# An Integrated GIS and AHP based Approach for Drone Optimized Large Scale Flood Imaging


By

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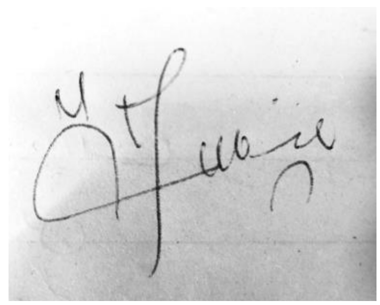

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# DEDICATION

To My Wonderful Mother, My Loving Wife and kids, Thanks for bearing the stressful moments I had, for the prayers and support to overcome them and for all the joy you have brought to me.

# ACKNOWLEDGEMENTS

Glory be to Allah, the Almighty and the Magnificent, perfect in His creations, enlightening us with the gift of knowledge and enabling us to complete our tasks successfully; Blessings upon Prophet Muhammad (peace be upon him) for guiding us towards the right path.

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Muhammad Farhan Nazir

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| | |
|---|---|
| GEE | Google Earth Engine |
| GHSL | Global Human Settlement Layer |
| JRC | Joint Research Center |
| LULC | Land use land cover |
| NDVI | Normalized Difference Vegetation Index |
| SRTM | Shuttle radar topography mission |
| DEM | Digital elevation model |
| TRMM | Tropical Rainfall Measuring Mission |
| PBS | Pakistan Bureau of statistics |
| SAR | Synthetic aperture radar |
| LiDAR | Light detection and ranging |
| GRD | Ground Range Detected |
| DOFRM | Drone optimized flood risk map |

# ABSTRACT

A novel framework was introduced to integrate drone technology with flood risk mapping and was named Drone Optimized Flood Risk Map (DOFRM), it uses a GIS-based Multi-Criteria Decision Model (MCDM), Analytical Hierarchy Process (AHP) and drone optimized grid. After reviewing specifications of 178 contemporary drones, a grid size of 1.2x1.2 km was determined to be optimal for drone surveys. This grid was overlaid onto a flood risk map derived from multiple hazards and vulnerabilities, selected based on an in-depth literature review. Weights for these factors were determined using AHP, and the study area was District Rajanpur, Pakistan. Stakeholders, including emergency responders, drone operators, and GIS specialists, evaluated this map using the TAM survey method. This approach identified 17% of the study area as highly susceptible to flooding. Highly susceptible area was further subdivided based on critical features including urban areas (3%), active channel (5%), roads (6%), rail networks (1%) stream networks (3%) and all populated areas (9%) for smart drone employment in large scale floods. The method allows for further subdivision of critical features based on grid size and available drone effort for various survey objectives. This approach can be applied by disaster response organizations for incorporating drones into disaster mitigation planning and large-scale flood survey, marking a new paradigm in flood mitigation strategies.

**Keywords**: *disaster response, flood risk map, analytical hierarchy process, drone optimization, drone flood imaging, technology adaptation model survey*

# CHAPTER 1 INTRODUCTION

Chapter 1 highlights significance of flood mitigation with the help of drones, process adopted to create DOFRM, its efficacy and limitations in research application. Subsequent subsections highlight relevant studies for flood mitigation through drones and their efficacy, limitation posed due inherent characteristics of drones, studies that showed how to overcome these limitations and successfully employ drone is support of flood mitigation.

Flood management is considered one of the major constituents within the ambit of disaster management operations. According to the United Nations, during 1970-2019, flood represents 45% out of the 3,454 disasters that were recorded in Asia. Whereas drones have been used extensively in mapping pre and post disaster hit areas, however flood hit areas vary across the landscape due to their inherent phenomenon, therefore, it is pertinent to gauge the efficacy of drones in different flood extents and in different scenarios for effective utilization (UCLouvain, 2020). Drones have undergone a transformation from being exclusively used by militaries to being utilized in a diverse range of sectors, encompassing healthcare, agriculture, emergency response, and transportation. (Kyrkou et al., 2019) highlights that, drones along with their underlying enabling technologies, are progressing rapidly, offering the potential to disrupt and enhance our overall quality of life.

Pakistan is currently facing dual challenges of climate change and a struggling economy, making it imperative to develop innovative and homegrown solutions to address its unique problems. This research will focus on a novel approach for flood mitigation using drones, while considering the diverse topography found across the study area. This study aims to utilize remote sensing and GIS techniques along with MCDA and AHP weight criteria, to evaluate drones' effectiveness in large scale flood mapping. The same process would be leveraged to optimize flood risk map for optimum drone utilization in flood imaging. The process is called DOFRM, it will help to highlight optimized drone application in disaster hit or disaster-prone areas. DORFM will also provide guidelines for public and private stakeholders to utilize drone as a cost effective and flexible solution for disaster mapping and other GIS related problem / opportunities. The research includes a stakeholder engagement component, involving disaster management agencies, drone operators & technical associates, GIS analysts, local authorities, and community representatives. The Technology Adaptation Model Survey Technique (TAMST) is employed to systematically gather feedback, insights, and recommendations from stakeholders actively involved in flood response and mitigation.

The study aims to provide practical recommendations for enhancing flood preparedness, response, and mitigation efforts within the specified geographic area; nevertheless, model can be adopted for any other area. The implications of the research extend to drone manufacturers, decision-makers, disaster management agencies, and local communities. The research acknowledges certain limitations, including non-availability of detailed socio-economic data, budget constraints, and the potential for subjective bias in stakeholders' feedback. These limitations are considered when interpreting the results and drawing conclusions.

The prevalence of drones has become a defining characteristic of the modern technological landscape. These drones have permeated various sectors, playing pivotal roles in activities such as surveillance, agriculture, infrastructure maintenance, and entertainment. The ubiquity of drones is not a monolithic phenomenon but encompasses a spectrum of UAVs, each designed for specific applications, thereby contributing to the evolution of this technology. Categorization of drones is often based on factors such as size, purpose, and propulsion systems.

## 1.1 **Literature Review**

Drones are extensively used in disaster mapping, management and response. Mohd Daud et al., (2022) documented the employment of drones for: (1) mapping of disaster management, it remains the most significant impact, (2) search and rescue operations, (3) transportation, and (4) training. Erdelj et al. (2017) proposed to leverage the technology of wireless sensor networks (WSN) and drones to enhance the prediction, assessment, and response capabilities in the context of disasters. The financial ramifications of such calamities are substantial, with record losses reaching an approximate total of US$45 billion, coupled with an additional US$13 billion in insured losses. This underscores the critical necessity for heightened efforts in fortifying communities against the impact of natural catastrophes, not only to mitigate the staggering financial consequences but also to safeguard human lives and promote long-term sustainability. Restas (2018) primarily concentrated on the operational and tactical employment of drones in disaster management. Same was achieved through a temporal separation of their application, specifically pre-disaster activities, immediate response to the occurrence of a disaster, and post-disaster management. The paper explores a range of disasters, including hazardous material releases, floods, and forest fires. The findings and subsequent discourse highlight the pivotal role of drones in managing hazardous material leaks, where they prove to be highly effective and, at times, the sole tool available. In the context of floods, a protracted onset disaster, the management thereof is exceedingly intricate and challenging. It necessitates constant monitoring of embankments, inundated areas, and areas under threat. Drones offer substantial support in maintaining continuous surveillance over a designated area.

Iqbal et al. (2023) established that drones with advanced sensors and algorithms hold the capacity to be employed in a more efficient manner than current practices for flood detection activities. A detailed bibliometric analysis was executed to comprehend the extent and contemporary trends in the field of drones utilized for flood management. Furthermore, the examination of the most recent 28 papers was conducted, which enabled the identification of potential areas of research for future studies pertaining to the utilization of drones for flood detection activities. McDonald, (2019) highlighted Drones' capabilities to bolster the management of stormwater in urban areas through the provision of valuable data pertaining to flood prediction, monitoring of water quality, and inspection of infrastructure. The utilization of drones has the potential to enhance the efficiency and precision of activities related to stormwater management, thereby contributing to more informed decision-making and the implementation of more effective strategies for mitigation. However, there exist certain obstacles that necessitate attention, including matters of regulation, concerns regarding privacy, and the requirement for advanced techniques of data analysis.

Rizk et al. (2021) explained the importance and difficulties of automated systems for managing disasters, specifically in the context of floods. Among various types of data, the measurement of water levels significantly contributes to the analysis of the situation and the creation of meaningful emergency response plans. The proposed system is a method of learning to determine water levels from aerial images captured from drones, readily accessible with current drone technology. It operates through a two-step process: the detection of objects from a top-view perspective and the classification of the water level. In another study by Alsumayt et al. (2023), proposes Flood Detection Secure System (FDSS), which employs deep active learning (DeepAL) and blockchain-based learning to effectively identify and oversee floods employing drones in large scale area. This system provides precise information to ensure optimal response times. The inclusion of drones in flood management, prior to, during, and after flood occurrences, plays a critical role in ensuring secure and decentralized data collection, flood tracking, and aerial photography for investigations related to disaster management. The applications of drones in the post-flood management are reminiscent of those in pre-flood drone management, and the acquisition of high-resolution photographs through drones can be employed for re-assessment and constructing a "history of change detection" over time. Drones possess the capability to furnish high-resolution photographs for the evaluation of dam conditions, such as fissures, erosion, and distortions. Additionally, they can aid in the early detection of critical areas in fire service applications, surpassing traditional reports.

