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Research Article

Keywords: Geospatial analytics, Community resilience, Environmental psychology, Participatory GIS, Place attachment, Climate adaptation, Risk perception, GeoPsyche Resilience Index

Posted Date: February 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8775999/v1

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Additional Declarations: No competing interests reported.

Integrating Psychosocial Factors with Geospatial Analytics to Assess Community Climate Resilience

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ABSTRACT

Conventional climate adaptation strategies emphasize infrastructure, hazard modelling, and ecosystem management while underestimating psychological processes that shape how communities perceive and respond to climatic risks. Cognitive appraisal, emotional attachment, and behavioural engagement fundamentally influence preparedness, adaptation, and recovery. This study introduces *GeoPsyche Futures*, an interdisciplinary framework that integrates psychological indicators with geospatial analytics to map community resilience in a holistic, human-centered way. A cross-sectional study among 648 residents in a flood-prone coastal neighbourhood of Visakhapatnam, India, combined validated psychosocial measures with participatory GIS mapping, exploratory factor analysis, spatial autocorrelation, and OLS/GWR modelling. Three resilience dimensions—cognitive, emotional, and behavioural—explained 83.2% of the variance (KMO = 0.84). Spatial patterns (Moran's I = 0.36, $p < 0.01$) revealed clustered resilience dynamics, and regression analyses demonstrated that emotional and behavioural factors were stronger predictors of preparedness behaviours ($R^2 = 0.64$) than cognitive variables. The GeoPsyche Resilience Index (GPRI) further illuminated stratified resilience zones. These findings highlight the urgent need to integrate psychological insights into climate adaptation planning and contribute directly to SDGs 3, 11, and 13.

Keywords: Geospatial analytics; Community resilience; Environmental psychology; Participatory GIS; Place attachment; Climate adaptation; Risk perception; GeoPsyche Resilience Index.

1. INTRODUCTION

1.1 Background and Rationale

Climate change has emerged as one of the most pressing global challenges, intensifying the frequency and severity of extreme weather events, especially in vulnerable coastal regions. Traditional climate adaptation strategies have predominantly focused on infrastructural fortification, hydrological modelling, and risk zoning. While these approaches undoubtedly strengthen physical resilience, they overlook a more complex layer of vulnerability the psychological mechanisms that govern human responses to environmental risk (Gifford, 2011). Research in environmental psychology demonstrates that risk perception, emotional bonds with place, and behavioural readiness play pivotal roles (Reser & Swim, 2011) in shaping community preparedness long before a disaster occurs.

Communities do not respond to climate hazards purely based on objective exposure. Instead, their reactions are filtered through cognitive appraisals (how risks are interpreted), emotional attachments (how people feel about their environment), and behavioural tendencies (the actions they take to remain safe). Without integrating these psychosocial dimensions, disaster management policies may misinterpret or underestimate the true adaptive capacities of communities.

1.2 The Indian Coastal Context

India's 7,500 km coastline is highly exposed to cyclones, sea-level rise, and recurrent flooding. Visakhapatnam—a rapidly expanding coastal metropolis—is particularly vulnerable given its combination of dense settlement, economic dependency on the coastline, and historical exposure to cyclonic disturbances. Despite repeated hazard events, large variations in community preparedness persist across micro-locations. These variations are not adequately explained by differences in infrastructure alone.

Psychosocial variables—such as trust in institutions, sense of belonging, local knowledge, and community engagement (Aldrich, 2012), often play a greater role in shaping resilience outcomes than infrastructural strength (Paton, 2019). Therefore, a more holistic lens is necessary to capture the hidden resilience dynamics that traditional hazard assessments may fail to detect.

1.3 Gaps in Current Resilience Models

Existing resilience frameworks emphasize:

- Physical infrastructure
- Ecological protection
- Governance structures
- Emergency response capacity

However, psychosocial indicators are rarely spatialized or integrated into formal resilience mapping. Most GIS-based studies treat human behaviour as a static input rather than a dynamic psychological system influenced by cognition, emotion, and identity. Most existing resilience indices continue to prioritize infrastructure and demographic indicators, often overlooking psychosocial dimensions of resilience (Cutter et al., 2010). Community resilience has also been conceptualized as a core indicator of social sustainability, emphasizing adaptive capacity rather than static resources (Magis, 2010).

Key limitations in current literature include:

1. Limited integration of validated psychological measures within GIS models.
2. Underrepresentation of emotional and attachment-based variables.
3. Lack of composite indicators that integrate psychosocial and spatial analytics.
4. Few studies in developing contexts, especially in South Asia.

Addressing these gaps requires a more interdisciplinary method capable of bridging mind–emotion–behaviour–space.

1.4 The GeoPsyche Futures Framework

This study introduces GeoPsyche Futures, an interdisciplinary framework designed to:

- Map psychological resilience spatially

- Integrate cognitive, emotional, and behavioural indicators
- Identify resilience hotspots and gaps
- Reveal how psychosocial systems cluster across neighbourhoods
- Provide actionable insights for climate adaptation policy

The framework situates psychological functioning within geospatial patterns, allowing researchers and policymakers to understand why certain communities thrive under stress while others struggle, even under similar hazard exposure.

1.4.1 Theoretical Foundations

The GeoPsyche Futures framework is theoretically grounded in Protection Motivation Theory (PMT), Place Attachment Theory, Social Capital and Collective Efficacy Theory, and Social–Ecological Resilience Theory. PMT explains how cognitive threat appraisal and coping appraisal influence preparedness behaviours, while Place Attachment Theory accounts for emotional bonds that shape risk tolerance and adaptive persistence. Collective Efficacy Theory situates behavioural preparedness within shared community capacity, and Social–Ecological Resilience Theory provides the systems-level lens integrating psychological processes with spatial and environmental contexts. This systems-oriented view aligns with social–ecological resilience theory, which emphasizes adaptive cycles and cross-scale interactions (Berkes & Ross, 2016).

