A Simulation-Driven Decision Support System Using Fuzzy Inference and Greedy Algorithm for Humanitarian Logistics in Disaster Response

Maria Loura Christhia[1*], Ahmad Ardi Wahidurrijal[1], Abimanyu Bagarela Anjaya Putra[2]
[1]Industrial Engineering Department, BINUS Online Learning, Bina Nusantara University, Jakarta, Indonesia 11480
[2]Computer Science Department, BINUS Online Learning, Bina Nusantara University, Jakarta, Indonesia 11480
Email: [1*]maria.loura@binus.ac.id, [1]ahmad.wahidurrijal@binus.ac.id, [2]abimanyu.putra@binus.ac.id

***Abstract*—This document is a model and instructions for LaTeX. This and the IEEEtran.cls file define the components of your paper [title, text, heads, etc.]. *CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Natural disasters are among the most persistent threats to human life and infrastructure worldwide. Globally, climate-related disasters accounted for 91% of the 7,255 major recorded events between 1998 and 2017, with floods (43.4%) and storms (28.2%) being the most frequent types [1].

Indonesia is particularly vulnerable due to its unique geological location at the convergence of three major tectonic plates, making it prone to both geophysical and climate-induced disasters, including earthquakes, volcanic eruptions, floods, and tsunamis [2]. Historically, the Indonesian archipelago has played a central role in the narrative of global natural disasters. Traditional records from Java and Bali, dating back to the eighth century, provide rich documentation of disaster occurrences across centuries [3].

Among the various types of disasters, floods remain the most frequent and disruptive hazard in Indonesia, especially in urban centers such as Jakarta [4]. Based on Table I, the occurrence of natural disasters in Indonesia is still predominantly caused by floods. Therefore, the ability to respond rapidly to such disasters is critical, as it can significantly impact the well-being of affected populations.

TABLE I
Number of Disaster Events by Type in Indonesia (2025)

Disaster Type	Number of Events
Earthquake	11
Volcanic Eruption	4
Flood	1,137
Extreme Weather	402
Forest and Land Fires	306
Landslide	163
Tidal Wave and Abrasion	10
Drought	10

Source: https://gis.bnpb.go.id/arcgis/apps/sites/#/public/pages/bencana-besar-tahun-2025.

Despite their recurring nature, flood mitigation capacity in Indonesia remains limited, highlighting the urgent need for comprehensive and strategic improvements in disaster preparedness and response [5].

In disaster response operations, the efficiency of logistics and supply chain systems is a critical determinant of how quickly and effectively aid reaches affected populations. However, Indonesia's current disaster logistics systems are hindered by systemic issues, such as the lack of integrated control mechanisms and insufficient coordination among stakeholders [6]. These weaknesses often result in delayed response times, misallocation of resources, and reduced service coverage in disaster-stricken areas. Figure 1 illustrates the distribution of impacts caused by flood disaster events in Indonesia from 2010 to 2025, highlighting flood-related damage as the most frequent and significant consequence. This underscores the urgent need for effective decision support systems to enhance the responsiveness and efficiency of humanitarian logistics in disaster response scenarios.

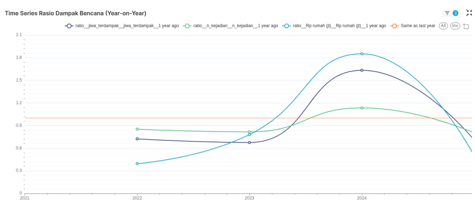

Fig. 1. Impact caused by floods in Indonesia (mio IDR)
Source: https://dibi.bnpb.go.id

Moreover, research on risk management within emergency supply chains remains scarce. Many existing studies lack the practical and integrated methodologies needed to support real-time decision-making under conditions of uncertainty [7]. This gap underscores the necessity for intelligent decision support tools capable of managing disruptions in complex humanitarian logistics environments.

One such emerging approach is the development of resilient supply chains, defined as systems that can recover and return to normal operations within an acceptable timeframe following a disruption [8]. Building this resilience requires not only robust planning but also adaptive, intelligent frameworks that can prioritize needs dynamically and optimize resource allocation in real time.

