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# Leveraging Latent Dirichlet Allocation and Fuzzy Clustering for Identifying Key UAV Applications in Disaster Response

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**Abstract –** Over the past few decades, there has been a significant increase in the occurrence of natural disasters, such as earthquakes and landslides, presenting a grave risk to the safety of people's lives and their possessions. Drones, also known as unmanned aerial systems (UAVs), are increasingly attracting the attention of organizations engaged in disaster events, especially in the context of post-disaster emergency response. This research aims to assess the use of UAV applications in the post-disaster phase through a descriptive literature analysis. The evaluation is conducted using the Latent Dirichlet Allocation (LDA) topic modelling and clustering approach, namely the fuzzy c-means algorithm. A total of 433 papers are extracted from the Scopus database. The analysis offers valuable insights into three primary domains: imaging-based damage assessment, emergency communication networks, and vehicle routing optimization. These findings emphasize the significance of technology and streamlined systems in effectively handling complex situations, such as disaster response and network management. By integrating UAVs into disaster response strategies, policymakers can significantly enhance the agility and efficiency of their operations, ultimately saving lives and minimizing the impact of natural disasters on communities. This study can assist in achieving these goals by providing valuable insights and guidance.

## 1. Introduction

Drones or unmanned aerial vehicles (UAVs) are aircraft capable of autonomous flight without human intervention (Calamoneri et al., 2024). UAVs can capture aerial images that are valuable for analyzing large areas of land using geospatial techniques. UAVs are encompassed within the realm of remote sensing (Garnica-Peña and Alcántara-Ayala, 2021). They have gained growing attention from organizations engaged in disaster response activities. They serve a variety of purposes in post-disaster activities, including damage assessment using UAV images (Zou et al., 2024), bushfire detection (Qadir et al., 2024), network communication (Lei et al., 2024; Wu et al., 2024), and vehicle routing issues (Faiz et al., 2024; Zhang et al., 2022). The literature we reviewed contained a paper that addressed the use of UAVs in the aftermath of a disaster. The following are some of them: Freeman et al. (2021) outlined the findings of a comprehensive examination of the utilization of aerial robotic technology in the field of civil engineering. Civil engineering applications can be categorized into three primary areas: (i) monitoring and inspecting civil infrastructure; (ii) managing sites, constructing using robots, and maintaining structures; and (iii) conducting surveys and assessing damage quickly after a disaster. The authors conducted a review focusing on these issues. Mohd Daud et al. (2022) seek to assess the current viability of drone projects and address various obstacles associated with deploying drones in large-scale disasters, with the intention of empowering and motivating potential future endeavors. According to the identified papers, the use of drones in disasters was categorized into four main areas: (1) mapping or disaster management, (2) search and rescue, (3) transportation, and (4) training. Lozano and Tien (2023) concentrated on the tools,

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including UAVs, employed to evaluate the physical harm in lifeline networks and structures. The tools provided encompass several lifeline networks, such as water, gas, transportation, power, and building infrastructure. They also cover a wide range of hazards, such as earthquakes, flooding caused by hurricanes, and heavy rainfall. The paper provided a comprehensive evaluation of each tool, examining important factors such as scope, accuracy, and long-term accessibility. Their analysis aimed to facilitate the integration of datasets across different tools and pinpoint any deficiencies in current data collection methods. Phadke and Medrano (2023) investigated a wide range of application scenarios for UAV swarms in order to highlight the various components that collaborate to enhance the overall resilience of the swarm. Swarm applications are classified using a three-category system. Although systemic resilience is a complex topic, most practical implementations of UAV swarm research primarily aim to enhance the resilience of certain components against unexpected events. Ishiwatari (2024) investigated the function of drones in disaster management by studying different uses of drones in reaction to the Noto Peninsula earthquake in January 2024. Multiple concerns were identified, such as the necessity to integrate drone capabilities into disaster management plans, formulate suitable laws and regulations, establish coordination mechanisms between the public and private sectors, tackle technological limitations arising from advancements in technology, and implement specialized training programs for drone operators. Garnica-Pena and Alcantara-Ayala (2021) seek to examine the role of the global landslide research community in reducing the risk and managing the consequences of disasters, specifically focusing on the utilization of UAVs, as discussed in the existing literature. The initial section highlighted the significance of research contributions on disaster risk for the execution of initiatives and strategies related to disaster risk management. The second half focused on providing background information and discussing the present applications of drones in the field of hazards and risk. Zhang et al. (2024) presented a classification scheme for the drone cooperative delivery problem (TDCDP) and provided a comprehensive summary of the relevant studies. The analysis focused on the detailed examination of the effects of changes in clients and environments on truck and drone delivery modalities. The suggested taxonomy categorized the delivery modes in TDCDP into four types: Parallel delivery, mixed delivery, drone delivery with truck-assisting, and truck delivery with drone-assisting.