Multiple types of drones are currently being employed in flood imaging and response endeavors to augment situational awareness and assist in the management of disasters. In a study by Kumar & Singh, (2022), an intelligent approach utilizing multiple drones for relief operations was used, it yielded superior outcomes compared to a centralized method. Aforesaid study conducted a drone surveillance of the flood-impacted region by employing Euclidean distances to determine the optimal routes for survey. Subsequently, Firefly Algorithm was used to ascertain the most efficient path. The results indicated that the proposed model is effective in improving the performance of relief operations compared to a centralized method. By deploying multiple drones with distinct capabilities, the effectiveness of the rescue mission can be enhanced. These drones have the capacity to capture aerial visuals of regions affected by flooding, which can subsequently be employed to generate 3D models, DEMs, as well as stitched orthophotos. In a study by Whitehurst et al. (2022) simulations of the flood event were carried out using HEC-RAS software, utilizing the pre-flood DEM and available weather data. These simulations were verified against water height values that were measured, and it was determined that the results were highly accurate. Following this verification, simulations were conducted using DEMs that were obtained after the flood, and it was discovered that if a similar rainfall event were to occur on the new terrain, the resulting flooding would be even more severe, with water depths between 29% and 105% higher. In a study by (Exadaktylos et al., 2022), drones were used to acquire real-time data pertaining to water depth and velocity, thus furnishing decision-makers with vital information for informed decision making and response strategies. To demonstrate the proposed framework, a flashflood was simulated which could potentially affect the city of Nicosia. Overall, the use of drones in flood imaging and response has the potential to significantly aid in mitigation efforts for natural disasters.

Drones although effective in disaster management, nevertheless their limited range and endurance remains a challenge for effective employment. A study by Zhang & Zhu (2023), highlighted various challenges in utilizing drones in large scale flood imaging. Drones Limited Field of View remains a limitation that allows their utilization only in small areas. Difficulties arise in capturing drone imagery during flood events due to adverse weather conditions. Timely processing and analysis of the vast volumes of drone imagery data are necessary to generate up-to-date and precise flood maps. The integration of drone imagery with other data sources, such as satellite imagery and ground-based observations, serves to enhance the accuracy and reliability of flood mapping. The management and interpretation of the variability in flood patterns and dynamics captured by drone imagery, including changes in water levels, flow velocities, and flood extents, must be adequately addressed. In another study by Backes et al. (2019), limitations in providing accurate and detailed data for flood imaging through remote sensing technologies, including satellite and airborne imaging surveys were mentioned. The standard of topographic input data represent a significant source of uncertainty in urban flood modeling, which can affect the accuracy of drone-based flood imaging. High resolution topographic data helps to capture the complexities of urban terrain, enabling precise flood mapping, whereas, low resolution topographic data can lead to modeling errors, undermining the effectiveness of flood risk assessment and mitigation strategies.

One of the main challenges faced by stakeholders during GIS operations is the lack of standardization in drone hardware and software (Șcheau et al., 2023). This leads to interoperability issues and difficulties in integrating drone data with existing GIS systems. Another inherent challenge is the limited flight time and range of drones which can result in incomplete data collection and the need for multiple flights (Zong et al., 2019). Drone operators also face challenges related to data management and processing. For example, the large volume and high resolution of drone data can overwhelm traditional GIS processing methods, leading to processing delays and storage issues (Singh & Hoskere, 2023). In addition, the accuracy of drone data in GIS analysis can be affected by environmental factors such as wind and temperature, leading to errors (Essel et al., 2022). Another challenge faced by drone stakeholders is regulatory compliance. Drone operations are subject to various regulations and guidelines, such as airspace restrictions and data privacy laws (Lohani & Ghosh, 2017). Adhering to regulations can be time and cost intensive, and non-compliance can result in legal hurdles (Iselborn et al., 2023). The optimization of the UAV route allows for the attainment of maximum coverage in a given area while minimizing both time and cost. To achieve this, the UAV swarm was proposed by Albani et al., (2017) for capturing images of the region and subsequently transmitting the collected data to the control center. Albani et al. employed a macroscopic model to monitor a specific area through the utilization of UAVs. To efficiently allocate these UAVs, a parametrization approach was proposed. Furthermore, study by Shandilya & Kuamr, (2023) focused on algorithms that enhance the effectiveness of multi-UAV surveillance systems deployed for disaster management purposes. The study delves into different algorithms employed for surveillance utilizing drones and assesses their performance based on key metrics including battery longevity, target quantity, response time, and energy utilization. These results provide insights into the needs of multi-agents for effective surveillance in disaster mitigation. When drones are employed in a segregated manner in such a way that they are being controlled by a centralized station for enhanced coverage and efficiency, then the biggest challenge becomes safeguarding drones' data being transported. The study by Derhab et al., (2023) furnishes an all-encompassing examination regarding the cyber and physical safeguarding of drones. Additionally, it puts forth three classifications pertaining to assets, attacks, and countermeasures, thus offering a comprehensive overview.

The limitations of drones can be overcome by different mitigation strategies, for example limitation of reduced coverage and endurance can be overcome with the help swarm drones operated in a decentralized way. The application of autonomous aircraft for the purposes of flood monitoring is currently considered to be a financially feasible choice. Moreover, this application can reap the advantages of automation. By employing drone swarms, it becomes possible for these aircraft to independently produce inundation maps in almost real-time. As a result, the planning of relief efforts can be greatly enhanced. This study by (Baldazo et al., 2019) focuses on the examination of Deep Q-Networks (DQN) as a means of optimal utilization of manpower and material by optimizing flight route, storage, flight time and travel resources. In a study by Ochoa Zezzatti et al., (2017) an ideal configuration of drones' equipment, instrumentation, and medical personnel was proposed for the purpose of providing humanitarian assistance during flood-related catastrophes.

The contemporary landscape of drone technology is marked by discernible shortcomings that pose challenges in their effective utilization. One notable issue is the proliferation of a vast array of drones in the market, contributing to a paradox of choice for potential users. This diversity, while indicative of technological innovation, has the unintended consequence of complicating decision-making for individuals seeking drones for specific objectives. The risk arises from the possibility of consumers acquiring drones that may not align optimally with their intended purposes, leading to suboptimal outcomes and underutilization of these technological tools. Consequently, addressing the real shortfalls in drone technology requires a sound understanding of user needs, enhanced industry standards, and effective education to ensure that the acquisition and deployment of drones align with specific objectives, fostering a more efficient and purpose-driven integration into modern practices. Drones are efficient and effective means in an environment where human movement due to floods is hindered. However, their current state of the art, remains insufficient for mapping floods spread over a large area, and needing integrated mapping and assistance. It is therefore necessary to critically examine this complexity and propose solutions that can help the research communities devise new approaches towards managing their mapping and response needs through drones. In the light of literature, it is inferred that drones are effective in disaster response operations and can augment overall mitigation efforts, however their effectiveness in case of large-scale flood response remains a challenge.

## 1.2 **Research Objective**

This study aims to utilize remote sensing and GIS techniques along with MCDA and AHP weight criteria, to evaluate drones' effectiveness in support of large-scale flood mapping. Furthermore, this process would be leveraged to create a Drone Optimized Flood Risk Map (DOFRM) for optimum drone utilization in large scale flood mitigation strategies.

# CHAPTER 2 MATERIALS & METHOD

To assess drones' effectiveness and their optimization, flood mapping for entire Rajanpur District, Pakistan was undertaken. A Flood risk map was created by incorporating Flood Vulnerability Index (FVI) and Flood Hazard Index (FHI), comprising vulnerabilities and hazards within study area. Factors for FVI and FHI were selected and mapped to gauge flood risk associated within study area. RIWs (Relative Important Weights) were calculated for each map based on AHP weight criterion and were reclassified into five zones indicating their contribution in overall flood susceptibility. Weighted overlay was performed to incorporate each layer within flood risk map. This flood risk map was optimized for drones by overlaying drone optimized grid, calculated through parameters of drones' current state of the art to evaluate extent of their effectiveness. Drone optimized flood risk map was also shared with stakeholders for their evaluation based on TAM survey method. Workflow during the study have been summarized in Fig 2.1 and elaborated in subsequent paragraphs.

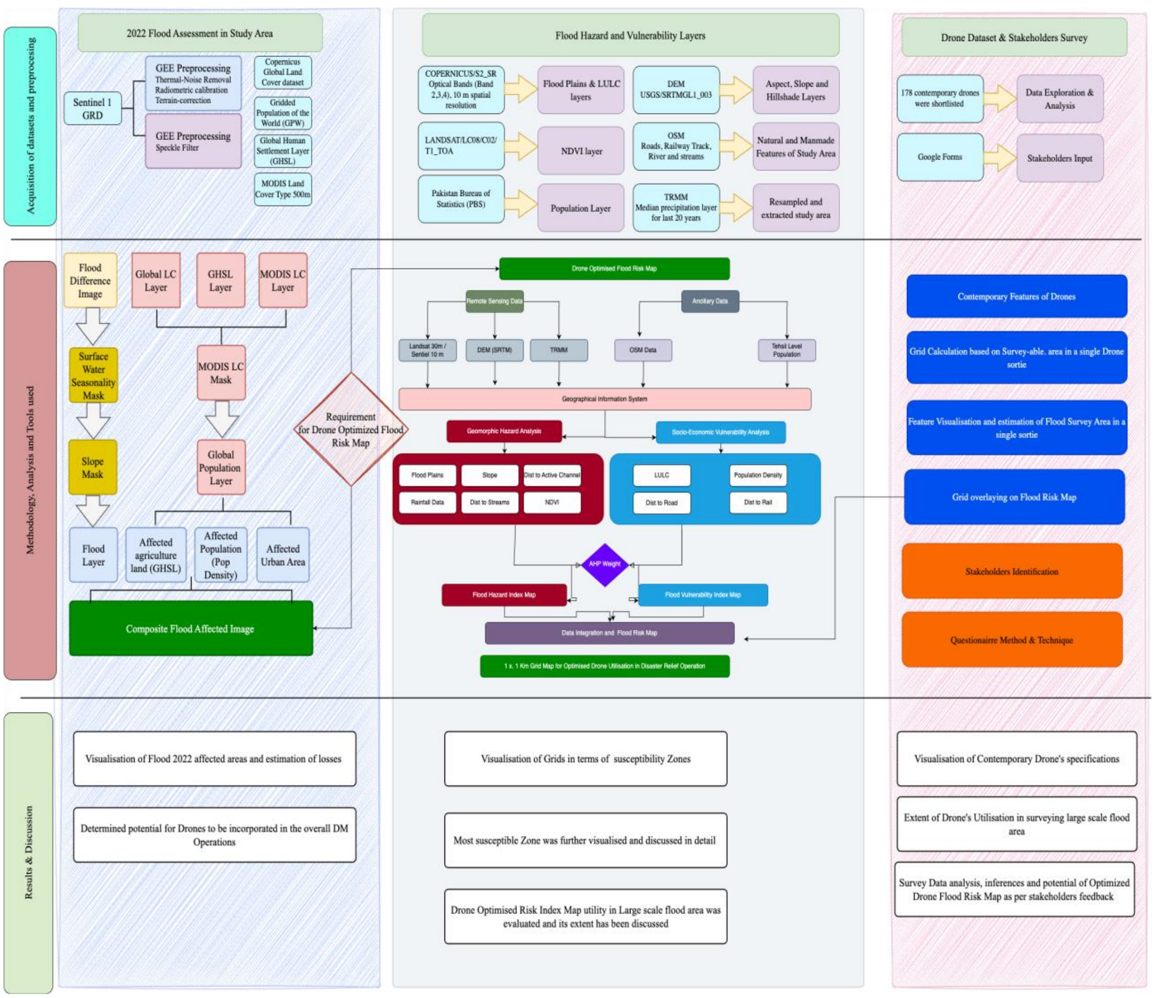



*Fig 2.1. Workflow methodology of drone optimized flood risk map. Assessment of 2022 flood in Rajanpur District was carried out using RS & GIS techniques while utilizing GEE platform. Subsequently FHI and FVI were generated with the help of pre-determined hazards.*

