Optimizing Site Selection Under Extreme Weather Conditions Based on Multi-Layered Raster Overlay Technology

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Abstract. With the increasing likelihood of more severe weather and natural disasters due to climate change, extreme weather events are becoming a crisis for property owners and insurance companies. The Resilient Property Assessment Model (RPE) is established based on geostatistical kriging techniques to evaluate property locations under extreme weather conditions in the United States, aiding decision-making for real estate and insurance industries. Initially, discrete meteorological data is extrapolated into continuous fields, forming the optimization model. Subsequently, it integrates GIS's multi-layered raster overlay technology to precisely identify prime areas for property development and insurance coverage through comprehensive assessments of 13 natural and social factors. Findings reveal that 8 states possess high-quality insurance markets, primarily concentrated in the eastern and central border regions of the United States. Additionally, leveraging existing data, it investigates the spatial dynamics of North Atlantic tropical cyclones, tracking them to enhance regional insurance strategies, further affirming the reliability of the RPE model. This paper aims to provide corresponding recommendations for local real estate site selection and insurance model adjustments through the RPE model, to better cope with the crisis of frequent extreme weather events.

Keywords: Extreme Weather, RPE, Optimization Model, GIS, Site Selection.

1. Introduction

The recent data from the World Meteorological Organization (WMO) underscores the severe impact of extreme weather, climate change, and flooding events spanning from 1970 to 2021 [1-2]. During this period, 11,778 recorded disasters resulted in over two million deaths and economic losses totaling 4.3 trillion. Munich Re's statistics further reveal that in 2020 alone, global economic losses from natural disasters surged to 210 billion, marking a 26.5% increase from the previous year [3]. Moreover, the insurance sector experienced a significant rise in claims, reaching 82 billion—a 43.9% jump compared to the preceding year. The escalation in natural disasters has profoundly affected the global insurance industry, leading to rapidly increasing premiums, which are projected to rise by 30-60% by 2040 as a consequence of climate change. In the face of increasingly frequent extreme weather events, determining where to build and how to adjust insurance systems poses a significant challenge for both the real estate and insurance industries.

Traditional methods to make site selection or insurance range can be broadly categorized into the following four types: 1. statistical analysis; 2. land valuation; 3. SWOT analysis; 4. expert judgment. The statistical analysis method selects the most promising locations by analyzing data such as

population density, economic activities, transportation convenience, and so on. Cheng W. et al. conducted big data statistical analysis by distributing questionnaires to collect users' opinions on various factors such as environmental preferences, cost-effectiveness, overall reputation, and cultural customs [4]. This enabled them to derive address characteristics that better meet consumer preferences. However, this approach requires a large amount of data, which can be challenging to collect, and it overlooks certain subjective factors. The land evaluation method assesses the suitability of land by considering factors such as land quality, land use planning, and the surrounding environment, thus selecting the appropriate land use. Omidipoor et al. developed a geographic marketing decision system by starting from the spatial layout of the land, integrating basic criteria such as land price and area, as well as geographic distribution standards such as neighboring facilities [5]. While this method takes into account the characteristics of the land, it requires considerable manpower and resources, and the evaluation process is complex. The SWOT analysis method involves conducting a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis of the site, considering both internal and external factors, to determine the optimal location. Zhou J et al. conducted a comprehensive SWOT analysis of twelve factors influencing the implementation of prefabricated construction, including prefabricated construction standards, ecological benefits, and transportation capacity [6-7]. Based on the analysis results, they formulated strategies for the development of prefabricated construction. However, this method necessitates the collection of vast amounts of information and intricate analysis of numerous interrelated factors, potentially consuming considerable time. The final method, expert judgment, relies on the experience and expertise of professionals or teams to make site selection decisions. Comu S et al. utilized the Fuzzy Analytical Hierarchy Process (AHP) to identify suitable locations for real estate projects in Turkey based on interviews with professionals [8]. Meanwhile, Fang Y et al. conducted expert field surveys and professional judgments, guided by residents' real experiences and needs, to refine and validate the initial elements of the 12-site evaluation model using AHP [9]. Although this approach allows for flexible judgment based on real-world considerations, it is susceptible to significant influence from individual subjective factors, potentially introducing biases.

