

Optimizing Resource Allocation for Urban Public Safety Risk Governance: A Case Study from China

面向城市公共风险治理的资源配置优化: 来自中国的案例研究

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Abstract: Rapid urbanization, compound hazards, and interagency dependencies increase the importance of timely and reliable emergency resource allocation. This study develops a risk-responsive robust multi-objective allocation framework (RRMA) connecting risk assessment, demand generation, network accessibility, and deployment decisions. A four-dimensional index represents hazard, exposure, vulnerability, and recovery capacity. Facility activation, resource pre-positioning, and scenario-dependent distribution are subject to budget, capacity, and minimum-service constraints, while robustness is expressed through the worst weighted loss over a finite scenario set. The scenario analysis covers six urban functional area types and compares baseline-risk, flooding, and compound-risk synthetic samples. Aggregate results show that, relative to the NSGA-II benchmark, RRMA increases high-risk demand coverage by 3.2–3.7 percentage points, reduces mean response time by 2.9–3.1 minutes, lowers unmet demand by 2.7–2.8 percentage points, and reduces the coverage Gini coefficient by 0.031–0.032. These differences indicate that risk-responsive allocation can reconcile service efficiency and spatial equity in the synthetic settings examined. The comparisons provide descriptive evidence at the framework level and do not identify the independent contribution of individual model constraints. The study provides an explicit basis for coordinating risk priorities, minimum-service protection, and cross-district resource allocation under limited budgets.

Keywords: Urban public safety; Risk governance; Emergency resource allocation; Scenario-based robust optimization; Service equity; Urban resilience

摘要: 快速城市化、复合灾害以及部门间相互依赖, 对应急资源配置的及时性与可靠性提出了更高要求。本研究构建了一套风险响应型鲁棒多目标资源配置框架 (risk-responsive robust multi-objective allocation, RRMA), 将风险评估、需求生成、网络可达性与资源部署决策纳入统一分析框架。采用灾害危险性、暴露度、脆弱性和恢复能力四个维度构建风险指数, 并在预算、容量及最低服务水平约束下, 对设施启用、资源预置和不同情景下的资源分配进行联合优化; 同时, 通过有限情景集下的最坏加权损失刻画配置方案的鲁棒性。情景分析涵盖六类城市功能区, 并基于合成样本比较基准风险、洪涝灾害和复合风险三种情景。汇总结果显示, 与 NSGA-II 基准方法相比, RRMA 将高风险需求覆盖率提高了 3.2 – 3.7%, 平均响应时间缩短了 2.9 – 3.1 分钟, 未满足需求比例降低了 2.7 – 2.8%, 覆盖率基尼系数降低了 0.031 – 0.032。上述结果表明, 在本文所设定的合成情景中, 风险响应型资源配置能够兼顾服务效率与空间公平。相关比较提供的是框架层面的描述性证据, 尚不能识别各项模型约束的独立贡献。本研究为有限预算条件下统筹风险优先级、最低服务保障与跨区域资源配置提供了一套明确的分析与决策框架。

关键词: 单城市公共安全; 风险治理; 应急资源配置; 基于情景的鲁棒优化; 服务公平; 城市韧性



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Introduction

Urbanization concentrates population, industry, transport, and critical infrastructure within interconnected urban

spaces. Public safety risks consequently extend across sectors and administrative boundaries and may involve interacting hazards. China's resident-population urbanization

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rate reached 67.00% in 2024 (National Bureau of Statistics of China, 2025). Nationally, natural disasters affected people on 94.13 million occasions and caused CNY 401.11 billion in direct economic losses that year (Ministry of Emergency Management of China, 2025). These national statistics motivate the study but do not identify local emergency demand, road accessibility, or the effects of a particular allocation policy.

Under a limited budget, resource allocation must account for the spatial distribution of risk, population exposure, vulnerable groups, and rescue accessibility. Additional stock does not guarantee timely delivery. Concentrating resources in easily served areas may also widen service gaps in peripheral communities. Urban resilience scholarship emphasizes the importance of conceptual clarity, system adaptation, and differences in governance objectives (Meerow et al., 2016). Research on urban safety in China identifies related challenges in decision-making, local implementation, and social coordination (Liu et al., 2025). Translating these concerns into explicit decision variables and testable constraints motivates the present study.

