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GAP: Geospatial Analyzing Patterns Methods and Renewable Energy applications

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Abstract: *This paper illustrates the Analyzing Patterns Methods and renewable energy application. The objectives are Analyze, design and implement : Average Nearest Neighbor, High/Low Clustering, Incremental Geospatial Autocorrelation, Geospatial Autocorrelation, Multi-Distance Geospatial Cluster Analysis (Ripley's k-function). The methodologies are Analysis, Design, Develop, Implementation, and Evaluation for GIS Analyzing Patterns for renewable energy. There are many results such as GIS Analyze Patterns (Average Nearest Neighbor, High/Low Clustering, Incremental Geospatial Autocorrelation, Geospatial Autocorrelation, Multi-Distance Geospatial Cluster Analysis (Ripley's k-function)), Design Geodatabase (Average Nearest Neighbor, High/Low Clustering, Incremental Geospatial Autocorrelation, Geospatial Autocorrelation, Multi-Distance Geospatial Cluster Analysis (Ripley's k-function)), and implementations (Average Nearest Neighbor, High/Low Clustering, Incremental Geospatial Autocorrelation, Geospatial Autocorrelation, Multi-Distance Geospatial Cluster Analysis (Ripley's k-function)). In conclusion we recommendations and future researches: Geospatial Analyzing Patterns integrated GIS Data Cloud, GIS IoT, GIS AI, and GIS Cyber Security.*

Keywords: *Geostatistical, Mapping Clusters, Measuring Distributions, Modeling Relationships, Rending, Utilities.*

1. Introduction

In recent years, the utilization of spatial information and geospatial technologies has gained increasing prominence across a variety of sectors, including applications in renewable energy. The spatial distribution of tree species, for example, is a product of interactions between biological factors and ecological processes, making it crucial to understand their dynamics. Point process modeling serves as a valuable tool for describing these spatial patterns and identifying areas with high concentrations of events or points, which is essential in renewable energy analysis and other fields. The application of spatial statistical methods and econometric models based on national patent system data has enabled the analysis of spatiotemporal characteristics and changes in renewable energy innovation patterns. Surprisingly, this has revealed contradictions to public perception, such as differences in spatial distribution compared to resource distribution. Furthermore, there has been a tendency to focus on direct effects rather than spatial effects when discussing influencing factors, highlighting the importance of identifying significant impacts on renewable energy innovation through spatial effects. Human activity events are inherently linked to specific locations and timestamps, which form spatial patterns that evolve over time. This presents challenges when dealing with events involving multiple types that require careful consideration for accurate analysis of spatiotemporal clustering. Integrating space-time pattern mining analytics with advanced prediction simulations yields comprehensive insights into diseases from a spatial-temporal perspective. While previous studies have focused on spatial-temporal analyses for vector disease risk modeling, integrating typical geo-information models with advanced analytics-based techniques can offer more effective insights. Recognizing the importance of space as a fundamental component impacting areas such as cultural heritage and business information underscores the significance of a strong foundation in geographic information for growth and competitiveness. Additionally, machine learning methods have shown promise in non-big data analysis by complementing spatial statistics and econometrics. In conclusion, it is evident that geospatial analyzing patterns methods play a crucial role in understanding renewable energy applications through various methodologies such as point process modeling, spatiotemporal analyses for innovation patterns, spatiotemporal autocorrelation measures for human activity events, space-time pattern mining analytics for disease risk modeling, and integration with machine learning methods[1][2][3][4][5][6][7]. Identifying Geospatial patterns is very important for understanding how Geospatial phenomena behave. Although you can get a sense of the overall pattern of features and their associated values by mapping them, calculating a geostatistic quantifies the pattern. Often the Methods in the Analyzing Patterns Method are a starting point for more in-depth analyses. The Methods in the Analyzing Patterns Method are inferential statistics; they start with the null hypothesis that your features, or the values associated with your features, exhibit a Geospatially random pattern. They then compute a p-value representing the probability that the null hypothesis is correct (that the observed pattern is simply one of many possible versions of complete Geospatial randomness). The Analyzing Patterns Methods provide statistics that quantify broad Geospatial patterns. These Methods answer questions such as, "Are the features in the dataset, or the values associated with the features in the dataset, Geospatially clustered?" and "Is the Geospatial clustering becoming more or less intense over time?". [8],[9][10].

