Geographical Imbalance and Influential Characteristics of the Green Building Market

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Abstract: Green buildings have gained increasing momentum during the past decade, evidenced by an uptick in green building construction worldwide. To facilitate green building development, it is crucial to understand the current geographical distribution of green buildings, thereby identifying emerging markets and opportunities for future growth. However, very few studies investigated the spatial characteristics of the green building market and the factors influencing the distribution of green buildings. By examining the national green building market in the United States, we studied the spatial distribution patterns and significant influencing factors of the county-level US green building markets. Cluster mapping and hot spots of the green building markets were identified through spatial autocorrelation analysis. A spatial regression model with high performance (R^2 of 0.83) was developed to identify the significant influencing factors. We found a statistically significant clustering phenomenon of county-level US green building markets. The spatial error model reveals that three factors, namely, the number of housing units, gross domestic product, and the local green building company index, significantly influence the number of green buildings at the county level. We also found that the county-level green building market is influenced by these factors of not only the host county, but also the neighboring counties. Our findings provide a useful reference for stakeholders' decision-making process concerning local green building market development. **DOI: 10.1061/JCEMD4.COENG-12971.**

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Introduction

The building sector has a significant impact on the environment (Chang et al. 2016a), accounting for about 32% of the world's resource consumption (Ma and Cheng 2017) and contributing to nearly 40% of annual global greenhouse gas emissions (Zuo and Zhao 2014). Green buildings are designed to mitigate these negative impacts on the natural environment during the building life cycle (design, construction, operation, and demolition) (Wu et al. 2021). Through a systematic approach, green buildings can help preserve natural resources without compromising project quality (Zou et al. 2017). As the leading green building rating system, Leadership in Energy and Environmental Design (LEED) was launched by the US Green Building Council (USGBC) in 2000. An industry-wide green building movement has gradually formed over the past two decades (Cole and Jose Valdebenito 2013). Approximately 1.04 billion m^2 of green building space (an area 10 times the size of Paris) were certified by green building councils worldwide by 2016 (WGBC 2020). By the end of 2019, more than 100,000 building projects were registered or certified by the LEED system in more than 167 countries and territories (Stanley 2019). It was reported that 47% of industry practitioners are willing to make more than 60% of their projects green by 2021 (Petrullo et al. 2018).

As the green building market continues to grow, researchers have sought to understand the variation and differentiation of local green building market development. Some studies investigate the spatial distribution of green building markets, aiming to identify the location and distribution patterns of green building projects in a given region. For instance, Zou et al. (2017) investigated the regional imbalance and policy incentives for the spatial distribution of green buildings in China. Ma and Cheng (2017) analyzed the US local green building markets in leading counties, and similarly, Zhao and Lam (2012) utilized support vector regression to investigate the LEED building markets in the US East Coast cities. Kaza et al. (2013) went a step further and examined the spatial-temporal clustering of the green building market across the entire US. Another stream of research focuses on identifying the factors influencing the spatial distribution of green building projects. Rakha et al. (2018), for instance, applied statistical analysis to investigate the predictors of residential LEED community adoption trends. They revealed that social demographics (such as education level) and community policies (such as energy efficiency incentives) significantly influence the proliferation of green building projects. In contrast, Cidell and Cope (2014) utilized logistic and linear regressions to investigate the impacts of green building policies at the municipal level, discovering that the presence of green building policies rather than demographic factors contributes to more green buildings. Fuerst et al. (2014) emphasized the role of economic factors as substantial determinants of green building adoption.

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Despite studies investigating the spatial distribution and influencing factors of green building markets, significant knowledge gaps remain. For example, there is a lack of studies investigating the granular county-level spatial distributions of the green building projects of an entire country. Previous studies such as Zhao and Lam (2012) and Ma and Cheng (2017) focused on certain counties and regions, such as the East Coast cities in the US. Without a county-level study covering a whole country, it remains unclear what factors impact countries' local green building market development. A study conducted by Kaza et al. (2013) is one of the few studies that utilized geographical methods to test the spatial patterns of green building markets. Existing studies tend to rely on descriptive statistics (e.g., the number of green building projects in the region) to reveal the geographical imbalance phenomena but fail to test the significance level of the clustering effect (Ma and Cheng 2017; Zou et al. 2017; Prum and Kobayashi 2014). Without statistical tests, there is a lack of confidence in the assessment of the geographical imbalance and clustering of green building projects. It remains unclear whether the regional imbalance of green building development revealed by previous studies is statistically valid and robust. More importantly, even though previous studies preliminarily show that a geographical imbalance of green building markets exists worldwide (Zou et al. 2017; Kaza et al. 2013), there is no consensus regarding the factors leading to the imbalance phenomena. Previous studies revealed multiple categories of factors affecting the development of local green building markets, such as demographic features (e.g., population density), economic features (e.g., household income), and policy features (e.g., mandatory requirements regarding public buildings) (Ma and Cheng 2017; Rakha et al. 2018). Different studies revealed different categories of factors impacting green building markets using various analysis scales and region samples. It remains unclear what factors significantly impact the spatial distribution of green building projects at a national level.

To address the knowledge gaps identified, this study employed geographical statistical methods to investigate the geographical imbalance and influencing factors of green building markets at the county level throughout the US, based on the latest LEED data set for projects in the US. By taking the national US green building market as an example, this study aims to statistically test whether a geographical imbalance exists in green building markets, and, if so, identify the influencing factors that cause the imbalance phenomena. Because the number of green buildings continues to grow globally, this study presents a vital reference for relevant stakeholders to understand the differentiation of green building markets and its influencing factors, thus facilitating the decision-making and policy-making processes for green building development.

Literature Review

To tackle environmental challenges, such as climate change and natural resource depletion, the building sector must undergo a deep transition toward sustainability (Chang et al. 2017, 2018), where green buildings play a significant role. Prior studies have investigated various aspects of green buildings, including costs and benefits (Dwaikat and Ali 2018; Kim et al. 2014), the drivers for and barriers to green building development (Liu et al. 2020; Olanipekun et al. 2017), design optimization and performance simulations (Lin et al. 2021; Abdallah et al. 2016), innovative green building assessment methods (Sartori et al. 2021; Gultekin et al. 2013), project management (Abidin and Azizi 2021; Raouf and Al-Ghamdi 2019), government policies (Franco et al. 2021; Adekanye et al. 2020), and behavioral economics (e.g., purchasing behavior) in the decision-making (Zhang and Tu 2021). Existing review studies on green buildings suggest most research on green buildings focuses on project-level investigations of technologies, impacts, and performances (Khoshbakht et al. 2018; Ahmad et al. 2019), while market-level investigations such as market selections and distribution patterns of green buildings remain a niche research area and are relatively inadequate (Wu et al. 2021). The knowledge in geographical distributions of green building markets and their impacting factors contributes to corporate decision-making and governments' policy making of developing or promoting green buildings (Zou et al. 2017; Kaza et al. 2013). Why are certain regions hot spots of green building development while other regions attract few green projects? Where do green building projects tend to be located and why does this happen? What are the factors influencing developers' region choice of developing green buildings? Without understanding these questions, it is difficult to formulate policies to enable balanced and rapid development of green building markets.

In this niche area of market-level investigations, one stream of research examines the spatial distribution of green building projects, aiming to identify the regions with the highest or lowest number of green buildings to assess the degree of market development imbalance. Spatial clustering denotes the phenomenon that similar or related projects, industries, and firms tend to assemble (or concentrate, agglomerate, colocate, and cluster) in particular places, leading to geographical imbalance of industries (Malmberg and Maskell 2002). Some studies on green buildings show that a geographical imbalance of the green building market occurs not only in countries that are in the developing stage of green building markets, such as China and India (Zou et al. 2017; Gao et al. 2020), but also in countries that have already formed a mature green building market such as the US (Johansson 2012). For countries with a developing green building market, Zou et al. (2017) revealed the regional imbalance of the Chinese green building markets by analyzing three-star-certified green buildings in China, where the number of certified green buildings in the eastern region far outperformed that of the western region. Smith (2015) also demonstrated the uneven and complex geographical distribution of green building projects in India by analyzing the LEED projects and the Green Rating for Integrated Habitat Assessment projects across the country. A series of studies focused on the green building market in the US, especially LEED projects. For instance, through investigating LEED buildings and LEED Accredited Professionals (APs), Cidell and Cope (2014) revealed the spatial diffusion of the green building markets in the US, which are moving from the major coastal cities to a relatively more even distribution among multiple cities. This is echoed by Kaza et al. (2013), who argued that the hot spots of the green building markets first appeared in the metropolitan regions in the coastal areas and then gradually expanded to the mixed rural counties.

Another stream of research explores the influencing factors of the spatial distribution, aiming to find out why certain regions have a larger number of green building projects than others. For instance, Zou et al. (2017) found that gross domestic product (GDP) is statistically significant with a positive coefficient for provincial green building development in China, while real estate price and energy efficiency policies are not. Ma and Cheng (2017) developed a numerical model of the US leading counties in green building development with 89 county-level features, identifying that economic features (e.g., personal income) and educational features (e.g., number of universities in the region) are key factors that may explain why these leading local green building markets outperform other areas. In another case, by analyzing the LEED commercial buildings in 174 areas in the United States, Fuerst et al. (2014) revealed that the size of the local market, educational attainment, economic growth, and mandatory policy requirements played a significant role in the prediction of green building market penetration. Focusing on the US East Coast cities, Zhao and Lam (2012) discovered that the LEED policy factor in their model does not play an essential role in predicting the quantity of LEED buildings. Rakha et al. (2018) conducted a state-level analysis of the residential LEED building market in the US, indicating that social demographics (such as household income and statewide GDP per capita) and community policies (related to energy efficiency incentives and adoption of renewable energy) play a significant role in influencing residential LEED projects.

