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Socio-Spatial Inequity in Post-Disaster Reconstruction: A GIS-Based Analysis of Community Resilience and Housing Subsidies

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ABSTRACT

Post-disaster recovery programs frequently aim to restore built environments quickly, yet uniform resource allocation often exacerbates underlying socio-spatial vulnerabilities. This study investigates the spatial distribution and equity of post-disaster housing subsidies, examining how recovery outcomes intersect with existing baseline community resilience. Integrating parcel-level municipal recovery disbursements with census-derived demographic indicators, we employ geographic information systems (GIS), spatial autocorrelation techniques (Hot Spot Analysis / Getis-Ord *Gi*∗), and multiscale geographically weighted regression (MGWR) to model recovery trajectories across impacted census tracts. The empirical findings reveal significant spatial clustering of recovery disparities: historically marginalized, low-income, and minority neighborhoods experienced longer disbursement delays, lower per-capita aid allocations, and diminished rebuilding rates despite sustaining comparable or higher baseline physical damage. Conversely, wealthier tracts with high institutional and financial capital captured disproportionate shares of rebuilding grants, compounding spatial stratification and heightening gentrification pressures post-event. Spatial regression diagnostics indicate that traditional, standardized recovery criteria systematically penalize renters and informal settlements by over-indexing property tenure and pre-disaster appraised asset valuations. By illustrating how disaster financing reproduces spatial injustice, this research provides a spatial decision-support framework to shift recovery policies from asset-centric allocation models toward targeted, vulnerability-weighted disbursement mechanisms.

Keywords: Disaster recovery, Socio-spatial equity, GIS spatial analysis, Housing subsidies, Community resilience, Environmental justice

INTRODUCTION

Natural hazards are increasingly recognized not as purely physical phenomena, but as socio-environmental disruptions whose impacts are deeply mediated by existing structural inequalities. In the aftermath of catastrophic events, the reconstruction phase offers a critical window for mitigating vulnerability and enhancing adaptive capacity. However, post-disaster recovery interventions—particularly public housing assistance, reconstruction grants, and repair subsidies—frequently operate under market-centric or asset-protecting logics. By prioritizing rapid physical restoration and tying eligibility to pre-disaster homeownership or property value, these programs often systematically disadvantage historically marginalized populations, transforming what should be a safety net into an engine of compounded socio-spatial stratification.

The geographic manifestation of this disparity is stark: disaster recovery is rarely spatially uniform. While affluent enclaves often mobilize financial, political, and institutional resources to reconstruct rapidly, lower-income neighborhoods, communities of color, and high-density tenant settlements frequently encounter procedural delays, smaller subsidy disbursements, and prolonged displacement. This spatial divergence underscores the concept of socio-spatial equity—the recognition that equitable recovery requires not merely equal per-capita spending, but resource distribution that accounts for historical disinvestment, structural marginalization, and baseline resilience deficits.

Despite a robust body of literature addressing social vulnerability and disaster recovery separately, conventional evaluation frameworks often treat policy implementation as spatially neutral. Traditional non-spatial econometric and demographic models frequently obscure localized spatial autocorrelation, neighborhood-level spillover effects, and spatial non-stationarity—the phenomenon where the relationship between subsidies and recovery outcomes varies systematically across geographic space. Geographic Information Systems (GIS) and spatial analytical techniques (such as Multiscale Geographically Weighted Regression and Hot Spot Analysis) offer critical methodological advantages by contextualizing recovery outcomes within specific built and social environments.

To address these empirical and methodological gaps, this study investigates the intersection of post-disaster housing subsidies, community resilience, and reconstruction trajectories. Specifically, this research addresses three primary objectives:

1. Mapping the spatial patterns and clustering of housing subsidy allocations across disaster-impacted communities.
2. Assessing how baseline community resilience (social, economic, and institutional capital) influences the speed, magnitude, and equity of subsidy disbursement.
3. Modeling the degree to which asset-based recovery frameworks perpetuate or alleviate pre-existing spatial inequalities.

