Flood Risk GIS Mapping Using Unmanned Aerial Vehicles: A Case Study at Chennai 2023 Floods

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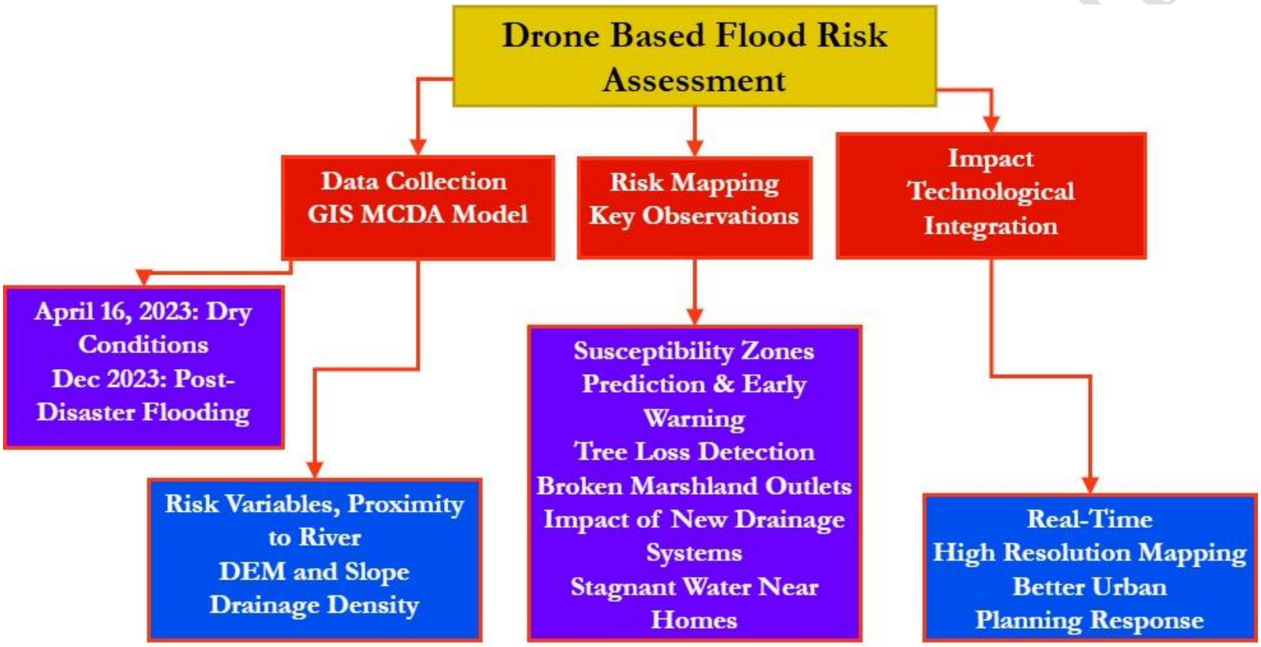
Graphical abstract



Abstract

Floods are among the most destructive natural calamities, endangering both people and property. The present project aims to create a mesoscale state-wide flood risk map for the Chennai district in Tamil Nadu, India, using drone data and a GIS-MCDA model. The Chennai cloudburst of 2023 was a disastrous meteorological event that caused widespread flooding and damage, killing over 50 people. As a result, creating a flood risk map is critical for mitigating future calamities. In the present investigation, a flooding risk map created with drones is used to estimate damage assessment, create risk susceptibility zone maps, predict disasters, propose alternatives, and manage rescue and rehabilitation by considering flood risk variables such as precipitation (mm), proximity to river (km), Digital Elevation Models, DEM (m), slope (%), Land Use and Land Cover, LULC, drainage rate (km/km2), type of soil, and lithology. The results of this study may provide policymakers and managers with more full information and precise ideas concerning systems for early warning, rescue activities, and flooding mitigation strategies.

Keywords: Chennai Floods 2023; Drone Technology; Flood Risk; GIS Mapping; Digital Elevation Models

1. Introduction

Floods are one of the most devastating natural catastrophes because they risk both life and property [1] [2]. Flooding has grown increasingly frequent as a consequence of growing populations, industrialization, and changing climates [3] [4][5][6]. It is an unavoidable event that will most certainly intensify humanity's existence in the next years and jeopardize several regions throughout the planet. The existing and potential sensitivity to flood events needs a significant amount of geographic and temporal data for anticipating floods in the future [7] [8] [9]. To decrease storm-related hazards and damages, it is required to assess the risk of floods, locate storm-prone areas, and implement appropriate mitigation and control measures. Flood risk assessment is useful for prevention measures, warning mechanisms, and rescue strategies [10]. In disaster assessments, computational approaches are widely used for assessing flood risk [11] [12]. Hydrodynamic and hydrologic models are commonly used to assess floods severity, degree, and recurrence [13]. In particular, rainwater-runoff models and stream navigation models are presently utilized to forecast floods [14][15], as well as the run-off yielding method, a type of hydrologic framework, to investigate the flooding path in channels of flow [16]. Such models are capable of processing vast amounts of data and provide useful flooding data. An extremely difficult and pervasive component of these systems is a lack of hydro meteorological monitoring [17]. Furthermore, there is a shortage of precise information, making estimating flood risks difficult. To alleviate this constraint, a robust flooding risk assessment methodology must be developed. GIS systems are commonly used in flooding assessment and management because of their ability to organize and evaluate large databases such as hydrologic and meteorological predictions, digitally produced elevation models (DEM), and land use information. An essential feature of GIS for such application is the ability to combine numerous sources of information, such as satellite images and topographical maps, and produce entire risk to flooding maps for making judgments. Additionally, GIS systems may be used to model flood events and predict their consequences. GIS may be used to analyze the effectiveness of a mitigation approach. The use of GIS for flooding management and evaluation is known to be an effective strategy for finding flooding-prone sites, forecasting flooding incidents, and assessing the effectiveness of mitigation techniques. [18][19][20]. Several research [21] [22] have used GIS and multi-criteria decision analysis (MCDA) to assess the consequences of flooding-related elements. The MCDA-GIS approach, which integrates the spatial datamining skills of GIS with the ability of MCDA to link current data (such as rainfall, slopes, quantity of drainage, soil, and land usage) to decision-based data, has been found to be successful [23][24][25]. Flood risk mapping has advanced significantly with the incorporation of drone technology, which has the potential to record high-resolution, real-time geographical data. Several studies have demonstrated the efficacy of drones, notably in enhancing flood risk assessment and management [26][27]. For example, Unmanned Aerial Vehicles (UAVs) are shown to provide exact topographic mapping to detect hazardous flood zones, which is crucial input for disaster preparedness [28]. Drones outfitted with LiDAR sensors are used to produce Digital Elevation Models (DEMs), which improve floodplain delineation and hydrological modelling accuracy. [29]. Furthermore, the usefulness of UAVs in monitoring flood extent and damages during post-flood assessments is emphasized, ensuring a quick and informed decision -making [30][31][32]. Another study investigates multi-spectral imaging with UAVs, which was useful in determining plant cover, soil moisture, and surface runoff characteristics that influence flood risk [33]. The integration of drones and Geographic Information Systems (GIS) has been further researched; the study emphasized the integration for mapping flood-prone zones and measuring community resilience [34]. These studies highlight the expanding relevance of drone technology in improving flood risk mapping due to its low cost, accessibility to dangerous areas, and capacity to capture spatial-temporal changes with high precision. In this study, a flood prediction model for Chennai was created using an Extended Elman Spiking Neural Network (EESNN) optimized with a Robust Chaotic Artificial Hummingbird Optimizer (RCAHO). The model was created to increase flood forecasting accuracy by capturing complicated hydrological patterns and avoiding local minima during optimization. Trained on historical flood data, the methodology outperformed existing prediction approaches, indicating that it is a viable tool for early warning systems and disaster management [35]. An integrated model for an early flood prediction system is created by combining Sentinel-2 satellite images to improve flood forecasting accuracy[36]. A flood prediction model was suggested that uses a Light-weighted Dense and Tree-structured Simple Recurrent Unit (LDTSRU) to assess meteorological data. The LDTSRU architecture is intended to efficiently capture complicated temporal correlations in meteorological data while being computationally simple. By analysing inputs such as rainfall, temperature, and humidity, the model strives to deliver accurate and fast flood forecasting. This technique provides a simplified solution for flood prediction, balancing model complexity and performance to improve catastrophe planning and response [37]. In India, an autonomous, data-driven methodology was developed to forecast long-term rainfall. Their solution makes use of a Convolutional Residual Attentive Gated Circulation Model that has been optimized via the Humboldt Squid algorithm. This model incorporates complex temporal and geographical trends in climate data, increasing the accuracy of rainfall forecasts. The Humboldt Squid optimization refines the model's parameters, resulting in better prediction performance. This technique provides a reliable tool for predicting rainfall trends, which aids in agricultural planning and water resource management [38]. This study assesses flood vulnerability in the Pallikaranai region using high-resolution aerial imagery and GIS-based mapping, giving important insights for disaster preparedness, mitigation, and urban flood risk assessment. To do this, the study uses UAVs outfitted with multispectral and LiDAR sensors to collect high-resolution aerial images of flood-affected areas. GIS-based flood risk maps are created by combining drone data with satellite images and hydrological models in order to examine flood effect patterns such as water stagnation, drainage networks, and land use change. The study assesses important flood risk characteristics such as precipitation levels, proximity to rivers, digital elevation models (DEM), slope, land use and land cover (LULC), drainage density, soil type, and lithology. In addition, socioeconomic risks connected with flooding are evaluated in order to develop appropriate mitigation techniques for urban design and catastrophe management. The 2023 Chennai floods were triggered by a violent cloudburst driven by cyclonic rains from the Bay of Bengal, resulting in substantial devastation and the loss of over 50 people. The Pallikaranai wetland, an important natural flood buffer, has grown more susceptible owing to development and poor drainage infrastructure. Traditional flood mapping methods lack real-time, high-resolution data, therefore drone-based GIS mapping is a more effective option for accurate and speedy flood assessment. This study aims to improve disaster resilience and preparedness in Chennai by merging real-time drone data with GIS.

