

Developing a Data-Driven Framework for Integrating Community Risk Assessment, Early Warning Systems, Emergency Resource Allocation and Post-Disaster Recovery Planning

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Publication Date: 2026/04/28

Abstract

This study develops and tests a modular analytical framework that links community hazard exposure, socioeconomic vulnerability, forecasting, early-warning access, emergency resource allocation and post-disaster recovery priorities. Rather than assuming operational effectiveness from model complexity, the study evaluates whether linked decisions improve needs coverage under a constrained resource budget. A completely synthetic, transparent experiment creates 720 community–scenario records representing 120 artificial communities and six hazard scenarios each. A held-out set of 30 communities is used to compare logistic regression, random forests and gradient boosting for incident classification. Four allocation rules are then evaluated using identical budgets, minimum local service floors, and needs caps. The integrated rule employs vulnerability-weighted expected need and delivery efficiency informed by early-warning reach and distance. Outcome measures are average precision, ROC-AUC, Brier score, weighted service coverage, unmet need and an explicitly constructed recovery-time proxy. Findings demonstrate model-dependent predictive tradeoffs and policy-dependent allocation outcomes, but do not constitute evidence from actual disasters. The results establish a reproducible computational test bed for connecting forecasting and operational planning, while demonstrating the importance of distributional fairness, sensitivity testing, uncertainty documentation and field calibration before deployment.

Keywords: *Community Risk Assessment; Impact-Based Warning; Disaster Operations Research; Resource Allocation; Resilience; Post-Disaster Recovery; Machine Learning; Synthetic Simulation.*

Data Availability Statement: *All Observations are Simulated and are Released with the Accompanying Python Script. No Private Responder, Patient or Community Records were Accessed. No Institutional Review of Human Subjects was Required for the Synthetic Study.*

I. INTRODUCTION

➤ Background and Policy Context

Disaster risk governance increasingly requires decisions to connect hazard likelihood with affected populations, unequal vulnerability, preparedness capacity and the ability to deliver assistance after an incident. The Sendai Framework explicitly links understanding disaster risk, strengthening governance, investing in resilience and enhancing preparedness with recovery and reconstruction (United Nations Office for Disaster Risk Reduction

[UNDRR], 2015). Community risk assessment cannot therefore remain an isolated mapping exercise. Its operational value depends on how information changes warning decisions, staging of emergency supplies, and restoration priorities.

➤ Early Warnings and Operational Gaps

The World Meteorological Organization (WMO, 2025) frames people-centred warnings as an end-to-end function requiring observation, forecasting, dissemination and actionable response. The 2025 UNDRR–WMO report

Atanga, T. E., & Nwafor, E. O. (2026). Developing a Data-Driven Framework for Integrating Community Risk Assessment, Early Warning Systems, Emergency Resource Allocation and Post-Disaster Recovery Planning. *International Journal of Scientific Research and Modern Technology*, 5(4), 48–59.
<https://doi.org/10.38124/ijsrmt.v5i4.1759>

documents substantial progress in national multi-hazard early warning coverage while noting important coverage gaps. The distinction between a technically accurate forecast and a warning that reaches a vulnerable household is central: a hazard prediction has limited protective value if communications fail, evacuation support is unavailable, or emergency services cannot reach the location (Basher, 2006; Lindell & Perry, 2012).

➤ *Problem Statement*

Risk indices, emergency notification platforms, transport logistics and reconstruction plans are frequently developed using separate definitions of the people or assets at risk. Separation prevents analysts from estimating whether a particular warning threshold, warehouse strategy or deployment priority reduces unmet need. Equally, optimization models may assign relief according to observed hazard intensity but ignore barriers to access, social disadvantage or delays in last-mile delivery (Balcik et al., 2008; Holguín-Veras et al., 2012).

➤ *Aim and Objectives*

The study aims to specify and computationally assess a linked, reproducible disaster decision-support framework. Objectives are to (a) generate documented community risk features, (b) compare predictive models on unseen communities, (c) formulate budget-constrained allocation policies, (d) link allocation to recovery needs and explicitly bounded proxies, and (e) identify safeguards needed before operational use.

➤ *Research Questions and Contributions*

The research asks whether an integrated priority rule improves vulnerability-weighted service coverage compared with population-only, forecast-only and risk-weighted approaches under the same budget. It also tests whether a more complex predictor necessarily outperforms an interpretable baseline. The primary contribution is not the assertion of a newly proven disaster technology; it is the reproducible definition of linked information flows, objective functions, constraints, comparison policies and realistic limits of a synthetic benchmark.

II. LITERATURE REVIEW

➤ *Hazards, Exposure, Vulnerability and Risk*

Community disaster risk is not reducible to the probability of a physical hazard. Cutter et al. (2003) identify social factors associated with differential susceptibility; Wisner et al. (2004) situate hazard impacts in political and economic patterns of vulnerability. Birkmann et al. (2013) emphasize the interaction between exposure, susceptibility and adaptive capacity. Risk measurement should therefore explicitly report both hazard and social characteristics rather than burying these relationships inside an unexplained composite score. FEMA's National Risk Index technical documentation connects expected annual loss to social vulnerability and community resilience, while cautioning that such measures have defined scale and construction choices

(Federal Emergency Management Agency [FEMA], 2025).