This study addresses these challenges by proposing a simulation-based Decision Support System (DSS) that integrates fuzzy inference and a greedy algorithm to provide a rapid, adaptive response mechanism during natural disasters. The system is designed to improve the responsiveness and efficiency of humanitarian supply chains through real-time prioritization and resource allocation. To support this, the simulation utilizes data from the Indonesian National Statistics Agency (BPS) and historical disaster records from the National Disaster Management Authority (BNPB) to identify high-risk regions and evaluate logistical response scenarios.

II. Literature Review

Decision Support Systems (DSS) have become increasingly important in disaster management, providing tools for effective decision-making under uncertainty [9]. These systems integrate data analysis, modeling, and simulation to support emergency response [10]. The use of DSS in disaster management has been shown to enhance situational awareness, improve coordination among stakeholders, and optimize logistics operations [11]. For instance, Peron et al. (2022) demonstrated the effectiveness of a DSS in workforce management [12]. During disaster response, highlighting the importance of integrating demographic data and historical disaster records to inform decision-making [13].

Simulation-based approaches are widely used in disaster management to evaluate the performance of DSS and assess various scenarios without the need for real-world implementation [14]. These approaches allow for the modeling of complex systems and the assessment of different disaster scenarios, enabling decision-makers to identify the most affected regions and the number of victims. For example, Lobkov et al. (2023) utilized simulation techniques to estimate the impact of disasters on affected populations, demonstrating the importance of accurate data collection and processing in disaster response planning [15].

Fuzzy Inference Systems (FIS) are employed to assess the severity and urgency of disasters, providing a flexible framework for decision-making under uncertainty [16]. Understanding fuzzy logic is crucial for developing effective DSS, as it allows for the incorporation of expert knowledge and subjective assessments, enabling the system to handle imprecise and ambiguous data effectively [17].

Crisp input values are converted into fuzzy values using membership functions. A trapezoidal membership function is defined as:

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x < b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c < x < d \\ 0, & x \geq d \end{cases}$$

The fuzzy inference uses logical operators such as *AND* and *OR*. For example, for the **AND** operator (min function):

$$\mu_{\text{Rule}} = \min\left(\mu_{\text{Health}}(x), \mu_{\text{Age}}(y), \mu_{\text{Risk}}(z)\right)$$

If multiple rules produce output sets, they are combined using the max operator:

$$\mu_{\text{Output}}(z) = \max\left(\mu_{\text{Rule}_1}(z), \mu_{\text{Rule}_2}(z), .., \mu_{\text{Rule}_n}(z)\right)$$

To obtain a crisp output, the Centroid (Center of Gravity) method is commonly used:

$$z^* = \frac{\int z \cdot \mu(z)\, dz}{\int \mu(z)\, dz}$$

Where:

- z^* is the defuzzified output (e.g., prioritization score),
- $\mu(z)$ is the aggregated membership function of the output.

Fuzzy logic allows for the incorporation of expert knowledge and subjective assessments, enabling the system to handle imprecise and ambiguous data effectively [18]. The use of fuzzy rules to determine the relationship between independent and dependent variables has been shown to enhance the accuracy of disaster impact assessments [19].

III. Methodology

A. Data Simulation

Many studies involves a simulation-based approach to evaluate the performance of a Decision Support System (DSS) [20]. This approach allows for the modeling of complex systems and the assessment of various scenarios without the need for real-world implementation [21]. This study collects and processes data from the Indonesian National Statistics Agency (BPS) and the National Disaster Management Authority (BNPB) to simulate disaster scenarios. Determining the most affected regions and the number of victims is crucial for effective disaster response planning [22]. The simulation framework incorporates demographic data, historical disaster records, and geographical information [23]. Determining the most affected regions and the number of victims is shown in Figure 2.