To better integrate geographical location information and mitigate the complexity of manual data collection and land assessment processes, we propose the Resilient Property Assessment Model (RPE) based on GIS multi-layered raster overlay technology. This model is utilized for evaluating the value of properties and, in conjunction with optimization techniques, aids decision-making in the real estate and insurance industries. First, weights for natural and social factors influencing site selection are determined based on collected data. Next, meteorological station data undergo preprocessing to remove outliers, followed by vectorization of statistical data based on the spatial coordinates of the stations. Subsequently, discrete station data is extrapolated to continuous meteorological fields, and the likelihood of meteorological events is assessed. Then, terrain features such as valleys and slopes are extracted from the data. Finally, calculations are performed using the assigned weights.

2. Methodology

2.1. Resilient Property Evaluation Model

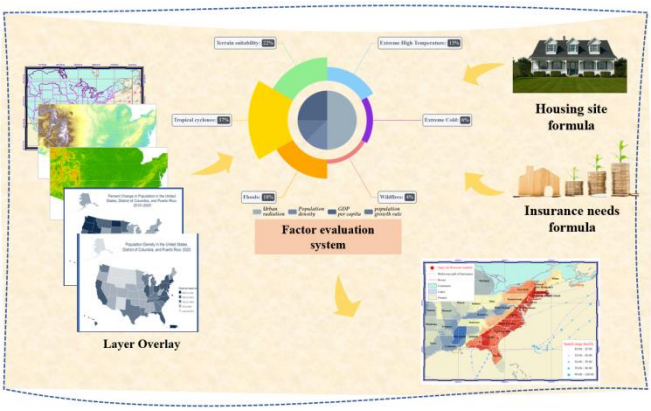


Figure 1 The flowchart of the RPE model

In this section, the focus shifts to the selection and weighting of factors, followed by the establishment of a geographic spatial analysis model based on these factors. Subsequently, the introduction of a comprehensive scoring model for natural and social aspects is presented. Finally, recommendations for property location are provided based on the computed results, with further refinement of the insurance model to align with insurance requirements. In summary, the RPE model comprises these four modules as shown in Figure 1 above.

2.1.1 Weighting Rules

In our rigorous evaluation of the impact of natural and socio-economic factors on real estate siting, we have meticulously selected six natural suitability factors, comprising nine sub-factors, along with two social supply and demand potential factors, incorporating a total of four sub-factors [10]. This comprehensive selection allows for a holistic assessment of both the natural environment and socio-economic influences on property locations.

To assign scores to these factors, we have meticulously applied the principles of physical and human geography, taking into account the distinctive geographical characteristics of the U.S. Subsequently, we have devised a five-grade scoring system for each factor, wherein higher grades indicate greater suitability for real estate siting [11]. This grading system facilitates a systematic and quantifiable evaluation of the influence of each factor on property siting decisions (see Table 1 and Table 2).

Table 1: Natural site suitability evaluation factors and weights

Evaluation Factors	Subfactor	Compound Weights
Extreme heat	Summer max temperature	0.13
Extreme cold	Winter minimum temperature	0.06
Wildfire	Summer max temperature	0.016
	High temperatures and concurrent rainfall	0.024
Flood	Maximum daily rainfall during the rainy season	0.12
	Gully topography	0.06
Tropical cyclone	Cyclone ring	0.37
Terrain suitability	Elevation	0.11
	Slope	0.11

Table 2: Factors and weights for evaluating social supply and demand potential.

Evaluation Factors	Subfactor	Compound Weights
Radiation effect of urban concentric circles	Distance to the main city	0.5
Home Buying Potential	Population density	0.125
	Average population growth rate	0.125
	GDP per capita	0.25

2.2. Geospatial Analysis Module

The geospatial analysis model comprises three main components: geographic data, a geographic information system (GIS), and a spatial analysis program [12].

2.2.1 Geographic Information System

GIS operates at the intersection of earth science, space science, and information science, serving as both a foundational discipline and an applied technology. It leverages geoscience principles, along with computer hardware and software, to explore theoretical and practical approaches for acquiring, processing, storing, managing, analyzing, modeling, and displaying spatial data. The goal is to address complex issues in management, planning, and decision-making.

