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Integrating Spatial Econometrics and Remote Sensing for Pixel-Level Wind Energy Corridor Identification: Evidence from West Bengal, India

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ABSTRACT

This study integrates remote sensing and spatial econometric techniques to identify pixel-level wind energy corridors in West Bengal, India. Weibull scale (A) and shape (K) parameter rasters at 100 m resolution were combined with Dynamic World land-cover data to evaluate the influence of landscape characteristics on wind potential. District-level zonal statistics were first extracted, and Ordinary Least Squares (OLS), Spatial Autoregressive (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) were subsequently estimated. Global Moran's I (0.723, $p < 0.01$) revealed significant positive spatial autocorrelation, justifying the application of spatial econometric models. Model comparison indicated that the Spatial Error Model (SEM) provided the best statistical fit among the tested specifications, showing that tree cover and built-up areas are negatively associated with wind potential, whereas flooded vegetation exhibits a positive association. The estimated spatial error coefficient ($\lambda = 0.945$) further confirms the importance of latent regional environmental processes. Based on these findings, a pixel-level wind suitability index was developed to identify potential contiguous wind energy corridors across the state. The results suggest that several districts located in the southern and coastal parts of West Bengal possess relatively high wind energy development potential and highlight the importance of integrated land-use planning. However, the identified corridors should be interpreted as planning-support outputs that require further engineering, environmental, and infrastructure assessments before implementation.

Keywords: *Spatial econometrics; Remote sensing; Wind energy corridors; Dynamic World; Weibull distribution; Renewable energy planning*

JEL Classification: *C21; C31; Q42; Q56; R14; R58*

1. Introduction

The successful development of wind energy infrastructure depends fundamentally on appropriate site selection. Conventional wind resource assessment has primarily focused on evaluating average wind speed or wind power density using meteorological observations and statistical distributions, particularly the Weibull distribution. The two principal parameters of the Weibull model, namely the scale parameter (A) and the shape parameter (K), provide complementary information regarding wind resources. While the scale parameter reflects the overall strength of the wind regime, the shape parameter measures wind consistency and stability. Higher values of the Weibull scale parameter generally indicate greater energy production potential, whereas higher values of the shape parameter imply smoother wind conditions, reduced mechanical stress on turbines, and lower maintenance costs. Therefore, considering both parameters simultaneously offers a more comprehensive understanding of the long-term economic viability of wind energy projects.

However, wind characteristics alone may not be sufficient for identifying high-suitability locations for wind farm development. Local land-use patterns significantly influence near-surface wind behavior through variations in surface roughness, vegetation density, urban structures, and landscape configuration. Dense forests and urban built-up areas can generate turbulence and reduce wind efficiency, whereas open landscapes and certain low-roughness environments facilitate smoother airflow. Moreover, from an energy economics perspective, the spatial relationship between wind resources and existing infrastructure is equally important. Extremely remote locations may exhibit favorable wind conditions but require substantial investment in transmission networks, road infrastructure, and maintenance logistics. Conversely, areas located reasonably close to existing urban infrastructure may reduce electricity delivery costs and improve overall project feasibility.

Recent advances in remote sensing technologies provide unprecedented opportunities for incorporating land-use information into renewable energy planning. The Dynamic World land-cover dataset, developed using high-resolution Sentinel-2 imagery and machine learning algorithms, offers near real-time global land-cover classification at a spatial resolution of 100 meters. Compared with conventional static land-use inventories, Dynamic World enables detailed pixel-level analysis of landscape characteristics, making it particularly suitable for renewable energy site selection studies. Nevertheless, most existing wind energy assessments continue to rely on district-level averages or simple overlay techniques, often neglecting the spatial heterogeneity embedded within high-resolution remote sensing data.

Another important limitation of the existing literature is the assumption of spatial independence. Wind regimes, topographic conditions, and land-use characteristics are inherently spatial phenomena, where neighboring locations tend to exhibit similar environmental properties. This concept is formally described by Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things." Ignoring such spatial dependence may lead to biased parameter

estimates and misleading policy conclusions. Spatial econometric models, including the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM), provide robust frameworks for explicitly accounting for spatial interactions and spillover effects. Despite their growing application in regional economics and environmental studies, their integration with remote sensing-based wind resource assessment remains relatively limited.

Furthermore, the majority of previous studies emphasize the identification of isolated high-potential sites rather than contiguous development zones. From the perspective of infrastructure planning and new economic geography, renewable energy investments are more efficiently organized as connected development corridors, where resource availability, accessibility, and transmission infrastructure can be jointly optimized. Corridor-based planning may reduce grid expansion costs, simplify maintenance operations, and encourage regional clustering of renewable energy investments. However, a systematic framework for identifying wind energy corridors through the integration of wind characteristics, land-use dynamics, and spatial econometric analysis has received little scholarly attention.

Against this background, the present study proposes an integrated spatial econometric and remote sensing framework for pixel-level wind energy corridor identification in West Bengal, India. West Bengal represents an interesting case study due to its highly heterogeneous landscape, encompassing coastal plains, agricultural regions, densely urbanized zones, forested uplands, and Himalayan foothills. Such diversity provides an ideal natural laboratory for examining how land-use patterns and spatial interactions influence wind resource distribution.

Specifically, this study combines Weibull scale (A) and shape (K) parameters with Dynamic World land-cover data to construct a high-resolution wind suitability index. Spatial autocorrelation is first examined using Moran's I statistic, followed by the estimation of Spatial Autoregressive (SAR), Spatial Error (SEM), and Spatial Durbin (SDM) models to evaluate the influence of various land-cover classes on wind characteristics. Building upon the best-performing spatial econometric specification, a pixel-level suitability framework is developed to delineate potential wind energy corridors across the state.

The main contributions of this study are fourfold. First, it extends traditional wind resource assessment by jointly considering both wind strength and wind stability through the integration of Weibull A and Weibull K parameters. Second, it incorporates high-resolution Dynamic World land-cover information to capture the effects of landscape heterogeneity on wind suitability. Third, it explicitly accounts for spatial dependence through spatial econometric modeling, thereby overcoming the limitations of conventional regression approaches. Finally, it shifts the focus from isolated site identification toward corridor-based renewable energy planning, providing a practical decision-support framework for sustainable infrastructure development and regional energy policy.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the theoretical framework. Section 3 describes the study area, datasets, and methodological approach. Section 4 presents the empirical findings and spatial

118 econometric results. Section 5 discusses the policy implications of pixel-level wind energy
119 corridor planning, and Section 6 concludes the study with recommendations for future research.

120 **2. Literature Review and Theoretical Framework**

121 **2.1 Wind Resource Assessment and the Weibull Distribution**

122 The identification of suitable locations for wind energy development has become an
123 increasingly important research topic as countries seek to accelerate the transition toward low-
124 carbon energy systems. Traditional wind resource assessment primarily relies on long-term
125 wind speed observations and statistical models that characterize the probability distribution of
126 wind regimes. Among these models, the Weibull distribution has emerged as the most widely
127 applied approach because of its flexibility and empirical performance across diverse climatic
128 regions (Justus et al., 1978; Seguro & Lambert, 2000).

129 The Weibull distribution is generally represented by two parameters: the scale
130 parameter (A) and the shape parameter (K). The scale parameter reflects the overall strength
131 of the wind regime and is strongly associated with expected energy production, whereas the
132 shape parameter measures wind consistency and temporal stability (Akdağ & Dinler, 2009).
133 Previous studies have largely focused on average wind speed or wind power density, often
134 emphasizing the scale parameter while paying comparatively less attention to the role of wind
135 stability in long-term infrastructure performance (Carta et al., 2009).

136 From an industrial energy economics perspective, however, sustainable wind energy
137 planning requires consideration of both energy output and infrastructure durability. Turbines
138 operating under highly variable wind conditions experience greater mechanical fatigue,
139 increasing maintenance costs and reducing operational life. Consequently, the simultaneous
140 consideration of Weibull A and Weibull K provides a more comprehensive measure of the
141 long-run economic feasibility of wind energy investments.

142 Despite the widespread application of the Weibull distribution in wind resource
143 assessment, relatively few studies have integrated both parameters into spatial planning
144 frameworks for identifying renewable energy development corridors.

