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Application of GIS and IOT Technology-Based MCDM for Disaster Risk Management: Methods and Case Study

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ABSTRACT

This study proposes a two-phase framework to enhance disaster management strategies for flooding using Geographic Information System (GIS) and Internet of Things (IoT) real-time data obtained using drones. The first phase aims to predict the governorate most prone to flooding using GIS and four forecasting models. The second phase involves selecting optimal locations for drone takeoff and landing using GIS with multi-criteria decision making. The neutrosophic ordinal priority approach is used to weight the criteria for selecting the best locations. A case study from the Egyptian Mediterranean Coast is used to measure the effectiveness and applicability of the framework. Results indicate that the Port Said governorate is the most vulnerable to flooding, and the top 10 suitable sites for drone takeoff and landing are suggested for this governorate. The limitations of the case study are discussed, such as data availability and reliability, as well as potential biases in the methodology. This study suggests future research directions to address these limitations and enhance the effectiveness of the proposed framework. Overall, this study contributes to the field of disaster risk management by providing a practical and innovative approach to enhance disaster preparedness and response using GIS and IoT technologies.

1. Introduction

Disasters play an important role in affecting societies across the globe. They can cause short-term and long-lasting impacts, which alter the everyday lives of individuals and whole communities [1]. The growing severity of damages caused by disasters worldwide has accentuated the importance of disaster risk management. Disaster risk management involves the planning, coordination and implementation of strategies to mitigate the impact of disasters on human lives, infrastructure and the environment [2].

Furthermore, disaster risk management aims to develop resilience strategies against disaster events by minimising their impact [4]. The challenges in disaster management are numerous and complex. Major contributing factors, such as climate change and rapid urbanisation, are increasing

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the frequency and intensity of disasters [5, 6]. For instance, climate change can lead to more frequent and severe weather-related disasters, such as floods, storms and heat waves. In the meantime, urbanisation can increase vulnerability to disasters by concentrating populations and assets in areas prone to hazards [7].

The management of these disasters becomes increasingly challenging due to these pervasive and escalating risks. Trends such as population growth, changing land use patterns and technological developments add further complexity [8, 9]. These factors underscore the need for continuous re-evaluation and adaptation of disaster management strategies. This span of influence highlights the imperative need for effective disaster management strategies to mitigate these impacts and foster resilience. This endeavour involves forward-thinking policies and innovative technologies, such as the Internet of Things (IoT), which can provide critical data for better decision-making processes during disaster events [10].

The IoT has emerged as a powerful tool in disaster management. It facilitates real-time monitoring and data collection, which allows for early warnings and rapid response [11]. With the advent of IoT, disaster management can be revolutionised through its integration into existing systems and processes. This integration can enable the collection and analysis of vast amounts of data, which lead to more accurate predictions and timely responses [12]. One of the key benefits of an IoT-enabled disaster management system is its ability to provide real-time alerts and analyse historical data [13]. This capability enables authorities to identify areas that may require emergency services, crisis management teams and critical relief in the event of a disaster. Furthermore, integrating IoT into smart cities is essential for enhancing disaster management capabilities. By leveraging IoT technologies, smart cities can optimise their disaster management facilities and reduce the harmful impact of disasters [14]. For example, by utilising IoT in smart city applications, the detection of disasters such as building fires, atmospheric pollution and route blockages can be achieved more efficiently and in a timely manner [15, 16]. In addition to improving response capabilities, IoT can play a vital role in the prevention and mitigation of disasters. IoT sensors can be deployed to monitor environmental conditions, such as humidity levels, temperature variations and water levels, for detecting potential hazards and taking proactive measures to prevent disasters or minimise their impacts [17]. Moreover, IoT can enable more effective coordination and communication during rescue events [18]. Therefore, IoT technologies can facilitate seamless communication and collaboration amongst different stakeholders involved in disaster response, including emergency services, government agencies, NGOs and volunteer organisations [19]. In conclusion, the integration of IoT in disaster management offers numerous benefits and opportunities for improving response capabilities, prevention and mitigation efforts [20].

In the field of disaster management, Geographic Information Systems (GIS) have proven to be invaluable tools for data collection and analysis. These systems allow for the visualisation, mapping and spatial analysis of data related to disaster events. By incorporating IoT technologies into GIS, disaster management practitioners can gain access to real-time data that can aid in decision-making processes. GIS complements IoT by providing a spatial context to the collected data. This way allows for the visualisation and analysis of the data on a map, which assist in the identification of high-risk areas, planning evacuation routes and allocating resources effectively [21, 22]. Intelligent multi-objective optimisation (IMOO) techniques also play a crucial role in disaster management. These techniques involve optimising multiple objectives simultaneously, such as minimising response time, maximising resource allocation efficiency and reducing the impact of disasters; this feature helps decision makers make informed decisions and allocate resources efficiently in real time during crisis situations [23–25]. Moreover, convolutional deep neural networks (CDNNs) are emerging as powerful tools in disaster management [26, 27]. They can process large amounts of data, including satellite imagery and social media data, to identify patterns and trends that can aid in disaster response efforts [28]. These technologies, when used together, can considerably enhance the capacity to expedite relief efforts during any emergency or disaster.

The research gap addressed by this study is the lack of effective IoT data collection strategies for disaster risk management, particularly in flood-prone regions. This study proposes the use of drones equipped with sensors capable of gathering and transmitting data in real time before, during and after disasters. This study also identifies the need for a comprehensive evaluation of criteria and sub-criteria in the multi-criteria decision making (MCDM) model to determine optimal locations for IoT data collection. Overall, a framework for utilising IoT and GIS technologies in disaster risk management is provided, which fills a research gap in the field.

1.1 Objectives of the Research

1. To explore the potential of IoT and GIS technologies in enhancing disaster risk management.
2. To predict the region most prone to flooding using GIS and forecasting models.
3. To identify the optimal locations for drone takeoff and landing using GIS with MCDM for maximising the efficiency and effectiveness of data collection.
4. To apply a neutrosophic-based MCDM method called neutrosophic ordinal priority approach (N-OPA) for weighting the criteria and sub-criteria to select the optimal locations.
5. To employ a case study from the Egyptian Mediterranean Coast for assessing the effectiveness and applicability of the framework in enhancing disaster management strategies.

1.2 Contributions of the Research

- This study improves disaster management strategies, particularly drone strategies in flood-prone areas along the Egyptian Mediterranean Coast. Precise determinations of flood-prone governorates are provided, which allows for targeted resource allocation and mitigation strategies.
- Traditional prediction models (curve fit forecast, exponential smoothing and forest-based forecast) are compared with the CDNN model (InceptionTime) to identify flood-prone governorates.
- The development of an MCDM model contributes to the academic literature, specifically in optimising the selection of locations for drone takeoff and landing, which is a novel aspect of disaster management.
- This study offers a remarkable contribution to data collection and processing methods by demonstrating effective approaches for gathering and analysing data in disaster management. A notable contribution of this study is the application of the N-OPA method to determine weights of criteria and sub-criteria in a decision-making context, which provides practical guidance for other researchers and practitioners.
- The application of GIS processing assists in identifying suitable locations for drone takeoff and landing, which represents an innovative approach in disaster management. This method could potentially inspire further studies or applications in similar contexts.

This study contributes to addressing research gaps in disaster risk management by proposing a two-phase framework that utilises IoT and GIS technologies to enhance disaster management strategies in flood-prone regions. Specifically, this study fills the gap in effective IoT data collection strategies by proposing the use of drones equipped with sensors capable of gathering and transmitting data. These drones can access inaccessible and unsafe areas for humans, which provides real-time data before, during and after disasters.

This study also employs a comprehensive evaluation of criteria and sub-criteria in the MCDM model to determine the best sites for drone takeoff and landing, which fills a research gap in selecting optimal locations for IoT data collection. The use of a neutrosophic-based MCDM model called N-OPA handles uncertainty in decision making, which is a crucial aspect in disaster management.

Furthermore, this study provides practical insights into the application of IoT and GIS technologies in disaster risk management through a case study in the Egyptian Mediterranean Coast region. The findings of this study can be utilised by policymakers, disaster management authorities and other stakeholders to develop better planning and decision-making strategies for minimising the risk and mitigating the impact of natural disasters.

1.3 Problem Statement and Research Questions

This study aims to address the challenge of effectively using IoT and GIS technologies in disaster risk management, specifically in predicting flood-prone regions and selecting optimal sites for drone takeoff and landing. The goal is to maximise the efficiency and effectiveness of data collection during and after disasters. The research statement identifies the problem of inadequate disaster risk management in flood-prone regions and highlights the usefulness of emerging technologies such as GIS, IoT, forecasting models and MCDM in addressing this issue. This statement is important because it sets the stage for the rest of the study, which guides the reader’s understanding of the problem and the proposed solutions and helps them engage with the findings. It also provides clarity and direction for future researchers who may wish to explore similar topics.

Based on the problem statement of this study, the following research questions are identified:

- How can IoT and GIS technologies be effectively used in disaster risk management?
- How can flood-prone regions be accurately predicted using these technologies?
- How can optimal sites for drone takeoff and landing be identified for data collection during and after disasters?
- How can the efficiency and effectiveness of data collection be maximised through the use of these technologies?

1.4 Organisation of the Paper

The rest of the paper is structured as follows. Section 2 presents an overview of previous research related to IoT and supporting techniques in disaster management. Section 3 discusses the research framework and the methods used. Section 4 presents the case study, which illustrates a real-world application in disaster management. Section 5 introduces the discussion and conclusion.

2. Literature Review

2.1 IoT for Disaster Management

An IoT system refers to a network of interconnected devices, sensors and software applications that collect and exchange data through the Internet. These devices, sensors and applications are embedded in various physical objects, such as buildings, vehicles and infrastructure [29, 30].

IoT technologies and applications in disaster management scenarios greatly improve response times, increase situational awareness and enhance overall disaster management capabilities. IoT technologies related to disaster management facilitate real-time monitoring, data collection and analysis. This way enables stakeholders to gain a comprehensive understanding of the situation on the ground and make informed decisions. For example, an IoT-enabled disaster management system can provide real-time alerts and collect historical data to determine areas in need of emergency services and critical relief during a disaster.

The IoT system for disaster management includes three main components, namely, edge, network and core, as shown in Figure 1.

- **IoT Edge**: The IoT edge refers to the devices and sensors that are deployed at the periphery of the network, close to where data are collected [31].
- **IoT Network**: The IoT network is the communication infrastructure that links these devices and sensors to the central processing and storage systems, which enables real-time decision making.
- **IoT Core**: The IoT core is a managed cloud service that handles secure connection, management and data processing from IoT devices. It simplifies device deployment and management whilst facilitating real-time data analytics in disaster management.