While these studies provided evidence on the spatial dynamics and influencing factors of local green building markets, there are several knowledge gaps in this field. First, although prior research explored the spatial distributions of the green building market and the market's transformation over the past decade (Ma and Cheng 2017; Wu et al. 2021), the green building market develops very fast (Awadh 2017) and previous studies on market distribution should be considered a snapshot of the previous period (Cidell and Cope 2014), which requires updates in a timely manner. Without an up-to-date study, it remains unclear how the green building projects developed so far are distributed geographically. Second, there is a lack of nuanced county-level analysis of the green building market covering the whole US. Previous studies only examined either certain regions such as the leading cities (Fuerst et al. 2014) or counties in the East Coast cities in the US (Zhao and Lam 2012), which can only be generalized to regions and cities with similar sociodemographic and economic bases. Some studies conducted a state-level analysis from a macroscopic scale (Gao et al. 2020; Cidell and Beata 2009), without investigating green building projects at a county level for the whole US. From the perspective of statistics, limited cases may lead to a high risk of bias in analyzing the influencing factors of the green building markets (Ma and Cheng 2017). Third, there is a serious lack of consensus regarding significant factors influencing green building markets. Prior studies investigated green building markets in different regions at various scales and discovered different factors that seem to be statistically significant. These factors include economic growth based on analysis of major cities in the US (Fuerst et al. 2014), as well as population and the number of higher education institutes based on investigation of East Coast cities by Zhao and Lam (2012). Overall, significant drivers for county-level green building markets in the US remain unclear. Furthermore, although previous studies investigated the nonlinear effect of the influencing factors with machine learning techniques (Ma and Cheng 2017), they neglected the influence of neighboring areas in the local green building market analysis (Gao et al. 2020). This may lead to spurious and incomplete conclusions when the influencing factors are spatially correlated with each other (Gao et al. 2020). To account for this spatial spillover effect, spatial correlation and spatial regression analysis should be adopted rather than the traditional linear regression used in previous studies. To address the aforementioned gaps, this research attempts to investigate the geographical imbalance of the US green building markets and develop spatial analysis models to investigate and identify the influencing factors of the market.

Methodology

Data Source and Processing

In line with previous county-level green building market studies, LEED-certified projects were recognized as the green building projects in this study, and the number of LEED-certified projects in each US county was used to measure the development of local green building markets. The data of certified LEED projects were collected from the US Green Building Council's official website (USGBC 2021). After data preprocessing and manual cleaning (including the removal of confidential projects), a total of 33,146 LEED-certified projects were obtained. The location information of these projects was collected and mapped to reveal the county-level geographic distribution of the US green building market.

In terms of influencing factors, we drew on previous studies (Ma and Cheng 2017; Zou et al. 2017; Zhao and Lam 2012) and proposed six categories that comprehensively cover all aspects of the green building market: demography, economy, energy, green building industry, education, and climate (Table 1). Both demographic and economic information represent the overall development situation of the area, and can represent the demand for building as well as the potential of the market. Previous studies demonstrated the promotion effect of the local economy on both demand and supply of the green building market (Ma and Cheng 2017; Zhao and Lam 2012). The energy category refers to the energy cost of building operations, one of the most fundamental elements taken into consideration during the design of green buildings (Eichholtz et al. 2013; Darko et al. 2017). We collected local energy-related price, production, consumption, and expenditure data to investigate their effect on local green building markets. For the green building industry category, the green building company index (Han et al. 2020), green building–related policies (Gou 2019; Choi 2010), and green building professionals (Bruce et al. 2009) were collected or calculated to reflect characteristics of the green building industry in each county. For the education category, because previous studies evaluated the effect of education level on people's decision-making in green buildings (Ahn et al. 2013; Rosner et al. 2022), we considered education level a critical factor for the development of the local green building market. As such, data of adults with a bachelor's degree or higher and the percentage of adults with a bachelor's degree or higher were collected. For the climate category, we utilized heating and cooling degree days, which assess the local heating and cooling needs of the year and additionally have a significant impact on the diffusion of green building technologies (Koebel et al. 2015).

Spatial Statistical Analysis

Spatial Autocorrelation

The spatial autocorrelation method was utilized to reveal the spatial agglomeration effect of the green building market and its potential influencing factors. Spatial autocorrelation is a method to reveal the spatial distribution pattern of objects (Soltani and Askari 2017). Anselin (1998) defined spatial autocorrelation as "the coincidence of value similarity with locational similarity." This method is widely applied in investigations of various market-level studies, including the real estate market (Anselin 1998), to reveal market characteristics with cross-sectional data where the correlation occurs among contiguous units (Barreca et al. 2020; Moralı and Yılmaz 2020; Ismail 2006). Specifically, in building market-related studies, spatial autocorrelation has been used to identify the regional spatial effects of green development in China (Zhang et al. 2020) and to investigate the impact of the Green Mark on the sale price of the apartments in Singapore (Dell'Anna and Bottero 2021). Spatial autocorrelation is also utilized in other domains, such as the electric vehicles (Morton et al. 2018), labor (Pośpiech and Mastalerz-Kodzis 2016), and digital markets (Lutz 2019). The broad implementation of this method in market analysis reveals its practicability in investigating market-level factors and characteristics.

Another reason for our choice of spatial autocorrelation in green building market analysis is the spatial dependence of the market variables. Previous studies in the real estate market identified that

Table 1. Independent variables with potential influence on the US green building markets

Category	Variable	Acronym index	Source	Unit
Demography	1. Population	De_Popu	US Census Bureau	People
	2. Housing units	De_HU	US Census Bureau	Unit
	3. Population density	De_PD	US Census Bureau	People per square mile of land area
	4. Housing unit density	De_HUD	US Census Bureau	Housing units per square mile of land area
Economy	5. Per capita personal income	Ec_PcPI	US Census Bureau	Dollars
	6. Employment rate	Ec_ER	US Bureau of Labor Statistics	Percentage
	7. GDP	Ec_GDP	US Bureau of Economic Analysis	Thousands of dollars
	8. House price index	Ec_HPI	Federal Housing Finance Agency	Index
Energy	9. County total energy consumption	En_Cons	US Census Bureau, US Energy Information Administration	Million Btu
	10. County total energy expenditures	En_Exp	US Census Bureau, US Energy Information Administration	Dollars
	11. Annual energy retail price index	En_Pric	US Census Bureau, US Energy Information Administration	Index
	12. State total energy production of the US share index	En_Pro	US Census Bureau, US Energy Information Administration	Index
Green building industry	13. Green company rank count	Gr_Count	*Engineering News-Record*	Index
	14. Green building requirement policies index	Gr_RPI	US Green Building Council	Index
	15. Green building incentive policies index	Gr_IPI	US Green Building Council	Index
	16. LEED AP count	Gr_AP	US Census Bureau, US Green Building Council	People
Education	17. Adults with bachelor's degree or higher	Edu_Deg	Data US	People
	18. Percentage of adults with bachelor's degree or higher	Edu_Perc	Data US	Percentage
Climate	19. Heating degree days	Cl_Heat	US Energy Information Administration	Degree days
	20. Cooling degree days	Cl_Cool	US Energy Information Administration	Degree days

real estate data are highly spatially dependent (Barreca et al. 2020; Ismail 2006). As noted by Wilhelmsson (2002), spatial autocorrelation must be considered if the analysis seeks to account for spatial effects with the inclusion of distance and submarket variables. Spatial autocorrelation is a more practical method of determining the correlation between the research variable and its spatial location with the statistical degree of spatial autocorrelation: the Moran's I statistic (Gao et al. 2020).

There are two levels of spatial autocorrelation analysis with the Moran's I statistic (Fischer and Getis 2009), namely, the global Moran's I that provides a single index to summarize the spatial pattern of the zone and the local Moran's I that analyzes the subzones to reveal the cluster area of high values (hot spots) or low values (cold spots) (Anselin 1995). Moran's I is calculated based on the following equation:

$$\text{Moran's } I = \frac{n\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_i \sum_j w_{ij}) \sum_i (x_i - \bar{x})^2} \tag{1}$$

where n = number of spatial units indexed by i and j; x_i and x_j = variables of interest; $\bar{x}$ = mean of x; and w_{ij} = matrix with spatial weights that define the spatial structure between units i and j. We utilized the queen contiguity weight matrix, where the criterion defines the neighbors as spatial units sharing a common edge or a common vertex (Anselin and Rey 2014).

The value of Moran's I index ranges from -1 to $+1$, where greater positive values indicate greater degrees of spatial clustering, and the negative values indicate spatial dispersion. In Moran's I index, $+1$ means similar values are in perfect clustering, while -1 means dissimilar values are in a perfect clustering pattern, and 0 means the feature is in a randomly distributed pattern with no autocorrelation (Yin et al. 2018). Based on the Moran's I value, the Z_I score can be further calculated to reveal the level of spatial autocorrelation

$$Z_I = \frac{I - E[I]}{\sqrt{V[I]}} \tag{2}$$

$$E[I] = -1/(n-1) \tag{3}$$

$$V[I] = E[I^2] - E[I]^2 \tag{4}$$

where $E[I]$ = expected value of Moran's I under the null hypothesis of no spatial autocorrelation; and $V[I]$ = variance of I. The Z_I scores and the p-values returned by the pattern analysis indicate whether the null hypothesis can be rejected or not. In this study, the confidence level was set at 99% with p-value < 0.01. A Z_I score >2.58 indicates there is a positive autocorrelation of the variable and justifies the existence of the spatial clustering pattern, while a Z_I score < -2.58 means there is a negative autocorrelation of the variable.

