

Article

Optimizing the Distribution of Relief Supplies Considering the Social Vulnerability Risk Index: A Case of Taiwan

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and or methodology.

- Couples FIS-based reasoning with FMOLP optimization in one two-stage relief-planning system.
- Models vulnerability as four interacting dimensions, revealing risks that single indicators miss.

What are the main findings and/or the implications of the main findings?

- Ranks high-risk regions to support government disaster preparedness.
- Delivers a validated, risk-weighted relief allocation plan for all 17 regions.

Abstract

Disaster preparedness and the equitable distribution of emergency relief supplies remain pressing priorities for governments worldwide. Situated along the Pacific Ring of Fire, Taiwan is particularly vulnerable to natural disasters that frequently cause severe property damage and endanger public safety, making the efficient allocation of limited relief resources in the immediate aftermath a persistent challenge for emergency management. Although prior research has addressed risk assessment and resource allocation as separate problems, few studies have incorporated region-specific social vulnerability values directly into an optimization framework for relief distribution. This raises the question of how region-specific social vulnerability can be quantitatively embedded into a relief-supply allocation model to achieve a more equitable, risk-sensitive distribution than conventional population-based approaches. To address this gap, the present study develops an integrated decision-making model combining a fuzzy inference system (FIS) with fuzzy multiple objective linear programming (FMOLP). The FIS first derives social risk values from four vulnerability dimensions, namely exposure, disaster mitigation and preparedness, readiness, and recovery, for Taiwan's 17 counties and municipalities, drawing on multidimensional indicators from the National Science and Technology Center for Disaster Reduction (NCDR) Disaster Mitigation Database. These values are subsequently incorporated as weighting coefficients within the FMOLP model, which jointly maximizes distributional utility and minimizes procurement cost under population-based supply constraints. The results identify Hsinchu, Taichung, Chiayi, Yunlin, and Hualien as the five highest-risk regions. The model further yields a compromise allocation plan spanning all



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17 administrative units, with sensitivity analysis confirming its robustness across alternative performance metrics. This study offers a replicable, data-driven decision-support tool to assist disaster preparedness planners and government agencies in relief resource allocation.

Keywords: social vulnerability; relief allocation; fuzzy inference system; FMOLP

1. Introduction

Natural disasters strike without warning and frequently trigger cascading secondary hazards, resulting in substantial human casualties and economic losses worldwide. Taiwan is particularly exposed to such risks: situated along the Pacific Ring of Fire, the island experiences frequent earthquakes, typhoons, debris flows, and flooding, each capable of inflicting widespread damage within a compressed timeframe. The scale and suddenness of these events place enormous pressure on government agencies to identify the most vulnerable populations and deploy limited relief resources with precision and speed. Social vulnerability, defined as the sensitivity of a population to natural hazards and its capacity to recover from disaster impacts [1], provides a theoretically grounded basis for prioritizing emergency response. Regions characterized by high social vulnerability require not only immediate rescue efforts, but also pre-positioned relief supplies commensurate with their risk profiles; failure to account for spatial differences in vulnerability risks misallocating scarce resources, leaving the most at-risk communities underserved at the most critical juncture [2].

Despite growing recognition of the importance of socially differentiated disaster risk, the operational link between quantified social vulnerability and optimized supply allocation remains underdeveloped in both research and practice [3]. Emergency managers frequently rely on population size alone to guide distribution decisions, thereby overlooking the compound vulnerabilities arising from intersecting dimensions of exposure, preparedness capacity, response readiness, and recovery potential [4]. This gap represents both a scholarly opportunity and a practical imperative that the present study seeks to address.

A review of the existing literature reveals two principal limitations. First, although risk assessment methods, including multi-criteria decision making (MCDM), fault tree analysis (FTA) [5], and heuristic algorithms, have been applied to quantify disaster risk [6,7], most of these approaches rank regions according to individual dimensions or weighted composite scores without accounting for nonlinear interactions among vulnerability factors. Fuzzy inference systems (FIS), which simulate expert judgement through IF-THEN rule structures and membership functions, offer a more nuanced mechanism for aggregating multidimensional vulnerability data [8]; however, their application to national-level social risk assessment remains limited. Second, the post-disaster resource allocation literature focuses predominantly on logistical factors such as transportation cost, delivery time, and depot location, while the incorporation of region-specific risk values as allocation weights is rare [7]. Integrating FIS-derived risk values into a fuzzy multi-objective linear programming (FMOLP) framework for relief supply planning therefore constitutes a methodological contribution that addresses both limitations simultaneously. Based on the above limitations, two major gaps exist. First, existing social vulnerability assessment methods (MCDM, FTA, heuristic algorithms) do not adequately capture nonlinear interactions among vulnerability dimensions. Second, existing relief-supply allocation models rarely embed region-specific risk values as allocation weights.

Against this background, the present study pursues three specific objectives: (1) to develop a novel FIS-based model for evaluating social vulnerability risk values across Taiwan's 17 counties and municipalities using multidimensional government data and expert-derived fuzzy rules; (2) to construct an FMOLP model that embeds the FIS-derived risk values as allocation weights, simultaneously optimizing distributional utility and minimizing procurement costs for relief supplies; and (3) to validate the proposed integrated framework through empirical analysis and sensitivity testing, deriving actionable recommendations for disaster preparedness policy.

The FIS approach offers several advantages over conventional scoring methods. By encoding expert knowledge in linguistic rules and triangular membership functions, FIS captures the uncertainty and imprecision inherent in vulnerability data without imposing strong distributional assumptions [8]. The min–min–max Mamdani inference mechanism accounts for the interactive effects among vulnerability dimensions, ensuring that no single dimension dominates the final risk score, while expert-validated rules further enhance the interpretability and credibility of the outputs. In the optimization stage, the augmented max–min FMOLP model proposed by Arikan [9] avoids the limitations of conventional weighted-additive and preemptive priority approaches by simultaneously maximizing total utility across all objectives, thereby guaranteeing a non-dominated compromise solution even under conflicting criteria. The combination of these two methods produces a decision support tool that is analytically rigorous, computationally tractable, and directly applicable to operational planning contexts.