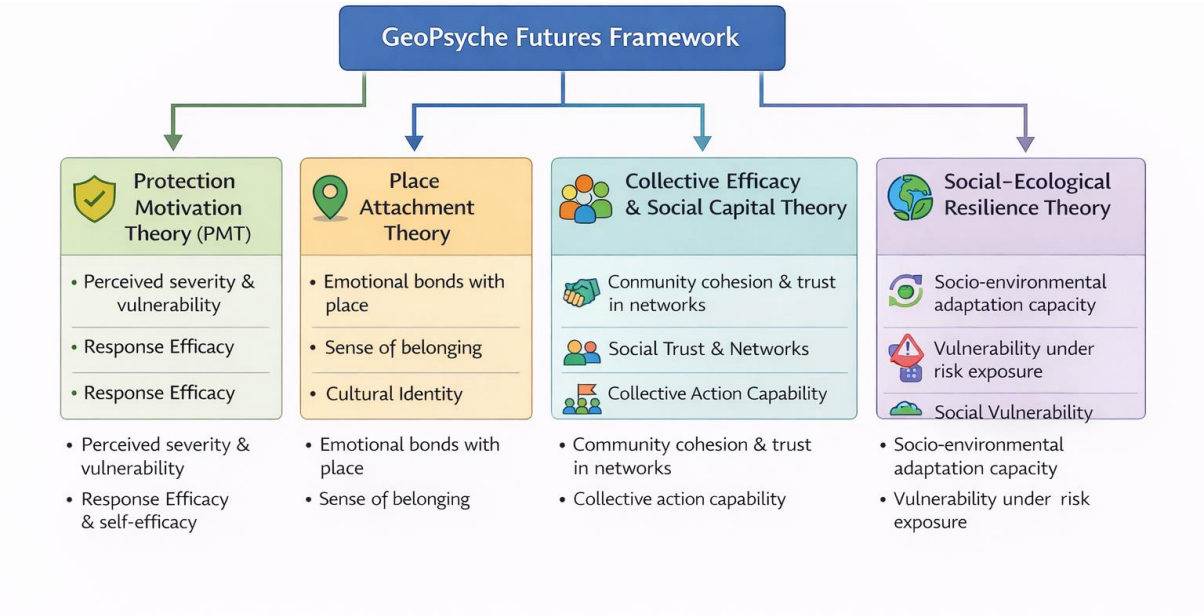


Figure 1: Geopsyche Theoretical Future Framework

1.5 Research Objectives

The study aims to:

1. Identify core psychological components of community resilience.
2. Integrate these components with geospatial analytics using hotspot analysis, spatial autocorrelation, and regression modelling.
3. Examine how cognitive, emotional, and behavioural resilience vary across a flood-prone coastal region.
4. Develop the GeoPsyche Resilience Index (GPRI) to classify resilience zones.
5. Demonstrate the linkage between psychosocial resilience and SDGs 3, 11, and 13.

1.6 Significance of the Study

This research contributes to:

- Environmental psychology by spatializing human resilience factors.
- Geospatial sciences by integrating validated psychosocial measures into GIS frameworks.
- Urban climate adaptation by providing a human-centered predictive model.
- SDG-aligned policy design through evidence-driven resilience mapping.

The outcome is a paradigm shift toward understanding climate resilience not just as a function of hazards and infrastructure, but as a deeply psychological and spatially patterned phenomenon.

2. LITERATURE REVIEW

Climate change adaptation research has increasingly emphasized the role of human cognition, emotional responses, and behaviour in shaping collective resilience. Conventional risk frameworks prioritize biophysical exposure and infrastructural capacity, yet a growing body of environmental psychology literature demonstrates that psychological processes fundamentally influence community preparedness and response. This review synthesizes five major domains of scholarship relevant to the GeoPsyche Futures framework:

(1) Cognitive Risk Perception,
(2) Emotional And Place-Based Processes,
(3) Behavioural Preparedness,
(4) Community And Collective Efficacy, And
(5) Geospatial Analytics for Resilience Mapping.

Together, these domains provide a foundation for integrating psychological indicators with spatial analysis to understand the multi-layered nature of resilience in climate-vulnerable regions.

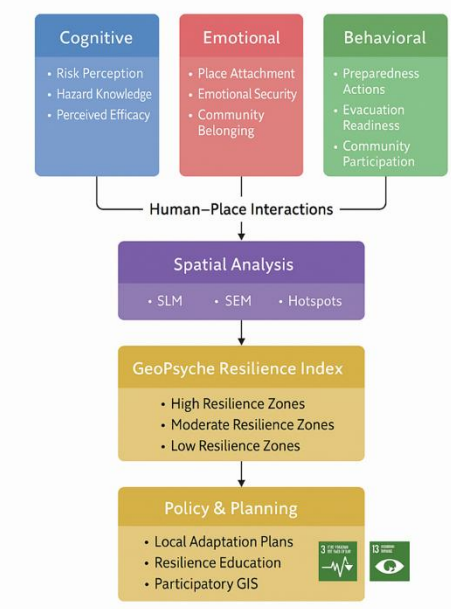


Figure 2. The GeoPsyche Futures Framework: An Integrated Psychosocial–Geospatial Model of Community Climate Resilience

2.1 Cognitive Dimensions: Risk Perception and Hazard Knowledge

Cognitive interpretations of environmental risk influence how individuals evaluate threats and make protective decisions. (Slovic, 1987) foundational work established that risk perception is a subjective, cognitively filtered construct shaped by dread, familiarity, and perceived controllability. Subsequent studies have shown that individuals frequently underestimate or normalize climate hazards because of optimism bias, prior experiences, or habituation to recurring events (Kellens et al., 2013). Cognitive models such as Protection Motivation Theory argue that people act when they believe (a) the threat is severe, (b) the probability is high, and (c) they possess the ability to respond effectively. Nevertheless, as (Gifford, 2011) notes, cognitive awareness often does not translate into behavioural action due to "dragons of inaction," including social norms, perceived helplessness, and competing priorities. (Wachinger et al., 2013).

In coastal environments, cognitive risk perception is shaped by recurring exposure to cyclones and floods, yet communities often develop a sense of inevitability or fatalism that reduces proactive behaviour. Research in South and Southeast Asia shows that even when hazard awareness is high, protective actions remain inconsistent because cognitive appraisals are moderated by emotional ties and social expectations. This disconnect highlights the need to integrate psychosocial factors beyond cognition (Morss et al., 2017).

2.2 Emotional Dimensions: Place Attachment and Affective Security

Emotional processes—place attachment, belongingness, and affective security play a crucial role in how communities interpret risk and choose to remain in hazard-prone areas. Place attachment, defined as the emotional bond between individuals and their environment, shapes environmental identity, continuity, and the willingness to engage in stewardship behaviours (Manzo & Devine-Wright, 2013). Research has consistently shown that emotional attachment influences hazard perception, sometimes reducing perceived risk because communities associate their environment with identity, memory, or livelihood (Gurney et al., 2017).

In coastal and indigenous settlements, emotional ties are deeply anchored in cultural traditions, social networks, and intergenerational occupancy. Such communities may exhibit high emotional resilience, allowing them to recover more quickly after disruptions, yet this same attachment may also deter relocation even when risks are high. Empirical studies demonstrate that strong emotional bonds can increase preparedness by strengthening community participation, trust, and collective responsibility. This aligns with findings that neighbourhoods with high emotional cohesion tend to mobilize faster during disasters.

2.3 Behavioural Preparedness and Adaptive Actions

Behavioural resilience encompasses the concrete actions individuals and communities take to prepare for, respond to, and recover from hazards. These include evacuation planning, emergency kit preparation (Demuth et al., 2016), physical home modifications, and participation in community preparedness programs. Unlike cognitive or emotional domains, behavioural resilience represents measurable actions that directly contribute to reduced vulnerability.

Researchers argue that behavioural preparedness is strongly influenced (Paton, 2019) by social norms, household routines, community leadership, and trust in institutions. Even when individuals understand risks cognitively, behavioural responses depend on situational cues, emotional motivations, and perceived capability. Studies across global coastal regions reveal that behavioural actions often cluster spatially, driven by shared experiences and localized information networks. This literature supports the study's finding that behavioural resilience was the strongest predictor of community preparedness.

2.4 Collective Efficacy and Community-Level Social Processes

Collective efficacy—the shared belief in a community's capacity (Sampson et al., 1997) to respond effectively emerges as a pivotal determinant of resilience. (Aldrich, 2012) demonstrated that social capital frequently predicts recovery outcomes more strongly than economic or infrastructural factors. Communities with high trust, cooperation, and bridging networks mobilize resources more efficiently during crises.