2.2.2 Spatial Analysis Program

To effectively tackle this issue, we've developed four essential GIS analysis modules, encompassing the entire workflow from data preprocessing to sophisticated spatial analysis:

1. Meteorological Data Preprocessing: This step involves cleaning up anomalies like garbled data and missing values, detrending data, and conducting normal Z tests. It also includes vectorizing statistical data based on the spatial coordinates of meteorological stations.

2. Meteorological Field Derivation from Discrete Station Data: This involves using Kriging Interpolation for spatial interpolation of meteorological variables and applying indicator kriging to verify the feasibility of derived meteorological fields.

3. Meteorological Field Derivation from Discrete Station Data: This process involves hydrological analysis to identify gully buffer zones and calculate elevation variability to determine slope gradients.

4. Spatial Suitability Evaluation: This final module includes reclassifying raster classes and performing spatial overlay calculations to weigh different factors.

2.2.3 Key Principle

1. Grid overlay analysis integrates geographic data from diverse sources, including population distribution and climatic conditions, into a multi-dimensional space. This integration enables the exploration of data interrelationships and interactions (see Figure 2). By delineating the intricate connections between geographic phenomena, grid overlay analysis aids in identifying and evaluating spatial patterns and trends. This approach fosters precise and thorough spatial decision-making, enhancing comprehension of the complex dynamics within a specified area (see Equation 1).

$$R = \sum_{i=1}^{n} (W_i \times L_i) \tag{1}$$

where R denotes the resultant raster layer, W_i is the weight of the i-th raster layer, L_i means the data value of the i-th raster layer, and n is the total number of raster layers.

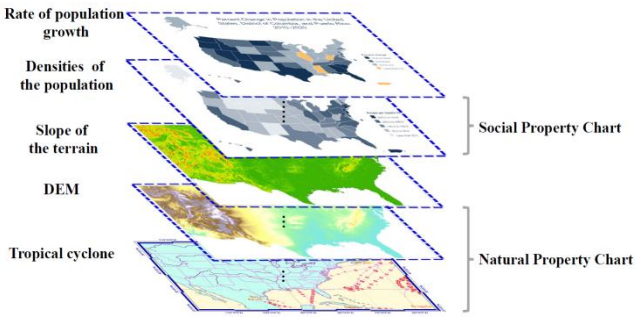


Figure 2. Layer overlay.

2. Kriging Interpolation, a statistically grounded technique, also referred to as spatial local interpolation, utilizes regionalized variables. It relies on variational functions as the primary tool for linearly unbiased and optimal estimation of unknown sample points (see Equation 2).

$$\hat{z}_0 = \sum_{i=1}^{n} \lambda_i \hat{z}_i \tag{2}$$

where $\hat{z}_0$ represents the estimate at point (x_0, y_0), λ_i denotes the weight of the i-th data point, and $\hat{z}_i$ means the estimate of the i-th observation or known value.

The objective function with constraints is shown as Equation 3.

$$\begin{aligned} &\min \quad Var(\hat{z}_0 - z_0) \\ &s.t. \quad E(\hat{z}_0 - z_0) = 0 \end{aligned} \tag{3}$$

2.2.4 Calculation of the combined nature and society score

1. Property Location Score

$$\begin{cases} S_{id} = S_{nf} + S_{sf} \\ S_{nf} = \sum Z_n \times P_n \\ S_{sf} = \sum Z_s \times P_s \end{cases} \tag{4}$$

where Z is the assessment level and P is the factor weights, the model shows that the higher the assessment level and the higher the factor weights, the higher the score and the more advantageous the property location.

2. Insurance Demand Score

$$\begin{cases} S_{id} = -S_{nf} + S_{sf} \\ S_{nf} = \sum Z_n \times P_n \\ S_{sf} = \sum Z_s \times P_s \end{cases} \tag{5}$$

Unlike property siting, natural factor scores are negatively correlated with demand scores due to extreme weather. The lower the natural factor score and the higher the social factor score, the higher the insurance demand level.

