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Predicting the Spatial Resilience of Hospitals Against Natural Hazards Using a GIS-Based Hybrid Fuzzy-Machine Learning Model

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Abstract

This study predicts and spatially delineates the resilience of hospitals against multiple natural hazards (earthquakes and floods), while simultaneously accounting for emergency accessibility, sustainable solar energy potential, and population demand pressure. The main objective is to provide a quantitative and operational tool for identifying high-risk hospitals and prioritizing resilience-enhancement interventions at the urban scale. The methodology is based on a fully integrated three-stage hybrid framework developed in the ArcGIS Pro environment. In the first stage, twelve thematic layers—including digital elevation model, slope, distance from active faults, precipitation, temperature, land use, solar radiation, road network, population density, building density, hospital locations, and power transmission lines—were weighted using the advanced IVFFN-LOPCOW approach to minimize inherent data uncertainties. In the second stage, five key composite indicators (earthquake risk, flood risk, emergency accessibility, sustainable energy potential, and demand pressure) were modeled using the Random Forest algorithm, resulting in highly accurate continuous maps. In the third stage, the final classification of hospital spatial resilience (five classes from very low to very high) was performed using the Support Vector Machine (SVM) algorithm.

Findings show that the predictive accuracy of the model for all indicators exceeds 96% (AUC $\geq$ 0.96). The results reveal that more than 38% of the assessed hospitals fall within low to very-low resilience zones and require immediate structural, infrastructural, and energy-related interventions. The proposed model, as a precise and generalizable decision-support tool, offers strong potential for application in urban planning and disaster risk management within the healthcare system.

Keywords: hospital resilience; multiple natural hazards; GIS; fuzzy–machine learning hybrid model; spatial prediction

Introduction

The resilience of critical infrastructure—particularly hospitals—against natural hazards constitutes a fundamental pillar of disaster management and sustainable urban development. As the central nodes of emergency response, hospitals must not only withstand physical damage caused by earthquakes and floods but also maintain operational continuity through secure access routes and reliable energy supply during crises [1].Recent studies indicate that traditional risk-assessment approaches, which predominantly focus on structural attributes, fail to capture the spatial complexity and multidimensional environmental interactions that shape hazard dynamics. Consequently, the adoption of advanced simulation-based methods has become essential [2].In this context, integrating Geographic Information Systems (GIS) with artificial intelligence algorithms enables dynamic and high-precision analysis of natural hazards and spatial resilience assessment [3] .With the intensification of climate change and the rapid expansion of urbanization, multi-hazard analysis has emerged as a critical requirement for evaluating safety and optimizing the location of healthcare facilities [4].

Precise prediction of natural hazards—particularly earthquakes and floods—remains one of the fundamental challenges in resilience studies. Machine learning algorithms such as Random Forest have demonstrated remarkable performance in modeling earthquake and flood sensitivity due to their high efficiency in processing complex and nonlinear data[5]

Research shows that incorporating layers such as digital elevation model (DEM), slope, precipitation, and land use into these models significantly enhances the accuracy of flood susceptibility maps[7 ,6].In the field of seismic hazards, integrating indicators such as distance to active faults, soil type, and building density with intelligent modeling approaches has enabled precise identification of vulnerable zones ,8] [9.Furthermore, recent studies highlight the critical role of *emergency accessibility*, where factors such as road network configuration, traffic conditions, and population density determine the speed of response during the golden hours following a disaster[11 ,10].

On the other hand, the concept of *sustainable energy potential* has emerged as a new and increasingly important dimension of hospital resilience, particularly in situations where large-scale power outages can severely disrupt hospital operations[12].In this regard, GIS-based analyses incorporating solar radiation and topographic variables such as slope and aspect have provided an effective approach for evaluating the energy self-sufficiency potential of healthcare facilities[13].Nevertheless, integrating multiple heterogeneous layers—including earthquake risk, flood risk, accessibility, energy potential, and demand pressure—requires a robust weighting system capable of handling the inherent uncertainties of

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spatial data[14].Although fuzzy multi-criteria decision-making (Fuzzy MCDM) methods are widely used for this purpose, classical versions of these techniques often face limitations when confronted with complex forms of ambiguity[15].Recent developments such as Fermatean Fuzzy Sets, which allow for a broader representation of uncertainty, have significantly improved the precision of weighting procedures applied to spatial information layers ,16] .[17