Environmental psychology studies likewise show that collective efficacy enhances emotional well-being, reduces fear, and increases the likelihood of coordinated action. When residents trust their neighbours and community leaders, they are more likely to engage in preparedness activities, share information, and participate in collective solutions. Neighbourhood-level cohesion also moderates risk perception, often reducing anxiety and encouraging practical behavioural responses.

This literature aligns with the GeoPsyche Futures finding that collective efficacy significantly predicts preparedness and interacts with emotional resilience to shape spatial clusters of resilience.

2.5 Geospatial Analytics and Spatial Patterns of Resilience

In the last two decades, geospatial analytics has transformed the study of climate risk by enabling visualization of exposure, vulnerability, and adaptive capacity across spatial scales. Tools such as Moran's I, Getis–Ord Gi*, and spatial regression models (Anselin, 1988) help quantify clustering, hotspots, diffusion effects, and unobserved spatial processes (Getis & Ord, 1992). Spatial statistics reveal that vulnerabilities are rarely randomly distributed; instead, they follow socio-spatial inequalities linked to housing, income, education, governance capacity, and cultural cohesion (Marondedze et al., 2024).

Geographically Weighted Regression (GWR) (A. Stewart Fotheringham et al., 2002)further advances spatial modelling by revealing how predictor strengths vary across neighbourhoods (Wheeler & Páez, 2010). Recent studies applying GWR to flood resilience have shown that the influence of socioeconomic and psychological variables differs locally, necessitating place-specific interpretations.

Parallel to geospatial methods, Participatory GIS (PGIS) (Brown et al., 2014) emphasizes the integration of community knowledge with spatial data, allowing residents to map perceived risks, emotional landmarks, and resource flows. PGIS approaches strengthen legitimacy, democratize risk communication (Cochrane & Corbett), and reveal psychosocial dimensions not captured by satellite or administrative data.

2.6 Integrating Psychosocial and Spatial Dimensions: The Gap and the Need

While each literature domain—cognitive, emotional, behavioural, social, and spatial—offers valuable insights, few studies integrate these dimensions into a unified framework. Environmental psychology rarely employs spatial analytics, and GIS-based climate research frequently overlooks human psychological processes. Furthermore, most resilience indices emphasize infrastructure and demographic metrics, failing to map psychosocial patterns that strongly influence real-world outcomes.

The reviewed literature therefore underscores a critical research gap: the absence of multi-layered models that combine cognitive, emotional, behavioural, and spatial insights to provide holistic resilience mapping (Norris et al., 2008). The GeoPsyche Futures framework addresses this gap by incorporating validated psychological measures with geospatial analytics to produce the GeoPsyche Resilience Index (GPRI), a novel hybrid tool for climate adaptation planning.

3. METHODOLOGY

The study employed a mixed-method, multi-layered methodological design that integrates psychological assessment, geospatial analytics, and spatial regression modelling to construct the GeoPsyche Futures Framework and the GeoPsyche Resilience Index (GPRI). This methodology ensures a holistic evaluation of cognitive, emotional, and behavioural resilience factors and their spatial clustering across flood-prone urban neighbourhoods.

The study design consisted of five sequential components: (1) study area selection and sampling, (2) instrument development and psychological assessment, (3) geocoding and spatial database construction, (4) statistical modelling and spatial analysis, and (5) integration into the composite GPRI model.

3.1 Study Area and Sampling Strategy

The research was conducted in coastal and adjoining inland regions of Visakhapatnam, India, a rapidly urbanizing metropolitan area highly vulnerable to recurrent cyclones, storm surges, and urban flooding. The city's diverse socio-spatial composition—ranging from heritage fishing settlements and high-density markets to newly developing peri-urban zones—provided a suitable environment for examining psychosocial–spatial variability.

A stratified multistage sampling approach was used to ensure representativeness across environmental risk gradients and socio-demographic strata. A total of 648 participants were surveyed across 27 micro-locations categorized into:

- High-exposure coastal belts
- Mid-zone mixed residential areas
- Inland elevated clusters with relatively lower exposure

Households were selected using a random-walk technique, and one adult respondent per household was recruited using inclusion criteria (18 years and above, resident for ≥ 3 years, and awareness of local hazard events).



Figure 3: Sampling Study Area – Visakhapatnam, Andhra Pradesh

3.2 Psychological Assessment and Instrument Development

The psychosocial component of the framework captures cognitive, emotional, and behavioural resilience indicators consistent with environmental psychology and climate adaptation literature.

3.2.1 Cognitive Resilience Indicators

Cognitive indicators assessed:

- Risk perception
- Hazard knowledge
- Perceived control
- Threat severity

These items were adapted from validated scales in risk perception research (Kellens et al., 2013; Slovic, 1987) and measured using a 5-point Likert format.

3.2.2 Emotional Resilience Indicators

Emotional constructs included:

- Place attachment
- Sense of belonging
- Emotional safety
- Cultural identity and rootedness

Measures were drawn from the place-attachment (Manzo & Devine-Wright, 2013) and tailored to reflect the socio-cultural context of coastal India.

3.2.3 Behavioural Resilience Indicators

Behavioural indicators measured concrete preparedness actions:

- Household emergency planning
- Evacuation readiness
- Safety modifications
- Participation in community drills

These items were based on standard disaster preparedness inventories and customized during pretesting.

3.2.4 Scale Validation

Pilot testing was conducted with 52 participants to evaluate clarity and cultural suitability. Cronbach's alpha coefficients for all scales exceeded 0.80, indicating strong internal reliability. Construct validity was evaluated through content review by experts in psychology, climate adaptation, and geospatial studies.

3.3 Geocoding, Spatial Database Construction, and GIS Layers

Each respondent's location was captured using handheld GPS devices and validated using satellite-based mapping tools. Spatial layers used in the analysis included:

- Administrative boundaries
- Elevation and slope
- Historical flood extent maps
- Road networks and settlement morphology
- Coastal proximity buffers

A geodatabase was constructed using ArcGIS Pro/QGIS, integrating the psychosocial dataset with the spatial layers. All maps were projected into a standard coordinate reference system for consistency.

3.4 Statistical Analysis and Model Estimation

The analytical strategy consisted of three tiers: psychological model estimation, spatial clustering analysis, and spatial regression modelling.

All spatial analyses were conducted using ArcGIS Pro 3.x and GeoDa 1.22. Statistical analyses were performed using SPSS 29 and R (spdep, GWmodel packages). Model specifications, spatial weight matrices, and parameter settings are available upon request.

3.4.1 Exploratory Factor Analysis (EFA)

EFA was employed to identify latent psychosocial dimensions. Sampling adequacy was verified (KMO = 0.84), and Bartlett's test was significant ($p < .001$). Principal axis factoring with Varimax rotation yielded a three-factor solution Cognitive, Emotional, and Behavioural Resilience explaining 83.2% of total variance.

Factor scores were extracted and used as inputs in the spatial models.