The scope of this study covers Pallikaranai and its neighbouring flood-prone areas, using UAVs equipped with modern sensors to conduct topographic and hydrological studies. The study combines drone-derived imagery with GIS-based spatial analysis, giving important insights for disaster response teams, urban planners, and government organizations. Furthermore, the approach used in this study may be duplicated for flood vulnerability evaluations in other metropolitan areas, adding to long-term flood risk management methods on a larger scale.

2. Study Area

The study was carried out at Pallikaranai, Chennai, the capital of Tamil Nadu in India. Chennai district, formerly known as Madras Provincial, is one of Tamil Nadu's 38 districts and has the state's greatest population density despite its tiny size. Furthermore, it encompasses the great majority of Metropolitan Chennai, which was previously divided between Chengalpattu, Kancheepuram, and Tiruvallur districts. Madras is located at latitudes (13.0° N and 13.1° N) and longitudes (80.16° E to 80.3° E) (Figure 1), with a total area of 426 km2. The area has the classic severe tropical environment, while most of the time is characterized by hot climate. The climate of Chennai is typically hot, with temperatures ranging from 26 to 35 degrees Celsius with an average annual precipitation of 1400 mm. Pallikaranai, located in southern

Chennai, Tamil Nadu, is a low-lying, flood-prone area near the Bay of Bengal. Pallikaranai Marsh is a critical natural flood barrier that absorbs surplus precipitation. Chennai has witnessed multiple significant floods, including those in 2005, 2015, and 2023, with Cyclone Michaung dropping more than 550 mm of rain in two days. The hydrographic network comprises of the Adyar River, Pallikaranai Marsh, and several canals, which assist drain surplus water, although urban encroachments have limited its efficiency. The elevation ranges from 2 to 6 meters, and the slope is flat (0°-2°), which delays water drainage and increases flood threats. Rapid development and wetland loss have exacerbated drainage issues. This work focuses on drone-based GIS mapping to detect flood-prone locations, drainage paths, and topography differences, assisting in improved flood management and disaster planning.

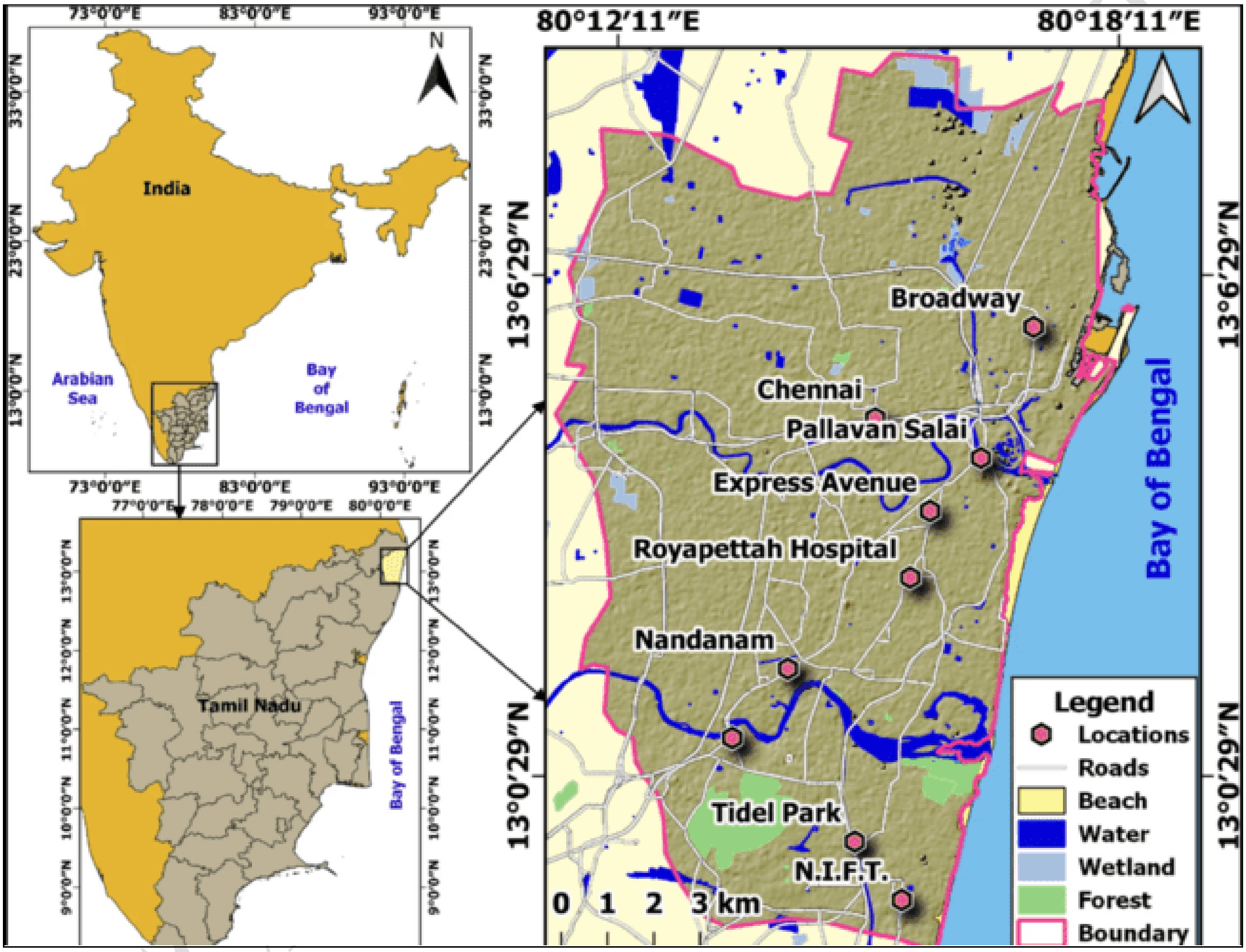


Figure 1: Map view of Hydrographic Network

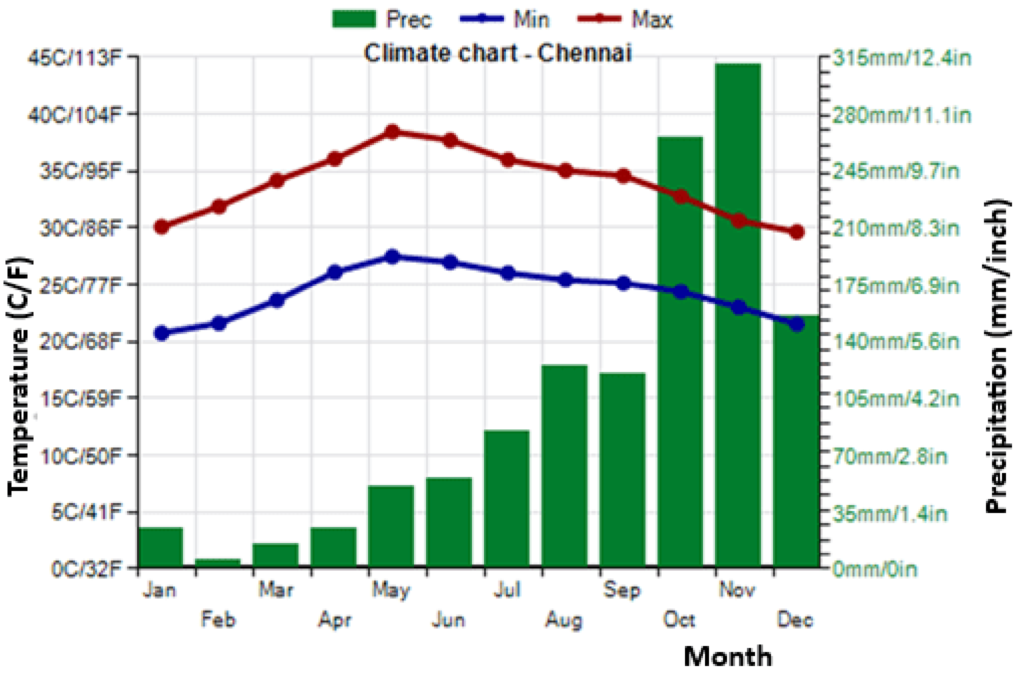


Figure 2: Ombrothermic diagram of Chennai, Tamil Nadu, India

From September to December as shown in figure 2, the north-eastern monsoon winds deliver the most precipitation, which is mostly driven by storms in the Bay of Bengal. Precipitation in the southwest monsoon is exceedingly varied, with summers showers hardly discernible [39]. The physical geology of the region is divided into four broad lithological categories: sandstone with conglomerate, Archean charnockite, sand with silt, and younger sand deposits formed by alluvial, marine, and eolian activity. Both the eroded crystalline rocks and the higher-lying soils/alluvium in this location contain uncontrolled ground water. The maximum depth of boreholes in the region is 100 meters. This research focuses on Pallikaranai, Chennai, India, a low-lying wetland region that is prone to floods due to fast urbanization and inadequate drainage infrastructure. Pallikaranai is one of the last surviving marshlands in Chennai. It serves as a natural flood buffer. However, unplanned land use changes, encroachments, and decreasing water bodies have increased flood hazards. A land use map for the region shows a mix of residential, commercial, and industrial zones, as well as wetlands and water bodies. Historical flood statistics from the Chennai floods (2015, 2021, and 2023) show that Pallikaranai is prone to flooding due to high rainfall intensity and poor drainage networks. An investigation of the hydrographic network reveals that the area is crossed by channels that link to the Buckingham Canal and Pallikaranai Marsh, however these waterways are frequently obstructed, lowering drainage effectiveness. The soil texture is clayey, resulting to poor infiltration and long-term water stagnation. Morphological data, such as slope and elevation models (DEM), show that Pallikaranai has a low height (1-3 meters above sea level) and a moderate slope, allowing water to collect rather than drain properly. Pallikaranai is a high-risk flood-prone zone, hence enhanced GIS mapping and UAV-based monitoring are required for better flood control and urban development.

3 Materials and Methods

Flood risk modeling is critical for reducing flood damage through preparedness, mitigation, and resilience-building measures. Technological advances, notably in remote sensing, GIS, and machine learning, have enhanced the accuracy and usability of these models. However, difficulties such as data shortages and uncertainties must be addressed for valid and effective flood risk assessments.