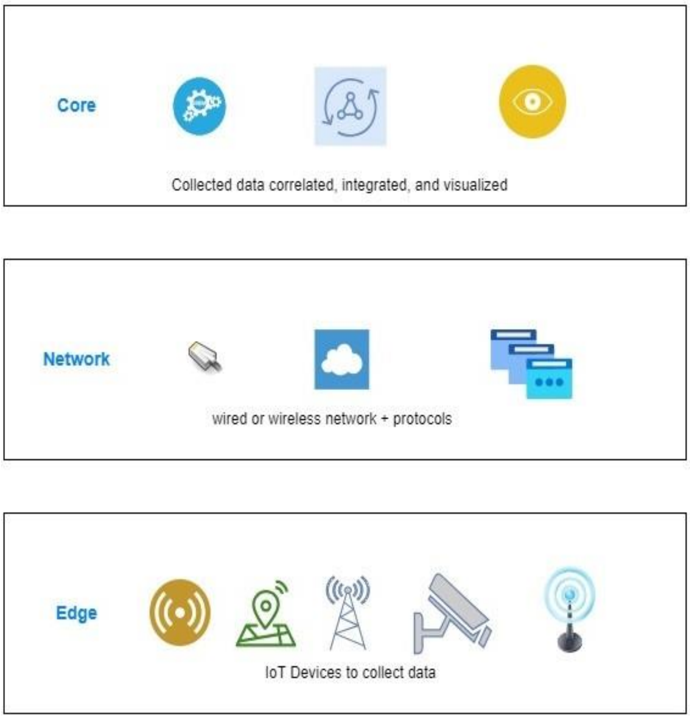

Fig. 1. IoT system components

2.2 IoT Applications in Disaster Management

IoT has various applications in disaster management, which can be categorised into four main phases: mitigation, preparedness, response and recovery. Mitigation: IoT helps minimise the impact of disasters by predicting and preventing incidents before they occur. Examples of IoT applications in mitigation include [32–34] monitoring environmental changes and predicting natural disasters like forest fires, floods and landslides. IoT also identifies weak infrastructure and structural flaws in buildings that may be vulnerable to natural disasters. Preparedness: IoT devices assist in effective planning and communication during disasters. Applications of IoT in preparedness include creating early warning systems to alert communities about impending disasters [35], enhancing communication networks for first responders and emergency management agencies and developing real-time monitoring systems to track the availability of critical resources like food, water and medical supplies [36, 37]. Response: IoT devices play a crucial role in managing disaster response operations by providing accurate real-time data. Applications of IoT in disaster response include deploying unmanned aerial vehicles (UAVs), which are aircraft operated without a human pilot on board. These vehicles are often equipped with various sensors, cameras and other technologies that allow them to perform various tasks. For example, during flooding, real time data collected by UAVs can be used to gather information, assess damage and locate survivors [38]. This feature enables smart tracking of rescue teams and equipment to optimise response times and resource allocation [39] and facilitates remote medical consultations and telemedicine during disasters. Recovery: IoT technology is instrumental in efficient recovery and rebuilding efforts after a disaster.

Some applications of IoT in recovery include [40] assessing the extent of damage using remote sensing and AI-based image analysis, managing the distribution of critical resources and supplies to affected areas based on real-time data, monitoring and analysing post-disaster environmental conditions to ensure safety for recovery efforts and implementing IoT-enabled systems to automate and streamline recovery processes, such as debris removal and reconstruction.

2.3 Challenges and Limitations of IoT for Disaster Management

Despite the tremendous potential of IoT in disaster management, several challenges and limitations need to be addressed to ensure its effective implementation [41, 42]:

- **Connectivity and network issues**: Disasters often result in infrastructure damage, which leads to disrupted communication networks. Reliable connectivity is essential for IoT devices to operate efficiently, and network failures can severely hamper real-time data transmission and coordination efforts.
- **Power supply:** Ensuring a continuous power supply to IoT devices during disasters can be challenging, which is due to that power outages are common in disaster-hit areas. Developing energy-efficient devices and alternative power sources like solar panels or batteries is crucial to address this concern.
- **Scalability concerns**: The rapid deployment of IoT devices in large numbers can pose challenges to scale, especially in managing, monitoring and processing vast amounts of data generated during disasters.
- **Data security and privacy issues**: The sensitive nature of data collected and shared during disasters raises concerns on data security and privacy. Ensuring that data are protected from unauthorised access and tampering is important to maintain trust and confidentiality.
- **Interoperability**: Efficient disaster management requires seamless integration of IoT devices with various platforms, agencies and systems. IoT devices from different manufacturers may have differing protocols and standards, which makes interoperability a primary challenge.
- **Limited resources and budgets**: Many disaster-prone areas, particularly in developing regions, have limited resources and budgets. The cost of implementing and maintaining complex IoT-based disaster management systems can be prohibitive for these regions. Addressing these challenges requires a holistic approach that combines IoT with other technologies and strategies.

2.4 Supporting Techniques for Disaster Management

- **GIS**: GIS is a technology that enables the capture, analysis and visualisation of geospatial data [43–45]. GIS is an essential tool in disaster management because it can be used to map areas prone to disasters, analyse their vulnerability and identify critical infrastructures that may be affected [46, 47]. GIS can also be used to monitor the spread of disasters and support search and rescue operations by providing real-time updates on affected areas and routes for evacuation [48]. Moreover, the use of GIS facilitates effective mapping and visualisation of disaster-affected areas, which provides decision makers with vital information for resource allocation [49, 50].
- **CDNN**: CDNNs are a type of artificial neural network optimised for image processing tasks, such as object recognition and classification [51]. In the context of disaster management, CDNNs can be used to analyse satellite and drone imagery for damage assessment in affected areas. Furthermore, CDNNs in disaster management assist in identifying critical infrastructures that may be affected by disasters and support decision making on resource allocation and rescue operations [52–56].
- **MCDM**: MCDM is an analytical approach designed to consider multiple, often conflicting, criteria in decision-making processes in the context of disaster management [57, 58]. It provides a structured, objective methodology for prioritising or ranking various options in response to a disaster scenario [59]. MCDM helps in evaluating different disaster management strategies based on multiple criteria, such as cost, effectiveness, feasibility and impact on society. By considering multiple criteria, MCDM provides a comprehensive view of potential outcomes of different strategies and helps decision makers choose the best course of action [60, 61]. This approach is particularly useful in disaster scenarios where decisions often need to be made quickly, under high stress and with limited resources. MCDM offers a rational, flexible and systematic approach adaptable to various types of disasters and disaster management scenarios [62].
- **IMOO**: IMOO techniques refer to a set of algorithms and methods that can optimise multiple conflicting objectives simultaneously whilst considering constraints [63]. In the context of disaster management, IMOO techniques can be used to optimise resource allocation during response operations [64, 65]. For example, they can help in determining the optimal distribution of relief supplies to maximise their impact and minimise wastage [66]. IMOO techniques can also assist in decision making under uncertainty by generating multiple solutions to a problem, which allows stakeholders to choose the best option based on their specific needs and preferences [67]. These techniques have also been utilised to optimise resource allocation and decision making during disaster response.

2.5 Applications of Integrating IoT with Supporting Techniques for Improved Disaster Management

The integration of IoT, GIS, MCDM, IMOO and CDNNs can highly improve disaster management in various ways and can be applied to various aspects of disaster management. **Real-time Monitoring and Quick Response**: IoT devices, when deployed in disaster-prone areas, facilitate real-time monitoring. They can promptly detect changes in environmental conditions and send alerts. Through MCDM, decisions regarding rapid response, considering various conflicting criteria, can be made efficiently. **Geospatial Analysis and Prediction**: A collaboration of IoT and GIS can offer considerable geospatial analysis benefits. Sensors and satellite data can be visualised over geographical scales to better understand disaster patterns and predict vulnerable areas**. Efficient Resource Allocation**: Applications of IMOO in disaster management involve optimising limited resources during emergencies. The techniques focus on meeting multiple objectives like minimising casualties and ensuring prompt responses. **Data-Driven Decision Making and Predictive Modelling**: IoT provides a large amount of real-time data that can be analysed through CDNNs. CDNN algorithms process the data, identify patterns and deliver crucial insights for better decision making. These neural networks can also predict potentially disastrous scenarios, which enables early mitigation measures. **Improvement in Mitigation Strategies**: The integration of MCDM with other technologies enhances the decision-making process, especially when various performance criteria are involved. In this way, mitigation strategies can be continuously evaluated and improved. **Assistance in Post-Disaster Recovery**: After a disaster, large amounts of data collected by IoT devices can help in effective relief operations, damage assessment and rehabilitation efforts**. Enhanced Communication**: The collaboration of these technologies can improve information sharing and communication amongst different stakeholders involved in disaster management.

2.6 Challenges and Potential Solutions of Integrating IoT with Supporting Techniques forImproved Disaster Management

Challenges include the following: **Technical Challenges**: The integration of IoT, GIS, MCDM, IMOO and CDNN requires complex programming and data management skills. The ability to capture, process, store and analyse vast amounts of data in real time can be challenging. **Data Privacy and Security**: Given the sensitivity of data gathered during disaster management, ensuring data security from malicious entities is important. The large datasets involved may also raise privacy and data ownership issues. **Interoperability**: Each technology (IoT, GIS, MCDM, IMOO and CDNN) uses specific protocols and standards that may not be compatible with one another. This mismatch can lead to limited communication and functionality amongst integrated systems. **Infrastructure**: The effective operation of these technologies requires a reliable and robust infrastructure. In disaster-prone areas, consistent power supply and connectivity might be challenging.

Potential solutions include the following: **Training and Capacity Building**: These technologies can be effectively managed by investing in technical teams and enhancing their skills. Capacity-building opportunities can be provided for data scientists, network engineers, disaster management professionals and other related personnel. **Implementing Data Security Measures**: Data encryption, strict data access rules and secure cloud storage options can be used to protect data privacy and security. **Standardisation**: The interoperability issue can be addressed by standardising data formats and communication protocols. This solution would likely require coordination amongst technology manufacturers, academics, and disaster management authorities. **Robust Infrastructure**: Investment in reliable and resilient infrastructure can be considered, which can include the use of solar power or other forms of renewable energy to ensure a consistent power supply and the construction of hardened data centres that can withstand adverse conditions.

2.7 Future Outlook and Research Gaps of Integrating IoT with Supporting Techniques for Improved Disaster Management

Future outlooks and directions may focus on the following: **Scale and Scope**: The application of IoT, GIS, MCDM, IMOO and CDNN technologies in disaster management will widen in the future. As these technologies mature, their integration will become even more seamless and impactful, which facilitate a comprehensive, real-time understanding of disaster scenarios. **Predictive Capabilities**: Enhancements in AI and machine learning capabilities will likely improve the predictive capabilities of these technologies, which enhances risk assessment, early warning and disaster response efforts. **Smart Cities**: As more cities become ‘smart’, the integration of these technologies within urban planning and infrastructure will be critical in improving their resiliency against disasters. Research gaps include the following: **Human Factors**: Current research lacks comprehensive studies on human factors in technological adoption. Although these technologies offer vast possibilities, the implementation, usage and acceptance by end-users, especially disaster management professionals, need more attention. **Ethical and Privacy Considerations**: Future research should focus on ethical guidelines and methods to protect sensitive data collected during disaster management. **Case Studies**: More case studies are needed to demonstrate the practical application of integrating IoT, GIS, MCDM, IMOO and CDNN in real-world disaster scenarios. **Efficacy Studies**: Research is needed to effectively quantify and compare the benefits of this technological integration over traditional disaster management methods. **Interoperability**: A knowledge gap exists in understanding the effective integration of these different technologies and ensuring their efficient communication to enhance disaster management.

Existing studies have largely explored the individual applications of IoT and GIS technologies in disaster risk management. IoT has been used for real-time data collection and analysis in disaster response, whilst GIS has been utilised for spatial analysis and mapping of disaster-prone areas. However, few works have investigated the integration of these technologies to enhance disaster risk management strategies. Recent study proposed an integrated framework combining IoT and GIS to improve flood monitoring and early warning systems [68]. The framework utilised IoT sensors to collect hydrological and meteorological data, which were then analysed using GIS for flood modelling and mapping. A similar framework were used to predict urban flash floods using machine learning algorithms and IoT sensors [69]. These studies demonstrate the potential of integrating IoT and GIS technologies in disaster risk management. However, a gap in the literature still exists in the selection of optimal drone site locations for data collection in disaster management. Our research aims to address this gap by utilising MCDM for prioritising criteria for drone site selection and considering uncertainty in decision making using a neutrosophic approach. Neutrosophic MCDM is well suited for our research because it allows for the consideration of uncertain and incomplete information in decision making. The use of neutrosophic sets, which account for uncertainty and indeterminacy, can provide a more accurate and comprehensive representation of complex decision-making criteria in disaster management. This approach is particularly important when dealing with multiple competing criteria and uncertainty in site selection for drone deployment during disasters. Overall, previous studies have analysed the individual benefits of IoT and GIS technologies in disaster risk management, but fewer works have integrated these technologies and utilised MCDM to optimise drone site locations for data collection. Our research aims to address this gap in the literature and utilise a neutrosophic approach to account for uncertainty in decision making.