The study addresses a specific question: when resources are limited and demand and transport conditions are simultaneously disrupted, how can planners make transparent trade-offs among demand coverage, response time, cost, and spatial equity? We connect risk identification, demand generation, accessibility assessment, and multi-objective optimization in the applied RRMA decision framework. Its contribution is to connect risk assessment to deployment through capacity-constrained service coverage and to distinguish preparedness from response through common pre-disaster decisions and scenario-dependent distribution. National statistics establish the study context, while the discussion of allocation performance draws on synthetic scenario comparisons.

Literature Review

Urban public safety governance and resilience

Research on urban public safety increasingly connects emergency response with prevention, adaptation, and recovery. Liu et al. (2025) discuss challenges to urban safety resilience in China in terms of managerial decision-making, local implementation, social collaboration, and critical areas. Guo et al. (2025) develop a planning and design framework that relates risk sources, exposed systems, and mitigation capacity. These studies help identify the governance objectives that resource allocation should address.

International research also emphasizes the need to specify whose resilience is being considered, over what period, and with which normative priorities (Meerow et al., 2016). Accordingly, this study focuses on resource deployment and distribution within a defined emergency response window. Demand fulfillment and the distribution of service provide operational measures of allocation performance. This scope does not encompass long-term recovery, social learning, or

institutional adaptation; service performance across scenarios represents only one operational dimension of resilience.

Emergency preparedness and resource allocation

Emergency pre-positioning research already integrates facility location, inventory decisions, and post-disaster distribution. Rawls and Turnquist (2010) examine emergency supply pre-positioning for disaster response, illustrating the need to consider storage locations and quantities jointly under uncertainty. Robust optimization scholarship also examines the trade-off between protection against uncertainty and objective performance (Bertsimas & Sim, 2004). Building on this research, RRMA connects risk-related demand and minimum-service protection with allocation across disruption scenarios.

The application problem examined here is the explicit representation of risk-related demand, road accessibility, facility capacity, and minimum-service requirements within a common allocation framework. NSGA-II is an algorithm for obtaining multi-objective candidate solutions (Deb et al., 2002). Its performance depends on the formulation, constraints, and computational budget. In this study, NSGA-II identifies the optimization algorithm used for a comparator allocation. An optimization algorithm and a risk-responsive allocation framework operate at different analytical levels, so performance differences must be interpreted in relation to their respective objectives and constraints.

Digital governance and data security

Cheng and Chen (2025) discuss a shift toward resilience-oriented governance of urban public data security, highlighting the relevance of technical, institutional, and accountability arrangements. In emergency allocation, differences in the spatial resolution, update frequency, and access permissions of population, road, facility, and inventory data directly affect demand and accessibility estimates. Mathematical feasibility alone does not establish that interagency transfers can be implemented.

The framework therefore connects data preparation with governance constraints. Risk indicators require consistent scales, cross-district transfers require predefined capacity or agreement limits, and sensitive population information should be represented through aggregated demand wherever possible. The study examines how these governance requirements can be expressed operationally and how allocation strategies perform under scenario disturbances.

Methods

Overall framework

The risk-responsive robust multi-objective allocation framework (RRMA) follows four steps. First, population distributions, historical incidents, critical facilities, road networks, and inventory records are organized into a baseline representation of risk and resources. Second, demand scenarios are generated from hazard, exposure, vulnerability, and baseline recovery capacity. Third, common pre-disaster

deployment decisions are determined subject to budget, capacity, timeliness, and minimum-service constraints. Finally, distribution decisions may vary across scenarios, and the resulting deployment is evaluated on independent test scenarios.

The analysis covers a fixed response window. Let D_{is} denote demand units, candidate facilities, and a finite set of disruption scenarios. Resources are initially measured as a single divisible, standardized emergency service unit. Firefighting equipment, medical capacity, and relief supplies are not directly aggregated as interchangeable resources. Applications involving non-substitutable resources require a resource-type index and separate supply-demand balances. The mathematical specification makes the allocation relationships explicit. Aggregate scenario comparisons assess overall strategy performance and do not independently validate each formal constraint.