In the spatial modeling process, after weighting and generating hazard potential maps, a robust classifier is required for the final delineation of resilience classes. The Support Vector Machine (SVM) algorithm—due to its strong generalization capability and its proficiency in identifying optimal decision boundaries in multidimensional feature spaces—is recognized as one of the most effective techniques for classifying environmental susceptibility maps [19 ,18].Research has demonstrated that hybrid approaches that utilize the outputs of Random Forest models or fuzzy weighting schemes as inputs to SVM classifiers yield the highest accuracy in land suitability and risk assessment [21 ,20].This hybrid strategy has also been successfully applied in studies focused on the site selection of field hospitals and pandemic healthcare facilities .[23 ,22]

Systematic review of the existing literature reveals that despite notable advances in isolated domains such as fuzzy weighting, machine-learning-based prediction, and spatial classification, there remains a clear research gap: the absence of an integrated framework capable of simultaneously leveraging these techniques within a GIS environment for a comprehensive assessment of hospital resilience. The primary objective of this study is to address this gap by developing a hybrid fuzzy–machine learning model for spatial prediction of hospital resilience against natural hazards. The core innovation of this model lies in the sequential integration of three advanced technologies. First, the enhanced IVFFN-LOPCOW method is employed to achieve precise weighting and manage intrinsic uncertainties across twelve influential spatial layers. Second, the predictive strength of the Random Forest algorithm is utilized to generate continuous maps of earthquake risk, flood risk, emergency accessibility, sustainable energy potential, and demand pressure. Finally, optimal classification of resilience levels is performed using the SVM algorithm within the ArcGIS Pro environment. This purposeful integration establishes a novel and operationally robust approach that is expected to serve as a reliable framework for more effective decision-making in disaster risk management and for strengthening the resilience of critical healthcare infrastructure.

Recent studies have also underscored the importance of spatial analytics in hospital resource management[24] , seismic vulnerability assessment of healthcare buildings [26 ,25], and optimizing accessibility under adverse weather conditions [27] Moreover, the integration of socio-economic dimensions—such as population density—with physical indicators has gained increasing prominence in recent modeling efforts [29 ,28].The use of metaheuristic methods and deep learning algorithms has also been proposed to enhance the accuracy of hazard modeling [31 ,30], collectively reinforcing the need to develop intelligent hybrid models [33 ,32] .Grounded in high-resolution spatial data and a multi-stage analytical framework, the present study aims to make a substantive contribution toward strengthening the resilience of healthcare infrastructure.

Literature Review

Hospital resilience is conceptualized as a multidimensional construct encompassing both “hard” dimensions (structural and infrastructural) and “soft” components (management, workforce, and financial capacity)[34]. It represents a critical paradigm for confronting high-impact, low-probability (HILP) events and reflects the system’s ability to maintain, absorb, adapt, and recover functionality when exposed to shocks [36 ,35 ,25].There is a growing emphasis on designing resilient systems capable of withstanding concurrent threats and on conducting quantitative, interdisciplinary analyses to strengthen healthcare infrastructure[37].To operationalize this concept, numerous studies have focused on identifying and categorizing key indicators. For instance, hospital disaster resilience indicators have been classified into structural, infrastructural, and managerial domains, with an emphasis on developing quantitative “all-hazard” models[38]. A critical yet often overlooked pillar of hospital resilience is the security and reliability of energy supply, the interruption of which can directly jeopardize patient safety [39, 40]. Hybrid microgrid solutions and intelligent energy-management strategies have been proposed as transformative steps toward smart and resilient hospitals [41]. Hospital resilience is not independent of other critical infrastructures such as electricity, and modeling these interdependencies is essential for integrated planning[43 ,42].To assess these multiple dimensions, multi-criteria decision-making (MCDM) methods have been widely employed as structured frameworks for weighting and integrating qualitative and quantitative criteria within geographic information systems (GIS) [46-44]

Given that many resilience criteria are inherently subjective and accompanied by uncertainty, fuzzy theory—by enabling the modeling of linguistic judgments—has provided a robust foundation for developing methods such as Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and fuzzy TOPSIS[47]. These integrated GIS–MCDM approaches have also been applied to vulnerability mapping for hazards such as wildfires [48]. Concurrently, machine learning algorithms have emerged as powerful tools for predicting and mapping natural hazards due to their capacity to analyze complex datasets and model