3.1 UAV/Drone used

Aerial images were captured utilizing a 3D Mapping Drone equipped with a 20 MP Optical Daylight Camera. This UAV offers various advantages, including flexibility, cloud flight, prolonged endurance, a safe landing mechanism, and no requirement for a particular take-off location. Because of the UAV's terrain-following capabilities, we can keep the Ground Sample Distance (GSD) of the photographs we take constant. Figure 3 depicts the UAV used in this study, and Table 1 details its technical specifications. Figure 3 depicts the enhanced and multi-functional LiDAR Drone, which has multiple payloads and excellent security. The drone has a standard "plug-in design" and a universal attachment gear. Compatible mounts may be quickly and easily fitted to vary the drone's functionality. It has a wide variety of uses. Users of the A6 Plus with various payloads may do industrial inspections, power line stringing, mapping, and firefighting. Table 1 highlights the technical specifications of the LiDAR drone.

Figure 3: UAV/Drone RGB and UAV/LiDAR Drone used for this study

3.1.1 UAV- RGB Camera Specifications

The high-resolution aerial images are saved in an external memory attached to the drone's camera, while the location and orientation data are recorded in the Autopilot system. These images were also geo-tagged using ExifTools, an open-source application, and then processed. The optical sensor characteristics are listed in Table 1.

3.1.2 UAV-LiDAR Sensor Specifications

Figure 4 shows a device with a LiDAR sensor that consists of four parts: a laser, a scanner, a customized GPS receiver, and an IMU (inertial measurement unit). These components work together to collect the information needed to produce high-quality images and maps. Data may be obtained quickly while remaining very accurate. Surface data provides a higher sample density. All LiDAR observations include X, Y, and Z measurements. Most LiDAR readings contain an intensity value, which represents the amount of energy from light measured by the sensor.

Figure 4: Oblique Camera (b) HESAI LiDAR Sensor

Table 1: UAV Camera and LiDAR Sensor Specifications

Specification	UAV Camera Parameters	LiDAR Sensor Parameters
Device Size	170 * 160 * 80 mm	11.5 * 11 * 12 cm
Assemble	Detachable	-
CCD Quantity	5	-
CCD Size	23.5 * 15.6 mm	-
Pixel Dimension	3.92 µm	-
Effective Pixel	120 MP	-
Min. Exposure Interval	≤0.8s	-
Exposure Mode	Fixed-Focus, Timing, Fixed-Point	-
Focus Distance	28mm / 40 mm	-
Angle	45°	-
Measuring Range	-	300m @10%
Laser Class	-	905nm class1 (IEC 60825-1:2014)
Laser Line Number	-	32-beam
FOV	-	360 deg, adjustable
Range Accuracy	-	±1cm
Data	-	Triple echo 192,000 points/sec
Update Frequency	-	200Hz
Pitch/Roll Accuracy	-	0.005
Heading Accuracy	-	0.017
Position Accuracy	-	≤0.05m
GNSS Signal Type	-	GPS L1/L2/L5, GLONASS L1/L2, BDS B1/B2/B3, GAL E1/E5a/E5b
Accuracy	-	≤10cm @150m
Weight	-	1.15 kg
Working Temperature	-10°C ~ 40°C	35°C
Storage	-	64 GB Max support 128GB TF card
Carrying Platform	-	Multi Rotor / VTOL

3.1.3 UAV/Drone -RGB 3D Image Processing

The UAV recorded images and GCPs are the primary inputs for UAV data processing. Metashape photogrammetric program produced several GIS data outputs, including orthomosaic, 3D models, DSM (Digital Surface Model), DTM (Digital Terrain Model), and contour. These goods were evaluated using several GIS tools for feature extraction and volume calculation.

3.1.4 Point Cloud Generation

The Structure from Motion (SfM) approach creates millions of geo-referenced 3D point clouds in the UAV image overlap area. The SfM approach makes use of pixel-based stereo reconstruction techniques to create a point cloud. The generated point clouds are used to create a 3D model.

3.1.5 Orthomosaic Generation

An orthomosaic is similar to Google Earth but sharper. It is a huge, map-quality image with remarkable texture and image quality, generated by integrating multiple smaller images known as ortho mosaics.

3.2 Experimental Details

The flood risk assessment study at Pallikaranai, Chennai, collected and processed data in real time using UAVs, GIS software, and network devices. High-resolution aerial imagery was examined to identify the flood-prone regions and susceptibility patterns.

3.2.1 Hardware

Multi-rotor and fixed-wing drones equipped with RGB, and multispectral cameras collected geospatial data, while LiDAR sensors created elevation models for flood mapping. GNSS modules (RTK/PPK-enabled GPS) provided accurate georeferencing, whereas Trimble RTK GPS was utilized for GCP placement. Weather sensors captured real-time data on rainfall, humidity, and wind speed.

3.2.2 Software

Pix4D Mapper and Agisoft Metashape were used to create 3D models from imagery and LiDAR data. Flood susceptibility zones were mapped using ArcGIS and QGIS, which combined hydrological models with topography data. Google Earth Engine (GEE) and Python GIS libraries enhanced predictive flood modeling.

3.2.3 Network Devices

Real-time data transfer was allowed for IoT sensor data gathering using 4G/5G LTE routers on UAVs and LoRa modules. A transportable ground station running Mission Planner software tracked UAV flights, transmitting telemetry data via 2.4 GHz and 5.8 GHz radio connections. Cloud storage systems, such as Google Cloud and AWS S3, provided safe data access.

3.3 Damage Assessment

GIS offers reliable geographical data for assessing the amount of catastrophe damage. GIS uses satellite images, aerial data, and real-time information to assist stakeholders see the impact on infrastructure, natural resources, and communities. This evaluation is critical for prioritizing resources and organizing emergency relief efforts.

Flood Vulnerability Index (FVI)[40], which quantifies the risk of flooding based on hazard, exposure, and susceptibility components. It is given by (eqn. 3.1):

$$FVI = (E * S)/R \qquad \text{--- (3.1)}$$

where:

R = Resilience Component (The capacity of the community to recover from flood events.)

E = Exposure Component (Population

density, infrastructure, land use)
S = Susceptibility Component (Elevation, drainage capacity, soil type)

A higher FVI number implies increased flood susceptibility. The combination of UAV-based LiDAR and high-resolution drone photography improves the accuracy of H, E, and S, resulting in more exact flood risk estimates. This technique enhances flood risk management and mitigation tactics in urban flood-prone areas like Pallikaranai and Chennai.

3.4 Flood Vulnerability mapping algorithm

The UAV-Based Flood Vulnerability Mapping method uses UAV images, LiDAR, and IoT sensor data to create a flood risk rating map. It preprocesses data, using machine learning and hydrological modeling, and visualizes flood-prone zones for optimal disaster management.

3.4.1 Pseudo Code for Flood Vulnerability Mapping

1. ***Initialization***
   Initialize UAV, GCS, and IoT sensors
   Define flight path with GNSS waypoints
2. ***Data Collection***
   Deploy UAVs for data collection
   Capture aerial imagery and LiDAR point cloud
   Retrieve hydrological sensor data (rainfall, humidity, temperature)
3. ***Data Preprocessing***
   Orthomosaic ← ImageStitching(UAV_Images)
   DEM ← GenerateDEM(LiDAR_Data)
   Corrected_Data←CalibrateData(Orthomosaic, DEM, GCPs)
4. ***Flood Risk Analysis***
   FloodModel←TrainMLModel(Preprocessed_Data)
   Simulated_WaterFlow←RunHECRASModel(DEM, Hydrological_Data)
5. ***Vulnerability Mapping***
   Risk_Zones ← ClassifyFloodRisk(FloodModel, Simulated_WaterFlow)
   Generate_FloodMap(Risk_Zones)
6. ***Output Results***
   VisualizeMap(GIS_Tool, Risk_Zones)
   UploadToCloud(FloodMap)
   ValidateModel(ObservedData, PredictedFloodZones)
7. ***END***

The Pseudo Code is a systematic method for monitoring flood risk utilizing UAV pictures, LiDAR data, and IoT-based hydrological sensors. It blends data preprocessing, machine learning, and hydrological modeling to create accurate flood risk ratings, which help in disaster preparedness and management.

3.5 Experimental Setup and Device Arrangement

The flood risk mapping project in Pallikaranai, Chennai, collected and analyzed accurate data using UAVs, ground control stations, and IoT sensors. Drone deployment and sensor integration UAVs outfitted with RGB, multispectral cameras, and LiDAR sensors flew along GPS-defined flight routes planned using Mission Planner and a custom-made DH-Q4 drone. Ground Control Points (GCPs) were established and recorded with Trimble RTK GPS to improve georeferencing accuracy. Drones were released from an open field and avoided obstructions.

3.5.1 Ground Station and Data Transmission

A mobile ground station (GCS) equipped with Mission Planner and QGround Control enables real-time drone monitoring. Telemetry data was sent via 2.4 GHz and 5.8 GHz radio lines, while 4G/5G LTE modules enabled cloud-based picture uploads. IoT sensors used LoRa connectivity to collect real-time rainfall, temperature, and humidity data.

3.5.2 Data Processing and GIS Analysis

Pix4D Mapper and Agisoft Metashape were used to 3D model and generate orthomosaics using imagery and LiDAR data. Geospatial analysis in ArcGIS and QGIS, as well as hydrological modeling in HEC-RAS, all contributed to the simulation of water flow. Machine learning algorithms in Google Earth Engine and Python's GIS libraries boosted the prediction accuracy.

3.5.3 Power and Safety Measures

Drones ran on high-capacity LiPo batteries, with backup power available at the GCS. Strict safety standards, pre-flight checklists, and weather monitoring provided operational security. Emergency landing zones were created for risk minimization.