Risk assessment and demand generation

For demand unit i in scenario s , hazard intensity H_{is} , exposure intensity E_{is} , vulnerability V_{is} , and baseline recovery capacity S_i are scaled to $[0,1]$. The risk-priority index is defined as:

$$R_{is} = \alpha H_{is} + \beta E_{is} + \gamma V_{is} + \delta(1 - S_i), \quad \alpha + \beta + \gamma + \delta = 1 \quad (1)$$

The four weights are nonnegative, ensuring $R_{is} \in [0,1]$. Expressing recovery capacity as a shortfall avoids negative risk scores and the negative demand they could generate. The index represents allocation priority, not a calibrated probability of disaster occurrence. Scaling endpoints and weights must be fixed before model evaluation. Test values outside the prescribed range should be clipped according to a predefined rule, with the frequency of clipping reported. Baseline recovery capacity remains exogenous so that the current allocation is not used retrospectively to determine its own demand.

Emergency resource demand is defined as:

$$D_{is} = \lambda_1 R_{is} P_{is} + \lambda_2 C_i + \lambda_3 G_{is}, \quad \lambda_1, \lambda_2, \lambda_3 \geq 0 \quad (2)$$

Here, P_{is} is the effective exposed population during the response window, C_i is the service load associated with critical facilities, and G_{is} is the population requiring additional assistance. The three coefficients convert these quantities into standardized service units. To limit double counting, E_{is} excludes population totals, V_{is} excludes the same demographic characteristics already represented by G_{is} , and C_i is not also entered as an exposure indicator. Where overlap cannot be eliminated, sensitivity analysis should remove the relevant component. Without calibration against historical demand, Equation (2) is a transparent scenario-generation rule rather than a validated forecasting model.

Network accessibility and service coverage

Let t_{ijs} denote travel time from facility j to demand unit i in scenario s , and let T_0 denote the response-time threshold. A time-decay function represents locational suitability:

$$A_{ijs} = \exp(-\mu t_{ijs}) \mathbf{1}(t_{ijs} \leq T_0), \quad \mu \geq 0 \quad (3)$$

The decay parameter μ is measured in inverse minutes. This indicator is not interpreted directly as a probability of successful service, and accessibility from different facilities is not treated as a collection of independent events. Fully disrupted links are removed from the feasible distribution network. Actual coverage depends on the quantity of resources that can be delivered.

Let $x_j \in [0,1]$ indicate facility activation, $r_j \geq 0$ pre-positioned stock, $y_{ijs} \geq 0$ the quantity delivered in a scenario, and $u_{is} \geq 0$ unmet demand. Demand balance and resource conservation require

$$\sum_{j \in J} y_{ijs} + u_{is} = D_{is}, \quad \sum_{i \in I} y_{ijs} \leq a_{js} r_j \quad (4)$$

The parameter $a_{js} \in [0,1]$ is the usable proportion of stock in scenario s . A disrupted distribution arc, or one exceeding T_0 , must have $y_{ijs} = 0$. For positive-demand units, coverage is

$$q_{is} = \frac{\sum_j y_{ijs}}{D_{is}} = 1 - \frac{u_{is}}{D_{is}}, \quad 0 \leq q_{is} \leq 1 \quad (5)$$

Zero-demand units are excluded from coverage and equity calculations. Equation (4) prevents the same finite stock from being counted as fully covering several demand units. This conservation requirement distinguishes locational accessibility from actual fulfillment and makes coverage responsive to resource scarcity.

Multi-objective optimization model

Let K_j denote facility capacity, f_j activation cost, c_j unit stocking cost, and $B_{\max} > 0$ the planning budget. Cost and capacity constraints are

$$B = \sum_j (f_j x_j + c_j r_j) \leq B_{\max}, \quad 0 \leq r_j \leq K_j x_j \quad (6)$$

This budget covers activation and stocking costs but does not yet include variable distribution costs. For a predefined set of priority units I_p , minimum coverage can be imposed as $q_{is} \geq q_i$ in every planning scenario. Cross-district distribution may be limited by $\sum_{(i,j) \in \mathcal{C}} y_{ijs} \leq M_s$, where M_s is the set of cross-district arcs and $\mathcal{C}$ is the transfer capacity authorized by coordination agreements. Minimum coverage must not be silently relaxed during optimization. Infeasibility requires explicit reporting and reconsideration of the budget, service requirements, or scenario scope.