This study makes three principal contributions. Methodologically, it demonstrates that FIS and FMOLP can be effectively integrated into a two-stage decision support framework for disaster management, an approach not previously applied to social vulnerability-based relief allocation. Empirically, it provides a comprehensive social risk ranking of all 17 Taiwanese counties and municipalities using the National Center for Disaster Reduction (NCDR) Disaster Mitigation Database, establishing a reference baseline for future research. Practically, the resulting allocation model and dimension-specific managerial insights derived from sensitivity analysis furnish government agencies and emergency planners with evidence-based guidance for improving both pre-disaster preparedness and post-disaster response.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the research methodology. Section 4 presents the empirical analysis. Section 5 discusses the results and managerial implications. Section 6 provides conclusions and directions for future research.

2. Literature Review

This section establishes the theoretical and empirical foundations of the proposed FIS-FMOLP framework. It begins by examining social vulnerability within the disaster risk literature, then reviews principal quantitative risk assessment methods with emphasis on fuzzy inference systems. Taiwan's institutional disaster management framework and the four vulnerability dimensions adopted in this study are subsequently described, followed by a survey of post-disaster relief supply distribution models. The section concludes by identifying the research gaps that motivate the integrated framework developed in this study.

2.1. Social Vulnerability and Disaster Risk

Disaster risk is broadly defined as the potential economic, social, and environmental consequences of hazardous events occurring within a specified time period [7]. Within this framework, social vulnerability occupies a central analytical role, capturing both the

degree of exposure of a population to natural hazards and its inherent capacity to cope with and recover from disaster impacts [1]. Vulnerability is not uniformly distributed, as socioeconomic conditions, demographic characteristics, infrastructure quality, and institutional capacity all mediate the relationship between a hazard event and its ultimate social consequences.

The concept of risk can be characterized along three interrelated dimensions. First, objective possibility denotes that risk exists independently of human perception; although preventive measures may reduce the likelihood or magnitude of losses, they cannot eliminate risk entirely. Second, contingency reflects the inherent uncertainty surrounding both the probability of occurrence and the severity of consequences for any individual event, rendering precise *ex ante* prediction infeasible. Third, measurability indicates that while individual events remain contingent, the aggregate behavior of large numbers of analogous risk events exhibits statistical regularity, thereby making probabilistic quantification feasible [10]. Building on these properties, risk indices that summarize risk through numerical scores or categorical labels have become a standard instrument for communicating risk to the public, monitoring temporal trends, and informing resource allocation decisions.

For operational risk assessment, risks are typically classified by nature (pure versus speculative), environmental origin (static versus dynamic), or causal domain (natural, social, or economic). Social risk, the category of primary concern in the present study, refers to the risk of social disruption arising from human behavioral and institutional factors, including inadequate emergency preparedness and deficient post-disaster recovery capacity. A holistic approach to disaster risk assessment, such as that demonstrated by Carreno et al. [7] in their evaluation of Manizales, Colombia, integrates physical damage estimates with socioeconomic vulnerability indicators to produce a more complete and actionable picture of regional risk.

2.2. Disaster Risk Assessment Methods

Three main categories of quantitative risk assessment methods are found in the disaster management literature. The first is multi-criteria decision making (MCDM), which aggregates multiple risk-related indicators into composite scores for comparative ranking. Sun et al. [11] demonstrated this approach in the Yangtze River Delta, constructing a flood risk analysis model that systematically incorporated five dimensions, namely hazard, exposure, vulnerability, emergency response and recovery capacity, and disaster losses, to derive regional risk rankings. MCDM methods are flexible and transparent but are sensitive to the weighting scheme adopted, which can introduce subjectivity. The second category is fault tree analysis (FTA), a deductive method used primarily in safety and reliability engineering to model system failures. Bhangu et al. [5] applied FTA to evaluate the reliability and risk of a thermal power plant, using plant failure data to identify critical components and evaluate maintenance strategies. FTA is well-suited to structured technical systems but is less applicable to the diffuse, socially complex environment of disaster risk. The third category employs heuristic algorithms. Asteris et al. [6] applied a heuristic approach to model and assess COVID-19 risk across six jurisdictions, using mortality data, demographic distributions, and environmental factors to derive predictive epidemic curves. While heuristic methods can handle high-dimensional data and nonlinear dynamics, they typically lack the interpretability and expert validation that is desirable in policy-relevant applications.

Among these approaches, fuzzy inference systems (FISs) represent an increasingly attractive alternative for risk assessment contexts characterized by linguistic uncertainty, incomplete information, and the need to incorporate expert knowledge. Unlike MCDM ranking methods, FISs capture nonlinear interactions among vulnerability dimensions

through expert-validated IF-THEN rule structures, producing risk scores that reflect the compound effects of multiple co-occurring conditions. This property is particularly valuable in social vulnerability assessment, where the combined influence of exposure, preparedness, readiness, and recovery factors cannot be adequately captured by simple additive or multiplicative aggregations.

2.3. Taiwan's Disaster Management Framework and Vulnerability Dimensions

Following the devastating Chi-Chi Earthquake of 1999, Taiwan substantially strengthened its institutional infrastructure for disaster prevention. Key milestones include the enactment of the Disaster Prevention and Protection Act [12], the restructuring of the National Science and Technology Program Office for Hazard Mitigation in 2003, and subsequent legislative amendments coordinated with Executive Yuan reorganization in 2013. The National Science and Technology Center for Disaster Reduction (NCDR) was established to drive science and technology research aligned with national disaster prevention needs and to translate research findings into operational improvements.

The analytical framework adopted in this study draws on the four-stage disaster management cycle recognized by Taiwan's National Debris Flow Disaster Prevention Information Network, which decomposes the disaster management process into mitigation, preparedness, response, and recovery. Each stage is associated with a distinct set of vulnerability indicators that collectively characterize a region's social risk profile. This study operationalizes the framework through four corresponding dimensions. Exposure captures the demographic and economic conditions that amplify disaster losses. Indicators include agricultural and industrial output values, average household consumption, residential area, the ratio of critical facilities located in hazard zones, resident population, and populations protected under debris flow and flood prevention plans. Higher exposure values reflect greater potential losses in the event of a disaster [11,13].

