# Data, Distribution, and Modeling Innovations in Spatiotemporal Energy Economics

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**Abstract**

The objective of the present review is to synthesize recent state-of-the-art advances in the field of energy economics. The present review aims to elucidate the interconnections among various applicable and practical methodologies that may facilitate a sustainable energy transition and therefore the novelty lies in the cross-cutting, methodological integration and forward-looking perspective that informs both academic research and practical policy development in the context of sustainable energy transitions. The contribution of this review is fourfold. First, it systematically compiles the core empirical advancements within different sectors of the energy domain, providing a structured assessment of contemporary research efforts. Second, it critically examines the challenges associated with data availability and reviews methodological innovations designed to address these limitations. Third, it consolidates developments in spatiotemporal econometric techniques, highlighting their significance in capturing dynamic spatial and temporal dimensions of energy systems. Fourth, it presents emerging machine learning-based approaches for forecasting, underscoring their potential to enhance predictive capabilities and inform policy and investment decisions. By integrating insights across these domains, the review offers a comprehensive framework for understanding the methodological evolution in energy economics and identifies pathways for future research that support the global pursuit of a sustainable energy future.

**Keywords:** energy economics; energy policy; energy transition; energy modelling and forecasting

## 1. Introduction

During the past decades, an extensive array of energy and environmental studies, focusing on determining the best practices for alleviating environmental pressure, predominantly referred to global or multiple country analyses [1–9]. Nevertheless, acknowledging the complexity of the interrelationship between economic and ecological systems, a growing number of scholars turned to scrutinization of a single or a certain group of emission sources of interest stemming from anthropogenic activity. For instance, Ma et al. [10] underline that air quality within a given region heavily depends on production based GHG's, natural emissions, climatic factors, and atmospheric circulation. This development engendered a dynamic trend constantly gaining ground in academia, according to which a comprehensive understanding of the interaction of pollution mechanisms with associated resource and energy consumption mandates conducting small-scale regional analysis. Furthermore, the real direct and indirect impact and magnitude of socioeconomic drivers of environmental burden can vary markedly across geographical zones.

Considering the multiple dimensions of these crucial parameters of environmental modeling, a series of sophisticated theoretical and empirical methods was published in academia, aiming to effectively capture the spatiotemporal patterns of emitted GHGs resulting from fossil fuel and natural resource consumption. Initially, the vast majority of pertinent scientific papers emphasize on identifying the actual geographical disbursement of air pollutants through time, most commonly including $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_x$, CO, $NH_3$, and VOC, locating specific hot points characterized by elevated concentrations. Subsequently, through the implementation of suitable econometric modeling techniques, the analyses are directed towards filling the void concerning the successful forecasting of the future course of environmental degradation while elucidating the exact contribution of specific socioeconomic factors to this phenomenon. Likewise, another set of relevant studies seeks to ascertain the optimal combination of resource/energy use and acceptable levels of environmental pressure for a prespecified level of economic or other anthropogenic activities (e.g., urban living, transportation, etc.).

As presented in this introduction, in recent decades, energy and environmental research has moved from broad global analyses toward localized studies, recognizing that regional air quality is shaped by both human-induced emissions and natural environmental factors, highlighting the need for more detailed, small-scale investigations. Leading to this paper's motivation to cover a significant gap in spatiotemporal energy economics literature as well as methodological pitfalls in data gathering and distribution issues.

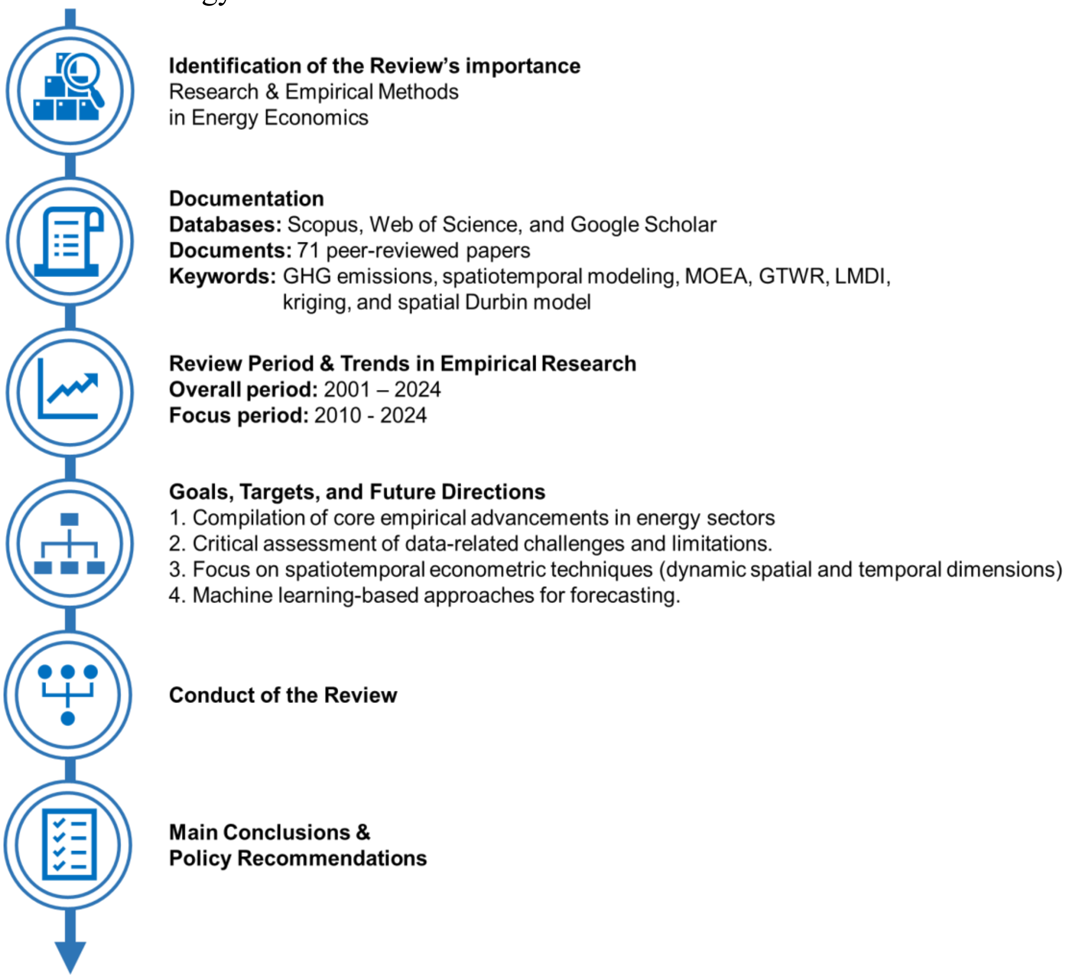
Hence, the aim of the present review is to collect state-of-the-art advances in energy economics research. The objective is to find the interlinkages between different applicable and practical methodologies that can pave the way for sustainable energy transition. The novelty of the review is four-fold as it (i) amasses the core empirical progress in energy sectors, (ii) finds the challenges related to data availability that are solved through different techniques, (iii), assembles spatiotemporal econometric methods, and (iv) presents interesting machine learning-based approaches for forecasting.

The structure of the paper is based on the contributions as presented previously; therefore, Section 2 refers to the materials and methods, Section 3 encompasses the significant methodological advances, Section 4 presents the challenges in data availability as well as different spatial distribution techniques, Section 5 monitors specifically the spatiotemporal econometric modelling, and additionally, Section 6 demonstrates the advances in spatiotemporal forecasting through machine learning approaches. Lastly, Section 7 concludes the paper and discusses future insights into the energy economics research.