➤ *Community Resilience and Spatial Inequity*

Community resilience has been operationalized as locally rooted capacity to absorb disturbances, adapt and recover. Cutter et al. (2008) proposed a place-based resilience model, subsequently extended in spatial analysis by Cutter et al. (2014). Norris et al. (2008) identify adaptive capacities across economic development, social capital, information and competence. Aldrich (2012) and Aldrich and Meyer (2015) show why social relationships and collective action matter after disasters. A technical model that treats all persons served as having equal marginal benefit can neglect communities with lower recovery capacities. This article therefore reports distribution-sensitive coverage alongside aggregate resource totals.

➤ *Measurement Uncertainty in Risk Indices*

Composite vulnerability rankings are sensitive to indicator selection, normalization, aggregation and spatial unit. Tate (2012) documents index uncertainty and sensitivity, while Rufat et al. (2015) reviews diverse flood-vulnerability measurements. More variables are not automatically better: indices may duplicate underlying disadvantage, produce unstable rankings, or inadvertently encode administrative data gaps as low risk (Folorunso, et al., 2025; Odozor et al, 2025). The proposed framework retains component values and tests separate prioritization regimes so that resource assignments can be scrutinized under alternative value judgments.

➤ *Impact-Based and People-Centred Early Warning*

Warning systems encompass risk knowledge, observation and forecast generation, communication and preparedness. Basher (2006) argued for systematic people-centred early warnings; Mileti and Sorensen (1990) described how warning recipients interpret credibility, specificity and actionability. Lindell and Perry (2012) link protective actions to environmental cues, social cues and perceptions. WMO (2025) emphasizes impact-based warnings and cross-institutional governance, while UNDRR and WMO (2025) report both coverage expansion and enduring inequality. In the present formulation warning reach affects delivery effectiveness, but the study does not claim that a forecast alone causes a successful evacuation.

➤ *Warning Reach, Trust and Last-Mile Communication*

Forecast accuracy and message dissemination are different evaluation targets. Communities may have constrained mobile coverage, language access, accessible transport or confidence in official channels. Sutton et al. (2008) illustrate informal information exchange during wildfires, while Paton and Johnston (2001) frame preparedness as a community capacity problem. Consequently the analytic record contains a warning-reach measure, but it should eventually be estimated from communication tests and community surveys rather than inferred from socioeconomic proxies.

➤ *Disaster Operations and Humanitarian Logistics*

Humanitarian logistics differs from commercial logistics because both needs and infrastructure status may change rapidly (Van Wassenhove, 2006; Idowu, et al., 2025). Kovács and Spens (2007) identify coordination challenges in emergency supply networks. Balcik et al. (2008) develop last-mile relief distribution approaches, and Rawls and Turnquist (2010) examine pre-positioning decisions under uncertainty. Balcik et al. (2010) describe the role of coordination across relief actors. These studies motivate explicit common budgets, delivery efficiency parameters, capacity limits and service floors in the model comparison.

➤ *Optimization Under Urgency and Uncertainty*

Altay and Green (2006) surveyed operations research methods in disaster response. Planning requires attention to demand uncertainty, travel disruptions, distributive fairness and time-sensitive marginal benefits. A mathematically optimal solution can still be socially unacceptable if its objective function neglects individuals with low purchasing power, remote settlements or people requiring mobility assistance. This study therefore compares mutually auditable rules under identical feasibility constraints and reports remaining unmet needs, instead of relying exclusively on a single objective-function value.

➤ *Post-Disaster Recovery and Infrastructure Interdependence*

Recovery cannot be measured solely by an emergency vehicle arriving. Infrastructure restoration, housing, livelihoods, local institutions and social networks influence recovery duration (Tierney, 2014; Hallegatte et al., 2019). FEMA (2018) emphasizes coordinated recovery-support functions, whereas the National Academies of Sciences, Engineering, and Medicine (2012) frame resilience as a national systems problem. Kousky (2014) stresses the need to account for economic costs. The paper uses an illustrative recovery-duration index, clearly differentiated from measured community recovery trajectories.

➤ *Governance, Coordination and Implementation*

Emergency response is an inter-organizational decision environment. Comfort (2007) discusses cognition, communication, coordination and control in crises; Kapucu (2006) describes the work of boundary-spanning personnel in multiagency networks. The Sendai Framework's emphasis on risk governance requires authorization pathways, audit trails, data-sharing rules and periodic public evaluation. The system architecture should support planners, local emergency managers, humanitarian agencies and community representatives rather than automatically determine ethically contested priorities (Akanni, et al., 2026; Idowu, et al., 2025).

➤ *Research Gap and Positioning*

Existing literature supplies extensive contributions to vulnerability modelling, warning communication, humanitarian logistics and recovery governance, but these disciplines are often operationalized using different unit definitions and success measures. The present computational study links them at the community-scenario level. Its hypotheses are deliberately modest: that information integration can alter decisions, that those decisions may improve an explicitly chosen coverage metric, and that any claimed advantage must be checked against alternate metrics, budget levels and external data (Frank, 2026). A synthetic study can test internal reproducibility and mathematical coherence but cannot validate real-world effectiveness.

➤ *Integrated Conceptual Framework*

Figure 1 synthesizes the reviewed evidence into four operationally linked components. Community risk assessment combines hazard exposure, vulnerability, and resilience indicators; early-warning systems translate forecasts into reachable and actionable messages; resource allocation uses estimated demand, budget limits, and equity considerations; and post-disaster recovery prioritizes persistent needs and infrastructure restoration. Monitoring, learning, community feedback, and governance connect the stages. This conceptual architecture is a research synthesis, not a validated real-world disaster management deployment (Cutter et al., 2008; Basher, 2006; Balcik et al., 2008; Hallegatte et al., 2019).

