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Assessing Flood Resilience Index (FRI) in rural communities using OLS and GWR modelling: Geospatial pattern and quantitative assessment

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Assessing Flood Resilience Index (FRI) in rural communities using OLS and GWR modelling: Geospatial pattern and quantitative assessment

Abstract

Flooding ranks among the most devastating natural hazards, causing heavy human and economic tolls, particularly in rural settlements, losses exacerbated by climate change, urbanization, and land-use changes. While resilience has emerged as a progressive paradigm in disaster risk management, most research has focused on urban and regional scales, leaving rural areas largely understudied. This study quantitatively assesses the Flood Resilience Index (FRI) for 30 rural sub-watersheds in the Germi region using Shannon entropy and Min-Max normalization, identifies key determinants among nine variables via stepwise OLS regression with AICc-based selection, and examines spatial heterogeneity through GWR model comparison. Nine variables were compiled per sub-watershed: internet access, Islamic councils, police stations, rural municipality offices, Basij bases, paved roads, paved streets, Emergency Medical Services (EMS), and health houses. Data were normalized via Min-Max, weighted using Shannon entropy, and a composite FRI was computed. Stepwise OLS regression (AICc-based) and GWR were applied to identify determinants and examine spatial non-stationarity, with model performance compared. Shannon entropy weighting identified police stations (0.2799) and paved streets (0.2558) as the most influential variables, while Islamic councils (0.0349) and paved roads (0.0441) contributed least. FRI values ranged from 0.032 (sub-watershed 18) to 0.594 (sub-watershed 25), indicating substantial spatial variability. Stepwise OLS identified health houses as the primary predictor (48.2% of variance alone), with the eight-variable model (excluding rural municipalities) selected as optimal (AICc = -261.47). Although GWR revealed minor spatial heterogeneity, the OLS model with eight variables outperformed GWR (OLS AICc = -261.47 vs. GWR AICc = -187.147), suggesting that resilience determinants are largely spatially stable and a parsimonious global approach is more appropriate for planning purposes. The integrated framework combining Shannon entropy, stepwise OLS, and GWR provides a robust and comprehensive methodology for quantitative assessment and spatial analysis of rural flood resilience. The results reveal that despite minor spatial heterogeneity, the most effective resilience strategies are paved streets (intra-village roads), police/Basij bases, and health houses

Keywords: Flood risk management, Flood Resilience Index (FRI), Rural communities, Shannon entropy, Rural infrastructure

1. Introduction

1.1. Background

Globally, natural hazards represent some of the most powerful and often unpredictable events, capable of causing widespread devastation (Chaudhary et al., 2024). Among these, flooding stands out as one of the most destructive natural phenomena, posing a serious threat to human settlements (Seravani et al., 2021). Global statistics indicate that between 1970 and 2019, floods accounted for the highest proportion of reported disasters (44%), the second highest economic losses (31%), and the third highest mortality rates (16%) among all natural hazards worldwide (Rindsfüser et al., 2024). These events threaten critical infrastructure systems and assets that are essential for the smooth functioning of society and the economy (Chakraborty et al., 2026). Such vital assets encompass transportation networks, energy grids, water supply systems, healthcare facilities, and communication networks (Chakraborty et al., 2026). Disruption to these essential systems has far-reaching consequences, undermining community resilience and economic stability (Michalis et al.,

2022). Consequently, a comprehensive understanding of the disaster cycle is crucial for informed policymaking and for enhancing the resilience of critical infrastructure (Chakraborty et al., 2026). The concept of resilience has garnered widespread attention in recent years, particularly within the domain of risk management and, more specifically, in environmental disaster and emergency management (Parker et al., 2023). However, resilience science remains in its early stages of development, with ongoing debates surrounding its conceptualization, interpretation, and operationalization (Parker et al., 2023). Numerous studies have assessed the benefits of flood resilience enhancement strategies (Chen et al., 2019). Nevertheless, many of these efforts focus primarily on flood impact reduction rather than resilience per se (Chen et al., 2019).

Flood resilience is defined as the capacity of a system to absorb disturbances, adapt to new conditions, and recover rapidly following a hazard event (Li et al., 2026). In rural communities, the concept of resilience assumes particular significance due to their greater dependence on natural resources, limited infrastructure, and reduced access to support services (Asadi et al., 2025). The majority of existing flood resilience research has concentrated on urban and regional scales, while rural settlements (owing to methodological complexities and data scarcity) have received considerably less attention (Dhungana et al., 2024). International studies reveal a substantial gap in flood resilience between urban and rural areas (Li et al., 2026), with rural regions exhibiting the lowest levels of such capacities due to spatial dispersion and institutional and financial constraints (Li et al., 2025). In many developing countries, including Iran, underdeveloped rural areas not only lack adequate infrastructure but also face heightened vulnerability to hazards such as floods due to geographical isolation, limited access to emergency services, and weak institutional capacity (Asadi et al., 2025).

1.2. Literature review

Numerous flood studies exist nationally and internationally, yet only a few integrate risk analysis, vulnerability, institutional response, and community adaptation within a comprehensive, outcome-oriented framework across the full disaster cycle. Most remain region-specific, descriptive, or reliant on expert judgment, leaving a critical gap in standardized, multi-case comparative flood resilience assessments (Chakraborty et al., 2026). Key studies from the existing literature are reviewed below. Hataminejad et al. (2021) examined economic and institutional resilience in Akbarabad and Beheshtabad, Izeh, using a descriptive-analytical approach with library and field surveys. They employed spatial autocorrelation (Geoda, ArcGIS) for indicator weighting. Results revealed that substantial portions of these neighborhoods' urban fabric fall within very weak to weak resilience categories. Najafi Kani et al. (2021) analyzed flood-affected villages in Aq Qala County, Golestan, surveying 270 households across six villages. Using SPSS (correlation, Friedman, Kruskal-Wallis, ANOVA/Duncan), they found that damage variation was attributed to land slope, elevation, and particularly proximity to the Qareh Su and Gorgan Rivers. Sadeghloo et al. (2022) examined risk perception effects on flood resilience in Binalood villages, surveying 190 rural households using Cochran's method and regression analysis. Results showed significant resilience differences across risk perception levels, with moderate-perception groups ranking highest. Rural women displayed greater flood risk awareness and consequently higher resilience. Azizi et al. (2022) analyzed the Flood Vulnerability Index (FVI) across 26 sub-watersheds in Ardabil Province. The FVI showed that 46.97% of the province has very high flood vulnerability, with nearly all areas under flood pressure except small portions in the center, east, and north. Kamali and Ghasemi (2022) assessed rural housing physical vulnerability in Dargaz County via a

field survey (Cronbach's α = 0.96). Foundation vulnerability (mean = 2.55) exceeded all other structural components, indicating the need for adaptive housing policies.

Nkeki et al. (2022) developed a flood hazard map for Nigeria's Ona River Basin using GIS and raster integration. Their study combined inundation, runoff, and raster overlay techniques with HEC-RAS. Results revealed that 48.2% of the basin faces moderate to very high flood risk. Abdrabo et al. (2022) integrated flood risk assessment with spatial planning in Egypt, identifying a critical gap between these domains. They showed challenges in implementing spatial planning for risk reduction, including coordination gaps, data accessibility issues, and subjectivity of analyses. They recommended enhanced stakeholder cooperation, risk communication, and data quality improvement. Babanawo et al. (2022) examined flood vulnerability indicators in Ghana's Ketu South coastal areas, addressing limited understanding of local vulnerability drivers. Their results revealed community-level variation driven by exposure, sensitivity, and adaptive capacity, showing that interventions should consider household characteristics and these key factors.

Bouaakkaz et al. (2023) assessed social vulnerability to flood hazard in Morocco's Souss basin using 26 socio-economic indicators with PCA and GIS to characterize the Social Vulnerability Index (SoVI). Few urban areas showed moderate to low vulnerability, while most rural areas displayed higher average social vulnerability scores. Rahnama and Elahi (2023) evaluated flood resilience dimensions in western Mazandaran cities using a descriptive-analytical approach. They found considerable variation among cities, with Nowshahr ranked first across all four resilience dimensions. Falahati and Garakani (2024) examined river and waterway safety planning in populated areas under the National Program for Reducing Disaster Risk in Rural Settlements. Analyzing field data from 1,418 villages, they assessed rural flood vulnerability and conducted hydrological/hydraulic modeling for one representative case. Dhungana and Liu (2024) evaluated flood hazard and social vulnerability across 66,543 U.S. census tracts using Mann-Whitney U tests, OLS, and GWR. They found significant urban-rural differences in flood hazard and social vulnerability, with spatial variation revealing notable regional inequalities. Rindsfüser et al. (2025) monitored flood risk evolution in Switzerland over a ten-year period (2014–2023), demonstrating that total flood risk increased by 26%, hazard-exposed areas by 32%, and exposure levels by 35%, showing the necessity of risk monitoring for adaptive flood risk management.