## 2. Materials and Methods

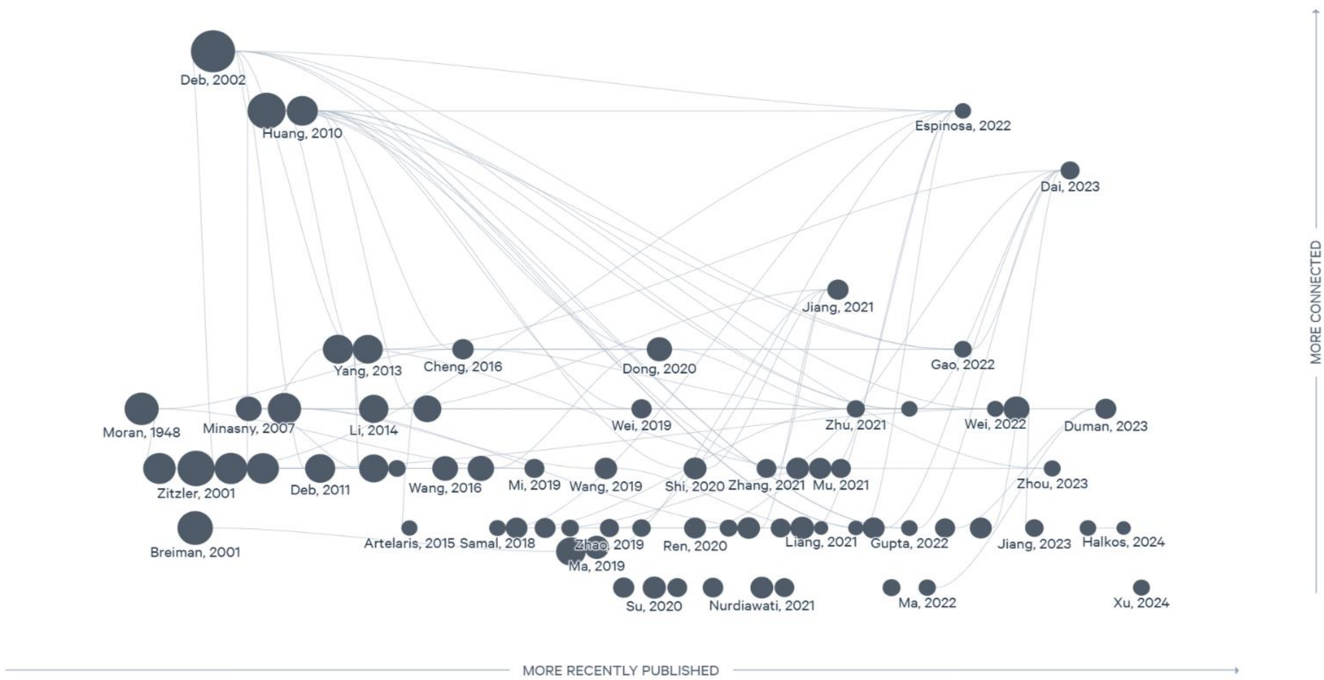
This study adopts a literature review methodology to examine and synthesize recent methodological advancements in energy-related environmental modeling, with a particular emphasis on GHG emissions, spatiotemporal econometrics, and spatial interpolation techniques. A total of 71 peer-reviewed articles published between 2001 and 2024 were selected based on their relevance to four thematic axes: (i) multi-objective optimization algorithms in energy modeling, (ii) spatial decomposition and environmental impact assessment techniques, (iii) geospatial data interpolation and autocorrelation analysis, and (iv) advanced econometric and machine learning approaches for spatiotemporal forecasting. Figure 1 presents the methodology structure of the paper.

**Figure 1:** Methodology flow



Articles were identified through academic databases such as Scopus, Web of Science, and Google Scholar using combinations of keywords including "GHG emissions," "spatiotemporal modeling," "MOEA," "GTWR," "LMDI," "kriging," and "spatial Durbin model." Studies were selected if they proposed, applied, or improved upon quantitative methods for estimating, forecasting, or decomposing environmental and socioeconomic drivers of pollution. Each study was classified based on methodological approach and application domain. The present review focuses on methodological innovations and applications in energy sectors, additionally, the paper aims to (i) assess the effectiveness of existing approaches, (ii) highlight best practices and trade-offs, and (iii) identify methodological gaps for future research in energy economics in order to achieve sustainable development.

**Figure 2:** Chronological flow of the studies based on their interconnectedness. Source: Author's creation through the litmaps.com application.




Moreover, Figure 2 graph illustrates the connectedness between the studied publications, highlighting how newer research tends to form densely interconnected clusters. These publications often reference one another and build upon shared topics or methodologies, indicating active areas of ongoing study in energy economics. In essence, the central nodes in the graph represent influential papers with high citation counts, while peripheral nodes show emerging works that are beginning to integrate into the broader scholarly network. Overall, the graph reflects a dynamic and evolving research landscape in energy sectors where recent publications are increasingly interconnected.

## 3. Important Methodological Advancements in Energy Sectors

This chapter contributes to the existing literature through the categorization of methodological innovations in modeling and optimizing energy-related GHG emissions, particularly through the application of multi-objective evolutionary algorithms, hybrid decision-making frameworks like TOPSIS, and decomposition techniques. It expands the analytical scope of environmental and energy studies by integrating high-dimensional, spatiotemporal, and multi-criteria optimization strategies that balance economic and environmental objectives.

This chapter reveals pivotal methodological advancements in energy sectors, as summarized in Table 1. Espinoza et al. [11], differentiating from all aforementioned academic articles, introduced an innovative GHG modelling approach relying on the multi-objective evolutionary algorithms (MOEA) of Deb [12]. Following the suggestion of Ehrgott [13], the study exploits MOEA to simultaneously minimize the RMSE and MAE loss functions of multiple linear regressions (LR) representing models forming a set of Pareto optimal solutions based on data from 3 of NO2 watch points in southeastern Spain. It is important to focus on how to dealing with a 3-factor optimization objective, the analysis tested the performance of 3 main MOEA algorithms, including NSGA-II of Deb et al. [14], MOEA/D of Zhang and Li [15], and SPEA2 of Zitzler et al. [16], concluding to the superiority of the latter in providing the optimal econometric solutions to the group of investigated LR models. In addition, Espinoza et al. [11] compared the outcomes of their proposed spatiotemporal methodology with IDW interpolation, verifying the dominance of the MOEA approach, yet at high computational cost.

Given the vital role of electricity generation in environmental quality, Dai et al. [17] developed a high-dimensional multi-objective optimal production strategy, which manages to simultaneously minimize both electricity generation costs and the volume of emitted air pollutants. Due to the large number of optimization objectives, including the spatiotemporal characteristics of GHG distribution and the self-purifying atmospheric and environmental ability, the proposed methodology utilizes three sophisticated MOEA algorithms. All NSGA-III, grid- and indicator-based evolutionary (IBEA) algorithms of Gupta and Nanda [18], Yang et al. [19], and Liu et al. [20], respectively, as well as the novel multi-objective evolutionary decomposition algorithm (MOEA) of Gao et al. [21], are capable of coping with more than three optimization tasks at the same time.

Next, in order to harmonize power plant dispatch planning with total volume and concentration optimization goals for GHG emissions, the study incorporates the TOPSIS multi-objective decision-making method developed by Wang et al. [22]. The model, allowing for specialized options corresponding to the air pollutant characteristics of each region, estimates the optimal solution for the input objectives by proceeding to a thorough evaluation of all decision options. Eventually, every potential solution to the system is determined and then ranked based on its distance from the best and poorest solutions. In the final stage, the model generates a compromised solution that is as close as possible to the optimal solution and furthest from the inferior one.

Having effectively approximated the distribution of air pollutants during a prespecified time horizon within the entire geographical area of interest, it is vital for environmental scientists to elucidate the drivers of air pollutants' concentration levels. Wu et al. [23] praised the merits of the STIRPAT framework, particularly emphasizing its adaptability to the special features inherent in each environmental analysis. Two interesting examples were made by Xu et al. [24] and Xu et al. [25], these publications implemented STIRPAT decomposition modeling to identify the coupling mechanism and spatial effect between certain socioeconomic parameters and GHG.