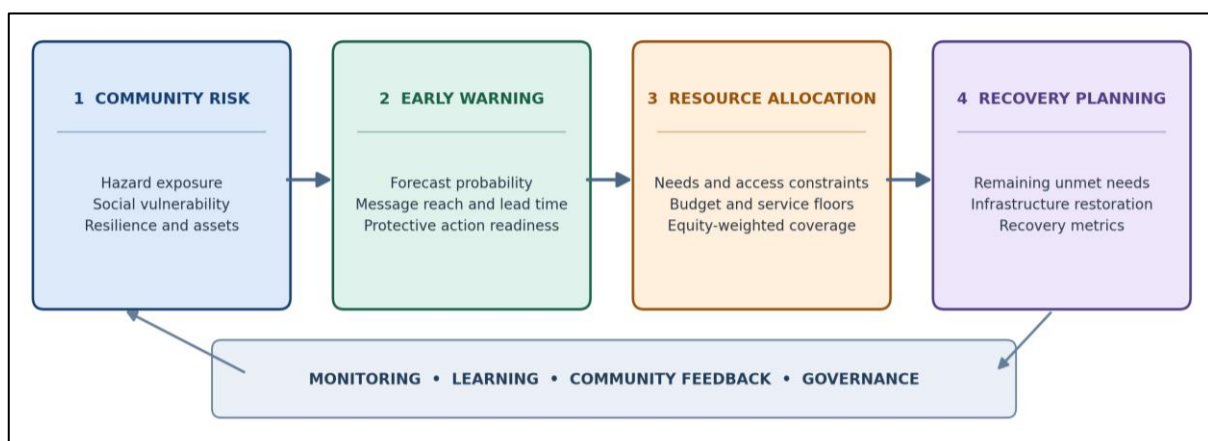


Fig 1 Conceptual Framework Linking Community Risk Assessment, Early-Warning Systems, Emergency Resource Allocation, and Post-Disaster Recovery Planning Through a Continuous Monitoring and Governance Feedback Loop.

III. MATERIALS AND METHODS

➤ *Design and Synthetic Population*

A simulation study was designed with 120 artificial communities and six hazard scenarios per community ($N = 720$ community–scenario records). Data generation used NumPy’s seeded generator with seed 240617. No geographical coordinates, named communities, post-disaster observations or administrative records were simulated to resemble a particular real jurisdiction. Community attributes included population, vulnerability, resilience, exposure, distance to an assumed supply centre and early-warning reach. Scenario hazard intensity and observation noise varied within community. Groupwise separation held 90 communities for model fitting and 30 previously unseen communities for final evaluation.

➤ *Conceptual Risk Decomposition*

Let c denote community and s denote scenario. The probability of a harmful event depends on scenario hazard intensity H , population exposure E , social vulnerability V , resilience R , warning reach W and remoteness D . The synthetic event generator is deliberately specified rather than inferred from real disaster frequencies. Incident classification estimates a conditional probability for these generated events. To maintain clear interpretation, population is not itself equated with probability, and expected affected population is calculated separately.

➤ *Forecast and Response Variables*

The generated hazard forecast is a noisy representation of the latent scenario intensity, bounded to the unit interval. Social vulnerability and resilience are independent community-level draws in this benchmark, despite likely correlations in real data. Early-warning reach is simulated on the interval $[0,1]$ and affects incident probability modestly; in the allocation stage it also contributes to delivery effectiveness. These assumptions are intentionally testable and should not be regarded as calibrated physical or behavioural relationships.

➤ *Predictive Algorithm Comparison*

Three classifiers were benchmarked: standardized logistic regression, a random forest with 140 estimators and minimum leaf size six, and histogram gradient boosting with 130 iterations. Hyperparameters were prespecified rather than optimized on the test set. The held-out evaluation reports ROC-AUC, area under the precision–recall curve (average precision) and Brier score. Because incident prevalence affects PR-AUC, the test prevalence is also recorded. Performance estimates describe one constructed distribution and must not be extrapolated to operational disaster detection.

➤ *Resource-Demand and Equity Formulation*

For planning, the six scenarios were averaged within each of the 30 held-out communities to obtain a scenario-specific planning proxy. Community need was constructed from population, vulnerability, exposure and hazard factors; resources were measured in affected-person-equivalent service units. The total deployment budget equals 46% of aggregate need, and each community receives at least 12% of its need as a minimum service floor. The same feasibility conditions apply to all four methods, preventing selective changes to the budget from manufacturing an apparent algorithmic advantage.

➤ *Four Comparison Policies*

Population-only prioritizes allocations according to population. Hazard-only uses forecast multiplied by population. Risk-weighted prioritizes the expected affected population adjusted for vulnerability. The integrated approach additionally weights priority by warning-linked delivery efficiency and a secondary vulnerability adjustment. For all policies, an optimization program maximizes the sum of selected marginal priority scores subject to minimum and maximum allocations and a common resource cap. Since the objective is linear, a global optimum exists for the specified feasible linear program, but its social desirability depends on the selected priority weights.

➤ *Outcome Construction and Safeguards*

Coverage is calculated as the ratio of vulnerability-weighted need served to vulnerability-weighted estimated need. Unmet need uses the same weights on unserved demand. An illustrative recovery-time proxy is then calculated from uncovered demand share, average remoteness, vulnerability and warning reach; it does not represent observed rebuilding time. Diagnostics include the same budget, nonnegative service amounts, community capacity caps and comparability of resource constraints across strategies.