3. Research Framework

This study takes advantage of integrating techniques and aims to predict which governorate across the Egyptian Mediterranean Coast is most susceptible to flooding in the next 5 years using GIS and CDNNs. Then, MCDM is used with GIS to identify the most suitable locations for drone takeoff and landing to monitor the flood-prone area for an early warning system. This study consists of a two-phase framework with five main steps, as illustrated in Figure 2. Phase one comprises the first step, where the primary aim is to accurately determine the flood-prone governorates along the Egyptian Mediterranean Coast. Phase two consists of steps 2–5. In Step 2, an MCDM model is defined. The MCDM model incorporates various criteria and attributes relevant to selecting the most suitable locations for drone takeoff and landing. Step 3 involves data collection and processing. In Step 4, the weights of criteria and sub-criteria are determined using the N-OPA method. In Step 5, GIS processing is conducted to identify suitable locations for drone takeoff and landing.

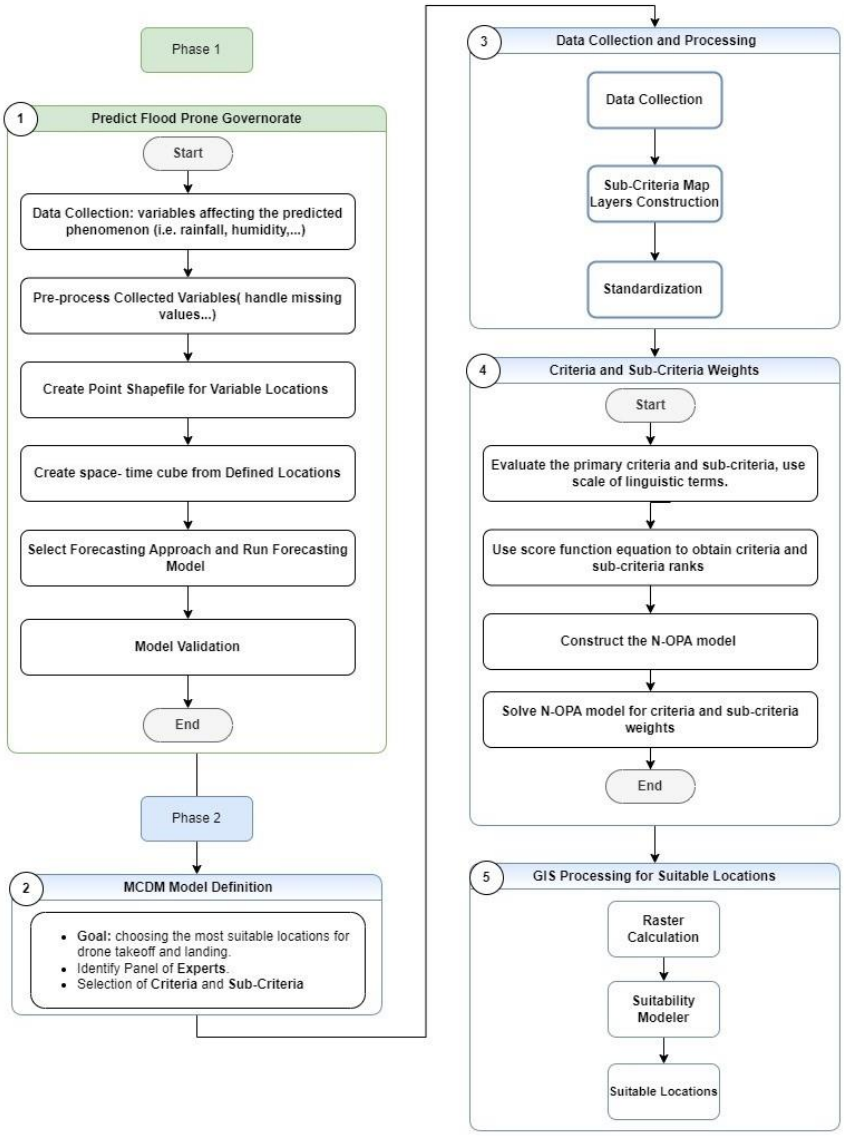

Fig. 2. Research framework

3.1 Study Area

The study area includes the governorates across the Egyptian Mediterranean Coast, as illustrated in Figure 3. This geographical region is particularly relevant to the study due to its susceptibility to flooding and its need for improved disaster management strategies [70–73]. By implementing the research framework within this context, the study aims to demonstrate the integration and effectiveness of GIS, MCDM and CDNN technologies in enhancing disaster preparedness and response.

Fig. 3. Study area

This goal is achieved through accurate predictions of flood-prone areas and the identification of suitable areas for drone deployment in emergency situations. The governorates across the Egyptian Mediterranean Coast include the following: **Alexandria**: It is the second-largest city in Egypt and is renowned for its historical landmarks. **Port Said**: This coastal governorate, which is situated along the Mediterranean, is known for its important economic and commercial activities due to the Suez Canal. **Damietta**: This region is famous for its furniture industry and is located at the Damietta branch of the Nile River. **Beheira**: It is located in the northern part of the country, and it has an extensive coastline along the Mediterranean Sea. **Kafr El Sheikh**: This governate is recognised for its agriculture, especially riceand fish farming. **Matrouh**: It is located on the western edge of Egypt along the Mediterranean coast, and it is renowned for its beautiful beaches. **North Sinai**: This region holds strategic importance due to its proximity to Israel and the Gaza Strip. **Dakahlyia**: This governorate of Egypt is located in the northeastern part of the country in the Nile Delta region. Its capital is Mansoura. It does not border the Mediterranean coast, but it is in close proximity and greatly influences the coastal region. It susceptible to the impacts of disasters, such as floods, due to its geographical location and dense population. Thus, it is a relevant area for disaster management studies. Each of these governorates has unique characteristics that can impact the application and effectiveness of IoT and its supporting techniques in disaster management.

3.2 Panel of Experts

The panel of experts for this study comprises professionals specialised in the fields relevant to the research. It includes representatives from the following disciplines:

- Disaster Management Professional (E1): An individual with experience and knowledge in disaster response, emergency planning and management strategies.
- Data Scientist (E2): An expert with the ability to process and analyse large datasets and a solid background in AI and machine learning methods, especially CDNNs.
- GIS specialist (E3): An expert with experience in GIS, who provides valuable insights into spatial data collection, processing and interpretation.
- Decision Science Specialist (E4): An expert who can assist in structuring MCDM model and validating the weighting and scoring process.
- Urban Planner (E5): A professional with knowledge of the infrastructure and unique characteristics of the study area, which includes the governorates across the Egyptian Mediterranean Coast.

3.3 Data Collection and Processing

A comprehensive data collection process is necessary to conduct research described in the previous steps. For the prediction phase of the research framework, historical data were collected from the website for accessing data from the National Aeronautics and Space Administration (NASA). The data and variables used for the prediction included rainfall and humidity historical data for 20 years, which were collected on an hourly basis from March 2003 to March 2023. To address missing values in the dataset, the approach of dropping locations (or observations) with missing data was used. This approach has several advantages:

- **Simplification**: It simplifies data handling given that advanced techniques like data imputation can be complex or may introduce bias in some cases.
- **Larger Datasets**: When dealing with large datasets, dropping records with missing values does not significantly impact statistical power.
- **Accuracy**: By dropping locations with missing data, the accuracy of predictions can be improved because incomplete or unreliable data are excluded from the analysis.

The collected datasets were converted to spatial layers (point shape files) using ArcGIS Pro 3.1 software. Then, the ‘Create Space Time Cubes’ (from defined locations) tool was used to examine data in space and time. This tool generates cube bins, with each bin representing a weather station for a particular 1 h time period. Each column in the cube corresponds to a location, with each location representing a weather station. The ‘Visualise Space Time Cube in 3D’ tool was used to visualise the created space time cubes. The MCDM model was built to find the best areas for drone takeoff and landing. The second part of the study framework involves collecting and processing data to support the MCDM model, as shown in Figure 4. Spatial data were collected from secondary sources, including the global digital elevation model (DEM) produced by NASA, data on roads and coastline from the Egyptian National Authority for Remote Sensing and Space Sciences (NARSS), information about airports and population from the Egyptian Central Agency for Public Mobilisation and Statistics (CAPMAS) and air quality index data from the Breezometer website. In addition, data such as slope, restricted areas and land use were generated using various analytic tools found in ArcGIS Pro 3.1 Pro software.

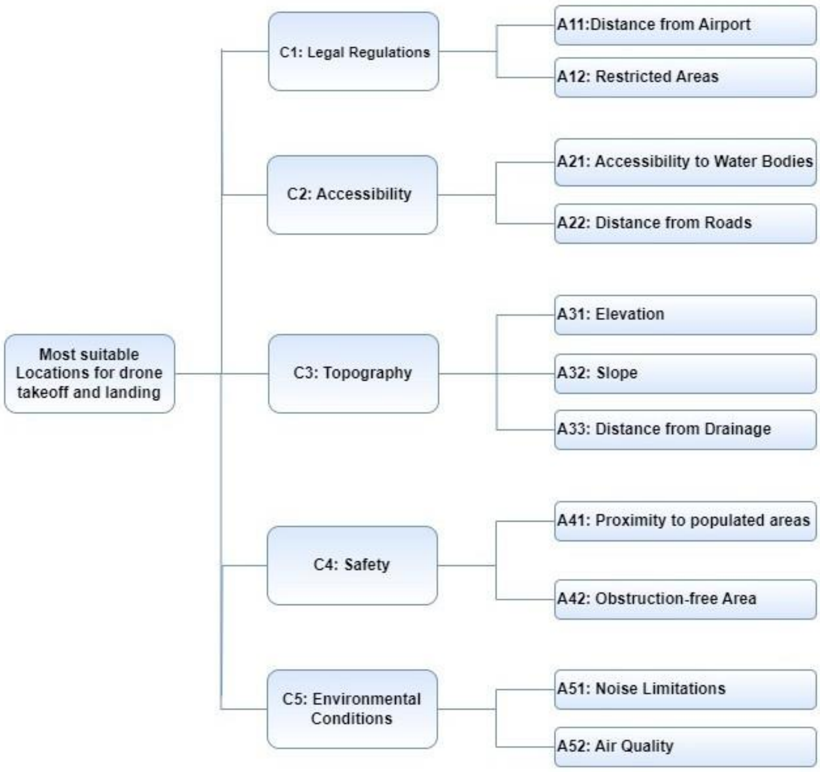

Fig. 4. Criteria and sub-criteria used in the MCDM model

Further details of the criteria and sub-criteria of the MCDM model are shown in Table 1. After data collection, standardisation was performed. This step is crucial in MCDM methods to ensure that all the criteria are on a common scale, which prevents any single criterion from dominating the decision-making process due to differences in numerical units. Standardisation ensures that each criterion contributes equally to the decision-making process, which facilitates accurate comparisons and effective decision making. The min–max normalisation method, which is one of the most commonly used standardisation methods, was used. This approach rescales the values of each criterion to a range of 0 to 1 [74]. It is achieved using the formula (x-min) / (max-min), where x is the original value, max is the maximum value and min is the minimum value. Following standardisation, the decision maker can effectively compare and aggregate the different criteria to arrive at a final decision.