**Table 1:** Advancements in Energy Sectors

| **Advancement** | **Reason** | **Impact on:** | **Ref.** |
|---|---|---|---|
| Use of (MOEAs) in GHG Modeling | To optimize GHG prediction models, minimizing RMSE and MAE simultaneously. | This approach created Pareto optimal solutions for multiple linear regressions and was compared favorably against traditional interpolation methods like IDW, albeit at a higher computational cost. | [11] |
| High-Dimensional Multi-Objective Optimization in Energy Systems: | Simultaneous minimization of electricity generation costs and pollutant emissions | A sophisticated MOEAs capable of handling more than three optimization objectives. | [17,21] |
| Decision-Making Framework Using TOPSIS | The TOPSIS method was employed to select optimal power plant dispatch strategies, evaluating solutions based on proximity to ideal (and distance from worst) outcomes. | To deal with regional pollutant characteristics. | [22] |
| Decomposition of Socioeconomic Drivers of Air Pollution | The STIRPAT framework was highlighted for its flexibility in environmental analyses to uncover links between socioeconomic factors and GHG emissions. | Finding the spatial effects and coupling mechanisms of the driving forces on GHGs. | [23–25] |
| Structural and Index Decomposition Analysis (SDA and IDA) | IDA, particularly the logarithmic mean Divisia index (LMDI), is favored for its low data needs and ability to avoid residuals and multicollinearity. | • Analyze water reserves consumption.<br>• Uncover internal environmental pollution dynamics.<br>• Show the changing relationship between GDP growth and GHG emissions across regions and sectors in China. | [26–31] |

Nonetheless, the majority of studies trying to decompose the effect of certain influencing factors on air quality utilize decomposition methodologies such as the structural (SDA) and index (IDA) based analysis. The latter is favored in environmental research due to its lower required volume of data and its efficacy in detecting the implications of potential structural changes in both environmental pollutants and the economy. Furthermore, the most popular variation of IDA is the logarithmic mean Divisia index (LMDI), a method with multiple econometric advantages, which, according to Ang et al. [26] and Shan et al. [27], avoids generation of residuals during the decomposition procedure while concurrently minimizing potential multicollinearity and endogeneity effects. Moreover, Long et al. [28], through LMDI modeling, determined the driving forces of water reserves consumption from a plethora of industrial and other sectors in specific Chinese provinces, while Zhang et al. [29,30] unveiled the internal dynamics of environmental pollution and particularly the role of energy consumption and technological pollution effects.

Similarly, Duman et al. [31] employed LMDI analysis to highlight the progressively diminishing effect of GDP growth on GHG emissions in China, specifying heterogenic production bases, energy intensities, and efficiencies as the latent causes of asymmetrical spatiotemporal patterns of environmental pollution. Interestingly, Duman et al. [31] relied on the same decomposition approach to designate the level of influence exerted by distinct socioeconomic indicators on the carbon emissions inventories of 287 Chinese cities as a result of the operational activity of 47 economic sectors consuming 17 primary fossil fuels.

## 4. Challenges in Data Availability and Spatial Distribution Techniques

One of the most crucial factors in energy economics modelling is the data-related challenges; moreover it is important to monitor spatial distributions techniques as presented in Table 2. A fundamental preliminary step prior to proceeding in such type of environmental modeling entails spatial autocorrelation analysis of the scrutinized GHGs, concerning the assessment of the extent of interdependency between air pollutants, as well as its potential spillover and diffusion ramifications in adjacent regions of a designated geographic space. Wang et al. [32] claim that spatial relevance characteristics of atmospheric activity tend to induce analogous regional concentrations of GHGs.

Global spatial correlation is typically statistically estimated by the Geary's and Moran's I indices, yet Dong et al. [33] observed that the latter is less susceptible to deviations from the normal distribution. Additionally, Global Moran's index utilizing geographic data can expose spatial dependence and spatial heterogeneity and ranges from -1 to 1, with values exceeding 0 indicating positive correlation and spatial agglomeration of the regional pollution control performance. On the contrary, for values lower than 0, negative correlation is verified, while values approaching -1 signify similar performance across all examined geographical areas under consideration. Moreover, Xu and Deng [34] assert that close to 0 values of global Moran's index indicate random distribution of pollutants or nonexistent spatial autocorrelation.

Hence, most environmental researchers, including Wang et al. [35], Mi et al. [36], Su and Yu [37], and Yan et al. [38], advance their research by analyzing regional environmental quality and especially air pollution in urban spatial agglomerations. Tang et al. [39] suggest the implementation of local indicators of spatial association (LISA) to discern the regional units contributing more to global spatial autocorrelation, as well as to evaluate whether spatial autocorrelation imbeds local instability. To exemplify, LISA is approximated via the local Moran's index initially proposed by Moran [40] and later adjusted by Geary [41]. Local Moran's index is predominantly employed to check for spatial heterogeneity and non-stationary characteristics, with Tepanosyan et al. [42] and Ren et al. [43] recommending the incorporation of the Getis-Ord statistic into the index so as to account for possible spatial clustering of the attributed variables across the entire geographical area of interest.

**Table 2:** Techniques for Spatial Distribution Techniques

| Technique(s) | Prerequisites and Tools | Ref. |
|---|---|---|
| Spatial Autocorrelation in Environmental Modeling | • Before modeling GHGs, researchers must assess spatial autocorrelation, the degree to which air pollutants are interdependent across neighboring regions.<br>• Global measures like Moran's I (preferred for normality-robustness) and Geary's C are used to detect overall spatial dependence.<br>**Interpretation of Moran's I:**<br>• Positive Moran's I (>0): pollution clustering.<br>• Negative Moran's I (<0): spatial dispersion.<br>• Near-zero Moran's I (~0): random spatial distribution or no autocorrelation. | [32–34] |
| Local Indicators of Spatial Association (LISA) | • Used to detect local clusters and instabilities within broader spatial autocorrelation.<br>• Local Moran's I and Getis-Ord statistics help identify hotspots or coldspots of pollution. | [39,42,43] |
| Spatial Statistical Techniques for Missing Data | • Standard Deviation Ellipse (SDE): tracks pollution concentration centers and dispersion patterns over time.<br>• SDE reveals expansion trends and movement dynamics of pollutants. | [31,44,45] |
| Spatial Interpolation Methods | • Ordinary Kriging (OKM): the preferred method for its precision and consistency in filling data gaps.<br>• Inverse Distance Weighting (IDW): widely used for simplicity, assigning more weight to closer data points.<br>• Spline interpolation: suggested for smoothing environmental data. | [46–51] |
| | **Key Factors Influencing Spatial Interpolation Accuracy:**<br>• Data quality and variable correlation are crucial for effective interpolation.<br>• Observation density is less important compared to data reliability.<br>• Randomly distributed data points yield better interpolation than evenly distributed ones. | [50,52,53] |

A major challenge concerning spatiotemporal analysis lies in the requirement for extensive data availability for each discrete part of the examined geographical zone. The absence of weather and air pollution check stations in every region, along with the lack of observations for certain socioeconomic parameters, frequently makes the task of obtaining the necessary continuous data at every spatial location complicated, if not unfeasible. In this case, environmental scientists employ the spatial statistical distribution techniques of geographical elements to approximate any missing data. To give an example, Ma et al [44], Wang et al., [45] and Duman et al [31] and many other environmental analyses rely on the standard deviation ellipse (SDE) method to approximate the concentration centers, as well as the geographical disbursement and changing trajectories of the scrutinized air pollutant elements in space. The SDE of geographic elements reveals expansion trends whenever these outside the ellipse grow faster than those inside and vice versa.

In contrast, Wang et al. [32] utilize the spatial interpolation methodology for estimating unspecified concentrations of air pollutants and meteorological factors, social and economic factors in the Beijing-Tianjin-Hebei urban agglomeration. However, Jiang et al. [54] advocate this type of mathematical modeling for getting a rough estimate of unknown GHG values based on existing neighboring data. The most widely implemented spatial interpolation approaches for regional-scale analysis encompass ordinary Kriging (OKM) and inverse distance weighted (IDW), as well as several variations of the two methods, with Li and Heap [46] alternatively recommending the use of the SPLINE method, especially when concerning environmental datasets.