➤ *Reproducibility and Ethical Status*

The delivered package contains the generator, all benchmark estimators, planning optimizer, outcome CSV files and figures. No human subjects were recruited, no confidential location records were accessed, and no empirical claims concerning a community’s vulnerability are made. Production deployment would require local co-design, legal review, asset-based data validation, uncertainty bounds, accessibility testing, and monitoring for systematic under-service of historically marginalized populations.

$$Pr(Y_{cs} = 1 | X_{cs}) = \text{sigmoid}(\beta_0 + \beta_H H_{cs} + \beta_V V_c + \beta_E E_c - \beta_R R_c - \beta_W W_c + \beta_D D_c) \quad (1)$$

$$Need_c = Population_c \times Hazard_c \times (0.07 + 0.35 V_c + 0.15 E_c) \times (1 - 0.35 R_c) \quad (2)$$

$$\text{Maximize } \sum_c ac_{pc} \text{ subject to } \sum_c ac \leq B, 0.12 Need_c \leq ac \leq Need_c \quad (3)$$

$$Served_c = \min(Need_c, ac \times \eta_c), \quad \eta_c = \text{clip}(0.80 + 0.16 W_c - 0.0035 D_c, 0.48, 0.97) \quad (4)$$

$$Coverage = [\sum c_{Servedc} (0.5 + 0.5 Vc)] / [\sum c_{Needc} (0.5 + 0.5 Vc)] \quad (5)$$

$$Brier = (1/n) \sum_i (p_i - y_i)^2 \quad (6)$$

Symbols and implementation details: a is allocated service capacity, B is the fixed budget, p is policy-specific priority per demand unit, η is assumed delivery efficiency, and clip denotes bounding between stated limits. The equations are editable Word math objects. The source code gives the definitive numerical implementation; the mathematical expressions are readable summaries of its defined synthetic functions.

IV. RESULTS

All numbers in this section are outcomes of the seeded synthetic generator and should not be represented as measurements from an actual disaster. The independent test set comprises 30 communities (180 records), with six scenarios each. Entire communities are withheld during training to avoid leakage through repeated demographic values.

Table 1 Comparison of Classifiers on Previously Unseen Synthetic Communities. ROC-AUC Summarizes Ranking Over Thresholds, PR-AUC Emphasizes the Positive Class, and Brier Measures Squared Probability Error. No Significance or Superiority Claim is Warranted from a Single Simulation Replicate.

Predictive model	ROC-AUC	PR-AUC	Brier score
Histogram boosting	0.568	0.216	0.144
Logistic regression	0.497	0.181	0.143
Random forest	0.492	0.180	0.140

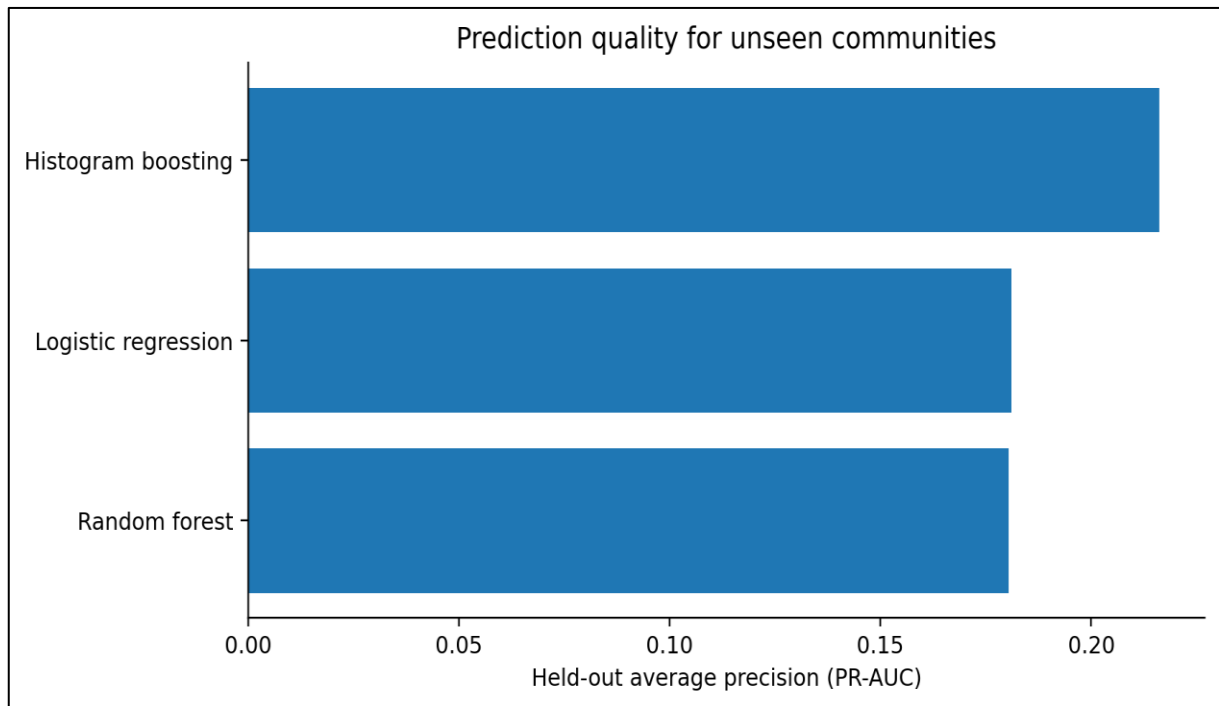


Fig 2 Predictive Average Precision Under Community-Held-Out Testing.