Historically, Pakistan has experienced several significant floods. The flood in 1973 resulted in the destruction of three million houses and the loss of ~160 lives (Schiermeier, 2014). According to (Atta-Ur-Rahman & Shaw, 2015) in 1988, around 508 people lost their lives due to flooding. Similarly, the flood in 1992 affected ~10 million people, and the number increased to ~20 million during the 2010 flood, which was the most devastating in Pakistan's history. To summarize historic floods over the past 70 years, peak fatality flood years were observed in 1950, 1965, 2010 and 2022 primarily caused by large-scale river floods or land falling tropical cyclones (Cigler, 2017). These floods have had a significant impact on the country, resulting in loss of life, destruction of property, and damage to the economy. Details of historical floods in Pakistan are given in the table 2.1. Floods although common along the length of the Indus River, have affected some districts more than other. Therefore, it was decided to study a district that uniquely portrays the complex hazards, including hill torrents and being located adjacent to river Indus, as well as vulnerabilities, including low income and illiterate population to gauge the effects of flood among the districts of Pakistan.

*Table 2.1 Detail of losses over the years during the history of floods in Pakistan. Due to a peculiar topography from North to South along the river Indus, Pakistan remains vulnerable to riverine, flash and urban flooding along with additional threat of GLOFs in the North due to global warming.*

| **Timeframe** | **Areas Affected** | **Extent of Damage** |
|---|---|---|
| 1950 | 17,920 km area affected | 2190 people killed & 10,000 villages affected |
| 1955 | 20,480 km area affected | 679 people killed & 6,945 villages affected |
| 1976 | 91,920 km area affected | 425 people killed & 18,390 villages affected |
| Sep 1992 | 38,758 km area of Azad Kashmir, KPK & Northern Punjab | 1008 deaths, 13,208 villages affected, heavy loss to livestock and agricultural crops in affected areas |
| 1995 | 16,686 km area affected | 591 people killed & 6,825 villages affected |
| Jul – Aug 2007 | KPK, Baluchistan & Sind | Approx 152 people died and 2,000 were evacuated in KPK, while 815 people died in Baluchistan and Sindh. |
| August 2010 | 160,000 km area of almost entire Pakistan | Approx 2,000 people died, more than 20 million people & 17,500 villages were submerged. |

| | | |
|---|---|---|
| Sep 2011 | 27,581 km area of Sind | Approx 500 fatalities, along with more than 5 million people and 1 million homes distressed |
| Sep 2012 | 4,746 km area of KPK, Southern Punjab & Northern Sind | 571 fatalities, and thousands of homes devastated, with vast area inundated. |
| Sep 2013 | 4,483 km area | 333 people killed & 8,297 villages affected. |
| Sep 2014 | Azad Kashmir, Gilgit / Baltistan, Punjab | 368 people killed & 4,065 villages affected. |
| August 2020 | Karachi | 41 people killed & city infrastructure damaged. |
| August 2022 | Baluchistan, Sind & Southern Punjab seriously affected | Rs 3.2 trillion loss to infrastructure and houses, Rs 3.3 trillion economic loss.<br><br>Approx 1,700 fatalities, more than 12,500 injured, over 2 million people displaced, more than 890,000 houses devastated, more than 11500,000 livestock wasted, more than 84,000 kilometer$^2$ area submerged and more than 13000 km roads destroyed. |

## 2.1 **Study Area**

Rajanpur district is located to the west of the Indus River and covers an area of 12,318 square kilometers. 3026 sq kms contains hill torrent towards the west, constituting part of Koh-e-Sulaiman range, 4814 sq kms constitute piedmont plain, 116 kms length of active channel flows through Rajanpur District through its eastern side. 8 major streams flow through the district with variable lengths. Average width of river Indus is from 2.5-3.5 kms along the district. Whereas average width of active plain within the study area is around 15 kms. District is illustrated in Fig 2.2, has overall 4 Tehsils, one being tribal area is excluded because of minimal population and less flood prone land features, the other three Rajanpur, Rojhan and Jampur will be considered for flood extent, hazards and vulnerabilities.

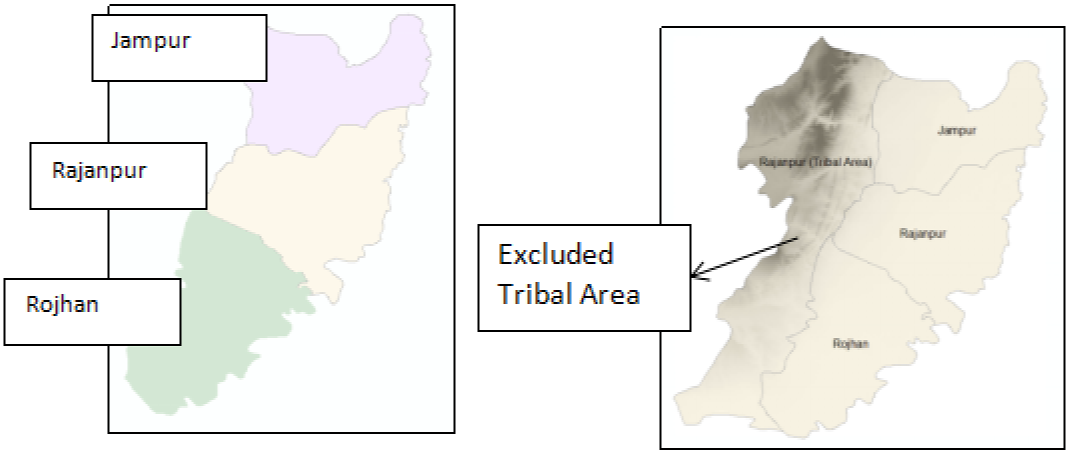



*Fig 2.2 Rajanpur District comprises four Tehsils; Jampur, Rajanpur, Rojhan and Tribal area. Tribal area was excluded due least population and raised terrain, thus remains less susceptible to flood and being least vulnerable.*

Rajanpur District in Pakistan is affected by hill torrents, which are fast-flowing streams that occur during heavy rainfall events in hilly areas. These hill torrents can lead to flash flooding in the district, causing significant damage and posing a threat to the local population (Kamran, 2014). A study by (Saleem, 2023) focused on the Koh-e-Suleiman mountain range, including parts of Rajanpur District, to assess the influence of hill torrents on riverine flooding. The research identified various hill torrents that serve as channels for floodwaters originating from the surrounding catchment areas. These torrents flow into the Indus River via the right bank of the Chashma River and surrounding canals, causing inundation along their course. The findings highlight their significant contribution over the period of 200 years, indicating their potential contribution to the Indus River during varying rainfall scenarios.

During the 2010 floods, the hill torrents in Rajanpur experienced severe flash flooding between late July and early August. (Hashmi, 2012), noted that intense rainfall over the Suleman Range Mountains, as well as the plains of Dera Ghazi Khan and Rajanpur, led to significant flooding in the hill torrents on the district’s western side, which in turn increased flood levels in the Indus River. The floodwaters inundated numerous settlements near the riverine areas. Rajanpur is characterized by an extremely hot climate with prolonged summers and it is highly vulnerable to severe flash floods due to its varying geography. Rajanpur District is the province's least developed and poorest district, characterized by the lowest literacy rates. In surveys like the Multiple Indicator Cluster Survey (2003-04) and research conducted by the Social Policy Development Centre in 2001, Rajanpur consistently ranked last among Punjab's districts across various indicators. The MICS (2003-04) results revealed that 66% of the district's population had a per capita income of less than Rs 750 per month, significantly lower than Punjab's average of Rs 1385, making it the province's lowest in terms of per capita income. Above socioeconomic figures from (Iqbal, 2015) study makes it one of the most vulnerable District among the flood prone regions in Pakistan. Many areas of this district were hit by the floods for the first time. According to the district official record, significant evacuations were conducted, displacing 1,118,898 people and submerging up to 711,142 acres of land. The flood damaged 33,645 houses, affecting 223,415 individuals. Additionally, crops on 310,888 acres were destroyed, and 70 km of road infrastructure was wiped out (Haider, 2022). Fazilpur town in Rajanpur District was affected by eight feet high tide of the flood water from west and four feet of flood water from east (Birmani, 2022). This means that the district is at risk of being inundated from both sides in the event of either excessive rainfall or riverine flooding. Fig 2.3 highlights flood inundation of study area during floods 2022.