Disaster mitigation and preparedness reflects pre-disaster protective engineering and institutional capacity. Relevant indicators encompass slope stabilization works, the deterioration susceptibility rate of water conservancy facilities, the proportion of low-seismic-resistance buildings, rates of hillside land overuse, debris flow drill participation, trained community disaster prevention personnel, and the number of community-based flood self-governance organizations per village. Readiness refers to the capacity for immediate response at the moment a disaster strikes. It encompasses emergency notification systems, multi-channel inter-agency communication protocols, and disaster response center activation procedures, all of which determine how rapidly and effectively government and civil society actors can mobilize in the critical first hours of a disaster event [3,14]. Recovery encompasses short-term and long-term measures to restore pre-disaster conditions. Short-term recovery prioritizes the rehabilitation of lifeline systems, including electricity, telecommunications, water supply, sewage, and transport networks, as well as the maintenance of public order [15]. Long-term recovery involves economic reconstruction, the rebuilding of social infrastructure, and the restoration of residents' livelihoods and well-being [7].

2.4. Disaster Relief Supply Distribution

Effective relief supply distribution is critical to minimizing disaster mortality and suffering. The foundational challenge is the allocation of finite resources across multiple affected locations so as to maximize welfare benefits subject to cost, logistical, and equity constraints. Relevant decision criteria include transportation costs, delivery speed, the proportional reduction in disaster victims' vulnerability, and the maintenance of minimum living standards for affected populations.

Recent research has increasingly applied optimization methods to this problem. Tao et al. [16] applied data envelopment analysis (DEA) combined with network flow theory to determine optimal resource allocation schemes across multiple decision-making units. Zong and Luo [17] developed a reinforcement learning framework for COVID-19 resource allocation, constructing a multi-agent simulation environment to identify flexible, adaptive strategies for deploying limited resources across multiple jurisdictions. These studies confirm that mathematical programming and computational intelligence methods can substantially improve allocation efficiency relative to ad hoc or population-proportional approaches. In addition, Geng [18] conducted a bibliometric and content-analysis review of resource management in disaster relief. Kapukaya and Satoglu [19] developed a multi-objective dynamic resource allocation model for search-and-rescue and first-aid tasks employing volunteers.

A critical limitation shared by most existing allocation models is that they treat all recipient locations as equivalent in terms of vulnerability or need, relying on population size or damage estimates as the primary allocation criterion. The risk value of a region, reflecting its compound social vulnerability, is rarely embedded as a weighting coefficient in the optimization objective. This gap means that high-vulnerability, low-population regions may receive insufficient resources relative to their actual need, a situation that can exacerbate post-disaster inequality and delay recovery.

3. Research Methodology

The foregoing review identifies two interconnected research gaps. First, existing risk assessment methods for disaster management either neglect nonlinear interactions among vulnerability dimensions (MCDM, FTA) or lack the expert validation and interpretability required for policy adoption (heuristic algorithms). FIS addresses both concerns but has rarely been applied to aggregate multidimensional social vulnerability indicators at the national or regional level. Second, resource allocation models for disaster relief do not systematically incorporate quantified social risk values as allocation weights, resulting in distribution plans that may not reflect the true urgency of need across regions.

This study addresses both gaps by proposing an integrated FIS-FMOLP framework in which FIS-derived social risk values serve as the utility coefficients in an FMOLP allocation model. In the first stage, an FIS is used to derive social risk values for each county and municipality by aggregating multidimensional vulnerability indicators through expert-validated fuzzy rules. In the second stage, these risk values are incorporated as utility weights in a fuzzy multiple objective linear programming (FMOLP) model, which determines the optimal allocation of relief supplies subject to cost and population constraints. The following subsections describe each methodological component.

3.1. Fuzzy Inference System

The FIS used in this study follows the Mamdani framework [20] and proceeds through three steps: fuzzification, rule-based inference, and defuzzification.

Step 1: Fuzzification

Each input variable is converted from a crisp value into a fuzzy membership degree through a triangular membership function, a standard technique in fuzzy inference systems for representing the degree to which an input belongs to a given linguistic category. For an input x defined on a normalized scale of $[0, 5]$, three linguistic terms are specified: Low/Poor (L/P), Medium/Fair (M/F), and High/Good (H/G), corresponding to the triangular fuzzy numbers $(0, 0, 2.5)$, $(0, 2.5, 5)$, and $(2.5, 5, 5)$, respectively. Each triangular number is defined by three parameters, representing the left boundary, the peak (where membership equals 1), and the right boundary of the fuzzy set, such that the

membership degree decreases linearly as the input value moves away from the peak in either direction. The four input dimensions were rescaled to this common [0, 5] interval to ensure comparability across variables measured on different original scales and to avoid introducing arbitrary asymmetries that are not supported by the underlying data. Without such rescaling, differences in the original units or ranges of the input variables could distort the shape of the membership functions and bias the resulting fuzzy inference outcomes. The symmetric triangular specification adopted here assumes that each linguistic term contributes equally across its respective range, thereby preserving consistency in how the model interprets varying levels of severity or performance across all input dimensions. We further note that this symmetric specification was reviewed and confirmed as appropriate by domain experts during the rule elicitation process, who verified that the equal-interval partitioning of the [0, 5] scale adequately reflects the practical distinctions between low, medium, and high levels of the underlying disaster-relief indicators. The triangular membership function is given by:

$$\mu(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{c-a}, & a \leq x < c \\ 1, & x = c \\ \frac{b-x}{b-c}, & c < x \leq b \\ 0, & x > b \end{cases} \quad (1)$$

where (a, b, c) denote the lower, modal, and upper bounds of the triangular fuzzy number.