Geospatial Average Nearest Neighbor : Calculates a nearest neighbor index based on the average distance from each feature to its nearest neighboring feature. The Average Nearest Neighbor Method returns five values: Observed Mean Distance, Expected Mean Distance, Nearest Neighbor Index, z-score, and p-value[11]. **Geospatial Measuring Clustering:** High/ Low Clustering Measures the degree of clustering for either high values or low values using the Getis-Ord General G statistic. The High/Low Clustering Method returns four values: Observed General G, Expected General G, z-score, and p-value[12]. **Incremental Geospatial Autocorrelation** :Measures Geospatial autocorrelation for a series of distances and optionally creates a line graph of those distances and their corresponding z-scores. Z-scores reflect the intensity of Geospatial clustering, and statistically significant peak z-scores indicate distances where Geospatial processes promoting clustering are most pronounced. These peak distances are often appropriate values to use for Methods with a Distance Band or Distance Radius parameter. This Method can help you select an appropriate Distance Threshold or Radius for Methods that have these parameters, such as Hot Spot Analysis or Point Density. **Geospatial Autocorrelation:** Geospatial Autocorrelation (Global Moran's I) Measures Geospatial autocorrelation based on feature locations and attribute values using the Global Moran's I statistic [13]. **Multi-Distance Geospatial Cluster Analysis :** Determines whether features, or the values associated with features, exhibit statistically significant clustering or dispersion over a range of distances[14]. This Method requires projected data to accurately measure distances. [15],[16],[17],[18],[19],[20],[21],[22],[23],[24],[25],

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2. Methodology

The Analyzing Patterns Methods are Average Nearest Neighbor, High/Low Clustering, Incremental Geospatial Autocorrelation, Geospatial Autocorrelation, Multi-Distance Geospatial Cluster Analysis (Ripley's k-function)) for renewable energy (Solar, Wind, and Biomass) .

2.1. Geospatial Average nearest Neighbor: The Average Nearest Neighbor Method measures the distance between each feature centroid and its nearest neighbor's centroid location for renewable energy (Solar, Wind, and Biomass). It then averages all these nearest neighbor distances. If the average distance is less than the average for a hypothetical random distribution, the distribution of the features of renewable energy (Solar, Wind, and Biomass) being analyzed is considered clustered. If the average distance is greater than a hypothetical random distribution, the features of renewable energy (Solar, Wind, and Biomass) are considered dispersed. The average nearest neighbor ratio is calculated as the observed average distance divided by the expected average distance (with expected average distance being based on a hypothetical random distribution with the same number of features covering the same total area) [26].[27]

The Average Nearest Neighbor ratio is given as:

$$ANN = \frac{\bar{D}_O}{\bar{D}_E} \quad (1)$$

where $\bar{D}_O$ is the observed mean distance between each feature and its nearest neighbor:

$$\bar{D}_O = \frac{\sum_{i=1}^{n} d_i}{n} \quad (2)$$

and $\bar{D}_E$ is the expected mean distance for the features given in a random pattern:

$$\bar{D}_E = \frac{0.5}{\sqrt{n/A}} \quad (3)$$

In the above equations, d_i equals the distance between feature i and it's nearest neighboring feature, n corresponds to the total number of features, and A is the area of a minimum enclosing rectangle around all features, or it's a user-specified Area value.