145 **2.2 Land Use, Remote Sensing, and Renewable Energy Planning**

146 Wind energy potential is influenced not only by atmospheric conditions but also by the
147 characteristics of the underlying landscape. Surface roughness generated by forests, urban
148 structures, and heterogeneous land-cover patterns modifies local airflow and influences turbine
149 performance (Wieringa, 1993). In particular, vegetation and built-up environments create
150 aerodynamic resistance and turbulence, whereas open landscapes facilitate smoother wind
151 movement.

152 The increasing availability of high-resolution remote sensing data information has
153 significantly improved the ability to incorporate land-use information into renewable energy
154 planning. Satellite-based datasets provide consistent and spatially explicit observations of
155 landscape dynamics that cannot be captured through conventional ground surveys. Recent
156 advances in Earth observation have led to the development of the Dynamic World dataset,

which provides near real-time global land-cover classification derived from Sentinel-2 imagery (Brown et al., 2022).

Most existing studies employ land-use information primarily as an exclusion criterion by removing forests, urban settlements, protected areas, and water bodies from candidate locations (Baban & Parry, 2001; Tegou et al., 2010). While such approaches are useful for preliminary screening, they often overlook the broader economic implications of landscape characteristics. For example, highly remote locations may offer excellent wind resources but require substantial investments in transmission infrastructure and maintenance logistics. Conversely, moderate proximity to existing urban infrastructure may reduce electricity delivery costs and improve overall project viability.

Therefore, land use should be viewed not merely as a physical constraint but also as an important determinant of renewable energy economics.

2.3 Spatial Dependence and Spatial Econometric Modeling

Conventional regression techniques generally assume that observations are independently distributed. However, geographical and environmental phenomena rarely satisfy this assumption because neighboring locations often share similar physical and socioeconomic characteristics. This principle is formally expressed by Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970).

Wind regimes, topography, and land-use patterns are inherently spatial processes that exhibit significant autocorrelation across neighboring regions. Ignoring such spatial dependence may produce biased coefficient estimates and unreliable statistical inference (Anselin, 1988). Spatial econometric models were developed specifically to address these challenges by incorporating spatial interactions directly into the estimation process.

Among the most widely applied approaches are the Spatial Autoregressive Model (SAR), which captures direct spillover effects through a spatial lag of the dependent variable; the Spatial Error Model (SEM), which accounts for spatially correlated unobserved factors; and the Spatial Durbin Model (SDM), which considers spillover effects in both dependent and explanatory variables (LeSage & Pace, 2009).

Although spatial econometric methods have become increasingly common in regional science, environmental economics, and urban studies, their application to wind energy planning remains relatively limited. Existing wind resource studies frequently rely on ordinary least squares estimation or simple GIS overlay methods, thereby neglecting the spatial interactions inherent in environmental systems.

The integration of spatial econometric modeling with high-resolution remote sensing data therefore represents an important methodological advancement for renewable energy planning.

2.4 Theoretical Framework

The theoretical foundation of this study integrates five complementary perspectives: Weibull wind resource theory, landscape ecology theory, Tobler's First Law of Geography, central place theory, and new economic geography.

Weibull theory suggests that both wind strength and wind stability jointly determine the technical and economic performance of wind energy systems. Landscape ecology argues that the structure and composition of land-cover patterns regulate the movement of physical flows, including wind, through variations in surface roughness (Forman & Godron, 1986).

Tobler's First Law provides the conceptual basis for applying spatial econometric techniques, recognizing that neighboring locations are not independent. Central Place Theory (Christaller, 1933) further emphasizes the importance of infrastructure accessibility and transport efficiency, implying that renewable energy facilities should balance resource quality with proximity to transmission networks and demand centers.

Finally, New Economic Geography proposes that economic activities tend to cluster spatially due to agglomeration economies and reduced transport costs (Krugman, 1991). Applying this perspective to renewable energy planning suggests that development should focus on contiguous corridors rather than isolated high-potential sites.

Integrating these theoretical perspectives leads to the central proposition of this study: potential wind energy development depends on the joint interaction between wind resource quality, landscape characteristics, spatial dependence, and infrastructure accessibility.

Accordingly, the following hypotheses are proposed:

H1: Wind resource characteristics exhibit significant positive spatial autocorrelation across districts.

H2: Land-use patterns significantly influence local wind characteristics.

H3: Urban built-up areas and vegetation exert heterogeneous effects on wind suitability through their influence on surface roughness and infrastructure accessibility.

H4: The integration of Weibull wind parameters, remote sensing data, and spatial econometric modeling facilitates the identification of potential wind energy development corridors.

3. Study Area, Data, and Methodological Framework

3.1 Study Area

The empirical analysis is conducted for the state of West Bengal, India. The state covers an area of nearly 88,752 square kilometers and exhibits remarkable geographical diversity, ranging from the Himalayan foothills in the north to the coastal plains bordering the Bay of Bengal in the south.

West Bengal provides an ideal case study for examining the interaction between land-use characteristics and wind resources because of its heterogeneous landscape composition. The northern districts are dominated by forests and mountainous terrain, the central region

consists primarily of agricultural land, while the southern part contains densely populated urban areas, coastal ecosystems, and extensive river networks. These variations generate substantial differences in surface roughness, atmospheric flow characteristics, and infrastructure accessibility.

From the perspective of renewable energy planning, West Bengal faces increasing electricity demand driven by rapid urbanization and industrial development. At the same time, the state has relatively limited conventional energy resources and is actively exploring opportunities for expanding renewable energy generation. The coexistence of diverse land-cover patterns and varying wind conditions makes West Bengal an appropriate region for identifying potential wind energy development corridors.

The administrative boundaries of the nineteen districts of West Bengal constitute the primary spatial units for the district-level econometric analysis, while pixel-level observations are employed for the final corridor identification framework.

3.2 Data Sources and Variable Construction

3.2.1 Weibull Wind Parameters

Wind resource information is represented using the Weibull scale parameter (A) and the Weibull shape parameter (K). The Weibull distribution is widely recognized as the standard statistical representation of wind speed frequency distributions (Justus et al., 1978; Seguro & Lambert, 2000).

The scale parameter (A) reflects the overall magnitude of the wind regime and serves as a proxy for potential energy production. The shape parameter (K) captures the regularity and stability of wind conditions, with larger values indicating smoother wind patterns and reduced turbine fatigue.

Raster datasets for Weibull A and Weibull K were obtained at a spatial resolution of approximately 100 meters. District-level average values were subsequently extracted through zonal statistical analysis using administrative boundary polygons.

3.2.2 Dynamic World Land-Cover Data

Land-use information was derived from the Dynamic World Version 1 dataset developed by Google earth engine and the World Resources Institute (Brown et al., 2022). Dynamic World provides near real-time global land-cover classification at a spatial resolution of 10 meters using Sentinel-2 imagery and machine learning algorithms.

Annual land-cover composites were generated through Google Earth Engine by applying the modal (majority) classification to all available observations during the study year. The resulting land-cover raster was clipped to the administrative boundary of West Bengal and subsequently resampled to match the spatial resolution of the Weibull datasets.

Table1. The Dynamic World classification system contains nine land-cover categories:

<i>Class Code</i>	<i>Land Cover Type</i>
-------------------	------------------------

0	Water
1	Trees
2	Grass
3	Flooded Vegetation
4	Cropland
5	Shrub and Scrub
6	Built Area
7	Bare Ground
8	Snow and Ice

Source: Google Earth Engine

For each district, the percentage share of each land-cover class was calculated through zonal histogram analysis. Due to potential multicollinearity among land-cover categories as depicted in table 1, only the most economically and environmentally relevant variables were retained for the spatial econometric models.

3.2.3 Spatial Weight Matrix

Spatial interactions among districts were represented through a first-order Queen contiguity spatial weight matrix. Under this specification, two districts are considered neighbors if they share either a common boundary or a common vertex.

The spatial weight matrix was row-standardized to ensure comparability across observations and was subsequently used for the calculation of Moran's I statistic and the estimation of spatial econometric models.

3.3 Pixel-Level Data Processing

The analysis integrates raster-based wind information with high-resolution land-cover data to construct a pixel-level wind suitability framework.

First, the Dynamic World raster was re-sampled from 10-meter resolution to match the 100-meter spatial resolution of the Weibull datasets using modal resampling. This procedure preserves the dominant land-cover category within each aggregated cell while minimizing classification distortion.

Second, the Weibull A and Weibull K rasters were normalized using min-max transformation:

$$X_i^* = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where, X_i^* denotes the normalized value of the variable, X_i is the original observation, and X_{min} and X_{max} represent the minimum and maximum values of the dataset, respectively.