Table 1
Description of the evaluation criteria and sub-criteria used in the MCDM model

Criteria	Description	Sub-criteria	Description
C1: Legal Regulations	It refers to all the legislation and rules that must be adhered to when operating drones.	A11: Distance from Airport	It refers to the physical distance of the potential drone operation site from the nearest airport.
		A12: Restricted Areas	It refers to zones where drone operations may be limited or prohibited due to various reasons.
C2: Accessibility	It refers to the ease of reaching the selected sites for drone takeoff and landing. It can be crucial for regular	A21: Accessibility to Water Bodies	It signifies the level of accessibility for a drone to reach

Criteria	Description	Sub-criteria	Description
	maintenance, emergencies, and equipment replacement purposes.		bodies of water from the selected location.
		A22: Distance from Roads	It refers to the proximity of a selected location to the nearest road infrastructure.
C3: Topography	It refers to the physical features of the selected locations. It consists of the detailed study of the surface features of the land.	A31: Elevation	It refers to the height above a fixed reference point, which is typically defined as sea level.
		A32: Slope	It refers to the degree of steepness or inclination of a surface.
		A33: Distance from Drainage	It refers to the separation distance between a particular location and the nearest drainage features, such as a river, stream or artificial drainage system.
C4: Safety	It refers to the suitability of the designated area for drone operations without posing a risk to property or individuals or the drone itself.	A41: Proximity to Populated Areas	It refers to the closeness or distance to regions with significant human populations.
		A42: Obstruction-free Area	It refers to spaces that are free from physical barriers or impediments that might hinder drone operations.
C5: Environmental Conditions	It refers to the climatic and environmental factors of the potential sites for drone takeoff and landing.	A51: Noise Limitations	It refers to restrictions or regulations on acceptable levels of noise in certain areas due to drones.
		A52: Air Quality	It refers to the condition of the air within a specific region or the overall atmospheric conditions. It is influenced by natural and man-made factors.

3.4 Forecasting Models
3.4.1 InceptionTime Model

InceptionTime is a type of CDNN that is specifically designed for time series data. It draws inspiration from the more general Inception network used for image processing but has been adapted to handle sequential data [75]. Each layer of InceptionTime consists of parallel branches of convolutional layers with different kernel sizes before their results are concatenated. This design enables the model to capture patterns of different time intervals.

InceptionTime essentially serves as a CDNN model designed for time series classification [76]. Its structural foundation is rooted in Google's Inception module for image classification. The key steps in InceptionTime include the following [77]:

- **Reshape the Dataset**: Time series data are usually reshaped into a format suitable for convolutional processing. If the dataset is a univariate time series sample of length n, then it is reshaped to (n, 1).
- **Construct Inception Module**: InceptionTime uses an inception module, which is a small collection of parallel convolutional layers with different kernel sizes. This module captures temporal patterns of different time frames.

- **Create Convolutional Blocks**: The inception modules are stacked together multiple times to create several convolutional blocks. Each block can capture multi-level abstractions of the data.
- **Global Average Pooling**: After passing the time series through the Inception modules, a global average pooling layer is applied. This way reduces the output to a 1D vector, which retains only the most significant features and reduces overfitting.
- **Fully Connected Layer and Softmax Function**: The output from the global average pooling undergoes processing through a fully connected layer, followed by a softmax function for multi-class classification.
- **Model Training**: The model is trained using backpropagation and an optimisation algorithm.
- **Prediction**: Following training, the model can classify new, unseen time series data.

InceptionTime is an appropriate method for this study for several reasons: **Handling Time Series Data**: InceptionTime is designed to handle time series data, which makes it suitable for this study that presumably involves chronological data, such as weather patterns or disaster incident reports. **Scalability**: InceptionTime can process large amounts of data without a significant decrease in speed or an increase in required computational resources. This scalability is important in disaster management, where extensive datasets are common. **Detecting complicated Patterns:** The InceptionTime model can detect complicated temporal patterns within the input by employing multiple convolutional layers with various kernel sizes concurrently. This capability helps in capturing short- and long-term dependencies, which is crucial in disaster management. **Robustness**: This model demonstrates robustness to noise and missing values in the dataset, which are common occurrences in disaster management data**. Reduced Risk of Overfitting**: The use of global average pooling, which handles regularisation automatically, reduces the risk of overfitting. Ultimately, the potential performance of the model on unseen data improves. **Predictive Performance**: InceptionTime has demonstrated high predictive performance on a wide range of tasks, which provides a solid basis for its application in this study.

3.4.2 Curve Fit Forecast Model

Curve fitting is a type of regression analysis used to find the ‘best fit’ curve or line for a series of data points. It can be used for forecasting, explaining variations in data or detecting anomalies.

Curve fitting involves the following steps [78]:

1. **Data Collection**: The relevant data points to be plotted on the curve are collected.
2. **Select an Appropriate Model**: A mathematical model or function that can best describe the data is selected. The function may be a simple line (linear regression) or a complex curve (polynomial regression). The model selection depends on the nature of the data and the purpose of the analysis.
3. **Estimate Parameters**: The values of the parameters in the model function that produce the best fit to the data are determined. This procedure is typically conducted by minimising the sum of the squared differences between observed and predicted values (using the least square method).
4. **Validate the Model**: The accuracy of the model is tested by predicting the values of the dependent variable and comparing them with the actual values.

Curve fitting can be suitable for this study for the following reasons: **Simplicity andFlexibility:** Curve fitting is a simple and flexible way to model complexrelationships between variables. Its simplicity makes it easy to implement and interpret. **Accurate Forecasts**: If the selected model closely matches the pattern ofthe data, then curve fitting can produce highly accurate forecasts.

Quantifying Uncertainty: Researchers can determine the degree of data variability around a best-fit curve through its generation. This feature helps quantify the uncertainty in predictions and aids in developing robust disaster mitigation strategies. **Detecting Trends:** Curve fitting enables researchers to identify and analyse trends in the data. This capability can be especially useful for understanding patterns in disaster incidents, forecasting and planning effective responses.

3.4.3 Exponential Smoothing Model

Exponential smoothing is a time series forecasting method for univariate data that involves the application of decreasing weights for past observations, with the weights decreasing exponentially. The method is popular due to its simplicity, efficiency and low computational resource requirements. The steps involved in this method are as follows:

1 **Choose Smoothing Constants:** An initial smoothing constant is selected, which is usually represented by the Greek letter alpha (α). The value of α is between 0 and 1, with values closer to 0 placing more weight to older data and values closer to 1 emphasising more recent data.
2 **Calculate Simple Moving Average**: A simple moving average is calculated as the initial forecast. This procedure can be conducted by averaging the first few data points in the series.
3 **Apply Exponential Smoothing**: To obtain the next forecasted value, α is multiplied by the actual value of the present time period. Then, it is added to the quantity (1 minus α) multiplied by the forecasted value in the previous period.
4 **Repeat the Process**: The process is repeated by using the new forecasted value as the previous forecasted value for the next calculation.

Exponential smoothing is suitable for this study because of several key reasons: **Adaptability**: It works effectively with datasets showing stable patterns over time and can adapt to changes in level, trend and seasonality in the data. **Efficiency**: It is computationally efficient, which enables immediate forecasting as soon as the latest data become available. **Simplicity**: It is relatively easy to understand, apply and explain to others, which make it an attractive choice in many forecasting situations. **Intuitive**: The exponential decay provides an intuitive way to ‘weigh’ the data, with more recent data having more influence on the smoothing process. When using exponential smoothing, model assumptions and the quality of the fit need to be checked regularly as more data become available to confirm that the statistical properties remain stable.

3.4.4 Forest-Based Forecast Model

Forest-based forecasting is a machine learning technique that utilises multiple decision tree models, which work as an ensemble to generate a final forecast. The ‘forest’ consists of individual ‘trees’, with each tree being unique and trained on different subsets of the original data. The final forecast is a combination of these individual forecasts. The steps involved in forest-based forecasting include the following [79]:

1 **Data Preparation**: The initial dataset is divided into multiple subsets, which often involves bootstrapping or random sampling with replacement.
2 **Building Trees**: Each subset is used to grow a decision tree. The tree is created by making several decisions or splits based on criteria such as reducing the variance in forecast error. Each tree is grown fully and is not pruned, as in a single decision tree model.
3 **Making Individual Forecasts**: After all the trees are grown, a new data point is passed through each tree to reach a forecast.

4 **Aggregating Forecasts**: The final step in a random forest is to calculate an average (for regression problems) or perform a majority vote (for classification problems) based on the results from all trees for each new data point.

Forest-based forecast approach is appropriate for this study because of its capabilities. **Handling Complex Relations:** Forest-based forecasting can capture complex nonlinear relationships between predictors and the variable to be forecasted. This capability is crucial for achieving accurate predictions in disaster management. **Robust**: It exhibits robustness to outliers and does not require extensive preprocessing and scaling. This feature is advantageous when dealing with real-world, messy data. **Multiple Variables**: This method can simultaneously handle multiple input variables, which allows for the consideration of various relevant factors, such as meteorological variables, in the prediction. **Interactions**: Random forests automatically model interactions between variables, which can be essential in this context.

3.5 N-OPA

The neutrosophic environment is a mathematical framework primarily based on neutrosophic set theory, which is an extension of fuzzy set theory. Neutrosophic set was proposed by Florentin Smarandache in 1995 to handle simultaneous indeterminate and inconsistent information [80]. It introduces three membership degrees: truth (T), indeterminacy (I) and falsity (F) [81], each of which independently ranges between 0 and 1. This method differs from previous models, which often consider true and false as complementary. The N-OPA is an element of neutrosophic MCDM. It focuses on decision-making processes where the available data are imprecise, undefined or uncertain. In a typical decision-making process, options are ranked based on a precise quantification of their qualities. However, this precise quantification is not always possible, which leads to potential inaccuracies. The N-OPA, instead, allows these qualities to be ranked in an ordinal manner, from 'most preferred' to 'least preferred', without needing defined numerical values of each quality. N-OPA uses neutrosophic numbers, rather than traditional ones. These neutrosophic numbers hold three independent values: truth (T), indeterminacy (I) and falsity (F). In practical terms, this way allows decision makers to consider not only the potential benefits (T) and drawbacks (F) of a decision but also the level of uncertainty or ambiguity (I) associated with it. For a real-time proposed approach like the N-OPA, the benefit lies in the ability to analyse and make decisions under indeterminate and inconsistent information. When fed with real-time data, N-OPA can quantify and encapsulate the uncertainty inherent in such data using the indeterminacy membership degree (I). By factoring in this degree whilst making decisions, N-OPA can provide outputs that are more reflective of the intricacies and uncertainties present in real-world data. This decision-making method has its advantages, such as the capacity to address complicated and vague problems or those with incomplete information. N-OPA can be a practical tool for decision makers facing complex uncertain scenarios.

3.5.1 Advantages of N-OPA

- Handling Ambiguous and Inconsistent Data: In real-life scenarios, data are frequently inconsistent or lacking. Such information can be used by N-OPA to produce accurate findings. N-OPA uses neutrosophic numbers to address ambiguities, which enhances its reliability in ambiguous contexts. It can handle para consistent information, which classical decision-making methods may struggle with.
- Expressing Confidence and Uncertainty: N-OPA allows decision makers to express their degree of confidence and uncertainty in their judgments. This feature is particularly valuable for capturing the complexity of decision-making situations.

- Representing Contradictions: Neutrosophic sets allow for the representation of contradictions, which can be useful in resolving conflicting criteria in decision-making situations.
- Systematic and Quantitative Decision Making: N-OPA provides stakeholders with a systematic and quantitative means to consider different criteria. This way improves clarity, reduces bias and allows for the weighting of criteria using their importance and non-importance. Ultimately, multiple perspectives are considered in decision making.