Peiris et al. (2025) examined anthropogenic factors and flood risk perception in Sri Lanka's Kelani River Lower Basin. Surveying 100 flood-affected communities with ordinal logistic regression of eight variables, they found employment type, property ownership, waste management, and sanitation significantly associated with perceived flood risk. Noli da Fonseca et al. (2025) evaluated flood risk communication challenges in Brazilian cities through document analysis and semi-structured interviews. They identified limited understanding of risk communication as an emergency-only measure as a key barrier, recommending continuous education, message personalization, multi-channel communication, professional training, and technological investment. Singh et al. (2025) examined flood risk and vulnerability in Atlanta across social, economic, technical, and institutional dimensions using a mixed-methods approach. Areas with the highest flood probability exhibited the greatest social, ecological, and technical vulnerabilities, proving the integrated nature of flood risk. Tocchi et al. (2025) used cluster analysis to identify urban-rural settlement archetypes based on open-source vulnerability and exposure indicators. Using two clustering techniques, they defined 18 primary archetypes for Italy encompassing geographic, demographic, and socio-economic characteristics. Aghayary et al. (2025) identified and zoned flood-prone areas in Germi County by examining ten influencing factors. Susceptibility mapping employed the ARAS multi-criteria algorithm within EDRISI, with layer valuation and

standardization via ANP. Lithology, land use, slope, and distance to rivers emerged as the primary flood hazard determinants.

Zhang and Sun (2026) evaluated disaster resilience in traditional rural settlements of southern Xinjiang using AHP, entropy, and K-means clustering. Villages in Turpan and Kucha showed relatively high resilience, while those in Hotan and Bayingolin exhibited lower resilience. Sarker et al. (2026) assessed flood resilience among 384 households in six riverine island communities in northern Bangladesh. They developed a Flood Resilience Index (FRI) using 48 indicators across eight components and three capacities (anticipative, absorptive, adaptive), with Min-Max normalization and equal weighting. The overall FRI of 0.326 indicated lower resilience to recurrent floods in impoverished areas. He et al. (2026) evaluated rural community resilience to natural hazards in Dechang County, China, using a contribution weight superposition and Shannon entropy method across physical, social, and informational dimensions. Entropy weighting revealed recovery and adaptation stages showed the greatest imbalance. Only 24% of villages had high resilience, with low-resilience areas concentrated in the western and southeastern parts.

The literature on flood resilience reveals a clear urban bias, leaving rural communities understudied despite their higher vulnerability. Most studies remain region-specific or descriptive, with few integrating quantitative and spatial analysis frameworks. A key gap exists in applying comparative regression approaches (OLS vs. GWR) to identify spatial heterogeneity in resilience determinants, particularly in rural settings of developing countries where data scarcity adds further complexity. This study addresses these gaps by developing an integrated framework combining Shannon entropy, stepwise OLS, and GWR to quantitatively assess the Flood Resilience Index (FRI) across rural sub-watersheds. By examining spatial patterns and determinants of resilience, this approach provides nuanced indications into location-specific factors, enabling more targeted and effective flood risk management interventions.

1.3. Scope and objective

Numerous studies indicate increased flood susceptibility and damages in Ardabil Province watersheds, driven by intensive land-use changes (rangeland conversion to rainfed agriculture), deforestation in northern highlands, poor lowland drainage, climate-induced rainfall intensification, and unplanned development along the Qareh Su and Khiavchai rivers (Mostafazadeh & Mehri, 2018; Esfandyari Darabad et al., 2023). Given its natural characteristics, topography, and history of high flood susceptibility in northern Ardabil Province, this region is considered one of the most prone areas to streamflow regime variability and flood occurrence at the provincial level (Mostafazadeh et al., 2025; Mostafazadeh & Alaei, 2025). Topographic analysis reveals that the watershed is bounded by the Salavat Mountains to the south and the Khoroslou Mountains to the north, where steep slopes can accelerate surface runoff and increase flow volumes, particularly during intense rainfall events. Many rural settlements have developed along riverbanks and waterways, and despite previous hydraulic modeling efforts, no comprehensive quantitative assessment of flood resilience has yet been conducted for the rural settlements in this area. The results of this study can assist local planners and managers in reducing future flood-related human and economic losses. Rural resilience encompasses multiple dimensions (social, economic, physical, institutional, and environmental) and identifying weaknesses in each is essential for effective disaster risk reduction planning. Given resource limitations, identifying villages with lower resilience levels and prioritizing sites for structural and non-structural interventions is of particular importance. Accordingly, this study pursues four specific objectives: (a) to quantitatively assess the Flood Resilience Index (FRI) for 30 rural sub-

watersheds using an integrated framework of Shannon entropy weighting and Min-Max normalization; (b) to identify the most influential resilience determinants among nine key variables (infrastructure, institutional, and health service indicators) using stepwise OLS regression based on the AICc criterion; (c) to examine spatial heterogeneity in the relationships between determinants and FRI using GWR, and to compare its performance against the OLS model; and (d) to provide evidence-based recommendations for prioritizing structural and non-structural interventions in vulnerable rural settlements to support local flood risk management.

2. Material and Methods

2.1. Description of the study area

The Germi watershed, encompassing an approximate area of 1,145 km², is situated in the northern extent of Ardabil Province, within the administrative boundaries of the Germi, Bileh Savar, and Angot townships. Its geographical coordinates range from 38°50′ N to 39°16′ N latitude and 47°45′ E to 48°15′ E longitude (Figure. 1).

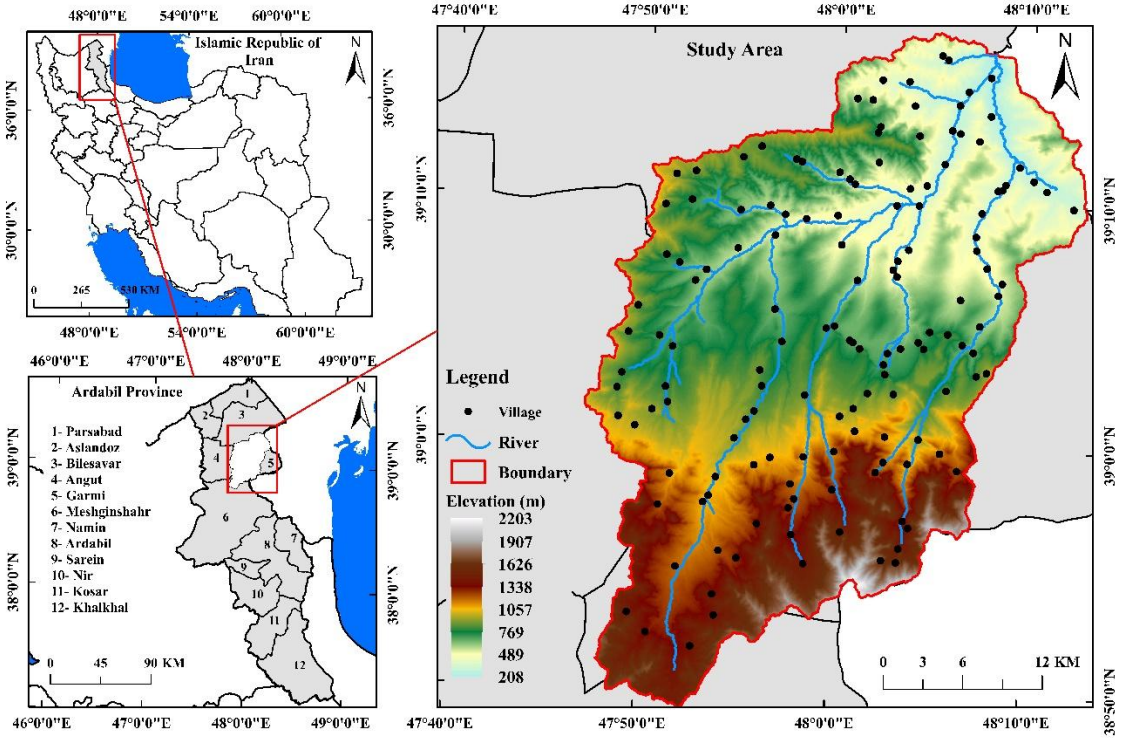


Figure 1. Location map of the study area within Ardabil Province and Iran.