In this study, the global Moran's I and Z_I score of the green building market indicator and the 20 potential influencing variables were computed to reveal their spatial pattern. We also calculated the local Moran's I of these variables to identify the location of the clusters. Distinct from the global Moran's I, the local Moran's I was calculated for every county as a local indicator of spatial association (LISA) to evaluate the clustering in those individual counties. A LISA can provide a location-based statistic with a significance assessment and establish a relationship between the sum of local statistics and the corresponding global statistic (Anselin 1995). The combination of the indication of significance and the value of the local Moran's I in the scatterplot can lead to the classification of significant locations, such as high-high and low-low spatial clusters, as well as high-low and low-high spatial outliers (Anselin 1995). LISA maps were derived from the statistics to indicate the local hot spots (high-high clusters), cold spots (low-low clusters), and irregular regions (high-low, low-high outliers). The LISA maps display the distributions of hot and cold spots of all independent and dependent variables. Some variables could show similar features of spatial distributions, which indicate strong correlations. To statistically test the correlations among the variables, we applied Pearson correlation analysis, which is one of the most universal methods to measure the monotonic association between two variables (Schober et al. 2018).

Spatial Regression Models

In this study, spatial regression analysis reveals the relationships between the local green building market development and its potential influencing factors. The results may be biased in traditional regression models when the variables are spatially autocorrelated (Wu et al. 2020). The spatial regression model can reduce the potential bias and provide higher conformity results (R^2) than other models. We applied two spatial regression models that are frequently used in the spatial statistics and spatial economics literature (Chi and Zhu 2008; Rhee et al. 2016; Fang et al. 2015), namely, the spatial lag model (SLM) and the spatial error model (SEM). These two spatial regression models have been widely used in market analysis with the presence of spatial autocorrelation among dependent and independent variables. For example, Wang et al. (2017) utilized both SLM and SEM to investigate the determinants of housing prices, and Zambrano-Monserrate et al. (2021) used SLM to explore the effect of urban green spaces on the housing market. When a value observed in one location depends on the values observed at neighboring locations, there is a spatial dependence that can be caused by the variables or measurement errors. First, our variables may have an important spatial dynamic, i.e., location and position may drive the variables, forming the basis for SLM. Second, our data collection process may induce measurement error. For instance, the spatial units (counties in this study) at which the data are processed may not reflect the underlying process. This forms the basis for SEM.

Specifically, SLM assumes that the dependent variables influence the dependent variables in the neighboring counties. The equation of the SLM model is shown in Eq. (5)

$$y = \rho W_y + X\beta + \varepsilon \tag{5}$$

where ρ = spatial autocorrelation coefficient; W_y = spatial weight matrix with spatial lag values; β = regression coefficient; X = vector of independent variables; and ε = vector of random error terms.

Different from SLM, SEM assumes that the error term of the regression is spatially autocorrelated, which may be caused by the spatial dependence of independent variables. The equation of the SEM model is shown in Eq. (6)

$$y = X\beta + \lambda W\varepsilon + \delta \tag{6}$$

where β = regression coefficient; X = vector of independent variables; λ = spatial autocorrelation coefficient; $W\varepsilon$ = spatial weight matrix with spatial error values; and δ = vector of the random error terms.

Before implementing the spatial regressions, we must conduct a multicollinearity test, because using redundant information in the regression model might lead to biased coefficient estimates (Salmerón et al. 2018). Variance inflation factors (VIFs) were computed to assess potential multicollinearity problems in the spatial regression analysis (O'brien 2007). The VIF value indicates the variable collinearity: the higher the VIF value, the higher the potential collinearity. A stepwise multiple linear regression was conducted to compute

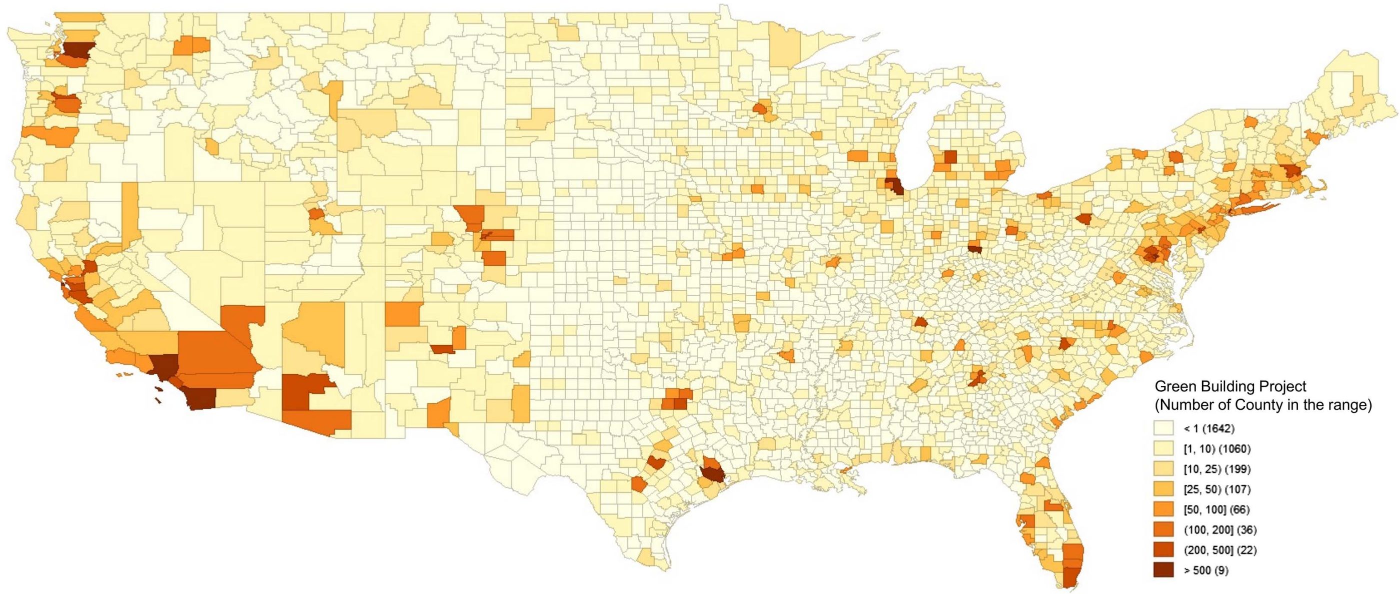

Fig. 1. Geographic distribution of the US green building market. (Sources: Esri, USGS Esri, Garmin, FAO, NOAA, USGS, EPA U.S. Census Bureau.)

VIFs. After calculating VIFs and removing independent variables with high VIF values, the final list of independent variables can be confirmed. Based on the spatial regression decision process, the Lagrange multiplier (LM) test is required in the determination of an appropriate spatial regression model for the statistics (Anselin 2005). The Lagrange multiplier test can evaluate hypotheses about parameters in a likelihood framework, and generate results of the spatial error condition (LM-error index, robust LM-error index) and the results of the spatial lag condition (LM-lag index, robust LM-lag index) (Anselin 2005). The model with a statistically significant LM index and robust LM index would be more appropriate to be applied in the spatial regression (Anselin 2005). If both SLM and SEM show statistical significance in the LM and robust LM index, the model with a higher value in the index would be more appropriate (Anselin 2005). In this study, Geoda software was utilized to run the spatial autocorrelation analysis and spatial regression models.

Results and Discussion

Spatial Distribution of the US Green Building Market and Potential Influencing Factors

The spatial distribution of the green building market in 3,141 counties is shown in Fig. 1. The zone of counties with LEED project between 50 and 200 largely occurs in areas surrounding the zone of counties with LEED projects above 200. For example, California has two clustering centers, namely, Los Angeles (1,297 LEED projects) and San Diego (636 LEED projects). Most of the clustering regions are distributed along the west and east coastal line,s while few clusters lie in the inland area. To further evaluate the spatial clustering characteristic of local green building markets, a queen contiguity weight matrix was developed and utilized to compute the global Moran's I of the green building projects (Table 2). The global Moran's I value of 0.224 (>0, p-value < 0.01) and Z-score value of 21.21 (>2.58, p-value < 0.01) both indicate the existence of a significant and positive spatial autocorrelation characteristic of local green building markets.

The global Moran's I values of the 20 potential influencing factors are listed in Table 2, revealing that most of the factors have significant spatial clustering characteristics. The values further justify the suitability of adopting spatial regression models rather than traditional ordinary least-squares (OLS) regression models. Specifically, 15 independent variables show significant spatial clustering (with global Moran's I value between 0.244 and 0.977), implying these variables in the local counties positively impact the surrounding neighbors. On the contrary, five other variables (population, local total energy consumption, local total energy expenditure, local

Table 2. Global Moran's I values of the variables

Category	Index	Moran's, I	Z-zcore
Green building market development	LEED Projects	0.224*	21.21*
Demography	De_Popu	0.055	5.60
	De_HU	0.360*	35.09*
	De_PD	0.447*	46.04*
	De_HUD	0.362*	41.57*
Economy	Ec_PCPI	0.393*	36.28*
	Ec_EmpR	0.610*	57.48*
	Ec_GDP	0.244*	24.01*
	Ec_HPI	0.608*	57.57*
Energy	En_Cons	0.026	2.48
	En_Exp	0.044	4.39
	En_Pric	0.437*	45.49*
	En_Pro	0.289*	3.94*
Green building industry	Gr_Comp	0.064	5.62
	Gr_AP	0.109	9.84
	Gr_RPI	0.841*	74.41*
	Gr_IPI	0.861*	76.19*
Education	Edu_Adu	0.373*	35.77*
	Edu_Perc	0.435*	4.43*
Climate	Cl_Heat	0.977*	89.59*
	Cl_Cool	0.964*	88.14*

Note: *p-value < 0.01.