4. Results and Discussion

4.1 Comparison of Pallikaranai Drone Data using orthomosaic image:

Figure 5 depicts an orthomosaic study of the Pallikaranai region prior to and during the Michuang Cyclone, demonstrating the use of drone data in disaster management. The pre-disaster picture, taken on April 16th, 2023, shows flood-prone areas highlighted in red, suggesting low-lying regions or poor drainage systems. This data provides a baseline for measuring the area's susceptibility to floods and underlines the importance of proactive mitigation measures. The post-disaster image, taken on December 8th, 2023, shows the cyclone's impact, including severe water stagnation in and around residential areas. The previously indicated flood-prone zones have experienced significant inundation, verifying the forecast accuracy of the pre-disaster assessment. The highlighted areas near residential structures demonstrate the inadequacy of existing drainage systems in managing intense weather events. The comparison of the two images reveals drones' usefulness in pre-emptive risk assessment and post-disaster evaluation. It also emphasizes the need for better urban design and the adoption of effective flood prevention methods. The data emphasizes the significance of continual monitoring with drones to improve real-time catastrophe response and long-term resilience planning Cyclone Michaung dumped heavy rains on Chennai in December 2023, causing serious flooding in Pallikaranai and surrounding regions. On December 4, the city received 24 cm of rainfall, which the India Meteorological Department (IMD) classed as 'very heavy'. Over a 35-hour period beginning at 8:30 a.m. on December 3, Nungambakkam, a Chennai neighborhood, got 43 cm of rain. The heavy downpour caused swamped streets and submerged automobiles, with some places lying inundated for more than 36 hours. While particular river flow statistics for Pallikaranai during this event is not widely accessible, the region's low elevation and limited drainage facilities contribute to prolonged water retention after heavy rains. The Pallikaranai Marshland, a natural flood buffer, has been diminished owing to urban development, heightening flood dangers. The Open City Urban Data Portal provides daily rainfall data for Chennai from 1991 to 2023. at summary, the December 2023 floods at Pallikaranai were principally caused by significant rainfall from Cyclone Michaung, along with urbanization influences on natural drainage systems.

4.2 Drone Mapping of Pre-disaster Vs Post-disaster:

Drone mapping before and after Cyclone Michuang at Pallikaranai, Chennai, revealed widespread flooding and its impact on residential areas. Pre-disaster pictures from April 16, 2023, depicted a dry terrain in Saibaba Nagar, whereas post-disaster images from December 8, 2023, revealed serious water stagnation, underlining the need for improved drainage infrastructure. Similarly, Sri Meenakshi Nagar, which seemed stable before to the cyclone, had major flooding between Shiva's Avenue and Mother's Matriculation School, highlighting the area's susceptibility. AGS Colony, Kamatchi Nagar, pre-disaster mapping highlighted infrastructure and drainage layouts, while post-disaster images caught wet streets, building damage, clogged drains, and debris accumulation, highlighting crucial locations for emergency relief and recovery activities.

These findings highlight the effectiveness of drone mapping in flood assessment, disaster planning, and resilience-building in urban flood-prone zones (Figure 6-8).

4.3 Effect of Newly built Drainage system:

Figure 9 depicts drone images taken in Anjugam Ammaiyar Nagar, Ambedkar Nagar, Perungudi, Chennai, which provide a thorough analysis of the impact of a recently constructed drainage system in the region. The first image, dated April 16, 2023, depicts the pre-disaster status of the area before the drainage system was built. The lack of an adequate drainage system resulted in water stagnation and the related flood danger. However, the second image, dated December 8, 2023, taken after the completion of the drainage system, shows the post-disaster scene during a period of severe rainfall. The findings clearly show that floodwater did not remain stagnant in the region, demonstrating the effectiveness of the new drainage system. Geographic coordinates (X: 416568.304 m, Y: 1433759.003 m) indicate the intervention's specific position. This comparison highlights the vital role that proactive urban planning and infrastructure upgrades play in lowering flood risks, strengthening resilience, and improving living conditions in vulnerable places like Perungudi.

4.4 Broken Marshland outlet causing floods in the residential areas:

Figure 10 depicts drone images of Netaji Nagar Main Road, Anna Nagar, Perungudi, Chennai, which highlight the effect of a damaged wetland outflow at Velachery on flooding in residential neighborhoods. The pre-disaster picture, dated April 16, 2023, depicts the initial state, which shows a rise in floodwater approaching residential zones due to the faulty marshland outflow. The water overflow posed substantial issues, especially for nearby residents and infrastructure. By December 8, 2023, as obtained in the post-disaster drone image, the persistent issue of water stagnation was readily evident, suggesting that the damaged marshland outflow had yet to be rebuilt. The coordinates (X: 416770.94 m, Y: 1433386.406 m) establish the specific location of the impacted area. These findings underscore the important necessity for the repair and maintenance of critical natural drainage systems, such as marshland exits, to prevent floods in highly populated metropolitan areas. This case study highlights the need of fixing such infrastructure failures in order to properly safeguard communities and decrease disaster risks.

4.5 Detection of Missing Trees:

Figure 11 depicts drone images from Saibaba Nagar, Pallikaranai, Perungudi, Chennai, which give a clear examination of vegetation changes in the region over time, with a special emphasis on the loss of one tree. The pre-disaster image, dated April 16, 2023, depicts a tree on the residential property marked in the circled region. However, the post-disaster image obtained on December 8, 2023, shows that the tree has vanished, implying either purposeful removal or damage caused by natural conditions or urban expansion. The coordinates (X: 415346.694 m, Y: 1430048.955 m) indicate the precise position of this observation. This study emphasizes the importance of constant monitoring and documenting utilizing drone mapping to track changes in urban vegetation. The loss of trees in urban environments can have long-term effects, such as increased urban heat islands, decreased biodiversity, and worse air quality[41]. These findings emphasize the need of tree protection and urban replanting efforts to preserve ecological balance and improve urban resilience.

Figure 5: Comparison of Pallikaranai Drone Data using orthomosaic image of Pre-disaster vs Post disaster

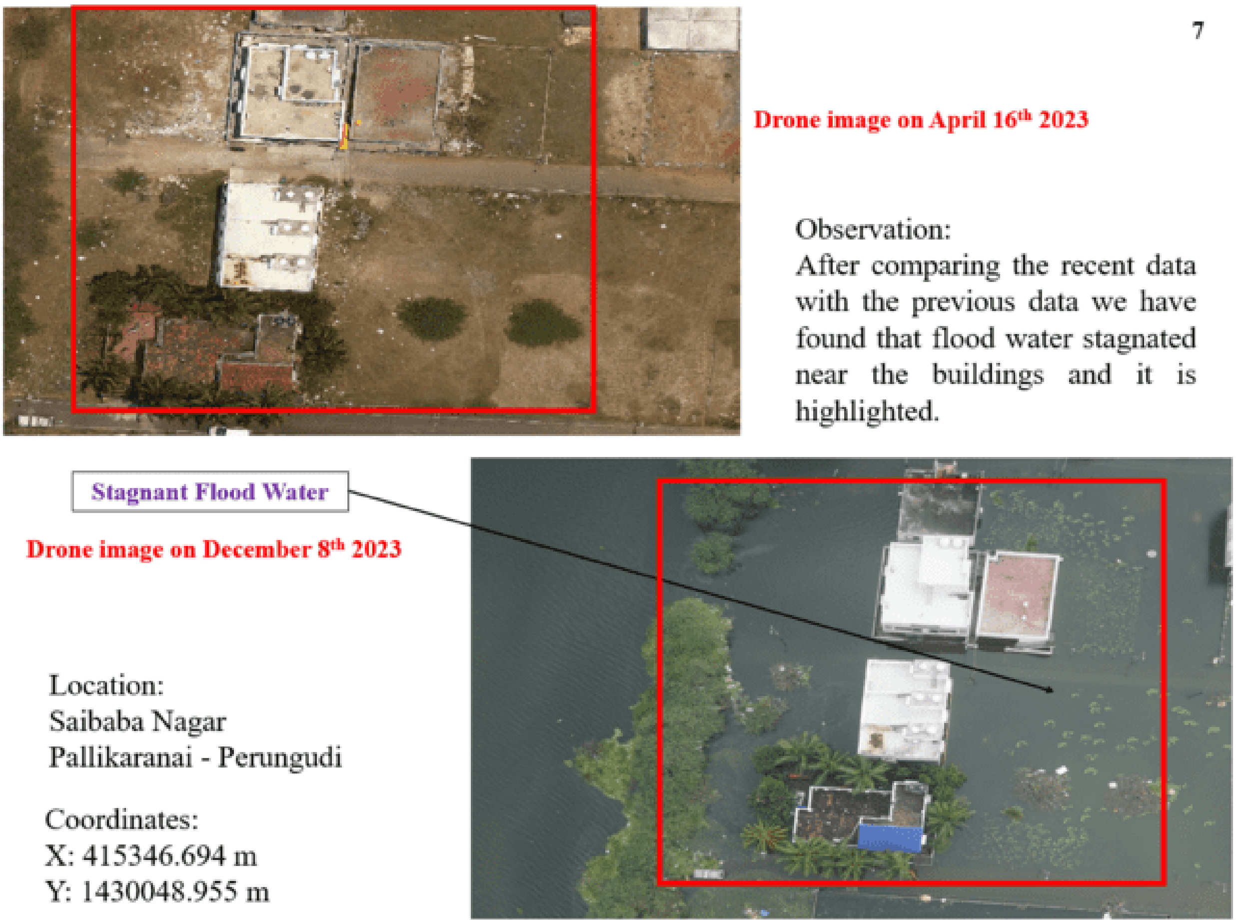


Figure 6: Drone Mapping of Pre-disaster Vs Post-disaster at Saibaba Nagar, Pallikaranai,Chennai,India