By integrating parcel-level recovery data with spatial demographic analysis, this paper provides an empirical foundation for transitioning from asset-based disaster aid models toward spatially explicit, equity-driven recovery frameworks.

PROPOSED MODELS AND METHODOLOGIES

This study employs an integrated spatial-econometric methodology that combines multi-source geospatial data harmonization, spatial autocorrelation statistics, composite resilience indexing, and spatial regression modeling. The workflow is organized into four sequential phases: data harmonization, index construction, spatial clustering analysis, and multiscale spatial regression.

2.1 Analytical Framework & Spatial Conceptual Model

The conceptual model evaluates post-disaster recovery as an interaction between hazard exposure, baseline structural vulnerability, and public fiscal intervention.

2.2 Data Acquisition, Sources, and Spatial Preprocessing

Data are aggregated and harmonized at the **census tract** and **parcel block** levels using a unified spatial coordinate reference system (e.g., EPSG:6543 / WGS 84 State Plane):

- **Housing Subsidies & Recovery Grants:** Microdata comprising individual grant application IDs, requested vs. approved disbursement amounts, award dates, and program types (e.g., FEMA Individual Assistance, HUD Community Development Block Grant-Disaster Recovery / CDBG-DR, Small Business Administration disaster loans).
- **Physical Damage & Exposure Layers:** Satellite/aerial remote sensing damage assessments (e.g., Copernicus EMS or NOAA imagery) and hazard boundary extents.
- **Socioeconomic Demographics:** Census / American Community Survey (ACS) 5-year estimates, including median household income, racial/ethnic composition, housing tenure (renter vs. owner-occupied), linguistic isolation, and pre-event housing cost burdens.
- **Cadastral & Real Estate Valuations:** Municipal tax assessor parcels detailing pre-disaster appraised structural value, year built, foundation type, and land tenure.

2.3 Baseline Resilience Metric Construction: Modified BRIC

To quantify pre-disaster capacity across affected census tracts, we construct an adapted **Baseline Resilience Indicators for Communities (BRIC)** framework. Six primary sub-indices are formulated:
MDPI

1. **Economic Capital:** Median household income, income equality (Gini coefficient), employment rates, and homeownership percentage.
2. **Social Capital:** Educational attainment, vehicle access, health insurance coverage, and English language proficiency.
3. **Housing & Built Infrastructure:** Age of housing stock, percentage of single-family units, pre-disaster code enforcement standards, and vacancy rates.
4. **Institutional Capital:** Coverage of municipal mitigation plans, emergency response stations, and civil society non-profit presence.

Each variable xi is normalized via min-max scaling relative to its directional contribution to resilience:
$zij=\max(xj)-\min(xj)xij-\min(xj)$
Sub-index scores are computed through equal or principal component analysis (PCA) weighting, yielding a continuous resilience index $Ri\in[0,1]$ for each spatial unit.

2.4 Spatial Pattern Mining & Autocorrelation

To assess whether housing subsidies and recovery outcomes exhibit spatial concentration or structural segregation, two levels of spatial autocorrelation are conducted:

***Global Moran's* I**

Evaluates whether subsidy distributions and recovery speeds are clustered, dispersed, or random across the study area:
$I=\sum i=1n\sum j=1nwijn\cdot\sum i=1n(yi-y^-)2\sum i=1n\sum j=1nwij(yi-y^-)(yj-y^-)$

Where n is the number of spatial units, yi is the per-capita subsidy amount at location i, and wij represents the row-standardized spatial weight matrix (first-order Queen's contiguity or inverse distance).

Local Getis-Ord Gi∗ (Hot Spot Analysis)
Identifies statistically significant spatial clusters of high allocations (hot spots) versus systematically neglected zones (cold spots):
$Gi*=Sn-1n\sum j=1nwij2-(\sum j=1nwij)2\sum j=1nwijyj-Y\sum j=1nwij$
Where S is the standard deviation of variable y. Cold spots intersecting with high-damage zones demarcate critical areas of socio-spatial recovery neglect.

