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

1st Maria Loura Christhia
Industrial Engineering Dept.
BINUS Online Learning, Bina Nusantara University
Jakarta, Indonesia
maria.loura@binus.ac.id

2nd Ahmad Ardi Wahidurrijal
Industrial Engineering Dept.
BINUS Online Learning, Bina Nusantara University
Jakarta, Indonesia
ahmad.wahidurrijal@binus.ac.id

3rd Abimanyu Bagarela Anjaya Putra
Computer Science Dept.
BINUS Online Learning, Bina Nusantara University
Jakarta, Indonesia
abimanyu.putra@binus.ac.id

4th Mariana Syamsoeyadi
Graduate Program in Industrial Engineering
Bina Nusantara University
Jakarta, Indonesia
mariana.syamsoeyadi@binus.ac.id

***Abstract*—Floods are among the most common and damaging natural disasters in Indonesia, creating major challenges for emergency response and humanitarian logistics. This study develops a simulation-based Decision Support System (DSS) that combines fuzzy logic and a greedy algorithm to support more effective logistics planning in flood situations.**

The DSS assigns priority to sub-districts based on key indicators, such as population characteristics, risk exposure, and access to health services, using a fuzzy inference system. The output from this system is then processed using a greedy algorithm that considers both the urgency of each location and its distance from nearby warehouses. This helps determine the order and routing of aid delivery.

The simulation was applied to eleven flood-prone sub-districts in Bogor Regency, using data from the National Disaster Management Authority (BNPB) and the Indonesian Central Statistics Agency (BPS). The results show that the system is able to schedule aid distribution across six days using three warehouses. All high-priority areas received assistance within the first two days.

The DSS shows potential to improve disaster response by supporting faster and fairer decisions under uncertainty. Its design allows for adaptation to other disaster types and different regions. The use of simple algorithms and structured data also makes it suitable for real-world application by government agencies or humanitarian organizations. This study highlights how data-driven approaches can be used to strengthen logistics planning in Indonesia's disaster management system.

***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.

Eventhought flood frequency happened, 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.

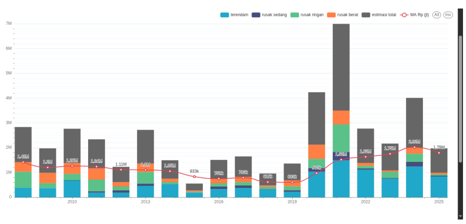

Fig. 1. Impact caused by floods in Indonesia (mio IDR)

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 [10]. 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 [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

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].

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].

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:

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

A. 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

B. 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) for humanitarian logistics in disaster response. The proposed framework is designed to integrate fuzzy inference and greedy optimization, enabling adaptive prioritization and routing of aid under uncertain and time-sensitive conditions. The research framework comprises four key components: data acquisition, fuzzy inference system (FIS), greedy algorithm, and simulation-based evaluation. Figure 2 illustrates the sequential flow from data preprocessing to logistics simulation.

The system begins by collecting spatial, demographic, and disaster data from the Indonesian National Statistics Agency (BPS) and the National Disaster Management Authority (BNPB). This data includes

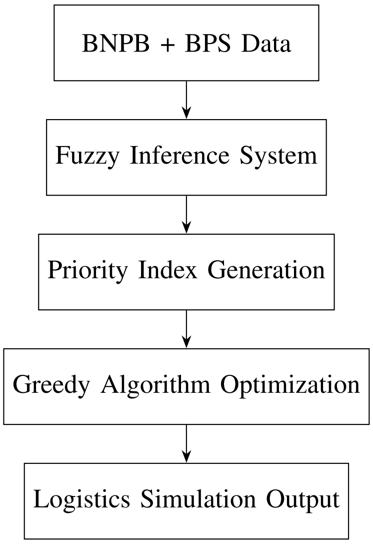

Fig. 2. Research Framework: From Data Acquisition to Logistics Simulation

sub-district population characteristics, health facility availability, disaster frequency, and geographic coordinates. These data points are transformed into qualitative variables such as health vulnerability, age-based sensitivity, hazard exposure, and accessibility. A Fuzzy Inference System (FIS) is employed to convert these inputs into a continuous priority index using linguistic rules aligned with humanitarian standards (e.g., SPHERE Handbook).

