

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

Maria Loura Christhia^{1*}, Ahmad Ardi Wahidurrijal¹, Abimanyu Bagarela Anjaya Putra²

¹Industrial Engineering Department, BINUS Online Learning, Bina Nusantara University, Jakarta, Indonesia 11480

²Computer Science Department, BINUS Online Learning, Bina Nusantara University, Jakarta, Indonesia 11480

Email: ^{1*}maria.loura@binus.ac.id, ¹ahmad.wahidurrijal@binus.ac.id, ²abimanyu.putra@binus.ac.id

Abstract—This document is a model and instructions for L^AT_EX. 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.

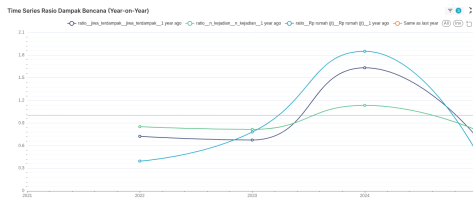


Fig. 1. Impact caused by floods in Indonesia (mio IDR)

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, pro-

viding 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):

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

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

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

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.

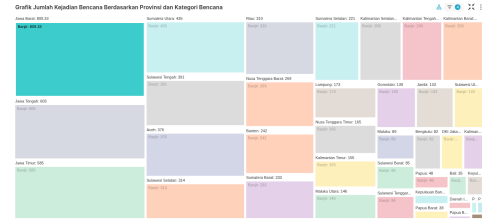


Fig. 2. Most Affected Regions in 2021 - 2025
Source: <https://dibi.bnpb.go.id>

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

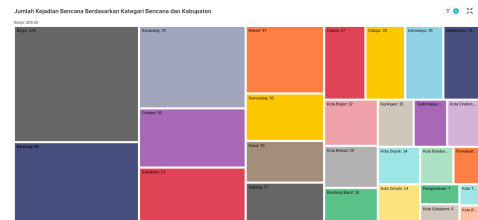


Fig. 3. Heatmap of Floods in West Java in 2021 - 2025
Source: <https://dibi.bnpb.go.id>

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 districts 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.

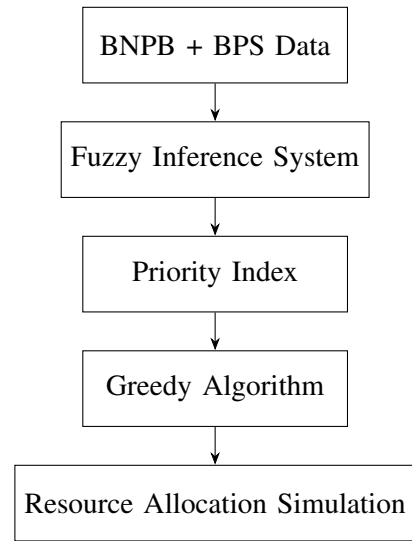


Fig. 4. Research Framework Flow: From Data to Simulation Output

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/km²
- 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/km²) to low (Megamendung 646/km²) 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**

V. CONCLUSION

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] 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.
- [5] H. Riza, E. W. Santoso, I. G. Tejakusuma, and F. Prawiradisastara, "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.
- [6] 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.
- [7] O. J. Chukwuka, J. Ren, J. Wang, and D. Paraskevadis, "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.
- [8] 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.
- [9] S. M. Khan, I. Shafi, W. H. Butt, I. d. I. 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.
- [10] 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.

- [11] T. Adetiloye, "Collaboration planning of stakeholders for sustainable city logistics operations," *arXiv preprint arXiv:2107.14049*, 2021.
- [12] 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.
- [13] 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.
- [14] 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.
- [15] K. Lobkov, D. Ereemeev, A. Rubinskaya, E. Melnikova, and I. Panfilov, "Determination of the degree of impact of natural 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.
- [16] A. Anjomshoe, 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.
- [17] 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.
- [18] 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.
- [19] 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.
- [20] 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.
- [21] T. Latchmore, S. Lavalley, 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.
- [22] 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.
- [23] 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.
- [24] 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.
- [25] 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.
- [26] 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.
- [27] 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>
- [28] 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.
- [29] Y. Wang and Y. A. Nanekaran, "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.
- [30] 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.
- [31] 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.
- [32] 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.
- [33] A. Hamidoğlu, "A game theoretical approach for finding near-optimal solutions of an optimization problem," *Optimization*, vol. 72, no. 10, pp. 2561–2583, 2023.
- [34] E. Mahmoodi, M. Fathi, M. Tavana, M. Ghobakhloo, and A. H. Ng, "Data-driven simulation-based decision support system for resource allocation in industry 4.0 and smart manufacturing," *Journal of Manufacturing Systems*, vol. 72, pp. 287–307, 2024.