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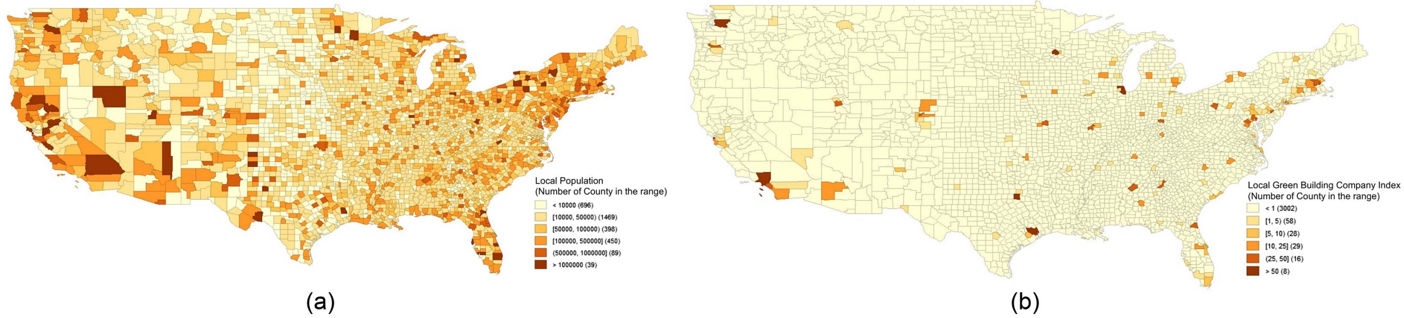

Fig. 2. Spatial distribution of (a) population; and (b) green building company index in the US. (Sources: Esri, USGS Esri, Garmin, FAO, NOAA, USGS, EPA U.S. Census Bureau.)

green company index, and local LEED APs) are not significantly clustered. The reasons for this spatial randomness vary. For the population variable, the spatial distribution pattern is random without a clustering tendency [Fig. 2(a)], while for the local green company index, the number of counties with a local green building market is very low compared to the total number of counties in the US, leading to the random clustering pattern [Fig. 2(b)].

Local Moran's I values were further calculated to reveal the county-level hot spots of these variables (Figs. 3 and 4). The high-high areas demonstrate that the county and its surrounding areas both have high local Moran's I values. Similarly, the low-low areas indicate that the county has low values and is also surrounded by counties with low values. As shown in Fig. 3, for county-level green building markets, most of the high-high areas are cities, such as Seattle, Denver, Los Angeles, San Francisco, Chicago, Atlanta, Miami, Washington, DC, Philadelphia, New York, and Boston. On the other hand, the low-low areas lie in the central part of the country.

In terms of the independent variables (potential influencing factors), three types of spatial distribution patterns can be identified based on their LISA maps (Fig. 4). The first group of variables shows a similar spatial clustering pattern as the green building projects, namely, the clustering of high (low) values in metropolitan (central and rural) areas. These variables include population, number of housing units, GDP, total energy consumption, and number of adults with a bachelor's degree or higher. These variables may be closely correlated with local green building market development beecause they share similar spatial clustering patterns. The second group of variables demonstrates clear clustering patterns at the state level, including the green requirement policies index, green incentive policies index, and heating and cooling degree days. For the green building–related policies indexes, the hot spots occur in Washington, California, Colorado, Florida, and New York. The remaining variables have various spatial clustering patterns. For example, employment rates display hot spots (high-high clustering) in the central area and cold spots (low-low clustering) in the coastal areas, the inverse of the geographical features of the house price index.

Because the preceding spatial autocorrelation analysis indicates the dependent variable (number of green buildings) and some independent variables (the 20 influencing factors) share similar spatial distribution patterns, a correlation analysis between the variables was conducted. Pearson correlation coefficients of all variables used in this study are given in Table 3. All of the independent variables are significantly correlated with the dependent variable, with various correlation levels. Some influencing factors demonstrate a strong

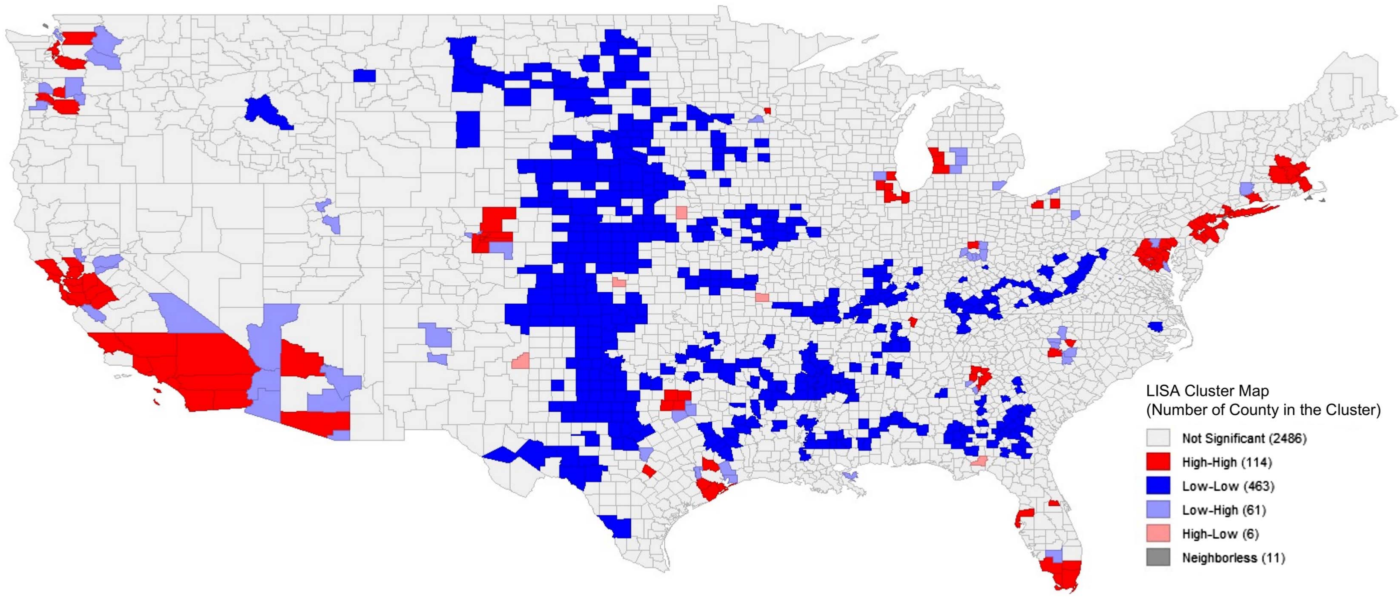

Fig. 3. LISA map of green building projects. (Sources: Esri, USGS Esri, Garmin, FAO, NOAA, USGS, EPA U.S. Census Bureau.)

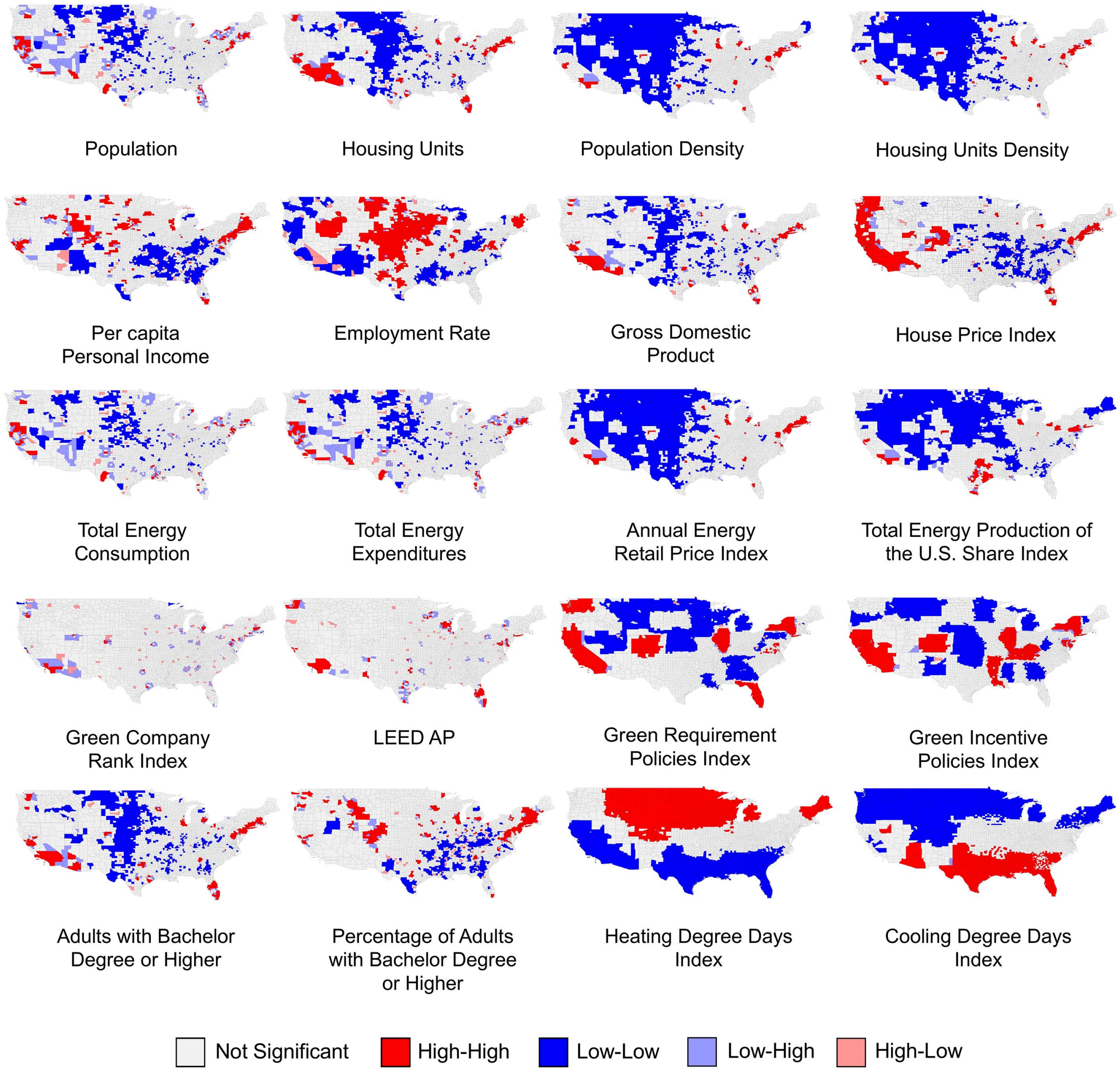

Fig. 4. LISA map of the independent variables. (Sources: Esri, USGS Esri, Garmin, FAO, NOAA, USGS, EPA U.S. Census Bureau.)

correlation with the number of local green building projects, such as demographic variables (e.g., the number of housing units), economy variables (e.g., per capita personal income, GDP, and house price index), energy variables (e.g., the price index and production index), green building industry variables, and education variables. On the other hand, some variables demonstrate a negligible correlation with the local green building market, such as population, employment rate, total energy expenditures, total energy consumption, and climate variables.