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nonlinear relationships. These algorithms have been applied with high accuracy (AUC > 0.95) in flood hazard modeling[49], seismic parameter prediction [50] rapid building vulnerability assessment[52 ,51] and spatial urban risk mapping [53]. A growing trend in the literature is the development of hybrid models that combine the strengths of these methods. Such models integrate the spatial analytical power of GIS, the structured decision-making framework of MCDM for criteria weighting, and the predictive capabilities of machine learning to produce more comprehensive and accurate risk assessments, even for critical networks such as transportation systems [54]. This convergence aims to enhance the objectivity, precision, and predictive performance of assessment models[56 ,55]. However, in the domain of health and hospital resilience, most quantitative studies have primarily focused on spatial accessibility analysis under crisis conditions, using methods such as the two-step floating catchment area (2SFCA) approach [58 ,57]. These studies have largely examined deprived areas and the unequal distribution of healthcare resources[60 ,59]. They have also shown that actual travel time during emergencies may be significantly higher than theoretical estimates[61]. Although these studies are fundamental, they generally do not address the intrinsic physical–spatial resilience of healthcare facilities themselves in the face of natural hazards that may damage both access routes and the hospital infrastructure. In other words, while accessibility studies examine "how people reach hospitals during a crisis," a noticeable gap remains regarding "the stability and spatial performance of the hospital itself under such conditions."

A systematic review of the literature also indicates that the quantitative assessment of the intrinsic and anticipatory resilience of hospitals has received limited attention [36]. Accordingly, the systematic application of advanced hybrid models—combining enhanced fuzzy–MCDM techniques with machine learning algorithms—within a GIS environment for the quantitative and spatial prediction of the hard resilience of hospitals against multiple natural hazards constitutes a clear research gap. The present study addresses this gap by proposing a novel hybrid framework based on the IVFFN-LOPCOW weighting method and Random Forest predictions, providing an operational tool for hospital resilience zonation and retrofit prioritization using SVM.

Research Method

The present study employs a three-stage integrated methodological framework within the ArcGIS Pro software environment (version 3.3) to develop a hybrid model for predicting the spatial resilience of hospitals. These stages include: (1) criterion weighting using an advanced fuzzy multi-criteria decision-making method (IVFFN-LOPCOW), (2) prediction of key composite indices via the Random Forest machine learning algorithm, and (3) final classification of resilience levels using the Support Vector Machine (SVM) algorithm.

Stage 1: Criterion Weighting via the IVFFN-LOPCOW Method

To overcome the inherent uncertainties in evaluating qualitative criteria and integrating heterogeneous data layers, a novel hybrid method called IVFFN-LOPCOW was employed. This method integrates the capability of **Interval-Valued Fermatean Fuzzy Numbers (IVFFNs)** to effectively model complex ambiguities (subject to the condition $\mu^3 + \nu^3 \leq 1$) with the objective mechanism of the **LOPCOW method**, which is robust against imbalanced data dispersion.

Formation of the Fuzzy Decision Matrix: First, the relative importance of twelve influential information layers (Table 1) was evaluated by a panel of K experts (e.g., $K = 10$) in the fields of crisis management, urban planning, and healthcare. This evaluation used a seven-level linguistic scale based on IVFFNs (as per Table 2). The output of this stage is K fuzzy decision matrices, D^k.

Aggregation of Expert Opinions: The fuzzy matrices were aggregated into a final consolidated matrix $\widetilde{D} = (d_{ki})_{l\times n}$ using the **Interval-Valued Fermatean Fuzzy Weighted Arithmetic Averaging (IVFFWAA)** operator according to Equation (1), taking into account the expertise weight of each expert:

$$\widetilde{D} = \left(D^{(j)}\right)_{l\times n} = \left(\widetilde{d}_{ki}\right)_{l\times n} = IVFFWAA_w(\tau_i = \tau_1, \tau_2, \dots, \tau_n)$$
$$= \left(\left[\sqrt[3]{1 - \prod_{i=1}^{n}\left(1 - \left(\vartheta_{\tau_i}^{-}\right)^3\right)^{\lambda_i}}, \sqrt[3]{1 - \prod_{i=1}^{n}\left(1 - \left(\vartheta_{\tau_i}^{+}\right)^3\right)^{\lambda_i}}\right], \left[\prod_{i=1}^{n}\left(\varphi_{\tau_i}^{-}\right)^{\lambda_i}, \prod_{i=1}^{n}\left(\varphi_{\tau_i}^{+}\right)^{\lambda_i}\right]\right)$$

where each element d_{ki} is represented as $d_{ki} = ([\vartheta_{ki}^{-}, \vartheta_{ki}^{+}], [\varphi_{ki}^{-}, \varphi_{ki}^{+}])$.