Step 2: Fuzzy Inference

The inference engine applies a set of IF-THEN rules of the form: IF Exposure is X AND Mitigation is Y AND Readiness is Z AND Recovery is W, THEN Risk is V. Rules were elicited from four domain experts familiar with Taiwan's disaster management environment. The four input dimensions, each with three membership levels, yielded 81 distinct rule combinations. The min–min–max formulation of the Mamdani model was adopted [21]: the antecedent membership degrees were combined by a Min (AND) operation; the resulting degree was applied to the consequent membership function by a second Min operation; and the final output was obtained by a Max (OR) aggregation across all fired rules, producing a fuzzy output set on [0, 1].

Step 3: Defuzzification

The centroid (center of gravity) method is used to convert the aggregated fuzzy output set into a crisp risk value. For an output membership function $\mu(z)$, the crisp output z^* is:

$$z^* = \frac{\int z\mu(z)dz}{\int \mu(z)dz} \quad (2)$$

The output linguistic terms and their corresponding triangular fuzzy numbers are: Very Low (VL): (0, 0, 1.25); Low (L): (0, 1.25, 2.5); Medium (M): (1.25, 2.5, 3.75); High (H): (2.5, 3.75, 5); Very High (VH): (3.75, 5, 5). The crisp output represents the social risk value of each county or municipality.

3.2. Fuzzy Multiple Objective Linear Programming

The FMOLP model is solved in four steps following the augmented max–min approach of Arikan [9].

Step 1: Model Construction

The objective functions to be optimized are formulated, comprising minimization objectives (Cost/Min) and maximization objectives (Benefit/Max), as presented in Equations (3) and (4).

$$f_c, c = 1, 2, \dots, C \text{ (for minimization objective)} \quad (3)$$

$$f_b, b = 1, 2, \dots, B \text{ (for maximization objective)} \quad (4)$$

where f_c denotes the minimization objective functions and C represents the number of cost/minimization objectives; f_b denotes the maximization objective functions and B represents the number of benefit/maximization objectives.

Constraint sets are subsequently established, encompassing uncertainty constraints and deterministic constraints, as given in Equations (5) and (6).

$$\text{s.t. } \otimes g_y(t) \leq \otimes e_y, y = 1, 2, \dots, Y \text{ (for fuzzy constraints)} \quad (5)$$

$$\text{s.t. } g_r(t) \leq e_r, r = 1, 2, \dots, R \text{ (for deterministic constraints)} \quad (6)$$

$$t \geq 0, t = 1, 2, \dots, T$$

where the feasible solutions satisfying the constraint conditions are denoted accordingly. A tilde symbol $\otimes g_y$ placed before a variable indicates that the variable possesses a fuzzy character; for instance, $\otimes e_y = (e_y, e_y, \bar{e}_y)$ represents the upper, middle, and lower bounds of a fuzzy value, respectively. All decision variables in the model are non-negative.

Step 2: Positive and negative ideal solutions

Each objective is optimized individually under the same constraints to obtain the positive ideal solution F_p^* (best achievable value) and negative ideal solution F_p^- (worst value under individual optimization) for objective j . These bounds are compiled into a payoff table (Table 1) and used to define the range of achievement for each objective.

Table 1. Payoff table of each objective.

	f_c (Minimization)	f_b (Maximization)
F^*	$f_c^* = \min f_c$	$f_b^* = \max f_b$
F^-	$f_c^- = \max f_c$	$f_b^- = \min f_b$

Step 3: Construct the membership function

The membership function $\mu_{f_c}(f_c(t))$ for each minimization objective is computed as given in Equation (7). When the ideal level of a minimization objective is less than or equal to f_c^* , the membership degree equals 1; when it falls between f_c^* and f_c^- , the membership degree takes an intermediate value; otherwise, the membership degree equals 0 [22].

$$\mu_{f_c}(f_c(t)) = \begin{cases} 1, & f_c(t) \leq f_c^* \\ \frac{f_c^- - f_c(t)}{f_c^- - f_c^*}, & f_c^* \leq f_c(t) \leq f_c^-, \quad c = 1, 2, \dots, C \\ 0, & f_c(t) \geq f_c^- \end{cases} \quad (7)$$

The membership function $\mu_{f_b}(f_b(t))$ for each maximization objective is computed as given in Equation (8) [23]. When the ideal level of a maximization objective is greater than or equal to f_b^* , the membership degree equals 1; when it falls between f_b^* and f_b^- , the membership degree takes an intermediate value; otherwise, the membership degree equals 0.

$$\mu_{f_b}(f_b(t)) = \begin{cases} 1, & f_b(t) \geq f_b^* \\ \frac{f_b(t) - f_b^-}{f_b^* - f_b^-}, & f_b^- \leq f_b(t) \leq f_b^*, \quad b = 1, 2, \dots, B \\ 0, & f_b(t) \leq f_b^- \end{cases} \quad (8)$$

The membership function for fuzzy constraint conditions is computed as given in Equation (9) [24].

$$\mu_{gy}(t) = \begin{cases} 1, & g_y(t) \leq e_y - l_y \\ \frac{e_y - g_y(t)}{l_y}, & e_y - l_y \leq g_y(t) \leq e_y, \quad y = 1, 2, \dots, Y \\ \frac{g_y(t) - e_y}{u_y}, & e_y \leq g_y(t) \leq e_y + u_y, \quad y = 1, 2, \dots, Y \\ 0, & g_y(t) \geq e_y + u_y \end{cases} \quad (9)$$

where the lower, middle, and upper bounds of the fuzzy value $\otimes e_y = (\underline{e}_y, e_y, \bar{e}_y)$ are expressed as $(e_y - l_y, e_y, e_y + u_y)$.

Step 4: Augmented max–min solution

The multi-objective problem is converted to the following single-objective linear program as Equations (10) and (11) [9]:

$$\max \quad \lambda + \left\{ \sum_{c=1}^C \mu_{fc}(f_c(t)) + \sum_{b=1}^B \mu_{fb}(f_b(t)) + \sum_{y=1}^Y u_{gy}(t) \right\} / (C + B + Y) \quad (10)$$

$$\text{s.t.} \quad \begin{cases} \lambda_c \leq \mu_{fc}(f_c(t)), \quad c = 1, 2, \dots, C \\ \lambda_b \leq \mu_{fb}(f_b(t)), \quad b = 1, 2, \dots, B \\ \lambda_y \leq \mu_{gy}(t), \quad y = 1, 2, \dots, Y \\ g_r(t) \leq e_r, \quad r = 1, 2, \dots, R \\ \lambda_c, \lambda_b, \lambda_y \geq \lambda \\ \lambda, \lambda_c, \lambda_b, \lambda_y \in [0, 1] \\ t \geq 0, \quad t = 1, 2, \dots, T \end{cases} \quad (11)$$

where λ is the minimum membership degree across all objectives and e_r is a small positive scalar ensuring that all objectives are considered [25–27].