3. Results

3.1. Real Estate Site Selection

Utilizing our model to calculate property location scores, we generate a thematic map depicting the spatial distribution of these scores (see Figure 3) by ArcGIS. Several key findings are shown below:



Figure 3. Property site selection score results in Thematic Map

1. Regions on the map with a deeper red color indicate higher property site selection scores. This signifies that these areas are more favorable for property development, as determined by our comprehensive assessment of natural and social factors.

2. In the U.S., areas deemed most suitable for property development are predominantly located to the west of the Appalachian Mountains and along the southwest coast. A comparison with the topographic map of the U.S. reveals that many of these preferred locations are situated in open plains. Furthermore, when comparing state development data, it becomes apparent that these areas are also among the most economically advanced.

3. 11 states are identified as prime candidates for real estate development: Minnesota, California, Colorado, Illinois, Indiana, Ohio, Tennessee, Wisconsin, New York, Pennsylvania, Michigan, along with the southeast corner of Florida. These areas combine favorable natural conditions and strong socio-economic potential, making them attractive for property development initiatives.

3.2. Insurance Requirements

Based on the model for calculating the insurance demand score, we obtained a thematic map of the spatial distribution of the insurance demand score by ArcGIS (see Figure 4). After analyzing the map, we come up with the following conclusions:

1. As the color of the map space deepens into red, the insurance demand score increases, indicating that, within our established comprehensive assessment framework considering both natural and social factors, these regions have a higher demand for insurance coverage.

2. In the United States, regions with heightened insurance demand are primarily concentrated in the southeastern coastal zones (east of the Appalachian Mountains) and the southwestern coastal areas. Upon comparing these areas with the topographical map of the U.S., it becomes apparent that the majority of these high-demand insurance zones are situated within coastal plains. In addition, upon scrutinizing the development statistics of diverse U.S. states, it is evident that these development-friendly locales often boast economic prosperity.

3. The 11 states in the U.S. with higher insurance demand are California, Connecticut, Massachusetts, Georgia, South Carolina, North Carolina, Virginia, New Jersey, New York, Pennsylvania, and the northwestern corner of Florida.

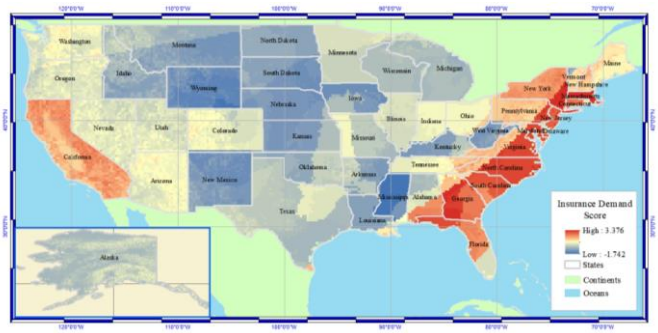


Figure 4. Insurance demand score thematic map

3.3. Insurance Placement Area Selection and Model Restructuring

We've identified a paradox when comparing the 11 states suitable for property development with the 11 states with higher insurance demand. It appears that some areas have both high insurance demand due to extreme weather and suitability for real estate development. Upon deeper consideration, we've discerned the underlying reason: these regions were prosperous in terms of social development before the frequent occurrence of extreme weather events. So, the damage caused by these extreme weather events is now leading to even greater insurance losses.

As a result of this analysis, we've defined the following regions as unsuitable for insurance coverage: California, New York, Pennsylvania, and Florida. Conversely, the remaining areas suitable for real estate development are defined as suitable for insurance coverage: Minnesota, Colorado, Illinois, Indiana, Ohio, Tennessee, Wisconsin, and Michigan.

For regions where insurance coverage is not advisable but necessary, we adjust the insurance plans as follows: Increase premiums and reduce payout ratios based on the likelihood and severity of extreme weather events, while also limiting the scope of business. Specifically for Florida, consider adopting a "one state, two systems" insurance strategy: in the northwestern part, raise premiums, reduce policy issuance, and continuously assess risks; meanwhile, consider the southeastern part as the recommended coverage area.