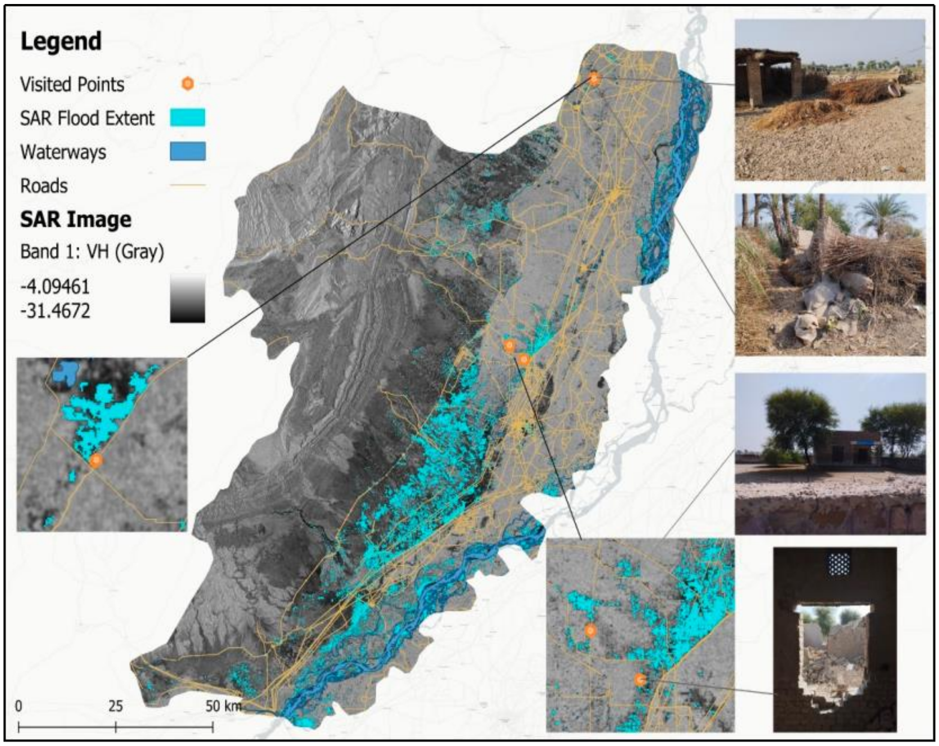



*Fig 2.3 SAR imagery of Rajanpur District during the Flood 2022, affected areas were physically visited to verify flood extent. Areas in Rojhan and Jampur were severely affected due to combined effect of alluvial flow from the west as well as inundation from river.*

## 2.2 2022 Flood Assessment in Study Area

Flood-2022 assessment of the study area was conducted using various GEE tools to determine flood vulnerability and its effects on ground. (Tazmul Islam & Meng, 2022) explored the use of Sentinel-1 SAR imagery for rapid and accurate urban flood mapping, highlighting its advantages over optical imagery in terms of data collection capability in any weather conditions. SAR Sentinel-1 GRD imagery was acquired utilizing Google Earth Engine (GEE) repository to assess the flood damage assessment, using a change detection approach. A change detection approach was chosen, where a before- and after-flood event image was compared. The study by (Haghighi, 2022) demonstrated the potential of Sentinel-1 SAR data for large-scale flood mapping, using a normalization technique based on the cosine squared of incidence angle to homogenize the data. GRD imagery includes preprocessing steps of Thermal-Noise Removal, Radiometric calibration and Terrain-correction. Therefore, only a Speckle filter was applied in the pre-processing. GEE was used to determine flood extent before flood for 1-3-2022 to 15-3-2022, whereas after the flood for 22-7-2022 to 7-8-2022. Other variables include VH polarization, descending orbit and threshold of 1.25 to be applied on the difference image, it was chosen by trial and error. After obtaining tiles for before and after flood duration, tiles were mosaicked and smoothened by reducing radar speckles, smoothing radius was kept 50. Once both Images were prepared, difference image was created. This Difference Image was further refined to mask flood pixels utilizing JRC data set for surface water seasonality highlighting "permanent" water area in instances where water > 10 months during an entire year. Flooded layer where perennial water layer is present more than 10 months is given 0 value. Flooded Image was further refined by Masking out areas with more than 5 percent slope using a DEM. Flooded area was calculated and then all the flooded pixels were added and converted into Hectares.

Pandey et al. (2022) utilized Copernicus Global Land Cover dataset to obtain the disturbed agricultural area and flood-affected neighborhood. They also used Gridded Population of the World (GPW) data set, and Global Human Settlement Layer (GHSL) population dataset to determine flood extents. Damage assessment was done by assessing exposed population density, affected agriculture land and affected urban area. Exposed population density was calculated utilizing JRC Global Human Settlement Population Density layer Resolution: 250m by calculating number of people in the flooded area, flooded layer was re projected to the GHSL resolution before calculating number of exposed people. Affected agriculture land was assessed utilizing MODIS Land Cover Type Yearly Global 500m, cropland pixels by determining classes of cropland (>60%) and Cropland/Natural Vegetation aggregates of small-scale cultivation (40-60 %) including natural vegetation, for this step flooded layer was again re-projected to MODIS layer, and then affected vegetated area was calculated using affected pixels area and then converted into hectares. Using the same MODIS land cover product, affected urban area was extracted, by first, calculating affected urban areas using the resampled flood layer, then getting pixel area of affected urban layer, followed by adding pixels of affected cropland layer and then converting affected area into hectares. Fig 2.4 illustrates all layers including, before and after flood SAR mosaic, Difference layer, Flooded areas, Population Density, Exposed Population, MODIS Land Cover, Affected cropland and Affected urban areas.

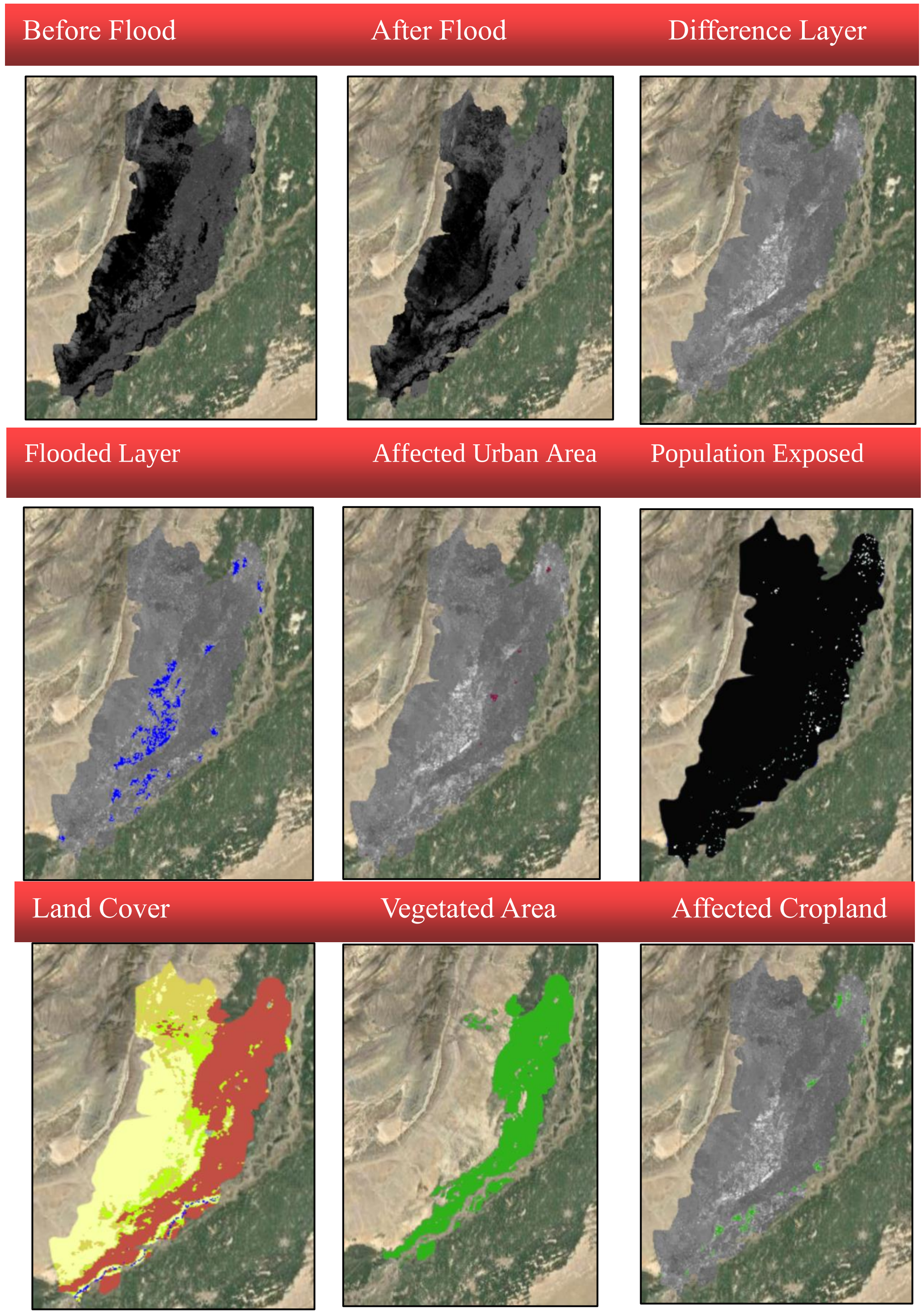



*Fig 2.4 GEE was utilized to obtain affected flood area through SAR imagery, difference image was obtained based on the pre and post flood images and then affected area was calculated. MODIS GHSL and Land Cover layers were utilized to obtain affected cropland and population within study area.*

Based on the above-mentioned flood assessment between the duration 22-07-2022 to 07-08-2022, estimated flood extent was ~61,089 hectares, estimated number of exposed people were ~38126, affected cropland was ~10,396 hectares and estimated affected urban areas include 298 hectares as mentioned in Fig 2.5.