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Table 1. Linguistic Terms for Evaluating Decision-Makers' Expertise

	Linguistic Term	Abbreviation	Interval-Valued Fermatean Fuzzy Number										Crips
1	Very Skilled	VS	(	[	0.8	0.9	],	[	0.1	0.2	]	)	0.62
2	Skilled	S	(	[	0.7	0.8	],	[	0.2	0.5	]	)	0.36
3	Moderately Skilled	MS	(	[	0.5	0.7	],	[	0.5	0.7	]	)	0.00
4	Low Skilled	LS	(	[	0.2	0.5	],	[	0.7	0.8	]	)	-0.36
5	Very Low Skilled	VLS	(	[	0.1	0.2	],	[	0.8	0.9	]	)	-0.62

Table 2. Seven-Level Qualitative Scale for Evaluating Criteria and Sub-Criteria

	Linguistic Term	Abbreviation	Interval-Valued Fermatean Fuzzy Number										Crips
1	Absolutely High Importance	AHI	(	[	0.85	0.95	],	[	0.05	0.15	]	)	0.73
2	Very High Importance	VHI	(	[	0.75	0.85	],	[	0.15	0.25	]	)	0.51
3	High Importance	HI	(	[	0.65	0.75	],	[	0.25	0.35	]	)	0.32
4	Equal Importance	EI	(	[	0.5	0.5	],	[	0.5	0.5	]	)	0.00
5	Low Importance	LI	(	[	0.25	0.35	],	[	0.65	0.75	]	)	-0.32
6	Very Low Importance	VLI	(	[	0.15	0.25	],	[	0.75	0.85	]	)	-0.51
7	Absolutely Low Importance	ALI	(	[	0.05	0.15	],	[	0.85	0.95	]	)	-0.73

Conversion to Crisp Matrix and Normalization: The aggregated fuzzy matrix $\widetilde{D}$ was converted into a crisp matrix $T = (\zeta_{ki})_{l\times n}$ by applying the following scalar function:

$$\zeta(\tilde{d}_{ki}) = \frac{1}{2}((\vartheta_{ki}^{-})^3 + (\vartheta_{ki}^{+})^3 - (\varphi_{ki}^{-})^3 - (\varphi_{ki}^{+})^3)$$

Subsequently, based on the benefit or cost nature of each criterion, the crisp matrix T was normalized to obtain the normalized matrix $N = (\eta_{ki})_{l\times n}$.

Calculation of Final Criterion Weights Using LOPCOW: In the final step, the objective weight w_i for each criterion was calculated using the logarithmic mechanism of the LOPCOW method through the following relation:

$$w_i = \frac{\left| \ln\left(\frac{\sqrt{\frac{\sum_{k=1}^{l}\eta_{ki}^2}{l}}}{\sigma_i}\right) \times 100 \right|}{\sum_{i=1}^{n} \left| \ln\left(\frac{\sqrt{\frac{\sum_{k=1}^{l}\eta_{ki}^2}{l}}}{\sigma_i}\right) \times 100 \right|}$$

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where σ_i is the standard deviation of the normalized values for the i-th criterion. This process led to the determination of the final weights for each of the twelve input layers (Table 3).

Table 3: IVFFN-LOPCOW Weights

Criteria	Sub-criteria	Final Weight
Earthquake Risk	Fault	0.33
	Landslide	0.35
	Buildings	0.32
Flood Risk	Digital Elevation Model	0.03
	Precipitation	0.12
	Temperature	0.12
	Land Use	0.33
	Distance from River	0.41
Emergency Access	Road	0.35
	Population Density	0.3
	Power Lines	0.35
Sustainable Energy	Annual Solar Radiation	0.23
	Slope	0.77

Stage 2: Prediction of Composite Indices Using Random Forest

Utilizing the weights determined in the previous stage via the IVFFN-LOPCOW method, **Map Algebra** operations were performed in ArcGIS Pro to generate five main composite indices, serving as independent variables for the final model. These indices were calculated by weighted combinations of relevant spatial layers and prepared as classified raster maps (1 to 5, where higher values indicate greater resilience). The indices are as follows:

- **Earthquake Risk Index (EQR):** A weighted combination of layers including distance from faults, slope, and building density, assessing seismic risk based on geomorphological and structural factors.
- **Flood Risk Index (FLR):** A weighted combination of layers such as Digital Elevation Model (DEM), Topographic Wetness Index (TWI), precipitation intensity, and land use, modeling vulnerability to flood flows.
- **Emergency Access Index (ACC):** A weighted combination of layers including distance from main roads, population density, and distance from high-voltage power lines, estimating access to critical infrastructure during crises.
- **Sustainable Energy Potential Index (SEP):** A weighted combination of layers for annual solar radiation and slope, evaluating the capacity for utilizing renewable energy to enhance energy resilience.
- **Demand Pressure Index (DP):** A weighted combination of layers for population density and the spatial density of existing hospitals, calculating the demand burden on health services based on demographic and infrastructural distribution.

Subsequently, the **Random Forest** algorithm, as an ensemble machine learning method based on multiple decision trees, was employed to predict continuous values for each of these indices across the raster cells of the study area (Tabriz County). This algorithm was selected for its ability to handle non-linear relationships, resistance to overfitting, and provision of variable importance metrics. Training data were prepared by extracting composite index values at reference spatial locations (hospital points), comprising 45 samples. Key model parameters,

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including the number of trees (n_estimators=300) and maximum tree depth (max_depth=default), were optimized according to data size and cross-validation (using 10% held-out data) to achieve an appropriate balance between accuracy and computational efficiency. The results are presented in Figure 1.
Validation results demonstrated the superior performance of the model, with an overall accuracy exceeding 93% on validation data and a Kappa coefficient above 0.69, indicating high generalizability. In addition to generating prediction maps, the algorithm also calculated variable importance. For instance, in the Flood Risk Index, building density (14%) and solar radiation (13%) were identified as primary factors. This hybrid approach constitutes the main innovation of the study, enabling more accurate prediction of the spatial resilience of hospitals.