UAVs have gained prominence as a cutting-edge technology for disaster management. Their capabilities in aerial imaging, communication, and navigation make them ideal for enhancing disaster response efforts. In recent literature, the utilization of UAVs in disaster management has been extensively explored across various domains, including infrastructure monitoring, disaster response, and hazard assessment. However, our study distinguishes itself by offering a comprehensive descriptive literature review that specifically assesses UAV applications in post-disaster scenarios. Unlike previous works, which often emphasize specific applications or technologies, our research applies the LDA topic modelling to systematically identify and categorize the main topics and trends within the literature related to UAV applications in disaster response. Furthermore, by employing the fuzzy c-means algorithm, we provide a nuanced analysis of UAV applications, clustering them to offer insights into their effectiveness and potential for future enhancements. This dual approach of topic modelling and clustering not only enriches the understanding of current UAV applications but also highlights emerging trends and gaps, setting the stage for more targeted and effective disaster response strategies.

The subsequent sections of the paper are structured in the following manner: Section 2 outlines the methodology that is relevant to the topic. Section 3 provides a concise overview of the findings and the subsequent discussions. Section 4 serves as the conclusion of the study.

## 2. Materials and Methods

This section outlines the process of identifying the most important publications in the dataset using LDA topic modelling combined with the fuzzy c-means algorithm. The search syntax is provided in Table 1.

**Table 1.** Search strings on Scopus

| Database | Search strings |
|---|---|
| Scopus (July 17, 2024) | (TITLE-ABS-KEY ("drone") OR TITLE-ABS-KEY ("unmanned aerial vehicles") AND TITLE-ABS-KEY ( "post-disaster" ) |

The search yields 433 papers. The abstracts of all publications are examined. The pre-processing stage, which involves the cleansing and preparation of data for subsequent operations, is implemented on the data set using the MATLAB R2021a software. URLs (Uniform Resource Locators), also referred to as web addresses, have been eliminated due to their tendency to cause text misclassification. Punctuations and search strings (such as “drone”, “unmanned aerial vehicles”, “UAVs”, and “post disaster”) are eliminated. Finally, tokenization is implemented, which involves the division of sequences into distinct tokens. After the pre-processing stage, the LDA procedure is implemented on the dataset. The fuzzy c-means algorithm is implemented after the LDA to acquire center documents.

### *2.1. Latent Dirichlet allocation (LDA)*

Blei et al. (2003) introduced the LDA, a probabilistic model that generates a corpus. The fundamental concept is that documents are represented as stochastic combinations of latent topics, with each subject being defined by a probability distribution of words.

$$p(D|\alpha,\beta) = \prod_{d=1}^{M} \int P(\theta_d|\alpha)\left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn}|\theta_d)p(w_{dn}|z_{dn},\beta)\right)d\theta_d \quad (1)$$

The concentration parameter of the Dirichlet prior for the topic distribution of each document is denoted by α in (1), while β represents the same parameter for the word distribution within each topic. $z_{dn}$ represents the topic assignment for the nth word in document d, $w_{dn}$ represents the nth word in document d, and $\theta_d$ represents the topic distribution for document d. The total number of words in the document is denoted by N, the number of documents being analyzed is denoted by M, and the corpus of M documents is represented by D.