Significant Influencing Factors of the US Green Building Market

Table 3 shows that among the 20 influencing factors, some are strongly correlated with each other. For instance, within the same factor category, the local population density and housing unit density share a high correlation coefficient of 0.99, and between different categories, the numbers of adults with a bachelor's degree and GDP are closely correlated with a correlation coefficient of 0.91. The high correlation between certain pairs of variables indicates potential multicollinearity issues. Therefore, VIFs of variables are computed to assess multicollinearity (Table 4). Based on the Pearson correlation results and the VIF values, four independent variables with large VIF values were excluded, namely, population density, housing unit density, energy expenditure index, and the number of adults with a bachelor's degree. After removing these four variables, the new VIF testing shows all VIFs are below 10, which is the commonly used threshold for VIF testing (Salmerón et al. 2018). A VIF score of the independent variable larger than 10 indicates excessive collinearity. As such, the remaining 16 independent variables passed the multicollinearity testing, and were then applied in the spatial regression models.

To determine the most suitable spatial regression model, a LM test was conducted. As shown in Table 5, the LM test statistic for the spatial lag statistics is not statistically significant (p-value > 0.05), while the LM test statistic for the spatial error statistics is highly significant (p-value < 0.01). In addition, the value of the spatial error model (22.825) is much higher than that of the spatial lag model (0.088), which indicates there is a strong spatial dependence in the spatial error model and it would perform better than the spatial lag model (Yin et al. 2018). The results of the robust LM test also show that the spatial error model is more appropriate to use in this study

Table 3. Pearson correlation coefficients of the variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
2	0.08**	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
3	0.06**	0.37**	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
4	0.05**	0.33**	0.99**	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
5	0.15**	0.27**	0.28**	0.29**	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
6	−0.03	0.03*	0.03	0.02	0.30**	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
7	0.06**	0.88**	0.55**	0.56**	0.36**	0.05*	—	—	—	—	—	—	—	—	—	—	—	—	—	—
8	0.20**	0.50**	0.26**	0.23**	0.49**	0.13**	0.43**	—	—	—	—	—	—	—	—	—	—	—	—	—
9	0.93**	0.05*	0.03	0.03	0.11**	−0.03	0.04	0.14**	—	—	—	—	—	—	—	—	—	—	—	—
10	0.99**	0.07**	0.05**	0.04*	0.14**	−0.03	0.05**	0.19**	0.97**	—	—	—	—	—	—	—	—	—	—	—
11	0.06**	0.34**	0.99**	0.98**	0.27**	0.02	0.53**	0.24**	0.04*	0.05**	—	—	—	—	—	—	—	—	—	—
12	0.04*	0.45**	0.61**	0.60**	0.21**	0.01	0.53**	0.24**	0.03	0.04*	0.58**	—	—	—	—	—	—	—	—	—
13	0.04*	0.62**	0.54**	0.56**	0.29**	0.04	0.80**	0.29**	0.03	0.04*	0.52**	0.55**	—	—	—	—	—	—	—	—
14	0.06**	0.46**	0.39**	0.41**	0.24**	0.01	0.56**	0.27**	0.04*	0.05**	0.38**	0.32**	0.6**	—	—	—	—	—	—	—
15	0.21**	0.31**	0.17**	0.16**	0.16**	−0.08**	0.27**	0.35**	0.12**	0.17**	0.17**	0.10**	0.17**	0.22**	—	—	—	—	—	—
16	0.16**	0.21**	0.14**	0.13**	0.11**	−0.15**	0.18**	0.23**	0.10**	0.13**	0.15**	0.08**	0.10**	0.11**	0.65**	—	—	—	—	—
17	0.08**	0.97**	0.40**	0.38**	0.34**	0.06**	0.91**	0.53**	0.05**	0.07**	0.38**	0.44**	0.67**	0.51**	0.31**	0.21**	—	—	—	—
18	0.09**	0.34**	0.23**	0.22**	0.66**	0.33**	0.33**	0.59**	0.05**	0.08**	0.20**	0.18**	0.25**	0.22**	0.20**	0.11**	0.40**	—	—	—
19	−0.09**	−0.1**	−0.01	−0.01	0.23**	0.18**	−0.06**	−0.01	−0.10**	−0.10**	0.00	−0.06**	−0.01	−0.05**	−0.15**	−0.08**	−0.07**	0.17**	—	—
20	0.02	0.02	−0.03	−0.02	−0.23**	−0.05**	0.00	−0.15**	0.05**	0.03	−0.03	0.04*	−0.03	0.03	0.01	−0.06**	−0.01*	−0.21**	−0.89**	—
LEED projects	0.074**	0.835**	0.401**	0.399**	0.313**	0.045*	0.876**	0.475**	0.045*	0.064**	0.379**	0.432**	0.767**	0.578**	0.267**	0.162**	0.88**	0.34**	−0.056**	−0.018**

Note: $^{*}p$-value < 0.05; and $^{**}p$-value < 0.01.

Table 4. Variance inflation factor of independent variables

Category	Index	VIF	VIF (after feature selection)
Demography	De_Popu	98.7	8.4
	De_HU	19.9	6.2
	De_PD	203.7	—
	De_HUD	104.3	—
Economy	Ec_PCPI	2.2	2.2
	Ec_EmpR	1.3	1.3
	Ec_GDP	2.0	9.8
	Ec_HPI	2.4	2.3
Energy	En_Cons	5.3	8.0
	En_Exp	249.5	—
	En_Pric	99.7	2.0
	En_Pro	2.1	1.8
Green building industry	Gr_Comp	3.6	3.6
	Gr_AP	1.7	1.7
	Gr_RPI	2.0	2.0
	Gr_IPI	1.8	1.8
Education	Edu_Adu	32.0	—
	Edu_Perc	2.6	2.3
Climate	Cl_Heat	6.8	6.7
	Cl_Cool	6.6	6.5

Table 5. LM test results

Test	Value	p-value
LM (spatial lag)	0.088	0.765
Robust LM (spatial lag)	6.027	0.014
LM (spatial error)	22.825	0.001
Robust LM (spatial error)	28.763	0.001

compared to the spatial lag model. Therefore, we selected the spatial error model to develop the spatial regression model for the analysis.

After standard normalization, the 16 selected independent variables and the dependent variable (number of LEED projects) were applied in the SEM. Table 6 presents the results of the SEM estimates across the entire sample of 3,141 US counties. The R^2 of SEM 1 is 0.84, and the Akaike information criterion (AIC) value of the model is 3,268.79, which are both indicators of the goodness of fit for the spatial model. The Moran's I of residuals of the model is very close to zero, indicating that introducing the spatial error model to allow the spatial correlation of the error terms reduces the spatial autocorrelation of the residuals and thus improves the model fitness. However, the coefficients of some variables are significant while others are not. The insignificant factors are local population, employment rate, local energy consumption index, two variables regarding the green building industry, and variables in the education and climate categories. In addition to these insignificant variables, some variables have a very low coefficient (lower than 0.1), which suggests these variables explain very little variance of the dependent variable (the number of green buildings). These variables include per capita personal income, energy price index, energy production index, and LEED AP counts. These variables, together with the insignificant variables, were removed from the independent variable data set and the SEM was reestimated to generate SEM 2 as shown in Table 6. All variables retained in SEM 2 are significant. The results of R^2, AIC, and the Schwarz criterion (SC) all indicate the model performance of SEM 2 is not reduced compared to SEM 1 (Table 6).

Table 6. Spatial error model coefficients and performance

Category	Variable	SEM 1	SEM 2
	Constant	0.00	0.00
Demography	De_Popu	0.01	—
	De_HU	0.31*	0.37*
Economy	Ec_PCPI	−0.03*	—
	Ec_EmpR	0.00	—
	Ec_GDP	0.39*	0.32*
	Ec_HPI	0.10*	0.09*
Energy	En_Cons	0.00	—
	En_Pric	−0.09*	—
	En_Pro	−0.05*	—
Green company industry	Gr_Comp	0.25*	0.26*
	Gr_AP	0.09*	—
	Gr_RPI	0.01	—
	Gr_IPI	−0.03	—
Education	Edu_Perc	0.01	—
Climate	Cl_Heat	−0.02	—
	Cl_Cool	−0.03	—
Model performance	Lambda	0.21*	0.27*
	R^2	0.84	0.83
	Log likelihood	−1,617.39	−1,732.7
	AIC	3,268.79	3,475.41
	SC	3,371.68	3,505.67
	Moran's I of residuals	−0.01*	−0.01*

Note: *p-value < 0.05.