The average nearest neighbor z-score for the statistic is calculated as:

$$z = \frac{\bar{D}_O - \bar{D}_E}{SE} \quad (4)$$

where:

$$SE = \frac{0.26136}{\sqrt{n^2/A}} \quad (5)$$

If the index (average nearest neighbor ratio) is less than 1, the pattern exhibits clustering. If the index is greater than 1, the trend is toward dispersion. The equations used to calculate the average nearest neighbor distance index (1) and z-score (4) are based on the assumption that the points being measured are free to locate anywhere within the study area (for example, there are no barriers, and all cases or features are located independently of one another). The p-value is a numerical approximation of the area under the curve for a known distribution, limited by the test statistic. [28],

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2.2. Geospatial Measuring Clustering: The High/Low Clustering Method measures the concentration of high or low values for a given study area for renewable energy (Solar, Wind, and Biomass).

The General G statistic of overall spatial association is given as:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j}, \ \forall j \neq i \qquad (1)$$

where x_i and x_j are attribute values for features i and j, and $w_{i,j}$ is the spatial weight between feature i and j. n is the number of features in the dataset and $\forall j \neq i$ indicates that features i and j cannot be the same feature.

The z_G-score for the statistic is computed as:

$$z_G = \frac{G - \mathrm{E}[G]}{\sqrt{\mathrm{V}[G]}} \qquad (2)$$

where:

$$\mathrm{E}[G] = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}}{n(n-1)}, \ \forall j \neq i \qquad (3)$$

$$\mathrm{V}[G] = \mathrm{E}[G^2] - \mathrm{E}[G]^2 \qquad (4)$$

Notice that the only difference between the numerator and the denominator is the weighting (wij). High/Low Clustering will only work with positive values. Consequently, if your weights are binary (0/1) or are always less than 1, the range for General G will be between 0 and 1. A binary weighting scheme is recommended for this statistic. Select Fixed Distance Band, Polygon Contiguity, K Nearest Neighbors, or Delaunay Triangulation for the Conceptualization of Geospatial Relationships parameter. Select None for the Standardization parameter[[29]].,[[30]],

2.3. Incremental Geospatial Autocorrelation : With much of the Geospatial data analysis you do, the scale of your analysis will be important. The default Conceptualization of Geospatial Relationships for the Hot Spot Analysis Method, for example, is FIXED_DISTANCE_BAND and requires you to specify a distance value. For many density Methods you will be asked to provide a radius value. The distance you select should relate to the scale of the question you are trying to answer or to the scale of remediation you are considering. Suppose, for example, you want to understand childhood obesity. What is your scale of analysis? Is it at the individual household or neighborhood level? If so, the distance you use to define your scale of analysis will be small, encompassing the homes within a block or two of each other. Alternatively, what will be the scale of remediation? Perhaps your question involves where to increase after-school fitness programs as a way to potentially reduce childhood obesity. In that case, your distance will likely be reflective of school zones. Sometimes it's fairly easy to determine an appropriate scale of analysis; if you are analyzing commuting patterns and know that the average journey to work is 12 miles, for example, then 12 miles would be an appropriate distance to use for your analysis. Other times it is more difficult to justify any particular analysis distance. This is when the Incremental Geospatial Autocorrelation Method is most helpful. Whenever you see Geospatial clustering in the landscape, you are seeing evidence of underlying Geospatial processes at work. Knowing something about the Geospatial scale at which those underlying processes operate can help you select an appropriate analysis distance. The Incremental Geospatial Autocorrelation Method runs the Geospatial Autocorrelation (Global Moran's I) Method for a series of increasing distances, measuring the intensity of Geospatial clustering for each distance. The intensity of clustering is determined by the z-score returned. Typically, as the distance increases, so does the z-score, indicating intensification of clustering. At some particular distance, however, the z-score generally peaks. Sometimes you will see multiple peaks [31][32].