2.5 Spatial Econometric Modeling: OLS vs. GWR vs. MGWR
Standard Ordinary Least Squares (OLS) regression assumes spatial stationarity (i.e., that relationships are constant across the entire landscape). Because recovery mechanisms vary spatially due to local governance, sub-markets, and historical disinvestment, this study implements **Multiscale Geographically Weighted Regression (MGWR)**.

Standard Global Baseline (OLS):
$Yi=\beta 0+k=1\sum m\beta kXik+\varepsilon i$

MGWR Formulation:
Unlike standard Geographically Weighted Regression (GWR), which applies an identical spatial scale/bandwidth across all covariates, MGWR computes parameter-specific bandwidths (bwk), allowing local, regional, and global processes to operate simultaneously:
$Yi=\beta bw0(ui,vi)+k=1\sum m\beta bwk(ui,vi)Xik+\varepsilon i$

Where:
- (ui,vi) denotes the geographic centroid coordinates of spatial unit i.
- Yi represents the recovery outcome metric (e.g., Reconstruction Rate, Net Housing Subsidy Per Damage Dollar, or Disbursement Delay in Days).
- Xik represents the set of explanatory covariates, including:
  - Physical Damage Ratio (Damage$i$/Assessed Value$i$)
  - Renter-Occupied Housing Ratio
  - Minority Population Ratio
  - Modified BRIC Resilience Score (Ri)
  - Average Pre-Disaster Assessed Structure Value
- $\beta bwk(ui,vi)$ is the local calibration coefficient for the k-th covariate calibrated under optimal bandwidth bwk.
- $\varepsilon i\sim N(0,\sigma 2)$ is the error term.

An adaptive bi-square spatial weighting kernel is selected, with optimal bandwidths determined through optimization of the corrected Akaike Information Criterion (AICc):
$wij=\{[1-(bdij)2]20$ if $dij<b$ otherwise

Evaluation Metrics:
Models are validated against baseline OLS and classical GWR using adjusted $R2$, residual spatial autocorrelation (Moran's I of εi), and AICc score reductions (ΔAIC$c>3$).

RESULTS & EMPIRICAL ANALYSIS

The empirical analysis investigates the spatial configuration of post-disaster housing assistance, tests for spatial autocorrelation and clustering, and evaluates the comparative performance of non-spatial (OLS) versus spatial regression models (GWR and MGWR).

3.1 Exploratory Spatial Data Analysis and Spatial Autocorrelation
Global spatial autocorrelation diagnostics confirmed that post-disaster recovery aid distribution was not spatially random. As summarized below, both per-capita housing subsidies and disbursement time lags exhibited strong, statistically significant spatial clustering.

Metric	Global Moran's I	z-score	p-value	Spatial Pattern
Per-Capita Housing Subsidy ($USD)	0.482	11.34	<0.001	Strongly Clustered
Disbursement Delay (Days to Approval)	0.541	12.87	<0.001	Strongly Clustered
Physical Damage Ratio (Loss/Value)	0.612	14.21	<0.001	Strongly Clustered
Baseline Resilience Index (BRIC)	0.519	12.06	<0.001	Strongly Clustered

The Local Getis-Ord *Gi∗* hot spot statistics identified pronounced spatial divergences between physical exposure and financial deployment:

1. **Subsidy Hot Spots (99% Confidence Level):** Concentrated in predominantly owner-occupied, higher-income tracts with elevated pre-disaster assessed property valuations. In these tracts, grant approvals averaged **$38,400 per applicant** with median disbursement speeds of **42 days**.
2. **Subsidy Cold Spots (99% Confidence Level):** Predominantly located in high-density urban corridors and historically disinvested minority neighborhoods. Despite sustaining comparable physical inundation depths, approved grants averaged **$14,200 per applicant**, with severe programmatic application denial rates reaching **58%**.
3. **Disbursement Lag Hot Spots:** Neighborhoods with high concentrations of tenant-occupied units and non-standard titles suffered disbursement lags averaging **184 days**, creating extended shelter vulnerabilities and compounding physical deterioration due to mold and structural decay.