Subsequently, the priority index is passed to a greedy algorithm, which integrates proximity to warehouses and urgency of need to compute a composite delivery score. This step facilitates optimized resource allocation by ranking the districts based on a trade-off between importance and logistical distance. Finally, the entire DSS pipeline is evaluated through simulation, where disaster scenarios are modeled over multiple days. The system performance is assessed based on delivery efficiency, prioritization accuracy, and coverage of affected populations. This simulation-based evaluation ensures that the DSS is both theoretically sound and practically applicable to real-world disaster 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) [30]. This approach allows for the modeling of complex systems and the assessment of various scenarios without the need for real-world implementation [31]. This study collects and processes data from the Indonesian National Statistics Agency (BPS) and the National Disaster Management Authority (BNPB) to simulate disaster scenarios using Docling to extract the data [32]. 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. Based on

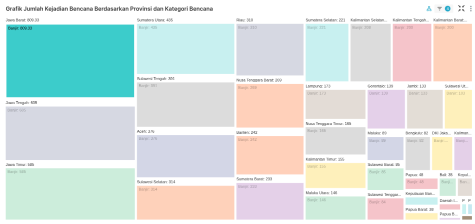

Fig. 3. Most Affected Regions in 2021 - 2025
Source: https://dibi.bnpb.go.id

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. After identifying the most

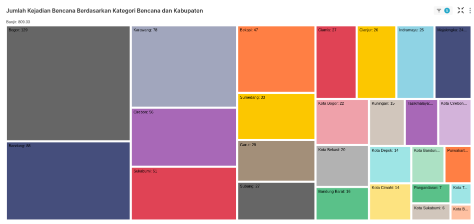

Fig. 4. Heatmap of Floods in West Java in 2021 - 2025
Source: https://dibi.bnpb.go.id

affected regions, the next step is to analyze the flood potential in each sub-district. This analysis is based on spatial data and hydrological information, which are crucial for understanding the flood risk and planning effective disaster response strategies. 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**

This simulation utilizes three strategic warehouse locations in West Bogor to ensure optimal disaster logistics deployment:

- Warehouse 1: $(-6.484578, 106.838395)$
- Warehouse 2: $(-6.524798, 106.770716)$
- Warehouse 3: $(-6.576941, 106.777883)$

These points represent accessible positions distributed across Bogor Regency, enabling effective coverage of both central and remote sub-districts. Figure 5 shows the locations of all three warehouses.

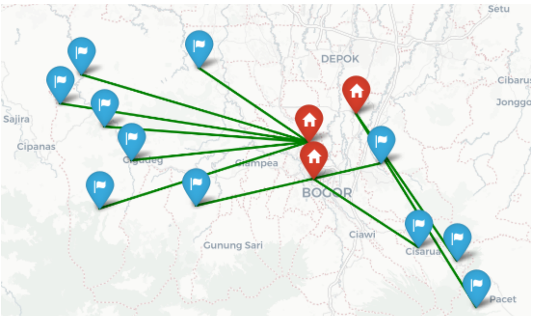

Fig. 5. Logistics Warehouse Locations in West Bogor
Source: Google Maps

The simulation calculates the distance from each district to the nearest warehouse using the haversine formula, which accounts for the curvature of the Earth. The coordinates of each district are obtained from BPS data, while the warehouse locations are based on strategic logistics planning. Using these locations, the haversine distance formula was applied to calculate the shortest distance between each district and the closest warehouse. This proximity is then combined with fuzzy logic prioritization and Sphere-based needs assessment. A greedy algorithm is implemented to generate a ranked delivery sequence for each district.

Distances from each district to the nearest warehouse were shown in Table IV.

TABLE IV
DISTANCE (IN KM) FROM EACH DISTRICT TO ALL WAREHOUSES

District	Warehouse 1	Warehouse 2	Warehouse 3
Babakanmadang	16.52	12.38	8.65
Pamijahan	27.33	19.64	14.04
Megamendung	26.92	23.77	18.51
Tanjungsari	25.18	32.45	37.92
Nanggung	36.87	30.34	34.10
Cigudeg	39.55	30.44	33.88
Sukamakmur	29.88	36.78	40.33
Sukajaya	49.12	39.21	42.75
Jasinga	53.06	42.96	46.52
Rumpin	27.66	19.45	22.93
Tenjo Panjang	54.77	45.30	48.67

Source: Author's calculation using haversine formula based on BPS sub-district coordinates and warehouse locations.

