Fuzzy-Greedy Simulation-Based DSS for Humanitarian Logistics in Disaster Response

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Abstract—**Floods are among the most frequent and destructive natural disasters in Indonesia, posing significant challenges to humanitarian logistics and emergency response. This study presents a simulation-driven Decision Support System (DSS) that integrates fuzzy inference and a greedy algorithm to improve disaster response effectiveness. The proposed DSS prioritizes affected districts based on demographic conditions, risk exposure, and health infrastructure, aligning with Sphere Handbook principles.**

The methodology involves generating fuzzy-based priority scores for each sub-district using health, age, risk, and accessibility variables. A greedy scoring function is then applied to optimize logistics routes from a centralized warehouse based on urgency and travel distance. The simulation covers ten flood-prone districts in Bogor Regency, incorporating data from the Indonesian National Statistics Agency (BPS) and the National Disaster Management Authority (BNPB).

Results demonstrate the DSS's ability to generate a five-day distribution schedule that balances proximity and urgency, ensuring that high-risk, high-need districts receive timely aid. The framework enables scalable and adaptive decision-making under uncertainty, offering a practical solution to improve logistics responsiveness in Indonesian flood disasters.

Index Terms—**Disaster response, decision support system, fuzzy logic, greedy algorithm, humanitarian logistics.**

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 these disaster types, floods stand out as the most frequent, damaging, and recurrent events in Indonesia [4]. They pose a significant threat to both urban and rural communities and are consistently the leading cause of natural disaster events and losses [5]. Floods remain the central focus of this study due to their overwhelming frequency and wide-reaching impact. In urban centers like Jakarta, floods regularly disrupt transportation, damage infrastructure, and threaten livelihoods [6].

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 [7].

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 [8]. 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 [9]. 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.

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 [10]. This gap underscores the necessity for intelligent decision support tools capable of managing disruptions in complex humanitarian logistics environments.

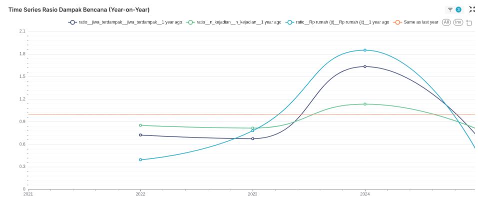

Fig. 1. Impact caused by floods in Indonesia (mio IDR)

Source: https://dibi.bnpb.go.id

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 [11]. 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 [12].

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 specifically with flood response scenarios in mind, aiming 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

A. Decision Support Systems (DSS) in Disaster Management

Decision Support Systems (DSS) play a crucial role in disaster management by supporting data-driven decisions under uncertainty [13]. These systems integrate real-time information, simulation models, and analytical tools to guide emergency response actions [14]. DSS have been shown to improve situational awareness, stakeholder coordination, and response time [15]. For example, Peron et al. (2022) demonstrated how a DSS improved workforce management, highlighting its utility in coordinating limited human resources during crises [16]. Furthermore, Suarez et al. (2024) emphasized the importance of incorporating demographic data and historical records to enhance system responsiveness [17].

B. Simulation in Humanitarian Logistics

Simulation-based methods have been widely adopted in logistics and disaster management research due to their ability to model complex, dynamic systems without the risk and cost of real-world deployment [18]. These models can forecast affected regions, estimate victim counts, and test operational strategies before implementation. Lobkov et al. (2023) used simulation to predict population-level impact zones, emphasizing the need for precise data preprocessing [19].

C. Fuzzy Inference Systems for Disaster Prioritization

Fuzzy Inference Systems (FIS) provide a robust framework for reasoning in situations involving uncertainty and ambiguity. In disaster contexts, fuzzy systems help prioritize victims and areas based on partially known data such as health status, risk levels, and location [20]. FIS supports flexible and adaptive logic that mirrors human reasoning, allowing for better interpretation of uncertain field conditions [21].

Fuzzy logic allows the translation of expert judgment into computational rules. Crisp inputs are fuzzified using membership functions such as the trapezoidal function:

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

Rules are evaluated using logical operators like *min* for AND and *max* for aggregation:

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

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

Crisp outputs are obtained using defuzzification techniques like the centroid method:

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

D. Greedy Algorithms for Disaster Logistics Optimization

Greedy algorithms offer computational efficiency by selecting the locally optimal choice at each step with the aim of finding a global optimum. In logistics, they are used for route optimization, resource allocation, and task scheduling, especially under real-time constraints [22].