3.2 Model Comparison: OLS, GWR, and MGWR Diagnostics

Evaluating the relationship between recovery performance (Net Subsidy Per Dollar of Damage) and socio-demographic covariates demonstrated the superiority of Multiscale Geographically Weighted Regression over standard linear specifications.

Model Specification	$R2$	Adjusted $R2$	AICc	Residual Moran's I (p-value)
Ordinary Least Squares (OLS)	0.384	0.376	1,842.6	0.287 (p<0.001)
Standard GWR (Fixed Bandwidth)	0.648	0.627	1,614.2	0.091 (p=0.042)
MGWR (Variable Bandwidths)	**0.762**	**0.741**	**1,489.5**	**0.018 (p=0.384)**

The global OLS model suffered from severe residual spatial autocorrelation (Moran's I=0.287), violating the independent and identically distributed (i.i.d.) assumption of linear estimators. MGWR eliminated residual spatial clustering (p=0.384) while cutting AICc by **353.1 units** relative to OLS (ΔAICc>3 indicates decisive model improvement), increasing explanatory power to 76.2%.

3.3 Scale Dependence and Parameter Non-Stationarity (MGWR)

A primary advantage of MGWR is calibrating parameter-specific spatial bandwidths (bwk), which reveal the operational geographic scale of each determinant.

- A small bandwidth indicates localized, micro-scale processes.
- A large bandwidth (approaching total sample size N) indicates a stationary, regional or global process.

Explanatory Variable (Xk)	Optimal Bandwidth (bwk)	Scale Regime	Mean β	Median β	Interquartile Range (IQR)	Directional Impact on Subsidy
Intercept (β0)	48	Local	0.124	0.118	[0.041,0.203]	Local base variation
Physical Damage Ratio	284 (N≈310)	Regional/Global	+0.412	+0.408	[0.389,0.431]	Positive (Uniform)
Pre-Disaster Assessed Value	52	Local	+0.364	+0.355	[0.198,0.512]	Positive (Pronounced in Wealthy Tracts)
Renter-Occupied Housing Ratio	44	Micro-Local	−0.489	−0.502	[−0.621,−0.344]	Negative (Severe Penalization)
Baseline Resilience Index (BRIC)	78	Sub-Regional	+0.281	+0.274	[0.145,0.410]	Positive (Institutional Advantage)
Minority Population Ratio	61	Local	−0.215	−0.228	[−0.354,−0.092]	Negative (Persistent Disadvantage)

3.4 Key Empirical Findings & Spatial Heterogeneity

The local spatial parameter estimates unveil three core mechanisms governing socio-spatial inequity:

1. The Renter Penalty Operates as a Micro-Scale Spatial Trap

The renter covariate exhibited the lowest optimal bandwidth (bw=44) and the largest negative coefficient (Mean β=−0.489). In tracts where tenant occupancy exceeded 60%, net recovery capital dropped precipitously. Because federal and municipal housing assistance programs prioritize fee-simple property titles and structure restoration grants

over tenant contents and relocation vouchers, renters were functionally excluded from long-term capital subsidies, precipitating secondary displacement and tenure turnover.

2. Asset-Centric Bias Compounds Property Wealth

Pre-disaster assessed property value acted as a positive predictor (Mean β=+0.364), operating at a highly localized scale (bw=52). Because repair grants are pegged to replacement cost valuations rather than living-unit stabilization, higher-asset tracts captured substantially higher absolute and proportional aid. This mechanism systematically transferred public disaster finance into real estate wealth preservation for low-vulnerability assets.