An examination of the physiographic attributes reveals that the watershed is topographically delineated by the Salavat Mountains to the south and the Khoroslou Mountains to the north. These orographic barriers, coupled with steep natural gradient slopes, exert a significant control on the hydrological response, notably accelerating surface runoff velocity and discharge volumes during intensive precipitation episodes. The Dareh-roud and Balha-roud river systems, draining the western and eastern sectors respectively, constitute pivotal hydrographic features. These fluvial networks exhibit a heightened propensity for overbank flooding during peak precipitation seasons and vernal snowmelt events, posing substantial inundation risks to adjacent low-lying terrains. Consequently, specific geomorphological zones within the watershed are distinctly predisposed to flood hazards. Riparian corridors along the Dareh-roud (west) and Balha-roud (east) are

particularly vulnerable due to their lower hypsometric elevations. Concentrated orographic rainfall within the upstream sub-catchments rapidly translates into heightened stream discharge, frequently culminating in channel overtopping and the subsequent inundation of arable land and riparian residential settlements.

Furthermore, the distal zones of the mountain piedmonts constitute high-hazard areas. The foothills of the Salavat and Khoroslou ranges, characterized by steep declivities and specific pedological properties (including low infiltration capacity and high erodibility) generate substantial overland flow during extreme rainfall events. This surface runoff concentrates rapidly within secondary valleys and primary watershed outlets, frequently triggering high-magnitude flash floods characterized by significant geomorphic efficacy and destructive power.

Land surfaces exhibiting sparse or degraded vegetation cover demonstrate an exacerbated susceptibility to flood impacts. Vegetative cover is critical for rainfall interception, soil erosion mitigation, and the hydraulic retardation of surface runoff. Consequently, localities subjected to anthropogenic degradation (arising from overgrazing, deforestation, and land-use/land-cover (LULC) alterations) exhibit a markedly diminished capacity for runoff regulation, thereby amplifying their inherent flood risk profile.

The study area encompasses 145 rural settlements with a total population of approximately 17,762 inhabitants. Owing to the heterogeneous spatial distribution of developmental infrastructure, these communities manifest differential resilience capacities. The confluence of specific physiographic constraints and climatic forcings renders this region acutely susceptible to natural hazards, particularly flooding, predisposing it to substantial human casualties and significant economic losses.

This inherent vulnerability was starkly evidenced in the spring of 2023, when unprecedented and torrential flood events resulted in severe human and material losses. According to official statements by the Minister of the Interior, these floods were unparalleled in the preceding five decades, induced by intense, convective spring cloudbursts. The human toll included seven fatalities within the Germi and Angot counties, notably involving four children, highlighting the profound humanitarian dimensions of the disaster. Critical infrastructure suffered extensive damage: transportation networks were severed (including the Anjirlou Bridge, which blocked the primary thoroughfare connecting Germi to Bileh Savar) and over 35 rural roads were rendered impassable. Essential potable water distribution networks also sustained substantial disruption. The agricultural and pastoral sectors bore a heavy economic burden, characterized by widespread destruction of rain-fed farmlands, orchards, livestock shelters, and significant animal casualties. Total direct and indirect losses were preliminarily estimated at approximately 150,000 billion Rials (about USD 300 million). These catastrophic events critically prove the urgent imperative for the implementation of proactive flood risk mitigation strategies and the reinforcement of integrated disaster crisis management frameworks within this vulnerable region.

2.2. Research methodology

The overarching objective of this study is to quantitatively appraise the flood resilience of the thirty constituent sub-watersheds and their associated rural settlements, while simultaneously identifying the principal determinants governing spatial variations in resilience. To achieve this, a hybrid analytical framework integrating Ordinary Least Squares (OLS) regression with Geographically Weighted Regression (GWR) was employed. The methodological protocol was operationalized through the following sequential phases:

(i) delineation of the fundamental spatial units of analysis, comprising the thirty sub-watersheds and the geocoding of rural settlement centroids;
(ii) specification and selection of nine proxy indicators pertinent to flood resilience, drawn from the existing literature;
(iii) data transformation and normalization to ensure inter-indicator comparability;
(iv) objective weighting of the selected indicators using the Shannon Entropy method, facilitating an unbiased integration into the composite resilience metric;
(v) computation of a synthetic Flood Resilience Index (FRI) for each individual sub-watershed;
(vi) identification of the most statistically significant explanatory variables underpinning resilience variability, conducted via linear regression using the OLS estimator;
(vii) investigation of spatial heterogeneity and geographically non-stationary relationships between the dependent and independent variables, operationalized through the application of the GWR model to account for localized contextual effects.

2.2.1. Delineation of the Base Spatial Unit of Analysis

In the present study, the drainage network of the study region was initially extracted using ArcMap software and its Hydrology Tools. Subsequently, the main catchment basin, encompassing an area of 1,145 km², was delineated into 30 constituent sub-watersheds, within which the rural settlements are spatially distributed. These sub-watersheds were designated as the fundamental spatial units of analysis.

2.2.2. Selection and Specification of Indicators Influencing Resilience

Data availability and applicability constituted the two primary screening criteria for indicator selection, as many indices commonly utilized in developed nations are often inaccessible or inapplicable in countries of the Global South, including Iran, due to data scarcity (Pazhuhan & Amirzadeh, 2024). Adhering to this critical principle and following an extensive review of the relevant scientific literature (Dewa et al., 2023), the key indicators were identified. These indicators were required to be representative of flood resilience capacity. A pivotal reference informing this selection was the research conducted by Cutter and colleagues (Cutter et al., 2014). In the current study, the determination of resilience indicators among the rural communities of the study area was operationalized as follows:

Resilience is recognized as one of the most fundamental tenets of disaster risk reduction and crisis management (Parker et al., 2023). As defined by the United Nations Office for Disaster Risk Reduction (UNDRR), resilience denotes the ability of a system, community, or society exposed to hazards to resist, absorb, accommodate, adapt to, transform, and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions via risk management (UNDRR, 2009). This comprehensive definition aptly illustrates the multi-dimensional nature of resilience, simultaneously encapsulating physical (resistance and absorption), social (adaptation and transformation), and institutional (risk management) dimensions.

Although conceptual models for disaster resilience are abundant in the literature (Cutter et al., 2014), there remains considerable scholarly debate regarding its defining characteristics, the most robust analytical frameworks for its measurement, and the appropriate reference unit for resilience assessment (e.g., an individual, a household, infrastructure, or broader systems) (Cutter et al.,

2014; Sarker et al., 2026). Flood resilience is inherently a multi-dimensional concept; contemporary research has identified six principal dimensions: social, economic, institutional, infrastructural/physical, social capital, and environmental. These dimensions have been operationalized within a well-established conceptual framework, namely the Baseline Resilience Indicators for Communities (BRIC), as developed by Cutter and co-authors (Cutter et al., 2010; 2014).

Table 1 presents the baseline community resilience indicators across these six dimensions.

Table 1. The six dimensions of community resilience to natural hazards (Cutter et al., 2014).

Dimension	Conceptual Definition	Key Indicators
1) Social	The capacity of the population to cope with hazards based on demographic characteristics	Educational attainment, non-elderly population ratio, access to private vehicle, health insurance coverage
2) Economic	The livelihood status and financial capacity of the community for post-crisis recovery	Homeownership rate, employment rate, income equality, business diversity
3) Infrastructure and Housing	The quality and robustness of physical structures and infrastructure to withstand hazards	Housing construction quality, capacity of healthcare facilities, emergency evacuation routes
4) Institutional	Management capacity, programs, and governance policies pertaining to resilience	Management capacity, programs, and governance policies pertaining to resilience
5) Social Capital	Social networks and bonds among individuals and groups within the community	Place attachment, political participation, civic organizations, preparedness volunteers
6) Environmental	The quality of the natural environment and its capacity to absorb hazard impacts	Presence of wetlands, percentage of permeable surfaces, energy efficiency

Each of these dimensions is elaborated below:

1) Social Resilience: This dimension refers to the demographic and human characteristics of the community that are associated with physical and psychological health, which in turn enhance awareness, communication, and mobility (Hamidi et al., 2025; Asl et al., 2025). Key indicators within this dimension include: educational attainment, non-elderly population ratio, access to personal vehicles, health insurance coverage, and the absence of physical and mental disabilities (Cutter et al., 2014; Hamidi et al., 2025; Asl et al., 2025).