### *2.2. Fuzzy c-means*

Bezdek et al. (1984) introduced the renowned fuzzy $c$-means clustering algorithm, which differs from the classic $k$-means approach by enabling a sample to be assigned to multiple clusters rather than a single one. The fuzzification factor, which determines the degree of fuzziness within the clusters, is used to assign membership values to data items for the clusters within a range of 0 to 1. The objective function is minimized by the methodology. The fuzzy c-means model is as follows (Mao and Xu, 2024):

$$\sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^{m} \left\|x_i - v_j\right\|^2 \quad (2)$$

$$\mu_{ij} \geq 0, \sum_{j=1}^{C} \mu_{ij} = 1, 0 < \sum_{j=1}^{N} \mu_{ij} < N \quad (3)$$

where $x_i$ represents the ith data point from the dataset X, which is a set of real numbers in an n-dimensional space. $v_j$ represents the jth prototype of the cluster in this context. $u_{ij}$ is the membership grade of the individual data point $x_i$ belonging to $v_j$. As a coefficient, the fuzzification factor is represented by the scalar "$m$" (where $m > 1$). The parameter $m$, known as the fuzzification factor, has a substantial influence on the formation of clusters during the process. (2) and (3) require that the overall sum of membership grades for each data point in all clusters is 1. Each cluster must contain at least one data point, although no cluster may completely dominate all data points. (4) determines the degree to which a data point is associated with a cluster by evaluating its distance from the cluster's prototype. (5) adjusts the cluster prototypes with the weighted sum of data points' membership grades, adjusted by the fuzzification factor. The objective function described above is minimized by iteratively computing modifications to the membership degree and prototypes, specifically,

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|}\right)^{\frac{2}{m-1}}} \quad (4)$$

$$v_j = \frac{\sum_{i=1}^{N} (x_i \mu_{ij}^{m})}{\sum_{i=1}^{N} \mu_{ij}^{m}} \quad (5)$$

## 3. Results and Discussion

By using 433 papers, the LDA process is implemented to gather important topics and their probabilities. Figure 1 helps to determine the appropriate number of topics.

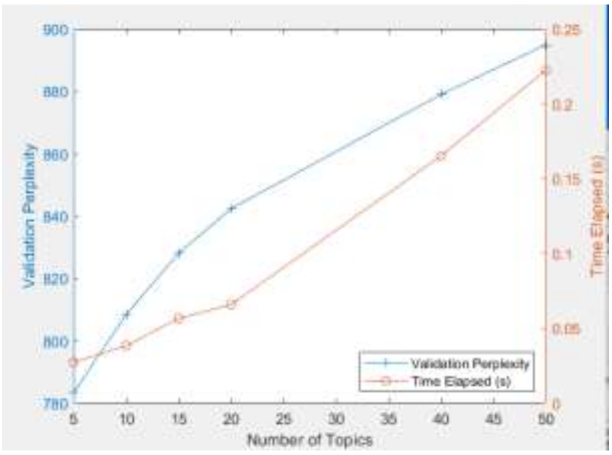


**Figure 1.** Relationship between the number of topics, validation perplexity and time elapsed

Figure 1 shows the relationship between the number of topics and two metrics: validation perplexity and time elapsed. Taking the Figure 1 into account, we determined the number of topics as 7. At 7 topics, there's a good balance between model complexity and efficiency. The perplexity is relatively low, ensuring clearer topic distinction. The time required for processing is minimal, making the model computationally efficient.

After the LDA process, a matrix with dimensions of 433x7 is acquired. This matrix displays the probability of 7 significant topics across 433 documents. The number of clusters is computed using the elbow approach based on the data from the resulting matrix. Figure 2 demonstrates the results of the elbow method.