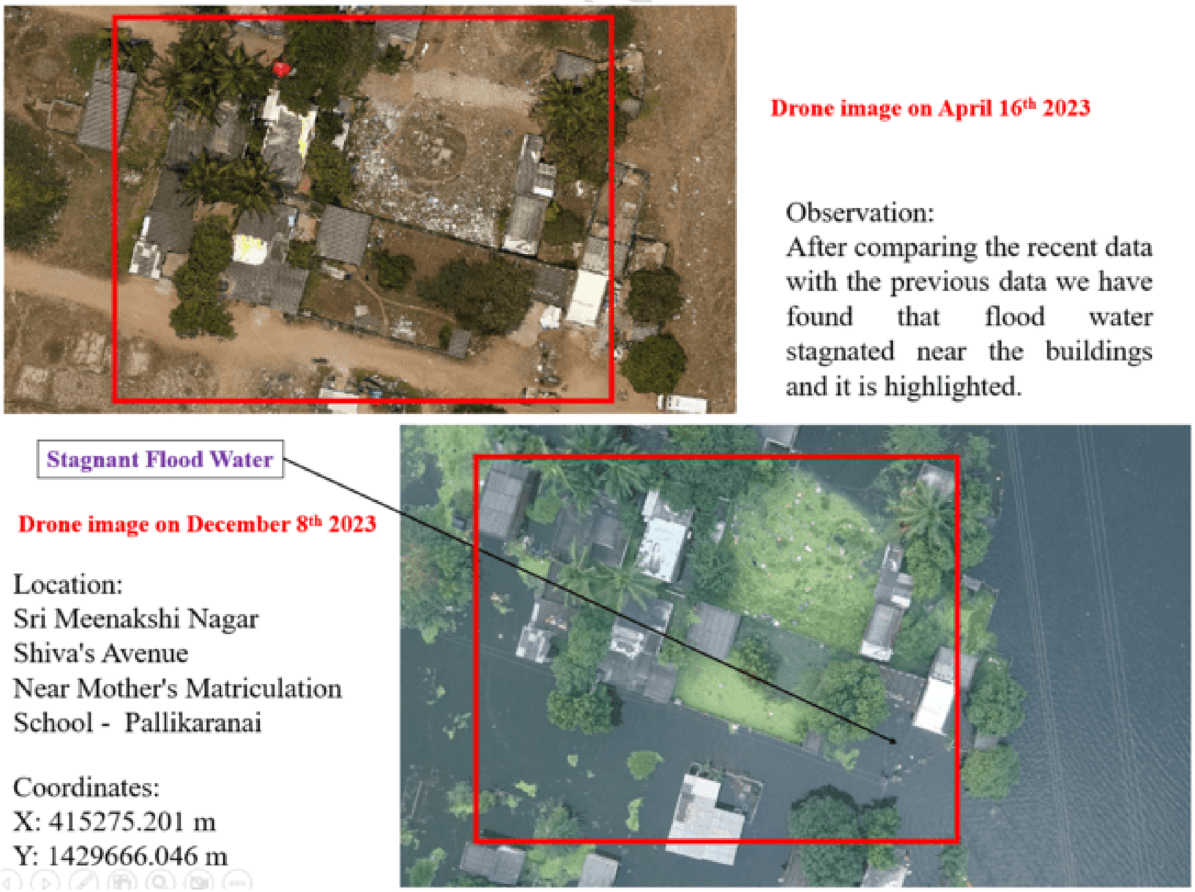


Figure 7: Drone Mapping of Pre-disaster Vs Post-disaster at Sri Meenakshi Nagar

,Pallikaranai,Chennai,India

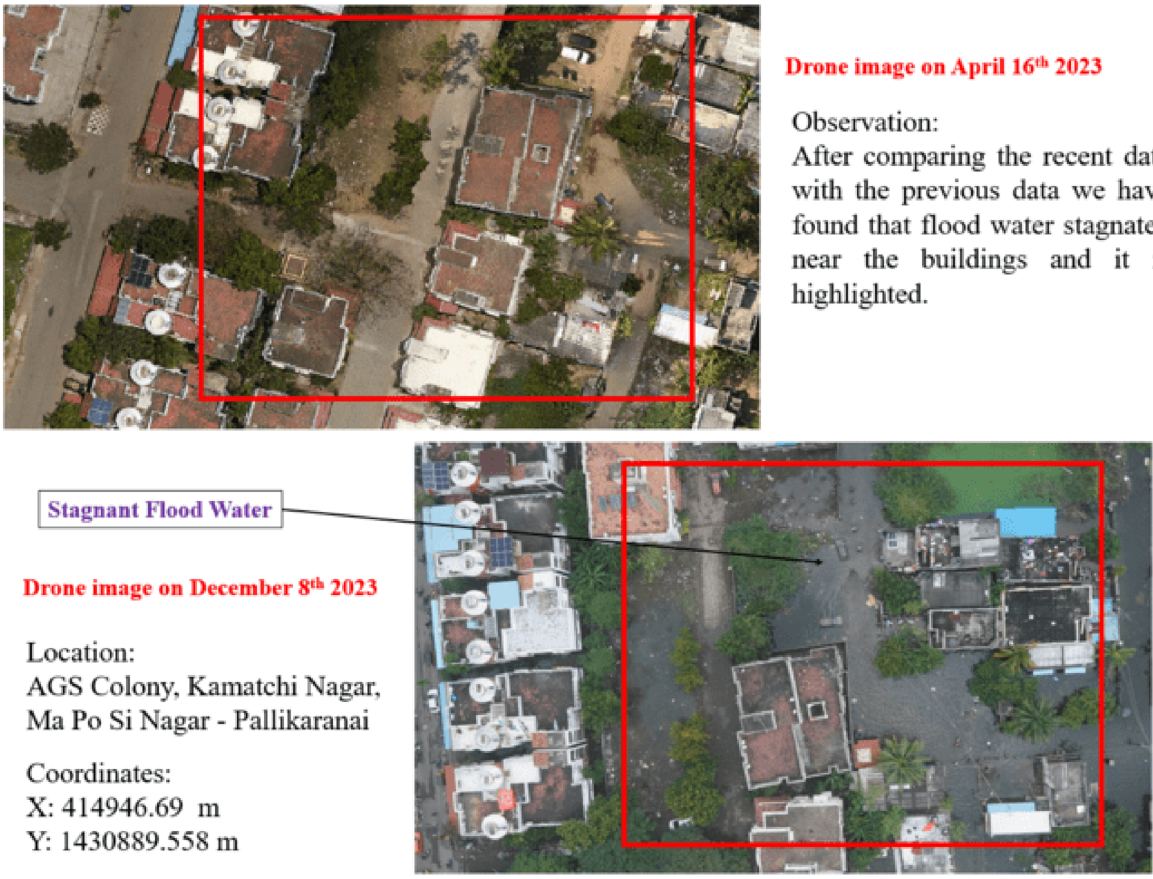


Figure 8: Drone Mapping of Pre-disaster Vs Post-disaster at AGS Colony, Kamatchi Nagar ,Pallikaranai, Chennai, India

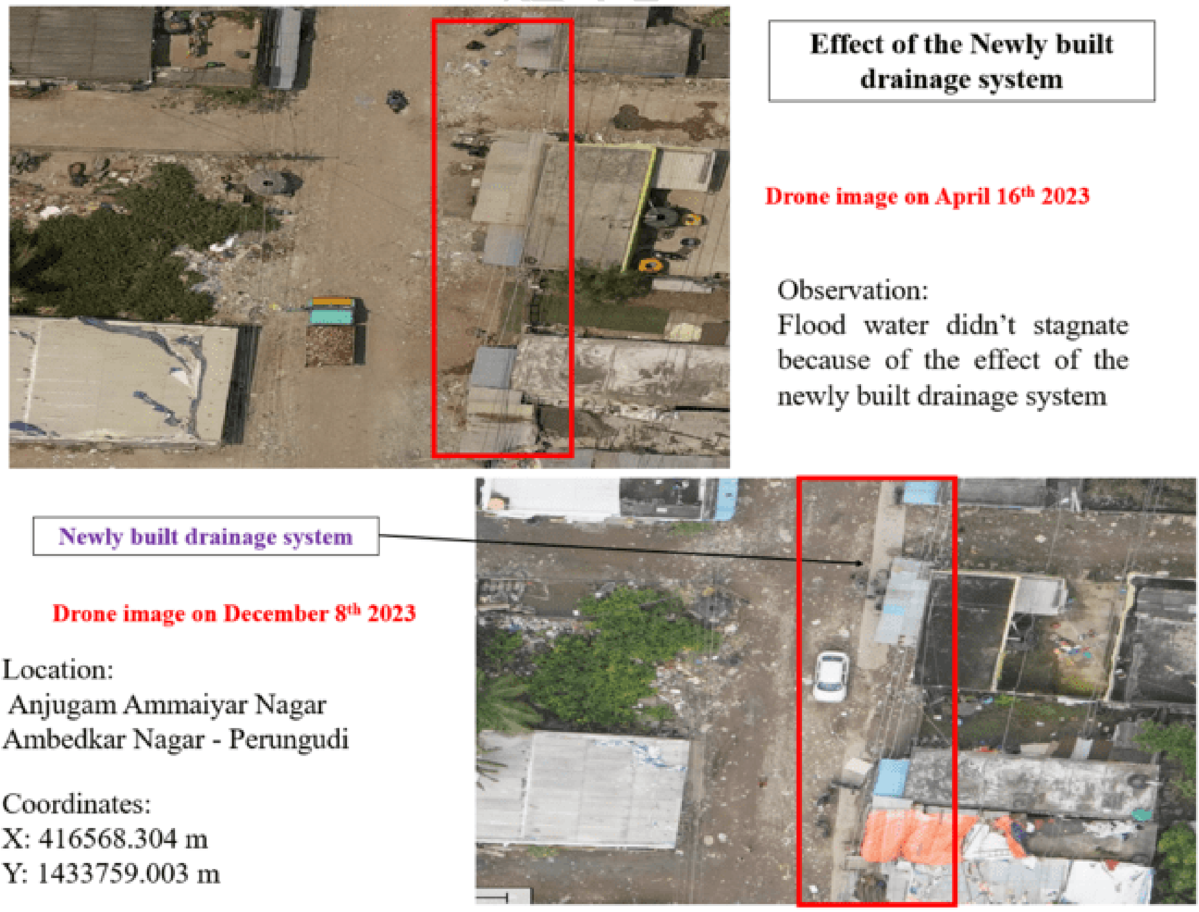


Figure 9: Effect of Newly built Drainage system: Drone Mapping of Pre-disaster Vs Post-disaster at