Let I_s^+ be the set of positive-demand units and n_s its size. The overall unmet-demand rate, mean response time for served demand, and a time measure that penalizes non-service are defined as follows:

$$U_s = \frac{\sum_i u_{is}}{\sum_i D_{is}}, \quad T_s = \frac{\sum_{ij} t_{ijs} y_{ijs}}{\sum_{ij} y_{ijs}} \quad (7)$$

$$L_s = \frac{\sum_{ij} t_{ijs} y_{ijs} + \tau \sum_i u_{is}}{\sum_i D_{is}}, \quad \tau \geq T_0 > 0 \quad (8)$$

Travel-time sums include only available arcs with finite travel times. If no demand is served, T_s is undefined and must not be recorded as zero; L_s remains defined. The parameter τ is a policy penalty for unmet demand, not an observed arrival time. Optimization uses L_s , while both T_s and U_s are reported. This reduces the incentive to obtain a shorter conditional response time simply by abandoning remote demand.

Spatial equity is represented by the unweighted Gini coefficient of coverage across positive-demand units:

$$G_s = \frac{\sum_{i,k \in I_s^+} |q_{is} - q_{ks}|}{2n_s \sum_{i \in I_s^+} q_{is}} \quad (9)$$

When no unit receives service, $G_s = 1$ is assigned as a penalty convention. This measure gives equal weight to spatial units and captures differences in service relative to demand. It is not a measure of individual-level equity and does not replace minimum coverage for priority groups. Scenarios with zero total demand are excluded from optimization.

To coordinate the four objectives and limit performance losses across scenarios, the model minimizes the worst weighted scenario loss:

$$\min_{x,r,y,u,z} z + w_3 \frac{B}{B_{\max}} \quad (10)$$

$$z \geq w_1 U_s + w_2 \frac{L_s}{\tau} + w_4 G_s, \quad s \in S \quad (11)$$

The weights satisfy $w_k \geq 0$ and $\sum_{k=1}^4 w_k = 1$. All objective components are dimensionless. The pre-disaster variables x_j and r_j are common across scenarios, while distribution and shortage variables are scenario-dependent, yielding a two-stage scenario-based robust formulation. Robustness is limited to the explicitly specified finite scenario set; no probabilistic guarantee is asserted for events outside that set. This construction is distinct from other robust formulations, including budgeted uncertainty sets (Bertsimas & Sim, 2004).

High-risk demand coverage is reported separately as

$$C_{H,s} = \frac{\sum_{i \in IH} D_{is} q_{is}}{\sum_{i \in IH} D_{is}}. \quad \text{The high-risk set } IH \text{ is determined from baseline risk using a prespecified threshold and is held con-}$$

stant across methods. The measure is not reported when high-risk units have no demand. Overall coverage complements U_s , whereas coverage within the high-risk subset generally does not complement the overall unmet-demand rate.

The model contains binary decisions and a Gini ratio. Candidate solutions can be obtained with a solver supporting mixed-integer nonlinear optimization or with a multi-objective heuristic subject to explicit feasibility checks. An NSGA-II implementation must specify how common deployment and scenario-dependent distribution are encoded, how demand and capacity constraints are repaired, and how the reported solution is selected from the non-dominated set. Varying weights explores some trade-offs but does not guarantee recovery of the complete Pareto frontier in a non-convex problem. Minimum coverage and cost bounds can also be varied as additional constraints. Interpretation of the resulting solutions must account for feasibility, computational effort, and the rule used to select the reported allocation.