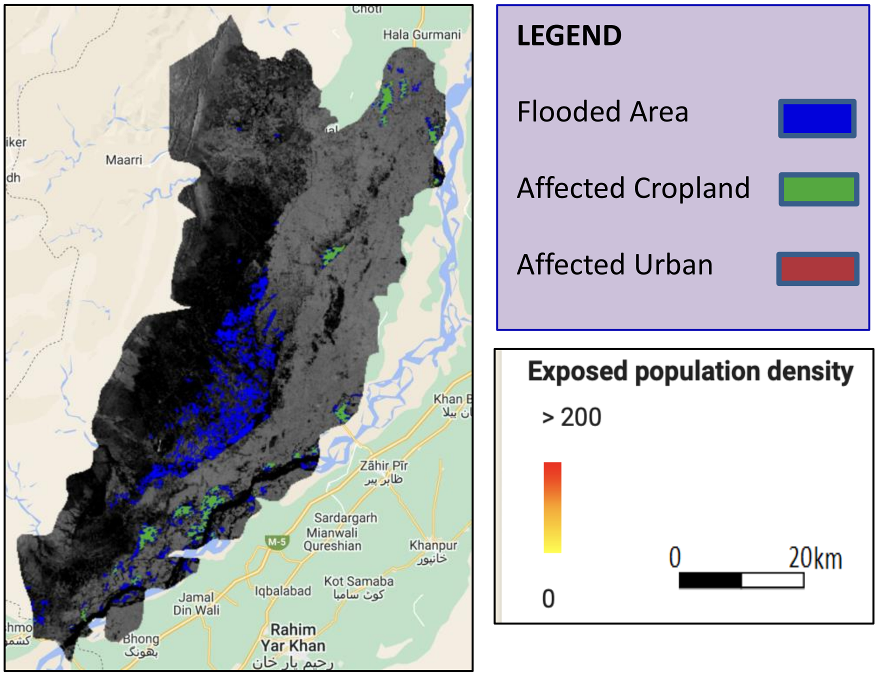



*Fig 2.5 Composite flood extent layer was created in GEE after overlaying all layers to identify combined flood affected imagery of study area. It includes exposed population, flooded areas, affected cropland and affected urban area.*

2.3 **Data / Software Used**

*Table 2.2 Description and source of datasets / software used during research. Datasets contained hazards and vulnerabilities within study area; whereas, software comprise of RS / GIS and AHP tools.*

| **S/N** | **Data & Software** | **Specification** | **Source** |
|---|---|---|---|
| 1 | MODIS SAR Imagery | COPERNICUS/S1_GRD | GEE Explorer |
| 2 | Sentinel-2a | COPERNICUS/S2_SR<br>Optical Bands (Band 2,3,4), 10 m spatial resolution | GEE Explorer |
| 3 | GHSL & JRC | JRC/GHSL/P2016/POP_GPW_GLOBE_V1/2016<br><br>MODIS/006/MCD12Q1 | GEE Explorer |
| 4 | Landsat | LANDSAT/LC08/C02/T1_TOA | GEE Explorer |
| 5 | Population | Pakistan Bureau of Statistics (PBS), Global Human Settlement Layer (GHSL) | PBS website & GEE Explorer |
| 6 | DEM | USGS/SRTMGL1_003 | GEE Explorer |
| 7 | OSM | Roads, Railway Track, River and streams | OSM website |
| 8 | ArcMap | Weighted overlay, Euclidean Distance, Classification, Raster clip, Times function, Reclassify tool etc. | Esri |
| 9 | QGIS, SAGA GIS | Basic terrain analysis | QGIS |
| 10 | Microsoft Excel | Exploratory Analysis, AHP weight assignments | MS |

## 2.4 Methods

Typically, three factors play a significant role in determining the impact of floods. These are a) Hazard, which refers to the occurrence of a natural event that poses a threat, including its likelihood and magnitude; b) Exposure, which pertains to the presence of assets or individuals at the location in question; and c) Vulnerability, which relates to the lack of resistance to destructive forces. Consequently, within a designated flood hazard area, there may exist similar levels of exposure or risk of flooding, while simultaneously exhibiting a wide range of vulnerabilities.

### 2.4.1 Generating a Flood Risk Map for Delineating Susceptibility within Study Area

Flood risk is a product of the hazard and vulnerability (Ologunorisa, 2001)

$$Risk = Hazard\ (H)\ x\ Vulnerability\ (V) \qquad (1)$$

Flood risk combines both natural and human-related factors, highlighting the importance of obtaining accurate information about the spatial extent of flooded areas. Achieving this objective can be accomplished by utilizing multiple layers of data with varying degree of flood impact weightage, which act as a valuable source of information for developing more reliable approaches in flood management and mitigation (Mishra & Sinha, 2020). Among the various methodologies for MCDA, the AHP formulated by (Saaty, 1980) is widely acknowledged and extensively utilized in the context of flood susceptibility mapping, hydrology, and water resource management. This technique involves the utilization of a pairwise comparison matrix to calculate the weights assigned to different factors that influence flood hazard and vulnerability. It assumes the complete confluence of multiple criteria and derivatives, meaning the assessment, integration, and ranking of the numerous conflicting factors based on a certain level of information. Additionally, it provides a more adaptable, economically feasible, and easily understandable solution for complex decision-making challenges (Saaty et al., 2003).

The evaluation of flood risk extends beyond the consideration of hydrological extremes. It encompasses a range of intricate processes that are characterized by numerous physical hazard as well as anthropogenic vulnerabilities (Alexander, 2000). To conduct an effective assessment of flood risk, it is essential to have access to long-term data and to appropriately analyze the spatial scale. However, in many instances, the local aspects of analysis tend to be disregarded in assessments (Jha & Gundimeda, 2019). Given the spatial extent and data availability at the Tehsil level, the flood risk assessment of the Rajanpur District has been conducted by considering various factors that influence both flood hazard and vulnerability. These aforementioned factors undergo a conversion process to generate thematic layers. This conversion process involves the utilization of remote sensing and ancillary datasets, such as satellite and topographic maps, Tehsil-level boundary maps, road network maps, stream and river network maps, SRTM DEM, and rainfall data. The process of generating the database is depicted in Figure 2.1, while the subsequent sections provide a detailed explanation of the methodology employed for analyses.

## 2.5 Parameters Used for Flood Risk Map

Parameters as shown in Table 2.3 were selected to create hazards and vulnerability raster for flood risk map. Factors involved in Flood Vulnerability Index (FVI) and Flood Hazard Index (FHI) are highlighted in Figures 2.7 and 2.8 respectively.

*Table 2.3 Description of all factors that were utilized to create various hazards and vulnerability raster.*

| **Parameters** | **Spatial Resolution** | **Temporal Resolution** | **Source** |
|---|---|---|---|
| Flood plains | 10m | 2022 | Sentinel 2A / GEE |
| Slope | 30m | | USGS SRTM |
| NDVI | 30m | | Landsat 8 |
| Rainfall Data | 0.25 deg | 2003-2022 | TRMM |
| Proximity to streams | - | 2023 | OSM |
| Proximity to Active channels | - | 2023 | OSM |
| LULC | - | 2023 | Sentinel 2A / GEE |
| Population Density | 250m | 2023 | GHSL |
| Proximity to road/rail network | - | 2023 | OSM |

### 2.5.1 Flood Plains

The role of geomorphology is critical in determining flood susceptibility. In the district studied, the floods plains include active, paleo channels and alluvial fans on the piedmonts. Table 2.4 highlights differentiation between characteristics of various flood plains associated with the study area.

*Table 2.4 Three types of flood plains could be identified within study area, these included active channels, paleo channels and piedmont / alluvial plains. Each plain represents certain characteristics and potential threat with respect to floods.*

| Geomorphic Element | Characteristics | Satellite Identification |
|---|---|---|
| Active Channels | The active channels are exclusively comprised of features that look like channels, such as elongated forms indicative of water flow, however, rest of the water bodies are considered as part of the floodplain. The active channel includes water, bars, and the bare bed of the channel. This component is identified as the section of the river and floodplain that is inundated at both ends. | **Hue**: Varies from dark blue to lighter shade of blue.<br><br>**Form/Dimensions:** Long and narrow, seemingly sculpted by flowing water. |
| Paleo Channels | The channels, which may have been recently active, are at present filled with sedimentary deposits like alluvium, gravel, sand, or, otherwise, with tills. | **Tone**: characterized by shades ranging from medium to dark blue.<br>**Pattern**: displaying a curvilinear design, consistent with the flow of an older stream.<br>**Association**: aligned with a specific arrangement of the vegetation. |
| Piedmont / Alluvial Plains | A Piedmont plain is a plain situated at the foot of mountains or hills. | **Hue**: Relatively bright, like urban features.<br>**Pattern**: Form Alluvial fan along the plain. |

### 2.5.2 **Slope**

The USGS SRTM dataset was employed to create a DEM of the study area at a resolution of 30 meters, utilizing GEE. To further refine the hazard risk assessment for Rajanpur district, slope raster was created, it was derived from aforesaid DEM. Steeper slopes are generally less susceptible to floods, whereas lower slope areas tend to have a higher runoff potential and are more susceptible. Subsequently five slope zones based on equal slope angle intervals were created within Rajanpur District. A hypsometric curve was also created to check slop variability, 60% area is below 100 meters, and 80% area is below 200 meters, whereas max elevation was 400 meters in less than 2% of the study area.

Hypsometric curve is illustrated in Fig 2.6 besides DEM, drainage basins and slope variability layer.