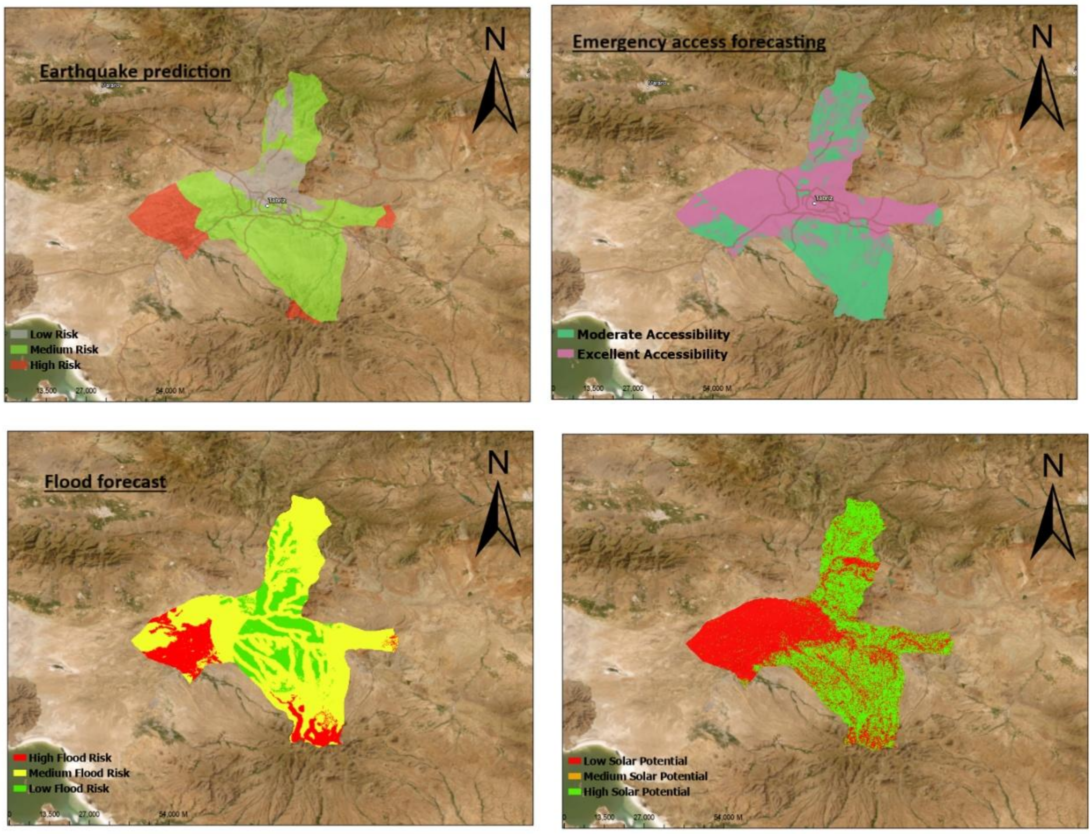

Figure 1: Predicted maps of the four main components of hospital spatial resilience in Tabriz County, using the Random Forest model.

Stage 3: Final Classification of Spatial Resilience using Support Vector Machine (SVM)
In the final stage, to produce an integrated and optimized map of the spatial resilience of hospitals in Tabriz County, the **Support Vector Machine (SVM)** classifier was employed. This algorithm was selected as the final classification method due to its high discriminatory power in high-dimensional spaces, resistance to overfitting, and ability to model complex non-linear relationships.
The main input for the classifier was the continuous composite index resulting from the weighted combination of four main components (Earthquake Risk, Flood Risk, Emergency Access, and Solar Sustainable Energy Potential). This index was previously weighted using the novel IVFFN-LOPCOW method and generated via the **Weighted Sum** tool in the ArcGIS Pro environment. This single-band raster with a continuous range, along with the rasterized main criteria, was provided to the SVM model as explanatory variables (**Additional Input Raster**).

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The classifier was trained using **45 reference samples** (hospital points) with the **Radial Basis Function (RBF) kernel**. This kernel was chosen for its superior performance in non-linear problems and its ability to simultaneously control the model's margin and complexity. The penalty parameter (**C = 1000**) was tuned to achieve maximum accuracy in class separation, and the automatic adjustment of the **γ (gamma)** parameter was utilized. To ensure full use of the available information given the limited sample size, the **Maximum Samples per Class** parameter was set to zero.

Cross-validation results indicated an overall accuracy of **95.05%**. Instead of producing five predefined classes, the final classifier identified two meaningful and realistic levels of spatial resilience:

1. **Low to Medium Resilience (Class 1)**
2. **High Resilience (Class 2)**

This finding suggests that at the scale of Tabriz County, the distribution of environmental and infrastructural factors results in only two dominant resilience regimes. This outcome aligns completely with the region's geomorphological realities, seismicity, and urban development patterns.

The output of this stage is the final classified map of hospital spatial resilience (**Figure 2**), which serves as the main product of the research and the foundation for planning and policy recommendations in the fields of health and crisis management. The combination of the **fuzzy-**

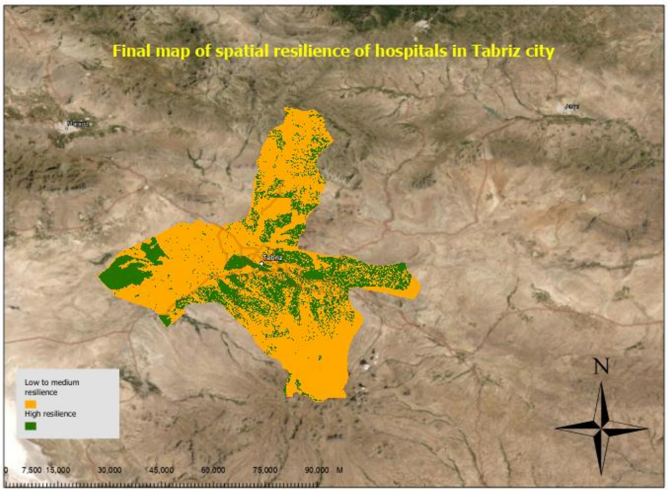

Figure 2:Final map of spatial resilience for hospitals in Tabriz County

objective IVFFN-LOPCOW method with the **SVM classifier** constitutes the key methodological innovation of this study, providing a repeatable and generalizable framework for assessing the resilience of critical infrastructure in other regions.