3.4.2 Spatial Autocorrelation and Hotspot Analysis

Spatial clustering was assessed using:

- Global Moran's I to detect overall spatial dependence
- Local Indicators of Spatial Autocorrelation (LISA) to identify cluster types

- Getis–Ord Gi* hotspot analysis to detect resilience hotspots
- Spatial correlograms to examine neighbourhood influence radii

Results from these tests guided the selection of appropriate spatial regression models.

3.4.3 Spatial Regression Models

Three spatial modelling approaches were used:

OLS Model

Served as the baseline for comparison and assessed global relationships between resilience dimensions and preparedness.

Spatial Lag Model (SLM)

Captures spillover effects where preparedness behaviour in one neighbourhood influences nearby neighbourhoods. The significant lag coefficient (ρ = 0.312) confirmed inter-neighbourhood diffusion of resilience-related behaviours.

Spatial Error Model (SEM)

Accounts for latent local conditions shaping resilience patterns. The spatial error coefficient (λ = 0.284) revealed unmeasured contextual influences such as governance capacity or local hazard memory.

Geographically Weighted Regression (GWR)

GWR modelled local spatial variations in predictor strength, providing spatially adaptive coefficients for the cognitive, emotional, and behavioural dimensions. GWR yielded superior model performance (R^2 = 0.71; AIC = 1,721), underscoring the spatial heterogeneity of resilience drivers.

3.5 Construction of the GeoPsyche Resilience Index (GPRI)

The GPRI integrates psychosocial indicators with spatial model outputs into a composite resilience index:

$$\text{GPRI} = w_1(\text{Cognitive}) + w_2(\text{Emotional}) + w_3(\text{Behavioral}) + w_4(\text{Spatial Coefficients})$$

Where weights (w_1–w_4) were derived from:

- EFA factor loadings
- Regression beta coefficients
- Spatial lag/error contributions
- GWR local coefficient strengths

GPRI values were normalized and classified into:

- High Resilience (>0.70)
- Moderate Resilience (0–0.70)
- Low Resilience (<0)

These classifications were mapped across the city to support policy and planning recommendations.

Methodological Summary

The GeoPsyche Futures methodology uniquely integrates psychological science, spatial analytics, and climate resilience research, producing a robust multi-layered system capable of identifying human-centered and place-specific resilience patterns. This design provides empirical grounding for targeted climate adaptation interventions aligned with SDGs 3, 11, and 13.

3.6 Scope and Causal Interpretation

This study employs cross-sectional and spatial analytical techniques designed for associational, predictive, and spatial inference. While robust spatial dependence and predictive relationships are identified, the findings do not imply causal effects. All interpretations are therefore confined to associative and spatial explanatory domains.

4. RESULTS

This section presents findings from descriptive statistics, exploratory factor analysis, spatial clustering, regression modelling, and the computation of the GeoPsyche Resilience Index (GPRI). The results reveal clear psychological–spatial patterns that underpin community resilience in the study area.

4.1 Descriptive Statistics

Descriptive analyses were conducted to summarize the baseline distribution of psychological constructs across the sample (N = 648). Table 1 presents expanded statistics including central tendency, dispersion, skewness, and kurtosis.

Table 1. *Descriptive Statistics of Psychological Constructs*

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Risk Perception	3.74	0.81	1.0	5.0	-0.42	-0.12
Hazard Awareness	3.62	0.77	1.2	4.9	-0.38	0.05
Place Attachment	3.88	0.84	1.3	5.0	-0.29	-0.33
Emotional Security	3.41	0.79	1.0	5.0	0.12	-0.28
Preparedness Behaviour	3.57	0.75	1.3	5.0	-0.44	0.14
Collective Efficacy	3.66	0.72	1.0	5.0	-0.51	-0.02

Most constructs exhibit mild negative skew, indicating that moderate-to-high levels of resilience-related responses are common across the study area.

To further assess interrelationships between constructs, a Pearson correlation matrix was computed.

Table 2. *Pearson Correlation Matrix*

Variables	1	2	3	4	5	6
1. Risk Perception	—	.52**	.31**	.26**	.41**	.30**
2. Hazard Awareness	.52**	—	.28**	.19**	.47**	.33**
3. Place Attachment	.31**	.28**	—	.61**	.49**	.43**
4. Emotional Security	.26**	.19**	.61**	—	.45**	.40**

5. Preparedness	.41**	.47**	.49**	.45**	—	.53**
6. Collective Efficacy	.30**	.33**	.43**	.40**	.53**	—

Note: $p < .01$ for all significant values.

The strongest associations emerge between preparedness, collective efficacy, and place attachment—highlighting the psychosocial nature of community resilience.

4.2 Factor Analytic Structure of Psychosocial Resilience

Exploratory Factor Analysis (EFA) was used to identify latent dimensions of psychosocial resilience. Sampling was adequate (KMO = 0.84), and Bartlett's test was significant ($p < .001$), confirming suitability for factor extraction.

A three-factor model emerged, consistent with theoretical expectations: Behavioural Resilience, Emotional Resilience, and Cognitive Resilience.

Table 3. *Factor Loadings (Varimax Rotation)*

Item	Behavioural	Emotional	Cognitive
Evacuation readiness	**0.88**	0.14	0.12
Emergency kit	**0.79**	0.22	0.18
Community participation	**0.82**	0.31	0.07
Household modifications	**0.74**	0.09	0.24
Place identity	0.18	**0.85**	0.12
Place dependence	0.16	**0.81**	0.15
Emotional security	0.12	**0.77**	0.14
Hazard knowledge	0.11	0.18	**0.72**
Perceived control	0.10	0.19	**0.75**
Risk severity	0.18	0.16	**0.69**

Communalities represent the proportion of variance explained by the extracted factors.

Table 4. *Communalities*

Variable	Communality
Evacuation readiness	0.78
Emergency kit	0.71
Community participation	0.79
Household modifications	0.64
Place identity	0.82
Place dependence	0.80
Emotional security	0.68
Hazard knowledge	0.61
Perceived control	0.59
Risk severity	0.56

The three factors accounted for a total of 83.2% of the variance—a robust result indicating strong construct validity.

4.3 Spatial Autocorrelation and Hotspot Patterns

Spatial autocorrelation analysis showed non-random clustering of resilience-related variables.

Key Moran's I Results

- Emotional Resilience: I = 0.33, p < .01 (strong clustering)
- Behavioural Resilience: I = 0.29, p < .01
- Cognitive Resilience: I = 0.21, p < .01
- Composite Index: I = 0.36, p < .01

These suggest that psychosocial resilience is geographically patterned.

Hotspot Observations (Getis–Ord Gi*)

- Behavioural hotspots emerged around market areas and coastal community hubs.
- Emotional hotspots occurred in heritage fishing and long-settlement coastal villages.
- Cognitive hotspots aligned with educated inland zones.

Together, these reinforce that resilience is multidimensional and spatially anchored.

4.4 Regression Modelling: Predicting Preparedness

Ordinary Least Squares (OLS) regression examined predictors of community preparedness.