Third, binary masks representing major land-cover constraints were generated for built-up areas, tree cover, and flooded vegetation. These variables were selected because they exhibited the strongest relationships with wind characteristics during the econometric analysis.

Finally, a composite wind suitability index was constructed by combining normalized wind parameters with land-cover characteristics:

$$WSI_i = \alpha_A A_i^* + \alpha_K K_i^* - \alpha_B B_i - \alpha_T T_i - \alpha_F F_i \quad (2)$$

Where,

A_i^* = normalized Weibull scale parameter,

K_i^* = normalized Weibull shape parameter,

B_i = built-up land indicator,

T_i = tree cover indicator,

F_i = flooded vegetation indicator.

The weighting scheme assigns greater importance to wind resource quality while incorporating the effects of landscape characteristics identified through the spatial econometric analysis.

3.4 Spatial Econometric Framework

The presence of spatial dependence was initially evaluated using Global Moran's I statistic:

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (3)$$

Where,

$$S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$$

Where, w_{ij} denotes the spatial weight between locations i and j , X_i and X_j are the observed values, and $\bar{X}$ is the sample mean.

A statistically significant positive Moran's I indicates the presence of spatial clustering and justifies the application of spatial econometric techniques.

To account for potential spatial dependence, three alternative model specifications were estimated.

A statistically significant Moran's I indicates that conventional regression methods may produce biased estimates, thereby justifying the application of spatial econometric techniques.

Three alternative spatial specifications were estimated:

Spatial Autoregressive Model (SAR)

$$Y = \rho WY + X\beta + \epsilon \quad (4)$$

where ρ is the spatial autoregressive coefficient that measures the influence of neighboring observations.

Spatial Error Model (SEM)

$$Y = X\beta + u \quad (5)$$

With

$$u = \lambda Wu + \varepsilon \quad (6)$$

Where, λ captures the degree of spatial dependence contained within the disturbance process.

Spatial Durbin Model (SDM)

$$Y = \rho WX + X\beta + WX\theta + \epsilon \quad (7)$$

Where, WX denotes the spatially lagged explanatory variables and θ measures the indirect spillover effects from neighboring regions.

The final model specification was selected based on statistical significance, model diagnostics, and information criteria.

3.5 Wind Energy Corridor Identification Framework

The final stage of the analysis extends conventional site-selection approaches by identifying spatially connected wind energy development corridors.

A pixel-level suitability surface was generated using the integrated wind suitability index. High-potential pixels were subsequently identified using a percentile threshold criterion:

$$Corridor_i = \begin{cases} 1, & \text{if } WSI_i \geq Q_{0.90}(WSI), \\ 0, & \text{if } WSI_i < Q_{0.90}(WSI) \end{cases} \quad (8)$$

where, $Q_{0.90}(WSI)$ represents the 90th percentile of the Wind Suitability Index distribution.

Unlike conventional binary exclusion methods, this framework enables the identification of contiguous zones where favorable wind characteristics, suitable land-cover patterns, and infrastructure accessibility jointly maximize the long-term feasibility of wind energy development.

4. Empirical Findings and Spatial Econometric Results

Table 2. Ordinary Least Squares (OLS) Estimates of the Determinants of the Weibull Scale Parameter (A)

Dependent Variable: Weibull Scale Parameter (Weibull A)

VARIABLES	COEFFICIENT
CONSTANT	5.143*** (0.284)
BUILT-UP AREA	-0.001 (0.006)
TREES	-0.027*** (0.007)
GRASS	-0.094 (0.345)
SHRUB AND SCRUB	0.048 (0.037)
BARE LAND	-0.259** (0.118)
FLOODED VEGETATION	0.586** (0.209)
MODEL STATISTICS	
OBSERVATIONS	19
R ²	0.809
ADJUSTED R ²	0.714
F-STATISTIC	8.479***
PROB > F	0.0009
LOG-LIKELIHOOD	-6.306
AKAIKE INFORMATION CRITERION (AIC)	26.612
BAYESIAN INFORMATION CRITERION (BIC)	33.223
DURBIN-WATSON STATISTIC	1.982
OMNIBUS TEST (P-VALUE)	0.535
JARQUE-BERA TEST (P-VALUE)	0.626
CONDITION NUMBER	133.0

Source: Calculated by Author

4.1 Ordinary Least Squares Estimation

Table 2 presents the baseline Ordinary Least Squares (OLS) estimation results for the determinants of the district-level Weibull scale parameter (A). The model explains approximately 80.9% of the cross-district variation in wind potential R² (0.809), while the adjusted R² (0.714) suggests that the explanatory variables collectively provide substantial predictive power even after accounting for model complexity. The overall F-statistic (8.479) is highly significant p-val (0.01), indicating that the null hypothesis that all slope coefficients are jointly equal to zero can be rejected.

Among the land-cover variables, tree cover exhibits a statistically significant negative relationship with the Weibull scale parameter. The estimated coefficient (-0.027), p-val (0.01) implies that, holding other factors constant, districts with larger shares of forested land tend to experience lower average wind intensity. This finding is consistent with the principles of landscape ecology and boundary-layer meteorology, according to which dense vegetation

increases surface roughness and creates greater aerodynamic resistance, conditions that are generally associated with lower near-surface wind speeds.

Similarly, bare land also displays a negative and statistically significant coefficient (-0.259), p-val (0.05). Although open terrain is often considered favorable for wind energy development, the present result suggests that, within the context of West Bengal, districts containing relatively larger proportions of bare surfaces are generally associated with lower Weibull scale parameters. This outcome may reflect the geographical concentration of bare land in regions that naturally possess weaker wind regimes rather than a direct causal relationship.

In contrast, flooded vegetation exerts a positive and statistically significant influence on wind potential. The estimated coefficient (0.586), p-val(0.05) indicates that districts containing larger shares of wetlands and seasonally inundated landscapes tend to exhibit higher average wind intensity. Such environments typically present relatively smooth surfaces with limited physical obstructions, allowing more stable air movement and potentially enhancing local wind flow characteristics.

The coefficients associated with built-up areas, grasslands, and shrublands are statistically insignificant at conventional significance levels. The estimated coefficient for built-up land is extremely small (-0.0001) and insignificant, suggesting that, after controlling for other land-cover characteristics, the proportion of urbanized land does not independently explain cross-district variation in the Weibull scale parameter. Likewise, the effects of grassland and shrubland are not statistically distinguishable from zero.

From a policy perspective, these findings imply that the spatial distribution of wind resources in West Bengal is influenced more strongly by natural landscape characteristics than by the current extent of urban development. In particular, extensive tree cover is associated with lower average wind intensity, whereas flooded vegetation is associated with relatively favorable wind conditions. These relationships provide an initial empirical basis for integrating land-use information into wind energy planning and motivate the subsequent application of spatial econometric models.

The diagnostic statistics further support the adequacy of the baseline specification. The Durbin-Watson statistic (1.982) is close to the benchmark value of two, suggesting little evidence of first-order serial correlation in the residuals. In addition, the Omnibus and Jarque-Bera tests fail to reject the null hypothesis of normally distributed residuals, indicating that the model satisfies the standard distributional assumptions reasonably well.

Finally, the table 3 represents the Variance Inflation Factor (VIF) diagnostics reported in Table 2 suggest that multicollinearity is not a major concern. All explanatory variables exhibit VIF values substantially below the conventional threshold of 10, with the maximum VIF equal to only 2.627. Consequently, the estimated coefficients are unlikely to suffer from instability arising from strong linear dependence among the regressors, thereby increasing confidence in the interpretation of the estimated effects.