2) Economic Resilience Dimension: This dimension describes the economic status of the community and incorporates indicators of economic vitality, diversity, and equity in compensating losses (Zou et al., 2025). Relevant indicators include: homeownership rate, employment rate, income equality, non-dependence on primary economic sectors (agriculture and tourism), and business diversity. In rural areas where economies are heavily reliant on agriculture and natural resources, this dimension assumes particular significance (Zou et al., 2025; Cutter et al., 2014; Hamidi et al., 2025).

3) Infrastructure/Housing Resilience Dimension: This dimension addresses the quality and robustness of physical structures and infrastructure (UNDRR, 2022). Its indicators encompass: housing construction quality (materials used, building age), availability of temporary housing and emergency shelters, capacity of healthcare facilities (number of hospital beds), emergency evacuation routes (access roads), and communication infrastructure (broadband internet access) (Cutter et al., 2014; UNDRR, 2022; Taheri et al., 2025).

4) Institutional Resilience Dimension: This dimension refers to management capacities, programs, and governance policies related to disaster resilience (Cutter et al., 2014; Hamidi et al., 2025). Key indicators include: preventive expenditures (average per capita expenditure on risk reduction), flood insurance coverage, experience in receiving disaster assistance, local disaster preparedness training, and population stability (Cutter et al., 2014; Hamidi et al., 2025).
5) Community Capital Dimension: This dimension refers to social networks and bonds among individuals and groups within the community (Cutter et al., 2014). Its indicators include: place attachment (percentage of native-born residents), political participation, number of civic and religious organizations, disaster preparedness volunteers (e.g., Red Crescent Society), and citizenship training in disaster response (Cutter et al., 2014).
6) Environmental Resilience Dimension: This dimension refers to the quality of the natural environment and its capacity to absorb the impacts of natural hazards (Pelone & Sanchez, 2025). Key indicators include: the presence of wetlands and water bodies as natural flood buffers, the percentage of permeable surfaces, and energy and water efficiency (Pelone & Sanchez, 2025; Cutter et al., 2014).

In determining the resilience indicators, and with reference to the baseline community resilience indicators (Table 1), other scientific sources, and the principle of data availability and applicability, the resilience indicators at the study area level were established across nine key components, as specified in Table 2.

Table 2. Selected flood resilience indicators, classified by constituent dimension, with corresponding operational notes and justifications for inclusion within the study context.

Indicator	Dimension	Notes	Rationale for Selection
Internet Access	Social	Receipt of early warnings and information dissemination	Internet serves as a critical infrastructure for rapid notification of flood-exposed communities
Paved Roads	Physical Infrastructure	Rapid evacuation of residents and emergency responder access	Quality of access roads directly influences the speed of emergency evacuation and emergency response team arrival times
Paved Alleys	Infrastructure	Extent of access to paved internal thoroughfares	Quality of intra-village roads directly impacts the speed of relief delivery and emergency evacuation of residents
Emergency Medical Services (EMS)	Infrastructure	Therapeutic response and reduction of human casualties	Access to healthcare service centers is the most critical factor in reducing human casualties immediately following flood events
Health Post	Infrastructure	Availability of primary healthcare service centers	Access to primary healthcare services constitutes a fundamental component of social and infrastructural resilience
Village Council (Dehyari)	Institutional	Local executive management	Implementation of crisis response operations at the village level
Islamic Council	Institutional	Local coordination and advisory body	Community representation and coordination with authorities
Police Station	Institutional	Provision of security and order during crises	Overseeing mandatory evacuations, preventing looting, and traffic management are vital functions of law enforcement during flood crises
Basij Organization Base	Social Capital	Relief coordination and public participation	As a community-based and local structure, it plays a significant role in collecting donations,

			organizing volunteer forces, and coordinating with crisis headquarters

2.2.3. Data Transformation and Normalization

The resilience indicators were selected based on the dual criteria of data availability and applicability. A critical consideration following this selection is that the units of measurement employed for these indicators can significantly influence data analysis (Han et al., 2012). For instance, changing units of measurement from meters to kilograms may yield substantially different results (Han et al., 2012; Sarker et al., 2026). To mitigate this effect, data must be normalized or standardized (Han et al., 2012). This entails transforming the data so that they fall within a smaller or common range, such as [-1, 1] or [0.0, 1.0] (Han et al., 2012). Data normalization seeks to assign equal weight to all features (Han et al., 2012). Several normalization methods exist, including min-max normalization, z-score normalization, and decimal scaling normalization. Min-max normalization, which is employed in the present study, performs a linear transformation on the original data according to Equation (1) (Han et al., 2012):

$$X_{normalized} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

In the above expression, X denotes the value of a feature to be normalized, while Xmin and Xmax represent the minimum and maximum values of that feature, respectively. As is evident, all variable values are transformed to the [0, 1] interval, thereby enabling their comparison and aggregation. Under min-max scaling, the minimum value of X yields a normalized value of 0, the maximum yields 1, and any intermediate value falls within the [0, 1] range**.**

2.2.4. Weighting of Selected Indicators in Resilience Calculation Using the Shannon Entropy Method

The term entropy is derived from Boltzmann's principle (Bhandari et al., 2024), which measures the disorder or uncertainty of a system and is defined for discrete probability distributions (Shannon, 1948; Bhandari et al., 2024). Currently, entropy values are extensively utilized in natural hazard analysis (Bhandari et al., 2024; Sarker et al., 2026). In this study, this method was adopted to assign objective weights to the variables and to preclude expert-induced biases.

This method is predicated on the principle that an indicator exhibiting greater variability in its data (higher dispersion) conveys more information and is consequently assigned a higher weight (Shannon, 1948; Cover et al., 2006; Bhandari et al., 2024; Șerban et al., 2025). Initially, a decision matrix is constructed comprising the values of all nine indicators for the respective spatial units. Following data normalization and the computation of each value's proportion, the entropy of each indicator is calculated. An indicator with lower entropy (i.e., whose data exhibit less order and certainty) is assigned a greater weight (Shannon, 1948; Cover et al., 2006; Șerban et al., 2025). Finally, the resultant weights for each of the nine indicators are normalized as fractions between zero and one, summing to unity. These weights denote the relative importance of each indicator in the flood resilience assessment and are subsequently utilized in subsequent analytical stages to composite the indicators and compute the final resilience score.

The sequential steps for calculating the weights of resilience indicators using the Shannon Entropy method are as follows (Shannon, 1948; Cover et al., 2006; Bhandari et al., 2024; Șerban et al., 2025; He et al., 2026):

Step 1: Formation of the decision matrix and data normalization (calculation of Pij)

A matrix is constructed containing the values of all nine studied indicators. Subsequently, to eliminate the effects of differing units and scales, the data are normalized using Equation (2). In this step, the proportion of each alternative for each indicator is computed:

$$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \quad (2)$$

Step 2: Calculation of the entropy value (Ej) for each indicator:

For each of the nine indicators, the entropy value is calculated using Equation (3):

$$E_j = -K \sum_{i=1}^{m} P_{ij} \ln P_{ij} \quad (3)$$

$$K = \frac{1}{\ln(m)}$$

Where and m represents the number of alternatives (which, in this research, equals 30, corresponding to the number of sub-watersheds). The entropy value ranges between zero and one. A value closer to one indicates that the data for that indicator exhibit lower dispersion and thus provide less novel information.

Step 3: Calculation of the degree of deviation (dj):

Subsequently, the degree of deviation (dj) is computed using Equation (4), which expresses the extent of useful information that indicator j provides for decision-making. When the measured values for an indicator are highly similar across alternatives, it signifies that the competing options do not differ substantially with respect to that indicator; accordingly, its role in the decision-making process should be proportionally reduced:

$$d_j = 1 - E_j \quad (4)$$

Step 4: Calculation of the final weight (Wj) for each indicator:

The final weight for each indicator is computed using Equation (5), by dividing the degree of deviation of that indicator by the sum of the degrees of deviation across all nine indicators:

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (5)$$

where n = 9, corresponding to the total number of resilience indicators.