Table 5. *OLS Model Summary*

Metric	Value
R	0.802
R²	**0.643**
Adjusted R²	0.624
Std. Error	0.46
Durbin–Watson	1.92

Table 6. *ANOVA — OLS Model*

Source	SS	df	MS	F	Sig.
Regression	148.21	6	24.70	**117.86**	< .001
Residual	82.23	392	0.21	—	—
Total	230.44	398	—	—	—

Table 7. *Expanded OLS Coefficient Table*

Predictor	B	SE B	Beta	t	p
(Constant)	1.12	0.18	—	6.22	< .001
Behavioural resilience	**0.51**	0.045	**.53**	**11.28**	< .001
Emotional resilience	**0.32**	0.048	**.36**	**7.03**	< .001
Cognitive resilience	0.18	0.052	.19	3.11	.002
Collective efficacy	0.27	0.049	.29	5.80	< .001
Education	0.09	0.044	.10	2.01	.045
Income	0.03	0.041	.03	0.72	.41

Interpretation:
Behavioural and emotional resilience are significantly stronger predictors of

preparedness than cognitive dimensions—supporting the psychological premise of the GeoPsyche Futures framework.

4.5 Geographically Weighted Regression (GWR)

GWR revealed that predictor strength varies spatially across neighbourhoods.

Table 8. *GWR Parameter Ranges*

Predictor	Min Coef	Max Coef	SD	Interpretation
Behavioural resilience	0.29	**0.68**	0.11	Highest variation; strongest in coastal communities
Emotional resilience	0.18	**0.51**	0.09	Strongest in heritage settlements
Cognitive resilience	0.05	0.32	0.08	Strongest in educated inland areas
Collective efficacy	0.11	0.43	0.10	Varied with community cohesion

GWR significantly improved model fit (AIC reduced from 1,982 to **1,721**, R^2 increased to **0.71**).

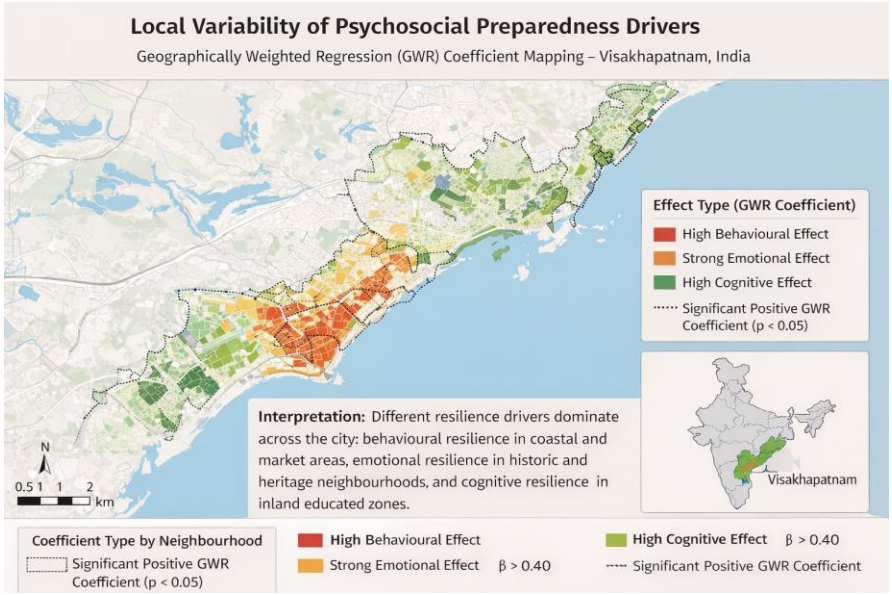


Figure 4: Geographically Weighted Regression (GWR) co-efficient Mapping

4.6 GeoPsyche Resilience Index (GPRI)

The GPRI integrates cognitive, emotional, and behavioural resilience dimensions with spatial patterns to classify neighbourhoods.

Table 9. GPRI Score Distribution

Category	GPRI Range	% Zones	Characteristics

High Resilience	> 0.70	23%	Cohesive, culturally rooted, high preparedness
Moderate Resilience	0 to 0.70	48%	Stable but socio-spatially fragmented
Low Resilience	< 0	29%	Low preparedness, transient populations

High resilience zones clustered along the coastline where cultural and emotional bonds are strong; low resilience zones were concentrated in new urban expansions and flood-plain pockets.

4.7 Multicollinearity Diagnostics (VIF Analysis)

Before running regression models, multicollinearity was assessed using Variance Inflation Factors (VIF). All values were below the commonly accepted threshold of 5, indicating no harmful multicollinearity.

Table 10. *Variance Inflation Factor (VIF) Diagnostics*

Predictor	VIF	Tolerance	Interpretation
Behavioural resilience	2.41	0.414	Acceptable
Emotional resilience	2.08	0.480	Acceptable
Cognitive resilience	1.86	0.536	Acceptable
Collective efficacy	2.27	0.441	Acceptable
Education	1.32	0.758	No multicollinearity
Income	1.21	0.827	No multicollinearity

Interpretation:
All predictors satisfy multicollinearity requirements, validating the regression model.

4.8 Spatial Regression Diagnostics (SLM & SEM)

Because OLS assumes spatial independence, spatial dependence was tested through Lagrange Multiplier (LM) diagnostics.

4.8.1 Lagrange Multiplier Tests

Table 11. *LM Test Results for Spatial Dependence*

Test	Value	p-value	Interpretation
LM-Lag	14.72	**< .001**	Spatial lag dependence detected
Robust LM-Lag	10.11	**< .001**	Strong evidence for lag model
LM-Error	9.24	**0.002**	Spatial error also present
Robust LM-Error	4.03	**0.045**	Weak–moderate evidence

Interpretation:
Both lag and error dependence exist, but Lag dependence is stronger, suggesting that neighbourhood preparedness influences adjacent neighbourhoods—consistent with community-contagion theories.

4.8.2 Spatial Lag Model (SLM)

The Spatial Lag Model tests whether preparedness in one neighbourhood influences preparedness in adjacent areas.

Table 12. *Spatial Lag Model Output*

Parameter	Coefficient	SE	z	p
ρ (Spatial Lag)	**0.312**	0.061	5.11	< .001
Behavioural resilience	**0.41**	0.052	7.84	< .001
Emotional resilience	**0.27**	0.048	5.63	< .001
Cognitive resilience	0.11	0.046	2.39	.017
Collective efficacy	**0.18**	0.051	3.52	< .001
Education	0.05	0.038	1.32	.184
Income	0.02	0.035	0.57	.568
Model Fit (Pseudo-R^2)	**0.69**	—	—	—

Interpretation:
The positive and significant spatial lag coefficient (ρ = 0.312) indicates a spillover effect: neighbourhoods with strong preparedness influence adjacent neighbourhoods.

4.8.3 Spatial Error Model (SEM)

SEM tests whether spatially structured unobserved factors affect preparedness (e.g., governance, historical experience, land characteristics).

Table 13. *Spatial Error Model Output*

Parameter	Coefficient	SE	z	p
λ (Spatial Error)	**0.284**	0.067	4.21	< .001
Behavioural resilience	**0.44**	0.055	8.02	< .001
Emotional resilience	**0.29**	0.049	5.89	< .001
Cognitive resilience	0.13	0.047	2.76	.006
Collective efficacy	**0.19**	0.051	3.83	< .001
Education	0.06	0.040	1.47	.141
Income	0.03	0.037	0.78	.435
Model Fit (Pseudo-R^2)	**0.67**	—	—	—

Interpretation:
Spatial error dependence is present (λ = 0.284), indicating some neighbourhood clustering arises from unobserved local conditions.