4. Empirical Analysis

The empirical application proceeds in three stages. First, the data sources and pre-processing procedures are described. Second, the FIS model is applied to derive social risk values for each county and municipality. Third, the FMOLP model is constructed and solved using the FIS-derived risk values. Together, these stages constitute a fully traceable, reproducible analysis pipeline.

4.1. Data Sources and Preprocessing

All vulnerability indicator data were sourced from the NCDR Disaster Mitigation Database, which aggregates statistics compiled by multiple government ministries and agencies and is recognized as the authoritative reference for disaster risk information in Taiwan. The dataset originally covers 358 townships and districts across the island. To ensure data integrity, townships and districts with missing values for any sub-indicator were excluded, yielding a working sample of 162 administrative units with complete data. As the original 162 township-level units were overly fragmented, and some townships lacked complete data, townships within the same county or city were merged into a single unit, while counties or cities with incomplete data were excluded. These were subsequently aggregated by county and municipality to form the 17 final evaluation units.

Raw indicator values span heterogeneous measurement scales. Accordingly, all variables were first transformed to positive integers and subsequently normalized to a common scale of [0, 5] using a min–max normalization procedure. This normalization facilitates the construction of triangular membership functions and enables a direct comparison across

dimensions. Population registration data for each county and municipality were obtained from the National County and Municipal Important Statistical Indicators Query System and used to derive the upper and lower supply bounds in the FMOLP model.

4.2. FIS-Based Social Risk Assessment

The normalized values of the four vulnerability dimensions (exposure, disaster mitigation and preparedness, readiness, and recovery) serve as the FIS input variables. Each input is mapped to one of three linguistic terms using the triangular membership functions defined in Table 2.

Table 2. Linguistic terms and triangular fuzzy numbers for input variables.

Linguistic Terms	Fuzzy Triangular Number
Low/poor (L/P)	(0, 0, 2.5)
Medium/fair (M/F)	(0, 2.5, 5)
High/good (H/G)	(2.5, 5, 5)

A structured questionnaire was administered to four domain experts in disaster management and emergency planning. All experts possessed over 20 years of experience in this field, comprising three experts from the NCDR and one from academia, with ages ranging between 45 and 60 years. The questionnaire presented all 81 possible combinations of input linguistic terms arising from four dimensions each with three membership levels, and asked experts to specify the corresponding output risk level for each scenario. Expert responses were aggregated and any disagreements resolved through deliberation. The resulting 81-rule base is presented in Table 3. All rules assume a simultaneous AND interaction among the four input dimensions, consistent with the Mamdani min–min–max inference procedure.

Table 3. Expert-derived fuzzy rule base.

Recovery		P			F			G		
Readiness		P	F	G	P	F	G	P	F	G
Exposure	Mitigation and Preparedness									
L	P	H	M	L	M	M	L	M	L	VL
	F	H	M	M	M	L	L	M	L	L
	G	M	M	M	M	L	L	M	VL	VL
M	P	H	H	M	M	M	M	M	M	M
	F	H	H	H	M	M	M	M	M	M
	G	H	M	M	M	M	M	L	M	VL
H	P	VH	H	H	VH	H	H	H	H	L
	F	VH	H	H	H	H	H	H	L	H
	G	H	H	H	VH	M	M	H	L	L

The output variable, social risk value, is expressed in five linguistic levels with the triangular fuzzy numbers defined in Table 4. The centroid defuzzification method was applied to convert the aggregated Mamdani output into a crisp risk score on the scale [0, 5] for each of the 17 counties and municipalities. Computations were implemented in MATLAB 2024a.

Table 4. Linguistic terms and triangular fuzzy numbers for output variable (social risk value).

Linguistic Terms	Fuzzy Triangular Number
Very low (VL)	(0, 0, 1.25)
Low (L)	(0, 1.25, 2.5)
Medium (M)	(1.25, 2.5, 3.75)
High (H)	(2.5, 3.75, 5)
Very high (VH)	(3.75, 5, 5)

The FIS analysis produced crisp risk values for all 17 counties and municipalities. The five regions with the highest overall social risk values were Hsinchu County (2.621), Taichung City (2.616), Chiayi County (2.480), Yunlin County (2.463), and Hualien County (2.432). A critical observation is that these rankings differ substantially from rankings based on any single dimension in isolation, confirming that the compound, nonlinear interactions captured by the FIS yield a qualitatively distinct and more informative assessment of regional risk than simple single-criterion approaches.

4.3. FMOLP-Based Relief Supply Allocation

The FMOLP model parameters are defined in Table 5. Risk values were drawn from the FIS output. Population constraints were derived from registered population figures for each county and municipality. A uniform spot cost of 850 NT\$ per unit and a packaging cost of 67 NT\$ per unit, with a batch size of $k = 150$ units, were assumed based on prevailing procurement estimates. Both the spot cost (850 NT\$ per unit) and the packaging cost (67 NT\$ per unit) were applied on a per-unit basis in the cost objective; the batch size defines the standard procurement lot size used to derive these unit-cost estimates rather than a rounding unit applied to the decision variables, and since the allocation quantities are treated as continuous in the FMOLP formulation, no fractional-batch rounding rule is required in the model itself. The cost parameters were based on prevailing government relief-supply procurement estimates.

Table 5. FMOLP model parameters.