Interestingly, Zhang et al. [47] argue in favor of OKM as the most precise and consistent interpolation methodology in simulating air quality levels in locations with discontinuous or nonexistent monitoring, since it facilitates the approximation of a relative value for a certain point in a region through the weighted averages of available data from adjacent areas. Consequently, Liang and Wang [48] opted for OKM to capture the spatial appearance and progress of GHGs through time. Whereas, Li and Heap [49], based on an extensive review of 53 comparative environmental studies, verified that kriging methodology systematically outperformed traditional non-geostatistical methods, further emphasizing that most scholars qualify kriging with an external drift (KED) as the most fitting interpolation methodology.

Nonetheless, a wide range of environmental studies adopted the IDW approach as originally formulated by Li [50] and modified by Van Brummelen [51]. Allocating more weight on forecasts to the most proximate geographical spot to be interpolated, Espinoza et al. [11] capitalized on the merits of this econometric technique to predict 7-day $NO_2$ concentrations in Spain. Likewise, Wei et al. [55] and Wei et al. [56] utilize IDW methodology to approximate meteorological data and observations for $PM_{2.5}$, $SO_2$, $NO_2$, $PM_{10}$, CO, and $O_3$ emissions, thereby facilitating subsequent spatiotemporal analysis in certain agglomerations where weather stations and local air pollution monitoring are not available. Notably, Long et al. [28], in effort to determine the underlying forces of water resource exhaustion in Chinese provinces, they estimate through IDW interpolation the average disposable income of inhabitants in specific local urban and rural areas of interest.

Regardless of the selected method, certain fundamental factors influence the predictability of spatial interpolation. According to Hengl [52], these predominantly involve the quality of data sampling and the statistical significance of variable correlation, while observation density appears to be inconsequential. In alignment with this assertion, Minasny and McBratney [53] posit that putting more emphasis on implementing the most sophisticated statistical approaches frequently fails to enhance the interpolation outcomes to such a degree as collecting meaningful and trustworthy data. What is more, Li and Heap [50] assert that processing regional datasets coming from randomly distributed stations boosts spatial interpolation precision in contrast to datasets from normally distributed spots.

## 5. Advances in Spatiotemporal Econometric Modeling

The present chapter contributes to the existing literature by critically evaluating and contrasting the capabilities of various spatiotemporal econometric models in capturing the spatial heterogeneity and dynamic evolution of air pollution and its drivers. Moreover, it is going to highlight how recent advancements have enhanced the precision and contextual relevance of environmental impact assessments.

**Table 3:** Techniques, applications, and characteristics in spatiotemporal econometric modelling.

| Technique | Applications | Advantages/Disadvantages | Ref. |
|---|---|---|---|
| SDM | • Studies using SDM show strong spillover effects in pollution across urban areas.<br>• Key determinants of pollution include urbanization, economic growth, industrial structure, and government expenditure on technology. | • SDM accounts for spatial and temporal correlations simultaneously.<br>• It captures spillover effects and is not limited by assumptions about the scale of these effects.<br>• SDM is seen as more robust and reliable than SLM and SEM. | [25,57] |
| GTWR | • GTWR effectively models various environmental drivers: industrial structure, energy use, urban green coverage, population density, and weather conditions.<br>• It helps understand regional discrepancies in how these factors influence pollution. | • New versions of GTWR (e.g., GTWR with spatiotemporal kernels, GWR-TSF) offer more precise modeling of complex spatiotemporal relationships.<br>• Model selection still depends heavily on the dataset and research goals.<br>• GTWR better captures spatiotemporal heterogeneity by factoring in both spatial and temporal dynamics.<br>• GTWR's advantages in handling non-stationary, localized pollution impacts across different regions and timeframes. | [55,56,58–65] |
| GeoDetector Model | • GeoDetector analyzes spatial heterogeneity and identifies interactions between different environmental factors.<br>• Modified versions of GeoDetector have been used to pinpoint factors like urbanization rates and energy structures as key pollution drivers. | • Decomposition approaches (e.g., LMDI, SDA) are criticized for their inability to perform quantitative causal analysis.<br>• They are seen as less robust than spatial panel models in explaining the true influence of environmental drivers. | [26–32,66,67] |

The discussion underscores the importance of selecting appropriate modeling techniques based on data characteristics and policy objectives, thereby enriching the methodological toolkit for spatial econometric analysis and informing more effective, localized policy interventions.

Spatiotemporal econometric modeling is crucial in the energy sector because it captures how energy production, consumption, and pollution vary across different regions and evolve over time; hence it enables more accurate policy-making as some insights are presented in Table 3. Nevertheless, the SDM model demonstrated that discrepancies concerning geographical characteristics, as well as the level and structure of socio-economic development, significantly alter both the magnitude and actual effect of air quality drivers. In a similar panel SDM study, Xu et al. [25] highlighted the impact of trade openness, volume of urban population, energy intensity, GDP, and level of technological development as the principal causal factors of GHG pollution in 26 rapidly growing metropolitan areas in the Yellow River Delta region. The study further designated signs of spatial autocorrelation, reflecting some type of synergistic management between groups of neighboring cities, yet an evident disparity was present in the spillover effects of air pollution and its main contributors.

Nonetheless, Zhu et al. [57] scrutinizing the impact of renewable energy technology innovation on air pollution stemming from industrial production, allege that spatial panel econometric models failed to capture the provincial characteristics of the interrelationship between the examined parameters and could only provide statistically significant results for the whole of the region of interest. On the contrary, the study managed to fill this gap and explore spatial heterogeneity of industrial pollution by incorporating the Geographically Temporally Weighted Regression (GTWR) model of Huang et al [58] and Yu [59]. In harmony with the previous conclusion, Wei et al [55] verified the superiority of GTWR over spatial panel models in capturing the spatiotemporal impact of several causal factors of $PM_{2.5}$ pollution. Similarly, Rodrigues et al. [60] claim that GTWR is more suitable for such type of analysis since accounting for time uncertainty allows GTWR to successfully process cross-sectional datasets with temporal non-stationarity. In essence, the spatiotemporal distance function of GTWR allows it to accurately approximate the decay in the effect of the explanatory parameters of environmental pollution or economic variables.

Cheng et al. [61] was one of the first studies that utilized GTWR methodology to analyze provincial spatiotemporal heterogeneity of the emitted GHG attributed to industrial activity. The econometric outcomes derived from GTWR revealed that the proportion of public enterprises, total industrial output, number of heavy industries, and emission taxation crucially affected air quality across the 31 Chinese provinces under examination. However, the model highlighted notable discrepancies concerning the direction and magnitude of these parameters from one geographical zone to another.

Benefiting from its econometric virtues and wide range of options for environmental analyses, Shi et al. [62] and Zhou et al. [63] applied the GTWR method to investigate the spatiotemporal ramifications of a plethora of contributory factors on most hazardous air pollutants. Therefore, the studies conducted using GTWR effectively delineate the impact of a range of factors on all major particulate matter and gaseous atmospheric pollutants. These factors include the roles of secondary and tertiary industry, such as (i) the large number of industrial enterprises, (ii) domestic and industrial solid waste management, industrial electricity consumption, (iii) GDP per unit of electricity use, (iv) percentage green coverage rate of metropolitan areas, (v) population density, (vi) retail sales, and (vii) weather conditions on all principal particulate matter and gaseous atmospheric pollutants. Notably, Jiang et al. [64] employed the GTWR model to highlight the spatial discrepancy concerning the influence of the causal factors of $CO_2$-$PM_{2.5}$ synergistic degree, which pertains to the potential simultaneous mitigation of carbon emissions alongside other particulate matter pollutants.