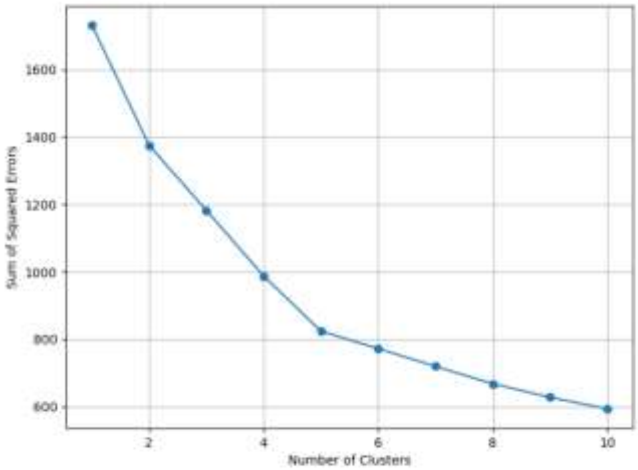


**Figure 2.** Results of the elbow method

The Figure 2 suggests an "elbow" around 3-5 clusters. This is where the rate of decrease in the sum of squared errors starts to slow, indicating a potential optimal number of clusters. We selected a cluster count of 5 to observe the range of variety. However, in this case, three of the five clusters overlapped at the same point. Consequently, we gather three clusters. The center coordinates of the clusters are obtained from documents 224, 64, and 218.

### *3.1. Center papers of the clusters*

**Cluster 1:** This center paper (224) employed UAV-based aerial imagery as a flood detection method, utilizing a Convolutional Neural Network (CNN) to extract flood-related features from the images of the disaster zone. The study area was situated in a flood-prone region of the Indus River in Pakistan, and UAVs were employed to capture images of the area both before and after the disaster. 2150 image replacements were generated during the training phase by resizing and cropping the source images. To validate the model, it was tested against both pre- and post-disaster images. The model has a 91% accuracy rate for affirmative flood detection results (Munawar et al., 2021).

**Cluster 2:** This center paper (64) proposed a joint data aggregation and computational outsourcing (JDACO) scheme for UAV-enabled IoT systems in post-disaster scenarios. The primary goal of JDACO is to reduce the overall energy consumption and latency in the aggregation and computation processes. It accomplishes this by utilizing UAVs as mobile edge computing servers and deploying numerous UAVs (Raivi and Moh, 2024).

**Cluster 3:** This center paper (218) examined a cognitive satellite-UAV network (CSUN), in which the satellite and UAVs are administered in a coordinated manner and opportunistically share spectrum to alleviate the spectrum scarcity issue. In particular, the paper proposed the UAV swarm to reduce the interference between satellites and UAVs. The proposed algorithm's superiority can be seen in the simulation results, which suggest that it may be a viable solution for enhancing the coverage performance of terrestrial 4G/5G networks (Liu et al., 2020).

These center papers collectively illustrate the diverse applications of UAV technology in disaster management and communication networks, highlighting innovative approaches to improve efficiency and effectiveness.

The 1st cluster contains 246 documents, the 2nd cluster contains 102 documents, and the 3rd cluster contains 85 documents. We identified the five critical topics in each cluster using LDA. Table 2 illustrates the significant topics of cluster 1 along with their probabilities.

**Table 2.** Important topics of cluster 1

| **Cluster 1** | | | | |
|---|---|---|---|---|
| **Topic 1** | **Topic 2** | **Topic 3** | **Topic 4** | **Topic 5** |
| **Word, Probability** | **Word, Probability** | **Word, Probability** | **Word, Probability** | **Word,Probability** |
| "damage" 0.036289 | "network" 0.016966 | "rescue" 0.025189 | "remote" 0.01757 | "data" 0.01952 |
| "data" 0.022717 | "vehicle" 0.01523 | "emergency" 0.021701 | "sensing" 0.016471 | "accuracy" 0.018097 |
| "images" 0.022275 | "operations" 0.011567 | "relief" 0.014532 | "management" 0.016288 | "response" 0.017893 |
| "assessment" 0.019914 | "performance" 0.010796 | "vehicles" 0.0091068 | "technology" 0.011896 | "area" 0.01708 |
| "information" 0.017849 | "compared" 0.0096395 | "delivery" 0.008913 | "field" 0.010981 | "learning" 0.01342 |

Table 2 presents a cluster analysis with five topics, each containing words and their corresponding probabilities. The words with higher probabilities within each topic are considered more representative of that topic. Each topic contains keywords related to a specific subject, indicated by their probabilities. Higher probability words are more central to the topic. For example, in Topic 1, "damage" is the most significant word with a probability of 0.036289, followed by "data" and "images". Figure 3 shows the word cloud of cluster 1.