405

Table 3. Variance Inflation Factor (VIF) Diagnostics

VARIABLES	VIF
CONSTANT	8.489
BUILT-UP AREA	1.292
TREES	1.912
GRASS	2.627
SHRUB AND SCRUB	1.601
BARE LAND	1.835
FLOODED VEGETATION	1.600

406

Source: Calculated by Author

407

Table 4. Spatial Autoregressive (SAR) Model Estimates

408

Dependent Variable: Weibull Scale Parameter (Weibull A)

VARIABLES	SAR MODEL
CONSTANT	2.171*** (0.599)
BUILT-UP AREA	-0.005 (0.003)
TREES	-0.021*** (0.004)
GRASS	-0.260 (0.181)
SHRUB AND SCRUB	0.023 (0.019)
BARE LAND	0.038 (0.080)
FLOODED VEGETATION	0.393*** (0.107)
SPATIAL LAG (RHO)	0.628*** (0.115)
MODEL STATISTICS	
OBSERVATIONS	19
MEAN DEPENDENT VARIABLE	4.481
STANDARD DEVIATION OF DEPENDENT VARIABLE	0.793
DEGREES OF FREEDOM	11
PSEUDO (R ²)	0.925
SPATIAL PSEUDO R ²	0.821
LOG-LIKELIHOOD	1.081
SIGMA-SQUARE ML	0.045
STANDARD ERROR OF REGRESSION	0.211
AKAIKE INFORMATION CRITERION (AIC)	13.838
SCHWARZ BAYESIAN CRITERION (BIC)	21.394

409

Source: Calculated by Author

410

Table 5. Direct, Indirect, and Total Effects from the Spatial Autoregressive (SAR) Model

VARIABLES	DIRECT EFFECT	INDIRECT EFFECT	TOTAL EFFECT
BUILT-UP AREA	-0.0047	-0.0079	-0.0125
TREES	-0.0207	-0.0349	-0.0556
GRASS	-0.2603	-0.4401	-0.7004
SHRUB AND SCRUB	0.0226	0.0382	0.0607
BARE LAND	0.0381	0.0644	0.1025
FLOODED VEGETATION	0.3935	0.6651	1.0585

411

Source: Calculated by Author

4.2 Spatial Dependence and Spatial Autoregressive Model Results

The presence of significant spatial dependence has important methodological implications. Conventional Ordinary Least Squares estimation assumes that observations are spatially independent. However, the significant Moran's I statistic suggests that this assumption is violated, implying that OLS estimates may suffer from bias or inefficiency due to the omission of spatial interactions. Consequently, the application of spatial econometric techniques is justified.

Table 4 reports the estimation results from the Spatial Autoregressive (SAR) model. Compared with the baseline OLS specification, the SAR model provides a substantially better fit to the data. The pseudo- R^2 increases to 0.925, indicating a substantial improvement in model fit after accounting for spatial interactions. Moreover, the Akaike Information Criterion (AIC) value of 13.838 is considerably lower than that obtained from the OLS model, further suggesting improved model performance.

The most notable result is the estimated spatial autoregressive coefficient (RHO) (0.628), which is positive and highly significant at the one percent level. This coefficient measures the degree to which wind conditions in one district are influenced by neighboring districts. The positive estimate implies that districts tend to inherit or share similar wind characteristics with adjacent districts, reflecting the continuous nature of atmospheric circulation processes. This finding provides strong empirical support for Tobler's First Law of Geography, which argues that nearby locations are more strongly related than distant ones.

The estimated coefficients for the explanatory variables reveal several important relationships. Tree cover maintains a negative and highly significant association with wind potential. The estimated coefficient (-0.0207), p-val (0.01) indicates that higher forest coverage is associated with lower average local wind intensity. This result is consistent with the principles of landscape ecology and boundary-layer meteorology, according to which dense vegetation increases aerodynamic roughness and is generally associated with weaker near-surface wind flow.

Flooded vegetation, by contrast, exerts a positive and statistically significant effect (0.3935), p-val (0.01). Districts containing relatively larger proportions of wetlands and seasonally inundated landscapes tend to experience stronger wind conditions. Such surfaces generally offer fewer physical barriers to airflow and therefore facilitate smoother atmospheric movement.

The estimated coefficients for built-up areas, grasslands, shrublands, and bare land are not statistically significant after accounting for spatial interactions. In particular, the built-up coefficient becomes small and insignificant, suggesting that the direct effect of urban land cover on wind potential is relatively weak once regional spatial dependence is explicitly modeled.

An important feature of the SAR model is that the estimated coefficients cannot be interpreted solely as local effects because changes in one location may propagate through neighboring regions. Therefore, Table 5 decomposes the estimated impacts into direct, indirect, and total effects.

The direct effects measure the influence of land-cover characteristics within a district on its own wind potential. The indirect effects, often referred to as spatial spillovers, capture how changes in one district affect neighboring districts through spatial interactions. The total effects represent the combined influence of both channels.

The decomposition reveals that tree cover generates both substantial local and regional impacts. The direct effect (-0.0207) indicates a negative association between forest cover and district-level wind potential. while the indirect effect (-0.0349) suggests that this influence extends beyond administrative boundaries and also affects adjacent districts. The total effect (-0.0556) therefore implies that vegetation-induced surface roughness has consequences at a broader regional scale.

Flooded vegetation exhibits the opposite pattern. The direct effect (0.3935) indicates a positive association between flooded vegetation and local wind potential. whereas the indirect effect (0.6651) demonstrates an even stronger spillover influence on neighboring districts. The resulting total effect (1.0585) represents the largest estimated impact among all explanatory variables, highlighting the importance of open wetland landscapes in sustaining favorable wind regimes.

Although grassland and built-up areas are statistically insignificant in the coefficient estimates, their spillover effects remain informative. Grassland exhibits a relatively large negative total effect (-0.7004), whereas built-up land displays only a modest overall influence (-0.0125). Shrubland and bare land show small positive total effects, although these estimates should be interpreted cautiously given their lack of statistical significance.

Overall, the SAR results indicate that the spatial distribution of wind resources in West Bengal is governed not only by local land-cover characteristics but also by strong interactions among neighboring districts. The significant positive spatial lag coefficient and the presence of meaningful indirect effects suggest that wind energy planning should move beyond isolated site selection and instead adopt a corridor-based regional perspective. These findings provide empirical support for the theoretical framework developed in Section 2 and motivate the subsequent estimation of the Spatial Error Model, which further investigates whether unobserved spatial processes contribute to the observed clustering patterns.

Table 6. Global Moran's I Test for Spatial Autocorrelation

STATISTIC	VALUE
MORAN'S I	0.723***
P-VALUE	0.001
SPATIAL WEIGHT MATRIX	First-order Queen Contiguity
NUMBER OF OBSERVATIONS	19

Source: Calculated by Author

Before estimating the spatial econometric models, the existence of spatial dependence was examined using the Global Moran's I statistic. As reported in Table 6, Moran's I equals (0.723) and is highly significant p-val (0.01). This finding indicates a strong positive spatial autocorrelation in district-level wind potential across West Bengal. In practical terms, districts characterized by relatively high Weibull scale parameters tend to be geographically surrounded by other districts with similarly favorable wind conditions, while districts with lower wind potential are generally clustered together. Such a pattern confirms that wind resources are not randomly distributed across space but instead exhibit clear regional clustering.

Table 7. Spatial Error Model (SEM) Estimates

Dependent Variable: Weibull Scale Parameter (Weibull A)

VARIABLES	SEM MODEL
CONSTANT	5.250*** (0.559)
BUILT-UP AREA	-0.011*** (0.003)
TREES	-0.027*** (0.003)
GRASS	-0.041 (0.094)
SHRUB AND SCRUB	0.013

	(0.015)
BARE LAND	-0.023
	(0.050)
FLOODED VEGETATION	0.281***
	(0.079)
SPATIAL ERROR COEFFICIENT (LAMBDA)	0.945***
	(0.035)
MODEL STATISTICS	
OBSERVATIONS	19
MEAN DEPENDENT VARIABLE	4.481
STANDARD DEVIATION OF DEPENDENT VARIABLE	0.793
DEGREES OF FREEDOM	12
PSEUDO (R ²)	0.598
LOG-LIKELIHOOD	6.297
SIGMA-SQUARE ML	0.017
STANDARD ERROR OF REGRESSION	0.130
AKAIKE INFORMATION CRITERION (AIC)	1.406
SCHWARZ BAYESIAN CRITERION (BIC)	8.017

Source: Calculated by Author

4.3 Spatial Error Model Results

Table 7 presents the estimation results obtained from the Spatial Error Model (SEM). Unlike the Spatial Autoregressive (SAR) model, which assumes that wind potential directly spills over across neighboring districts, the SEM assumes that spatial dependence arises primarily through unobserved geographical and environmental factors that are spatially correlated. In the context of wind resource assessment, these latent factors may include topography, atmospheric circulation patterns, micro-climatic conditions, and other omitted physical characteristics that cannot be directly measured by the available land-cover variables.