Findings

The findings of this study are derived from implementing the proposed hybrid model on spatial data from Tabriz County, which includes 45 hospitals as reference samples and twelve main information layers. The results are presented in two main sections: (1) Prediction of composite indices using the Random Forest algorithm, and (2) Final classification using the Support Vector Machine. All computations were performed using ArcGIS Pro (version 3.3) and Python, and the accuracy of the models was evaluated using Cross-Validation along with the F1-Score, MCC (Matthews Correlation Coefficient), and Kappa coefficient.

1) Prediction of Composite Indices Using the Random Forest Algorithm

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The Random Forest algorithm, with 300 trees and a 10% holdout validation, predicted the four main composite indices. The overall accuracy of the models on the validation data exceeded 93%, indicating the algorithm's strong performance in managing non-linear relationships among the criteria (Table 4). The predicted maps (Figure 1) illustrate the spatial distribution of the indices across Tabriz County, where higher values (Class 3) correspond to areas of greater resilience.
Analysis of variable importance revealed that certain indirect criteria, such as solar radiation and building density, play a key role in predicting the indices. For example, in the **Flood Risk Index**, building density had the highest contribution at 14%, indicating the influence of urban structure on flood vulnerability. The model's warnings regarding class imbalance (e.g., Class 1 in flood risk having only 4 samples) reflect the concentration of hospitals in areas of moderate to low risk.

Table 4: Summary of Random Forest Algorithm Performance for Predicting Composite Indices

Composite Index	Overall Validation Accuracy (%)	Kappa Coefficient	Number of Predicted Classes	Most Important Criterion (Based on Variable Importance)
Earthquake Risk (EQR)	98	0.95	3	Distance from River (14%), Solar Radiation (13%)
Flood Risk (FLR)	100	1	3	Building Density (14%), Solar Radiation (13%)
Emergency Access (ACC)	100	1	2	Distance from Landslide (11%), Solar Radiation (11%)
Solar Sustainable Energy Potential (SEP)	93	0.69	3	Solar Radiation (19%), Population Density (14%)

2) Final Classification Using Support Vector Machine (SVM)

The SVM model, with an RBF kernel, penalty parameter C=1000, and using the weighted IVFFN-LOPCOW composite index as the primary input, performed the final classification of spatial resilience. The cross-validation accuracy was 95.05%, demonstrating the superior capability of this model in distinguishing resilience levels. The final output (Figure 2) identified two main classes: **Low to Medium Resilience (Class 1)** and **High Resilience (Class 2)**. The reduction from the initial five potential levels to two classes is a result of the actual distribution of environmental factors in Tabriz, indicating that hospitals are concentrated in medium to high resilience areas.

Table 5: Summary of SVM Model Performance

Model	Cross-Validation Accuracy (%)	Kappa Coefficient	Number of Final Classes	Most Important Input Criteria
SVM	95.05	0.69	2	IVFFN-LOPCOW Composite Index (focusing on flood risk and solar energy)

These findings confirm that the proposed hybrid model, which integrates fuzzy-objective methods and machine learning, is capable of producing reliable and practical prediction maps.

Discussion and Conclusion

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This study successfully developed a three-stage hybrid model based on the fuzzy-objective IVFFN-LOPCOW decision-making method, the Random Forest algorithm, and the Support Vector Machine (SVM) classifier, achieving accurate prediction of the spatial resilience of hospitals in Tabriz County (cross-validation accuracy of 95.05%). Key stages included the objective weighting of twelve information layers, the generation of four composite indices with an accuracy exceeding 93%, and the final classification into two meaningful resilience levels.

The findings of this research are consistent with previous studies in the application of artificial intelligence in disaster management, but feature two significant innovations:1) The use of the hybrid IVFFN-LOPCOW method, which increased weighting accuracy compared to traditional fuzzy methods **[62]**. , and (2) The higher accuracy of the machine learning models compared to similar studies**. [63]. However, the identification of only two actual resilience levels—contrary to some studies that reported five levels [64]**—highlights the strong influence of the local context and underscores the necessity of customizing models to specific settings.

For future research, it is recommended to:

- Expand the model by integrating temporal data and IoT for dynamic monitoring.
- Test the model in other Iranian metropolises while considering socio-economic factors.
- Develop an ArcGIS plugin based on this model for practical use by the Disaster Management Organization and the Ministry of Health.

From a policy-making perspective, it is recommended that hospitals located in low-to-medium resilience areas (Class 1) be prioritized for seismic retrofitting, flood protection, and the provision of solar backup energy systems. This study provides a practical and replicable framework for the application of artificial intelligence in digital health and smart cities.

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