3.5.2 Disadvantages of N-OPA

- Complexity: The N-OPA-based decision-making process incorporates multiple matrices and priorities, which can introduce complexity.
- Knowledge Prerequisite: N-OPA relies on the availability of experts with knowledge and experience in the decision-making field. Obtaining such expertise can be challenging in some situations.
- Data Requirement: N-OPA needs a large amount of data to produce precise and accurate decisions. Using N-OPA in situations where data are scarce can be challenging.
- Specialised Software and Tools: The complexity of the method may require specialised software and tools, which may be impractical or inaccessible for all decision makers.
- The following justifications can be used to support the choice of N-OPA for problem solving in disaster mitigation measures, with special emphasis on flood-prone areas, and why it is superior to other MCDM techniques:
- Full Treatment of Ambiguity and Uncertainty: N-OPA fully considers these factors for a more realistic analysis, whilst other methods either struggle with them or neglect them entirely.
- No Demand for Exact Values, Instead Uses Ordered Rankings: Other techniques require that the exact numerical value of each criterion be provided. By contrast, N-OPA uses ordinal rankings, which evades the limitations of exact quantification.
- Handling of Numerous Criteria: Many decision-making techniques face challenges when multiple criteria are present. The MCDM technique N-OPA can handle this circumstance.
- Greater Sensitivity to Changes (Flexibility): N-OPA is extremely adaptable and versatile, which are essential in dynamic situations like disaster mitigation techniques for flood-prone areas.

3.5.3 Steps in N-OPA for evaluating main criteria and sub-criteria

-The appropriate panel of experts is defined, and the clear objectives of the study are identified.

-The expert panel selects the suitable set of criteria and sub-criteria related to the study domain.

-The relative importance ratings given by the panel of experts to the criteria and sub-criteria are collected. As shown in Table 2, each expert must rank the criteria and sub-criteria in the form of triangular neutrosophic numbers (TNNs) $(\mathrm{L}, \mathrm{M}, \mathrm{U}; \mathrm{CD})$.

Table 2
Linguistic variables for determining the importance degree of criteria and sub-criteria.

Linguistic terms	Lower, median, and upper value of number (L, M, U)	Confirmation degree of expert Opinion (CD)
Absolutely not important	$\langle(\mathbf{0},\mathbf{0},\mathbf{0})\rangle$	Absolutely not sure (0,1,1)
Not important	$\langle(\mathbf{0},\mathbf{0},\mathbf{1})\rangle$	Not sure (0.25 ,0.75, 0.75)
Slightly important	$\langle(\mathbf{1},\mathbf{2},\mathbf{3})\rangle$	Slightly sure $(\mathbf{0.45}\ ,\mathbf{0.60},\mathbf{0.60})$
Median important	$\langle(\mathbf{2},\mathbf{3},\mathbf{4})\rangle$	Median sure $(\mathbf{0.50}\ ,\mathbf{0.50},\mathbf{0.50})$
Important	$\langle(\mathbf{3},\mathbf{4},\mathbf{5})\rangle$	Sure $(\mathbf{0.75}\ ,\mathbf{0.20},\mathbf{0.20})$
Strongly important	$\langle(\mathbf{5},\mathbf{6},\mathbf{7})\rangle$	Strongly sure $(\mathbf{0.85}\ ,\mathbf{0.15},\mathbf{0.15})$
Very strongly important	$\langle(\mathbf{6},\mathbf{7},\mathbf{8})\rangle$	Very strongly sure $(\mathbf{0.90}\ ,\mathbf{0.10},\mathbf{0.10})$
Absolutely important	$\langle(\mathbf{7},\mathbf{8},\mathbf{9})\rangle$	Absolutely sure $(\mathbf{1.00}\ ,\mathbf{0.00},\mathbf{0.0})$

In the presence of multiple experts, their individual perspectives will be combined using an aggregation method. The aggregator operator, which is symbolised as ‘G’, acts as a mapping function expressed as $G\colon \psi n\ \rightarrow\ \psi$. In other words, ‘G’ helps transition from multiple opinions to a single one. During this aggregation procedure, the focus is on deriving the average value of each importance degree of criteria and sub-criteria. This procedure is achieved by dividing the total importance of each attribute ‘j’ by the number ‘k’ of experts or decision makers. Here, ‘n’ represents the total count of the experts or decision makers involved in this process.

As shown in Table 2, each expert needs to rank the criteria and sub-criteria using TNNs, which are expressed as (L, M, U; CD). For instance, if the expert ranks the first criterion as superior, then it is assigned as ‘absolutely important’ linguistic variable. If the expert is extremely confident about the ranking of this first criterion, then the final assessment value will adopt the form of the TNN (7, 8, 9); 0.90, 0.10, 0.10. The first part of this representation (7, 8, 9) represents the lower, median and upper limits of the TNN. The second part (0.90, 0.10, 0.10) stands for the degree of confirmation, which incorporates the maximum degree of truth, minimal abstruseness and falsity levels associated with a triangular number.

After the opinions of experts on the relative importance of the criteria and sub-criteria are aggregated, a score function equation is used to determine the final ranking or priority of the consolidated values. For instance, let $A^{\sim}\ =\ \langle(L,M,U);\mu\ ,\gamma,\lambda\rangle$ be a TNN. Then, the score function is calculated from Eq.(1) as follows:

$$S(A) = 1/12\ \ (L +\ 2M +\ U) * [2 + \mu - \gamma - \lambda] \tag{1}$$

The subsequent score function generated from these criteria and sub-criteria is used to determine priority. If the score of C˜1 is higher than that of C˜2, then C˜1 would have a higher priority than C˜2. Similarly, if the score of C˜1 is less than that of C˜2, then C˜1 would have a lower priority. If the scores of C˜1 and C˜2 are equal, then both of them hold the same priority.

After the criteria and sub-criteria are ranked based on their aggregated final rank, the traditional ordinal priority approach (OPA) is used. OPA is a decision-making process used to determine priorities, where the alternatives or options are ranked in order of preference or importance, but the difference between each rank may not be equal or easily quantifiable. In this approach, alternatives are compared not in terms of their exact values, but as being better, worse or equivalent to other options. This approach can be used when other sub-criteria or factors contribute to the ranking process, and the scores on them are not easily comparable. To use OPA, weights need to be assigned to each of the criteria or sub-criteria being evaluated. Then, the options need to be ranked according to their level of compliance with each criterion. The options are subsequently compared, and the one with the highest composite rank is considered the most suitable option. The three main steps of OPA are criteria and sub-criteria identification, weighting of the criteria and ranking of alternatives. This approach is often used in situations where decision makers have limited information or data about the alternatives or where quantitative methods are inappropriate. The constructed model, according to Equations 2–9 introduced by Abdel-Basset *et al.* [81] is as follows:

-This explanation elucidates the ranking of sub-criteria A based on various 'c' sets of criteria values. The equation is formatted from Eq.(2) as follows:

$$A_{ca}^{1} \geq A_{ca}^{2} \geq \cdots \geq A_{ca}^{r} \geq A_{ca}^{r+1} \geq \cdots \geq A_{ca}^{m} \qquad \forall\, c, a \tag{2}$$

-The dominance of the i[th] sub-criteria over the I[th] sub-criteria follows a similar structure, with the weights (W_{ca}) replacing the sub-criteria:

$$W_{ca}^{1} \geq W_{ca}^{2} \geq \cdots \geq W_{ca}^{r} \geq W_{ca}^{r+1} \geq \ldots \geq W_{ca}^{n} \qquad \forall\, c, a \tag{3}$$

-To demonstrate the significance of sub-criteria weights, both sides of the equation are multiplied by 'c' with rank 'r' as calculated in Eq.(4):

$$c(r(W_{ca}^{r} - W_{ca}^{r+1})) \geq 0, \tag{4}$$

-To compute the weights of the sub-criteria, a model is proposed in which the reference for each criterion is maximised, subject to the total weights equalling 1 and each weight being positive as in Eq.(5).

$$\begin{aligned} &\mathrm{Max}\left\{c\left(r(W_{ca}^{r} - W_{ca}^{r+1})\right), cmW_{ca}^{m}\right\} \\ &\quad \text{Subject to:} \\ &\quad \textstyle\sum_{c=1}^{n}\sum_{a=1}^{m} W_{ca}^{r} = 1 \\ &\quad W_{ca}^{r} \geq 0, \end{aligned} \tag{5}$$

-Given that the model is multi-objective and nonlinear and aims to maximise the minimisation objectives, it now reads as Eq.(6).

$$\begin{aligned} &\mathrm{Max\ Min}\left\{c\left(r(W_{ca}^{r} - W_{ca}^{r+1})\right), cmW_{ca}^{m}\right\} \\ &\quad \text{Subject to} \\ &\quad \textstyle\sum_{c=1}^{n}\sum_{a=1}^{m} W_{ca}^{r} = 1 \\ &\quad W_{ca}^{r} \geq 0, \end{aligned} \tag{6}$$

-To express the model linearly in Eq.(7):

$$\begin{aligned} &\mathrm{Max}\ Z \\ &\quad \text{Subject to} \\ &\quad c\left(r(W_{ca}^{r} - W_{ca}^{r+1})\right) \geq Z \\ &\quad cmW_{ca}^{m} \geq Z \\ &\sum_{c=1}^{n}\sum_{a=1}^{m} W_{ca}^{r} = 1 \\ &\quad W_{ca}^{r} \geq 0 \end{aligned} \tag{7}$$

where $Z = \mathrm{Min}\left\{c\left(r(W_{ca}^{r} - W_{ca}^{r+1})\right), cmW_{ca}^{m}\right\}$ and it is unrestricted in sign.

-This model can be solved using various software solutions like LINGO or Excel. The weights of the sub-criteria and criteria are calculated as follows in Eq.(8) and Eq.(9):

$$W_{a} = \textstyle\sum_{c=1}^{n} W_{ca}^{r} \qquad \forall\, a, \tag{8}$$

$$W_{c} = \textstyle\sum_{a=1}^{m} W_{ca}^{r} \qquad \forall\, c, \tag{9}$$

-The final rank of the sub-criteria can be then obtained based on their global weight.

N-OPA is appropriate for this case study specifically due to the following reasons: **Uncertain Information:** Owing to various factors, such as weather conditions and drone battery life, uncertainty could exist in the information regarding optimal locations for takeoff and landing. N-OPA can handle this issue effectively. **Multiple Experts**: Decisions on drone navigation could involve inputs from multiple experts. N-OPA aggregates the rankings given by various experts, which provides an overall judgment. **Variable Criteria**: Aspects, such as terrain, wind speed and proximity to populated areas, could all influence the optimal location decision. N-OPA can consider multiple criteria for decision making.

4. Case Study

Flooding on the Egyptian Mediterranean Coast has led to notable losses, which require a proactive approach to analyse vulnerable areas. The complexities of environmental patterns and the absence of real-time data, inherent uncertainty and the high risks associated with conventional surveillance increase this difficulty. In addition, finding locations for drone takeoff and landing presents challenges. UAVs or drones are crucial in disaster management, especially in hard-to-reach areas. The selection of suitable sites for drone operation influences operational efficiency, area coverage, data collection effectiveness and the safe use of drones, especially considering the unique geographic and demographic characteristics of Egypt. Effective disaster management depends on overcoming these obstacles and establishing a reliable method for the selection of drone locations. This study proposes a multifaceted approach to address these challenges within a comprehensive research framework aimed at providing a unified disaster management strategy.

The case study focuses on the use of IoT, GIS and drones for flood risk management in the Egyptian Mediterranean Coast. This region is prone to flooding due to its geographical location, with several towns and cities experiencing severe flooding during the winter months. This study aims to develop a framework for selecting optimal drone sites using MCDM to enhance flood management in the region. This study utilised historical data from the past decade on flood occurrences in the region to identify the most vulnerable areas. Furthermore, hydrological and meteorological data were collected from weather stations to predict flooding. Spatial data, such as satellite images, DEMs and land cover maps, were also used to map flood-prone areas. This study assumes that drone technology is available and feasible for deployment during flood events. In addition, IoT and GIS technologies are effective tools in flood monitoring and modelling. Lastly, the study assumes that the MCDM framework is suitable for the selection of optimal drone sites in flood management.