The distances were calculated using the haversine formula, which is suitable for calculating distances between two points on the Earth's surface given their latitude and longitude coordinates. To determine routing priority, a greedy scoring function was used, 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 (High = 2, Low = 1)
- D_i: Distance from the nearest warehouse (km)
- $\alpha = 100$, $\beta = 1$

This formula balances the urgency of need (fuzzy priority) against the logistical efficiency (distance), allowing for rapid prioritization of districts based on both their immediate requirements and accessibility. Using the above formula, the greedy scores for each district were calculated as follows:

- Babakanmadang (Warehouse 3): $G = 100 \cdot 3 - 8.65 = 291.35$
- Pamijahan (Warehouse 3): $G = 100 \cdot 2 - 14.04 = 185.96$
- Megamendung (Warehouse 3): $G = 100 \cdot 3 - 18.51 = 281.49$
- Tanjungsari (Warehouse 1): $G = 100 \cdot 3 - 25.18 = 274.82$
- Nanggung (Warehouse 2): $G = 100 \cdot 3 - 30.34 = 269.66$
- Cigudeg (Warehouse 2): $G = 100 \cdot 2 - 30.44 = 169.56$
- Sukamakmur (Warehouse 1): $G = 100 \cdot 3 - 29.88 = 270.12$
- Sukajaya (Warehouse 2): $G = 100 \cdot 2 - 39.21 = 160.79$

- Jasinga (Warehouse 2): $G = 100 \cdot 1 - 42.96 = 57.04$
- Rumpin (Warehouse 2): $G = 100 \cdot 1 - 19.45 = 80.55$
- Tenjo Panjang (Warehouse 2): $G = 100 \cdot 1 - 45.30 = 54.70$

The greedy algorithm ranks districts to balance urgency and logistics efficiency. Table V summarizes the results.

TABLE V
GREEDY-BASED ROUTING WITH MULTI-WAREHOUSE OPTIMIZATION

District	Assigned WH	Distance (km)	Fuzzy Priority	Greedy Score
Babakan madang	WH 3	8.65	Extreme (3)	291.35
Pamijahan	WH 3	14.04	High (2)	185.96
Mega mendung	WH 3	18.51	Extreme (3)	281.49
Tanjung sari	WH 1	25.18	Extreme (3)	274.82
Nanggung	WH 2	30.34	Extreme (3)	269.66
Cigudeg	WH 2	30.44	High (2)	169.56
Suka makmur	WH 1	29.88	Extreme (3)	270.12
Suka jaya	WH 2	39.21	High (2)	160.79
Jasinga	WH 2	42.96	Low (1)	57.04
Rumpin	WH 2	19.45	Low (1)	80.55
Tenjo Panjang	WH 2	45.30	Low (1)	54.70

This prioritization forms the foundation for an adaptive logistics routing strategy. Table VI presents the optimized delivery schedule, in which each warehouse operates concurrently and delivers to the nearest high-priority district based on the remaining greedy scores. To maximize efficiency and reduce idle time, each warehouse is limited to serving one district per day. This approach ensures rapid aid deployment while balancing urgency and geographical proximity.

TABLE VI
SIMULATED MULTI-WAREHOUSE DELIVERY SCHEDULE
(GREEDY PRIORITY + NEAREST PROXIMITY)

Day	Target District	Assigned Warehouse
Day 1	Babakanmadang (Greedy: 291.35)	Warehouse 3
Day 1	Tanjungsari (Greedy: 274.82)	Warehouse 1
Day 1	Nanggung (Greedy: 269.66)	Warehouse 2
Day 2	Megamendung (Greedy: 281.49)	Warehouse 3
Day 2	Sukamakmur (Greedy: 270.12)	Warehouse 1
Day 2	Cigudeg (Greedy: 169.56)	Warehouse 2
Day 3	Pamijahan (Greedy: 185.96)	Warehouse 3
Day 3	Sukajaya (Greedy: 160.79)	Warehouse 2
Day 4	Rumpin (Greedy: 80.55)	Warehouse 2
Day 5	Jasinga (Greedy: 57.04)	Warehouse 2
Day 6	Tenjo Panjang (Greedy: 54.70)	Warehouse 2

Note: Only one district is served per warehouse per day. Prioritization is based on greedy scores, using proximity to assigned warehouse.