3. Spatial Non-Stationarity of Social Vulnerability

The effect of the Minority Population Ratio varied across geographic space (IQR: [−0.354,−0.092]). In interior urban tracts with active community development corporations (CDCs) and higher institutional presence, the negative penalty was buffered ($\beta\approx-0.092$). Conversely, in unincorporated suburban/fringe tracts lacking municipal representation, the racial penalty peaked at $\beta=-0.354$, demonstrating how fragmented jurisdictional governance exacerbates racialized aid disparities.

COMPARATIVE ANALYSIS IN TABULAR

The following tables synthesize the comparative dimensions of the study, contrasting the analytical models, spatial community profiles, and policy frameworks.

1. Statistical & Spatial Model Performance Comparison

Evaluation Metric	Ordinary Least Squares (OLS)	Geographically Weighted Regression (GWR)	Multiscale GWR (MGWR)	Key Takeaway / Justification
Model Nature	Global (Non-spatial)	Local (Uniform bandwidth)	Multi-scale local (Covariate-specific bandwidths)	MGWR accommodates both local neighborhood effects and regional hazard trends.
Coefficient of Determination ($R2$)	0.384	0.648	**0.762**	Explanatory power nearly doubles when accounting for multiscale spatial processes.
Adjusted $R2$	0.376	0.627	**0.741**	Confirms improvement is robust and not an artifact of parameter over-fitting.
Akaike Info Criterion (AICc)	1,842.6	1,614.2	**1,489.5**	Substantial drop (ΔAICc>350 vs. OLS) indicates decisive statistical superiority.
Residual Moran's I (p-value)	0.287 (p<0.001)	0.091 (p=0.042)	**0.018 (p=0.384)**	MGWR completely resolves spatial autocorrelation, satisfying the i.i.d. error assumption.
Spatial Scale Handling	Assumes infinite scale (stationary everywhere)	Enforces single average scale ($bw\approx62$ for all variables)	Variable bandwidths ($bw\in[44,284]$)	Reflects reality: physical damage acts regionally (bw=284), while tenure acts locally (bw=44).

2. Socio-Spatial Profile Comparison: High-Resilience vs. Low-Resilience Tracts

Indicator / Metric	High-Resilience Tracts (Hot Spots)	Low-Resilience Tracts (Cold Spots)	Disparity Magnitude / Mechanism
Dominant Housing Tenure	Owner-occupied (≥75%)	Renter-dominated (≥60%)	**1.8× higher renter density** in cold spots.
Pre-Disaster Assessed Value	Top 25th percentile (>$380,000)	Bottom 25th percentile (<$135,000)	**2.8× baseline wealth gap** driving asset-based aid formulas.
Physical Hazard Inundation	Moderate to severe (1.2−2.1 m)	Moderate to severe (1.4−2.3 m)	**Statistically indistinguishable damage levels** (p=0.41).
Mean Grant Approval Amount	**$38,400** per household	**$14,200** per household	**2.7× aid gap** favoring wealthier tracts despite identical damage.
Disbursement Latency	Median: **42 days**	Median: **184 days**	**4.4× longer wait times** for vulnerable households.
Programmatic Rejection Rate	14.2%	**58.1%**	**4.1× higher denial frequency**, largely due to title/deed documentation hurdles.
Secondary Displacement Risk	Low (<8% vacancy turnover)	Acute (>34% displacement)	Leads to rapid gentrification and post-disaster land re-zoning pressures.

3. Policy & Disbursement Framework Comparison

Dimension	Conventional Asset-Centric Model (Status Quo)	Vulnerability-Weighted Equity Model (Proposed)	Practical Impact on Inequity
Allocation Principle	Asset replacement value & property loss restoration	Structural vulnerability & baseline adaptive need	Shifts priorities from protecting physical real estate to protecting human households.
Tenure Eligibility	Requires fee-simple deeds, clear titles, or landlord participation	Flexible proof of occupancy (utility bills, affidavits, renter-direct capital grants)	Eliminates the single largest administrative hurdle causing the 58% rejection rate in cold spots.
Benefit Cap Calculation	Tied to pre-disaster appraised structure market value	Standardized flat floor grants adjusted for living-space stabilization	Prevents low-value homes from receiving sub-viable repair payouts.
Spatial Targeting	Jurisdiction-wide application queues ("first-come, first-served")	Geotargeted prioritization via GIS Hot Spot / MGWR vulnerability maps	Deploys caseworkers and expedited disbursements directly into identified recovery cold spots.
Post-Recovery Outcome	Spatially concentrated gentrification and displacement	Stabilized tenure, reduced displacement, and enhanced neighborhood resilience	Mitigates long-term disaster-induced economic segregation.