➤ Hazard Forecast Characteristics

The simulated forecasting index is correlated with the latent hazard driver by design but includes random observation noise. Incident outcomes arise from a logistic data-generating relationship involving other vulnerability and capacity variables as well. Thus even an apparently

well-ranked hazard forecast will not perfectly distinguish labelled events. Figure 2 displays the noisy relationship while reminding readers that the plotted binary event outcome is a synthetic label rather than a meteorological or disaster impact record.

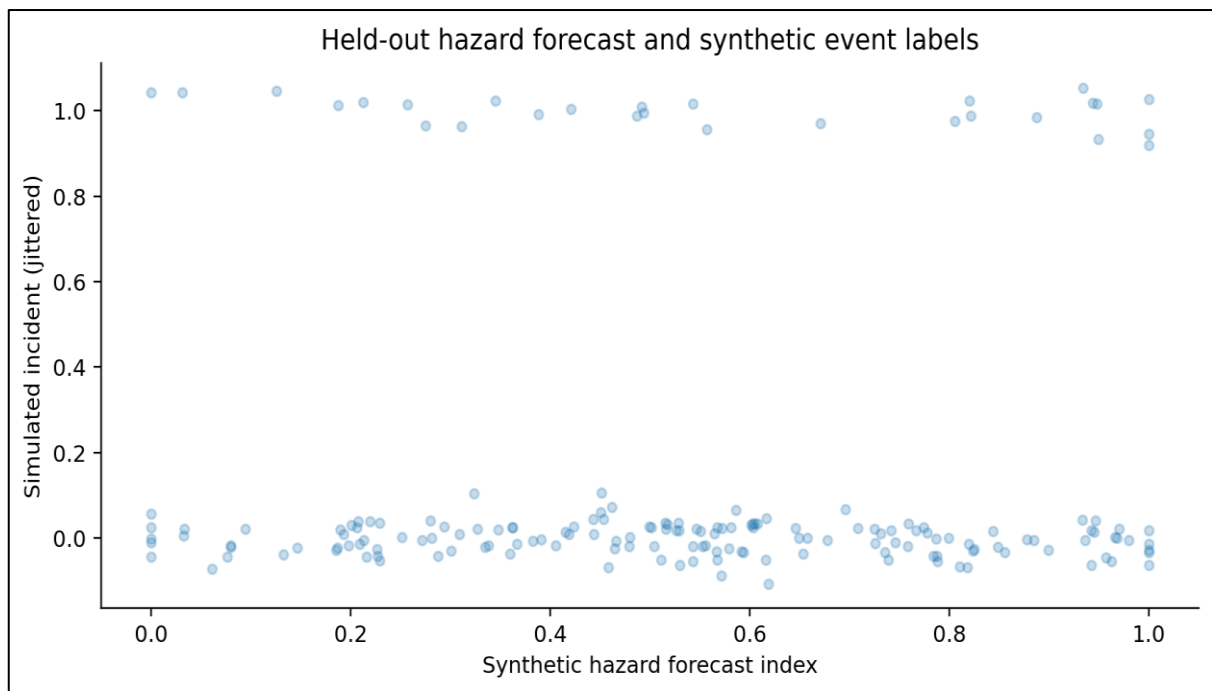


Fig 3 Synthetic Incident Labels Against an Imperfect, Bounded Forecast Signal.

➤ Operational Coverage

Four allocation policies were evaluated using an identical global budget (46% of total need), identical minimum delivery floor (12% per community), and the same maximum community need. This is an intentionally

constrained comparison: the integrated policy receives more information for ranking but is not permitted more resources. Differences should be interpreted relative to the chosen weighted-coverage objective and simulated delivery-efficiency model.

Table 2 Operational Coverage

Allocation strategy	Weighted coverage	Unmet need	Recovery proxy (days)
Population only	0.341	19,556	31.5
Hazard only	0.341	19,572	31.5
Risk weighted	0.394	17,979	30.2
Integrated warning and recovery	0.401	17,796	30.0