Symbol	Definition
i	Index for county or municipality ($i = 1, \dots, 17$)
x_i	Quantity of relief supplies allocated to county/municipality i
R_i	FIS-derived social risk value for county/municipality i
k	Batch packaging quantity (units per batch)
CS_k	Unit spot cost (NT\$ per unit)
CW_k	Packaging cost per k units (NT\$ per batch)
Pl_i	Lower allocation bound (0.05% of registered population)
Pu_i	Upper allocation bound (0.07% of registered population)

The allocation bounds and risk values for all 17 counties and municipalities are summarized in Table 6.

The objective functions to be optimized are first established, comprising a minimization objective (Cost/Min) and a maximization objective (Benefit/Max). In this study, the assumed objective functions were the maximization of total utility and the minimization of cost. The first objective function incorporates the risk values derived from the fuzzy inference system, whereby the utility value for each county or municipality is computed as the product of its corresponding risk value and the quantity of relief supplies allocated. Maximizing this objective ensures that regions with higher risk values receive proportionally greater allocations of relief supplies, as specified in Equation (12). The second objective

function minimizes total cost, which comprises the estimated spot procurement cost and packaging cost of relief supplies, as given in Equation (13).

Table 6. FIS risk values and FMOLP allocation bounds by county/municipality.

County/Municipality	FIS Risk Value	Registered Population	Lower Bound (0.05%)	Upper Bound (0.07%)
Keelung City	2.344	367,577	184	257
Taipei City	2.164	2,602,418	1301	1822
New Taipei City	2.196	4,030,954	2015	2822
Taoyuan City	2.206	2,268,807	1134	1588
Hsinchu County	2.621	570,775	285	400
Miaoli County	2.391	542,590	271	380
Taichung City	2.616	2,820,787	1410	1975
Changhua County	2.366	1,266,670	633	887
Nantou County	2.401	490,832	245	344
Yunlin County	2.463	676,873	338	474
Chiayi County	2.480	499,481	250	350
Tainan City	2.212	1,874,917	937	1312
Kaohsiung City	2.231	2,765,932	1383	1936
Pingtung County	2.113	812,658	406	569
Yilan County	2.140	453,087	227	317
Hualien County	2.432	324,372	162	227
Taitung County	2.167	208,152	104	145

$$Max = \sum_{i=1}^I R_i X_i \quad (12)$$

$$Min = \sum_{i=1}^I CS_k * X_i + \sum_{i=1}^I CW_k * X_i / k \quad (13)$$

The constraints are defined as upper and lower bounds on the estimated number of disaster-affected persons in each region. The lower bound is set at 0.05% of the registered population of each county or municipality, as specified in Equation (14), while the upper bound is set at 0.07% of the registered population, as given in Equation (15).

$$X_i \leq Pu_i \quad (14)$$

$$X_i \geq Pl_i \quad (15)$$

Each objective function is optimized individually under the set of constraints to establish the payoff table (Table 7). The positive ideal solution (f^*) represents the best value achievable for each objective when solved independently; the negative ideal solution (f^-) represents the worst value that objective takes under any individual optimization scenario. The range $|f^* - f^-|$ defines the normalization interval for the membership function of each objective.

Table 7. Payoff table of positive and negative ideal solutions.

	f_1 (Max)	f_2 (Min)
f^*	36,310.4	14,493,420
f^-	25,924.92	10,348,250
$ f^+ - f^- $	10,385.48	4,145,170

Membership functions are constructed from the payoff table values following Equations (7) and (8) with numerical details presented below. The FMOLP model is then solved using the augmented max–min formulation implemented in LINGO. The model

comprises 17 decision variables (x_1 through x_{17}) and 2 utility variables (λ_1 and λ_2). The optimal compromise solution is presented in Table 8.

$$\mu_2(f_2(x)) = \begin{cases} 1 & , f_2(x) \leq 10348250 \\ \frac{14493420 - f_2(x)}{4145170} & , 10348250 \leq f_2(x) \leq 14493420 \\ 0 & , f_2(x) \geq 14493420 \end{cases}$$

$$\mu_1(f_1(x)) = \begin{cases} 1 & , f_1(x) \geq 36310.4 \\ \frac{f_1(x) - 25924.92}{10385.48} & , 25924.92 \leq f_1(x) \leq 36310.4 \\ 0 & , f_1(x) \leq 25924.92 \end{cases}$$

Table 8. Allocated relief suppliers for various counties/municipality.

County/Municipality	Allocated Quantity (x_i)
Keelung City (x_1)	257
Taipei City (x_2)	1301
New Taipei City (x_3)	2015
Taoyuan City (x_4)	1134
Hsinchu County (x_5)	400
Miaoli County (x_6)	380
Taichung City (x_7)	1975
Changhua County (x_8)	887
Nantou County (x_9)	344
Yunlin County (x_{10})	474
Chiayi County (x_{11})	350
Tainan City (x_{12})	1072
Kaohsiung City (x_{13})	1936
Pingtung County (x_{14})	406
Yilan County (x_{15})	227
Hualien County (x_{16})	227
Taitung County (x_{17})	108
λ_1 (Utility membership)	0.5126
λ_2 (Cost membership)	0.5126
f_1 (Total utility value)	31,249
f_2 (Total cost, NT\$)	12,368,565

The near-equal membership values for both objectives ($\lambda_1 \approx \lambda_2 \approx 0.5126$) indicate a well-balanced compromise solution that achieves approximately equal proportional attainment for utility maximization and cost minimization. Notably, high-risk counties such as Hsinchu ($x_5 = 400$) and Taichung ($x_7 = 1975$) receive allocations at or near their upper bounds, while lower-risk, smaller-population counties receive allocations closer to their lower bounds. This pattern confirms that the risk-weighted objective function successfully redirects supplies toward the most vulnerable regions, without entirely disregarding population size as a constraint.