This schedule ensures full utilization of warehouse resources while maintaining alignment with priority rankings. All critical districts (greedy score > 260) are served within the first two days. The remaining moderate- and low-priority districts are systematically scheduled without overburdening any single warehouse. This structure highlights the ability of the DSS to support scalable, parallelized logistics planning under real-world constraints. The simulation results indicate that the proposed DSS can significantly enhance the efficiency and effectiveness of disaster response logistics in West Bogor.

V. CONCLUSION

This study presents a simulation-based Decision Support System (DSS) that integrates fuzzy inference and a greedy algorithm to enhance the effectiveness of humanitarian logistics in disaster response, specifically focusing on flood-prone regions in West Java, Indonesia. By leveraging demographic data, health infrastructure indicators, and risk exposure metrics, the system produces a dynamic prioritization of affected sub-districts through fuzzy logic. These priority scores are then combined with spatial proximity data using a greedy optimization approach to generate an efficient logistics delivery schedule from multiple warehouses.

The simulation results demonstrate the system's ability to:

- Prioritize regions with the greatest humanitarian need based on multidimensional vulnerability factors.
- Optimize resource allocation across three strategically located warehouses using proximity and urgency-based scoring.

- Ensure equitable and efficient logistics routing, with all high-priority districts served within the first two operational days.

The DSS shows strong potential in addressing common challenges in disaster logistics, including delayed response, resource misallocation, and limited accessibility to remote areas. The model provides a structured framework for rapid decision-making under uncertainty, aligning with the humanitarian standards outlined in the SPHERE handbook. From a methodological perspective, the integration of fuzzy inference and greedy heuristics proves to be a robust hybrid approach that balances qualitative expert rules with quantitative spatial optimization. The modular architecture of the system also enables adaptability to other disaster types and regional contexts. Future works may focus on several enhancements: (i) incorporation of real-time data streams (e.g., weather APIs, crowd-sourced reports) to improve responsiveness; (ii) integration with GIS-based route planning tools for more granular path optimization; and (iii) extension to multi-modal logistics scenarios (air, land, and sea transport) to increase system applicability in larger-scale disasters. Moreover, machine learning models could be introduced to predict demand patterns or dynamically adjust priority scores based on unfolding field conditions.

In conclusion, this research provides a novel contribution to the field of humanitarian logistics by demonstrating how intelligent decision support tools can systematically enhance disaster preparedness and response. The proposed fuzzy-greedy DSS framework offers a scalable, adaptive, and context-sensitive solution to improve aid delivery outcomes in disaster-prone regions.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the National Disaster Management Authority (BNPB) and the Indonesian National Statistics Agency (BPS) for providing access to disaster and demographic datasets used in this study.

This research was supported by the BINUS Online Learning Program, Bina Nusantara University. The authors also thank the reviewers for their constructive feedback and insightful comments, which helped improve the quality of this paper.

REFERENCES

[1] D. Teh and T. Khan, "Types, definition and classification of natural disasters and threat level," in *Handbook of disaster risk reduction for resilience: new frameworks for building resilience to disasters*. Springer, 2021, pp. 27–56.

[2] W. L. Hakim and C.-W. Lee, "A review on remote sensing and gis applications to monitor natural disasters in indonesia," *Korean Journal of Remote Sensing*, vol. 36, no. 6_1, pp. 1303–1322, 2020.

[3] W. J. Sastrawan, "Portents of power: Natural disasters throughout indonesian history," *Indonesia*, vol. 113, no. 1, pp. 9–30, 2022.

[4] J. Merten, J. Ø. Nielsen, E. Soetarto, H. Faust *et al.*, "From rising water to floods: Disentangling the production of flooding as a hazard in sumatra, indonesia," *Geoforum*, vol. 118, pp. 56–65, 2021.

[5] A. Jamshed, J. Birkmann, D. Feldmeyer, and I. A. Rana, "A conceptual framework to understand the dynamics of rural–urban linkages for rural flood vulnerability," *Sustainability*, vol. 12, no. 7, p. 2894, 2020.

[6] Q. Sholihah, W. Kuncoro, S. Wahyuni, S. P. Suwandi, and E. D. Feditasari, "The analysis of the causes of flood disasters and their impacts in the perspective of environmental law," in *IOP conference series: earth and environmental science*, vol. 437, no. 1. IOP Publishing, 2020, p. 012056.

[7] H. Riza, E. W. Santoso, I. G. Tejakusuma, and F. Prawiradisastra, "Advancing flood disaster mitigation in indonesia using machine learning methods," in *2020 International Conference on ICT for Smart Society (ICISS)*. IEEE, 2020, pp. 1–4.