**Figure 3.** Word cloud of cluster 1

The word cloud in Figure 3 highlights the most frequently used terms in texts related to damage assessment using imaging technologies. The central term is "image" or "imaging", indicating that visual data is crucial in this context. "Information" may signify the data gathered from images, and "provide" may suggest that images supply essential data. This word cloud suggests a strong focus on the use of advanced imaging technologies for efficient and accurate damage assessment in disaster management, emphasizing practical applications, accuracy, and the types of disasters addressed. The important topics of the 2nd cluster are given in Table 3.

**Table 3.** Important topics of cluster 2

| **Cluster 2** | | | | |
|---|---|---|---|---|
| **Topic 1** | **Topic 2** | **Topic 3** | **Topic 4** | **Topic 5** |
| **Word, Probability** | **Word, Probability** | **Word, Probability** | **Word, Probability** | **Word, Probability** |
| "energy" 0.040873 | "communication" 0.089893 | "network" 0.087533 | "data" 0.041689 | "performance" 0.029091 |
| "emergency" 0.036508 | "coverage" 0.033542 | "networks" 0.050398 | "deployment" 0.032603 | "allocation" 0.026061 |
| "users" 0.033333 | "power" 0.026387 | "infrastructure" 0.017507 | "areas" 0.024052 | "task" 0.026061 |
| "optimization" 0.030159 | "area" 0.023703 | "strategy" 0.016976 | "transmission" 0.022983 | "mobile" 0.018788 |
| "simulation" 0.025 | "wireless" 0.023256 | "throughput" 0.014854 | "nodes" 0.018707 | "offloading" 0.018182 |

Table 3 shows a cluster analysis for cluster 2 with five topics, each containing words and their corresponding probabilities. For example, in Topic 2, "communication" is the most significant word with a probability of 0.089893, followed by "coverage" and "power". Figure 4 indicates word cloud analysis of cluster 2.


**Figure 4.** Word cloud of cluster 2

The word cloud in Figure 4 emphasizes key terms related to communication networks, particularly in scenarios requiring coverage and optimization. The word cloud shows that "communication" and "network" are the central themes, indicating a focus on the systems that facilitate information exchange. The emphasis on "Coverage" highlights the significance of maintaining network availability across various areas. Words like "energy", "rescue" and "emergency" indicate the critical role of these networks in urgent and high-stakes situations. The significant topics of the last cluster are provided in Table 4.

**Table 4.** Important topics of cluster 3

| **Cluster 3** | | | | |
|---|---|---|---|---|
| **Topic 1** | **Topic 2** | **Topic 3** | **Topic 4** | **Topic 5** |
| **Word, Probability** | **Word, Probability** | **Word, Probability** | **Word, Probability** | **Word, Probability** |
| "communication"<br>0.055787 | "performance"<br>0.029206 | "vehicles"<br>0.029309 | "network"<br>0.065954 | "networks"<br>0.027824 |
| "emergency"<br>0.027633 | "vehicle"<br>0.026869 | "optimal"<br>0.018171 | "rescue"<br>0.01842 | "coverage"<br>0.023372 |
| "area"<br>0.022941 | "data"<br>0.021612 | "planning"<br>0.017585 | "areas"<br>0.016637 | "scenarios"<br>0.021703 |
| "optimization"<br>0.019812 | "routing"<br>0.015187 | "channel"<br>0.016999 | "tasks"<br>0.012478 | "energy"<br>0.02059 |
| "ground"<br>0.017727 | "base"<br>0.012267 | "efficient"<br>0.016413 | "transmission"<br>0.011884 | "number"<br>0.018364 |

Table 4 indicates a cluster analysis for cluster 3 with five topics. For example, in Topic 1, "communication" is the most significant word with a probability of 0.055787, followed by "emergency" and "area". Topic 2 emphasizes performance, vehicle, data, and routing words. The word cloud of the last cluster is given in Figure 5.


**Figure 5.** Word cloud of cluster 3

The word cloud in Figure 5 is similar to the one in Figure 4, but it is seen that vehicle routing problems stand out in the third one. The word cloud highlights essential terms associated with communication networks, particularly in the context of vehicles and optimization. The central theme revolves around "network" and "communication", indicating a focus on systems facilitating information exchange. The term "vehicle" is prominent. This indicates that the problems related to vehicle routing and optimization are focused inside this cluster.