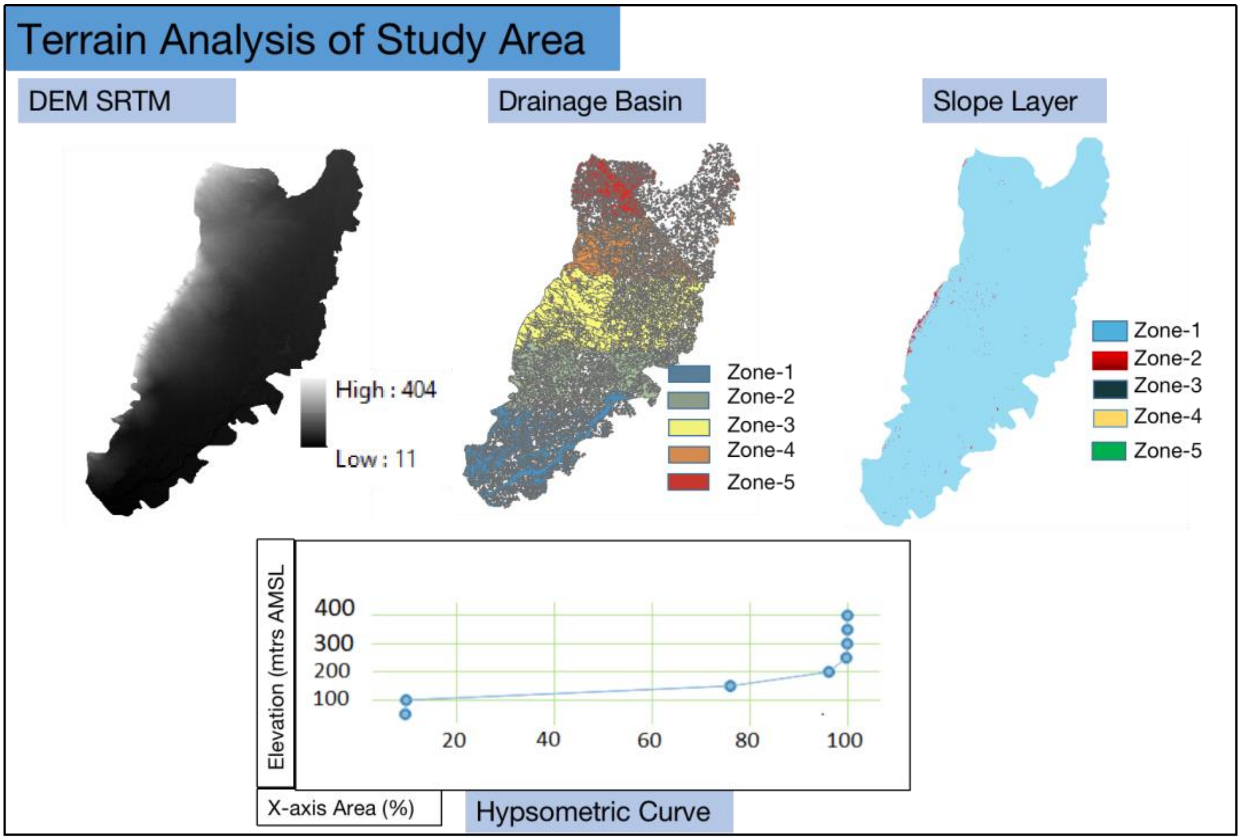



*Fig 2.6   SRTM DEM was utilized to conduct basic terrain analysis of the study area, various raster were generated including Slope, Drainage Basins and Catchment areas. Slope variation was generally lower, as can be verified with the hypsometric curve.*

### 2.5.3 **NDVI**

(Hasanloo et al., 2019) employed the NDVI layer as a parameter to evaluate the existence and density of flora within the designated region, a factor of utmost importance in the assessment of flood incidence and risk. In instances where vegetation is densely populated, the likelihood of water absorption and subsequent obstruction in its flow is heightened, while areas with sparse or absent vegetation are more susceptible. The Landsat 8 imagery was employed to compute the NDVI through the application of the GEE NDVI function, utilizing Bands 5 and 4 from the dataset.

### 2.5.4 **Rainfall**

Average rainfall per hour over a span of 20 years in the study area was obtained using the TRMM data set through GEE. The TRMM collection data set, covering the years 2003 to 2022, was used for this purpose. In comparison to other global satellite-derived rainfall products like GPCP, CMAP, and CPC-Global, the TRMM data set offers a significantly higher spatial and temporal resolution on a global scale (ranging from 2.5◦ to 0.5◦). To generate the rainfall map, the TRMM data with a spatial resolution of 0.25◦ was employed and extracted specifically for the assigned study area through the utilization of ArcGIS (Mishra & Sinha, 2020). By utilizing these RGB, DEM, and TRMM data sets, multiple layers were generated and subsequently integrated with each other to calculate the Flood Hazard Index Map.

### 2.5.5 **Proximity to Active Channel**

Variables that exhibit the most significant influence on flood modeling include the distance to active channel. Map of Distance to the Active Channel was created using sentinel data. On the imagery, active river channel was identified and digitized on ArcMap, river feature available in OSM was also utilized for river correlation. Then Euclidean distance tool was used where each point shows its distance from the river. Raster was Reclassified into five zones based on equal distance intervals. Finally, raster was clipped using district boundary. (Jagtap et al., 2023) constructed utilizing seven parameters that influence flooding, such as river and stream characteristics, precipitation patterns, terrain steepness, soil composition (clay and loam), population distribution, and land use and land cover (LULC) information.

### 2.5.6 **Distance to streams**

This raster has been used in several studies to assess flood susceptibility (Santos & others, 2019; Meraj et al., 2015). Building on the previous method, another raster was created to highlight distance zones from streams within Rajanpur district. Streams were identified and mapped on high-resolution imagery and further correlated with OSM stream features. Subsequently, Euclidean Distance tool was utilized to generate a distance raster using the stream network as the input. This new raster was reclassified into five distance zones, maintaining the same criteria used for the river zones. This will provide two complimentary rasters: one showing distance zones from the river and another highlighting distance zones from streams, offering a more comprehensive understanding of how distance to both water sources varies across Rajanpur district.

### 2.5.7 **Distance to Roads**

Proximity to roads is a critical factor in flood vulnerability, as it affects the ability of residents to evacuate quickly and safely during flood events. The closer a location is to a road, the easier it is for emergency services to reach and for residents to evacuate, thereby reducing flood vulnerability (Drejza et al., 2019; Durga Rao et al., 2019). To gauge the proximity to roads within study area, a raster was created. Sentinel-2 Imagery and OpenStreetMap data were used to identify the road network. Subsequently, ArcGIS software generated a raster where each pixel's value represents its distance from the nearest road, raster was divided into five zones based on the equal distance intervals from the roads.

### 2.5.8 **Population density**

Tehsil population data (Tehsil) and JRC Global Human Settlement Layer (GHSL) data with 250-meter resolution (A Pixel) were acquired. Both were overlaid to proportionally distributed Tehsil population across built-up areas (P Distributed) within study area (Tascón-González et al., 2020; Fox et al., 2023). Then, population density (Pop Density) was calculated using following formula to create a detailed raster.

$$Pop\ Density\ (people/m^2)\ = Distributed\ /\ A\_pixel \qquad (2)$$

This procedure does have limitations as the assumption of evenly distributed population is a simplification and urban pockets have high and low density of population; nevertheless, as population disaggregation is only available at Tehsil level. Therefore, focusing on built-up areas from JRC's data, refines the calculation by excluding non-residential areas. Finally, Pop Density raster was reclassified into five zones based on equal population density intervals.

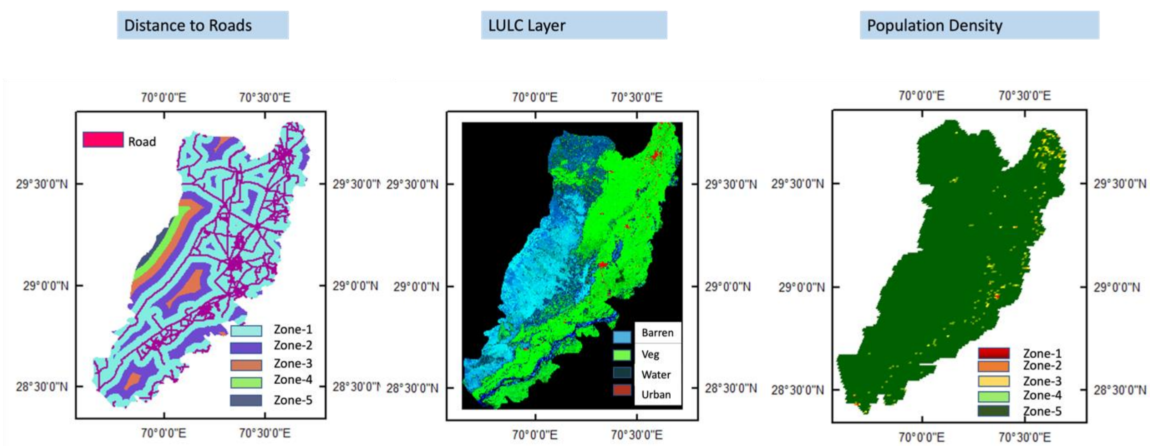



*Fig 2.7 FVI parameters included population density, Urban, vegetation, water and barren LULCs, and proximity to roads within study area.*

### 2.5.9 **LULC**

To further refine the Flood Vulnerability Index (FVI) for Rajanpur District, a Land Use/Land Cover (LULC) raster was derived from Sentinel-2 RGB imagery. This raster provides critical insights into how various land cover types' of influence flood vulnerability. The Sentinel-2 images underwent a series of preprocessing steps to ensure spatial accuracy and consistency. These steps included georeferencing, co-registration, and histogram equalization. Georeferencing aligned the imagery with geographic coordinates, while co-registration corrected any spatial misalignments between images. Histogram equalization was applied to enhance the contrast of the images, ensuring that features were more distinguishable. Following preprocessing, a supervised maximum likelihood classification algorithm was employed to categorize the land cover in Rajanpur District.

This classification process divided the district into four key classes: water, barren, urban, and vegetated areas. The resulting LULC raster serves as a foundational dataset for assessing and refining the FVI, providing a detailed understanding of the spatial distribution of land cover types and their respective impacts on flood vulnerability.