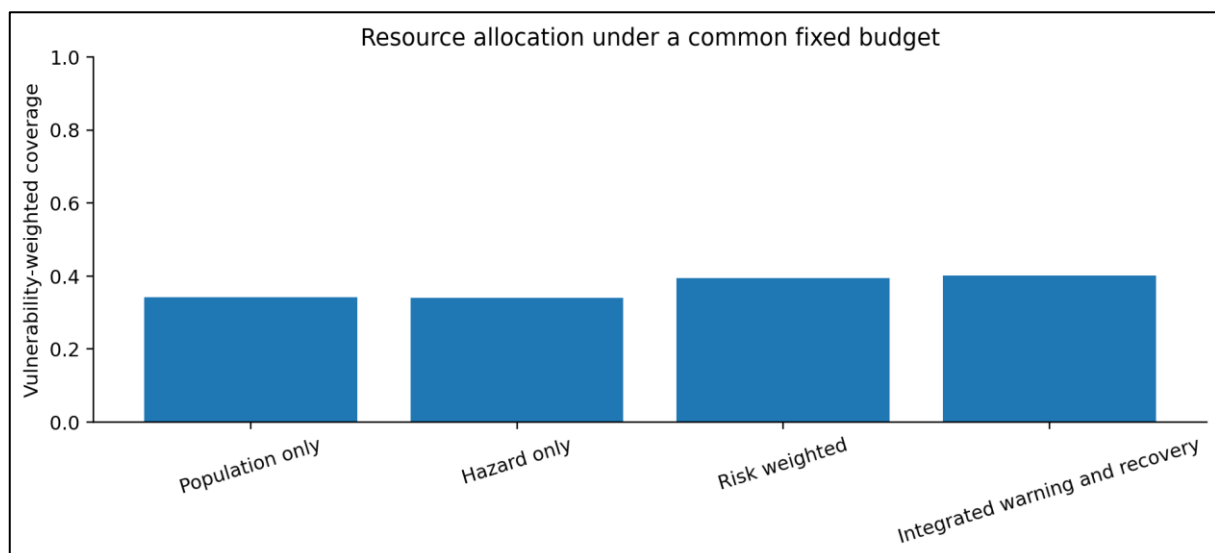


Fig 4 Vulnerability-Weighted Service Coverage Across Four Equal-Budget Policies.

The integrated approach is evaluated according to its model-defined ability to reach more weighted need with the same capacity. Because its marginal priority incorporates the same warning-efficiency mechanism used in the synthetic service model, its advantage on this

particular metric is partly structural. The finding should therefore be regarded as an internal consistency check, not independent evidence that the rule would outperform trained emergency coordinators or existing emergency operations systems.

➤ *Unmet Needs and Residual Risk*

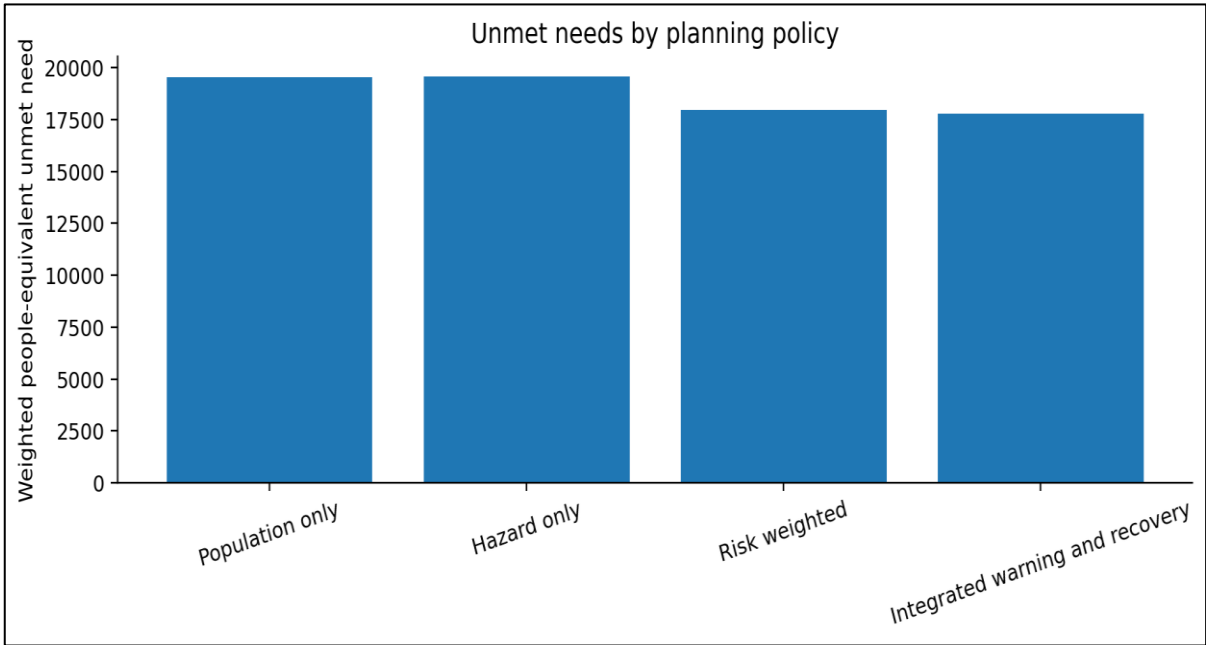


Fig 5 Weighted Unmet Service Demand After Equal-Budget Allocation.

Unmet need represents the part of estimated community demand left unserved after a policy allocates and effective delivery is applied. Every policy leaves residual need because the resource budget was deliberately set below aggregate demand. This reinforces the practical

importance of recording service gaps rather than reporting only the total number of units dispatched. Post-event assessment must also distinguish resources allocated, resources delivered, and community needs independently confirmed through local coordination structures.