SEM 2 suggests that three key influencing factors, namely, the number of housing units, local GDP, and green building company index, explain the most variance of LEED project numbers across the US counties. Specifically, the number of housing units in the local area represents the county scale, and previous studies indicated a strong correlation with local green building market development (Ma and Cheng 2017). Local GDP measures the local economic development (Chernis et al. 2020), and previous studies confirmed its strong association with the green building market (Zou et al. 2017; Ma et al. 2017). Green building projects are abundant in a region with a strong economy, as reflected by its high GDP. In addition, as the economy develops, it gradually transitions from a consumption orientation to a greener outlook, where companies tend to invest more in sustainability and environmental protection (Gibbs and O'Neill 2012), facilitating the green building market. Previous studies have not specifically investigated the impact of the number of green building companies on local green building market development. This study reveals that the number of green companies is a key influencing factor. Local green building companies tend to develop green buildings locally before entering markets in other regions (Chan et al. 2009). These local green companies also act as role models for traditional building companies in the region, accelerating the diffusion of green buildings (Yang and Zou 2014). Compared to these three key influencing factors, the house price index is statistically significant but with a much lower coefficient. This might be because a considerable percentage of green buildings are public buildings such as government buildings, hospitals, and schools (Olubunmi et al. 2016), which naturally have little association with real estate prices. This result is also in line with Zou et al. (2017), who found that real estate price has a minimal impact on the number of green buildings in Chinese provinces. Apart from the influence of these three key variables, the significant coefficient of 0.21 for lambda in the spatial weight matrix indicates that these variables in the neighboring areas have a positive spillover effect on local green building market development. In other words, the number of green buildings in a focal county is not only influenced by the GDP, number of housing units, and number of green building companies in this county, but is also impacted by these factors in neighboring counties.

All other variables do not show high explanatory power in the model. Specifically, this study reveals that county population, per capita personal income, and employment rate do not significantly impact the number of green buildings. This suggests it is the economic capacity of the county reflected by its GDP, rather than its population or employment rate, that has a significant impact on green building development. This study reveals that per capita personal income does not have a high impact on green building development. This finding contrasts previous studies such as Ma and Cheng (2017), who demonstrated that personal income has a large numerical impact on identifying the leading counties in green building development. The present study suggests that with the inclusion of all counties as study subjects, personal income does not strongly influence the number of green buildings. Feldstein (2017) suggested that personal income only illustrates the wealth level of individuals without reflecting the overall economic capacity of the whole county. Some counties may have high per capita income but a small population, which leads to low GDP. Because the dependent variable is the absolute number rather than the percentage of green buildings in the county, the scale of the economy matters more than per capita indicators such as personal income. Similarly, this study reveals that all variables related to energy and climate do not strongly influence the number of green buildings. This is echoed by Zou et al. (2017), who found that energy-related factors are not significant in promoting green buildings at present.

Besides climate- and energy-related factors, this study also indicates that policy-related factors (including regulatory and incentive policies) are insignificant in differentiating green building development in different counties. There is currently no consensus regarding the role of policies in promoting green building development. Some studies suggest policies play a significant role; for example, Rakha et al. (2018) indicated that policies (particularly policies focusing on energy efficiency incentives and renewable energy adoption) significantly influence the residential LEED building market in the US. Other studies revealed that different policies may have various significance in promoting green buildings. For instance, using an OLS regression analysis, Choi (2010) investigated the impact of regulations and incentives on green building designations in US central cities, finding that municipal regulatory policy is a useful tool to promote green office building designations, while incentive-based policies are not effective. Fuerst et al. (2014) found that only mandatory requirements impact LEED commercial buildings in the US, while Zou et al. (2017) demonstrated that incentive policies such as subsidies are statistically significant for promoting green buildings, but regulatory policies are not significant in China. Another stream of research found that policies have no significant impact on green building development. Ma and Cheng (2017) indicated that policies may not be a robust differentiable factor for green buildings, because the US is now a developed green building market and many counties have already implemented policies. This is echoed by Zhao and Lam (2012), who found unexpectedly that the direct policy factor in their model does not show an important role in predicting the quantity of LEED buildings. Interestingly, Cidell and Cope (2014) found that there is a statistically significant relationship between municipal green building policy and the number of registered green buildings but not with the number of certified buildings. These mixed findings are likely due to the varying samples used to investigate green buildings in different regions and different periods of time. By analyzing the latest, county-level data sets for green buildings covering more than 3,000 counties in the US, this study finds that policies (including both regulatory and incentive policies) do not show statistical significance in differentiating the number of green buildings in different counties. This is in line with the argument of Ma and Cheng (2017), who indicated that policies are no longer a differentiable factor for green buildings because most counties have already established suitable policies.

Contributions to the Global Body of Knowledge

This study contributes to the global body of knowledge both theoretically and practically. Theoretically, this study reveals the existence of a geographical imbalance and identifies the significant influencing factors in green building development based on evidence from the US. The geographical distribution pattern of the green building market is identified with up-to-date data (LEED-certified projects), which accommodate the fast-growing green building market (Awadh 2017) and provide the latest snapshot of green building market development. This empirical study also explores the green building market at a more detailed scale (county level) with more cases across the country (3,141 counties in the US) compared with previous studies (Ma and Cheng 2017; Cidell and Cope 2014; Gao et al. 2020). Future research seeking to explore the spatial distribution and evolution of the green building market in the US can rely on previous literature (Ma and Cheng 2017; Kaza et al. 2013; Cidell and Cope 2014) and findings in the present study to investigate the spatial-temporal development of the market.

From a methodological perspective, this study highlights the application of spatial analysis techniques, such as spatial autocorrelation and regression, in the investigation of the green building market. Previous studies such as Zou et al. (2017) relied on descriptive statistics to investigate the spatial distribution of green buildings, and Ma and Cheng (2017) used density-based clustering analysis to demonstrate a geographical imbalance of green building development. Distinct from prior studies, this study used spatial autocorrelation analysis with specific statistical measures, namely, the global and local Moran's I statistic, to investigate the US green building market, statistically proving significant spatial clustering phenomenon does exist in the national green building distribution. The spatial statistical techniques employed in this study provide new perspectives for understanding the distribution of green building markets globally.

Furthermore, previous studies, based on various data samples, primarily developed traditional regression or classification models to identify factors that influence green building market development, such as the logistic and linear regression models developed by Cidell and Cope (2014) and various classification models (e.g., logistic regression, support vector machine, random forest) proposed by Ma and Cheng (2017). These traditional regression and classification analyses are not able to capture the spatial spillover effect revealed by this study, whereby green building development in a region could be impacted by factors not only within this region, but also in its neighboring regions (Li and Gan 2021). Different from previous studies, this study takes this spillover effect into consideration by using spatial regression models rather than the widely used ordinary least-squares regression models to identify the significant influencing factors of green building markets. The spatial regression model developed in this study highlights three key influencing factors, namely, the number of housing units, local GDP, and local green building company development, in influencing local green building markets. Of these factors, local green building company development is novel. The spatial regression model developed in this study also echoes the call by Wu et al. (2021) to build new analysis models for the green building market. The significant spatial clustering phenomenon and the revealed spatial spillover effect all contribute to knowledge discovery of green buildings globally.

Practically, this study offers important decision-making implications for relevant stakeholders of green building development. Building and construction enterprises face increasing pressure to transition toward sustainability (Chang et al. 2016b) and need to make decisions on sustainable construction practices such as undertaking green building projects. For green building companies, the spatial autocorrelation in this study shows that green buildings do significantly cluster in certain counties and the spatial regression results show that factors such as GDP and number of housing units in surrounding regions impact the number of green buildings in a county. This offers important references for companies to optimize their market entry strategies of developing green buildings.

For local governments, this study reveals that the continuous development of mature green building markets, such as the US market investigated in this study, is dependent on the economic development of the corresponding regions. This is an important implication for not only other mature green building markets such as the UK market, but also developing green building markets such as the China market. Incentive policies and regulations could differentiate local green building market development at the initial stage to a certain degree, as indicated in Zou et al. (2017), who found incentive policies show statistical significance in differentiating provincial green building developments in China. However, once the market grows to a certain scale, incentive policies lose their effectiveness; instead, local GDP separates green building markets, as discovered by this study. Therefore, by investigating the significant factors influencing the largest national green building market in the world, namely, the US market, this study offers important policy implications and lessons to all other countries and regions, regardless of their development stage in the local green building markets. At the initial stage of promoting the local green building market, the incentive policies can greatly help the market development, while for the long term, economic development of the corresponding regions is still the major factor driving green building market growth.

The findings in this study provide a reference for building companies' decision-making of region selection to develop green building projects, and for the government to formulate geographically specific policies to enable a more balanced green building market development at the national level. Future studies can rely on the findings in this study to further explore the strategic actions these stakeholders should take to accommodate or alleviate the spatial imbalance phenomena of the green building market.

Conclusion

This study identified spatial patterns of US local green building markets by investigating 33,146 LEED-certified projects in 3,141 counties using spatial autocorrelation analysis. It further investigated the factors influencing the spatial distribution of green building projects in these counties. The Moran's I value of 0.224 indicates spatial clustering in US green building development, with the LISA map identifying development hot spots (high-high clustering areas). After feature selection through Pearson correlation analysis and variance inflation factor analysis, 16 factors were chosen among the total of 20 factors to be input in the spatial error model. The model reached high performance with an R^2 value of 0.83. Based on the coefficients of the influential features in the model, we identified three important factors in differentiating the number of green buildings in different counties: the number of housing units, local gross domestic product, and the green building company index. The spatial weight matrix played a significant role in the model, which indicates the development of green building markets in neighboring areas has a significant effect on the local green building market in the counties. Differing from previous studies investigating the spatial patterns using merely descriptive statistics, this study utilized spatial autocorrelation to quantitatively evaluate the geographical imbalance of the US green building market. Related studies often neglect the spatial spillover effects of potential influencing factors. The spatial regression models developed in this study take the spatial spillover effects of influential factors into consideration, and thus form an unbiased spatial numerical analysis and a more precise green building market model. Drawing on the lessons from this study, future studies could also employ spatial autocorrelation and regression analysis to investigate other building markets.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Abdallah, M., K. El-Rayes, and L. Liu. 2016. "Minimizing upgrade cost to achieve LEED certification for existing buildings." *J. Constr. Eng. Manage.* 142 (2): 04015073. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001053.