2.2.5. Calculation of the Flood Resilience Index (FRI)

In the present study, in order to assess flood resilience across the study basin, the entire watershed was partitioned into 30 sub-watersheds, and the Flood Resilience Index (FRI) was computed for each individual sub-watershed. This computational approach is consistent with contemporary methodologies in flood resilience studies; indeed, Batica's doctoral dissertation (2015) similarly emphasizes the integration of Min-Max normalization and entropy weighting techniques for the construction of composite indices (Batica, 2015). The selection of indicators was informed by the comprehensive study of Cutter and colleagues (2014) (Cutter et al., 2014). Ultimately, nine key

indicators spanning multiple dimensions (social, infrastructural, and institutional) were considered for the resilience assessment (Cutter et al., 2014). To this end, data pertaining to all nine indicators were first compiled for the 30 sub-watersheds. Owing to the differing measurement scales, the data were standardized using Min-Max normalization within the [0, 1] range to render them comparable and composable (Batica, 2015; Ullah et al., 2025; Chakraborty et al., 2026; Sarker et al., 2026). Subsequently, the Shannon Entropy weighting method was employed to determine the relative importance of each indicator in the resilience calculation. Under this approach, indicators exhibiting greater variability across sub-watersheds (i.e., lower entropy) are assigned higher weights and consequently contribute more substantially to the final resilience score (Shannon, 1948; Cover et al., 2006; Bhandari et al., 2024; Șerban et al., 2025). Finally, the composite Flood Resilience Index (FRI) for each sub-watershed was computed as the weighted sum of the normalized values of the nine indicators, using the weights derived from the Shannon Entropy method. The general equation for calculating the FRI for sub-watershed k is as follows (Batica, 2015; Ullah et al., 2025; Chakraborty et al., 2026; Sarker et al., 2026):

$$FRI_k = \sum_{i=1}^{n} (W_i \times X_{ik}) \tag{6}$$

Where FRIk is the Flood Resilience Index value for sub-watershed k (ranging from 1 to 30), n is the number of indicators (9 indicators), Wiis the weight obtained for indicator i using the Shannon Entropy method, and X_{ik} is the normalized numerical value for indicator i in sub-watershedk . Consequently, for each sub-watershed, a value between zero and one is derived.

2.2.6. Statistical Analyses and Identification of the Most Important Explanatory Variables of Resilience: Ordinary Least Squares (OLS) Regression Analysis

After calculating the FRI, the subsequent step is to identify the factors influencing resilience and to elucidate its spatial pattern (Alaei et al., 2026; Dhungana et al., 2024). Linear Ordinary Least Squares (OLS) regression, as a global method, serves as the initial tool for examining the linear relationship between the FRI (dependent variable) and the social, infrastructural, and institutional indicators (independent variables), and, by providing significant coefficients, indicates the overall importance of each factor across the entire watershed (Miller et al., 2022; Darlington et al., 2016). However, given that resilience data at the sub-watershed level exhibit spatial heterogeneity, the assumption of constant coefficients across the entire region, upon which OLS is predicated, is typically violated (Alaei et al., 2026; Dhungana et al., 2024). Consequently, Geographically Weighted Regression (GWR) is employed, which permits the calculation of regression coefficients locally for each sub-watershed, thereby revealing the spatial variations in the influence of each indicator on resilience (Alaei et al., 2026; Dhungana et al., 2024; Comber et al., 2023). By incorporating distance-based weighting between sub-watersheds, GWR uncovers latent and heterogeneous patterns that are not observable in OLS (Alaei et al., 2026; Dhungana et al., 2024; Comber et al., 2023). Indeed, the integration of these two methods provides both a synoptic (global) and a granular (local) perspective on the relationships among variables (Alaei et al., 2026; Dhungana et al., 2024). This approach assists managers in prioritizing interventions not uniformly, but rather in accordance with the specific conditions of each sub-watershed (Dhungana et al., 2024; Comber et al., 2023).

Subsequently, in order to identify the most important factors influencing the Flood Resilience Index (FRI) at the sub-watershed level, the Ordinary Least Squares regression method was utilized. The OLS regression model is a global approach that assumes the relationships between the independent and dependent variables are constant and uniform across the entire study area (Alaei et al., 2026; Dhungana et al., 2024). In this analysis, the derived output of the FRI served as the dependent variable, while the independent variables comprised the indicators of internet access, presence of a local council, village administration (Dehyari), Basij base, police station, paved roads, paved alleys, access to emergency medical services (EMS), and the presence of a health post. Ordinary Least Squares regression fits a single regression equation for all spatial units and provides fixed coefficients (β), which denote the average effect of each factor across the entire watershed (Alaei et al., 2026; Dhungana et al., 2024). The application of OLS for the Flood Resilience Index is presented in Equation (7):

$$FRI_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i \quad (7)$$

where FRI_i is the Resilience Index for observation i , β_0 is the intercept, β_j are the regression coefficients, Xij are the values of the independent variables, k is the number of variables, and ε_i denotes the random error term or residual of the regression model. This component represents the difference between the actual value of the dependent variable (FRI) and the value predicted by the model for each observation i (Darlington et al., 2016).

To execute this regression model, a stepwise method was employed. Stepwise regression is a technique that utilizes an automated procedure to determine the selection of predictor variables. At each step, a variable is selected from the group of explanatory variables for subtraction or addition, as determined by a criterion based on an array of t or F tests (Miller et al., 2022; Darlington et al., 2016). At each step, the algorithm enters the variable that yields the greatest reduction in the model's prediction error, while simultaneously removing variables that no longer contribute significantly after the inclusion of new variables (Miller et al., 2022; Darlington et al., 2016). The variable selection process was continued until the corrected Akaike Information Criterion (AICc) reached its minimum value, and the addition of a new variable could no longer improve it. To obtain the AICc value, Equations (8) and (9) were utilized (Song et al., 2021; Sutherland et al., 2023).

$$AIC = n \times \ln(\frac{RSS}{n}) + 2k \quad (8)$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \quad (9)$$

In these equations, n represents the number of sub-watersheds (30 sub-watersheds), RSS denotes the residual sum of squares (from the ANOVA table), and k indicates the number of independent variables (9 variables).

2.2.7. Geographically Weighted Regression (GWR) Analysis

To investigate spatial non-stationarity in the relationships among variables (that is, to examine how the influence of each factor on resilience varies across different locations within the study area) the Geographically Weighted Regression (GWR) model was employed (Dhungana et al., 2024). Geographically Weighted Regression (GWR) is a spatial analysis method first introduced by Brunsdon and Fotheringham (1996) (Brunsdon et al., 1996; Fotheringham et al., 2009; Comber

et al., 2023). GWR provides measures of process heterogeneity (geographical diversity in data relationships) through the generation of mappable, variable regression coefficients and associated statistical inference (Brunsdon et al., 1996; Fotheringham et al., 2009; Comber et al., 2023). The standard GWR model is an advanced local technique that permits the relationships between flood resilience factors and their spatial manifestations to vary across space (Alaei et al., 2026; Comber et al., 2023). Unlike global models such as OLS, which estimate a fixed relationship for the entire region, the GWR model allows regression coefficients to vary across different locations (Dhungana et al., 2024; Comber et al., 2023). This model fits a separate regression equation for each spatial unit and assigns greater weight to nearer neighboring points. The optimal bandwidth is determined using an adaptive method and the AICc criterion (Alaei et al., 2026). Studies indicate that GWR can provide higher accuracy (higher R^2 and lower AICc) compared to OLS in the presence of substantial spatial non-stationarity, and is useful for prioritizing protective measures in heterogeneous regions (Alaei et al., 2026; Dhungana et al., 2024; Comber et al., 2023). However, its relative performance is data-dependent, and as will be shown in our results, a parsimonious OLS model may be more appropriate when spatial heterogeneity is minimal. The standard GWR can be defined as Equation (10) (Alaei et al., 2026; Comber et al., 2023):

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (10)$$

Where β_0 is the intercept, (ui ،vi) are the spatial coordinates of observation i, and β_k (ui ،vi) are the estimated coefficients at those locations, and k is the number of independent variables.

3. Results and Discussion

3.1. Data normalization

The results of data normalization using the Min-Max method are presented in Table 3.

Table 3. Results of Min-Max normalization for the selected flood resilience indicators across the 30 sub-watersheds.