2.4. Geospatial Autocorrelation: The Geospatial Autocorrelation (Global Moran's I) Method measures Geospatial autocorrelation based on both feature locations and feature values simultaneously. Given a set of features and an associated attribute, it evaluates whether the pattern expressed is clustered, dispersed, or random. The Method calculates the Moran's I Index value and both a a z-score and p-value to evaluate the significance of that Index. P-values are numerical approximations of the area under the curve for a known distribution, limited by the test statistic. The Geospatial Autocorrelation (Global Moran's I) Method is an inferential statistic, which means that the results of the analysis are always interpreted within the context of its null hypothesis. For the Global Moran's I statistic, the null hypothesis states that the attribute being analyzed is randomly distributed among the features in your study area; said another way, the Geospatial processes promoting the observed pattern of values is random chance. Imagine that you could pick up the values for the attribute you are analyzing and throw them down onto your features, letting each value fall where it may. This process (picking up and throwing down the values) is an example of a random chance Geospatial process [33][34],[35],.

The Moran's I statistic for spatial autocorrelation is given as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - \bar{X})$, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2}$$

The z_I-score for the statistic is computed as:

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{V}[I]}} \tag{3}$$

where:

$$\mathrm{E}[I] = -1/(n-1) \tag{4}$$

$$\mathrm{V}[I] = \mathrm{E}[I^2] - \mathrm{E}[I]^2 \tag{5}$$

2.5. Multi-Distance Geospatial Cluster Analysis: The Multi-Distance Geospatial Cluster Analysis Method, based on Ripley's K-function, is another way to analyze the Geospatial pattern of incident point data. A distinguishing feature of this method from others in this Method (Geospatial Autocorrelation and Hot Spot Analysis) is that it summarizes Geospatial dependence (feature clustering or feature dispersion) over a range of distances. In many feature pattern analysis studies, the selection of an appropriate scale of analysis is required. For example, a Distance Band or Threshold Distance is often needed for the analysis. When exploring Geospatial patterns at multiple distances and Geospatial scales, patterns change, often reflecting the dominance of particular Geospatial processes at work. Ripley's K-function illustrates how the Geospatial clustering or dispersion of feature centroids changes when the neighborhood size changes,[36],[37],.

When using this Method, specify the number of distances to evaluate and, optionally, a starting distance and/or distance increment. With this information, the Method computes the average number of neighboring features associated with each feature; neighboring features are those closer than the distance being evaluated. As the evaluation distance increases, each feature will typically have more neighbors. If the average number of neighbors for a particular evaluation distance is higher/larger than the average concentration of features throughout the study area, the distribution is considered clustered at that distance. Use this Method when you are interested in examining how the clustering/dispersion of your features changes at different distances (different scales of analysis). A number of variations of Ripley's original K-function have been suggested [38]. Here, a common transformation of the K-function, often referred to as L(d), is implemented:

The K-Function is given as:

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} k_{i,j}}{\pi n(n-1)}} \qquad (1)$$

where d is the distance, n is equal to the total number of features, A represents the total area of the features and $k_{i,j}$ is a weight. If there is no edge correction, then the weight will be equal to one when the distance between i and j is less than d, and will equate to zero otherwise. Using a given edge correction method will modify $k_{i,j}$ slightly.

With the L(d) transformation, the Expected K value is equal to Distance

3. Results

Geospatial analysis is of paramount importance in evaluating the viability of renewable energy sources due to the pressing environmental concerns and climate change. The focus on solar energy has gained considerable traction with the increasing adoption of renewable energy. For example, Saudi Arabia aims to incorporate approximately 40 GW of solar PV technologies for renewable energy generation by 2030. However, the high installation costs for solar energy projects necessitate thorough research into the availability of solar energy in different locations before project implementation. Geospatial analysis plays a pivotal role in identifying suitable sites for the deployment of solar energy projects. Various studies have utilized Geographical Information System (GIS) in conjunction with methods like Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Making (MCDM) to carry out precise spatial analysis. Furthermore, integrating spatial analytical approaches with advanced space-time pattern mining analytics and prediction can offer deeper insights into diseases such as vector-borne diseases like Dengue Fever. By combining traditional geo-information models with advanced analytics-based techniques, a comprehensive evaluation and understanding of disease data can be achieved. It is also crucial to consider the spatial aspect when examining factors influencing COVID-19 mortality rates. The significance and impact of socioeconomic and health determinants differ across various spatial contexts, including metropolitan vs. non-metropolitan areas, areas with shelter-in-place orders vs. those without, and Democratic vs. Republican counties. In summary, geospatial analysis in renewable energy applications is essential for addressing environmental challenges, determining appropriate sites for energy projects, comprehending disease patterns, and analyzing factors that affect public health outcomes[39][40].