Abidin, N. Z., and N. Z. M. Azizi. 2021. "Soft cost elements: Exploring management components of project costs in green building projects." *Environ. Impact Assess. Rev.* 87 (May): 106545. https://doi.org/10.1016/j.eiar.2020.106545.

Adekanye, O. G., A. Davis, and I. L. Azevedo. 2020. "Federal policy, local policy, and green building certifications in the US." *Energy Build.* 209 (Feb): 109700. https://doi.org/10.1016/j.enbuild.2019.109700.

Ahmad, T., A. A. Aibinu, and A. Stephan. 2019. "Managing green building development—A review of current state of research and future directions." *Build. Environ.* 155 (May): 83–104. https://doi.org/10.1016/j.buildenv.2019.03.034.

Ahn, Y. H., A. R. Pearce, Y. Wang, and G. Wang. 2013. "Drivers and barriers of sustainable design and construction: The perception of green building experience." *Int. J. Sustainable Build. Technol. Urban Dev.* 4 (1): 35–45. https://doi.org/10.1080/2093761X.2012.759887.

Anselin, L. 1995. "Local indicators of spatial association—LISA." *Geogr. Anal.* 27 (2): 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Anselin, L. 1998. "GIS research infrastructure for spatial analysis of real estate markets." *J. Hous. Res.* 9 (1): 113–133. https://doi.org/10.1080/10835547.1998.12091930.

Anselin, L. 2005. *Exploring spatial data with GeoDaTM: A workbook*. Urbana, IL: Center for Spatially Integrated Social Science.

Anselin, L., and S. J. Rey. 2014. *Modern spatial econometrics in practice: A guide to GeoDa*. Chicago: GeoDa Press.

Awadh, O. 2017. "Sustainability and green building rating systems: LEED, BREEAM, GSAS and Estidama critical analysis." *J. Build. Eng.* 11 (Feb): 25–29. https://doi.org/10.1016/j.jobe.2017.03.010.

Barreca, A., R. Curto, and D. Rolando. 2020. "Urban vibrancy: An emerging factor that spatially influences the real estate market." *Sustainability* 12 (1): 346. https://doi.org/10.3390/su12010346.

Bruce, R. D., R. J. Gebken, and S. D. Strong. 2009. "The impact of the leadership in energy and environmental design accredited professional (LEED-AP) credential on prime/general contractor employees." *Int. J. Constr. Educ. Res.* 5 (3): 182–196. https://doi.org/10.1080/15577770903152807.

Chan, E. H. W., Q. K. Qian, and P. T. I. Lam. 2009. "The market for green building in developed Asian cities—The perspectives of building designers." *Energy Policy* 37 (8): 3061–3070. https://doi.org/10.1016/j.enpol.2009.03.057.

Chang, R.-D., V. Soebarto, Z.-Y. Zhao, and G. Zillante. 2016a. "Facilitating the transition to sustainable construction: China's policies." *J. Cleaner Prod.* 131 (May): 534–544. https://doi.org/10.1016/j.jclepro.2016.04.147.

Chang, R.-D., J. Zuo, V. Soebarto, Z.-Y. Zhao, G. Zillante, and X.-L. Gan. 2016b. "Sustainability transition of the Chinese construction industry: Practices and behaviors of the leading construction firms." *J. Manage. Eng.* 32 (4): 05016009. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000439.

Chang, R.-D., J. Zuo, V. Soebarto, Z.-Y. Zhao, G. Zillante, and X.-L. Gan. 2017. "Discovering the transition pathways toward sustainability for construction enterprises: Importance-performance analysis." *J. Constr. Eng. Manage.* 143 (6): 04017013. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001295.

Chang, R.-D., J. Zuo, Z.-Y. Zhao, V. Soebarto, Y. Lu, G. Zillante, and X.-L. Gan. 2018. "Sustainability attitude and performance of construction enterprises: A China study." *J. Cleaner Prod.* 172 (Aug): 1440–1451. https://doi.org/10.1016/j.jclepro.2017.10.277.

Chernis, T., C. Cheung, and G. Velasco. 2020. "A three-frequency dynamic factor model for nowcasting Canadian provincial GDP growth." *Int. J. Forecasting* 36 (3): 851–872. https://doi.org/10.1016/j.ijforecast.2019.09.006.

Chi, G., and J. Zhu. 2008. "Spatial regression models for demographic analysis." *Popul. Res. Policy Rev.* 27 (1): 17–42. https://doi.org/10.1007/s11113-007-9051-8.

Choi, E. 2010. "Green on buildings: The effects of municipal policy on green building designations in America's central cities." *J. Sustainable Real Estate* 2 (1): 1–21. https://doi.org/10.1080/10835547.2010.12091802.

Cidell, J., and A. Beata. 2009. "Spatial variation among green building certification categories: Does place matter?" *Landscape Urban Plann.* 91 (3): 142–151. https://doi.org/10.1016/j.landurbplan.2008.12.001.

Cidell, J., and M. A. Cope. 2014. "Factors explaining the adoption and impact of LEED-based green building policies at the municipal level." *J. Environ. Plann. Manage.* 57 (12): 1763–1781. https://doi.org/10.1080/09640568.2013.835714.

Cole, R. J., and M. Jose Valdebenito. 2013. "The importation of building environmental certification systems: International usages of BREEAM and LEED." *Build. Res. Inf.* 41 (6): 662–676. https://doi.org/10.1080/09613218.2013.802115.

Darko, A., A. P. C. Chan, E. E. Ameyaw, B.-J. He, and A. O. Olanipekun. 2017. "Examining issues influencing green building technologies adoption: The United States green building experts' perspectives." *Energy Build.* 144 (Jun): 320–332. https://doi.org/10.1016/j.enbuild.2017.03.060.

Dell'Anna, F., and M. Bottero. 2021. "Green premium in buildings: Evidence from the real estate market of Singapore." *J. Cleaner Prod.* 286 (Mar): 125327. https://doi.org/10.1016/j.jclepro.2020.125327.

Dwaikat, L. N., and K. N. Ali. 2018. "The economic benefits of a green building—Evidence from Malaysia." *J. Build. Eng.* 18 (Jul): 448–453. https://doi.org/10.1016/j.jobe.2018.04.017.

Eichholtz, P., N. Kok, and J. M. Quigley. 2013. "The economics of green building." *Rev. Econ. Stat.* 95 (1): 50–63. https://doi.org/10.1162/REST_a_00291.

Fang, C., H. Liu, G. Li, D. Sun, and Z. Miao. 2015. "Estimating the impact of urbanization on air quality in China using spatial regression models." *Sustainability* 7 (11): 15570–15592. https://doi.org/10.3390/su71115570.

Feldstein, M. 2017. "Underestimating the real growth of GDP, personal income, and productivity." *J. Econ. Perspect.* 31 (Feb): 145–164. https://doi.org/10.1257/jep.31.2.145.

Fischer, M. M., and A. Getis. 2009. *Handbook of applied spatial analysis: Software tools, methods and applications*. New York: Springer.

Franco, M. A. J. Q., P. Pawar, and X. Wu. 2021. "Green building policies in cities: A comparative assessment and analysis." *Energy Build.* 231 (Aug): 110561. https://doi.org/10.1016/j.enbuild.2020.110561.

Fuerst, F., C. Kontokosta, and P. McAllister. 2014. "Determinants of green building adoption." *Environ. Plann. B: Plann. Des.* 41 (3): 551–570. https://doi.org/10.1068/b120017p.

Gao, Y., G. Yang, and Q. Xie. 2020. "Spatial-temporal evolution and driving factors of green building development in China." *Sustainability* 12 (7): 2773. https://doi.org/10.3390/su12072773.

Gibbs, D., and K. O'Neill. 2012. "Green entrepreneurship: Building a green economy?—Evidence from the UK." In *Social and sustainable enterprise: Changing the nature of business*. London: Emerald Group.

Gou, Z. 2019. *Green building in developing countries: Policy, strategy and technology.* New York: Springer.

Gultekin, P., S. Mollaoglu-Korkmaz, D. R. Riley, and R. M. Leicht. 2013. "Process indicators to track effectiveness of high-performance green building projects." *J. Constr. Eng. Manage.* 139 (12): A4013005. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000771.

Han, Y., T. He, R. Chang, and R. Xue. 2020. "Development trend and segmentation of the US green building market: Corporate perspective on green contractors and design firms." *J. Constr. Eng. Manage.* 146 (11): 05020014. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001924.

Ismail, S. 2006. "Spatial autocorrelation and real estate studies: A literature review." *Malays. J. Real Estate* 1 (1): 1–13.

Johansson, O. 2012. "The spatial diffusion of green building technologies: The case of leadership in energy and environmental design (LEED) in the United States." *Int. J. Technol. Manage. Sustainable Dev.* 10 (3): 251–266. https://doi.org/10.1386/tmsd.10.3.251_1.

Kaza, N., T. W. Lester, and D. A. Rodriguez. 2013. "The spatio-temporal clustering of green buildings in the United States." *Urban Stud.* 50 (16): 3262–3282. https://doi.org/10.1177/0042098013484540.

Khoshbakht, M., Z. Gou, Y. Lu, X. Xie, and J. Zhang. 2018. "Are green buildings more satisfactory? A review of global evidence." *Habitat Int.* 74 (Feb): 57–65. https://doi.org/10.1016/j.habitatint.2018.02.005.

Kim, J.-L., M. Greene, and S. Kim. 2014. "Cost comparative analysis of a new green building code for residential project development." *J. Constr. Eng. Manage.* 140 (5): 05014002. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000833.