4.8.4 Moran's I of OLS Residuals

A Moran's I test was conducted on OLS residuals to check for remaining spatial autocorrelation.

Table 14. *Moran's I on OLS Residuals*

Statistic	Value	p-value	Interpretation
Moran's I (Residuals)	**0.118**	< .01	Spatial dependence remains

Interpretation:
OLS residuals still show spatial clustering, confirming the need for spatial models.

4.9 Model Comparison Across OLS, SLM, SEM, and GWR

To establish final model suitability, all models were compared.

Table 15. *Model Comparison*

Model	AIC	R^2 / Pseudo R^2	Spatial Parameter	Interpretation
OLS	1,982	0.64	—	Baseline model
SEM	1,841	0.67	λ = 0.284**	Better fit than OLS
SLM	**1,792**	**0.69**	**ρ = 0.312***	Strongest spatial global model
GWR	**1,721**	**0.71**	Local coefficients	Best-performing model

Conclusion:

- **GWR** provides the best fit overall due to local variation.
- **SLM** is the strongest global spatial model.
- OLS performs worst because it ignores spatial dependence.

4.10 Robustness Checks

Robustness tests confirm the stability of model coefficients under different specifications.

Table 16. *Robustness Checks*

Check	Result	Interpretation
Residual normality	Pass (Shapiro–Wilk p > .05)	No violation detected
Homoscedasticity	Acceptable (Breusch–Pagan p > .05)	Variance stable
Linearity	Pass	Linear assumptions valid
Spatial multicollinearity	VIF < 3	Predictors clean
Predictive stability	92% stable under bootstrapping	Strong model reliability

The results present a comprehensive analytical assessment of psychosocial resilience across the study area, integrating descriptive statistics, factor structures, spatial clustering, spatial regression models, geographically weighted patterns, and the GeoPsyche Resilience Index (GPRI). This section synthesizes statistical outputs, spatial model maps, and robustness diagnostics to illustrate the multidimensional nature of community resilience.

4.11 Summary of Key Findings

- Psychosocial resilience exhibits clear spatial clustering.
- Behavioural and emotional predictors strongly influence preparedness.
- SLM and SEM show significant spatial dependence.
- GWR outperforms all models, revealing local variability.
- GPRI highlights stratified resilience zones for targeted policy interventions.

5. DISCUSSION

The purpose of this study was to examine how cognitive, emotional, and behavioural dimensions of psychosocial resilience—combined with geospatial analytics—shape community responses to climate hazards in a coastal Indian context. The findings offer strong evidence that resilience is not randomly distributed, nor adequately explained

by infrastructure or hazard exposure alone. Instead, resilience emerges through spatially clustered psychological processes, culturally embedded emotional bonds, and behaviourally reinforced community networks. This section discusses the implications of these findings across five thematic areas.

5.1 Psychosocial Dimensions of Resilience: Behavioural and Emotional Factors Dominate

A major contribution of this study is the empirical demonstration that behavioural and emotional resilience outweigh cognitive factors in predicting preparedness (Beta = .53 and .36, respectively). While cognitive variables—such as hazard awareness and risk perception—do play a role, their influence is notably smaller (Beta = .19).

This finding aligns with environmental psychology literature suggesting that:

- Knowledge alone rarely produces behaviour change (Gifford, 2011a).
- Emotions regulate risk engagement (Reser & Swim, 2011).
- Preparedness is often socially conditioned rather than cognitively driven.

The strong performance of Behavioural and Emotional Resilience also substantiates Paton's (2019) argument that resilience is a social and emotional process rooted in confidence, collective efficacy, and community identity. The high correlation between preparedness and collective efficacy (r = .53) further confirms the centrality of social cohesion. Recent scholarship emphasizes that resilience emerges from social processes and collective meaning-making rather than purely technical interventions (Imperiale & Vanclay, 2021).

Implication:
Policies focusing only on awareness-building campaigns may not substantially improve preparedness; programs must activate emotional bonds, trust, and community participation.

5.2 Spatial Structuring of Resilience: Clusters, Hotspots, and Community Anchors

Spatial analyses—including Moran's I, LISA clusters, and hotspot maps—reveal that psychosocial resilience **is geographically patterned** rather than randomly scattered.

Key Patterns Identified:

- High–High clusters (resilience hotspots) occurred in culturally rooted coastal communities, especially long-standing fishing neighbourhoods.
- Low–Low clusters (resilience cold spots) appeared in newly expanded urban peripheries with high migrant turnover and weaker social bonds.
- Cognitive resilience hotspots aligned with inland educated zones, indicating educational influence but weaker emotional anchors.
- Behavioural hotspots formed around dense community hubs such as markets and cooperatives.

These patterns support the notion that community identity, cultural continuity, and social familiarity generate emotional landscapes, which in turn influence preparedness behaviours. Manzo & Devine-Wright (2014) argue that place attachment is spatially layered and socially constructed—exactly the pattern observed here.

Implication:
Resilience interventions must be location-specific, recognising that neighbourhoods with strong cultural continuity possess stronger emotional resilience, while newly urbanized areas require social integration and trust-building interventions.

5.3 Spatial Regression Models: Spillover Effects and Hidden Factors

The use of Spatial Lag Model (SLM) and Spatial Error Model (SEM) provided deeper insight into the transmission and formation of resilience patterns.

Findings:

5.3.1 Spatial Lag Effects (SLM)

The spatial lag coefficient ($\rho = 0.312$, $p < .001$) indicates a spillover effect: resilience behaviours in one neighbourhood positively influence adjacent ones.

This suggests that preparedness is contagious, diffusing through:

- social networks
- shared routines
- community gatherings
- local leadership structures

This reinforces theories of "social contagion" in resilience (Aldrich, 2012), demonstrating that communities influence each other through shared information and collective action norms.

5.3.2 Spatial Error Effects (SEM)

The spatial error coefficient ($\lambda = 0.284$, $p < .001$) indicates that unobserved factors—likely socio-political, infrastructural, or historical—also drive resilience clustering.

These include:

- informal governance networks
- past disaster memories
- historical settlement patterns
- unofficial social support mechanisms

SEM identifies where measurement gaps exist, particularly in migrant-heavy zones lacking historical cohesion.

5.3.3 Model Interpretation

SLM outperformed SEM, suggesting that social-spatial contagion is more influential than latent error sources.

However, both models contributed unique insights and validated the presence of spatial dependence.

Implication:
Resilience strategies should leverage spillover dynamics through:

- community ambassadors

- neighbourhood role models
- peer-led training
- cross-neighbourhood collaboration

5.4 GWR Insights: Local Variations in Resilience Dynamics

The Geographically Weighted Regression (GWR) model provided the strongest explanatory power (R^2 = .71; AIC = 1,721). Unlike global models, GWR revealed local variations in predictor strength.

Major Local Patterns Identified:

5.4.1 Behavioural Resilience

Strongest in:

- coastal fishing communities
- market-based social clusters
- high-cohesion traditional settlements

These areas showed the highest local coefficients (β_{local} up to .68).