4.1 Determination of Flood-Prone Governorates

4.1.1 Curve Fit Forecast

In ArcGIS Pro 3.1, the curve fit forecast tool works by applying one of four equations or curves to the training dataset. Curve fit mathematical models are used to describe the relationship between variables in a dataset and predict future data points. These models use mathematical formulas adjusted to best fit the data and include [82]:

- **Linear Regression**: This model assumes a linear relationship between the dependent and the independent variable. It is represented by the equation $y = mx + c$, where m and c are the parameters, our model will try to learn to produce the best fit line.
- **Exponential Regression**: It is used when data show exponential growth or decay. The generic form of its equation is in Eq. (10)

$$y = ab^X \tag{10}$$

- **Parabolic Curve**: In a parabolic curve fit, the data are modelled to a quadratic function of the form as in Eq. (11)

$$y = ax^2 + bx + c \tag{11}$$

This model can capture rising and falling trends in the data that other simple models like linear fit may not successfully represent.

- **Gompertz Model**: It is also called Gompertz function. It is a type of mathematical model for a time series and is often used in forecasting scenarios, especially when the growth is expected to asymptote at a maximum level. Its equation is usually expressed in the form in Eq. (12).

$$y = ae^{-be^{-ct}} \tag{12}$$

Where a, b and c are the parameters of the function fit by the data.

A single curve type can be selected manually to apply it to all the locations in the cube, or it can be auto-detected by the software, with each location in the cube using different equation or curve that is the best fit. In the curve fit forecast tool, the following parameters were selected: the analysis variables were historical hourly humidity and rainfall datasets from 2003 to 2023.

Humidity and rainfall are crucial prediction parameters when forecasting floods in a prone area due to the following reasons: **Direct Impact on Floods**: Rainfall is the most direct contributor to floods. Excessive rainfall, particularly in a short period, can overwhelm the ability of the soil to absorb it, which leads to runoff that fills rivers, streams, and other water bodies. This phenomenon often causes them to overflow their banks or the drainage capacities in urban areas. **Soil Saturation**: Humidity levels can provide information on the amount of moisture already present in the environment. High humidity levels might indicate recent rainfall, and the soil could already be saturated. Saturated or nearly saturated soil is less able to absorb additional rainfall, which increases the likelihood of flooding. **Predicting Rainfall:** Higher humidity levels often precede rainfall. Thus, monitoring humidity can help anticipate periods of heavy rains, which increases the accuracy of flood prediction models. **Climate Patterns**: Both parameters also influence longer-term climate patterns, which can have implications for flood risk. Extended periods of high humidity can lead to increased cloud formation and frequent rainfall, which raise the likelihood of flood events.

By monitoring changes in these parameters, emergency planners can improve the accuracy of their flood predictions, deploy resources more effectively and potentially save lives and property by warning residents in a timely manner. Other parameters included selecting number of time steps to forecast in this study; 63 or 5 years were selected. In the meantime, the selected curve type was auto-detected by the tool. Figure 5 shows the forecast results using the curve fit forecast.

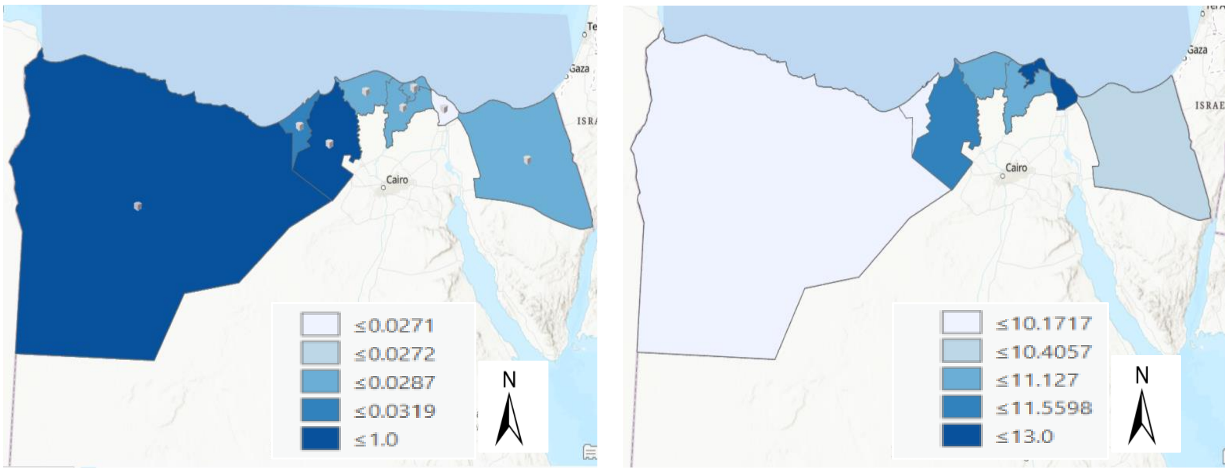

Fig. 5. Prediction using curve fit forecast (left: rainfall variable, right: humidity variable)

4.1.2 Exponential Smoothing

In ArcGIS Pro 3.1, the exponential smoothing tool functions by utilising past observations to forecast future points in the time series. The method estimates three components, namely, level, trend and seasonal, depending on the selected model type. Each time step influences the next time step in an exponentially decreasing manner. Users can specify the season span. In this study, a span of 4 months was used. Parameters, such as the input feature layer, time field, value field(s), prediction length and confidence level for prediction intervals, were defined following the previous method. Figure 6 shows the forecast results.

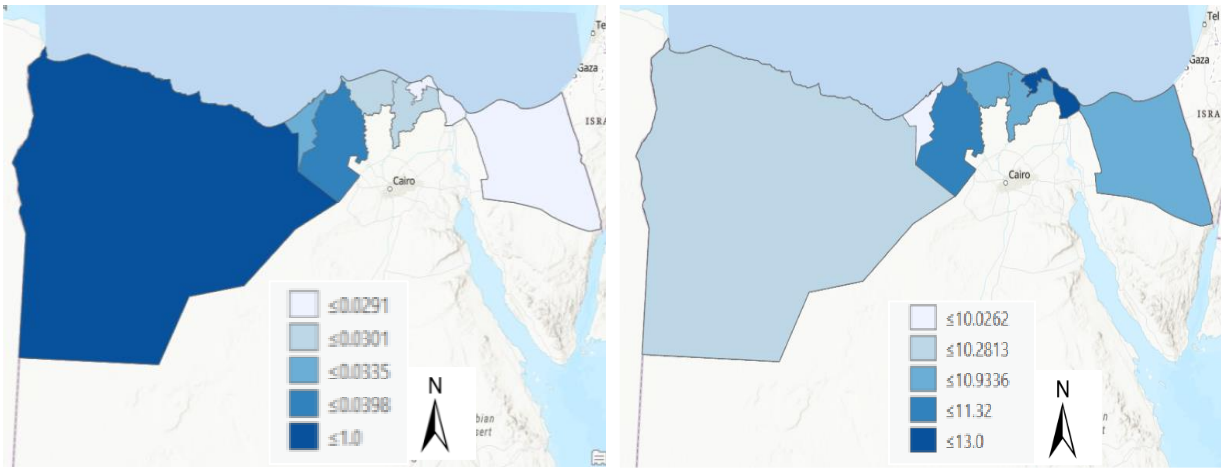

Fig. 6. Prediction using exponential smoothing (left: rainfall variable, right: humidity variable)

4.1.3 Forest-based Forecast

In ArcGIS Pro 3.1, the ‘Forest-based Classification and Regression’ tool uses a machine learning method based on decision trees known as random forest. The tool creates a multitude of decision trees and combines their outcomes to produce either a classification or regression analysis. The sliding time window parameter guides the tool with the number of time steps to use as the training set. The model runs location by location across the space–time cube, and the tool can be used to select the appropriate time step window. Other parameters were defined similarly to the previous tools in running the tool. The results are shown in Figure 7**.**

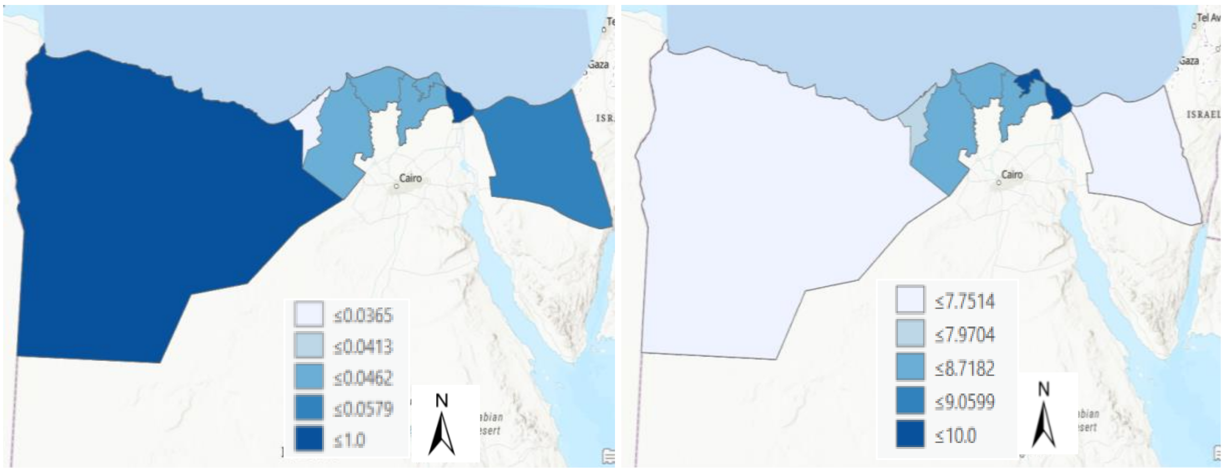

Fig. 7. Prediction using forest-based forecast (left: rainfall variable, right: humidity variable)

4.1.4 Inception Time

Although curve fitting, exponential smoothing and forest-based forecasting are excellent forecasting methods, they may fall short in handling certain types of complex data structures. InceptionTime, which is a type of CDNN, excels in this aspect. In ArcGIS Pro 3.1, before we can run the CDNN model, we firstly need to use another tool to prepare the datasets, which is called the train time series forecast model. It uses time series data from a space–time cube to build a deep learning-based time series forecasting model. Then, the outcomes with the previously selected variables can be used to run the forecast using the time series model based on the CDNN method InceptionTime for prediction. The results are shown in Figure 8.

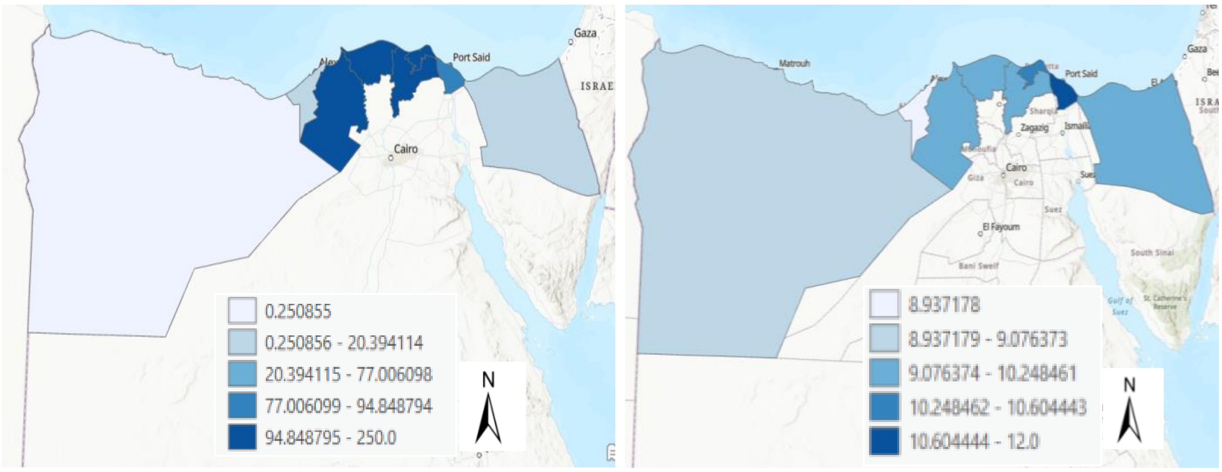

Fig. 8. Prediction using InceptionTime (left: rainfall variable, right: humidity variable)

4.1.5 Model Validation and Evaluation

Root mean square error (RMSE) is a frequently used measure of the differences between values predicted by a model and the values actually observed from the environment being modelled. In other words, it quantifies how closely the data align with the line of best fit [83].