All in all, the cluster analysis highlights distinct thematic areas across multiple topics, each characterized by specific keywords and their probabilities. These topics are further illustrated by word clouds, emphasizing the center papers. The analysis provides insights into three main areas: Damage assessment through imaging, communication networks in emergency scenarios, and vehicle routing optimization. These findings highlight the importance of technology and efficient systems in managing complex situations, such as disaster response and network management. The emphasis on specific terms reflects the current focus areas and challenges within each cluster, offering a roadmap for future research and development.

## 4. Conclusion

In recent decades, the increase in natural disasters has underscored the critical need for effective disaster response strategies. UAVs have emerged as a valuable tool in managing these crises, offering innovative solutions for post-disaster scenarios. This study provides a comprehensive evaluation of UAV applications through a detailed literature analysis, utilizing LDA topic modelling and the fuzzy c-means clustering approach. Our analysis, based on 433 papers extracted from the Scopus database, identifies three primary domains where UAVs significantly contribute to disaster response: imaging-based damage assessment, emergency communication networks, and vehicle routing optimization. These domains reflect the diverse and impactful applications of UAVs technology in enhancing disaster management processes.

This paper stands out by providing a thorough descriptive literature analysis that uniquely evaluates the use of UAVs in post-disaster situations. In contrast to prior studies that often focus on particular applications or technologies, our research utilizes LDA topic modelling to methodically identify and classify the primary subjects and patterns in the literature concerning UAV applications in disaster response. Moreover, using the fuzzy c-means technique, we provide a detailed examination of UAV applications, grouping them to provide valuable information on their efficiency and prospects for future improvements. This combined method of subject modelling and clustering enhances the comprehension of present UAV applications and identifies developing patterns and deficiencies, therefore clearing the way for more focused and efficient disaster response operations.

Overall, the cluster analysis and word clouds illustrate distinct thematic areas within UAV applications, each characterized by specific challenges and focus areas. These findings provide a valuable roadmap for future research and development in UAV technology, guiding efforts to enhance disaster response strategies. By integrating UAVs into disaster management frameworks, policymakers and practitioners can improve the agility and efficiency of their operations, ultimately saving lives and reducing the impact of natural disasters on communities.

### Ethics Permissions

This paper does not require ethics committee approval.

### Author Contributions

Zeynep Yüksel conducted research and contributed to the drafting of the manuscript. Nazmiye Eligüzel created the original draft and complete the methodology and analysis. Süleyman Mete provided review, editing and verification.

### Conflict of Interest

Authors declare that there is no conflict of interest for this paper.

### References

Bezdek, J. C., Ehrlich, R., and Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers and Geosciences*, 10(2–3), 191–203. https://doi.org/10.1016/0098-3004(84)90020-7

Blei, D., Jordan, M., and Ng, A. Y. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3, 993–1022. https://doi.org/10.1162/jmlr.2003.3.4-5.993

Calamoneri, T., Corò, F., and Mancini, S. (2024). Management of a post-disaster emergency scenario through unmanned aerial vehicles: Multi-depot multi-trip vehicle routing with total completion time minimization. *Expert Systems with Applications*, 251(February), 123766. https://doi.org/10.1016/j.eswa.2024.123766

Faiz, T. I., Vogiatzis, C., and Noor-E-Alam, M. (2024). Computational approaches for solving two-echelon vehicle and UAV routing problems for post-disaster humanitarian operations. *Expert Systems with Applications*, 237(PB), 121473. https://doi.org/10.1016/j.eswa.2023.121473

Freeman, M. R., Kashani, M. M., and Vardanega, P. J. (2021). Aerial robotic technologies for civil engineering: Established and emerging practice. *Journal of Unmanned Vehicle Systems*, 9(2), 75–91. https://doi.org/10.1139/juvs-2020-0019

Garnica-Peña, R. J., and Alcántara-Ayala, I. (2021). The use of UAVs for landslide disaster risk research and disaster risk management: a literature review. *Journal of Mountain Science*, 18(2), 482–498. https://doi.org/10.1007/s11629-020-6467-7