[8] K. Ma, H. Yan, Y. Ye, D. Zhou, and D. Ma, "Critical decision-making issues in disaster relief supply management: A review," *Computational intelligence and neuroscience*, vol. 2022, no. 1, p. 1105839, 2022.

[9] S. Rustian, H. Sumartono, and H. Wardhono, "Implementation of supply chain and logistics for natural disaster management in indonesia: a smart governance perspective," *International Journal of Criminology and Sociology*, vol. 10, pp. 1699–1706, 2021.

[10] O. J. Chukwuka, J. Ren, J. Wang, and D. Paraskevadakis, "A comprehensive research on analyzing risk factors in emergency supply chains," *Journal of Humanitarian Logistics and Supply Chain Management*, vol. 13, no. 3, pp. 249–292, 2023.

[11] K. L. Orengo Serra and M. Sanchez-Jauregui, "Food supply chain resilience model for critical infrastructure collapses due to natural disasters," *British Food Journal*, vol. 124, no. 13, pp. 14–34, 2022.

[12] L. J. Ramirez Lopez and A. I. Grijalba Castro, "Sustainability and resilience in smart city planning: A review," *Sustainability*, vol. 13, no. 1, p. 181, 2020.

[13] S. M. Khan, I. Shafi, W. H. Butt, I. d. l. T. Diez, M. A. L. Flores, J. C. Galán, and I. Ashraf, "A systematic review of disaster management systems: approaches, challenges, and future directions," *Land*, vol. 12, no. 8, p. 1514, 2023.

[14] H. Alghodhaifi and S. Lakshmanan, "Autonomous vehicle evaluation: A comprehensive survey on modeling and simulation approaches," *Ieee Access*, vol. 9, pp. 151 531–151 566, 2021.

[15] T. Adetiloye, "Collaboration planning of stakeholders for sustainable city logistics operations," *arXiv preprint arXiv:2107.14049*, 2021.

[16] M. Peron, S. Arena, G. J. L. Micheli, F. Sgarbossa *et al.*, "A decision support system for designing win–win interventions impacting occupational safety and operational performance in ageing workforce contexts," *Safety science*, vol. 147, pp. 1–14, 2022.

[17] D. Suarez, C. Gomez, A. L. Medaglia, R. Akhavan-Tabatabaei, and S. Grajales, "Integrated decision support for disaster risk management: aiding preparedness and response decisions in wildfire management," *Information Systems Research*, vol. 35, no. 2, pp. 609–628, 2024.

[18] K.-H. Chang, Y.-Z. Wu, and S.-S. Ke, "A simulation-based decision support tool for dynamic post-disaster pedestrian evacuation," *Decision Support Systems*, vol. 157, p. 113743, 2022.

[19] K. Lobkov, D. Eremeev, A. Rubinskaya, E. Melnikova, and I. Panfilov, "Determination of the degree of impact of natu-

ral disasters on the level of migration of the population by simulation modelling," in *2023 22nd International Symposium INFOTEH-JAHORINA (INFOTEH)*. IEEE, 2023, pp. 1–6.

[20] A. Anjomshoae, A. Hassan, K. Y. Wong, and R. Banomyong, "An integrated multi-stage fuzzy inference performance measurement scheme in humanitarian relief operations," *International Journal of Disaster Risk Reduction*, vol. 61, p. 102298, 2021.

[21] G. Improta, V. Mazzella, D. Vecchione, S. Santini, and M. Triassi, "Fuzzy logic–based clinical decision support system for the evaluation of renal function in post-transplant patients," *Journal of evaluation in clinical practice*, vol. 26, no. 4, pp. 1224–1234, 2020.

[22] A. García, "Greedy algorithms: a review and open problems," *Journal of Inequalities and Applications*, vol. 2025, no. 1, p. 11, 2025.

[23] Z. Zhao, M. Zhou, and S. Liu, "Iterated greedy algorithms for flow-shop scheduling problems: A tutorial," *IEEE Transactions on Automation Science and Engineering*, vol. 19, no. 3, pp. 1941–1959, 2021.

[24] S. Steinhauser, "Understanding decision support adoption by european physicians: shifts in micro-and macro-level influences over time," *Information Technology and Management*, pp. 1–35, 2025.

[25] O. Ampaw and E. Ansah, "Developing a sustainable last-mile transport system for ghana and burkina faso: A modeling approach," *Available at SSRN 5161300*, 2025.