Sub Basin	Internet access	Islamic Council	Police station	Village Council (Dehyari)	Basij base	Paved road	Paved Alleys	Emergency Medical Services (EMS)	Health post
1	0.000	1.000	0.000	0.429	0.571	0.286	0.143	0.714	0.286
2	0.571	0.143	0.143	0.143	0.143	0.286	0.143	0.571	0.286
3	0.000	0.500	0.125	0.500	0.500	0.250	0.125	0.375	0.500
4	0.000	0.250	0.000	0.250	0.750	0.000	0.000	0.500	0.500
5	0.250	0.625	0.000	0.375	0.000	0.750	0.000	0.125	0.250
6	0.000	0.500	0.000	0.167	0.167	0.167	0.000	0.333	0.000
7	0.333	0.500	0.000	0.333	0.333	0.500	0.250	0.667	0.167
8	0.000	0.500	0.000	0.500	0.000	0.500	0.000	0.250	0.250
9	1.000	0.400	0.000	0.300	0.100	0.700	0.000	0.800	0.100
10	0.000	0.375	0.000	0.375	0.250	0.375	0.000	0.500	0.250
11	0.000	0.500	0.000	0.500	0.500	0.500	0.000	0.000	0.000
12	0.500	0.750	0.000	0.250	0.125	0.250	0.000	0.000	0.000
13	0.500	0.500	0.000	0.000	0.500	1.000	0.000	0.500	0.000
14	0.167	0.833	0.000	0.833	0.833	0.667	0.333	0.667	0.833
15	0.111	0.556	0.000	0.444	0.333	0.333	0.000	0.444	0.222
16	0.500	1.000	0.500	0.500	1.000	1.000	0.000	1.000	0.750
17	0.250	0.750	0.000	0.250	0.500	0.250	0.000	0.500	0.500

18	0.286	0.000	0.000	0.000	0.000	0.143	0.000	0.000	0.000
19	0.500	0.500	0.500	0.500	0.000	0.500	0.000	0.000	0.000
20	1.000	0.667	0.333	0.333	0.667	0.667	0.000	0.000	0.000
21	0.400	0.800	0.000	0.200	0.000	0.000	0.000	0.600	0.200
22	0.500	1.000	0.500	1.000	0.500	1.000	0.000	0.500	0.500
23	1.000	0.000	0.000	0.333	0.000	0.667	0.000	0.667	0.333
24	0.250	0.500	0.000	0.000	0.250	0.500	0.000	0.250	0.000
25	0.000	0.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
26	0.000	1.000	0.000	1.000	1.000	1.000	0.000	0.000	0.000
27	0.667	0.667	0.000	0.667	0.333	0.667	0.667	0.667	0.000
28	0.000	0.667	0.000	0.333	0.333	0.333	0.333	0.667	0.333
29	1.000	1.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
30	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

3.2. Weighting of variables

The results of variable weighting using the Shannon entropy method are presented in Table 4.

Table 4. Weight of each variable influencing flood resilience using the Shannon entropy method.

	Internet access	Islamic Council	Police station	Village Council (Dehyari)	Basij base	Paved road	Paved Alleys	Emergency Medical Services (EMS)	Health post
Wj	0.0908	0.0349	0.2799	0.0514	0.0776	0.0441	0.2558	0.0566	0.1088

As can be observed, the weights of the variables range from 0.0349 to 0.2799. The police station (Kalantari) variable, with a weight of 0.2799, was assigned the highest weight, while the Islamic Council variable, with a weight of 0.0349, received the lowest weight. The high weights of the police station and paved street variables emphasize the substantial importance of access infrastructure and security-institutional services in determining rural resilience. In contrast, the low weights of the Islamic Council and paved road variables indicate the limited variability of these variables across sub-watersheds and, consequently, their lesser importance from the perspective of the entropy method.

3.3. Flood Resilience Index results

The results of the composite Flood Resilience Index (FRI) calculation for the 30 sub-watersheds are presented in Table 5.

Table 5. Flood Resilience Index (FRI) values for each sub-watershed.

Sub Basin	FRI	Sub Basin	FRI
1	0.222	16	0.506
2	0.228	17	0.194
3	0.236	18	0.032
4	0.163	19	0.251
5	0.131	20	0.306
6	0.065	21	0.130
7	0.233	22	0.437
8	0.107	23	0.211
9	0.215	24	0.096
10	0.124	25	0.594
11	0.104	26	0.208
12	0.105	27	0.382

13	0.174	28	0.240
14	0.395	29	0.182
15	0.142	30	0.091

The FRI values range from 0.032 to 0.594, indicating considerable variation in the level of resilience across sub-watersheds. Sub-watersheds 25 (0.594), 16 (0.506), and 22 (0.437) exhibit the highest levels of resilience, while sub-watersheds 18 (0.032), 6 (0.065), and 24 (0.096) display the lowest levels of resilience.

Based on the statistical analyses, the results of which are presented in Table 6, the mean FRI across all sub-watersheds is 0.216, with a standard deviation of 0.132, indicating a relatively high dispersion of resilience across the study area.

Table 6. Statistical summary of the Flood Resilience Index (FRI).

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
FRI	30	0.5621	0.0322	0.5944	.216809	0.1318993	0.017

These disparities indicate that the spatial distribution of resilience indicators across the region is non-uniform, with certain sub-watersheds exhibiting significantly lower levels of resilience than others.

The results of the stepwise Ordinary Least Squares (OLS) regression analysis are presented in Tables 7-8. Table 7 demonstrates that, throughout the stepwise procedure, all nine variables were sequentially entered into the model.

Table 7. Stepwise order of entry of variables into the OLS regression model.

Model	Variables Entered	Method
1	Health post	Stepwise
2	Paved road	Stepwise
3	Paved Alleys	Stepwise
4	Police station	Stepwise
5	Emergency Medical Services (EMS)	Stepwise
6	Basij base	Stepwise
7	Internet access	Stepwise
8	Islamic Council	Stepwise
9	Village Council (Dehyari)	Stepwise

Table 8 presents a summary of the stepwise regression models.

Table 8. Summary of stepwise regression models.

Model	R	R^2	Adjusted R Square	Std. Error of the Estimate
1	0.694	0.482	0.463	0.0966421
2	0.829	0.687	0.664	0.0764909
3	0.879	0.773	0.747	0.0663255
4	0.958	0.918	0.905	0.0406538
5	0.974	0.949	0.939	0.0326024
6	0.982	0.964	0.955	0.0281030
7	0.994	0.988	0.984	0.0168873
8	0.998	0.997	0.995	0.0090652
9	1.000	1.000	1.000	0.0000000

As can be observed, with the increasing number of variables, the coefficient of determination (R^2) and the adjusted coefficient of determination (Adjusted R^2) consistently increase, while the standard error of the estimate decreases. In the first step, the health post variable alone explains 48.2% of the variance in the FRI. In the second step, with the addition of the paved road variable, R^2 increases to 0.687. In the third step, with the addition of the paved street variable, R^2 reaches 0.773. This trend continues until the ninth step, when all nine variables are entered into the model and R^2 reaches 1 (100%). Model 9 with all nine variables shows perfect fit ($R^2 = 1.000$), but this is a clear indication of overfitting, as the model has exhausted all degrees of freedom. Therefore, this model is statistically invalid and should not be considered for interpretation.

Table 9 presents the results of the analysis of variance (ANOVA) for the different models.

Table 9. Analysis of variance (ANOVA) results for the stepwise regression models.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0.243	1	0.243	26.019	0.000
	Residual	0.262	28	0.009		
	Total	0.505	29			
2	Regression	0.347	2	0.173	29.615	0.000
	Residual	0.158	27	0.006		
	Total	0.505	29			
3	Regression	0.390	3	0.130	29.563	0.000
	Residual	0.114	26	0.004		
	Total	0.505	29			
4	Regression	0.463	4	0.116	70.067	0.000
	Residual	0.041	25	0.002		
	Total	0.505	29			
5	Regression	0.479	5	0.096	90.132	0.000
	Residual	0.026	24	0.001		
	Total	0.505	29			
6	Regression	0.486	6	0.081	102.637	0.000
	Residual	0.018	23	.001		
	Total	0.505	29			
7	Regression	0.498	7	0.071	249.591	0.000
	Residual	0.006	22	0.000		
	Total	0.505	29			
8	Regression	0.503	8	0.063	764.796	0.000
	Residual	0.002	21	0.000		
	Total	0.505	29			
9	Regression	0.505	9	0.056	-	-
	Residual	0.000	20	0.000		
	Total	0.505	29			
-= F-statistic and Sig. are undefined for Model 9 due to zero residual variance (complete overfitting).						

In all steps, the calculated F-value is greater than the critical value, and the significance level (Sig.) is less than 0.05, indicating the statistical significance of all models at the 95% confidence level. This demonstrates that the variables entered at each step contribute significantly to explaining the dependent variable (FRI).

Table 10 presents the standardized and unstandardized regression coefficients, t-statistics, and significance levels for the variables entered into the final model.

Table 10. Regression coefficients of the final model.