GTWR's adaptability and wide acceptance within academia have incited a series of proposed alterations aimed at further enhancing its robustness as well as rendering it more suitable for specialized environmental and energy analyses. For example, Fotheringham et al. [65] introduced a GTWR model with distinct spatial and temporal estimates, which are subsequently integrated via spatiotemporal kernel functions. This modification allows for more reliable representation of the spatiotemporal relationships among observations. Furthermore, Wei et al. [56], through a comparative analysis of the statistical performance of 12 GTWR-type models, concluded that the GWR-TSF model constituted a secondary process of model residuals statistically meaningful in the interpolation process of regional PM2.5 concentrations, thereby conferring a noteworthy enhancement in the precision of the model's outcomes. Nevertheless, Artelaris [68] alleges that the selection of the most suitable model is predominantly dependent upon the characteristics of the underlying dataset and research objectives.

As an alternative to decomposition approaches, Wang et al. [32] discerned the causal factors of ozone pollution in urban locations via the GeoDetector model of Wang et al. [66]. The study exploited the model's capability to harness spatial heterogeneity to process qualitative data and statistically assess the interrelations of two examined objects, encompassing the intensity, direction, and linearity of their interaction. The analysis revealed a reciprocal relationship of ozone inventories with $NO_2$, CO, PM10, PM2.5, and $SO_2$ pollutants, meteorological conditions, and GHG emissions from the secondary industry.

Furthermore, applying Liu and Hao's [67] modified version of GeoDetector, Huang et al. [69] identified the rate of land urbanization and structure of energy consumption as the main threats for PM2.5 atmospheric pollution in urban agglomerations, while Wei et al. [56] validated the crucial contribution of weather phenomena and zenith tropospheric delay on the spatial distribution of this hazardous air pollutant.

Nevertheless, Duman et al. [31] postulate that an essential shortcoming of decomposition and other similar methodologies lies in their incapacity to facilitate quantitative causal analysis and draw more robust conclusions. In contrast, spatial panel models can account for air pollutants unbalanced spatiotemporal distributions, providing econometric outcomes with better representation of the actual effect of key drivers of air quality in specific spatial agglomerations. These models combine simultaneous spatial and temporal analysis of the characteristics investigated environmental and socioeconomic variables, capturing any potential heterogeneity embedded within the generated statistical relationships. Spatial econometric analysis primarily encompasses the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). The latter basically comprises a generalized combination of the first two models, which, under certain parameter conditions, can turn into an SLM or SEM model, respectively. The SDM model integrates spatial autoregressive processing of all dependent and explanatory variables at the same time, rendering it more suitable for capturing potential spatial spillovers. Another important econometric advantage of the SDM model is that its final outcomes are not subject to prior constraints relative to the scale of spillover effect. Mu et al. [70], exploring the spatiotemporal features of water reserves exploitation in megalopolises, verified the statistical merits of the SDM model, which enable it to generate more robust outcomes compared to SLM or SEM models, constituting it superior.

Fan et al. [71] conducted quantitative panel analysis via the SDM approach to assess the potential asymmetric and nonlinear influence of the accelerated enlargement of urban population and economic agglomeration on the level of haze pollution inventories across 342 Chinese cities. The econometric outcomes of the SDM model, accounting for spatial heterogeneities of geographical parameters, provided evidence of a strong spillover effect in terms of haze pollution contamination between adjacent urban areas, underscoring the adverse impact of elevated levels of economic agglomeration and industrial structure. Correspondingly, Jiang et al. [54], through SDM panel modelling, corroborated the presence of an air pollution spillover effect between 103 cities within the Yellow River economic belt zone, identifying government technical expenditure, GDP growth, urbanization, and meteorological conditions as pivotal determinants of Air Quality Index.

## 6. Machine Learning Approaches for Spatiotemporal Forecasting

This chapter will reveal the advances on machine learning techniques into econometrics and spatiotemporal environmental forecasting; for instance, there is emphasis on novel techniques' potential to complement traditional models by addressing complex, high-dimensional decision-making problems under uncertainty, especially in predicting anthropogenic pollution (e.g., air pollutant concentrations). The discussion also underscores the importance of methodological adaptations, such as model tuning for inference and hybrid frameworks for enhanced spatial-temporal accuracy, marking a shift toward more data-driven, flexible approaches in environmental and economic analysis.

The introduction of algorithmic-based (e.g., machine learning) has been utilized as an alternative way to deal with novel challenges, along with the traditional statistic models (i.e., stochastic data models) [72]. In essence, machine learning presents a potential family of methods and algorithms that can greatly increase the range of problems that can be analyzed in structural econometrics, with machine learning to be a "practically oriented" with three pivotal categories, i.e., supervised, unsupervised, and reinforced learning; whereas structural econometrics be "academically oriented" that work in parallel to achieve societal goals and are similar to the "supervised learning" from the machine-learning categories [73].

Furthermore, the machine learning models have lately been incorporated in economics and econometrics, especially when dealing with decision-making issues under uncertainty. Nevertheless, it is imperative that the machine learning models undergo "tuning and adaptation" in order to obtain statistical inference; for example, Athey and Imbens [74], based on the literature, proposed adaptation techniques such as causality, endogeneity, monotonicity, sample splitting, and orthogonality. Additionally, dynamic programming has been proved essential in dealing with the "curse of dimensionality" [75], especially when machine learning methods might alleviate (but not entirely solve) the above issue by using neural networks that may approximate specific kinds of multivariate functions with vector parameters that do not grow exponentially [73].

A growing trend in spatiotemporal forecasting of GHGs is the use of advanced models like long short-term memory LSTM-based graph attention mechanisms, which simulate pollutant concentrations using data from nearby, well-monitored locations. Hybrid approaches, combining convolutional neural network (CNN) for spatial prediction and LSTM for temporal forecasting, sometimes enhanced with IDW interpolation, are also being successfully applied to predict air pollution levels in heavily affected regions.

Alternatively, to traditional spatial interpolation, a growing number of up-to-date models rely on the LSTM algorithm to develop specialized models, which in turn will be employed for spatiotemporal forecasting of GHGs. More specifically, Seng et al. [76], Huang et al. [69], Zhou et al. [57], and Zhang et al. [47,77] proposed individual LSTM-based graph attention mechanisms to simulate concentrations of PM2.5, SO2, NO2, O3, and CO using as inputs observations from proximate locations with reliable long-term monitoring.

Interestingly, Zhao et al. [78] developed a hybrid methodological framework wherein the spatial component of air pollution compounds in certain agglomerations in the Beijing and Tianjin regions is prognosticated through the CNN model, while the temporal component is prognosticated through LSTM. Following a similar philosophy, Chae et al. [79] and Samal et al. [80] combine hybrid CNN-LSTM modelling with the IDW interpolation technique to predict concentrations of inhalable microparticles in hot zones in South Korea and India, respectively.

## 7. Conclusions and Discussion

To recapitulate, the present paper reviews the advances in energy economics research, aiming to compile the latest developments in energy economics research. Its goal is to uncover the connections between various practical and applicable methodologies that can support a sustainable energy transition. The review offers four key contributions: (i) it gathers major empirical advancements in the energy sector, (ii) highlights challenges in data availability and the techniques used to address them, (iii) brings together spatiotemporal econometric approaches, and (iv) showcases innovative machine learning methods for forecasting.

In essence, the global energy sector today faces a multitude of challenges that significantly impact the progress toward a sustainable future. Traditional reliance on fossil fuels continues to contribute heavily to greenhouse gas emissions, driving climate change and environmental degradation. Energy security, fluctuating prices, aging infrastructure, and unequal access to modern energy services further complicate the sector's ability to meet growing demand sustainably. As a result, energy systems are under immense pressure to evolve, but the path to transition is fraught with technological, financial, and policy-related obstacles. These issues not only hinder the adoption of cleaner technologies but also slow the decarbonization of industries critical to economic development.