According Zhao et al. basic greedy algorithm for routing logistics aid can be formulated as follows [23]:

Initialize list of affected districts $D = \{d_1, d_2, ..., d_n\}$
Let $P(d_i)$ be the priority score (based on fuzzy output)
Let $Dist(d_i)$ be the distance from the warehouse to district d_i
Compute Greedy Score $G(d_i) = \alpha \cdot P(d_i) - \beta \cdot Dist(d_i)$
Sort D by $G(d_i)$ in descending order
for each d_i in sorted D **do**
  Dispatch logistics to d_i (if resources available)
  Update resource and capacity
end for

Where:

- α and β are weight coefficients for priority and distance
- $P(d_i)$ reflects urgency and need (e.g., fuzzy score: 0 to 2)
- $Dist(d_i)$ is the geographical distance from logistics center

E. State of Art

Despite the advancements in DSS, simulation, fuzzy logic, and greedy algorithms, several gaps remain in the current literature that this study aims to address:

- **DSS Limitations:** Many systems focus on strategic or macro-level planning, with limited capability for real-time, field-level decision-making. There is also a lack of integration with community-specific vulnerability indicators [24].
- **Simulation Constraints:** Existing simulation studies often overlook last-mile logistics and demographic variability, limiting their usefulness for granular, operational decisions [25].
- **FIS Application Gaps:** While fuzzy systems are widely accepted for classification tasks, they are rarely embedded into real-time logistics pipelines. There's minimal exploration of how fuzzy rules based on humanitarian principles can shape logistical resource allocation [20], [21], [26], [27].
- **Greedy Algorithm Narrow Use:** Most greedy algorithms are used for cost or distance minimization alone, neglecting contextual factors such as population vulnerability, urgency, or fairness in resource allocation [28], [29].

By addressing these gaps, this study proposes an integrated fuzzy-greedy simulation-based DSS tailored for prioritizing victims and optimizing humanitarian logistics in Indonesian disaster scenarios.

III. Methodology

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 [30]. Figure 2 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.

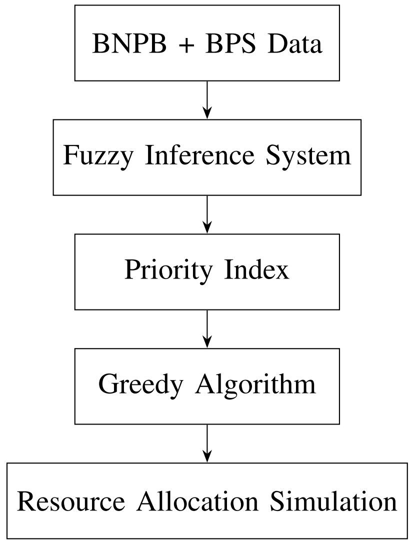

Fig. 2. Research Framework Flow: From Data to Simulation Output

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

A. Data Simulation

Many studies involves a simulation-based approach to evaluate the performance of a Decision Support System (DSS) [31]. This approach allows for the modeling of complex systems and the assessment of various scenarios without the need for real-world implementation [32]. 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 [33]. The simulation framework incorporates demographic data, historical disaster records, and geographical information [34]. Determining the most affected regions and the number of victims is shown in Figure 3.

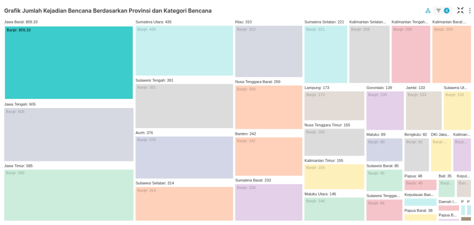

Fig. 3. Most Affected Regions in 2021 - 2025
Source: https://dibi.bnpb.go.id

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 4.

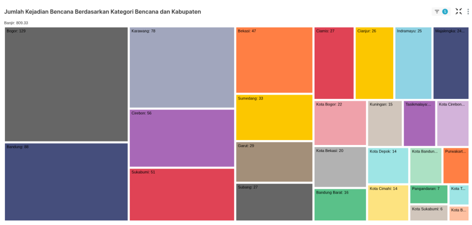

Fig. 4. Heatmap of Floods in West Java in 2021 - 2025
Source: https://dibi.bnpb.go.id

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 [35]. 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 [35].

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 [36]. Warehouse locations is based on the proximity to affected areas, ensuring that resources can be deployed quickly and efficiently [37].

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 [38]. 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 [26]. 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 [39]. fuzzy rules were made to determine the relationship between independent and dependent variables [27]. The rules are defined based on expert knowledge and historical data, allowing the system to evaluate the impact of disasters on affected regions [40]. 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 [41]. 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 [42]. Greedy algorithm is used to optimize resource allocation and routing based on the priority indices generated by the FIS [28]. 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 [29]. 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.