Koebel, C. T., A. P. McCoy, A. R. Sanderford, C. T. Franck, and M. J. Keefe. 2015. "Diffusion of green building technologies in new housing construction." *Energy Build.* 97 (Aug): 175–185. https://doi.org/10.1016/j.enbuild.2015.03.037.

Li, C., and Y. Gan. 2021. "The spatial spillover effects of green finance on ecological environment—Empirical research based on spatial econometric model." *Environ. Sci. Pollut. Res.* 28 (5): 5651–5665. https://doi.org/10.1007/s11356-020-10961-3.

Lin, Y.-H., M.-D. Lin, K.-T. Tsai, M.-J. Deng, and H. Ishii. 2021. "Multi-objective optimization design of green building envelopes and air conditioning systems for energy conservation and CO_2 emission reduction." *Sustainable Cities Soc.* 64 (Jun): 102555. https://doi.org/10.1016/j.scs.2020.102555.

Liu, G., X. Li, Y. Tan, and G. Zhang. 2020. "Building green retrofit in China: Policies, barriers and recommendations." *Energy Policy* 139 (May): 111356. https://doi.org/10.1016/j.enpol.2020.111356.

Lutz, S. U. 2019. "The European digital single market strategy: Local indicators of spatial association 2011–2016." *Telecommun. Policy* 43 (5): 393–410. https://doi.org/10.1016/j.telpol.2018.10.003.

Ma, G., J. Lin, N. Li, and J. Zhou. 2017. "Cross-cultural assessment of the effectiveness of eco-feedback in building energy conservation." *Energy Build.* 134 (Jan): 329–338. https://doi.org/10.1016/j.enbuild.2016.11.008.

Ma, J., and J. C. Cheng. 2017. "Identification of the numerical patterns behind the leading counties in the US local green building markets using data mining." *J. Cleaner Prod.* 151 (May): 406–418. https://doi.org/10.1016/j.jclepro.2017.03.083.

Malmberg, A., and P. Maskell. 2002. "The elusive concept of localization economies: Towards a knowledge-based theory of spatial clustering." *Environ. Plan. A Econ. Space* 34 (Mar): 429–449. https://doi.org/10.1068/a3457.
Moralı, O., and N. Yılmaz. 2020. "An analysis of spatial dependence in real estate prices." *J. Real Estate Finance Econ.* 64 (Oct): 93–115. https://doi.org/10.1007/s11146-020-09794-1.
Morton, C., J. Anable, G. Yeboah, and C. Cottrill. 2018. "The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom." *J. Transp. Geogr.* 72 (Sep): 119–130. https://doi.org/10.1016/j.jtrangeo.2018.08.020.
O'brien, R. M. 2007. "A caution regarding rules of thumb for variance inflation factors." *Qual. Quant.* 41 (5): 673–690. https://doi.org/10.1007/s11135-006-9018-6.
Olanipekun, A. O., B. Xia, C. Hon, and Y. Hu. 2017. "Project owners' motivation for delivering green building projects." *J. Constr. Eng. Manage.* 143 (9): 04017068. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001363.
Olubunmi, O. A., P. B. Xia, and M. Skitmore. 2016. "Green building incentives: A review." *Renewable Sustainable Energy Rev.* 59 (Nov): 1611–1621. https://doi.org/10.1016/j.rser.2016.01.028.
Petrullo, M., S. Jones, B. Morton, and A. Lorenz. 2018. *World green building trends 2018 SmartMarket report*. Hamilton, NJ: Dodge Data & Analytics.
Pośpiech, E., and A. Mastalerz-Kodzis. 2016. "A spatial and temporal analysis of labour market characteristics." *Folia Oeconomica Stetinensia* 16 (2): 60. https://doi.org/10.1515/foli-2016-0025.
Prum, D. A., and T. Kobayashi. 2014. "Green building geography across the United States: Does governmental incentives or economic growth stimulate construction?" *Real Estate Law J.* 43 (1): 5–37.
Rakha, T., T. W. Moss, and D. Shin. 2018. "A decade analysis of residential LEED buildings market share in the United States: Trends for transitioning sustainable societies." *Sustainable Cities Soc.* 39 (Aug): 568–577. https://doi.org/10.1016/j.scs.2018.02.040.
Raouf, A. M., and S. G. Al-Ghamdi. 2019. "Effectiveness of project delivery systems in executing green buildings." *J. Constr. Eng. Manage.* 145 (10): 03119005. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001688.
Rhee, K. A., J. K. Kim, Y. I. Lee, and G. F. Ulfarsson. 2016. "Spatial regression analysis of traffic crashes in Seoul." *Accid. Anal. Prev.* 91 (Sep): 190–199. https://doi.org/10.1016/j.aap.2016.02.023.
Rosner, Y., Z. Amitay, and A. Perlman. 2022. "Consumer's attitude, sociodemographic variables and willingness to purchase green housing in Israel." *Environ. Dev. Sustainability* 24 (4): 5295–5316. https://doi.org/10.1007/s10668-021-01659-8.
Salmerón, R., C. García, and J. García. 2018. "Variance inflation factor and condition number in multiple linear regression." *J. Stat. Comput. Simul.* 88 (12): 2365–2384. https://doi.org/10.1080/00949655.2018.1463376.
Sartori, T., R. Drogemuller, S. Omrani, and F. Lamari. 2021. "A schematic framework for life cycle assessment (LCA) and green building rating system (GBRS)." *J. Build. Eng.* 38 (Jan): 102180. https://doi.org/10.1016/j.jobe.2021.102180.
Schober, P., C. Boer, and L. A. Schwarte. 2018. "Correlation coefficients: Appropriate use and interpretation." *Anesthesia Analg.* 126 (5): 1763–1768. https://doi.org/10.1213/ANE.0000000000002864.
Smith, R. M. 2015. "'Green' building in India: A comparative and spatial analysis of the LEED-India and GRIHA rating systems." *Asian Geogr.* 32 (2): 73–84. https://doi.org/10.1080/10225706.2015.1020065.
Soltani, A., and S. Askari. 2017. "Exploring spatial autocorrelation of traffic crashes based on severity." *Injury* 48 (3): 637–647. https://doi.org/10.1016/j.injury.2017.01.032.
Stanley, S. 2019. "LEED reaches new milestone, surpasses 100,000 commercial green building projects." Accessed December 13, 2020. https://www.usgbc.org/articles/leed-reaches-new-milestone-surpasses-100000-commercial-green-building-projects.
USGBC (US Green Building Council). 2021. "LEED project profiles." Accessed January 10, 2021. https://www.usgbc.org/projects.
Wang, Y., S. Wang, G. Li, H. Zhang, L. Jin, Y. Su, and K. Wu. 2017. "Identifying the determinants of housing prices in China using spatial regression and the geographical detector technique." *Appl. Geogr.* 79 (Feb): 26–36. https://doi.org/10.1016/j.apgeog.2016.12.003.
WGBC (World Green Building Council). 2020. "About green building." Accessed August 21, 2020. https://worldgbc.org/about-us/.
Wilhelmsson, M. 2002. "Spatial models in real estate economics." *Hous. Theory Soc.* 19 (2): 92–101. https://doi.org/10.1080/140360902760385646.
Wu, Z., Y. Chen, Y. Han, T. Ke, and Y. Liu. 2020. "Identifying the influencing factors controlling the spatial variation of heavy metals in suburban soil using spatial regression models." *Sci. Total Environ.* 717 (Jun): 137212. https://doi.org/10.1016/j.scitotenv.2020.137212.
Wu, Z., Q. He, Q. Chen, H. Xue, and S. Li. 2021. "A topical network based analysis and visualization of global research trends on green building from 1990 to 2020." *J. Cleaner Prod.* 320 (Oct): 128818. https://doi.org/10.1016/j.jclepro.2021.128818.
Yang, R. J., and P. X. Zou. 2014. "Stakeholder-associated risks and their interactions in complex green building projects: A social network model." *Build. Environ.* 73 (Nov): 208–222. https://doi.org/10.1016/j.buildenv.2013.12.014.
Yin, C., M. Yuan, Y. Lu, Y. Huang, and Y. Liu. 2018. "Effects of urban form on the urban heat island effect based on spatial regression model." *Sci. Total Environ.* 634 (Dec): 696–704. https://doi.org/10.1016/j.scitotenv.2018.03.350.
Zambrano-Monserrate, M. A., M. A. Ruano, C. Yoong-Parraga, and C. A. Silva. 2021. "Urban green spaces and housing prices in developing countries: A two-stage quantile spatial regression analysis." *For. Policy Econ.* 125 (Dec): 102420. https://doi.org/10.1016/j.forpol.2021.102420.
Zhang, D., and Y. Tu. 2021. "Green building, pro-environmental behavior and well-being: Evidence from Singapore." *Cities* 108 (Jan): 102980. https://doi.org/10.1016/j.cities.2020.102980.
Zhang, J., K. Zhang, and F. Zhao. 2020. "Research on the regional spatial effects of green development and environmental governance in China based on a spatial autocorrelation model." *Struct. Change Econ. Dyn.* 55 (Feb): 1–11. https://doi.org/10.1016/j.strueco.2020.06.001.
Zhao, J., and K. P. Lam. 2012. "Influential factors analysis on LEED building markets in US East Coast cities by using support vector regression." *Sustainable Cities Soc.* 5 (Apr): 37–43. https://doi.org/10.1016/j.scs.2012.05.009.
Zou, Y., W. Zhao, and R. Zhong. 2017. "The spatial distribution of green buildings in China: Regional imbalance, economic fundamentals, and policy incentives." *Appl. Geogr.* 88 (Aug): 38–47. https://doi.org/10.1016/j.apgeog.2017.08.022.
Zuo, J., and Z. Y. Zhao. 2014. "Green building research—Current status and future agenda: A review." *Renewable Sustainable Energy Rev.* 30 (Feb): 271–281. https://doi.org/10.1016/j.rser.2013.10.021.