Forecast RMSE (FRMSE): The FRMSE quantifies the difference between the values predicted by the model and the observed values during the training phase of the modelling process. Essentially, it assesses how accurately the model predicts sample data during training.

Validation RMSE (VRMSE): The VRMSE represents the difference between the values predicted by the model and the observed values on a hold-out validation set. This validation set consists of samples that were not used during the training phase and were set aside for testing. VRMSE is particularly useful because it provides insights into how well the model is likely to perform on new, unseen data.

As shown in Table 3, a lower FRMSE suggests a better fit to the data because it means the predictions of the model closely match the observed data. However, RMSE is a scale-dependent measure, which means whether a given RMSE value is considered good, or poor depends on the context, or the variable being predicted. It is also sensitive to outlier values, which suggests that a single highly inaccurate prediction can largely impact the FRMSE [84].

A low VRMSE suggests that the predictions of the model closely align with the actual values in the validation dataset, which indicates good generalisability. Therefore, the model can accurately predict new, unseen data. Conversely, a high VRMSE suggests significant disparities between the predictions of the model and the actual values in the validation dataset. This condition may suggest overfitting, where the model is too closely fitted to the training data and performs poorly on new, unseen data [85].

Table 3
FRMSE and VRMSE for prediction models

	Humidity Variable		Rainfall Variable	
Forecast Approach	FRMSE	VRMSE	FRMSE	VRMSE
Curve Fit Forecast	3.482	3.648	0.027	0.038
Exponential Smoothing	3.501	3.68	0.027	0.038
Forest-based Forecast	0.285	0.807	0.01	0.031
InceptionTime	2.096	0.732	0.032	0.02

4.1.6 Forecast Evaluation by Location

In ArcGIS Pro 3.1, a tool called ‘Evaluate Forecast by Location’ is used to select the most accurate forecasting approach amongst multiple forecasting results for each location of a space–time cube. This tool enables the comparison of multiple tools in the Time Series Forecasting toolset using the same time series data and helps in selecting the best forecast for each location. Figure 9 shows the results obtained from the evaluation tool, which indicates that the forest-based forecast provides the best fit.

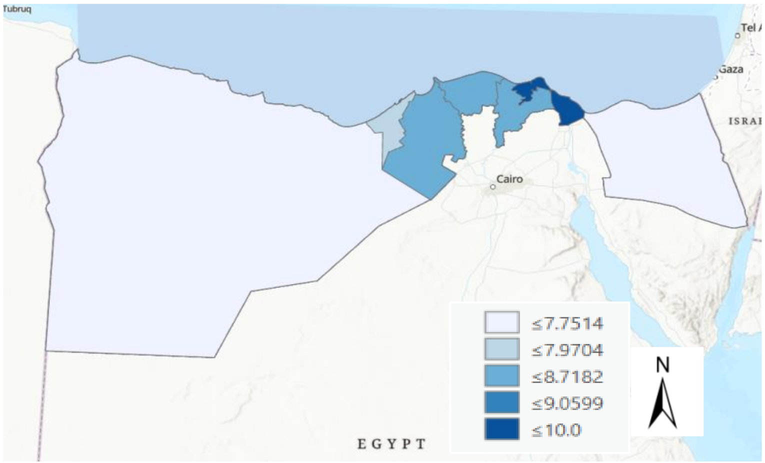

Fig. 9. Evaluation forecast by locations

4.2 Application of N-OPA

After comparing predictions generated using different approaches, the governorate most prone to floods in the next 5 years is Port Said. A combination of the MCDM method N-OPA and GIS processing was employed to identify the most suitable locations for drone takeoff and landing in Port Said for flood monitoring.

N-OPA was used to develop the weights for criteria and sub-criteria. The main criteria were assessed by all experts using linguistic variables, as previously presented in Table 2. The evaluation of the primary criteria by all experts is exhibited in Table 4. Tables A.1–A.5 (Appendix A) present the evaluation of sub-criteria related to each main criterion by all experts.

Table 4
Evaluation values of criteria according to each expert

E	(C1)	(C2)	(C3)	(C4)	(C5)	E	(C1)	(C2)	(C3)	(C4)	(C5)
1	⟨(6,7,8);	⟨(5,6,7);	⟨(2,3,4); (	⟨(3,4,5);	⟨(7,8,9);	4	⟨(5,6,7);	⟨(6,7,8);	⟨(3,4,5); (	⟨(5,6,7); (	⟨(6,7,8);
2	⟨(6,7,8);	⟨(2,3,4); (	⟨(2,3,4); (	⟨(2,3,4);	⟨(7,8,9);	5	⟨(5,6,7);	⟨(3,4,5);	⟨(5,6,7);	⟨(5,6,7); (	⟨(6,7,8);
3	⟨(7,8,9);	⟨(6,7,8);	⟨(6,7,8);	⟨(3,4,5);	⟨(7,8,9);						

We utilised the previously mentioned Equation (1) to determine the final rank of the aggregated value after the averaging of expert opinions regarding the significance of the criteria, as shown in Table 5.

Table 5
Neutrosophic computations of criteria for the ranking process

Computations	Criteria				
	(C1)	(C2)	(C3)	(C4)	(C5)
Sum of importance degree for criteria	(29,34,39; 0.45,0.60,0.60)	(22,27,32; 0.25,0.75,0.75)	(18,23,28; 0.25,0.75,0.75)	(18,23,28; 0.45,0.60,0.60)	(33,40,43; 0.75,0.20,0.20)
Score value of average importance degree	2.83	1.35	1.15	1.91	6.11
Final rank of criteria	2	4	5	3	1

The N-OPA model was constructed, and the total weight of the main criteria was calculated using LINGO software, as shown in Figure 10. The relative importance of sub-criteria according to each criterion is shown in Table 6.

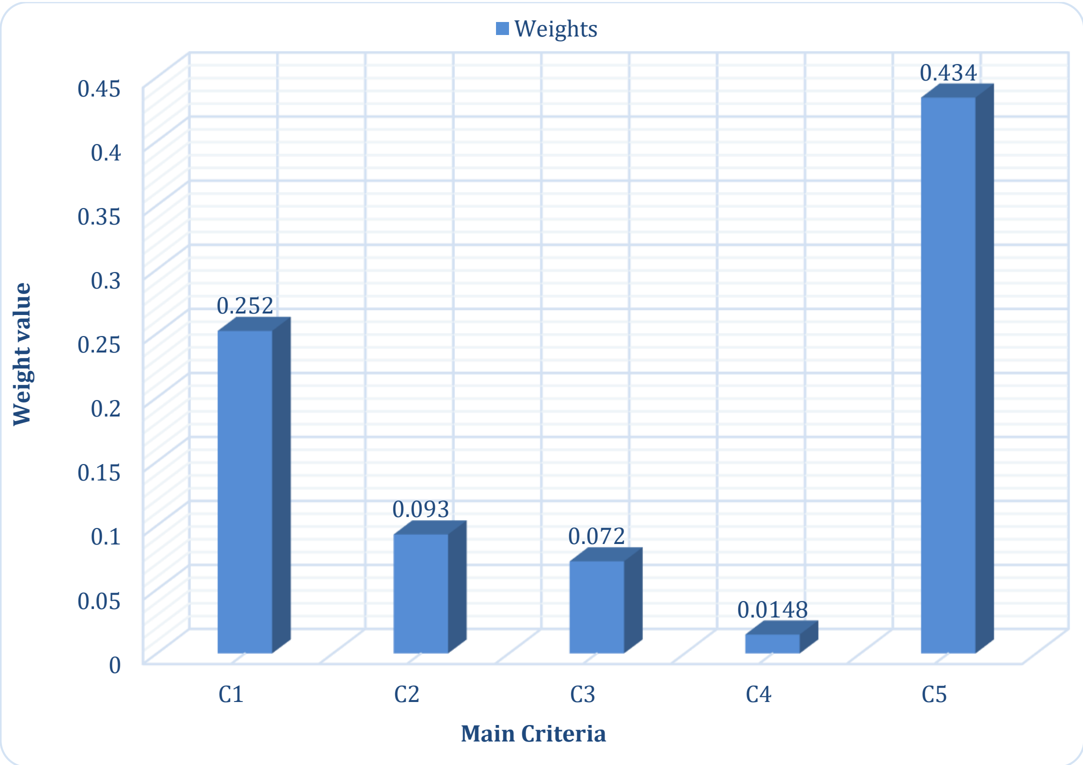

Fig. 10. Weights of the main criteria

Table 6
Global weights of main criteria and their sub-criteria

Main criteria	Weights of main objectives	Sub-criteria	Local weight of sub-criteria	Rank	Global weight	Rank global weights
C1	0.252	A11	0.359	2	0.090	1
		A12	0.641	1	0.162	10
C2	0. 093	A21	0.633	1	0.059	6
		A22	0.367	2	0.349	11
C3	0.072	A31	0.748	1	0.054	5
		A32	0.015	3	0.001	2
		A33	0.252	2	0.018	3
C4	0.148	A41	0.578	1	0.086	9
		A42	0.422	2	0.062	7
C5	0.434	A51	0.805	1	0.034	4
		A52	0.195	2	0.085	8

4.3 GIS Processing

GIS is a system used for capturing, managing, analysing and presenting geospatial data. GIS is important because it allows researchers and disaster management professionals to visualise geospatial data, analyse patterns and relationships and ultimately make informed decisions. GIS helps integrate data from multiple sources and present them in a unified and understandable format. In the context of disaster risk management, GIS can help identify high-risk areas, plan evacuation routes and assess the impact of disasters. Overall, GIS is an essential tool for effective disaster risk management and can help save lives and minimise damage. In this study, GIS plays a crucial role in providing a framework for disaster risk management. Specifically,

1 The region most prone to flooding is predicted by analysing historical data and identifying the governorate with the highest vulnerability to flooding using GIS and four forecasting models.
    - GIS is used for visualising the collected historical dataset involved in the prediction phase.
    - Pre-processing of the dataset, such as how missing values are handled within the dataset, is conducted via GIS tools, specifically ArcGIS Pro 3.1.
    - The datasets collected are then converted from variable locations into a point shape file using conversion tools in ArcGIS Pro 3.1.
    - Space–time cubes are created from the point shape files using ArcGIS Pro 3.1 tools.
    - Four forecasting models within the ArcGIS Pro 3.1 software are then applied to the dataset.
    - Model validation and evaluation are conducted using tools within ArcGIS.

2 The best locations for drone takeoff and landing are selected using GIS with MCDM to maximise the efficiency and effectiveness of data collection.
  - GIS is used in the second phase for the construction and standardisation of sub-criteria map layers using ArcGIS Pro 3.1 tools.
  - Sub-criteria map layers are created, and total weights are integrated using the raster calculator tool in ArcGIS Pro 3.1.
  - The final weighted layers are then used as inputs to the ArcGIS Pro 3.1 suitability modeler to locate the most suitable locations for drone takeoff and landing.
  - A total of 10 locations are selected to be suggested as suitable locations by the modeler based on the inputs, with a total area of 120 m^2 for each location, as shown in Figure 11.