Babakanmadang

- Total Population: 104,302

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

Cigudeg

- Total Population: 122,112
- Health Facilities: Low
- Demographic: Sparsely distributed rural settlements
- Risk: Extreme (runoff flood-prone)
- **Estimated Needs:** High logistics support for remote access and health
- **Fuzzy Output: Prioritized**

Jasinga

- Total Population: 112,356
- Population Density: 898 people/km^2
- Health Facilities: Moderate
- Risk: Low
- **Estimated Needs:** Moderate; capacity available but still needs for nutrition and water
- **Fuzzy Output: Not Prioritized**

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)
- **Estimated Needs:** High shelter demand in dense villages, moderate logistics need
- **Fuzzy Output: Prioritized**

Nanggung

- Total Population: 86,773
- Health Facilities: Limited
- Demographic: Remote, mountainous, low accessibility
- Risk: Extreme (landslide + flood)
- **Estimated Needs:** High for shelter, transport, medical aid due to terrain
- **Fuzzy Output: Prioritized**

Pamijahan

- Total Population: 135,738
- Health Facilities: Moderate
- Demographic: Hilly areas, diverse households
- Risk: High (landslide and flood-prone)
- **Estimated Needs:** Moderate to high, especially in early response logistics
- **Fuzzy Output: Prioritized**

Rumpin

- Total Population: 154,462
- Health Facilities: Limited
- Demographic: Scattered rural infrastructure
- Risk: Low
- **Estimated Needs:** Low to moderate; needs focused on health and early warning
- **Fuzzy Output: Not Prioritized**

Tanjungsari

- Total Population: 88,076
- Health Facilities: Limited
- Demographic: Rural runoff-prone slopes
- Risk: Extreme
- **Estimated Needs:** High for shelter and emergency transport
- **Fuzzy Output: Prioritized**

Sukajaya

- Total Population: 113,762
- Health Facilities: Low
- Demographic: Mountainous terrain, difficult road access
- Risk: High (landslide-prone)
- **Estimated Needs:** High need for emergency transport and health kits
- **Fuzzy Output: Prioritized**

Sukamakmur

- Total Population: 76,328
- Health Facilities: Limited
- Demographic: Semi-rural, several scattered settlements
- Risk: High (landslide and flood-prone)
- **Estimated Needs:** Moderate to high; focus on mobility, shelter, and water
- **Fuzzy Output: Prioritized**

Tenjo

- Total Population: 93,630
- Health Facilities: Low
- Demographic: Mostly rural with some peri-urban expansion
- Risk: Moderate
- **Estimated Needs:** Moderate; essential needs support, low mobility access
- **Fuzzy Output: Not Prioritized**

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.

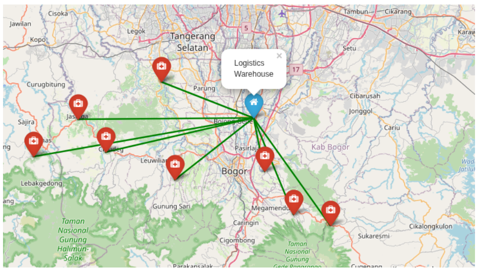

Fig. 5. Logistics Warehouse Location in West Bogor
Source: Google Maps

To prioritize routing from the central logistics warehouse, a greedy scoring function was used. The goal is to prioritize districts with both high urgency (fuzzy priority) and short distance from the warehouse.

The greedy score G_i is defined as:

$$G_i = \alpha \cdot P_i - \beta \cdot D_i \tag{1}$$

where:

- G_i: Greedy score for district i
- P_i: Fuzzy priority score (High = 2, Low = 1)
- D_i: Distance from the warehouse to the district in kilometers
- $\alpha = 100$: Weight for priority
- $\beta = 1$: Weight for distance penalty

Calculations:

- Babakanmadang: $G = 100 \cdot 2 - 12.82 = 187.18$
- Pamijahan: $G = 100 \cdot 2 - 23.63 = 176.37$
- Megamendung: $G = 100 \cdot 2 - 24.46 = 175.54$
- Tanjungsari: $G = 100 \cdot 2 - 30.94 = 169.06$
- Nanggung: $G = 100 \cdot 2 - 35.70 = 164.30$
- Cigudeg: $G = 100 \cdot 2 - 41.30 = 158.70$
- Rumpin: $G = 100 \cdot 1 - 23.33 = 76.67$
- Jasinga: $G = 100 \cdot 1 - 52.62 = 47.38$

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	Highest priority + closest distance
Day 2	Megamendung, Tanjungsari	High priority + moderate distance
Day 3	Nanggung	High priority + longer travel distance
Day 4	Cigudeg	High priority but farthest among high group
Day 5	Rumpin, Jasinga	Low priority districts; 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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