Model	Unstandardized Coefficients	Standardized Coefficients

		B	Std. Error	Beta
9	(Constant)	0.000	0.000	
	Health post	0.109	0.000	0.227
	Paved road	0.044	0.000	0.108
	Paved Alleys	0.256	0.000	0.439
	Police station	0.280	0.000	0.341
	Emergency Medical Services (EMS)	0.057	0.000	0.138
	Basij base	0.078	0.000	0.193
	Internet access	0.091	0.000	0.247
	Islamic Council	0.035	0.000	0.083
	Village Council (Dehyari)	0.051	0.000	0.113

All variables have positive coefficients, indicating a direct relationship with resilience. The highest standardized coefficient (Beta) belongs to the paved street variable with a value of 0.439, followed by police station (Kalantari) with a value of 0.341, and internet access with a value of 0.247. All coefficients are significant at the 0.01 level (Sig. < 0.01). The constant value is approximately zero (-2.429E-17), indicating a perfect model fit.

3.4. Results of the AICc criterion for model selection

Table 11 presents the AICc values for the different stepwise regression models.

Table 11. AICc values for the stepwise regression models.

Model Number	Model Name	n	Variable number	k	Residual (RSS)	AIC	AICc
1	Health post	30	1	2	0.26	-138.22	-137.77
2	Paved road	30	2	3	0.16	-151.39	-150.47
3	Paved Alleys	30	3	4	0.11	-159.18	-157.58
4	Police station	30	4	5	0.04	-187.86	-185.36
5	Emergency Medical Services (EMS)	30	5	6	0.03	-199.53	-195.87
6	Basij base	30	6	7	0.02	-208.56	-203.47
7	Internet access	30	7	8	0.01	-239.52	-232.66
8	Islamic Council	30	8	9	0.00	-270.47	-261.47
9	Village Council (Dehyari)	30	9	10	0.00	-	-
-= Note: AICc could not be computed for Model 9 due to zero residual variance (complete overfitting).							

As can be observed, with the increasing number of variables, the AICc value initially decreases, and then abruptly reaches zero in the ninth step, indicating overfitting of the model. The best model, based on the AICc criterion, is Model 8 with 8 variables (excluding Dehyari), which has the lowest AICc value of -261.47. This model, with an Adjusted R^2 of 0.995 (Table 8), explains more than 99% of the variance in the FRI, while avoiding the unnecessary complexity of the ninth

model (with 9 variables). Model 7 with 7 variables (excluding Islamic Council and Dehyari), with an AICc of -232.66, ranks second.

3.5. Geographically Weighted Regression (GWR)

The results of the Geographically Weighted Regression (GWR) model are presented in Table 12. To execute the GWR model, an adaptive bi-square kernel and an optimal bandwidth of 175,490.75 were employed, obtained through minimization of the AICc criterion. The effective number of parameters was estimated at 10.019, indicating the effective degrees of freedom of the model.

Table 12. Summary of the Geographically Weighted Regression (GWR) model.

Object ID	Variable Name	Variable value	Definition
0	Bandwidth	490175.7503	
1	Residual Squares	0.001009	
2	Effective Number	10.019744	
3	Sigma	0.007106	
4	AICc	-187.147244	
5	R2	0.998	
6	R2Adjusted	0.997097	
7	Dependent Field	0	FRI
8	Explanatory Field	1	Internet access
9		2	Islamic Council
10		3	Police station
11		4	Village Council (Dehyari)
12		5	Basij base
13		6	Paved road
14		7	Paved Alleys
15		8	Emergency Medical Services (EMS)
16		9	Health post

As observed in Table 12, the GWR model, with a coefficient of determination (R^2) of 0.998 and an adjusted coefficient of determination (Adjusted R^2) of 0.997, has successfully explained the majority of the spatial variation in the dependent variable. The AICc value for the GWR model is -187.147, which is substantially higher than that of the OLS model with eight variables (AICc = -261.47). This difference of approximately 74 units clearly indicates that the parsimonious global OLS model provides a superior fit compared to the locally weighted GWR model, despite the slightly higher R^2 of GWR (0.998 vs. 0.995). Therefore, the relationships between resilience determinants and FRI are largely spatially stationary, and the global approach is more appropriate for practical planning. The low Sigma value (0.0071) also indicates the model's low prediction error. A comparison of the OLS and GWR models reveals that the parsimonious OLS model provides a superior fit compared to the locally weighted GWR model, as indicated by the substantially lower AICc value.

3.6. Spatial Analysis of GWR Results

The output map of the GWR model illustrates the spatial distribution of predicted resilience values across the sub-watersheds (Figure 2).

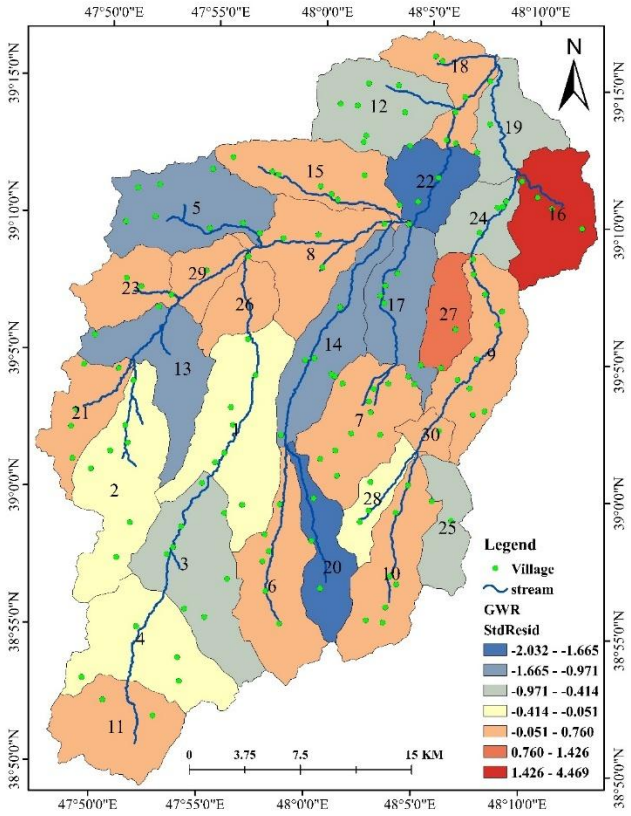


Figure 2. Output map of the Geographically Weighted Regression (GWR) model.

The Geographically Weighted Regression (GWR) model, as an advanced spatial analysis method, enables the investigation of spatial variability in the relationships among variables. In this study, the GWR model was implemented with an optimal bandwidth of 490,175.75 meters. The model output includes a matrix of local coefficients for each of the 30 sub-watersheds, predicted values, residuals, and diagnostic statistics, facilitating a more in-depth analysis of the spatial patterns of resilience.

A summary of the spatial analysis of the GWR model is presented in Table 13.

Table 13. Summary of the GWR model spatial analysis.

Analysis Component	Key Result	Spatial Interpretation
Overall Model Performance	(Adj. R^2 = 0.997) and (Sigma = 0.0071)	Excellent fit and very low prediction error
Coefficient Variability	Very negligible standard deviation	No significant spatial heterogeneity
Residual Pattern	Overestimation in south/center, underestimation in north/east	Presence of latent positive and negative factors in different areas
Outlier Sub-watersheds	16 (+4.469) and 20 (-2.032)	Require investigation of specific latent factors
Local R^2	0.997995 and 0.997998	Uniform and excellent performance across all areas

3.7. GWR (GWR Output Analysis)

In the following, based on Table 13, the various components of this output are analyzed:
- Excellent Performance of the GWR Model with (Adj. $R^2 = 0.997$) and (Sigma = 0.0071): This model has successfully explained the majority of the spatial variation in resilience and exhibits low prediction error.
- Spatial Stability of Coefficients: Consistent with the AICc comparison, the spatial variation of coefficients is very negligible, confirming that the relationships between variables are approximately stationary across the entire study area. The slightly higher R^2 of GWR does not compensate for its additional complexity, as indicated by the substantially higher AICc.
- Spatial Pattern of Residuals: The GWR model tends to overestimate resilience in the southern and central parts of the region and underestimate it in the northern and eastern parts, indicating the presence of latent (positive or negative) factors in these areas.
- Outlier Sub-watersheds: Sub-watersheds 16 (Std. Residual = 4.469) and 20 (Std. Residual = -2.032) were identified as outliers, requiring supplementary investigations into the latent factors affecting resilience.
- Importance of Variables: Based on local coefficients, the police station, paved street, health post, and internet access variables have the greatest influence on resilience, respectively, which is fully consistent with the results of the Shannon entropy and OLS methods.
- Investigation of Latent Factors: The identification of outlier sub-watersheds (16, 20) can contribute to the identification of latent factors affecting resilience, which should be examined in future research.
- Prioritization of Areas Based on Residuals: Sub-watersheds with large negative residuals (e.g., 20 and 22) meaning their actual resilience is lower than the model's prediction (require special attention, as despite having appropriate variables, their resilience is low, indicating the presence of structural or managerial barriers.