The estimated spatial error coefficient (LAMBDA) (0.945) is positive and highly significant at the one percent level p-val (0.01). The magnitude of this coefficient is remarkably high, indicating that a substantial proportion of the spatial dependence observed in district-level wind potential is embedded within the disturbance process rather than being transmitted directly through neighboring values of the dependent variable. In other words, adjacent districts appear to share common environmental characteristics that jointly influence their wind regimes. This result strongly supports the argument that wind resources are fundamentally spatial phenomena and validates the application of spatial econometric techniques.

The coefficient estimates further reveal several important relationships between land-cover characteristics and wind potential. Tree cover remains negative and highly significant (-0.0268), p-val (0.01), indicating that districts with greater proportions of forested landscapes tend to exhibit lower Weibull scale parameters. This finding is highly consistent across the OLS, SAR, and SEM specifications, suggesting that the negative influence of vegetation on wind intensity is robust to alternative model assumptions. From a physical perspective, dense tree cover increases surface roughness and creates turbulence, conditions that are generally associated with weaker near-surface wind flows.

Built-up land also becomes statistically significant in the SEM specification. The estimated coefficient (-0.0106), p-val (0.01) implies that increasing urbanization is associated with a reduction in average wind intensity. Compared with the OLS and SAR models, where the built-up coefficient was statistically insignificant, the SEM suggests that the effect of urban development becomes more apparent after controlling for latent spatially correlated factors. Urban structures such as buildings and infrastructure increase aerodynamic drag and create complex wind turbulence patterns, which may reduce the efficiency of wind energy generation.

Flooded vegetation continues to exhibit a positive and statistically significant association with wind potential (0.2809), p-val (0.01). Districts containing relatively larger

shares of wetlands and seasonally inundated landscapes tend to experience stronger wind conditions. Such environments typically present smooth and open surfaces with relatively few physical barriers, thereby facilitating stable atmospheric circulation. The persistence of this positive relationship across all model specifications indicates that flooded vegetation is one of the most important environmental determinants of wind potential within the study area.

The estimated coefficients for grassland, shrubland, and bare land are statistically insignificant. Although these land-cover categories may influence local surface roughness, their effects appear to be relatively weak once broader spatial processes are incorporated into the model. Consequently, there is insufficient statistical evidence to conclude that these variables independently affect district-level wind potential in West Bengal.

From a model performance perspective, the SEM exhibits several notable improvements over the previous specifications. Although its pseudo- R^2 (0.598) is lower than that reported for the SAR model, the SEM achieves a substantially higher log-likelihood value (6.297) and considerably lower information criteria (AIC) (1.406) and (BIC) (8.017). Since lower values of AIC and BIC indicate a superior balance between model fit and parsimony, these statistics suggest that the SEM provides the most appropriate representation of the underlying data-generating process.

Taken together, the empirical evidence indicates that the spatial variation in wind resources across West Bengal is driven less by direct interactions between neighboring districts and more by common latent environmental processes shared across space. This finding aligns closely with Tobler's First Law of Geography and the theoretical framework developed in Section 2, which emphasizes the importance of spatially continuous atmospheric and landscape processes.

Moreover, the superiority of the SEM specification has important policy implications. It suggests that wind energy planning should not focus exclusively on isolated local characteristics but should instead consider broader regional environmental systems. The strong and significant spatial error process implies that neighboring districts often share similar underlying wind-generating mechanisms, thereby supporting the concept of integrated regional wind corridors rather than fragmented site-specific development strategies.

Overall, Table 6 provides strong empirical evidence that unobserved spatial environmental factors play a dominant role in shaping the distribution of wind resources in West Bengal. Consequently, the Spatial Error Model is selected as the preferred econometric specification for the subsequent pixel-level wind corridor identification framework.

Table 8. Spatial Durbin Model (SDM) Estimates

Dependent Variable: Weibull Scale Parameter (Weibull A)

VARIABLES	SDM MODEL
CONSTANT	-2.246** (1.091)
BUILT-UP AREA	-0.011*** (0.004)
TREES	-0.025*** (0.002)
GRASS	-0.199* (0.110)
SHRUB AND SCRUB	0.019 (0.016)
BARE LAND	0.038 (0.041)
FLOODED VEGETATION	0.165**

	(0.080)
SPATIALLY LAGGED BUILT-UP (W \TIMES) BUILT-UP)	0.009
	(0.008)
SPATIALLY LAGGED TREES (W \TIMES) TREES)	0.041***
	(0.006)
SPATIALLY LAGGED GRASS (W \TIMES) GRASS)	-0.109
	(0.352)
SPATIALLY LAGGED SHRUB (W \TIMES) SHRUB)	-0.133***
	(0.048)
SPATIALLY LAGGED BARE (W \TIMES) BARE)	0.184
	(0.148)
SPATIALLY LAGGED FLOODED VEGETATION (W \TIMES) FLOODEDVEG)	-0.763**
	(0.351)
SPATIAL LAG (RHO)	1.500***
	(0.244)
MODEL STATISTICS	
OBSERVATIONS	19
MEAN DEPENDENT VARIABLE	4.481
STANDARD DEVIATION OF DEPENDENT VARIABLE	0.793
DEGREES OF FREEDOM	5
PSEUDO (R ²)	0.987
LOG-LIKELIHOOD	Not Reported
SPATIAL PSEUDO (R ²)	Omitted
ESTIMATION METHOD	Spatial Two-Stage Least Squares (S2SLS)

Source: Calculated by Author

Table 9. Diagnostic Tests for the Spatial Durbin Model¹

DIAGNOSTIC TEST	STATISTIC	P-VALUE
ANSELIN-KELEJIAN SPATIAL DEPENDENCE TEST	2.466	0.116
COMMON FACTOR HYPOTHESIS TEST	11.233	0.082

ADDITIONAL INFORMATION

INSTRUMENTED VARIABLE	(W \times) Weibull A
INSTRUMENTS USED	(W ²) Built-up, (W ²) Trees, (W ²) Grass, (W ²) Shrub, (W ²) Bare, (W ²) Flooded Vegetation
SPATIAL IMPACTS	Not Computed
REASON	Estimated spatial lag coefficient outside the admissible interval

Source: Calculated by Author

Table 8 depicts the results of the Spatial Durbin Model (SDM) examining how different land-use types influence the Weibull scale parameter (wind speed potential). The findings show that built-up areas, trees, and grass have negative and statistically significant effects on wind potential, indicating that urbanization and vegetation increase surface roughness and reduce wind speed. Flooded vegetation, however, has a positive and significant effect, suggesting that

¹**Model Selection Note:** Although the Spatial Durbin Model achieves the highest pseudo-R², the estimated spatial autoregressive parameter exceeds the theoretical stability boundary $\text{RHO} > 1$). Combined with the omission of impact decomposition, this suggests that the SDM is not the preferred specification for the present dataset. In contrast, the Spatial Error Model (SEM) exhibits stable parameter estimates together with the lowest AIC and BIC values, and is therefore adopted as the preferred econometric specification for subsequent wind corridor identification and policy analysis.

smoother and moisture-rich surfaces enhance wind flow. Shrub and scrub, as well as bare land, do not show significant direct effects.

The spatially lagged variables reveal spillover effects from neighboring regions. Tree cover in surrounding areas has a positive and significant influence, implying that it may help channel or redirect wind into a given location. In contrast, neighboring shrub areas and flooded vegetation exert significant negative spillover effects, indicating that these land covers may reduce wind movement across regions. Other lagged variables are not statistically significant. The spatial lag coefficient ($\rho = 1.500$) is positive and highly significant, suggesting strong spatial dependence in wind potential across regions. However, since this value exceeds the acceptable range, it indicates model instability and limits the reliability of spatial interpretations. Despite a very high pseudo R^2 (0.987), the small sample size and the issue with the spatial parameter suggest that the model results should be interpreted with caution. Additionally, Table 9 represents the diagnostic tests for the Spatial Durbin Model. The Anselin–Kelejian test for spatial dependence is not statistically significant ($p = 0.116$), indicating that there is no strong residual spatial autocorrelation and that the model has adequately captured spatial dependence. The Common Factor Hypothesis test is marginally insignificant ($p = 0.082$), suggesting that the SDM cannot be simplified into a more basic spatial model, and its specification is generally appropriate.