The strengths and limitations in combining traditional econometrics and novel machine learning applications show that there is a wide room for improvement in the energy economics literature. The strengths refer to the ability of machine learning algorithms to analyze complexity in energy and economics as well as their broad applicability (as mentioned in the supervised, unsupervised, and reinforcement learning) in comparison to the traditional econometrics. Moreover, the handling of the curse of dimensionality is a strong advantage of machine learning applications, even though they cannot fully deal with it but offers a helping hand to economists to apply such model in order to deal with uncertainty by providing alternative solutions in energy sectors decision making. Nevertheless, economists should be aware of the disadvantages of machine learning models, as they focus mainly on the predictive power, rather than on inference issues that traditional econometric models have widely focused; for example, machine learning models should focus on adaptation techniques to address issues regarding the causality, endogeneity, and sampling splitting. In essence, the economic research in energy sectors should observe with consciousness the complementary role between algorithmic modeling and stochastic data modelling as ways to deal with energy-related challenges in an ever-changing world.

The ongoing energy transition, aimed at shifting toward renewable sources and improving energy efficiency, is deeply intertwined with achieving the United Nations SDGs, particularly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). However, the challenges within the energy sector threaten delay or derail progress. High initial investment costs, regulatory uncertainties, and the need for large-scale grid modernization are barriers to scaling renewable energy solutions. Moreover, without a just transition strategy that ensures fair opportunities and protections for workers and vulnerable communities, the shift risks exacerbating social inequalities. Overcoming these challenges is crucial to align the energy transition with sustainable development pathways, ensuring that economic growth, environmental stewardship, and social inclusion move forward hand-in-hand.

## References


1. Halkos, G.E.; Aslanidis, P.-S.C. Green Energy Pathways Towards Carbon Neutrality. *Environ. Resour. Econ.* **2024**, doi:10.1007/s10640-024-00856-z.
2. Nurdiawati, A.; Urban, F. Towards Deep Decarbonisation of Energy-Intensive Industries: A Review of Current Status, Technologies and Policies. *Energies* **2021**, *14*, 2408, doi:10.3390/en14092408.
3. Halkos, G.E.; Aslanidis, P.-S.C. Sustainable Energy Development in an Era of Geopolitical Multi-Crisis. Applying Productivity Indices within Institutional Framework. *Resour. Policy* **2023**, *85*, 103854, doi:10.1016/j.resourpol.2023.103854.
4. Halkos, G.E.; Tzeremes, N.G. Measuring the Effect of Kyoto Protocol Agreement on Countries' Environmental Efficiency in CO2 Emissions: An Application of Conditional Full Frontiers. *J. Product. Anal.* **2014**, *41*, 367–382, doi:10.1007/s11123-013-0343-1.
5. Halkos, G.E.; Kitsou, D.C. Weighted Location Differential Tax in Environmental Problems. *Environ. Econ. Policy Stud.* **2018**, *20*, 1–15, doi:10.1007/s10018-016-0179-9.
6. Halkos, G.E.; Moll de Alba, J.; Aslanidis, P.-S.C. Examining Energy and Carbon Intensity of the European Fashion Industry: A Hybrid DEA Analysis for Circular Economy. *Circ. Econ. Sustain.* **2024**, doi:10.1007/s43615-024-00488-x.
7. Halkos, G.E.; Tsirivis, A.S. Electricity Prices in the European Union Region: The Role of Renewable Energy Sources, Key Economic Factors and Market Liberalization. *Energies* **2023**, *16*, 2540, doi:10.3390/en16062540.
8. Halkos, G.E.; Aslanidis, P.-S.C. Addressing Multidimensional Energy Poverty Implications on Achieving Sustainable Development. *Energies* **2023**, *16*, 3805, doi:10.3390/en16093805.
9. Halkos, G.E.; Tsirivis, A.S. Sustainable Development of the European Electricity Sector: Investigating the Impact of Electricity Price, Market Liberalization and Energy Taxation on RES Deployment. *Energies* **2023**, *16*, 5567, doi:10.3390/en16145567.
10. Ma, T.; Duan, F.; He, K.; Qin, Y.; Tong, D.; Geng, G.; Liu, X.; Li, H.; Yang, S.; Ye, S.; et al. Air Pollution Characteristics and Their Relationship with Emissions and Meteorology in the Yangtze River Delta Region during 2014–2016. *J. Environ. Sci.* **2019**, *83*, 8–20, doi:10.1016/j.jes.2019.02.031.
11. Espinosa, R.; Jiménez, F.; Palma, J. Multi-Objective Evolutionary Spatio-Temporal Forecasting of Air Pollution. *Futur. Gener. Comput. Syst.* **2022**, *136*, 15–33, doi:10.1016/j.future.2022.05.020.
12. Deb, K. *Multi-Objective Optimization Using Evolutionary Algorithms*; JohnWiley & Sons, Inc., 2001;
13. Ehrgott, M. *Multicriteria Optimization, in: Lecture Notes in Economics Andmathematical Systems*; 2nd ed.; Springer: Berlin, Heidelberg, 2005;
14. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197, doi:10.1109/4235.996017.
15. Qingfu Zhang; Hui Li MOEA/D: A Multiobjective Evolutionary Algorithm Based on Decomposition. *IEEE Trans. Evol. Comput.* **2007**, *11*, 712–731, doi:10.1109/TEVC.2007.892759.
16. Zitzler, E.; Laumanns, M.; Thiele, L. SPEA2: Improving the Strength Pareto Evolutionary Algorithm. *TIK Rep.* **2001**, doi:https://doi.org/10.3929/ethz-a-004284029.
17. Dai, H.; Huang, G.; Zeng, H. Multi-Objective Optimal Dispatch Strategy for Power Systems with Spatio-Temporal Distribution of Air Pollutants. *Sustain. Cities Soc.*

**2023**, *98*, 104801, doi:10.1016/j.scs.2023.104801.
18. Gupta, R.; Nanda, S.J. Solving Time Varying Many-Objective TSP with Dynamic <math Altimg="si56.Svg" Display="inline" Id="d1e4589"> <mi>θ</Mi> </Math> -NSGA-III Algorithm. *Appl. Soft Comput.* **2022**, *118*, 108493, doi:10.1016/j.asoc.2022.108493.
19. Yang, S.; Li, M.; Liu, X.; Zheng, J. A Grid-Based Evolutionary Algorithm for Many-Objective Optimization. *IEEE Trans. Evol. Comput.* **2013**, *17*, 721–736, doi:10.1109/TEVC.2012.2227145.
20. Liu, Z.-Z.; Wang, Y.; Wang, B.-C. Indicator-Based Constrained Multiobjective Evolutionary Algorithms. *IEEE Trans. Syst. Man, Cybern. Syst.* **2021**, *51*, 5414–5426, doi:10.1109/TSMC.2019.2954491.
21. Gao, W.; Xu, W.; Gong, M.; Yen, G.G. A Decomposition-Based Evolutionary Algorithm Using an Estimation Strategy for Multimodal Multi-Objective Optimization. *Inf. Sci. (Ny).* **2022**, *606*, 531–548, doi:10.1016/j.ins.2022.05.075.
22. Wang, Y.; Liu, P.; Yao, Y. BMW-TOPSIS: A Generalized TOPSIS Model Based on Three-Way Decision. *Inf. Sci. (Ny).* **2022**, *607*, 799–818, doi:10.1016/j.ins.2022.06.018.
23. Wu, R.; Li, Z.; Wang, S. The Varying Driving Forces of Urban Land Expansion in China: Insights from a Spatial-Temporal Analysis. *Sci. Total Environ.* **2021**, *766*, 142591, doi:10.1016/j.scitotenv.2020.142591.
24. Xu, Y.; Zhang, W.; Wang, J.; Ji, S.; Wang, C.; Streets, D.G. Investigating the Spatially Heterogeneous Impacts of Urbanization on City-Level Industrial SO2 Emissions: Evidence from Night-Time Light Data in China. *Ecol. Indic.* **2021**, *133*, 108430, doi:10.1016/j.ecolind.2021.108430.
25. Xu, Y.; Liu, Z.; Walker, T.R.; Adams, M.; Dong, H. Spatio-Temporal Patterns and Spillover Effects of Synergy on Carbon Dioxide Emission and Pollution Reductions in the Yangtze River Delta Region in China. *Sustain. Cities Soc.* **2024**, *107*, 105419, doi:10.1016/j.scs.2024.105419.
26. Ang, B.W. The LMDI Approach to Decomposition Analysis: A Practical Guide. *Energy Policy* **2005**, *33*, 867–871, doi:10.1016/j.enpol.2003.10.010.
27. Shan, Y.; Guan, Y.; Hang, Y.; Zheng, H.; Li, Y.; Guan, D.; Li, J.; Zhou, Y.; Li, L.; Hubacek, K. City-Level Emission Peak and Drivers in China. *Sci. Bull.* **2022**, *67*, 1910–1920, doi:10.1016/j.scib.2022.08.024.
28. Long, H.; Lin, B.; Ou, Y.; Chen, Q. Spatio-Temporal Analysis of Driving Factors of Water Resources Consumption in China. *Sci. Total Environ.* **2019**, *690*, 1321–1330, doi:10.1016/j.scitotenv.2019.06.311.
29. Zhang, J.; Zhang, K.; Zhao, F. Spatial Effects of Economic Growth, Energy Consumption and Environmental Pollution in the Provinces of China—An Empirical Study of a Spatial Econometrics Model. *Sustain. Dev.* **2020**, *28*, 868–879, doi:10.1002/sd.2042.
30. Zhang, P.; Yang, D.; Qin, M.; Jing, W. Spatial Heterogeneity Analysis and Driving Forces Exploring of Built-up Land Development Intensity in Chinese Prefecture-Level Cities and Implications for Future Urban Land Intensive Use. *Land use policy* **2020**, *99*, 104958, doi:10.1016/j.landusepol.2020.104958.
31. Duman, Z.; Mao, X.; Cai, B.; Zhang, Q.; Chen, Y.; Gao, Y.; Guo, Z. Exploring the Spatiotemporal Pattern Evolution of Carbon Emissions and Air Pollution in Chinese Cities. *J. Environ. Manage.* **2023**, *345*, 118870, doi:10.1016/j.jenvman.2023.118870.
32. Wang, Z.; Li, J.; Liang, L. Spatio-Temporal Evolution of Ozone Pollution and Its Influencing Factors in the Beijing-Tianjin-Hebei Urban Agglomeration. *Environ. Pollut.* **2020**, *256*, 113419, doi:10.1016/j.envpol.2019.113419.