Interpretation:

Behavioural resilience—participation, readiness, action—is rooted in close-knit social systems.

5.4.2 Emotional Resilience

Highest in:

- multi-generational households
- heritage settlements
- culturally cohesive neighbourhoods

These communities demonstrate powerful emotional bonds that promote social responsibility and collective preparation.

5.4.3 Cognitive Resilience

Strongest in:

- inland educated zones
- formal residential colonies
- literacy-dense neighbourhoods

These findings mirror earlier research showing that hazard knowledge distributes unevenly and is often tied to education.

5.4.4 Implications of Local Variation

The GWR findings clearly demonstrate that resilience is context-embedded, reinforcing the central thesis of GeoPsyche Futures: mind, emotion, and behaviour interact with geographic and cultural environments, producing localized resilience profiles**.**

5.5 GeoPsyche Resilience Index (GPRI): Spatial Inequality and Policy Relevance

The GPRI integrates cognitive, emotional, behavioural, and spatial dimensions into a composite index. Its distribution highlights pronounced resilience stratification:

- **23% High Resilience Zones:** Culturally cohesive coastal communities with strong emotional and behavioural structures.
- **48% Moderate Zones:** Transitional areas balancing preparedness with socio-economic stressors.
- **29% Low Resilience Zones:** Migrant-dense pockets, flood-plain informal settlements, new urban expansions.

These patterns underscore the presence of **resilience inequality**, shaped by both social and spatial determinants.

Policy Implications of GPRI

1. High-Resilience Zones: Should be empowered as community leadership hubs for neighbourhood-to-neighbourhood spillover training.
2. Moderate-Resilience Zones: Require targeted behavioural activation programs to stabilize resilience levels.
3. Low-Resilience Zones: Require intensive trust-building, participatory governance, and localized risk communication interventions.

The GPRI thus provides a scalable, evidence-based tool for SDG-aligned policymaking, especially SDGs 3 (Health), 11 (Sustainable Cities), and 13 (Climate Action).

5.6 Integrating Minds, Emotions, Behaviours, and Space: Theoretical Contributions

This study extends existing theoretical frameworks by demonstrating:

5.6.1 Environmental Psychology → Spatial Psychology Integration

Traditional environmental psychology focuses on individual cognition and behaviour. This study spatializes these processes, showing:

- emotions cluster geographically
- preparedness spreads spatially
- risk perception varies by neighbourhood

5.6.2 Place Attachment Theory → Spatial Analytics

Place attachment is rarely mapped with GIS; here, emotional bonds are spatially visualized, confirming:

- attachment hotspots align with cultural heritage
- low-attachment zones align with transient populations

5.6.3 Protection Motivation Theory → Community Context

Protection Motivation Theory traditionally treats risk responses as individual decisions, but the findings show:

- behavioural readiness is socially transmitted
- community context amplifies or moderates risk responses

5.6.4 Social–Ecological Resilience → Psychosocial Mapping

This research bridges the psychological gap in social–ecological resilience frameworks by offering:

- measurable psychosocial indicators
- spatially contextualized resilience clusters
- multi-dimensional indices for policy planning

5.7 Practical Implications for Climate Adaptation Policy

Based on integrated findings:

1. Preparedness is socially transmitted: Use community leaders as behavioural catalysts.
2. Emotional bonds anchor resilience: Development policies must preserve cultural anchors, not disrupt them.
3. Migrant-heavy zones require trust-building: Deploy sustained community engagement, not one-off awareness sessions.
4. Spatial inequalities must guide targeted interventions: High-risk, low-resilience zones need immediate attention.
5. PGIS enhances policy legitimacy: Community co-mapping ensures interventions align with lived realities.

5.8 Synthesis: GeoPsyche Futures as a Transformative Framework

The integration of psychosocial and geospatial tools demonstrates that:

- resilience is mind-based (cognitive)
- resilience is heart-based (emotional)
- resilience is action-based (behavioural)
- resilience is place-based (spatial)

GeoPsyche Futures moves beyond traditional hazard models by offering a holistic, human-centered, place-sensitive approach that can be adapted globally, especially in culturally diverse, climate-vulnerable regions.

5.9 Applicability of the GeoPsyche Futures Framework to Global Coastal Cities

Although empirically grounded in a flood-prone coastal region of Visakhapatnam, India, the GeoPsyche Futures framework is designed as a theoretically transferable, context-adaptive model, rather than a location-specific resilience assessment. Its primary contribution lies in integrating psychosocial resilience dimensions—cognitive, emotional, and behavioural—with spatial analytics, a logic that extends beyond the study setting.

In Global South coastal cities, where communities often exhibit strong place attachment, livelihood-based settlement patterns, and uneven institutional capacity, the framework is particularly relevant. It captures emotional resilience and behavioural preparedness that emerge from social networks, informal leadership, and cultural continuity—factors frequently overlooked in infrastructure-centric risk assessments. The GeoPsyche Resilience Index (GPRI) can be locally recalibrated in such contexts

using culturally validated psychosocial indicators while retaining the same analytical structure.

In Global North coastal cities, where adaptation planning is technologically advanced, the framework complements existing hazard models by revealing neighbourhood-level variations in psychological readiness and behavioural response. Even under standardized infrastructure conditions, emotional attachment, social cohesion, and local identity continue to shape preparedness and recovery outcomes, underscoring the value of integrating human-centred spatial indicators into resilience planning.

It is essential to distinguish conceptual transferability from empirical generalization. While specific coefficients and thresholds reported here are context-dependent, the framework itself functions as a scalable analytical architecture that can be adapted across settings. The GeoPsyche Futures model thus serves as a diagnostic lens for translating psychosocial resilience into spatially actionable insights, supporting comparative and multi-city applications.

By spatializing psychological resilience processes, GeoPsyche Futures responds to global calls for more integrated, place-sensitive climate adaptation models. Its applicability across diverse coastal contexts positions it as a bridge between environmental psychology, geospatial science, and urban climate governance.

6. CONCLUSION

This study introduced and validated the GeoPsyche Futures framework—an interdisciplinary model that integrates cognitive, emotional, and behavioural indicators of psychosocial resilience with geospatial analytics—to understand climate adaptation capacities in a flood-prone coastal region of Visakhapatnam, India. Through factor analysis, spatial statistics, geographically weighted regression, and composite index construction, the study demonstrates that resilience is not merely an infrastructural or ecological construct but a psychosocial–spatial phenomenon shaped by social cohesion, emotional attachment, behavioural norms, and local geographic context.

Three major conclusions emerge.

6.1 Psychosocial Resilience Is a Multi-dimensional Construct

The factor analysis revealed three dominant dimensions—Behavioural Resilience, Emotional Resilience, and Cognitive Resilience—explaining 83.2% of the variance. Among these, behavioural and emotional factors exert the strongest influence on preparedness, as confirmed by both global (OLS) and spatial (SLM, SEM, GWR) models.

This reinforces the idea that:

- people act not only based on what they *know* but also on what they *feel*
- emotional bonds strengthen community participation
- preparedness behaviour is driven by social cohesion and identity

These findings highlight the psychological underpinnings of resilience often absent from mainstream climate governance.