Results and Discussion

Data and scenario analysis

The scenario analysis uses a synthetic urban setting comprising six functional area types: a central urban district, a riverside industrial area, an older residential belt, a science and technology park, a transport hub, and a mountainous expansion area. Five scenario types represent pluvial flooding, industrial fire, transport disruption, extreme weather, and compound disturbance, with 300 simulation samples in total. Results are grouped into baseline risk (D1), high-density flooding (D2), and compound risk (D3). These categories examine allocation performance under different risk conditions; they are synthetic scenarios rather than independently collected datasets from three actual cities.

The comparison includes uniform allocation, experience-based allocation, a shortest-time strategy, an NSGA-II benchmark, and RRMA. Uniform and experience-based allocation represent rule-based approaches; the shortest-time strategy prioritizes response efficiency; the NSGA-II benchmark represents multi-objective allocation; and RRMA additionally emphasizes risk responsiveness and service protection across scenarios. Aggregate indicators are used to compare overall strategy performance. Because the comparison does not separately identify the contributions of resource budgets, computational effort, and individual constraints, the entire performance difference cannot be attributed exclusively to robustness.

Public statistical context and scope

China's resident-population urbanization rate reached 67.00% in 2024. Natural disasters affected people on 94.13 million occasions nationwide and caused CNY 401.11 billion in direct economic losses (National Bureau of Statistics of China, 2025; Ministry of Emergency Management of China, 2025). These figures illustrate the pressures associated with population concentration and disaster losses. National dis-

Table 1 | Resource allocation performance across three synthetic scenario categories

Set	Method	High-risk coverage %	Response time min	Unmet demand %	Gini
D1	Uniform	74.8	24.9	18.6	0.231
D1	Experience-based	79.2	21.5	14.7	0.205
D1	Shortest-time	81.6	19.0	13.5	0.221
D1	NSGA-II	86.1	17.7	9.4	0.173
D1	RRMA	89.3	14.8	6.7	0.142
D2	Uniform	70.5	26.3	21.2	0.246
D2	Experience-based	76.8	22.7	16.3	0.219
D2	Shortest-time	79.4	20.6	15.1	0.227
D2	NSGA-II	84.2	18.5	10.8	0.182
D2	RRMA	87.9	15.6	8.1	0.151
D3	Uniform	68.9	27.1	22.4	0.258
D3	Experience-based	75.6	23.4	17.0	0.226
D3	Shortest-time	77.8	21.5	15.9	0.235
D3	NSGA-II	82.7	19.2	11.6	0.191
D3	RRMA	86.4	16.1	8.8	0.159

Note. D1 represents baseline risk, D2 flooding, and D3 compound risk. Higher coverage is preferable; lower values are preferable for the other three measures. Values are scenario aggregates; statistical significance markers are not reported.

aster statistics also include rural areas, however, and differ in spatial scope from the synthetic urban setting. The statistics establish the governance context, while local allocation depends on scenario-specific demand, resources, and transport conditions.

Public expenditure supports emergency preparedness, but its translation into service performance depends on resource locations, usable capacity, and distribution arrangements. Central public security expenditure differs in scope from the emergency supply budget available to an individual district. Urban allocation therefore requires a budget based on locally available resources and an assessment of expenditure against coverage, shortages, and response time.

Risk-coverage diagnosis and allocation priorities

Joint assessment of risk and coverage distinguishes allocation needs within high-risk areas. Locations with high risk and relatively good coverage require assessment of backup facilities, inventory availability, and route redundancy. High-risk locations with inadequate service require evaluation of the marginal benefits of additional pre-positioning and facilities. Peripheral locations with lower assessed risk but poor accessibility may require minimum-service protection to reduce persistent exclusion.

Across functional area types, riverside industrial areas and central districts require particular attention to maintaining existing service capabilities during disruptions. Transport hubs and older residential areas require joint consideration of demand pressure and service gaps, while mountainous expansion areas emphasize road accessibility and basic-service protection. These distinctions guide planning, but the allocation order also depends on population demand, capacity, cost, and cross-district assistance. A single ranking of risk cannot determine the optimal allocation.

Allocation performance

Table 1 compares high-risk demand coverage, mean response time, unmet demand, and the coverage Gini coefficient across five strategies and three synthetic sample categories. High-risk coverage measures service in priority areas, whereas overall unmet demand measures shortages across the entire sample. Their denominators differ, so the two indicators require separate interpretation.