33. Dong, F.; Wang, Y.; Zheng, L.; Li, J.; Xie, S. Can Industrial Agglomeration Promote Pollution Agglomeration? Evidence from China. *J. Clean. Prod.* **2020**, *246*, 118960, doi:10.1016/j.jclepro.2019.118960.
34. Xu, H.L. and Deng, Y.P. Does Foreign Direct Investment Lead to Environmental Pollution in China? A Spatial Econometric Study Based on Chinese Provincial Panel Data. *Manage. World* **2012**, *2*, 31–43, doi:https://doi.org/10.19744/j.cnki.11-1235/f.2012.02.004.
35. Wang, S.; Fang, C.; Wang, Y. Spatiotemporal Variations of Energy-Related CO 2 Emissions in China and Its Influencing Factors: An Empirical Analysis Based on Provincial Panel Data. *Renew. Sustain. Energy Rev.* **2016**, *55*, 505–515, doi:10.1016/j.rser.2015.10.140.
36. Mi, K.; Zhuang, R.; Zhang, Z.; Gao, J.; Pei, Q. Spatiotemporal Characteristics of PM2.5 and Its Associated Gas Pollutants, a Case in China. *Sustain. Cities Soc.* **2019**, *45*, 287–295, doi:10.1016/j.scs.2018.11.004.
37. Su, Y.; Yu, Y. Spatial Agglomeration of New Energy Industries on the Performance of Regional Pollution Control through Spatial Econometric Analysis. *Sci. Total Environ.* **2020**, *704*, 135261, doi:10.1016/j.scitotenv.2019.135261.
38. Yan, D.; Kong, Y.; Jiang, P.; Huang, R.; Ye, B. How Do Socioeconomic Factors Influence Urban PM2.5 Pollution in China? Empirical Analysis from the Perspective of Spatiotemporal Disequilibrium. *Sci. Total Environ.* **2021**, *761*, 143266, doi:10.1016/j.scitotenv.2020.143266.
39. Tang, J.; Tong, M.; Sun, Y.; Du, J.; Liu, N. A Spatio-Temporal Perspective of China's Industrial Circular Economy Development. *Sci. Total Environ.* **2020**, *706*, 135754, doi:10.1016/j.scitotenv.2019.135754.
40. Moran, P.A.P. The Interpretation of Statistical Maps. *J. R. Stat. Soc. Ser. B Stat. Methodol.* **1948**, *10*, 243–251, doi:10.1111/j.2517-6161.1948.tb00012.x.
41. Geary, R.C. The Contiguity Ratio and Statistical Mapping. *Inc. Stat.* **1954**, *5*, 115, doi:10.2307/2986645.
42. Tepanosyan, G.; Sahakyan, L.; Zhang, C.; Saghatelyan, A. The Application of Local Moran's I to Identify Spatial Clusters and Hot Spots of Pb, Mo and Ti in Urban Soils of Yerevan. *Appl. Geochemistry* **2019**, *104*, 116–123, doi:10.1016/j.apgeochem.2019.03.022.
43. Ren, H.; Shang, Y.; Zhang, S. Measuring the Spatiotemporal Variations of Vegetation Net Primary Productivity in Inner Mongolia Using Spatial Autocorrelation. *Ecol. Indic.* **2020**, *112*, 106108, doi:10.1016/j.ecolind.2020.106108.
44. Ma, W.; Wei, F.; Zhang, J.; Karthe, D.; Opp, C. Green Water Appropriation of the Cropland Ecosystem in China. *Sci. Total Environ.* **2022**, *806*, 150597, doi:10.1016/j.scitotenv.2021.150597.
45. Wang, N.; Fu, X.; Wang, S. Spatial-Temporal Variation and Coupling Analysis of Residential Energy Consumption and Economic Growth in China. *Appl. Energy* **2022**, *309*, 118504, doi:10.1016/j.apenergy.2021.118504.
46. Li, J.; Heap, A.D. Spatial Interpolation Methods Applied in the Environmental Sciences: A Review. *Environ. Model. Softw.* **2014**, *53*, 173–189, doi:10.1016/j.envsoft.2013.12.008.
47. Zhang, H.; Zhan, Y.; Li, J.; Chao, C.-Y.; Liu, Q.; Wang, C.; Jia, S.; Ma, L.; Biswas, P. Using Kriging Incorporated with Wind Direction to Investigate Ground-Level PM2.5 Concentration. *Sci. Total Environ.* **2021**, *751*, 141813, doi:10.1016/j.scitotenv.2020.141813.
48. Liang, L.; Wang, Z. Control Models and Spatiotemporal Characteristics of Air Pollution in the Rapidly Developing Urban Agglomerations. *Int. J. Environ. Res.*