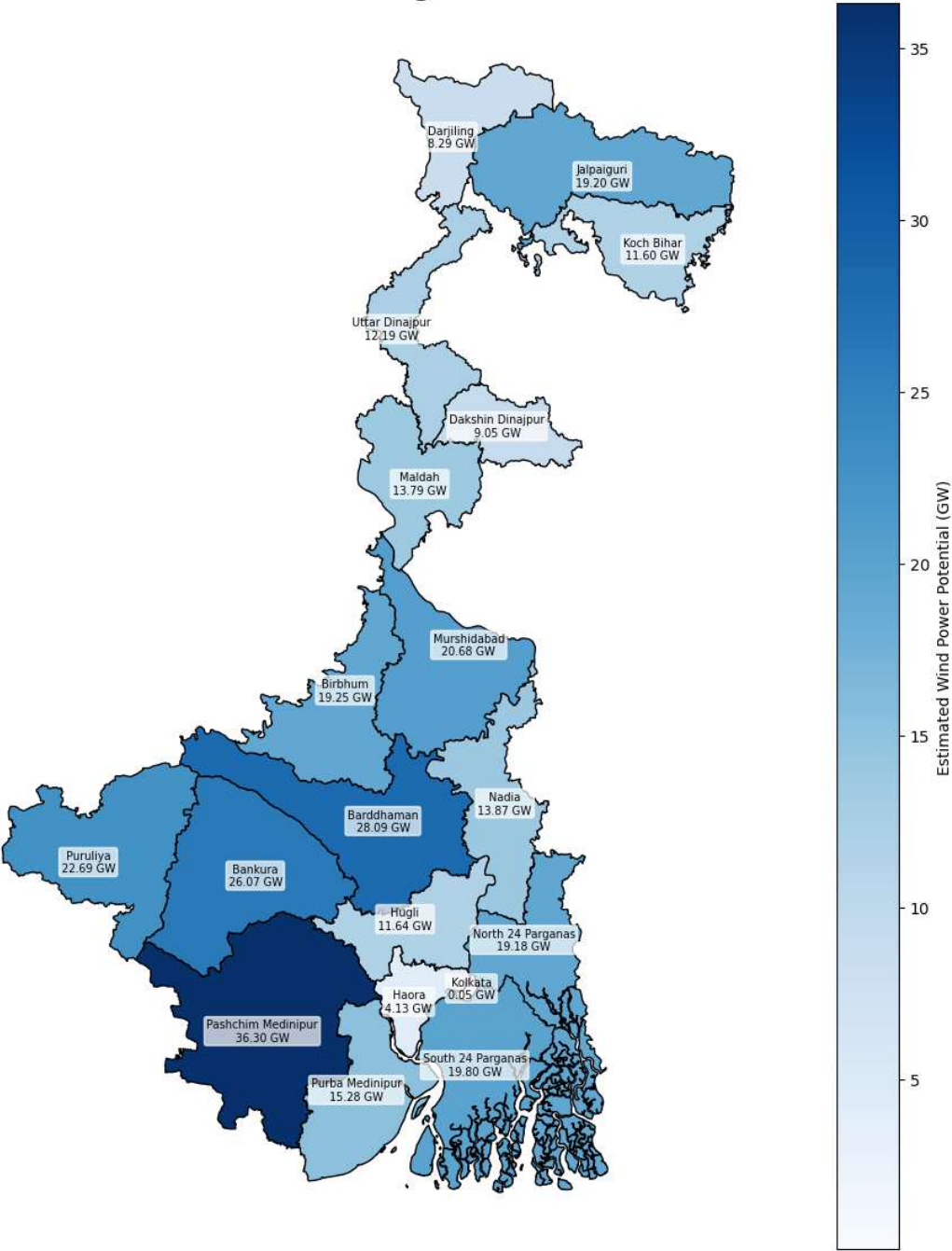
However, spatial impacts (direct, indirect, and total effects) were not computed because the estimated spatial lag coefficient falls outside the admissible range. This further confirms instability in the model and limits the ability to draw reliable conclusions about spillover effects. The model uses spatially lagged instruments (second-order lags of land-use variables) within a Spatial Two-Stage Least Squares framework, which is appropriate for addressing endogeneity, but the validity of results remains constrained by the spatial parameter issue.

5. Policy Implications of Pixel-Level Wind Energy Corridor Planning

The empirical findings and spatial visualizations presented in Figures 1 and 2 provide important insights for renewable energy planning in West Bengal. Rather than treating wind resource development as a district-level administrative exercise, the results demonstrate that wind potential exhibits substantial intra-district heterogeneity and forms continuous spatial clusters across the landscape. Consequently, effective wind energy policy should focus on the development of integrated wind energy corridors rather than isolated project locations.

Figure 1

**Estimated District-wise Wind Energy Potential
West Bengal**



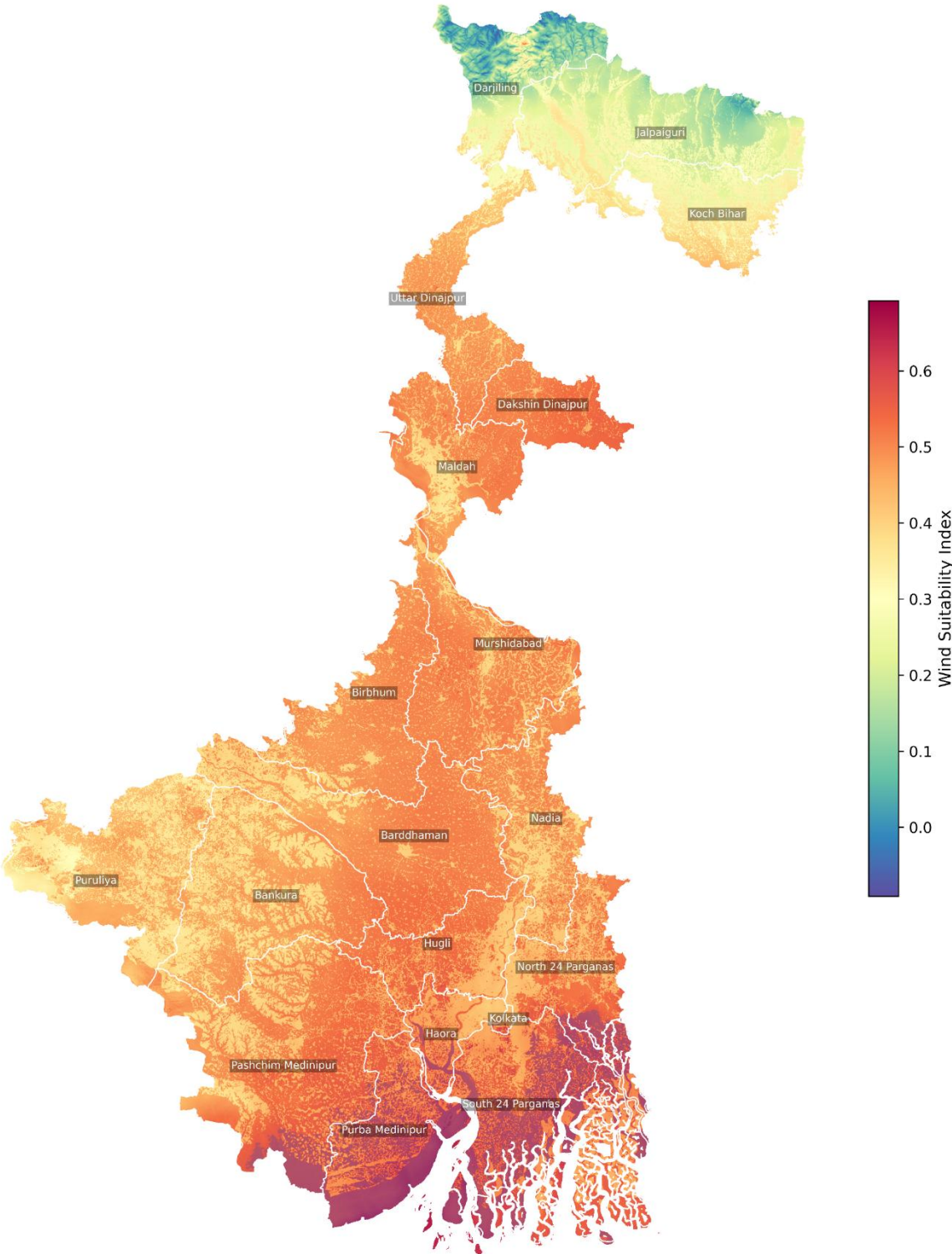
Source:

Calculated by Author

626
627

Figure 2.Pixel-Level Wind Energy Suitability and Proposed Development Corridors
in West Bengal

**Proposed Wind Energy Corridors
West Bengal**



628

Source: Calculated by Author

The results indicate considerable variation across districts. Pashchim Medinipur exhibits the highest estimated potential (36.30 GW), followed by Bardhaman (28.09 GW), Bankura (26.07 GW), Puruliya (22.69 GW), and Murshidabad (20.68 GW). In contrast, districts such as Kolkata (0.05 GW), Haora (4.13 GW), and Darjiling (8.29 GW) display relatively limited development opportunities due to either urban congestion or unfavorable topographical conditions.