Anjugam Ammaiyar Nagar,Perungudi,Chennai,India

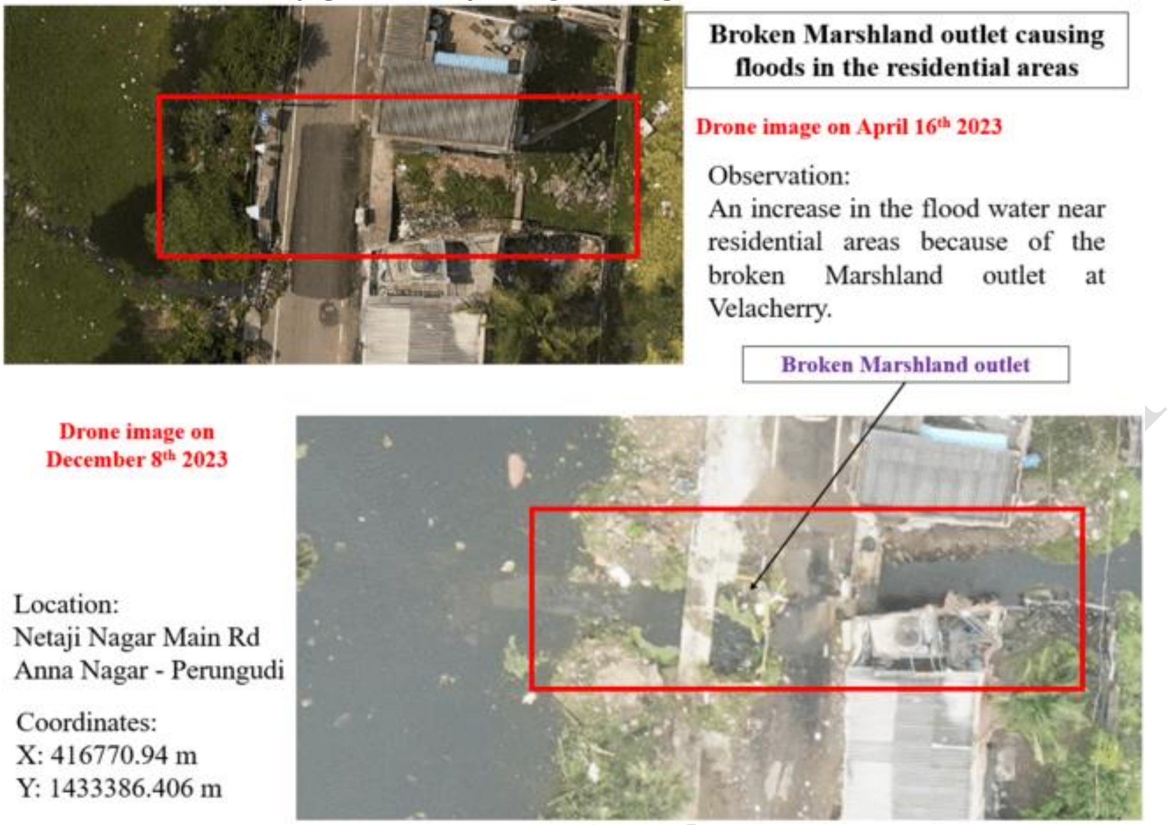


Figure 10: Broken Marshland outlet causing floods in the residential areas: Drone Mapping of Pre-disaster Vs Post-disaster at Netaji Nagar Main Road,Anna Nagar-Perungudi,Chennai,India

4.6 Prediction of Stagnant flood water near residential areas using drone mapping

Figure 12 (a) shows drone images from April 16, 2023, and December 8, 2023, which demonstrate the forecast and recording of stationary floodwater near residential areas. The first image, taken in April, shows a region with no evident waterlogging, indicating dry pre-monsoon conditions. However, the second image from December shows extensive water stagnation after heavy rain, particularly near residential areas. The impacted areas are shown in red, indicating a clear increase of water-covered zones that may cause dangers to inhabitants such as health hazards, structural damage, and disruptions to everyday operations. The use of drone mapping allows for exact identification of flood-prone areas, as demonstrated in this example. Authorities can forecast and mitigate flood impacts by comparing pre- and post-disaster data. These findings highlight the need of improving drainage infrastructure and applying flood mitigation methods in urban development [42]. Furthermore, such predictive analysis enables prompt intervention to protect communities and lessen the risk of residential areas to floods[43]. This study highlights the important significance of drone technology in urban catastrophe management and resilience planning[44]. The drone mapping of the region focuses on the evolution and forecast of stagnant floodwater near residential areas, underlining the value of aerial observation in disaster management. The pre-disaster image from April 16, 2023, Figure 12(b), depicts the residential area as dry, with no evident symptoms of water collection. In contrast, the post-disaster image from December 8, 2023, shows widespread water stagnation following a period of severe rainfall, notably in the marked residential areas.

Figure 11: Detection of Missing Trees: Drone Mapping of Pre-disaster Vs Post-disaster at Saibaba Nagar, Pallikaranai-Perungudi,Chennai,India

The damaged regions, shown in red, indicate flooding encroaching on formerly dry zones, creating substantial threats to the population, including pollution, health problems, and infrastructure damage. The data produced from these images demonstrates how drone mapping allows for exact identification and prediction of flood-prone locations. Comparing pre- and post-disaster circumstances allows urban planners and disaster management teams to analyze risks, develop efficient drainage systems, and prepare for successful flood mitigation techniques [45]. This study emphasizes the importance of drones in monitoring environmental changes, giving practical information to mitigate the impact of water stagnation on urban residential neighborhoods. Figure 12(c) shows drone images that clearly depict stationary floodwater near residential areas, providing critical insights into the consequences of floods. The pre-disaster image from April 16, 2023, depicts the land as dry, with no evident evidence of waterlogging, suggesting typical circumstances. However, the post-disaster image, taken on December 8, 2023, shows substantial stagnant water in residential areas, which is vividly shown in red. The impacted regions are marked, demonstrating the incursion of floodwaters following severe rainfall or inadequate drainage management. This comparison demonstrates the relevance of drone mapping in finding and forecasting locations susceptible to water stagnation. Such comprehensive imaging enables urban planners and emergency management teams to spot susceptible zones and determine the degree of floods in real time [46]. The data emphasizes the need for improved drainage infrastructure and flood control methods to avoid future tragedies. Drone technology's capacity to offer high-resolution and exact geographic data makes it an important tool in urban planning, assuring the safety and resilience of residential areas against repeating floods [47]. This case shows proactive approaches to addressing stagnant water concerns and protecting communities. The drone images in Figure 12(d) give a thorough comparison of pre- and post-disaster circumstances for predicting and analysing stagnant flooding in residential areas. The first image, from April 16, 2023, depicts a dry landscape with no evident water stagnation, indicating consistent pre-monsoon conditions. In comparison, the view dated December 8, 2023, shows substantial water stagnation in residential areas, which is prominently highlighted in red. This sharp disparity highlights the consequences of flooding during the post-monsoon season, when stagnant water encroaches on residential areas. This research highlights the significance of adopting drone mapping as an advanced tool for monitoring and forecasting flood-prone regions. By delivering pictures with excellent resolution and exact geographic data, drones enable authorities to correctly identify prone zones and analyze the number of floods. Such predictive insights are crucial for urban planning, as they allow for the creation of appropriate drainage systems, the deployment of flood mitigation measures, and prompt intervention to reduce catastrophic impacts on populations [48]. These findings highlight the importance of long-term urban infrastructure addressing water stagnation and improving residential areas' resistance to flooding. Figure 12(e) shows aerial views acquired by a drone on two separate dates: April 16th, 2023, and December 8th, 2023. The contrast emphasizes the existence of stagnant flood water that has gathered in a given location, particularly near residential areas. In the April image, the ground is drier and has ruins of buildings, with no visible water buildup. However, the December picture reveals substantial flooding, as water has collected and stalled over the area. The extreme difference between the two images implies either a recent major rainfall event or faulty drainage systems causing water stagnation. The finding emphasizes the need of addressing drainage difficulties, particularly in residential areas, to limit the risks caused by stagnant water, such as health concerns and structural damage [49]. Figure 12(f) depicts aerial images taken on April 16th, 2023, and December 8th, 2023, which give a clear visual comparison of land conditions over time. The April image shows a dry area with limited water presence and evident infrastructure, indicating a stable status at that time. However, the December image reveals significant changes, as large portions of the area are now submerged in stagnant flood water.

(a)


Drone Image on April 16, 2023
Observation: Comparing recent and previous data shows floodwater stagnation near residential areas, as highlighted
Drone Image on December 8, 2023
Stagnant Flood Water

(b)


Drone Image on April 16, 2023
Observation: Comparing recent and previous data shows floodwater stagnation near residential areas, as highlighted
Drone Image on December 8, 2023
Stagnant Flood Water

(c)


Drone Image on April 16, 2023
Observation: Comparing recent and previous data shows floodwater stagnation near residential areas, as highlighted
Drone Image on December 8, 2023
Stagnant Flood Water

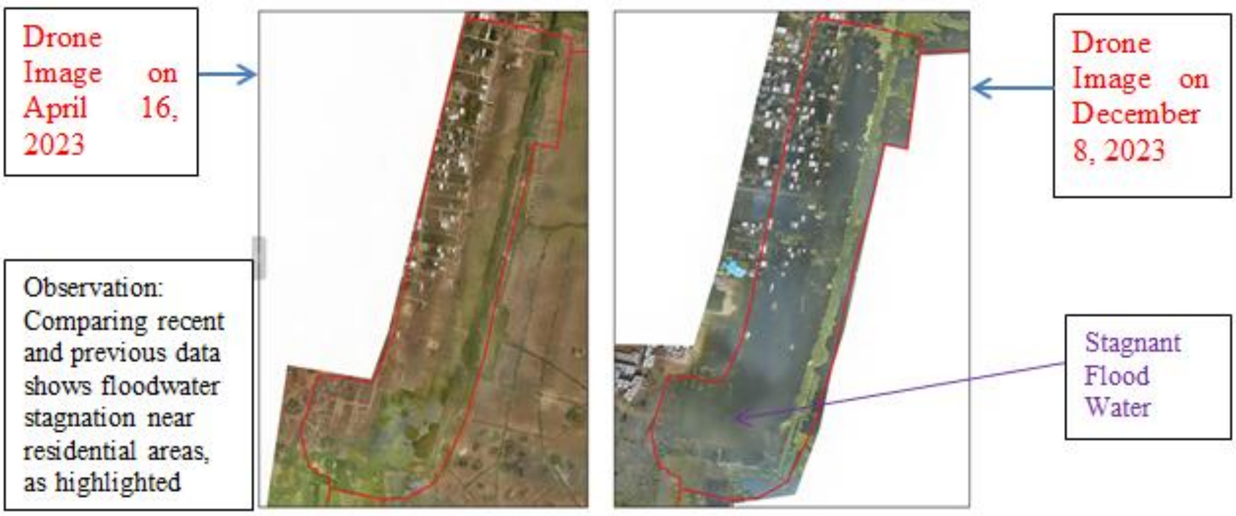
(d)