5. Discussion

This section is organized into three parts. The first presents and discusses the findings of this study. The second elaborates on the managerial implications. The third conducts a sensitivity analysis

5.1. Results Analysis

The FIS analysis revealed a risk landscape that differs meaningfully from what any single-dimension ranking would suggest. Hsinchu County and Taichung City emerged as

the two highest-risk regions, yet neither ranked consistently at the top across all four individual dimensions. This divergence arises because the FIS captures nonlinear interactions among exposure, preparedness, readiness, and recovery; a region that performs moderately across all four dimensions may generate a higher aggregate risk score than one that is extreme on a single dimension but strong on others. This finding underscores a fundamental limitation of conventional single-criterion or simple composite ranking methods: they can misidentify the most at-risk communities and thereby misdirect preparedness investment. The practical implication is significant. Emergency planners who rely on population size or single-dimension indicators to prioritize interventions risk overlooking counties such as Hsinchu and Taichung, which combine relatively high exposure with preparedness deficiencies that amplify their overall vulnerability. The FIS framework makes these compound risks visible and quantifiable, providing a more reliable basis for resource prioritization than conventional approaches.

The FMOLP solution achieved near-identical membership degrees for both the utility maximization and cost minimization objectives ($\lambda \approx 0.5126$), indicating that the augmented max–min model has identified a genuinely balanced compromise rather than sacrificing one objective for the other. The total cost of NT\$12,368,565 represents approximately 85% of the maximum feasible cost under the upper-bound scenario, reflecting a meaningful reduction in expenditure relative to unconstrained maximum allocation, while the total utility value of 31,249 represents approximately 85% of the ideal utility, indicating minimal compromise in distributional effectiveness.

Regions with elevated risk values receive allocations at or close to their upper bounds. Specifically, Hsinchu County receives 400 units (its upper bound), and Taichung City receives 1975 units (its upper bound). In contrast, Taipei City (risk value 2.164) and Pingtung County (risk value 2.113) receive allocations at their lower bounds of 1301 and 406 units, respectively. This pattern reflects the model's risk-weighted objective: regions with higher social vulnerability receive proportionally more supplies relative to their registered population than lower-risk regions of similar or larger population size. This constitutes a more equitable and need-sensitive allocation policy than simple population-proportional distribution.

5.2. Managerial Implications

The results of this study carry concrete implications for government agencies responsible for disaster preparedness planning and emergency supply management. First, with respect to overall risk prioritization, emergency management authorities should direct enhanced preparedness investment and pre-positioned supply stockpiles toward the five highest-risk counties, namely Hsinchu, Taichung, Chiayi, Yunlin, and Hualien. These regions warrant priority attention in annual disaster preparedness reviews, budget allocations for mitigation infrastructure, and community training programs. Because the composite risk scores reflect interactions among all four vulnerability dimensions, interventions that simultaneously address preparedness deficiencies and readiness gaps are likely to yield greater risk reduction than isolated improvements on a single indicator.

Second, with respect to dimension-specific policy action, the FIS results enable decision-makers to identify which dimensions contribute most to vulnerability in each region. In the exposure dimension, Pingtung County, Tainan City, and Taitung County exhibited the weakest performance, suggesting the need to strengthen critical facility coverage in hazard-prone zones and to expand the population covered under debris flow and flood protection plans. In the disaster mitigation and preparedness dimension, Taichung City, and Hsinchu County showed the greatest room for improvement, particularly through seismic retrofitting programs, expanded debris flow drill coverage, and stricter enforcement of

hillside land-use regulations. In the readiness dimension, Yunlin County, Tainan City, and Pingtung County require investment in emergency response capacity, including increases in firefighting personnel per capita and improvements in medical service coverage. In the recovery dimension, Pingtung County, Tainan City, and Taichung City showed lower financial resilience and social support capacity; policy measures such as expanding earthquake insurance uptake, increasing social welfare expenditures, and improving local government fiscal health are recommended.

Third, with respect to supply allocation policy, the FMOLP model provides a practical and transparent reference for pre-disaster stockpiling decisions. The compromise solution is designed to balance procurement economy with distributional equity, and the nearly equal membership degrees for both objectives confirm that neither goal is unduly compromised. However, actual implementation should treat the model outputs as a planning baseline rather than a fixed prescription. When a disaster occurs, updated information on affected population counts, infrastructure damage, and current procurement prices should be used to recalibrate the model parameters before finalizing the allocation. The model architecture is sufficiently flexible to accommodate such updates with minimal computational cost.

Fourth, the sensitivity analysis comparing FIS-based allocations with risk function-based and dimension-based allocations reveals an important finding for policy design. The overall allocation trends are largely consistent across performance metrics, confirming the robustness of the proposed framework. The divergences that do appear are themselves informative: for Taipei City and Taichung City, risk function-based and dimension-based allocations deviated most from FIS-based allocations, highlighting that the preparedness dimension makes a distinctive contribution to the composite risk score for these two municipalities. This suggests that targeted improvement in disaster mitigation and preparedness infrastructure in Taipei and Taichung would not only reduce their composite risk ranking, but also bring the FIS allocation more closely into alignment with simpler resource distribution methods, potentially simplifying operational implementation.

5.3. Sensitivity Analysis

To assess the robustness of the proposed model, two sets of sensitivity analyses were conducted. In the first, the performance coefficient in the utility maximization objective was replaced with the IPCC risk function, which evaluates earthquake disaster risk using four composite risk factors (Table 9). In the second, each of the four individual vulnerability dimensions was used in turn as the sole performance criterion in place of the integrated FIS risk value.

In the first sensitivity analysis, the risk function-based and FIS-based allocation results diverged for only a limited number of counties, most notably Taipei City and Taichung City. This limited divergence suggests that the performance metrics capture broadly similar risk signals at the regional level, and that the FIS-based allocation is therefore unlikely to produce results that are structurally inconsistent with alternative risk frameworks. Although the differences among regions are relatively modest, the risk values obtained in this study are more representative, as they simultaneously incorporate all four principal dimensions of social vulnerability, thereby reflecting the preparedness and response capacity of each region in the event of a disaster. The overall robustness of the allocation pattern across different performance metrics enhances confidence in the practical applicability of the proposed model.

Table 9. Allocation distribution using various risk values.