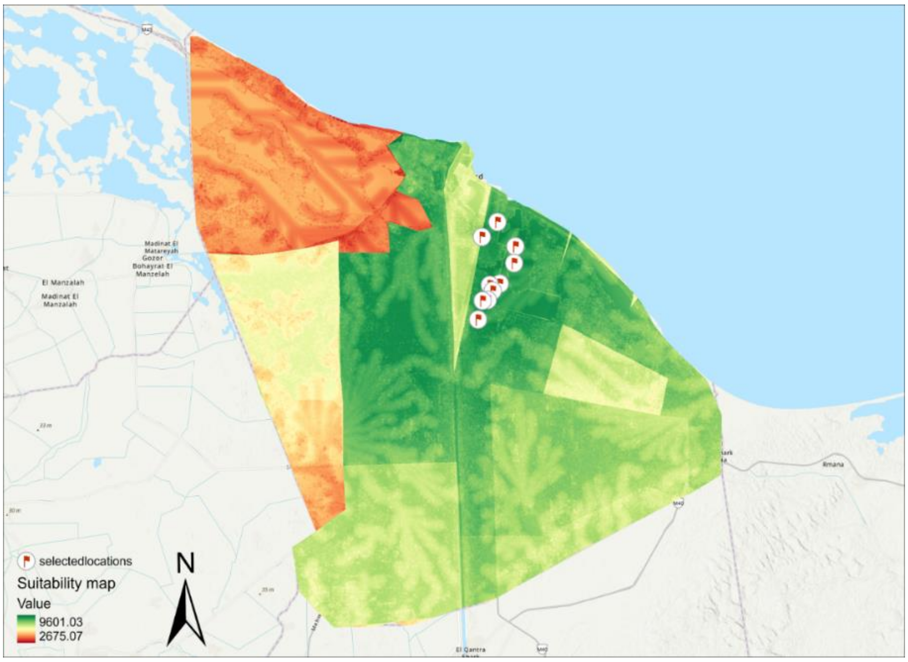

Fig. 11. Suitable locations for drone takeoff and landing in Port Said, Egypt

IoT refers to the network of physical objects or 'things' that are embedded with sensors, software and other technologies that enable them to connect and exchange data over the Internet. In the context of disaster risk management, IoT can be used to gather real-time data before, during and after a disaster to inform decision-making and response efforts. Using IoT requires prior planning for more efficiency. In this study, IoT is suggested to be used in conjunction with GIS to enhance disaster risk management. The following steps are conducted to facilitate the actual implementation of the IoT framework:

- Drones equipped with sensors and data-transmission capabilities are used to gather real-time data on the impact of the disaster before, during and after it occurs.
- The optimal locations for drone takeoff and landing are selected using GIS with MCDM to maximise the efficiency and effectiveness of data collection. This study uses MCDM to select the optimal locations for drone takeoff and landing. This method is a decision-making technique that involves evaluating and prioritising multiple criteria to choose the best option. A neutrosophic-based MCDM method called N-OPA is used to handle uncertainty and evaluate criteria and sub-criteria in a neutrosophic environment.
- The drones are implemented at the selected locations, and the data collected by drones are analysed to inform decision-making and response efforts.

One limitation of the case study is that it focuses only on flooding in the Egyptian Mediterranean Coast, which may not be representative of all regions or types of disasters. The study also relies on data from open sources rather than commercial data with higher resolution, which may affect the accuracy of the forecasting models and drone site selection. The panel of experts involved in the MCDM process may also introduce bias in the selection of criteria and sub-criteria. Future research directions can expand the case study to different regions and types of disasters to test the generalisability of the framework. Real-time data can also be used to improve the accuracy of the predictions and site selection process. Lastly, exploring the ethical considerations and implications of using drones for disaster response and management can be a valuable avenue for future research.

5. Conclusions

This study aims to achieve two primary objectives. Firstly, it aims to predict the region most prone to flooding using GIS in conjunction with forecasting models. Secondly, it aims to optimise the selection of drone takeoff and landing locations based on real-time IoT data. In this study, GIS with MCDM is used to harness the full potential of IoT real-time data obtained through drones. The research methodology employs a two-phase framework. Phase 1 focuses on predicting the governorate most prone to flooding. In this phase, GIS and four forecasting models—three traditional models and one based on CDNN—are used to analyse historical data and identify the governorate with the highest vulnerability to flooding. Phase 2 involves the selection of optimal locations for drone takeoff and landing using GIS with MCDM. This phase involves building an MCDM model by identifying suitable criteria and then collecting and processing the necessary data to implement the model. The criteria used in the MCDM model need to be prioritised by assigning weights to find the best locations. A neutrosophic-based MCDM method called N-OPA is used for weight assignment. The use of N-OPA, which is an extended form of the original OPA, handles decision-making uncertainties in a neutrosophic environment. GIS tools are then applied to find the total weights of all locations in the selected governorate. The top-ranked locations are identified as the most appropriate for drone takeoff and landing based on the weights. A case study from the Egyptian Mediterranean Coast is used to validate the effectiveness and applicability of the framework in disaster management strategies. Eight different governorates along the Egyptian Mediterranean Coast are selected to assess their vulnerability to flooding in the first phase of the framework. Predictions are made using four forecasting models, namely, curve fit forecast, exponential smoothing, forest-based forecast and InceptionTime. These predictions are based on historical hourly humidity and rainfall datasets from 2003 to 2023, which are acquired from the website for accessing data from NASA. The evaluate forecast by location tool in ArcGIS software is used to select the most accurate prediction model. The results indicate that the forest-based forecast provides the best fit, and the Port Said governorate is predicted as the most vulnerable to flooding. The second phase of the case study focuses on building an MCDM model to select the best sites across Port Said governorate for drone takeoff and landing. A panel of five experts with relative experience and knowledge assists in selecting the five main criteria and eleven sub-criteria for evaluation. Spatial data are collected from secondary sources, including NASA for DEM data, NARSS for road and coastline data, CAPMAS for airport and population data and the Breezometer website for air quality index information. Additional data, such as slope, restricted areas and land use, are generated using various analytic tools found in ArcGIS Pro 3.1 Pro software. The MCDM method N-OPA is then employed to evaluate the criteria and sub-criteria. Based on the weights assigned and using ArcGIS tools, locations in Port Said are ranked, and the top 10 suitable sites for takeoff and landing are recommended. Key findings from this research include the successful prediction of the most vulnerable governorate to flooding and the selection of top-ranked locations for drone takeoff and landing. The practical implications of this research suggest the use of similar frameworks to collect and analyse real-time data, which enables timely and effective decision making in response to disasters. Future research directions may explore the use of different IoT sensors and the application of the framework to different types of disasters. Furthermore, the actual implementation of the drones and the analysis of collected real-time data need to be considered. Although various predictive models are applied, our research is limited by the quantity and quality of available data, which potentially affects the accuracy of our results. Future research should expand on these findings by possibly integrating more complex models to address the unique challenges and dynamics of modern disaster management. Moreover, the case study focuses only on one type of disaster in one region and does not address the ethical considerations of using drones for disaster response and management. Overall, this study provides a comprehensive, rigorous and technologically advanced framework for enhancing disaster management strategies and can serve as a foundation for further research and practical applications in this field.

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Data availability statement
The datasets generated during and/or analysed during the current study are not publicly available due to the privacy-preserving nature of the data. However, they can be obtained from the corresponding author upon reasonable request.

Conflict of interest
The authors declare no conflicts of interest in this research.

Ethical approval
This article does not involve any studies with human participants or animals performed by any of the authors.

Appendix A

Table A.1
Evaluation values of legal sub-criteria according to each expert

Experts	A11	A12	Experts	A11	A12
1	⟨(5, 6, 7; 0.50 ,0.50, 0.5	⟨(7, 8, 9); ((1.00 ,0.00, 0.	4	⟨(6, 7, 8; 0.85 ,0.15, 0.1	⟨(7, 8, 9; (1.00 ,0.00, 0.0
2	⟨(6,7,8; 0.85 ,0.15,0.15	⟨(5, 6, 7; 0.50 ,0.50, 0.50	5	⟨(5, 6, 7; 0.50 ,0.50, 0.5	⟨(6, 7, 8; 0.85 ,0.15, 0.1
3	⟨(6, 7, 8; 0.85 ,0.15, 0.1	⟨(6, 7, 8); (1.00 ,0.0, 0.0			

Table A.2
Evaluation values of accessibility sub-criteria according to each expert

Experts	A21	A22	Experts	A21	A22
1	⟨(7, 8, 9; 1.00 ,0.00, 0.0	⟨(5, 6, 7; 0.85 ,0.15,0.15	4	⟨(6, 7, 8; 0.75 ,0.20, 0.2	⟨(3, 4,5; 0.50 ,0.50, 0.50
2	⟨(6, 7, 8); (1.00 ,0.0, 0.0	⟨(5, 6, 7; 0.85 ,0.15,0.15	5	⟨(3, 4,5; 0.50 ,0.50, 0.50	⟨(5, 6, 7; 0.85 ,0.15,0.15
3	⟨(5, 6, 7; 0.50 ,0.50, 0.5	⟨(6, 7, 8; 0.75 ,0.20, 0.2			

Table A.3
Evaluation values of topography sub-criteria according to each expert

Experts	A31	A32	A33	Experts	A31	A32	A33
1	⟨(7, 8, 9; 1.00 ,0.	⟨(3, 4,5; 0.50 ,0.	⟨(6, 7, 8; 0.75 ,0.	4	⟨(7, 8, 9; 0.85 ,0.	⟨(5, 6, 7; 0.85 ,0.	⟨(6, 7, 8; 0.75 ,0.
2	⟨(6, 7, 8; 0.75 ,0.	⟨(5, 6, 7; 0.85 ,0.	⟨(3, 4,5; 0.75 ,0.	5	⟨(6, 7, 8; 0.75 ,0.	⟨(3, 4,5; 0.50 ,0.	⟨(5, 6, 7; 0.75 ,0
3	⟨(6, 7, 8; 0.85 ,0.	⟨(5, 6, 7; 0.50 ,0.	⟨(7, 8, 9; 0.85 ,0.				

Table A.4
Evaluation values of safety sub-criteria according to each expert

Experts	A41	A42	Experts	A41	A42
1	⟨(5, 6, 7; 0.85 ,0.15,0	⟨(7, 8, 9; 0.90 ,0.10, 0	4	⟨(7, 8, 9; 0.85 ,0.15, 0	⟨(3, 4,5; 0.50 ,0.50, 0
2	⟨(3, 4,5; 0.75 ,0.20, 0	⟨(6, 7, 8; 0.90 ,0.10, 0	5	⟨(6, 7, 8; 0.90 ,0.10, 0	⟨(5, 6, 7; 0.85 ,0.15,0
3	⟨(7, 8, 9; 0.85 ,0.15, 0	⟨(5, 6, 7; 0.50 ,0.50, 0	⟨(6, 7, 8; 0.85 ,0.15, 0		

Table A.5
Evaluation values of environment sub-criteria according to each expert

Experts	A51	A52	Experts	A51	A52
1	⟨(7, 8, 9; 1.00 ,0.00, 0.0	⟨(5, 6, 7; 0.85 ,0.15,0.15	4	⟨(7, 8, 9; 0.85 ,0.15,0.15	⟨(6, 7, 8; 0.75 ,0.20, 0.20
2	⟨(6, 7, 8; 0.90 ,0.10, 0.1	⟨(5, 6, 7; 0.85 ,0.15,0.15	5	⟨(7, 8, 9; 0.90 ,0.10, 0.1	⟨(6, 7, 8; 0.90 ,0.10, 0.10
3	⟨(6, 7, 8; 0.75 ,0.20, 0.2	⟨(5, 6, 7; 0.50 ,0.50, 0.5			

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