[26] A. Jain and A. Sharma, "Membership function formulation methods for fuzzy logic systems: A comprehensive review," *Journal of Critical Reviews*, vol. 7, no. 19, pp. 8717–8733, 2020.

[27] J. H. Yoon, D. J. Kim, and Y. Y. Koo, "Novel fuzzy correlation coefficient and variable selection method for fuzzy regression analysis based on distance approach," *International Journal of Fuzzy Systems*, vol. 25, no. 8, pp. 2969–2985, 2023.

[28] A. Shirmarz and A. Ghaffari, "An adaptive greedy flow routing algorithm for performance improvement in software-defined network," *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 33, no. 1, p. e2676, 2020.

[29] A. Hamidoğlu, "A game theoretical approach for finding near-optimal solutions of an optimization problem," *Optimization*, vol. 72, no. 10, pp. 2561–2583, 2023.

[30] Z. He and W. Weng, "A dynamic and simulation-based method for quantitative risk assessment of the domino accident in chemical industry," *Process Safety and Environmental Protection*, vol. 144, pp. 79–92, 2020.

[31] T. Latchmore, S. Lavallee, P. D. Hynds, R. S. Brown, and A. Majury, "Integrating consumer risk perception and awareness with simulation-based quantitative microbial risk assessment using a coupled systems framework: A case study of private groundwater users in ontario," *Journal of Environmental Management*, vol. 331, p. 117112, 2023.

[32] D. S. Team, "Docling technical report," Tech. Rep., 8 2024. [Online]. Available: https://arxiv.org/abs/2408.09869

[33] A. Endo, S. Abbott, A. J. Kucharski, S. Funk *et al.*, "Estimating the overdispersion in covid-19 transmission using outbreak sizes outside china," *Wellcome open research*, vol. 5, p. 67, 2020.

[34] J. Santos, C. Yip, S. Thekdi, and S. Pagsuyoin, "Workforce/population, economy, infrastructure, geography, hierarchy, and time (weight): reflections on the plural dimensions of disaster resilience," *Risk analysis*, vol. 40, no. 1, pp. 43–67, 2020.

[35] F. Alkaesi, I. Kadar, and Y. Istiadi, "Spatial analysis of hydrometeorological vulnerability of natural disasters in the bogor region," *Journal of Science Innovare*, vol. 4, no. 2, pp. 50–56, 2021.

[36] K. T. Park, Y. H. Son, and S. D. Noh, "The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control," *International Journal of Production Research*, vol. 59, no. 19, pp. 5721–5742, 2021.

[37] F. Halawa, H. Dauod, I. G. Lee, Y. Li, S. W. Yoon, and S. H. Chung, "Introduction of a real time location system to enhance the warehouse safety and operational efficiency," *International Journal of Production Economics*, vol. 224, p. 107541, 2020.

[38] M. A. Berawi, S. A. O. Siahaan, Gunawan, and P. Miraj, "Determining the prioritized victim of earthquake disaster using fuzzy logic and decision tree approach," *Evergreen*, vol. 7, no. 2, pp. 246–252, 2020, kyushu University Institutional Repository. [Online]. Available: https://doi.org/10.5109/4055227

[39] M. R. Amiri Shahmirani, A. Akbarpour Nikghalb Rashti, M. R. Adib Ramezani, and E. M. Golafshani, "Application of fuzzy modelling to predict the earthquake damage degree of buildings based on field data," *Journal of Intelligent & Fuzzy Systems*, vol. 41, no. 2, pp. 2717–2730, 2021.

[40] Y. Wang and Y. A. Nanehkaran, "Gis-based fuzzy logic technique for mapping landslide susceptibility analyzing in a coastal soft rock zone," *Natural Hazards*, vol. 120, no. 12, pp. 10 889–10 921, 2024.

[41] Sphere Association, "Sphere handbook: Humanitarian charter and minimum standards in humanitarian response," https://spherestandards.org/wp-content/uploads/Sphere-Handbook-2018-EN.pdf, 2018, pDF version, 4th Edition, accessed YYYY-MM-DD.

[42] H. Herpratiwi, M. Maftuh, W. Firdaus, A. Tohir, M. I. Daulay, and R. Rahim, "Implementation and analysis of fuzzy mamdani logic algorithm from digital platform and electronic resource," *TEM Journal*, vol. 11, no. 3, pp. 1028–1033, 2022.