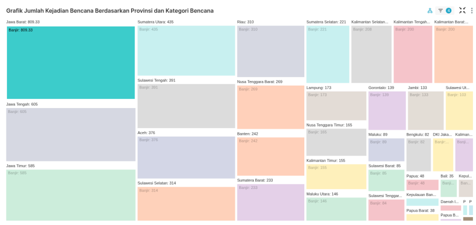

Fig. 2. Most Affected Regions in 2021 - 2025
Source: https://dibi.bnpb.go.id

Based on heatmap the west Java region is the most occurrences based on floods natural disaster, then districs of Bogor, Bandung, and Bekasi are the most affected areas, can be shwon in Figure 3.

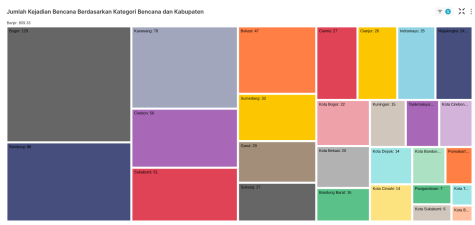

Fig. 3. Heatmap of Floods in West Java in 2021 - 2025
Source: https://dibi.bnpb.go.id

Making sure that the simulation accurately reflects the real-world conditions faced during disaster response operations. Spatial analysis hydrological data is also integrated to assess the impact of floods [24]. Result of analysis is shown in table II.

TABLE II
RUNOFF FLOODING POTENTIAL BY SUB-DISTRICT IN BOGOR REGION

Sub-district	**Flood Potential**
Nanggung	Extreme
Sukamakmur	Extreme
Tanjungsari	Extreme
Megamendung	Extreme
Babakanmadang	Extreme
Cigudeg	High
Pamijahan	High
Sukajaya	High
Jasinga	Low/Normal
Rumpin	Low/Normal
Tenjo Panjang	Low/Normal

Source: Adapted from [24].

Based on the analysis, the simulation will be taken on sub districs are identified as having extreme ,high, and normal flood potential. This information is used in simulation after adding demographic data from BPS, which includes population density and socio-economic indicators. The simulation framework is designed to model the logistics and supply chain operations during disaster response, focusing on the allocation of resources and routing of aid based on the severity and urgency of the situation [25]. Warehouse locations is based on the proximity to affected areas, ensuring that resources can be deployed quickly and efficiently [26].

B. Fuzzy Inference System (FIS) and Greedy Algorithm

The Fuzzy Inference System (FIS) is employed to assess the severity and urgency of disasters, providing a flexible framework for decision-making under uncertainty [27]. According Berawi et al. following Fuzzy rules are generated :

- IF Healthy Level is **Sick**, AND Age is **Adult** or **Kid**, AND Risk Level is **High** or **Moderate**, THEN the victim is **Prioritized**.
- IF Healthy Level is **Sick**, AND Age is **Adult** or **Kid**, AND Risk Level is **Low**, THEN the victim is **Prioritized**.
- IF Healthy Level is **Sick**, AND Age is **Elder**, AND Distance is **Far** or **Nearby**, THEN the victim is **Prioritized**.
- IF Healthy Level is **Sick**, AND Age is **Elder**, AND Distance is **Moderate**, THEN the victim is **Prioritized**.
- IF Healthy Level is **Healthy** or **Okay**, AND Age is **Elder** or **Kid**, AND Risk Level is **Moderate**, THEN the victim is **not Prioritized**.
- IF Healthy Level is **Healthy** or **Okay**, AND Age is **Elder** or **Kid**, AND Risk Level is **High**, THEN the victim is **not Prioritized**.
- IF Healthy Level is **Healthy** or **Okay**, AND Age is **Adult**, THEN the victim is **not Prioritized**.

Fuzzy logic allows for the incorporation of expert knowledge and subjective assessments, enabling the system to handle imprecise and ambiguous data effectively [18]. The model is highly flexible and can be adjusted according to the actual conditions of the damaged area. In the development of the membership function, contextual parameters must be carefully defined based on observed field data [28]. fuzzy rules were made to determine the relationship between independent and dependent variables [19]. The rules are defined based on expert knowledge and historical data, allowing the system to evaluate the impact of disasters on affected regions [29]. This study use SPHERE handbook as a reference for the fuzzy rules, which are designed to prioritize disaster impact zones based on severity, urgency, and accessibility [30]. Table III is dependent variables from SPHERE handbook.

