. At the same time, the estimated direct and indirect effects of nuclear energy consumption are negative and significant at the 1 % statistical level. The cumulative marginal effect is found to be negative and statistically significant. This suggests that nuclear energy consumption in a specific country allows for decreasing CO_2 emissions in local countries. Also, the result reveals that the increase in nuclear energy in neighbouring countries reduces the environmental degradation of the local country. The total impact is -0.035 when W_c is used, and -0.083 when W_d is employed. The positive marginal impact suggested a 1 % increase in nuclear energy consumption decreases CO_2 emissions by -0.035 % and -0.083 % when W_c and W_d are used, respectively.

4. Conclusion and policy implications

Increased degradation of environmental and ecological indicators has marked the latest decades. However, while there has been a boom in empirical research analyzing the effects of energy consumption on environmental degradation [77], the spatial spillover effects of energy use still need to be studied. This research aims to fill this gap by conducting a comparative analysis of the spatial effects of different energy sources on CO_2 emissions for a large sample of 135 countries from 2000 to 2019. The analysis accounts for total energy consumption, fossil energy consumption, renewable energy consumption, and nuclear energy consumption.

We may summarize the empirical results as follows. To start, Moran's I index, and scatter plots provide strong evidence that CO_2 emissions and energy consumption exhibit significant positive correlations. These results provide an argument for implementing the dynamic spatial model to assess the impacts of energy consumption on carbon dioxide emissions. The second significant result is that the DSDM model is more appropriate than our case's DSAR and DSEM models. We then estimated the DSDM model using the inverse distance weighting matrix and the contiguity weighting matrix. The findings suggest that total energy consumption has a direct detrimental effect on the environment. This effect is further exacerbated when accounting for the indirect spillover effect of total energy consumption. While the adverse effects of fossil energy are transmitted via direct and indirect effects, results suggest that the direct adverse effect of energy consumption exceeds the indirect spillover effect.

The empirical investigation also reveals similar results for fossil energy consumption, which is found to harm environmental

Table 8
Results of the cumulative marginal effects.

		Results with W_c				Results with W_d			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
GDP	Direct effect	0.174***	0.132***	0.154***	0.062	0.325***	0.280***	0.250***	0.199***
	Indirect effect	0.037***	0.039***	0.015***	0.025***	0.370**	0.312**	0.340**	0.351***
	Total effect	0.211***	0.171***	0.169***	0.087***	0.695***	0.592***	0.590***	0.550***
Squared GDP	Direct effect	−0.003***	−0.002***	−0.005***	−0.006***	−0.171***	−0.166***	−0.188***	−0.166***
	Indirect effect	−0.001	−0.002***	−0.001***	−0.000	−0.095***	−0.072***	−0.072***	−0.074***
	Total effect	−0.004***	−0.006***	−0.006***	−0.006***	−0.266***	−0.238***	−0.260***	−0.241***
Energy intensity	Direct effect	0.023	0.108***	0.133***	0.122***	0.005	0.028***	0.138***	0.092***
	Indirect effect	0.145***	0.298***	0.153***	0.119***	0.235***	0.179***	0.150***	0.119**
	Total effect	0.168**	0.406***	0.286***	0.241***	0.241***	0.207***	0.288***	0.212***
Population	Direct effect	0.007	0.043***	0.008***	0.029***	0.013***	0.019***	0.014***	0.032***
	Indirect effect	0.020***	0.020***	0,047***	0.024***	0.139***	0.091***	0.201***	0.104***
	Total effect	0.028***	0.063**	0.055***	0.054***	0.152***	0.110**	0.215***	0.136***
Human capital	Direct effect	−0.078***	−0.130***	−0.038***	−0.160***	−0.067***	−0.027***	−0.046***	−0.051***
	Indirect effect	−0.056***	−0,020***	−0.015	−0.052**	−0.207***	−0.220***	−0.272***	−0.526***
	Total effect	−0.124***	−0,156***	−0.054***	−0.212***	−0.274***	−0.247***	−0.318***	−0.577***
Economic globalization	Direct effect	−1.18E-03***	−1.44E-04	1.19E-03***	−2.27E-04	−3,68E-04***	−2.58E-04***	−5.16E-04***	−3,50E-04***
	Indirect effect	−1.65E-05	−6.17E-04***	−5.57E-04***	2.81E-05	−6,24E-03***	−6.13E-03***	−5.45E-03***	−5,24E-03**
	Total effect	−0.001***	−0.0007**	−0.001***	−0.0001	−0.006***	−0.006***	−0.005***	−0.005***
Financial development	Direct effect	−0.001***	−0.001***	−0.0005***	−0.0005***	−0.0005***	−0.0005***	−0.0005***	−0.0003***
	Indirect effect	−0.005***	−0.004***	−0.005***	−0.004***	−0.017***	−0.016***	−0.013***	−0.008***
	Total effect	−0.007***	−0.006***	−0.006***	−0.004***	−0.017***	−0.016***	−0.014***	−0.008**
Total energy consumption	Direct effect	0.129***	–	–	–	0.123***	–	–	–
	Indirect effect	0.052***	–	–	–	0.099***	–	–	–
	Total effect	0.181***	–	–	–	0.222***	–	–	–
Fossil energy consumption	Direct effect		0.297***	–	–	–	0.120***		
	Indirect effect		0.217***	–	–	–	0.487***		
	Total effect		0.514***	–	–	–	0.607***		
Renewable energy consumption	Direct effect			−0.001***	–	–	–	−0.001***	
	Indirect effect			−0.003***	–	–	–	−0.004***	
	Total effect			−0.005**	–	–	–	−0.005***	
Nuclear energy consumption	Direct effect				−0.010***	–	–	–	−0.0004***
	Indirect effect				−0.025***	–	–	–	−0.083***
	Total effect				−0.035***	–	–	–	−0.083***

Notes: ***, **, and * denote the statistical significance at 1 %, 5 %, and 10 %.

quality. In addition, the detrimental effects of fossil energy consumption are higher than total energy consumption for both weighting matrices. The analysis suggests that clean energy sources (renewable and nuclear) reduce CO_2 emissions via direct and indirect channels [78]. Two statements must be made. First, the indirect effects of clean energy consumption are lower than the direct effect. Second, the positive impact of nuclear energy consumption on CO_2 emissions is higher than that of renewable energy. The empirical investigation conducted in this research provides substantial evidence supporting the indirect spillover effects of energy consumption on CO_2 emissions. Therefore, most previous studies have underestimated the damaging impact of energy consumption on the environment, as they have ignored the indirect effects.

Data availability

Data will be made available on request.

CRediT authorship contribution statement

Kais Ben-Ahmed: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Oussama Ben-Salha:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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