Drone Image on April 16, 2023
Observation: Comparing recent and previous data shows floodwater stagnation near residential areas, as highlighted
Drone Image on December 8, 2023
Stagnant Flood Water

(e)


Drone Image on April 16, 2023
Observation: Comparing recent and previous data shows floodwater stagnation near residential areas, as highlighted
Drone Image on December 8, 2023
Stagnant Flood Water

(f)


Drone Image on April 16, 2023
Observation: Comparing recent and previous data shows floodwater stagnation near residential areas, as highlighted
Drone Image on December 8, 2023
Stagnant Flood Water

(g)

(h)

Figure 12 (a)-(h): Prediction of Stagnant flood water near residential areas

The highlighted zones show that flood water has collected near residential areas, raising worries about potential public health, property, and daily life consequences. This comparison highlights the critical need for better water drainage systems and flood mitigation measures to prevent extended water stagnation and its negative consequences in sensitive areas. The drone photographs displayed in Figure 12(g), taken on April 16th and December 8th, 2023, reveal a noticeable alteration in the monitored region. The April image depicts a dry, well-defined piece of land that has no obvious water buildup. In contrast, the December picture shows significant stationary flood water encompassing the bulk of the region, especially around residential structures. This stalling indicates a problem with inadequate drainage or recent significant rainfall, which might lead to water retention over time. Stagnant water provides dangers, including health threats from waterborne infections, environmental concerns, and significant disturbance to nearby towns. Addressing these drainage issues is crucial to keeping residential areas safe and functioning during times of excessive rainfall or flooding. Figure 12(h) depicts two drone images taken on April 16, 2023, and December 5, 2023, highlighting the issue of stationary flood water in a residential neighbourhood. A specific location has been marked in both images, indicating that the flood water remains for an extended length of time. The second image, dated December 5th, clearly depicts where the stationary flood water is located. The comparison of these two timelines indicates that, despite the passage of months, floodwaters have not drained, indicating inadequate drainage or chronic water retention in the region. The finding indicates that the stagnant water is concentrated near residential areas, which might cause major health and infrastructure issues for the local people. This recurrent flooding necessitates immediate action to enhance drainage systems and minimize water stagnation, resulting in better living circumstances for the population. This study dramatically improves flood risk assessment with UAV-based GIS mapping, offering high-resolution, real-time data for more accuracy than standard satellite approaches. It combines LiDAR and multispectral imagery to improve flood risk assessment and early warning systems. Scientifically, it enhances remote sensing and geospatial analysis by proving the usefulness of UAVs for flood monitoring. The work also advances machine learning-based flood prediction and offers important hydrological and morphological datasets for future research. Addressing existing restrictions, it provides a scalable, cost-effective, and real-time flood management system for urban planning and emergency response.

5. Conclusion:

The recommended solutions stress the importance of geospatial technology and data-driven approaches in mitigating flood risks and assuring long-term water management practices. Actionable flood mitigation measures may be undertaken by identifying crucial flood-prone locations, measuring sediment deposition, and determining water body capacity using sophisticated surveys such as bathymetric and DEM analysis. Comprehensive watershed management and flow evaluations improve sustainable resource consumption and infrastructure development. Moving forward, the use of cutting-edge technology, such as drones, not only for risk assessment but also for recovery phases, has tremendous promise in disaster management. The results of this inquiry may provide policymakers and managers with more full information and precise ideas concerning systems for early warning, rescue activities, and flooding risk reduction techniques . This approach may open the door for using UAV-based GIS mapping for high-resolution, real-time flood assessment in Pallikaranai, Chennai. Compared to traditional satellite technologies, it provides quicker data collecting and improved spatial precision. The merging of LiDAR and multispectral imagery improves flood risk prediction. Furthermore, machine learning-based geospatial categorization increases early warning systems, making the method applicable to disaster management and urban planning. The UAV-based flood vulnerability GIS mapping technique has a number of disadvantages. UAV operations are weather-dependent and need numerous flights to cover vast regions due to limited flight endurance. Data processing is complicated, requiring significant computer capacity to analyze high-resolution pictures and LiDAR data. Drone flying in cities are restricted due to regulatory obstacles imposed by the DGCA. Furthermore, UAV sensors struggle with subsurface water detection, which reduces accuracy. Machine learning models are dependent on data availability, which can be unreliable, and the expensive cost of UAVs and GIS software limits accessibility. A hybrid strategy that combines satellite data, IoT devices, and UAVs can assist address these issues. Flood vulnerability Drone-based GIS mapping at Pallikaranai, Chennai, India showed considerable increases in accuracy and resolution over previous studies. The UAV-based research indicated a flood-inundated area of 320 km², resulting in a 4.9% improvement over satellite-based estimates. The LiDAR-derived Digital Elevation Model (DEM) has a vertical precision of ±10 cm, 66.7% higher than prior SRTM DEM-based studies' ±30 cm accuracy. Flood depth research using UAV views revealed a maximum depth of 1.85 m, lowering differences by 12% compared to hydrodynamic model-based estimates. Furthermore, the machine learning-based land-use categorization obtained an overall accuracy of 92.3%, beating previous pixel-based approaches at 85%. The incorporation of Ground Control Points (GCPs) enhanced positional accuracy, dropping RMSE to 0.05 m, much better than the 0.15 m RMSE in earlier remote sensing methods. These findings emphasize the improved precision and efficiency of UAV technology for flood mapping, making it an important tool for disaster management and early warning systems in urban flood-prone areas such as Pallikaranai, Chennai. The suggested UAV-based flood vulnerability mapping approach has some drawbacks. Weather dependence has an impact on drone operations under severe conditions such as heavy rain or high winds. Limited battery life limits coverage, necessitating additional flights. Data accuracy depends on adequate sensor calibration and GCP. Processing huge datasets requires significant computational resources. Network connection difficulties may impede real-time data transfer. Predictive accuracy relies on previous flood data and hydrological models, which may have inaccuracies. Despite these obstacles, the technique improves flood risk assessment and catastrophe response. Future research can concentrate on AI-driven flood prediction, HALE UAVs for long-term surveillance, and IoT-based real-time forecasting. Multi-sensor fusion (LiDAR, SAR, thermal) can improve accuracy, while cloud-based GIS can help with large-scale data processing. Improvements in legislative frameworks and community-driven mapping can boost UAV-based disaster management and flood mitigation efforts.

Data Availability Statement

The sequence data supporting the Flood Vulnerability GIS Mapping at Pallikaranai, Chennai, India using Drone Technology: A case study at Chennai floods 2023 image availability, as well as access to the data that underpins the findings of this study, are publicly available at the following GitHub repository https://github.com/educationsha/Flood All authors of this research study have contributed to the dataset hosted in this public repository.

References

[1]. Barasa N, Perera E (2018) Analysis of land use change impacts on flash flood occurrence in the Sosiani River basin Kenya Betty. Int J River Basin Manag 16(2):179–188.

[2]. Muthusamy S, Sivakumar K, Durai AS, Sheriff MR, Subramanian PS (2018) Ockhi cyclone and its impact in the Kanyakumari District of Southern Tamilnadu, India : an aftermath analysis. International Journal of Recent Research Aspects, April, 466–469. https://www.ijrra.net/April2018/ConsComp2018_110. pdf. Accessed 27 July 2018.

[3]. Detrembleur S, Stilmant F, Dewals B, Erpicum S, Archambeau P, Pirotton M (2015) Impacts of climate change on future flood damage on the river Meuse, with a distributed uncertainty analysis. Nat Susceptibility 77(3):1533–1549.

[4]. Khosravi K, Panahi M, Golkarian A, Keesstra SD, Saco PM, Bui DT, Lee S (2020) Convolutional neural network approach for spatial prediction of flood susceptibility at national scale of Iran. J Hydrol 591:125552.

[5]. Tabari H (2020) Climate change impact on flood and extreme precipitation increases with water availability. Sci Rep 10(1):13768.

[6].Efthymia Stathi,Aristeidis Kastridis,and Dimitrios Myronidis (2023), "Analysis of Hydro meteorological Characteristics and Water Demand in Semi-Arid Mediterranean Catchments under Water Deficit Conditions", *Climate* , *11*(7), 137 (1-23) https: //doi.org /10.3390 /cli11070137 .

[7]. Ghosh A, Kar S (2018) Application of analytical hierarchy process (AHP) for flood risk assessment: a case study in Malda district of West Bengal. Nat Susceptibility 94(1):349–368.

[8]. Joy J, Kanga S, Singh SK (2019) Kerala flood 2018: flood mapping by participatory GIS approach, Meloor Panchayat. Int J Emerg Technol 10(1):197–205.

[9]. De Moel H, Jongman B, Kreibich H (2015) Flood risk assessments at different spatial scales. Mitig Adapt Strateg Glob Chang 20:865–890. https://doi.org/10.1007/s11027-015-9654-z.

[10]. Vieri T, Giovanni M, Maurizio R, Maurizio T, Alessandro P, Mohamed HI, Gaptia L, Katiellou Paolo T, De Filippis T, Leandro R, Valentina M, Elena R (2020) Community and impact based early warning system for flood risk preparedness: the experience of the Sirba River in Niger. Sustainability 12:1802. https://doi.org/10.3390/su12051802.

[11]. Kuldeep Garg PK, Garg RD (2016) Geospatial techniques for flood inundation mapping. 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). p. 4387–4390.