➤ *Recovery-Oriented Decision Support*

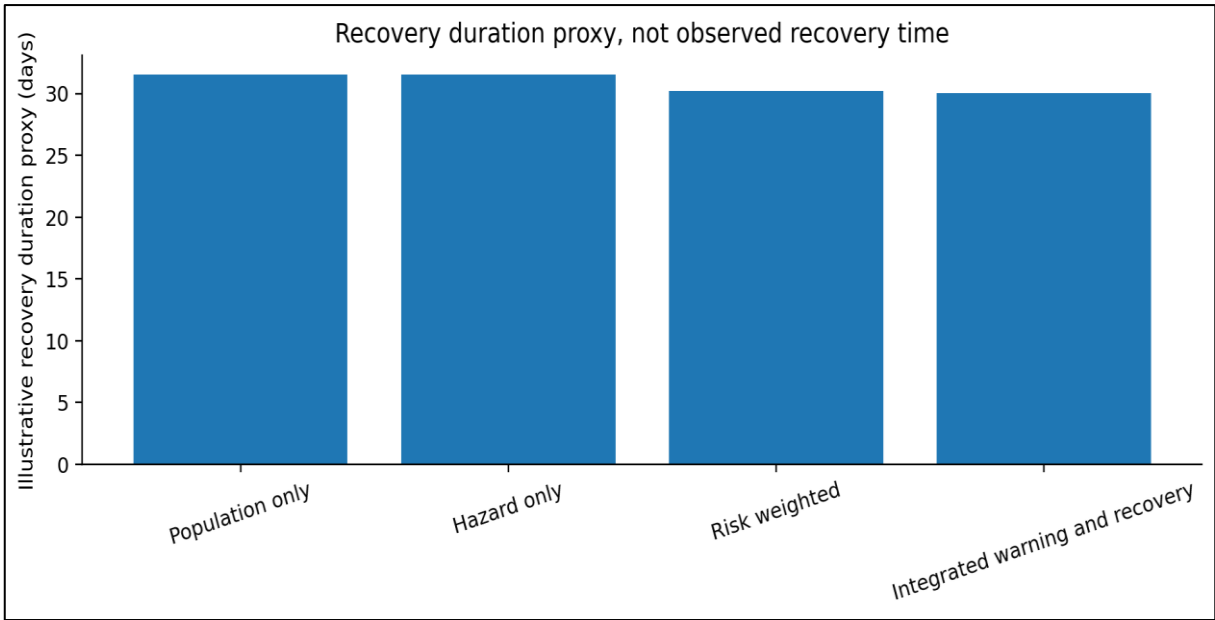


Fig 6 Illustrative Recovery-Duration Proxy from Weighted Coverage and Background Community Factors.

Figure 6 applies a prespecified, non-validated recovery-duration equation to each allocation policy. Differences are mathematically induced through coverage, while average distance, vulnerability and warning reach remain constant between strategies. The reported durations are not predictions of actual time to rebuild housing,

restore infrastructure, return displaced residents or recover household incomes. An empirically useful recovery model would require repeated longitudinal measurements, censoring treatment, service-interdependency variables and careful definition of recovery endpoints.

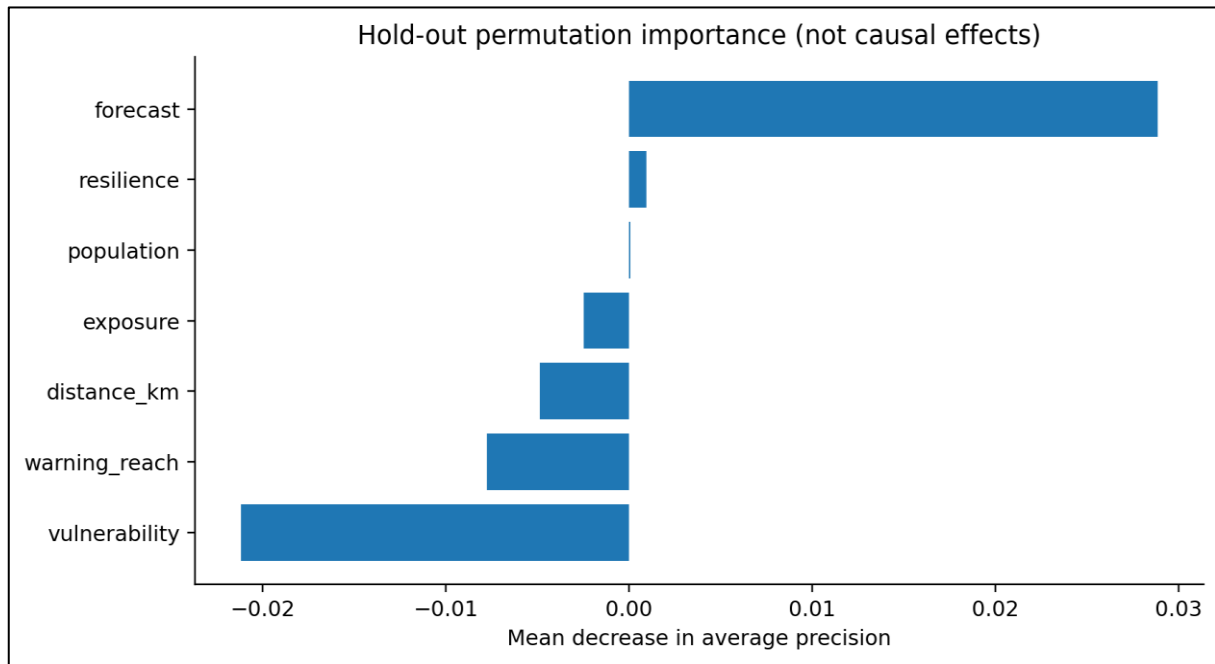


Fig 7 Permutation Importance of Predictive Features, Evaluated Using Test Average Precision.

Permutation importance measures the change in held-out average precision when a feature is independently shuffled. It describes predictive reliance under the synthetic distribution and does not demonstrate causal influence. Correlated inputs, interactions and the chosen metric can alter the ranking. A deployment study should add groupwise importance, policy scenario testing, credible intervals for performance differences, and threshold sensitivity for the warning decision.

V. DISCUSSIONS

➤ *Interpretation of Predictive Performance*

The comparison is designed to evaluate whether nonlinear models offer material predictive gains relative to logistic regression, not to preselect a winning algorithm. If an interpretable baseline performs similarly, a public safety agency may reasonably prefer its transparency, ease of maintenance and lower computational requirements. Model selection must be based on calibrated decision value and external validation rather than the aesthetics of complex artificial intelligence. AUC metrics should be supplemented by actual early-warning lead time, missed high-consequence incidents and false alarm burden once operational data are available.