RRMA achieves high-risk demand coverage of 89.3%, 87.9%, and 86.4% in D1, D2, and D3, respectively. Corresponding mean response times are 14.8, 15.6, and 16.1 minutes, and unmet-demand rates are 6.7%, 8.1%, and 8.8%. Relative to the NSGA-II benchmark, coverage increases by 3.2, 3.7, and 3.7 percentage points. Response time decreases by 2.9, 2.9, and 3.1 minutes, equivalent to reductions of 16.4%, 15.7%, and 16.1%. Unmet demand decreases by 2.7, 2.7, and 2.8 percentage points, while the Gini coefficient decreases by 0.031, 0.031, and 0.032. RRMA therefore combines better timeliness, coverage, and service distribution within the samples examined.

Response-time reductions range from 40.6% to 40.7% relative to uniform allocation and from 31.2% to 31.3% relative to experience-based allocation. These differences associate the incorporation of demand and accessibility into allocation decisions with shorter response times and fewer shortages. Although the shortest-time strategy outperforms the two rule-based approaches, its Gini coefficients remain above those of NSGA-II and RRMA. Prioritizing timeliness alone is consequently insufficient to ensure an even distribution of service.

From D1 to D3, coverage decreases and both response time and shortages increase for all five methods, reflecting the joint pressure of compound risk on resources and transport. RRMA's high-risk coverage decreases by 2.9 percentage points and its response time increases by 1.3 minutes, compared with 3.4 percentage points and 1.5 minutes for NSGA-

II. These changes support relatively favorable service performance for RRMA in the compound scenarios examined. They do not establish equivalent advantages under every possible extreme event.

Cost-coverage trade-offs and governance implications

The policy value of resource allocation lies in coordinating coverage, timeliness, and minimum-service protection under limited expenditure. A higher budget cap expands the feasible deployment choices, but candidate allocations may still involve trade-offs among ordinary-condition efficiency, protection against severe disruptions, and equity. A solution with a shorter mean response time requires examination of potential shortages in remote areas. A solution with better worst-scenario performance also requires assessment of its associated costs.

Allocation decisions should therefore report the resource budget, unmet demand, minimum unit coverage, and response time jointly, while specifying service floors for priority units. Areas combining high risk with substantial service gaps warrant assessment of additional resource benefits. Areas already enjoying high coverage require evaluation of service continuity when facilities or routes fail. Cross-district assistance must be translated into usable capacity through compatible resource standards, transfer authority, and clear responsibilities.

The results support risk-responsive allocation at the framework level. Because the analysis uses scenario aggregates, it does not establish the statistical significance of scenario-level differences or isolate the independent effects of risk weights, minimum coverage, and robust protection. Accordingly, the study does not prescribe an investment amount for a particular city or imply that every indicator improves simultaneously at every budget level.

Conclusion

This study develops the RRMA framework for resource allocation in urban public safety risk governance, connecting risk assessment, demand generation, accessibility analysis, and multi-objective decision-making. Explicit demand balance, budget and capacity constraints, minimum-service protection, and finite-scenario worst-case losses provide a common decision structure for pre-disaster deployment and scenario-dependent distribution.

Comparisons across three synthetic sample categories show favorable aggregate performance for RRMA in high-risk coverage, response time, unmet demand, and service distribution. Relative to NSGA-II, coverage increases by 3.2–3.7 percentage points and response time decreases by 15.7%–16.4%, alongside reductions in shortages and Gini coefficients. The findings support the joint consideration of risk-related demand, resource accessibility, and service pro-

tection, with additional resources assessed in relation to existing coverage gaps.

These conclusions apply to the synthetic settings examined. Framework-level performance comparisons do not substitute for independent validation of individual model constraints. Resources are also represented as homogeneous service units within a single response window. Specialized-resource non-substitutability, dynamic replenishment, road capacity, and institutional coordination costs require further attention. Future research can calibrate demand and transport parameters in actual urban districts and use independent scenario testing, paired statistical analysis, and ablation studies to identify the conditions under which each mechanism contributes to performance, thereby strengthening the basis for operational deployment.

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