From a policy perspective, these findings suggest that future investments should prioritize western and southwestern districts, particularly Pashchim Medinipur, Bankura, Puruliya, and Bardhaman, where large contiguous areas combine favorable wind characteristics with relatively low landscape constraints. The presence of high potential across adjacent administrative units further indicates the possibility of developing regional wind clusters capable of sharing transmission infrastructure, maintenance facilities, and grid integration systems.

However, district-level averages alone may conceal important local variations. Figure 2 addresses this limitation by presenting a pixel-level wind suitability surface generated through the integration of remote sensing and spatial econometric modeling. The map reveals that highly suitable locations are not uniformly distributed within districts but instead form spatially connected corridors extending across multiple administrative boundaries. These corridors reflect the combined influence of favorable Weibull parameters, lower tree density, reduced urban obstruction, and the positive contribution of open flooded landscapes identified by the Spatial Error Model. Additionally, the identified potential wind energy corridors cover approximately 105,776 hectares across West Bengal. Based on a simplified assessment using representative deployment assumptions for modern utility-scale wind turbines, these corridors may possess substantial renewable energy generation potential. However, the estimated contribution should be interpreted as an indicative planning scenario rather than a forecast of actual electricity production, as future generation outcomes will depend on turbine technology, capacity factors, land-use regulations, environmental clearances, grid connectivity, and investment feasibility. Nevertheless, the results suggest that strategically planned wind energy development could contribute meaningfully to the state's transition toward a more sustainable energy system.

The superiority of the Spatial Error Model has direct implications for renewable energy planning. The highly significant spatial error coefficient indicates that neighboring districts share common environmental characteristics that influence wind resources. This suggests that planning decisions based solely on local administrative boundaries may fail to capture the broader geographical processes governing wind availability. Instead, policymakers should adopt a corridor-based planning framework that recognizes the regional continuity of wind-generating environments. The maroon colored corridor approach of southern part of West Bengal near coastal regions offers several practical advantages.

First, it allows multiple wind farms to be strategically clustered, thereby reducing the costs associated with transmission lines direct to the southern industrial belt, substations, and operation and maintenance activities. Shared infrastructure can substantially improve the economic viability of renewable energy investments, particularly in developing regions where grid expansion costs remain significant.

Second, pixel-level suitability mapping enables more effective land-use management. Traditional renewable energy planning often relies on district averages or broad exclusion

criteria, which may overlook environmentally sensitive areas or fail to exploit highly suitable local sites. By integrating Dynamic World land-cover information with wind characteristics, the proposed framework allows planners to identify locations that minimize conflicts with dense forests and highly urbanized landscapes while utilizing relatively open terrain. Such an approach can reduce ecological disturbance and improve public acceptance of renewable energy projects.

Third, the results provide guidance for state-level energy diversification strategies. West Bengal has traditionally depended heavily on hydro and thermal power electricity generation, despite increasing national commitments toward renewable energy expansion. The estimated corridor network demonstrates that significant wind resources exist beyond the coastal belt and extend into western plateau regions and several central districts. These findings broaden the geographical scope for renewable energy deployment and support a more balanced regional energy portfolio.

The pixel-level corridor framework also has important implications for transmission planning. Rather than expanding the electricity network reactively after wind farms are constructed, planners can proactively identify future high-potential development zones and align grid investments accordingly. This integrated planning strategy has the potential to reduce transmission bottlenecks and facilitate the more efficient integration of renewable energy into the state electricity system.

Furthermore, the methodology developed in this study provides a transferable decision-support tool for regional renewable energy planning. By combining satellite-derived environmental information with spatial econometric analysis, the framework can be updated regularly as new remote sensing products become available. This dynamic capability allows policymakers to monitor changes in land cover, urban expansion, and environmental conditions, thereby supporting adaptive and evidence-based energy planning.

Overall, the findings suggest that future wind energy policy should move beyond conventional administrative planning approaches and embrace geographically continuous development strategies. The proposed wind energy corridors represent not merely zones of high wind availability but integrated landscapes where favorable atmospheric conditions, suitable land cover, and spatial spillover effects jointly create high-suitability environments for renewable energy investment. Such a corridor-based planning paradigm offers a practical pathway for maximizing renewable energy generation while minimizing infrastructure costs and environmental conflicts, thereby contributing to the broader objectives of sustainable regional development and energy transition in West Bengal.

In addition to identifying priority locations for renewable energy investment, the present findings highlight the importance of integrating wind resource conservation into broader urban planning policies. The Spatial Error Model indicates that built-up land exerts a statistically significant negative influence on wind potential, suggesting that rapid and unplanned urban expansion may disrupt the natural movement of near-surface air masses. Dense clusters of buildings, industrial structures, and other artificial obstacles increase aerodynamic roughness and generate turbulence, thereby reducing the efficiency of wind flow across the landscape. Consequently, indiscriminate urban sprawl may gradually degrade areas that are currently suitable for wind energy development.

From a policy perspective, this finding implies that land-use planning and renewable energy planning should not be treated as separate processes. Future urban development strategies should incorporate wind-sensitive zoning regulations, particularly within identified high-potential wind corridors. Preserving open landscapes and maintaining sufficient spatial continuity between major built-up areas can help sustain favorable wind conditions while simultaneously supporting long-term renewable energy generation. In this regard, the proposed pixel-level corridor framework can serve not only as a tool for identifying suitable sites for wind farms but also as a spatial planning instrument for preventing land-use changes that could undermine future wind energy resources.

Furthermore, the results suggest that environmental impact assessments for large urban and industrial projects should explicitly evaluate their potential effects on local wind regimes. Similar to the concept of ecological corridors used in biodiversity conservation, the establishment of protected wind corridors could help ensure that future infrastructure development does not obstruct the free movement of atmospheric flows necessary for efficient renewable energy production.

5.1 Limitations of the Study

Several limitations should be acknowledged when interpreting the findings of this study.

First, the spatial econometric analysis was conducted using district-level observations for West Bengal. Although the models reveal statistically significant spatial relationships, the relatively limited number of administrative units may constrain the generalizability of coefficient estimates and spatial spillover effects.

Second, the identification of wind energy corridors is based on a suitability framework that integrates Weibull wind parameters and land-cover characteristics. While this approach provides a useful planning tool, the delineated corridors should be interpreted as potential priority areas rather than definitive locations for wind farm development.

Third, the present analysis focuses primarily on environmental and landscape characteristics. Important factors such as transmission infrastructure, grid accessibility, land acquisition constraints, environmental regulations, investment costs, and engineering feasibility were not explicitly incorporated into the suitability model.

Fourth, the corridor identification procedure depends on the selected suitability threshold and weighting scheme. Alternative threshold values or weighting assumptions may generate somewhat different spatial patterns of corridor delineation.

Finally, the results represent a regional-scale planning assessment and should not be interpreted as a substitute for detailed site-specific wind measurements, engineering evaluations, or environmental impact assessments that would be required prior to project implementation.

Despite these limitations, the study provides an integrated framework that combines remote sensing and spatial econometric analysis for identifying potential wind energy development corridors and supporting evidence-based renewable energy planning.

6. Conclusion and Directions for Future Research

The present study demonstrates the value of integrating remote sensing data with spatial econometric techniques for renewable energy planning. Using high-resolution Weibull parameter rasters and Dynamic World land-cover information, this research developed a novel framework for identifying pixel-level wind energy corridors across West Bengal, India. Unlike conventional approaches that rely primarily on administrative averages or isolated site assessments, the proposed methodology explicitly accounts for both local landscape characteristics and spatial interactions among neighboring regions.

The empirical findings reveal that wind resources in West Bengal exhibit significant spatial clustering. The Global Moran's I statistic confirms the presence of strong positive spatial autocorrelation, indicating that districts with favorable wind conditions tend to be located near one another. Consequently, the assumption of spatial independence underlying conventional regression methods is violated, justifying the application of spatial econometric models.