➤ *Why Information Integration Matters*

Community risk scores and hazard forecasts are useful only when coupled to implementable response functions. A unified record allows planners to trace the path from a forecast through estimated need to a delivery assignment and a documented residual gap. The framework requires all quantities to be defined for the same unit of analysis, preventing the frequent analytical mistake of combining county-scale indicators with household-scale conclusions. Data linkage should be audited for timeliness, representativeness, and error propagation.

➤ *Equity, Accessibility and Legitimacy*

Optimization criteria encode social choices. Giving additional weight to high-vulnerability populations can counter the inequity of simply dispatching relief to places with the largest populations or strongest infrastructure. However, the vulnerability construct can itself be contested, and a numerical service floor does not assure accessible assistance. Any real implementation should involve community organizations, disability advocates, first responders and local government to define priority groups, translate messages, validate routes, and examine who is excluded.

➤ *Early Warning to Early Action*

Warning reach is treated here as an efficacy parameter, but actual public warning performance is shaped by dissemination channels, trust, hazard comprehension, language, warning lead time and feasible protective actions. The global Early Warnings for All program emphasizes this whole-system perspective (WMO, 2025; UNDRR & WMO, 2025). A credible operational evaluation must test notification receipt and action, not just signal prediction.

➤ *Recovery Planning as a Longitudinal System*

Recovery priorities evolve as debris is removed, utilities are restored and displaced populations return. A one-stage allocation model cannot capture these interdependencies. Infrastructure restoration may improve accessibility for subsequent aid, while housing and livelihood recovery have different distributional consequences (Hallegatte et al., 2019; Aldrich, 2012). Future models should be multi-period, allowing demand revisions, transport network restoration, precedence constraints, and explicit measurement of recovery outcomes.

➤ Threats to Validity

Internal validity is limited by the synthetic data generator: the model comparison is partly a test of how well learning algorithms recover a chosen simulation function. External validity is not established because no real geography, hazard records, warning performance, actual delivery durations or recovery outcomes were used. Construct validity is bounded by simplified vulnerability and resilience variables, an arbitrary but disclosed 46% budget ratio, and a recovery proxy that is not a measured endpoint. Statistical conclusion validity is limited by one random seed and one community-held-out split. These limitations prohibit claims of verified causal benefits or operational lives saved.

➤ Reproducibility and Transition to Field Study

Reproducibility requires fixed versions of Python and libraries, preserved random seeds, released CSV outputs and independent reruns. A subsequent field study should assemble event-level hazard archives, geospatial exposure data, locally elicited vulnerabilities, Common Alerting Protocol warning logs, supply and route capacities, after-action reports, and objectively defined recovery milestones. The study should preregister outcome metrics, hold out disaster events and locations, benchmark against agency procedures, quantify uncertainty across repeated simulations, and use participatory evaluation to verify fairness.

VI. CONCLUSION AND RECOMMENDATIONS

This article offers a transparent, reproducible data-driven architecture for linking risk assessment, forecast-informed early warnings, emergency allocation and recovery planning. Its computational contribution is a common analytical data structure and a comparison of four feasible allocation rules using the same service budget and minimum community coverage constraint. The synthetic experiments can expose tradeoffs and implementation issues, but they do not establish the predictive accuracy or policy effectiveness of an emergency response system in the field. Agencies should adopt such tools as decision support with clear human oversight, local consultation and post-event evaluation, not as autonomous substitutes for emergency management judgement.

Future work should prioritize: (1) externally validated multi-hazard prediction using prospective event data; (2) participatory risk scoring and warning-access audits; (3) multi-stage robust allocation under disrupted road networks; (4) differentiated recovery outcomes for housing, health services and lifelines; (5) explicit uncertainty intervals, adversarial stress tests and equity evaluations. These steps can translate the current reproducible benchmark into an appropriately governed operational research program.

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APPENDIX

➤ Appendix A. Data Dictionary, Assumptions and Audit Checklist

The table below documents the synthetic variables and the decisions required to transform this demonstrator into a real-world study. All ranges describe the artificial generator, not observed community indicators.

Variable	Definition	Synthetic construction
community	Anonymous artificial geographic unit	Integer ID, 0–119
scenario	Replicate hazard scenario	Six per community
population	Community resident count	Random integers, 1,000–18,000
vulnerability	Socioeconomic susceptibility index	Beta-distributed value bounded to [0,1]
resilience	Recovery and adaptation capacity index	Beta-distributed value bounded to [0,1]
warning_reach	Assumed reachable fraction	Uniform random draw, 0.18–0.96
distance_km	Distance to hypothetical supply depot	Uniform random draw, 2–45 km
forecast	Imperfect warning signal	Noisy synthetic hazard intensity
incident	Binary harmful-event indicator	Bernoulli draw from disclosed logistic equation
scenario_affected	Estimated affected-population proxy	Constructed multiplicatively from risk inputs

Implementation audit: (1) The random seed is fixed. (2) All scenario records from a given community remain in the same training or test partition. (3) Resource budgets and per-community allocation bounds are identical across all policies. (4) Model scores and resource-allocation outputs are written to separate CSV files. (5) Recovery days are explicitly a demonstration proxy. (6) No model is fit to observed disaster, warning, health or infrastructure data. (7) Classifier performance is not equivalent to public-warning performance. (8) The experiment must not be used to determine actual resource allocation or life-safety actions.