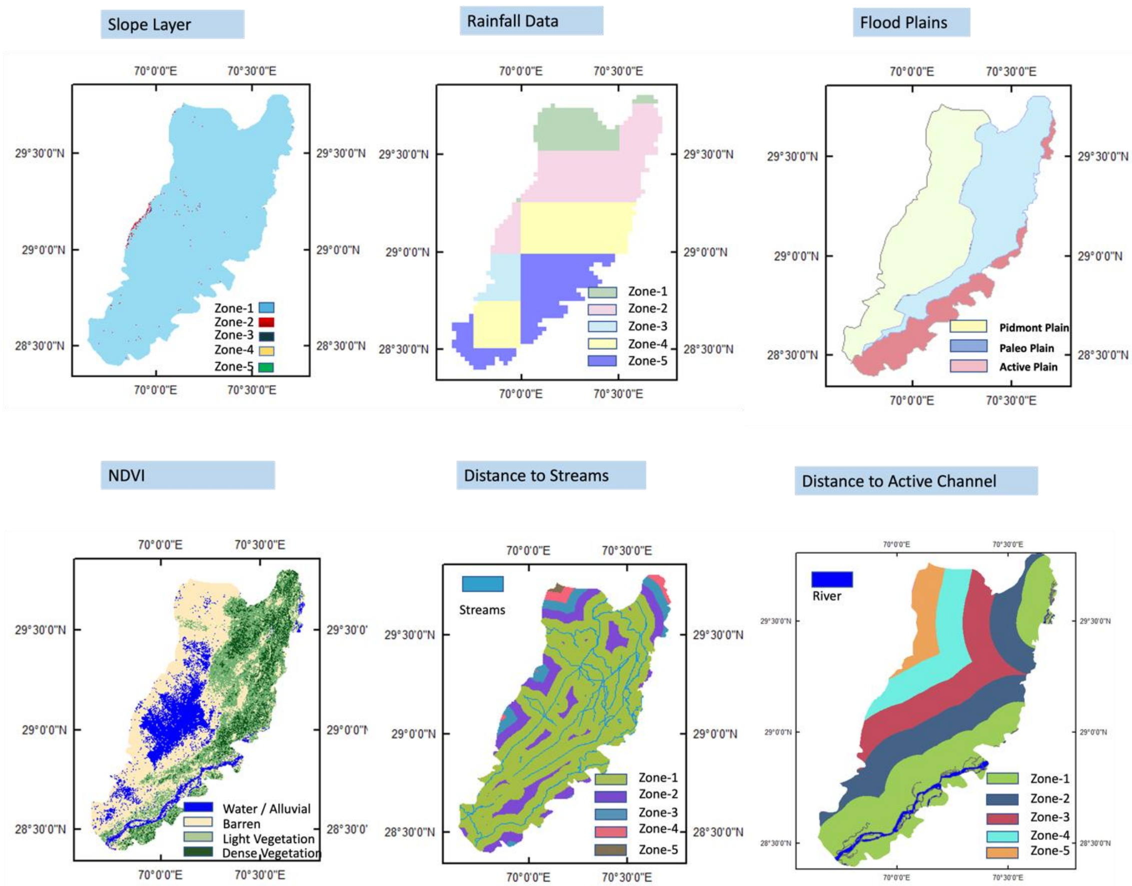



*Fig 2.8 FHI parameters including Flood plains, DAC, proximity to streams, rainfall data, NDVI and slope layers. DAC and rainfall contributed maximum weights in overall FHI map.*

## 2.6 **Preparation of Flood Hazard / Vulnerability Index Maps**

The Multi-Criteria Decision Making (MCDM) technique was used to integrate multiple thematic layers on a GIS platform. One of the most widely used methods is the Analytic Hierarchy Process (AHP), which was created by (Saaty, 1980). It entails breaking down the problem into a hierarchy that encompasses the essential components of the processes. According to Saaty et al., (2003), the first stage in the AHP analysis is to create a pairwise comparison matrix for each decision level. Determining each element's weight for the choice factor and its sub-factors is the second stage. The Estimated Eigen (EE) value is the name given to this weight.

$$\text{Estimated Eigen value (EE) of each element} = N\sqrt{aa * ab * ac * ad * aN} \qquad (3)$$

Where N is the number of row elements and the values of the row elements are aa, ab, ac, and aN.

The third step is to obtain the total of the EE values in a vertical orientation so that Relative Importance Weights (RIW) can be calculated for each individual component of that specific factor that determines outcome.

$$RIW = N \sqrt{\frac{aa * ab * ac * ad * aN}{EE1 + EE2 + EE3 + EE4 + EEN}} \tag{4}$$

Estimated Eigen value of each element are denoted as EE1, EE2, EE3 and, EEN.

In the last stage, the RIWs at each level of the hierarchy are added together to calculate the flood hazard index (FHI) and flood vulnerability index (FVI) for each parameter.

$$FHI/_{FVI} = \sum_{i=1}^{n^2} RIW\ 2 * RIW3 \tag{5}$$

level 2 decision factor is denoted as N2; RIWi2 is relative importance weight of level 2 decision factor i; RIW 3 is RIW of level 3 decision factor

Consistency Ratio (C.R.) is a useful tool for determining framework's accuracy. A pairwise comparison is considered to have a decent level of consistency if the consistency ratio (C.R) is less than 0.10 (the Cagayan State University-College of Information and Computing Sciences Philippines 3500 et al. 2015).

$$C.\ R = C.I / R.I. \tag{6}$$

R.I is used for the random inconsistency index. C.I is used for Consistency Index

$$CI = \frac{\lambda\,(max) - n}{n - 1} \tag{7}$$

The AHP was utilized to assign weights to all the available hazard / vulnerability layers, and then integrate them into a single layer. AHP weight assignment is a structural process, first each layer is assigned a weightage in terms of its relative importance (Level 2), subsequently each layer is divided into five zones, each zone is also assigned weightage based on the zones' relative importance within that layer (Level 3). Table 2.5 illustrates weights assigned at Level 2. For both the sub-factors at Level 3 and the hazard / vulnerability factors at Level 2, consistency ratios were calculated. By applying respective weights FHI and FVI were created as mentioned in Fig 2.9, and finally, both maps were integrated to produce flood risk map.

*Table 2.5 Level 2 weight matrices for Hazard and vulnerabilities Index Maps, DAC and rainfall contributed to almost 50% of weight within FHI; whereas, Population and urban land cover constituted 56% weight within FVI.*

| STANDARDIZED AHP MATRIX FOR FHI / FVI LEVEL-2 | | | | | | | |
|---|---|---|---|---|---|---|---|
| **FHI** | DAC | Rainfall | Dis To Streams | Slope | NDVI | Flood Plain | **Weight** |
| DAC | 1 | 3 | 5 | 7 | 6 | 4 | **37%** |
| Rainfall | 1/3 | 1 | 2 | 4 | 3 | 2 | **23.0%** |
| Floodplains | 1/5 | 1/2 | 1 | 3 | 2 | 1 | **15%** |
| Proximity to Streams | 1/7 | 1/4 | 1/3 | 1 | 1/2 | 1/3 | **9%** |
| Slope | 1/6 | 1/3 | 1/2 | 2 | 1 | 1/4 | **7%** |
| NDVI | 1/4 | 1/2 | 1 | 3 | 4 | 1 | **9%** |
| ***λmax*** *6.29* *CI* | *0.058* | *CR* | *0.046* | | | | |
| | | | | | | | |
| **FVI** | Population | Urban | Vegetation | Dis To Roads | Barren | **Weight** | |
| Population | 1 | 4 | 3 | 5 | 6 | **39%** | |
| Urban | 1/4 | 1 | 1/2 | 3 | 2 | **20%** | |
| Vegetation | 1/3 | 2 | 1 | 4 | 3 | **27%** | |
| Dis To Roads | 1/5 | 1/3 | 1/4 | 1 | 1/2 | **8%** | |
| Barren | 1/6 | 1/2 | 1/3 | 2 | 1 | **6%** | |
| ***λmax: 5.09*** *CI* | *0.0225* | *CR* | *0.018* | | | | |

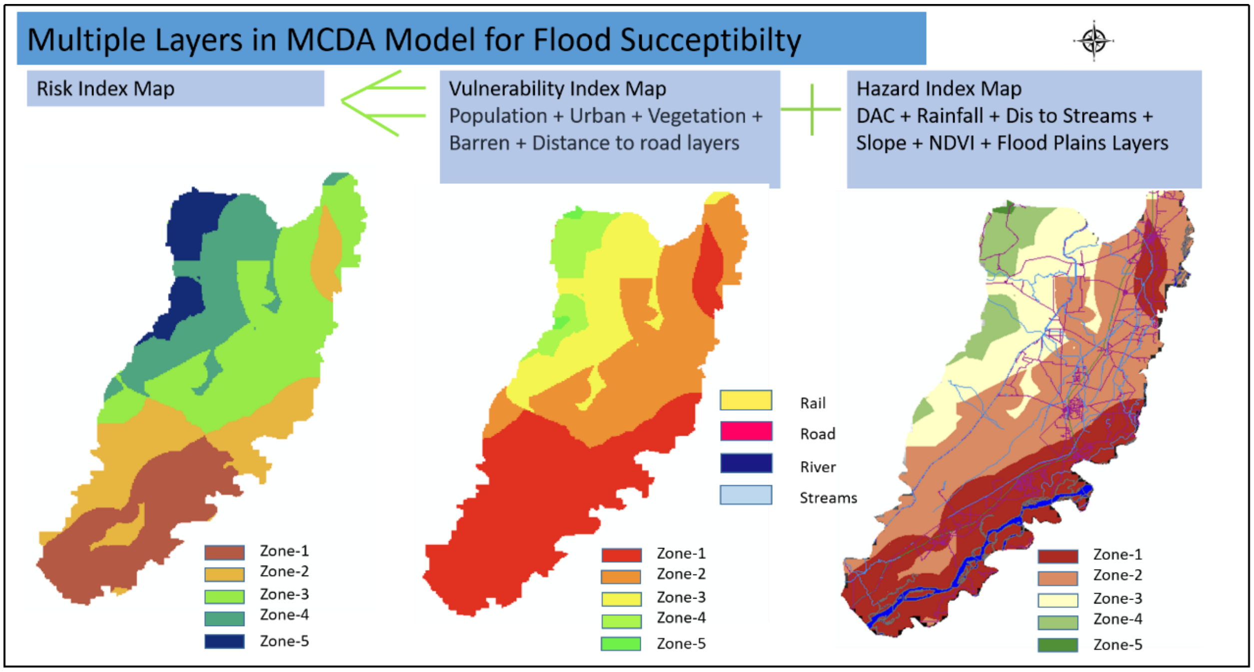



*Fig 2.9 For both the sub-factors at Level 3 and the hazard / vulnerability factors at Level 2, consistency ratios were calculated. By applying respective weights FHI and FVI were created, and finally, both maps were integrated to produce flood risk map.*