Among the alternative specifications considered, the Spatial Error Model (SEM) provided the best statistical fit among the evaluated models and was therefore selected as the preferred specification for subsequent analysis. The highly significant spatial error coefficient suggests that unobserved environmental and geographical factors shared across neighboring districts play an important role in shaping regional wind potential. The analysis further demonstrates that tree cover and built-up areas exert statistically significant negative effects on wind resources, while flooded vegetation contributes positively to wind suitability. These findings are consistent with the principles of landscape ecology and atmospheric boundary-layer theory, where vegetation and urban structures increase surface roughness and reduce wind flow, whereas open landscapes facilitate more stable atmospheric circulation.

Building upon these econometric results, the study developed a pixel-level wind suitability index that integrates wind characteristics with land-cover constraints. The resulting spatial visualization identified several geographically contiguous wind energy corridors, particularly across the southwestern near costal parts of the state. District-level estimates further indicate that Pashchim Medinipur, Purba Medinipur, Haora, North 24 Parganas, and South 24 Parganas exhibit relatively high renewable energy potential within the context of the present suitability assessment. The analysis therefore suggests that future wind energy planning should move towards isolated project locations and adopt a corridor-based regional development strategy.

An important policy implication emerging from this study concerns the interaction between urbanization and renewable energy sustainability. The significant negative relationship between built-up land and wind potential suggests that unplanned urban expansion may be associated with changes in local airflow conditions through increased aerodynamic roughness and physical barriers. Consequently, renewable energy planning and urban land-use planning should be integrated within a common spatial framework. The identification and protection of strategic wind corridors can help ensure that future infrastructure development does not compromise long-term renewable energy opportunities.

Despite its contributions, the study has several limitations that provide opportunities for future research. First, the analysis relies primarily on Weibull parameter surfaces representing average wind conditions. Future studies may incorporate long-term hourly or seasonal wind observations to capture temporal variability and improve the estimation of electricity

generation potential. Second, the present framework considers major land-cover characteristics but does not explicitly include topographic variables such as elevation, slope, and terrain exposure, which may further influence local wind dynamics. Third, the estimated power generation values represent theoretical technical potential and do not account for detailed engineering considerations, including turbine specifications, wake effects, grid connectivity, economic feasibility, or regulatory constraints.

Future research may also extend the proposed framework by incorporating additional geospatial datasets, including digital elevation models, transportation infrastructure, transmission networks, and nighttime light imagery, to construct a more comprehensive multi-criteria renewable energy planning model. Machine learning algorithms and hybrid spatial econometric approaches may further improve predictive performance and corridor delineation. In addition, the methodology developed in this study can be readily applied to other Indian states and developing regions where high-resolution meteorological observations remain limited but satellite-derived environmental information is increasingly available.

Overall, this study contributes to the growing literature on spatially informed renewable energy planning by demonstrating that the integration of remote sensing and spatial econometrics provides a robust framework for identifying wind energy development corridors at the pixel level. The proposed approach provides a useful decision-support framework for policymakers seeking to promote sustainable energy transitions while balancing land-use management, environmental conservation, and regional development objectives.

6.1 Limitations and Directions for Future Research

While the present study demonstrates the usefulness of integrating spatial econometrics and remote sensing for pixel-level wind energy corridor identification, several opportunities remain for extending the analytical framework. The current analysis primarily employs the Combined Weibull Scale Parameter (A) and Combined Weibull Shape Parameter (K) obtained from the Global Wind Atlas because these variables provide a robust statistical representation of long-term wind characteristics. However, the Global Wind Atlas offers several additional engineering and atmospheric datasets that could substantially improve future renewable energy planning studies.

Future research may further strengthen the proposed framework by incorporating additional high-resolution variables that are currently available through the Global Wind Atlas GIS platform. The present study primarily utilizes the Combined Weibull Scale Parameter (A) and Combined Weibull Shape Parameter (K) layers because these variables provide a comprehensive statistical representation of long-term wind behavior. However, the Global Wind Atlas offers several other meteorological and engineering datasets that could substantially enhance future spatial econometric analyses.

First, future studies may directly integrate wind speed surfaces at multiple hub heights (10 m, 50 m, 100 m, 150 m, and 200 m). Since modern utility-scale wind turbines operate at different hub heights depending on technology and site characteristics, height-specific wind speed information would allow the construction of more realistic estimates of electricity generation potential and turbine performance.

Second, the inclusion of wind power density (W/m^2) could improve the physical interpretation of wind resource quality. Unlike average wind speed alone, power density

explicitly incorporates the cubic relationship between wind velocity and available kinetic energy, making it one of the most important variables for commercial wind farm planning.

Third, future research may consider air density as an additional explanatory variable. Air density varies with elevation, atmospheric pressure, humidity, and temperature, directly influencing the amount of energy that can be extracted from moving air masses. Integrating this variable may improve the estimation of actual power generation capacity, particularly across regions with diverse topographical conditions.

Fourth, the Global Wind Atlas provides several capacity factor layers (IEC1, IEC2, and IEC3) corresponding to different International Electrotechnical Commission (IEC) turbine classes. These datasets estimate the expected operational efficiency of turbines under alternative wind regimes. Incorporating turbine-specific capacity factors would enable future studies to move beyond theoretical wind potential toward technology-specific energy production scenarios.

Fifth, future analyses could incorporate the IEC fatigue load and IEC fatigue load including wake effects layers. These engineering indicators measure the cumulative mechanical stress experienced by turbine components under varying wind conditions. Including such variables would facilitate simultaneous evaluation of energy production and long-term infrastructure durability, thereby improving investment decision-making.

Sixth, the IEC extreme load dataset may provide valuable information regarding structural safety and climate resilience. Areas characterized by frequent extreme wind events may require specialized turbine designs or additional engineering safeguards. Integrating extreme load indicators with spatial econometric models would therefore contribute to more comprehensive renewable energy risk assessments.

Beyond meteorological variables, future corridor identification frameworks could be extended by incorporating additional geospatial and socio-economic datasets. High-resolution digital elevation models may capture the effects of terrain, slope, and aspect on local wind acceleration. Road networks, transmission infrastructure, substations, and grid accessibility layers could improve the practical feasibility assessment of identified corridors. Similarly, nighttime light imagery and urban expansion datasets may provide dynamic indicators of anthropogenic surface roughness, enabling researchers to investigate how rapid and unplanned urbanization alters regional wind circulation over time.

The present findings indicate that built-up areas significantly reduce wind potential, suggesting that future work should pay particular attention to the interaction between urban growth and renewable energy sustainability. Longitudinal analyses using multi-temporal land-cover and urban expansion data could help quantify the extent to which uncontrolled urban sprawl disrupts natural wind flow and gradually degrades existing wind energy corridors.

Overall, the availability of multiple engineering, atmospheric, and environmental layers through the Global Wind Atlas presents significant opportunities for extending the present research from a resource assessment framework toward a comprehensive renewable energy planning and infrastructure optimization platform.

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PUBLICATION ETHICS STATEMENT

The author of the manuscript titled “*Integrating Spatial Econometrics and Remote Sensing for Pixel-Level Wind Energy Corridor Identification: Evidence from West Bengal, India*”, the author adhere to high standards of publication ethics as outlined by the Committee on Publication Ethics (COPE). Any instances of ethical misconduct in the preparation or submission of this manuscript will be addressed in accordance with the COPE guidelines.

DATA AVAILABILITY STATEMENT

The datasets analysed during the current study were obtained from publicly available sources. Dynamic World land-cover data are available through Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/GOOGLE_DYNAMICWORLD_V1). The Weibull Scale Parameter (A) and Weibull Shape Parameter (K) datasets are available from the Global Wind Atlas GIS database (<https://globalwindatlas.info>). The processed datasets, wind corridor maps, district-level renewable energy potential estimates, and supporting analytical outputs generated during this study are provided as Supplementary Information accompanying this article. Additional derived datasets are available from the corresponding author upon reasonable request.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [result.txt](#)
- [PotentialMWPotentialGW.png](#)
- [WindCorridorMap.png](#)
- [PotentialMWPotentialGW.txt](#)
- [RawdataINDcombinedWeibullk100m.tif](#)
- [RawdataINDcombinedWeibullA100m.tif](#)
- [WBDYNAMICWORLDLULC2024.tif](#)
- [WestBengalshapefile.zip](#)
- [finalprepearddata.csv](#)