When it comes to GIS Analyzing Patterns for Renewable Energy, the implementation methodology plays a critical role in the overall process. Once the methodology for geospatial analyzing patterns for renewable energy has been analyzed and designed, understanding how to effectively implement these methodologies becomes essential. One key aspect of implementation involves utilizing geospatial data approaches to tackle spatial expansion, forest encroachment, and sustainable energy infrastructure needs. This entails gathering and integrating diverse types of geospatial data related to land use, terrain characteristics, and assumptions about population growth. By linking these to urban growth models and predictions, as well as energy requirements, it becomes possible to simulate and predict spatial effects with a focus on meeting the expanding energy needs. Another crucial aspect is the comparison of different energy sources, such as solar and wind energy. This comparison aids in understanding the potential spatial conflicts between locating sustainable energy production facilities and preserving ecologically sensitive areas. Finding solutions such as leveraging existing mining infrastructures to enhance sustainable energy production and using combined land and water solar energy systems is a vital part of the implementation methodology. Furthermore, integrating machine learning methodologies for clustering regression coefficients through geographically weighted regression (GWR) can offer an efficient overview of spatial patterns. This can then be utilized in profiling locations assigned to different clusters, modeling spatial drift, addressing spatio-temporal stability, generalizing clusters based on inter-temporal data, and more. It is also crucial to consider potential challenges such as data availability, scalability, integrability, and the lack of clear frameworks when applying renewable energy in net zero energy buildings using GIS,[41].[42].. Overcoming these challenges requires a systematic mapping at multiple scales using GIS tools that help identify emission hotspots, locate spatial resources, restructure district energy mix, and achieve net zero energy targets. In conclusion, effectively implementing GIS Analyzing Patterns for Renewable Energy demands a comprehensive approach that integrates various geospatial data methodologies with machine learning techniques to address spatial expansion, forest encroachment, sustainable energy infrastructure requirements alongside overcoming potential challenges in applying renewable energy in net zero buildings[43][44],[45],[46],[47].

Evaluate competition or territory: Quantify and compare the Geospatial distribution of a variety of for renewable energy(solar, wind,and biomass energy) within a fixed study area; compare average nearest neighbor distances for different types of businesses within a city for renewable energy(solar, wind,and biomass energy). Monitor changes over time: Evaluate changes in Geospatial clustering for a single type for renewable energy(solar, wind,and biomass energy) business within a fixed *study area over time. Compare an observed distribution to a control distribution: In a renewable energy analysis, you may want to compare the pattern of renewable energy areas to the pattern of renewable energy areas to determine if energy areas are more clustered than you would expect, given the distribution of reneawable energy overall. in addition to Look for unexpected spikes in the number of emergency room visits, which might indicate an outbreak of a local or regional energy problem. Comparing the Geospatial pattern of different types of renewable energy(solar, wind,and biomass energy)within a city to see which types cluster with competition to take advantage of comparison shopping and which types repel competition. Summarizing the level at which Geospatial phenomena cluster to examine changes at different times or in different locations for renewable energy(solar, wind,and biomass energy). For example, it is known that cities and their populations cluster. Using High/Low Clustering analysis, you can compare the level of population clustering within a single city over time (analysis of urban growth and density). Help identify an appropriate neighborhood distance for a variety of Geospatial analysis methods by finding the distance where Geospatial autocorrelation is strongest for renewable energy(solar, wind,and biomass energy). Measure broad trends of renewable energy(solar, wind,and biomass energy). Summarize the diffusion for renewable energy(solar, wind,and biomass energy)—is for renewable energy(solar, wind,and biomass energy) remaining isolated and concentrated, or spreading and becoming more diffuse?

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