TABLE III
POTENTIAL DEPENDENT VARIABLES ALIGNED WITH THE SPHERE HANDBOOK PRINCIPLES

Dependent Variable	**Description**	**Relevance to Sphere Handbook**
Response Time	Time required to deliver aid to affected populations (e.g., hours)	Timeliness and accessibility of humanitarian assistance
Coverage of Affected Population	Proportion (%) of disaster victims who receive aid	Non-discrimination, equity, and universal access
Logistics Efficiency	Efficiency in terms of cost, distance, or load (e.g., ton/km or cost per beneficiary)	Effective resource utilization and accountability
Unmet Needs Score	Index measuring the gap in critical needs (e.g., shelter, food, WASH)	Fulfillment of minimum humanitarian standards
Protection or Satisfaction Index	Victim-reported perception of safety, dignity, and fairness (via surveys or scoring)	Protection, dignity, and community engagement

After rules are defined, the FIS is implemented using the Mamdani method, which is suitable for handling complex and non-linear relationships in disaster scenarios [31]. Greedy algorithm is used to optimize resource allocation and routing based on the priority indices generated by the FIS [32]. The greedy algorithm is chosen for its efficiency in finding near-optimal solutions in complex logistics problems, particularly in dynamic environments where rapid decision-making is crucial [33]. The combination of FIS and greedy algorithm allows for a robust decision support system that can adapt to changing conditions and prioritize resources effectively during disaster response operations.

C. Research Framework

This study adopts a simulation-based quantitative approach to evaluate the performance of an intelligent decision support system (DSS) in the context of humanitarian logistics for disaster response. The framework consists of three major components: data driven acquisition, DSS algorithms, and simulation-based evaluation [34]. Figure 4 illustrates the research framework, which integrates data acquisition, fuzzy inference, greedy algorithm, and simulation to assess the effectiveness of the proposed DSS in disaster response scenarios.

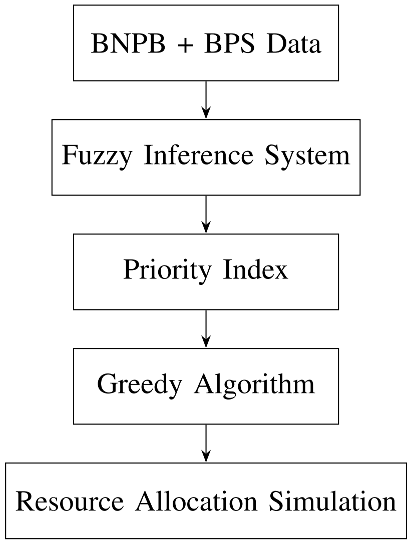

Fig. 4. Research Framework Flow: From Data to Simulation Output

The system receives input data from two key sources: the Indonesian National Statistics Agency (BPS), which provides demographic and regional data, and the National Disaster Management Authority (BNPB), which offers historical records of disaster occurrences. This data is processed and transformed into relevant indicators such as disaster severity, urgency, accessibility, and population density.

These indicators serve as inputs to a Fuzzy Inference System (FIS), which generates a priority index for each affected region. The FIS captures the uncertainty and complexity inherent in disaster impact assessment through a rule-based system of fuzzy logic. The resulting priority scores are then passed to a greedy algorithm that rapidly determines the optimal routing or allocation of resources based on proximity and urgency.

The entire process is simulated using various disaster scenarios to assess system performance in terms of response time, supply coverage, and the number of affected individuals reached. This research framework allows for comprehensive evaluation of the hybrid DSS under dynamic, high-stakes conditions, providing insights into its practical applicability for emergency logistics operations.

IV. Results and Discussion

Fuzzy Rule Mapping by Sub-district with Demographic Context

This section outlines the fuzzy rule construction for prioritizing disaster victims in each selected sub-district based on BPS and BNPB data, incorporating demographic indicators and rules derived from the SPHERE Handbook.