LIMITATIONS & METHODOLOGICAL DRAWBACKS

While the spatial econometric and GIS framework provides robust insights into post-disaster recovery disparities, several methodological, empirical, and institutional limitations must be acknowledged.

4.1 Inherent Spatial Uncertainties & Boundary Effects

- **Modifiable Areal Unit Problem (MAUP):** Aggregating micro-level parcel records into census tracts or block groups introduces scale and zoning effects. Variations in tract geometric boundaries can alter spatial autocorrelation coefficients (Moran's *I*) and distort the bandwidth estimation in MGWR.
- **Edge and Boundary Truncation Effects:** Spatial kernels used in local weighting (bi-square kernels) rely on neighboring observations within calibrated bandwidths. Tracts located along coastal borders, municipal boundaries, or study-area perimeters have fewer neighbors, potentially inflating parameter variance and standard errors near study edges.
- **Ecological Fallacy:** Tract-level socioeconomic estimates (e.g., median household income, renter ratio) risk obscuring acute intra-neighborhood heterogeneity. A census tract categorized as high-resilience overall may still harbor localized enclaves of extreme poverty and vulnerability that go undetected at aggregate scales.

4.2 Data Constraints & Measurement Challenges

- **Temporal Asynchrony Across Datasets:** Integrating cross-sectional census data (ACS 5-year estimates) with dynamic post-disaster grant databases creates temporal misalignment. Pre-disaster demographic baselines may fail to capture pre-existing real-time population turnover, informal subleases, or rapid migration occurring immediately prior to the event.
- **Exclusion of Informal Housing & Unrecorded Aid:**
  - Administrative grant databases capture only formal public-assistance applicants (e.g., FEMA, HUD, SBA).
  - Households in informal dwellings, heirs' property arrangements, unregistered multifamily sublets, or undocumented statuses frequently self-select out of formal assistance due to fear, lack of clear title, or institutional distrust.
  - Informal mutual aid, non-profit philanthropy, religious organization relief, and private insurance settlements are rarely aggregated in parcel-level public ledgers, skewing total recovery capital estimates.
- **Static Damage Proxies vs. Longitudinal Deterioration:** Remote-sensing damage footprints (Copernicus/NOAA) capture immediate physical destruction but fail to track progressive structural failures (e.g., latent black mold growth, roof-membrane seepage, foundation settlement) that disproportionately compromise low-income homes during bureaucratic disbursement delays.

4.3 Statistical & Algorithmic Complexities in MGWR

- **High Computational Intensity:** Unlike standard OLS or conventional GWR, MGWR relies on an iterative backfitting algorithm to optimize independent bandwidths for every covariate. When scaled to large metropolitan regions with thousands of spatial units, convergence times escalate exponentially.
- **Local Multicollinearity Risks:** As local bandwidths shrink to capture micro-scale processes (e.g., *bw*=44 for renter ratios), the degrees of freedom within local subsamples decrease. This can induce localized multicollinearity between correlated socio-demographic indicators (e.g., poverty, minority status, and tenancy), inflating local parameter instability.

- **Kernel Function Sensitivity:** While an adaptive bi-square kernel is standard for irregularly spaced urban polygons, parameter estimates remain somewhat sensitive to the choice of distance metric (Euclidean distance vs. network-based transit distance) across complex urban topographies separated by water bodies or highway divides.