3.4. In Depth - Tropical Cyclones in the North Atlantic Ocean

In our research, we discover that the costliest extreme weather events for the U.S. since the 21st century have been tropical cyclones in the North Atlantic [13-14]. Thus, in our analysis of historical meteorological data, we utilize regression analysis to model the consistent multi-year trajectories, wind speed thresholds, and prevalent landfall locations of tropical cyclones. This allows us to visualize the activity of North Atlantic tropical cyclones effectively and create a Tropical Cyclone Data Clock based on the tropical cyclones by Python (see Figure 5 and Figure 6).

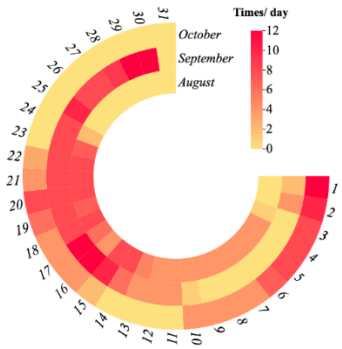


Figure 5. Tropical Cyclone Data Clock

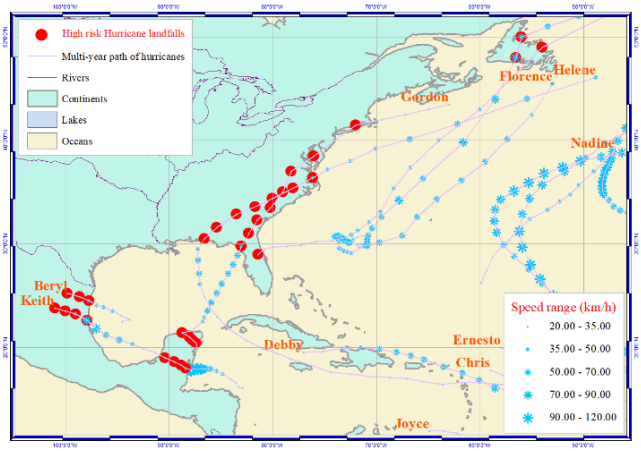


Figure 6. Thematic map of tropical cyclone activity in the North Atlantic Ocean

By integrating Figure 4 of insurance demand scores, we find that areas with high insurance demand scores are often located in regions where tropical cyclones make landfall. As Figure 7 shows below, this observation validates the reliability of the natural factors related to extreme weather that we select in the RPE model.

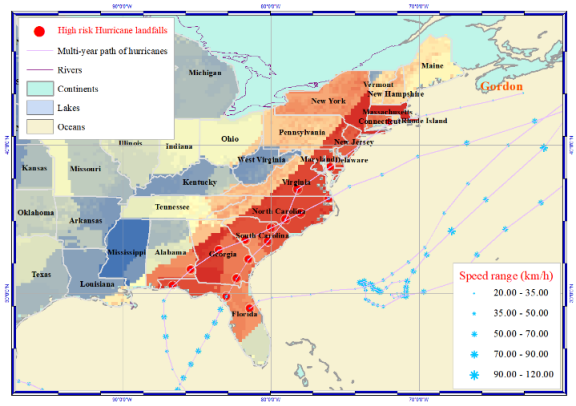


Figure 7. Insurance needs score high area

4. Conclusions

With the increasing occurrence of global warming and extreme weather events, both the real estate and insurance industries are significantly impacted. This paper proposes the Resilient Property Assessment Model (RPE) to address property assessment under extreme weather conditions and applies it to provide recommendations for the United States. The model results indicate that the regions of Minnesota, Colorado, Illinois, Indiana, Ohio, Tennessee, Wisconsin, and Michigan are suitable for real estate development and thus deemed suitable for insurance coverage. However, areas deemed unsuitable for insurance coverage require adjustments in insurance models. Based on the probability and magnitude of extreme weather occurrences, certain regions may necessitate premium increases or limitations on the coverage scope of insurance policies. Furthermore, through tracking North Atlantic tropical cyclones, we further validate the reliability of our model. However, there are still some limitations and areas for improvement: (1) the model assumes equal importance between natural and social factors; (2) to better apply the model in practice, more reliable meteorological and geographical data are needed. In the future, more efforts will be made to simplify the model and extend its application to site selection in other industries, such as hospitals, schools and so on.

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