Fuzzy Rule Base:

- IF Healthy Level is Sick, AND Age is Adult or Kid, AND Risk Level is High or Moderate, THEN the victim is Prioritized.
- IF Healthy Level is Sick, AND Age is Adult or Kid, AND Risk Level is Low, THEN the victim is Prioritized.
- IF Healthy Level is Sick, AND Age is Elder, AND Distance is Far or Nearby, THEN the victim is Prioritized.
- IF Healthy Level is Sick, AND Age is Elder, AND Distance is Moderate, THEN the victim is Prioritized.
- IF Healthy Level is Healthy or Okay, AND Age is Elder or Kid, AND Risk Level is Moderate, THEN the victim is not Prioritized.
- IF Healthy Level is Healthy or Okay, AND Age is Elder or Kid, AND Risk Level is High, THEN the victim is not Prioritized.
- IF Healthy Level is Healthy or Okay, AND Age is Adult, THEN the victim is not Prioritized.

A. Babakanmadang

- Total Population: 104,302
- Number of Households: 28,730
- Health Facilities: Moderate
- Demographic: Moderate density across 9 villages
- Risk: High (flood-prone)
- Distance to Capital: Moderate
- **Estimated Needs:** High shelter and health services demand (based on population size)
- **Fuzzy Output: Prioritized**

B. Cigudeg

- Total Population: [data not directly available — estimate based on similar districts: medium-sized population]
- Health Facilities: Low
- Demographic: Sparsely distributed rural settlements
- Risk: Extreme (runoff flood-prone)
- Distance to Capital: Far
- **Estimated Needs:** High logistics support for remote access and health
- **Fuzzy Output: Prioritized**

C. Jasinga

- Total Population: 112,356
- Population Density: 898 people/km^2
- Health Facilities: Moderate
- Risk: Low
- Distance to Capital: Near to Far (1–9 km)
- **Estimated Needs:** Moderate; capacity available but still needs for nutrition and water
- **Fuzzy Output: Not Prioritized**

D. Megamendung

- Total Population: 113,756
- Health Facilities: Moderate
- Demographic: Mix of very high (Sukamahi 5022/km^2) to low (Megamendung 646/km^2) density
- Risk: Extreme (runoff flood-prone)
- Distance to Capital: Moderate
- **Estimated Needs:** High shelter demand in dense villages, moderate logistics need
- **Fuzzy Output: Prioritized**

E. Nanggung

- Total Population: [Data inferred as moderate based on infrastructure]

- Health Facilities: Limited
- Demographic: Remote, mountainous, low accessibility
- Risk: Extreme (landslide + flood)
- Distance to Capital: Moderate
- **Estimated Needs:** High for shelter, transport, medical aid due to terrain
- **Fuzzy Output: Prioritized**

F. Pamijahan

- Total Population: [Data inferred as moderate-high from BPS]
- Health Facilities: Moderate
- Demographic: Hilly areas, diverse households
- Risk: High (landslide and flood-prone)
- Distance: Moderate
- **Estimated Needs:** Moderate to high, especially in early response logistics
- **Fuzzy Output: Prioritized**

G. Rumpin

- Total Population: [Not yet extracted; assumed rural population]
- Health Facilities: Limited
- Demographic: Scattered rural infrastructure
- Risk: Low
- Distance to Capital: Moderate
- **Estimated Needs:** Low to moderate; needs focused on health and early warning
- **Fuzzy Output: Not Prioritized**

H. Tanjungsari

- Total Population: [Needs verification — estimated small to medium population]
- Health Facilities: Limited
- Demographic: Rural runoff-prone slopes
- Risk: Extreme
- Distance to Capital: Far
- **Estimated Needs:** High for shelter and emergency transport
- **Fuzzy Output: Prioritized**

Simulation Warehouse Location and Routing Prioritization

In this simulation, a central logistics warehouse is assumed to be located at the following coordinates:

- Latitude: -6.4845775
- Longitude: 106.8383947

This point represents a strategic position in West Bogor that is relatively accessible to multiple sub-districts.