Ishiwatari, M. (2024). Leveraging drones for effective disaster management: A comprehensive analysis of the 2024 Noto Peninsula earthquake case in Japan. *Progress in Disaster Science*, 23(July), 100348. https://doi.org/10.1016/j.pdisas.2024.100348

Lei, J., Zhang, T., Mu, X., and Liu, Y. (2024). NOMA for STAR-RIS assisted UAV networks. *IEEE Transactions on Communications*, 72(3), 1732–1745. https://doi.org/10.1109/TCOMM.2023.3333880

Liu, C., Feng, W., Chen, Y., Wang, C. X., Li, X., and Ge, N. (2020). Process-oriented optimization for beyond 5G cognitive satellite-UAV networks (Invited Paper). 2020 29th Wireless and Optical Communications Conference, WOCC 2020. https://doi.org/10.1109/WOCC48579.2020.9114919

Lozano, J. M., and Tien, I. (2023). Data collection tools for post-disaster damage assessment of building and lifeline infrastructure systems. *International Journal of Disaster Risk Reduction*, 94, 103819. https://doi.org/10.1016/j.ijdrr.2023.103819

Mao, W., and Xu, K. (2024). Enhancement of the classification performance of fuzzy c-means through uncertainty reduction with cloud model interpolation. *Mathematics*, 12(7), 975. https://doi.org/10.3390/math12070975

Mohd Daud, S. M. S., Mohd Yusof, M. Y. P., Heo, C. C., Khoo, L. S., Chainchel Singh, M. K., Mahmood, M. S., and Nawawi, H. (2022). Applications of drone in disaster management: A scoping review. *Science and Justice*, 62(1), 30–42. https://doi.org/10.1016/j.scijus.2021.11.002

Munawar, H. S., Ullah, F., Qayyum, S., Khan, S. I., and Mojtahedi, M. (2021). Uavs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection. *Sustainability*, 13(14), 7547. https://doi.org/10.3390/su13147547

Phadke, A., and Medrano, F. A. (2023). Examining application-specific resiliency implementations in UAV swarm scenarios. *Intelligence and Robotics*, 3(3), 453–478. https://doi.org/10.20517/ir.2023.27

Qadir, Z., Le, K., Bao, V. N. Q., and Tam, V. W. Y. (2024). Deep learning-based intelligent post-bushfire detection using UAVs. *IEEE Geoscience and Remote Sensing Letters*, 21, 1–5. https://doi.org/10.1109/LGRS.2023.3329509

Raivi, A. M., and Moh, S. (2024). JDACO: Joint data aggregation and computation offloading in UAV-enabled internet of things for post-disaster scenarios. *IEEE Internet of Things Journal*, 11(9), 16529–16544. https://doi.org/10.1109/JIOT.2024.3354950

Wu, J., Chen, Q., Jiang, H., Wang, H., Xie, Y., Xu, W., Zhou, P., Xu, Z., Chen, L., Li, B., Wang, X., and Wu, D. O. (2024). Joint power and coverage control of massive UAVs in post-disaster emergency networks: An aggregative game-theoretic learning approach. *IEEE Transactions on Network Science and Engineering*, 11(4), 3782–3799. https://doi.org/10.1109/TNSE.2024.3385797

Zhang, J., Zhu, Y., Li, X., Ming, M., Wang, W., and Wang, T. (2022). Multi-trip time-dependent vehicle routing problem with split delivery. *Mathematics*, 10(19), 3527. https://doi.org/10.3390/math10193527

Zhang, R., Dou, L., Xin, B., Chen, C., Deng, F., and Chen, J. (2024). A review on the truck and drone cooperative delivery problem. *Unmanned Systems*, 12(5), 823-847. https://doi.org/10.1142/S2301385024300014

Zou, R., Liu, J., Pan, H., Tang, D., and Zhou, R. (2024). An improved instance segmentation method for fast assessment of damaged buildings based on post-earthquake uav images. *Sensors*, 24(13), 4371. https://doi.org/10.3390/s24134371