*Public Health* **2021**, *18*, 6177, doi:10.3390/ijerph18116177.
49. Li, J.; Heap, A.D. A Review of Comparative Studies of Spatial Interpolation Methods in Environmental Sciences: Performance and Impact Factors. *Ecol. Inform.* **2011**, *6*, 228–241, doi:10.1016/j.ecoinf.2010.12.003.
50. Li, J.; Heap, A.D. A Review of Spatial Interpolation Methods for Environmental Scientists. **2008**.
51. Van Brummelen, G. *Heavenly Mathematics: The Forgotten Art of Spherical Trigonometry*; Princeton University Press., 2017;
52. Hengl, T. A Practical Guide to Geostatistical Mapping of Environmental Variables. JRC Scientific and Technichal Reports. *Off. Off. Publ. Eur. Communities, Luxemb.* **2007**.
53. Minasny, B.; McBratney, A.B. Spatial Prediction of Soil Properties Using EBLUP with the Matérn Covariance Function. *Geoderma* **2007**, *140*, 324–336, doi:10.1016/j.geoderma.2007.04.028.
54. Jiang, W.; Gao, W.; Gao, X.; Ma, M.; Zhou, M.; Du, K.; Ma, X. Spatio-Temporal Heterogeneity of Air Pollution and Its Key Influencing Factors in the Yellow River Economic Belt of China from 2014 to 2019. *J. Environ. Manage.* **2021**, *296*, 113172, doi:10.1016/j.jenvman.2021.113172.
55. Wei, Q.; Zhang, L.; Duan, W.; Zhen, Z. Global and Geographically and Temporally Weighted Regression Models for Modeling PM2.5 in Heilongjiang, China from 2015 to 2018. *Int. J. Environ. Res. Public Health* **2019**, *16*, 5107, doi:10.3390/ijerph16245107.
56. Wei, P.; Xie, S.; Huang, L.; Liu, L.; Tang, Y.; Zhang, Y.; Wu, H.; Xue, Z.; Ren, D. Spatial Interpolation of PM2.5 Concentrations during Holidays in South-Central China Considering Multiple Factors. *Atmos. Pollut. Res.* **2022**, *13*, 101480, doi:10.1016/j.apr.2022.101480.
57. Zhu, Y.; Wang, Z.; Zhu, L. Spatiotemporal Effects of Renewable Energy Technology Innovation on Industrial Cleaner Production: A Geographically Temporally Weighted Analysis. *J. Clean. Prod.* **2021**, *312*, 127783, doi:10.1016/j.jclepro.2021.127783.
58. Huang, B.; Wu, B.; Barry, M. Geographically and Temporally Weighted Regression for Modeling Spatio-Temporal Variation in House Prices. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 383–401, doi:10.1080/13658810802672469.
59. Yu, D. Understanding Regional Development Mechanisms in Greater Beijing Area, China, 1995–2001, from a Spatial–Temporal Perspective. *GeoJournal* **2014**, *79*, 195–207, doi:10.1007/s10708-013-9500-3.
60. Rodrigues, M.; Jiménez-Ruano, A.; Peña-Angulo, D.; de la Riva, J. A Comprehensive Spatial-Temporal Analysis of Driving Factors of Human-Caused Wildfires in Spain Using Geographically Weighted Logistic Regression. *J. Environ. Manage.* **2018**, *225*, 177–192, doi:10.1016/j.jenvman.2018.07.098.
61. Cheng, J.; Dai, S.; Ye, X. Spatiotemporal Heterogeneity of Industrial Pollution in China. *China Econ. Rev.* **2016**, *40*, 179–191, doi:10.1016/j.chieco.2016.07.001.
62. Shi, T.; Zhang, W.; Zhou, Q.; Wang, K. Industrial Structure, Urban Governance and Haze Pollution: Spatiotemporal Evidence from China. *Sci. Total Environ.* **2020**, *742*, 139228, doi:10.1016/j.scitotenv.2020.139228.
63. Zhou, X.; Zhang, X.; Wang, Y.; Chen, W.; Li, Q. Spatio-Temporal Variations and Socio-Economic Drivers of Air Pollution: Evidence from 332 Chinese Prefecture-Level Cities. *Atmos. Pollut. Res.* **2023**, *14*, 101782, doi:10.1016/j.apr.2023.101782.
64. Jiang, F.; Chen, B.; Li, P.; Jiang, J.; Zhang, Q.; Wang, J.; Deng, J. Spatio-Temporal Evolution and Influencing Factors of Synergizing the Reduction of Pollution and Carbon Emissions - Utilizing Multi-Source Remote Sensing Data and GTWR Model.

*Environ. Res.* **2023**, *229*, 115775, doi:10.1016/j.envres.2023.115775.
65. Fotheringham, A.S.; Crespo, R.; Yao, J. Geographical and Temporal Weighted Regression (GTWR). *Geogr. Anal.* **2015**, *47*, 431–452, doi:10.1111/gean.12071.
66. Wang, J.; Li, X.; Christakos, G.; Liao, Y.; Zhang, T.; Gu, X.; Zheng, X. Geographical Detectors-Based Health Risk Assessment and Its Application in the Neural Tube Defects Study of the Heshun Region, China. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 107–127, doi:10.1080/13658810802443457.
67. Liu, M.; Hao, W. Spatial Distribution and Its Influencing Factors of National A-Level Tourist Attractions in Shanxi Province. *Acta Geogr. Sin* **2020**, *75*, 878–888, doi:https://doi.org/10.11821/dlxb202004015.
68. Artelaris, P. Local versus Regime Convergence Regression Models: A Comparison of Two Approaches. *GeoJournal* **2015**, *80*, 263–277, doi:10.1007/s10708-014-9551-0.
69. Huang, C.; Liu, K.; Zhou, L. Spatio-Temporal Trends and Influencing Factors of PM2.5 Concentrations in Urban Agglomerations in China between 2000 and 2016. *Environ. Sci. Pollut. Res.* **2021**, *28*, 10988–11000, doi:10.1007/s11356-020-11357-z.
70. Mu, L.; Fang, L.; Dou, W.; Wang, C.; Qu, X.; Yu, Y. Urbanization-Induced Spatio-Temporal Variation of Water Resources Utilization in Northwestern China: A Spatial Panel Model Based Approach. *Ecol. Indic.* **2021**, *125*, 107457, doi:10.1016/j.ecolind.2021.107457.
71. Fan, Q.; Yang, S.; Liu, S. Asymmetrically Spatial Effects of Urban Scale and Agglomeration on Haze Pollution in China. *Int. J. Environ. Res. Public Health* **2019**, *16*, 4936, doi:10.3390/ijerph16244936.
72. Breiman, L. Statistical Modeling: The Two Cultures (with Comments and a Rejoinder by the Author). *Stat. Sci.* **2001**, *16*, doi:10.1214/ss/1009213726.
73. Iskhakov, F.; Rust, J.; Schjerning, B. Machine Learning and Structural Econometrics: Contrasts and Synergies. *Econom. J.* **2020**, *23*, S81–S124, doi:10.1093/ectj/utaa019.
74. Athey, S.; Imbens, G.W. Machine Learning Methods That Economists Should Know About. *Annu. Rev. Econom.* **2019**, *11*, 685–725, doi:10.1146/annurev-economics-080217-053433.
75. Rust, J. Has Dynamic Programming Improved Decision Making? *Annu. Rev. Econom.* **2019**, *11*, 833–858, doi:10.1146/annurev-economics-080218-025721.
76. Seng, D.; Zhang, Q.; Zhang, X.; Chen, G.; Chen, X. Spatiotemporal Prediction of Air Quality Based on LSTM Neural Network. *Alexandria Eng. J.* **2021**, *60*, 2021–2032, doi:10.1016/j.aej.2020.12.009.
77. Zhang, K.; Zhang, X.; Song, H.; Pan, H.; Wang, B. Air Quality Prediction Model Based on Spatiotemporal Data Analysis and Metalearning. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, doi:10.1155/2021/9627776.
78. Zhao, G.; Huang, G.; He, H.; He, H.; Ren, J. Regional Spatiotemporal Collaborative Prediction Model for Air Quality. *IEEE Access* **2019**, *7*, 134903–134919, doi:10.1109/ACCESS.2019.2941732.
79. Chae, S.; Shin, J.; Kwon, S.; Lee, S.; Kang, S.; Lee, D. PM10 and PM2.5 Real-Time Prediction Models Using an Interpolated Convolutional Neural Network. *Sci. Rep.* **2021**, *11*, 11952, doi:10.1038/s41598-021-91253-9.
80. Samal, K.; Babu, K.; Das, S. Spatio-Temporal Prediction of Air Quality Using Distance Based Interpolation and Deep Learning Techniques. *EAI Endorsed Trans. Smart Cities* **2018**, 168139, doi:10.4108/eai.15-1-2021.168139.