Different Risk Values for Maximizing the Objective Function											
FIS (Risk Value)		IPCC Risk Value		Exposure		Mitigation & Preparedness		Readiness		Recovery	
Decision variable											
x_1	257	x_1	257	x_1	257	x_1	257	x_1	184	x_1	257
x_2	1301	x_2	1822	x_2	1822	x_2	1301	x_2	1301	x_2	1822
x_3	2015	x_3	2015	x_3	2015	x_3	2822	x_3	2822	x_3	2015
x_4	1134	x_4	1588	x_4	1473	x_4	1134	x_4	1588	x_4	1588
x_5	400	x_5	285	x_5	400	x_5	285	x_5	285	x_5	331
x_6	380	x_6	380	x_6	380	x_6	380	x_6	380	x_6	271
x_7	1975	x_7	1410	x_7	1975	x_7	1410	x_7	1975	x_7	1410
x_8	887	x_8	633	x_8	633	x_8	633	x_8	633	x_8	633
x_9	344	x_9	344	x_9	344	x_9	344	x_9	245	x_9	344
x_{10}	474	x_{10}	474	x_{10}	474	x_{10}	474	x_{10}	338	x_{10}	474
x_{11}	350	x_{11}	350	x_{11}	350	x_{11}	250	x_{11}	350	x_{11}	350
x_{12}	1072	x_{12}	937	x_{12}	937	x_{12}	1312	x_{12}	937	x_{12}	937
x_{13}	1936	x_{13}	1910	x_{13}	1383	x_{13}	1699	x_{13}	1471	x_{13}	1936
x_{14}	406	x_{14}	406	x_{14}	406	x_{14}	569	x_{14}	406	x_{14}	406
x_{15}	227	x_{15}	227	x_{15}	227	x_{15}	227	x_{15}	227	x_{15}	317
x_{16}	227	x_{16}	227	x_{16}	227	x_{16}	227	x_{16}	227	x_{16}	227
x_{17}	108	x_{17}	108	x_{17}	108	x_{17}	151	x_{17}	108	x_{17}	108
Membership											
λ_1	0.51257	λ_2	0.53914	λ_2	0.53074	λ_2	0.51659	λ_2	0.51614	λ_2	0.52742
λ_2	0.51261	λ_3	0.53896	λ_4	0.53053	λ_5	0.51653	λ_6	0.51637	λ_7	0.52756
Comprised solutions											
f_1	31,249	f_2	12,258,584	f_2	12,293,417	f_2	12,352,083	f_2	12,353,917	f_2	12,307,167
f_2	12,368,565	f_3	1,930,100	f_4	41,947	f_5	49,837	f_6	48,602	f_7	47,796

In the second sensitivity analysis, allocations derived from each individual dimension exhibited systematic divergence from the FIS-based benchmark. The exposure dimension yielded the largest discrepancies for Taipei City and Kaohsiung City, reflecting the contribution of the three remaining dimensions to their composite risk scores. Preparedness-based allocations diverged most for New Taipei City and Taichung City; readiness-based allocations diverged most for New Taipei City and Kaohsiung City; and recovery-based allocations diverged most for Taichung City and Taipei City. These results confirm that the FIS integration of all four dimensions produces a substantively different and more informative risk profile than any single-dimension approach. Regions that appear moderate or low-risk on individual dimensions may nonetheless rank as high-risk in the composite assessment, demonstrating the added value of the FIS framework for identifying hidden or compound vulnerabilities that would be missed by conventional single-criterion methods.

6. Conclusions

This study proposed and empirically validated an integrated decision support framework for disaster preparedness planning that combines an FIS with FMOLP. Applied to Taiwan's 17 counties and municipalities using data from the NCDR Disaster Mitigation Database, the framework yields three outputs of direct practical relevance: quantified social risk rankings for all administrative regions, an optimized relief supply allocation plan, and dimension-specific recommendations for targeted preparedness improvement.

Three principal contributions emerged from this work. The first is methodological. This study demonstrates, for the first time, the feasibility and effectiveness of integrating FIS-derived social risk values as weighting coefficients in an FMOLP relief allocation model.

The two-stage pipeline, risk assessment followed by risk-weighted optimization, ensures that supply distribution reflects the true urgency of need across regions rather than population size alone. The adoption of the augmented max–min formulation guarantees a non-dominated compromise solution, overcoming the theoretical limitations of conventional weighted additive and preemptive priority approaches. The second contribution is empirical. The study produces the first comprehensive FIS-based social risk profile of all 17 Taiwanese counties and municipalities using the government’s official Disaster Mitigation Database, identifying Hsinchu County, Taichung City, Chiayi County, Yunlin County, and Hualien County as the five highest-risk regions. Critically, these rankings reflect nonlinear interactions among the four vulnerability dimensions and cannot be replicated by ranking on any single indicator, underscoring the need for integrative risk assessment methods in policy applications. The third contribution is practical. The dimension-specific sensitivity analysis provides disaster managers with actionable, region-targeted recommendations for preparedness improvement. By identifying which dimensions contribute most to vulnerability in each county, the analysis enables prioritized, cost-effective policy interventions rather than broad, undifferentiated spending. The FMOLP model itself constitutes a replicable, updatable decision support tool that can be recalibrated with current data as conditions change.

Several directions offer opportunities to extend this study. First, each of the four vulnerability dimensions could be disaggregated into constituent sub-indicators treated as separate FIS inputs, yielding more granular risk profiles, though at the cost of an expanded rule base that may necessitate automated rule induction methods such as neuro-fuzzy systems. Second, the spatial unit of analysis could be shifted from county to township level, better capturing intra-county heterogeneity and supporting sub-regional supply pre-positioning decisions. Third, the FMOLP model could incorporate additional objectives, such as minimizing delivery time or maximizing geographic coverage equity, more faithfully representing the multi-criteria trade-offs inherent in real-world disaster logistics. Fourth, the framework could be extended to accommodate temporal dynamics, given that social vulnerability evolves with demographic change, infrastructure investment, and policy reform; a dynamic FIS model updated on a regular basis would provide a more accurate planning reference for government agencies. Finally, application of the integrated framework to other natural hazard contexts and geographic settings, particularly elsewhere in seismically and meteorologically active Asia, would test the generalizability of the proposed approach and contribute to the development of internationally transferable tools for vulnerability-based disaster preparedness planning.

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