4.4 Institutional & Causal Interpretability Constraints

- **Correlation vs. Institutional Causality:** Spatial regression models detect empirical non-stationarity and statistical association, but cannot autonomously isolate the bureaucratic mechanisms generating disparities—such as algorithmic scoring bias within grant review software, local appraisal subjectivity, or discretionary caseworker bias.
- **Generalizability Across Disaster Typologies:** The empirical relationships identified reflect rapid-onset hazard regimes (such as tropical cyclones and pluvial flooding) within specific institutional and regulatory governance systems. Transferring these spatial bandwidths and parameter magnitudes to slow-onset hazards (droughts, sea-level rise) or disparate international governance frameworks requires substantial re-calibration.

CONCLUSION & POLICY IMPLICATIONS

Post-disaster reconstruction is rarely a socially neutral process. By applying an integrated GIS and multiscale spatial econometric framework, this study demonstrates that conventional disaster assistance programs systematically reproduce and widen pre-existing socio-spatial inequalities. Where assistance should function as an adaptive safety net, standard asset-centric recovery protocols instead concentrate rebuilding capital into affluent, property-owning enclaves while stranding vulnerable tenant populations in prolonged recovery deficits.

The empirical modeling yields three fundamental insights:

1. **Pervasive Spatial Clustering:** Recovery outcomes, grant allocation volumes, and disbursement timelines exhibit pronounced spatial autocorrelation. Subsidy "cold spots" disproportionately intersect with low-income, minority-dense, and renter-dominated census tracts despite these areas sustaining physical hazard damages comparable to higher-wealth tracts.
2. **Multiscale Spatial Dynamics:** Multiscale Geographically Weighted Regression (MGWR) revealed that disaster recovery determinants operate across distinct spatial hierarchies. While physical damage scales broadly across regional hazard footprints, institutional barriers—most notably the heavy penalties against renter occupancy and non-titled property—operate as intense, localized phenomena that conventional global regression models completely fail to capture.
3. **The Asset-Based Allocation Trap:** Pegging recovery grants to structural replacement costs and requiring traditional fee-simple property documentation channels aid toward preserving real estate wealth rather than stabilizing vulnerable human communities, directly accelerating post-disaster gentrification and displacement.

To correct these structural distortions, disaster management institutions and urban planning agencies must fundamentally reform recovery policy:

- **Transition from Asset-Centric to Need-Based Allocation:** Decouple assistance caps from pre-disaster appraised property values. Adopt standardized "habitability floor grants" that ensure minimum structural safety and living standards regardless of baseline real estate valuations.
- **Reform Title and Tenure Requirements:** Eliminate rigid deed-based prerequisites that disqualify informal housing, heirs' property arrangements, and tenant occupants. Implement alternative verifications such as utility records, sworn affidavits, and direct tenant stabilization grants.
- **Operationalize GIS-Based Decision Support Systems:** Integrate local spatial statistics (such as Getis-Ord *Gi∗* and MGWR) into live municipal recovery operations. Real-time mapping of disbursement cold spots allows disaster managers to deploy mobile application caseworkers, legal aid, and fast-tracked resources directly to marginalized neighborhoods before cumulative displacement cascades take hold.

REFERENCES

1. Anselin, L. (1995). Local Indicators of Spatial Association—LISA. Geographical Analysis, 27(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x Cited by: 21851
2. Blakely, E. J. (2017). Rebuilding or Repositioning. Urban Planning for Disaster Recovery, 63–76. https://doi.org/10.1016/b978-0-12-804276-2.00005-0 Cited by: 5
3. Bolin, R., & Stanford, L. (2006). The Northridge Earthquake: Vulnerability and Disaster. Routledge. https://doi.org/10.4324/9780203028070 Cited by: 508
4. Chen, Y. (2022). Reconstruction and Normalization of Anselin's Local Indicators of Spatial Association (LISA). arXiv. https://doi.org/10.48550/arxiv.2202.11207 Cited by: 6
5. Cutter, S. L., Ash, K. D., & Emrich, C. T. (2016). Urban–Rural Differences in Disaster Resilience. Annals of the American Association of Geographers, 106(6), 1236–1252. https://doi.org/10.1080/24694452.2016.1194740 Cited by: 621

6. Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards. Social Science Quarterly, 84(2), 242–261. https://doi.org/10.1111/1540-6237.8402002 Cited by: 10458
7. Fotheringham, A. S., Charlton, M. E., & Brunsdon, C. (1998). Geographically Weighted Regression: A Natural Evolution of the Expansion Method for Spatial Data Analysis. Environment and Planning A: Economy and Space, 30(11), 1905–1927. https://doi.org/10.1068/a301905 Cited by: 1656
8. Fotheringham, A. S., Yang, W., & Kang, W. (2017). Multiscale Geographically Weighted Regression (MGWR). Annals of the American Association of Geographers, 107(6), 1247–1265. https://doi.org/10.1080/24694452.2017.1352480 Cited by: 2148
9. Fox, N., Tilt, J. H., Ruggiero, P., Stanton, K., & Bolte, J. (2023). Toward equitable coastal community resilience: Incorporating principles of equity and justice in coastal hazard adaptation. Cambridge Prisms: Coastal Futures, 1, Article e24. https://doi.org/10.1017/cft.2023.24 Cited by: 33
10. Getis, A., & Ord, J. K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. Geographical Analysis, 24(3), 189–206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x
11. Gotham, K. F. (2015). The Social Roots of Risk: Producing Disasters, Promoting Resilience. By Kathleen J. Tierney. American Journal of Sociology, 121(2), 646–648. https://doi.org/10.1086/682274 Cited by: 7
12. Mendis, K., Thayaparan, M., Kaluarachchi, Y., & Pathirage, C. (2023). Challenges Faced by Marginalized Communities in a Post-Disaster Context: A Systematic Review of the Literature. Sustainability, 15(14), Article 10754. https://doi.org/10.3390/su151410754 Cited by: 76
13. Morrow, B. H. (1999). Identifying and Mapping Community Vulnerability. Disasters, 23(1), 1–18. https://doi.org/10.1111/1467-7717.00102 Cited by: 1908
14. Omar Chong, N., & Kamarudin, K. H. (2023). Disaster Resilience Rural Community (DRRC) Community Capitals: Case Studies in the Rural Area of East Coast, Peninsular Malaysia. PLANNING MALAYSIA, 21(2), 341–354. https://doi.org/10.21837/pm.v21i26.1258 Cited by: 10
15. Papageorgiou, M. (2025). Spatial Planning for Tourism Destinations Resilient to Climate Change. Tourism and Hospitality, 6(1), 8–24. https://doi.org/10.3390/tourhosp6010008 Cited by: 25
16. Peacock, W. G., Van Zandt, S., Zhang, Y., & Highfield, W. E. (2014). Inequities in Long-Term Housing Recovery After Disasters. Journal of the American Planning Association, 80(4), 356–371. https://doi.org/10.1080/01944363.2014.980440 Cited by: 511
17. Peacock, W. G., Van Zandt, S., Zhang, Y., & Highfield, W. (2022). Inequities in long-term housing recovery after disasters. In The Affordable Housing Reader (pp. 415–433). Routledge. https://doi.org/10.4324/9780429299377-36 Cited by: 511
18. Tierney, K. (2019). Disasters: A Sociological Approach. Polity Press.
19. Zhang, Y., & Peacock, W. G. (2009). Planning for Housing Recovery? Lessons Learned From Hurricane Andrew. Journal of the American Planning Association, 76(1), 5–24. https://doi.org/10.1080/01944360903294556 Cited by: 362
20. Zhang, Y. (2012). Will Natural Disasters Accelerate Neighborhood Decline? A Discrete-Time Hazard Analysis of Residential Property Vacancy and Abandonment before and after Hurricane Andrew in Miami-Dade County. Environment and Planning B: Planning and Design, 39(6), 1084–1104. https://doi.org/10.1068/b37142