Based on this location, we calculate the geographic distance between the warehouse and each targeted sub-district using the haversine distance formula. Combined with fuzzy prioritization results and Sphere-based need estimation, a greedy algorithm is applied to sequence the response priorities. Loaction can be seen in Figure 5.

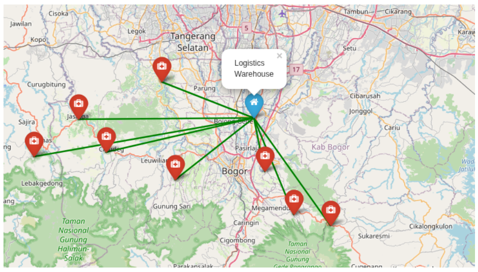

Fig. 5. Logistics Warehouse Location in West Bogor
Source: Google Maps

The greedy algorithm ranks each district by combining its fuzzy-based priority and its proximity to the warehouse. The goal is to maximize the total aid coverage to high-priority areas in the shortest possible time. Table IV summarizes the routing prioritization based on the calculated distances and fuzzy priority scores.

TABLE IV
GREEDY-BASED ROUTING PRIORITIZATION FROM LOGISTICS WAREHOUSE

District	**Distance (km)**	**Fuzzy Priority**	**Greedy Score**
Babakanmadang	12.82	High (2)	187.18
Pamijahan	23.63	High (2)	176.37
Megamendung	24.46	High (2)	175.54
Tanjungsari	30.94	High (2)	169.06
Nanggung	35.70	High (2)	164.30
Cigudeg	41.30	High (2)	158.70
Rumpin	23.33	Low (1)	76.67
Jasinga	52.62	Low (1)	47.38

This prioritization serves as the basis for route planning in emergency logistics response. Higher Greedy Scores indicate districts that are both critical and logistically efficient to respond to first. The districts with the highest greedy scores are prioritized earlier in the schedule to ensure timely aid distribution to the most critical and accessible areas.

Table V presents the final distribution schedule based on the greedy prioritization results. The schedule is designed to optimize resource allocation and ensure that aid reaches the most affected populations in a timely manner.

TABLE V
SIMULATED LOGISTICS DISTRIBUTION SCHEDULE

Day	**Target Districts**	**Distribution Justification**
Day 1	Babakanmadang, Pamijahan, Megamendung	High priority + close proximity
Day 2	Tanjungsari, Nanggung, Cigudeg	High priority + moderate distance
Day 3	Rumpin, Jasinga	Lower priority + longest distance

This schedule reflects an adaptive logistics strategy where the most at-risk and reachable regions receive assistance immediately, while less critical or more distant areas are queued for subsequent dispatches. The simulation supports planners in maximizing resource effectiveness under constrained conditions.

V. CONCLUSION

This study presents a simulation-driven Decision Support System (DSS) that integrates fuzzy inference and a greedy algorithm to enhance humanitarian logistics in disaster response. The system effectively prioritizes disaster-affected regions based on demographic data and historical disaster records, enabling rapid and adaptive resource allocation. The simulation framework utilizes data from the Indonesian National Statistics Agency (BPS) and the National Disaster Management Authority (BNPB) to model disaster scenarios and assess logistical response strategies. The fuzzy inference system captures the uncertainty and complexity of disaster impact assessment, while the greedy algorithm optimizes resource allocation based on priority indices generated by the FIS. The results demonstrate the system's potential to improve the responsiveness and efficiency of humanitarian supply chains, particularly in high-stakes disaster scenarios. By providing a robust decision support tool, this research contributes to the development of intelligent logistics systems that can adapt to dynamic conditions and prioritize resources effectively during disaster response operations. Future work will focus on further refining the fuzzy rules and expanding the simulation framework to include additional variables such as real-time data feeds and advanced routing algorithms. This will enhance the system's capabilities and applicability in diverse disaster response contexts.

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