3.8. Shannon entropy weighting and OLS results

The results of this study are generally consistent with the theoretical framework of multi-dimensional resilience, according to which resilience is a multi-faceted concept influenced by a combination of infrastructural, institutional, social, economic, and other factors (Cutter et al., 2014; Sarker et al., 2026).

The weighting results using the Shannon entropy method demonstrated that the police station (Kalantari) and paved street variables, with weights of 0.2799 and 0.2558 respectively, made the greatest contribution to determining resilience. The high weight of the police station variable indicates that the presence of security and law enforcement institutions in rural areas, in addition to providing security, plays an important role in crisis management, coordination of rescue and relief operations, and fostering a sense of security among residents. This result is consistent with previous research proving the role of local institutions in resilience (Cutter et al., 2014; Sarker et al., 2026; He et al., 2026). The high importance of the paved street variable is also aligned with the results of previous studies on the role of access roads in rural resilience (Khan et al., 2023). Paved roads not only facilitate mobility and access to services during normal times but also enable rapid evacuation, emergency team access, and casualty transportation during flood events.

The stepwise regression results indicated that the health post variable was the first variable entered into the model, explaining 48.2% of the variance in FRI alone. This result demonstrates the vital role of access to primary healthcare services in rural resilience. During flood events, rapid access to healthcare services can prevent the outbreak of communicable diseases, infections, and complications arising from inundation (Jamshed et al., 2020). This result is fully consistent with

the research of He et al. (2026), which showed that access to healthcare services is one of the most important indicators of resilience in rural areas of China.

The entry of the paved road variable in the second step and the paved street variable in the third step showed the importance of transportation infrastructure in resilience. Notably, the paved street variable, defined as an indicator of intra-village road quality, is more important than the paved road variable, which is an indicator of inter-village roads (standardized coefficients of 0.439 versus 0.108). This result indicates that, in addition to access to the main road network, the quality of intra-village roads is also critically important for resilience. In other words, even if a village is connected to main roads, if its internal streets are inadequate, mobility and relief delivery during floods will face significant challenges.

3.9. Model performance comparison and key findings

One of the most important findings of this study is the comparison between GWR and OLS model performance. Although the GWR model achieved a slightly higher adjusted R^2 (0.997 vs. 0.995), the AICc criterion, which penalizes model complexity, clearly favored the OLS model. The OLS model with 8 variables (AICc = -261.47) substantially outperformed the GWR model (AICc = -187.147), with a difference of approximately 74 units. This indicates that, despite the local flexibility of GWR, the global OLS model with parsimonious variable selection provides a superior fit for this dataset. This finding suggests that spatial heterogeneity in the relationships between resilience determinants and FRI is minimal, and that a global modeling approach is more appropriate for practical planning applications.

These results are consistent with previous studies that have demonstrated that the GWR model outperforms global models in many geographic applications, including the investigation of factors influencing resilience (Dhungana et al., 2024; Alaei et al., 2026). Although the GWR analysis revealed minor spatial variability in coefficients, the substantially better performance of the OLS model (AICc difference of ~74 units) indicates that the relationships between resilience determinants and FRI are largely stable across the study area. This suggests that local factors such as topography, distance from urban centers, and socio-economic structure do not substantially alter the influence of the key determinants. Therefore, a global modeling approach with parsimonious variable selection is more appropriate for practical planning applications. Indeed, rural communities located near cities generally exhibit lower vulnerability, primarily due to better transfer of services and facilities from urban areas and easier access to governmental and private institutions (Jamshed et al., 2020). For instance, the influence of the health post variable on resilience may be greater in piedmont and remote sub-watersheds, where access to healthcare services is more difficult, than in sub-watersheds closer to urban areas. Therefore, planning for resilience enhancement must be tailored to the local conditions of each area, and uniform strategies cannot be effective across all regions.

This study was conducted with the aim of quantitatively assessing the flood resilience of 30 rural sub-watersheds and identifying the most important factors influencing it, using an integrated approach combining Shannon entropy, stepwise OLS regression, and GWR methods. The results revealed that:

- The police station (Kalantari) variable (weight 0.2799) and the paved street variable (weight 0.2558) received the highest weights in determining resilience, revealing the high importance of access infrastructure and institutional-security services.

- The calculated FRI for the sub-watersheds ranges from 0.032 to 0.594, indicating considerable variation in resilience levels. Sub-watersheds 25 (0.594) and 16 (0.506) exhibit the highest levels of resilience, while sub-watersheds 18 (0.032) and 6 (0.065) display the lowest levels.
- The stepwise OLS regression results revealed that the health post variable is the first and most important factor influencing resilience, explaining 48.2% of the variance alone.
- The comparison between OLS and GWR models revealed that the OLS model with 8 variables (AICc = -261.47) outperformed the GWR model (AICc = -187.147). This indicates that spatial heterogeneity is minimal and that resilience determinants are largely stable across the study area, making the global OLS approach more suitable for planning purposes.

3.10. Recommendations

Based on the findings, the following priority actions are recommended:

1. Prioritize intra-village paving: Paved streets (weight = 0.2558, Beta = 0.439) were the strongest predictor of resilience. Investment should focus on improving internal village roads to enable rapid evacuation and relief access during floods.
2. Strengthen local security institutions: Police stations (weight = 0.2799, Beta = 0.341) and Basij bases (Beta = 0.193) play critical roles in crisis coordination. Equipping these institutions with resources, communication systems, and regular disaster drills will enhance their effectiveness.
3. Expand primary healthcare services: Health posts alone explain 48.2% of resilience variance and were the first variable entered in stepwise regression. Strengthening health post networks with adequate supplies, trained staff, and warning systems is essential.
4. Target low-resilience sub-watersheds first: Sub-basins 18, 6, 24, and 30 (FRI < 0.1) require immediate investment. Given that OLS outperformed GWR (AICc = -261.47 vs. -187.147), the same set of interventions (paved streets, police/Basij bases, health posts) can be applied uniformly across the region, with intensity adjusted to baseline resilience levels.

4. Conclusion

This study developed an integrated framework (Shannon entropy, stepwise OLS, and GWR) to quantitatively assess flood resilience in rural areas. The key finding is that police stations, paved streets, and health houses are the most influential resilience drivers. FRI values ranged from 0.032 to 0.594, with nearly half of sub-watersheds falling below the regional average—demanding urgent policy attention. Health posts alone explain 48% of resilience variance, and adding transport and institutional factors brings explanatory power to over 99%, confirming that resilience is multi-faceted yet highly predictable in these settings. The primary objectives of the research were fully achieved: we not only quantified the FRI for all 30 sub-watersheds but also identified the most parsimonious and robust set of predictors using AICc-based model selection. Importantly, our comparison of OLS and GWR models (a methodological contribution that addresses a clear gap in the rural resilience literature) demonstrated that spatial heterogeneity in the relationships between determinants and resilience is minimal, as the global OLS model with eight variables substantially outperformed the local GWR model. This novel insight suggests that, contrary to common assumptions, uniform interventions can be effective across the study area, provided they target the right set of universally important factors. From a practical perspective, investments should target intra-village street paving, police and Basij bases as crisis coordination hubs, and health post expansion with adequate supplies. Low-resilience sub-watersheds (18, 6, 24, 30) demand immediate support, while consistent effect sizes across the region allow uniform interventions at varying intensities. Methodologically, our integrated framework offers a replicable

template for resilience assessment in other rural regions and hazards. Strategically, the findings underscore that resilience is a necessity (reinforced by the 2023 floods) and shift the focus from reactive response to proactive, evidence-based planning.

Nevertheless, we acknowledge two main limitations: the small sample size (30 sub-watersheds) limits generalizability, and the lack of consistent data prevented inclusion of qualitative factors such as risk perception and local knowledge. Future work should adopt mixed-methods designs (integrating household surveys and participatory mapping) and longitudinal monitoring to assess whether infrastructure gains yield sustained resilience over time. In conclusion, this study proves that rigorous quantitative resilience assessment is both feasible and actionable even in data-scarce rural contexts, offering a practical roadmap to protect vulnerable communities from flooding.

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