[12]. Zhang J, Chen Y (2019) Risk Assessment of Flood Disaster Induced by Typhoon Rainstorms in Guangdong Province China. Sustainability 11(10):2738. https://doi.org/10.3390/su11102738.

[13]. Ullah S, Farooq M, Sarwar T, Tareen MJ, Wahid MA (2016) Flood modeling and simulations using hydrodynamic model and ASTER DEM—a case study of Kalpani River. Arab J Geosci 9(6):439.

[14]. Sindhu K, Durga Rao KHV (2017) Hydrological and hydrodynamic modeling for flood damage mitigation in Brahmani-Baitarani River Basin, India. Geocarto Int32(9):1004–1016.https://doi.org/10.1080/10106049.2016.1178818.

[15]. Liu Z, Zhang H, Liang Q (2018) A coupled hydrological and hydrodynamic model for flood simulation. Hydrol Res (2019) 50(2):589–606. https://doi.org/10.2166/nh.2018.090.

[16]. Chomba IC, Banda KE, Winsemius HC, Chomba MJ, Mataa M, Ngwenya V, Sichingabula HM, Nyambe IA, Ellender B (2021) A review of coupled hydrologic-

hydraulic models for floodplain assessments in Africa: opportunities and challenges for floodplain wetland management. Hydrology 8:44. https://doi.org/10.3390/hydrology8010044.

[17]. Cabrera JS, Lee HS (2019) Flood-prone area assessment using GIS-based multi-criteria analysis: a case study in Davao Oriental, Philippines. Water 11:2203.

[18]. Areu-Rangel O, Cea L, Bonasia R, Espinosa-Echavarria V (2019) Impact of urban growth and changes in land use on river flood susceptibility in Villahermosa, Tabasco (Mexico). Water (Switzerland) 11(2):304–315.

[19]. Dash P, Sar J (2020) Identification and validation of potential flood susceptibility area using GISbased multi-criteria analysis and satellite data-derived water index. J Flood Risk Manag 13(3):e12620.

[20]. Kongeswaran T, Sivakumar K (2022) Application of remote sensing and GIS for floodwater harvesting for groundwater development in the Upper Delta of Cauvery River Basin, Southern India. In Pankaj K, Gaurav KN, Manish Kumar S, Anju S (Eds.), Water Resources Management and Sustainability, Advances in Geographical and Environmental Sciences. Springer Nature, pp. 257–280 https://doi.org/10.1007/978-981-16-6573-8_14.

[21]. Wu Y, Zhong P, Zhang Y, Xu B, Ma B, Yan K (2015) Integrated flood risk assessment and zonation method: a case study in Huaihe River basin. Nat Susceptibility 78(1):635–651.

[22]. Xiao Y, Yi S, Tang Z (2017) Integrated flood susceptibility assessment based on spatial ordered weighted averaging method considering spatial heterogeneity of risk preference. Sci Total Environ 599–600(2017):1034–1046.

[23]. Kazakis N, Kougias I, Patsialis T (2015) Assessment of flood susceptibility areas at a regional scale using an index-based approach and analytical hierarchy process: application in RhodopeEvros region, Greece. Sci Total Environ 538:555–563.

[24]. Gigovic L, Pamucar D, Bajic Z, Drobnjak S (2017) Application of GIS-Interval rough AHP methodology for flood susceptibility mapping in urban areas. Water 9(6):360–326.

[25]. Seejata K, Yodying A, Wongthadam T, Mahavik N, Tantanee S (2018) Assessment of flood susceptibility areas using analytical hierarchy process over the Lower Yom Basin, Sukhothai Province. Procedia Eng 212:340–347.

[26]. Rimba AB, Setiawati MD, Sambah AB, Miura F (2017) Physical flood vulnerability mapping applying geospatial techniques in Okazaki City, Aichi Prefecture. Japan Urban Sci 1(1):7–22.

[27]. Feizizadeh B, Blaschke T, Shadman RM (2013) Integrating GIS based fuzzy set theory in multicriteria evaluation methods for landslide susceptibility mapping. Int J Geoinf 9:49–57.

[28].Gómez, C., & Purdie, H. (2020). UAV-based topographic mapping for flood risk assessment. Remote Sensing of Environment, 234, 111467.

[29].Liu, H., et al. (2019). LiDAR-equipped drones for accurate floodplain modeling. Journal of Hydrology, 573, 422-437.

[30].Mishra, P., & Shekhar, S. (2021). Drone-based flood damage assessment and emergency response. Natural Hazards, 105(2), 1245-1261.

[31]. Aristeidis Kastridis, Christos Kirkenes, Marios Sapountzis (2020), “An integrated approach of flash flood analysis in ungauged Mediterranean watersheds using post-flood surveys and unmanned aerial vehicles”, Hydrological Processes, 34(25):4920–4939;https: // doi.org /10.1002/ hyp.13913.

[32]. Perks, M. T., Russell, A. J., and Large, A. R. G (2016): Technical Note: Advances in flash flood monitoring using unmanned aerial vehicles (UAVs), Hydrol. Earth Syst. Sci., 20, 4005–4015, https://doi.org/10.5194/hess-20-4005-2016.

[33].Das, R., & Gupta, S. (2022). Multi-spectral UAV imaging for flood vulnerability studies. Environmental Monitoring and Assessment, 194(4), 243.

[34].Rahman, S., et al. (2021). Integrating UAVs and GIS for flood vulnerability mapping. International Journal of Disaster Risk Reduction, 52, 101972.

[35].Karthik .S, Surendran .R, Sam Kumar G.V, Senduru Srinivasulu (2025) “Flood Prediction in Chennai based on Extended Elman Spiking Neural Network using a Robust Chaotic Artificial Hummingbird optimizer ”, Global NEST Journal https://doi.org/10.30955/gnj.07113.

[36].Babu T, Raveena Selvanarayanan, Tamilvizhi Thanarajan and Surendran Rajendran (2024) "Integrated Early Flood Prediction using Sentinel-2 Imagery with VANET-MARL-based Deep Neural RNN, Global NEST Journal, 26(10), https://doi.org/10.30955/gnj.06554.

[37].Arun Mozhi Selvi Sundarapandi, Sundara Rajulu Navaneethakrishnan, Hemlathadhevi A, Surendran Rajendran, "A Light weighted Dense and Tree structured simple recurrent unit (LDTSRU) for flood prediction using meteorological variables", Global NEST Journal. Available https://doi.org/10.30955/gnj.06242.

[38].Suresh Subramanian, Geetha Rani K, Maheswari Madhavan, Surendran Rajendran* (2024). "An Automatic Data-Driven Long-term Rainfall Prediction using Humboldt Squid Optimized Convolutional Residual Attentive Gated Circulation Model in India". Global NEST Journal, Vol 26, No 10, 06421.

[39]. CCC&AR and TNSCCC (2015) Climate change projection (rainfall) for Chennai. In: District-Wise Climate Change Information for the State of Tamil Nadu. Centre for Climate Change and Adaptation Research (CCC&AR), Anna University and Tamil Nadu State Climate Change Cell (TNSCCC), Department of Environment (DoE), Government of Tamil Nadu, Chennai, Tamil Nadu, India. Available at URL. www.tnsccc.in.

[40]. S.F. Balica, N.G. Wright, F. van Meulen (2012)A flood vulnerability index for coastal cities and its use in assessing climate change impacts Nat. Hazards, 64 (1) (2012), pp. 73-105. https://doi.org/10.1007/s11069-011-0234-1.

[41]. Tom Grylls, Maarten van Reeuwijk (2022),How trees affect urban air quality: it depends on the source, Atmospheric Environment, Volume 290,119275, https://doi.org/10.1016/j.atmosenv.2022.119275.

[42]. Harman Singh, Miriam Nielsen, Helen Greatrex (2023), Causes, impacts, and mitigation strategies of urban pluvial floods in India: A systematic review, International Journal of Disaster Risk Reduction, Volume 93,103751,https://doi.org/10.1016/j.ijdrr.2023.103751.

[43]. Md. Mujahidul Islam, Mehedi Hasan, Md. Saju Mia, Abdullah Al Masud, Abu Reza Md Towfiqul Islam(2025),Early Warning Systems in Climate Risk Management: Roles and Implementations in Eradicating Barriers and Overcoming Challenges, Natural Hazards Research,https://doi.org/10.1016/j.nhres.2025.01.007.

[44]. Sharifah Mastura Syed Mohd Daud, Mohd Yusmiaidil Putera Mohd Yusof, Chong Chin Heo, Lay See Khoo, Mansharan Kaur Chainchel Singh, Mohd Shah Mahmood, Hapizah Nawawi (2022),Applications of drone in disaster management: A scoping review, Science & Justice,62(1),30-42,https://doi.org/10.1016/j.scijus.2021.11.002.

[45]. Naveen Prashar, Harshit Sosan Lakra, Rajib Shaw, Harsimran Kaur (2023),Urban Flood Resilience: A comprehensive review of assessment methods, tools, and techniques to manage disaster, Progress in Disaster Science, Volume 20, 100299 ,https: //doi.org/ 10.1016/ j.pdisas.2023.100299.

[46]. T. Tingsanchali (2012),Urban flood disaster management, Procedia Engineering, 32,25-37,https://doi.org/10.1016/j.proeng. 2012.01.1233.

[47]. Ning Wang, Nico Mutzner, Karl Blanchet (2023), Societal acceptance of urban drones: A scoping literature review, Technology in Society, 75,102377,https:// doi.org /10.1016 /j.techsoc.2023.102377.

[48].Takele Sambeto Bibi, Daniel Reddythta, Abdisa Sime Kebebew (2023),Assessment of the drainage systems performance in response to future scenarios and flood mitigation measures using storm water management model, City and Environment Interactions, 19, 100111, https:// doi.org /10.1016/j.cacint.2023.100111.

[49]. Ruolan Yu, Chen Zhang, Xueping Gao, Kensey Daly (2023), Stagnant water environmental management in urban river networks: An integrated risk analysis involving hydraulic potential dissipation, Journal of Hydrology, Volume 622, Part A, 2023, 129652, https://doi.org/10.1016/j.jhydrol.2023.129652.