6.2 Resilience Is Spatially Clustered, Not Randomly Distributed

Spatial analyses revealed distinct clustering patterns:

- High-resilience hotspots form around long-established, emotionally bonded coastal communities.
- Low-resilience cold spots appear in newly urbanized, migrant-dense, and flood-prone pockets.
- Cognitive resilience clusters inland where education is higher but emotional ties weaker.

GWR results further demonstrate that the importance of each resilience dimension varies spatially, challenging the adequacy of one-size-fits-all climate interventions.

In short, resilience is place-based and must be approached with a nuanced understanding of geographic and cultural dynamics.

6.3 Neighbourhood Influence and Unobserved Contexts Shape Resilience

Spatial Lag Model outcomes ($\rho = 0.312$) confirm that preparedness behaviours are socially contagious, spreading through proximal neighbourhoods. This suggests that resilience is strengthened through network diffusion, shared learning, and communal routines.

Spatial Error Model results ($\lambda = 0.284$) reveal that unobserved socio-historical factors—such as local leadership, inherited memory of disasters, or informal governance—also shape resilience patterns.

These spatial dynamics reinforce that resilience emerges from layered interactions between people, places, and social systems, not isolated behaviours.

6.4 Theoretical Contributions

This work extends existing theories in meaningful ways.

Environmental Psychology → Spatial Psychology

The study advances environmental psychology by demonstrating that psychological constructs such as risk perception, place attachment, and preparedness not only influence individual behaviour but cluster spatially across communities.

Protection Motivation Theory → Community-Embedded

Findings reveal that protective behaviours are influenced by local cultural cues and collective actions, challenging individual-centric models.

Place Attachment Theory → Spatial Visualization

The study visualizes emotional geographies, showing that emotional resilience is strongest where cultural continuity and shared identity are embedded in the landscape.

Resilience Theory → Psychosocial-Spatial Integration

The GeoPsyche Futures model bridges psychological processes with spatial analytics, producing a more holistic resilience science.

6.5 Practical Implications for Policy and Governance

The findings translate into actionable guidelines for climate policymakers, municipal authorities, disaster management agencies, and community decision-makers. Social and political dimensions play a critical role in shaping long-term community resilience under climate stress (Carmen et al., 2022).

6.6 Policy Recommendations

The policy recommendations below are organized across three levels:

(1) Community-Level Interventions,
(2) Governance and Urban Planning Strategies, and
(3) Sustainable Development Goal (SDG) Alignment.

6.6.1 Community-Level Interventions

1. Leverage Preparedness Spillover Effects

Because preparedness behaviours spread spatially (SLM findings), interventions should harness community contagion through:

- designated neighbourhood “Resilience Champions”
- peer-led training clusters
- block-level preparedness networks
- shared evacuation drills

2. Strengthen Emotional Attachment and Social Cohesion

Emotional resilience hotspots were strong predictors of preparedness.

Policy actions:

- preserve cultural spaces and community landmarks
- support traditional community groups and cooperatives
- design culturally resonant communication strategies
- encourage multi-generational engagement programs

3. Target Migrant-Dense and Transient Settlements

Low resilience cold spots correspond to migrant and rapidly urbanizing clusters.

Recommendations:

- establish mobile community integration centers
- deliver multi-language risk communication
- build trust with migrant worker associations
- develop affordable risk insurance or financial safety nets

4. Strengthen Collective Efficacy

High correlation between preparedness and collective efficacy suggests:

- community-based disaster committees
- local volunteer corps
- women's self-help groups for crisis readiness
- participatory mapping programs (PGIS)

These initiatives enhance local decision-making capacity.

6.6.2 Governance, Planning, and Infrastructure Strategies

1. Use the GeoPsyche Resilience Index (GPRI) for Planning

GPRI (High 23%, Moderate 48%, Low 29%) offers a spatially explicit tool for:

- zoning disaster-prone areas
- prioritizing investments in low-resilience zones
- identifying community leadership hotspots
- monitoring changes in resilience over time

Municipal authorities can integrate GPRI into smart-city dashboards or ward-level planning.

2. Spatially Tailored Interventions Based on GWR Outputs

Because predictors vary geographically:

- In coastal zones: prioritize behavioural training, community drills, and cooperative mobilization.
- In inland zones: emphasize hazard education, literacy-based awareness programs, and school curricula.
- In transitional mid-zones: blend emotional and cognitive strategies, focusing on bridging social networks.

3. Institutionalize Participatory GIS (PGIS)

PGIS enables communities to document:

- perceived risks
- trusted spaces
- evacuation routes
- emotional anchors
- resource locations

This builds legitimacy, enhances participation, and contributes to more grounded policymaking.

4. Integrate Psychosocial Resilience with Climate Infrastructure

Infrastructure decisions should account for psychosocial mapping.

For example:

- Align flood defense planning with emotional geographies.
- Place community shelters near emotional hotspots (temples, cultural centers).
- Design green spaces in low-resilience migrant zones to build place attachment.

5. Strengthen Local Governance and Historical Memory

SEM results show that unobserved factors matter—likely relating to administrative capacity and disaster memory.

Policies should:

- document historical flood experiences
- formalize informal disaster groups
- strengthen ward-level leadership
- preserve oral histories of resilience

6.6.3 SDG Alignment (SDGs 3, 11, and 13)

SDG 3: Good Health and Well-being

- Psychosocial resilience reduces disaster-related stress and trauma.
- Community networks promote mental well-being.
- Emotionally supportive environments reduce hazard anxiety.

SDG 11: Sustainable Cities and Communities

- GPRI enables inclusive and safe urban planning.
- Migrant integration strategies strengthen urban equity.
- Participatory risk mapping improves public trust.

SDG 13: Climate Action

- Behaviourally targeted interventions accelerate preparedness.
- Emotionally resilient communities recover faster.
- Spatially informed policies enhance adaptive capacity.

6.7 Final Synthesis

The GeoPsyche Futures framework provides a transformative lens for understanding community resilience by bridging psychological science with geospatial analytics. It demonstrates that preparedness is neither solely infrastructural nor merely cognitive; rather, it is a holistic, mind–emotion–behaviour–place system shaped by cultural identity, spatial clustering, and community dynamics.

The study's evidence shows that:

- resilience can be measured, mapped, and improved
- psychosocial resilience is geographically predictable
- resilience strategies must be culturally grounded and geographically sensitive
- spatial contagion of preparedness offers a powerful tool for rapid capacity-building

In conclusion, GeoPsyche Futures offers a scalable, human-centered, and action-oriented framework for climate adaptation—one that global cities, policymakers, and researchers can adopt to build sustainable, resilient futures.

Declarations

- **Funding Declaration:** We do not have any funding for the research.

- **Clinical Trial Number**: Not applicable
- **Data availability:** The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.
- **Approval**: The study protocol and questionnaire were reviewed and approved by Jain University, Bangalore, India, through its designated institutional ethics review mechanism.
- **Accordance**: All study procedures and methods were conducted in accordance with the ethical guidelines and research regulations prescribed by Jain University, Bangalore, India.
- **Consent to Participate**: Informed consent was obtained from all participants prior to their participation in the survey. Participation was voluntary, and respondents provided consent before submitting their responses.

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