## 2.7 Drone State of the Art

Contemporary attributes of drones used for flood imaging mostly involve multi-copter drones (Suroso, 2019). These drones are furnished with cameras and can be operated remotely by a pilot. They possess the capability to capture aerial photographs of flood-prone regions and landslides, delivering significant data for flood warning and prediction systems (Srikudkao et al., 2015). Additionally, the drones can be employed to reconstruct three-dimensional models, DEMs, and stitched orthophotos for flood simulations and damage assessment. Their flight autonomy is at least 90 minutes, and they can execute take-offs and landings on both land and water surfaces. Another noteworthy feature is the provision of real-time imagery, allowing the drones to cartographically delineate areas of specific interest as they are detected. The characteristics render contemporary drones an invaluable instrument for the facilitation of preparation, response, and recovery efforts in flood management (Exadaktylos et al., 2022). To validate the drones' effectiveness in the realm of disaster response, 178 contemporary drones from 63 different manufacturers were analyzed for their performance specifications. Drone type, endurance, range, transmission range, altitude and sensor specifications were analyzed. Most of the candidate drones were found to be quadcopter, as this type leads the present drone market. VTOL is also showing promise because of its favorable characteristics, but it is still in the evolving stage. Based on the correlation between endurance and range, most of the drone fell in the 30–40-minute endurance and 5-10 kms range. Correlation between range and altitude showed a bracket of 5-10 km range and 200–500-meter altitude is where most of the contemporary drones' flight envelope falls. Drone's limitations of endurance and range is due to the design characteristics; however, their altitude limitation is primarily due to the flight regulatory issues. These limitations pose major challenge in terms of its field of view. These 3 properties were pitched together, most of the drones were in 30-40 min endurance, 200–600-meter altitude and 5-20 kms range. Fig 2.10 and 2.11 illustrates correlation of drone performance parameters. Contemporary Drone requirement for Flood Imaging. Drone's specification in terms of key characteristics that they must possess before being used in response to disaster management also need to be determined, using the same contemporary drone's data, Table 2.6 highlights key drone characteristics.

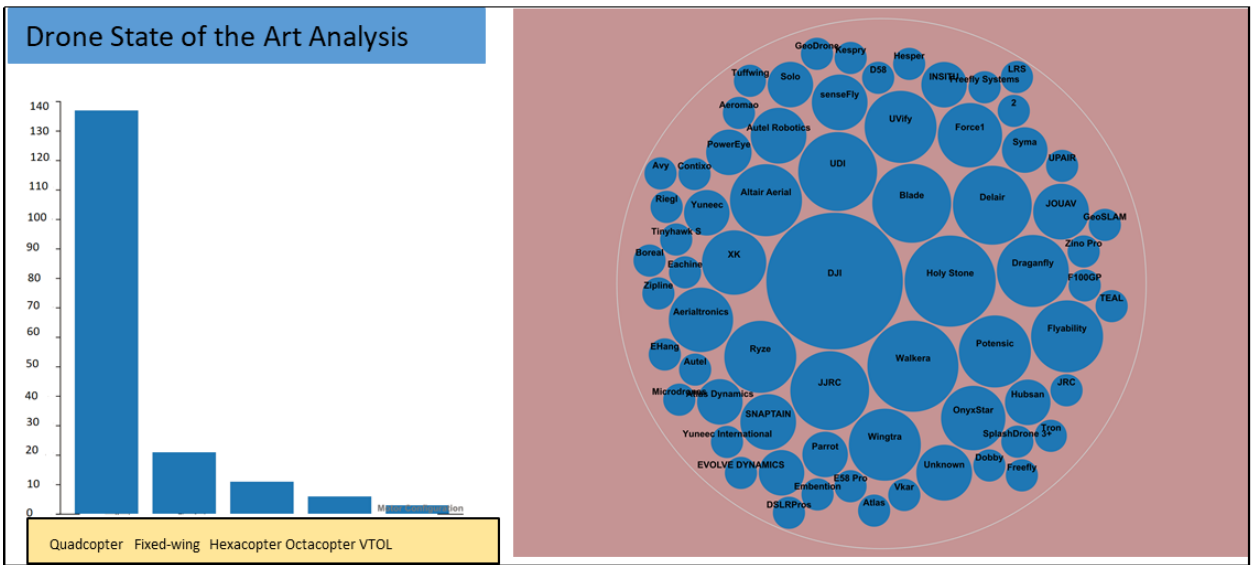



*Fig 2.10  178 Contemporary drones from 63 manufacturers were selected for review, Drone type, endurance, range, transmission range, altitude and sensor specifications were analyzed. Most of the candidate drones were found to be quadcopter, as this type leads the present drone market. VTOL is also showing promise because of its favorable characteristics, but it is still in the evolving stage.*

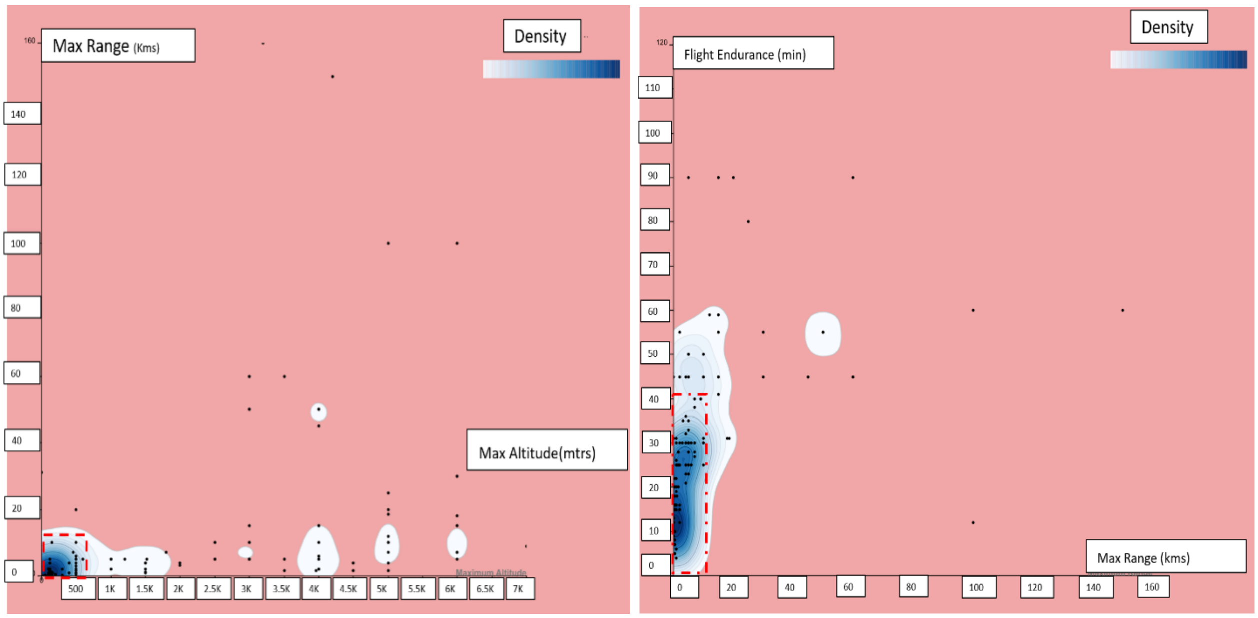


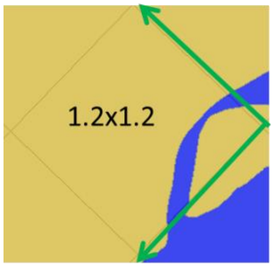

*Fig 2.11   Based on the correlation between endurance and range, most of the drone fell in the 30-40-minute endurance and 5-10 kms range. Correlation between range and altitude showed a bracket of 5-10 km range and 200-800-meter altitude is where most of the contemporary drones lie.*

*Table 2.6  Shortlisted Drone Specification requirements for Disaster response operation based on the drone's state of the art database. These specifications are based on commercial off the shelf available drones.*

| **Specifications** | **Requirements** |
|---|---|
| Endurance/Flight Time | 20-30 minutes or more |
| Battery Life/Capacity | 4000mAh to 6000mAh or more, exceeding 100 meters (300 feet) or more |
| Altitude/Maximum Flight Ceiling | Exceeding 100 meters (300 feet) or more |
| **Camera Specifications** | |
| Megapixel (MP) Count | Higher resolution for detailed images |
| Video Resolution | Full HD (1080p) or 4K capability |
| Adjustable Camera Settings | Exposure, shutter speed, white balance |
| Gimbal Stabilization | Ensures stable footage and sharper images |
| FPV Range | 2.4 or 5.8 G Hz |
| Motor Configuration | Quadcopter (four-rotor) for stability and redundancy |
| Obstacle Avoidance Systems | Ultrasonic, infrared, or vision sensors |
| GPS and Positioning Systems | Accurate georeferencing and mapping |
| Durability and Waterproofing | Designed to withstand moisture and adverse weather conditions |
| **Sensors** | |
| Thermal Sensors | Detects temperature variations |
| LiDAR Sensors | Creates detailed 3D maps of terrain and structures |
| RGB/NIR Sensors | Captures multi spectral data for analysis |

## 2.8 Grid Calculation for Drone Optimized Operations

With the help of drone's state of the art analysis, a computation to define an area appropriate for a drone that can be surveyed based on contemporary drone's state of the art was made using following relationships. Parameters for calculations were 600 meters altitude, 90 FOV and ground resolution of 10cm/pixel. Fig 2.12 illustrates a single grid based on following calculations.




$$Horizontal\ Coverage\ (meters) = 2 * Altitude * tan\ (FOV/2) \quad (8)$$

$$Vertical\ Coverage\ (meters) = 2 * Altitude * tan\ (FOV/2) \quad (9)$$

$$Imaging\ Area\ (square\ meters) = Horizontal\ Coverage * Vertical\ Coverage \quad (10)$$

*Fig 2.12 To represent the imaging area as a square or grid at 600m altitude, 90 deg FOV and ground resolution of 10 cm/pixel, each side would be about 1.2 kilometers in length.*

### 2.8.1 Integrating Flood risk layer with drone optimized grid

This grid was applied to the flood risk image (Fig 2.13), to see how much drone effort would be required to cover the study area by a single drone operating round the clock, or

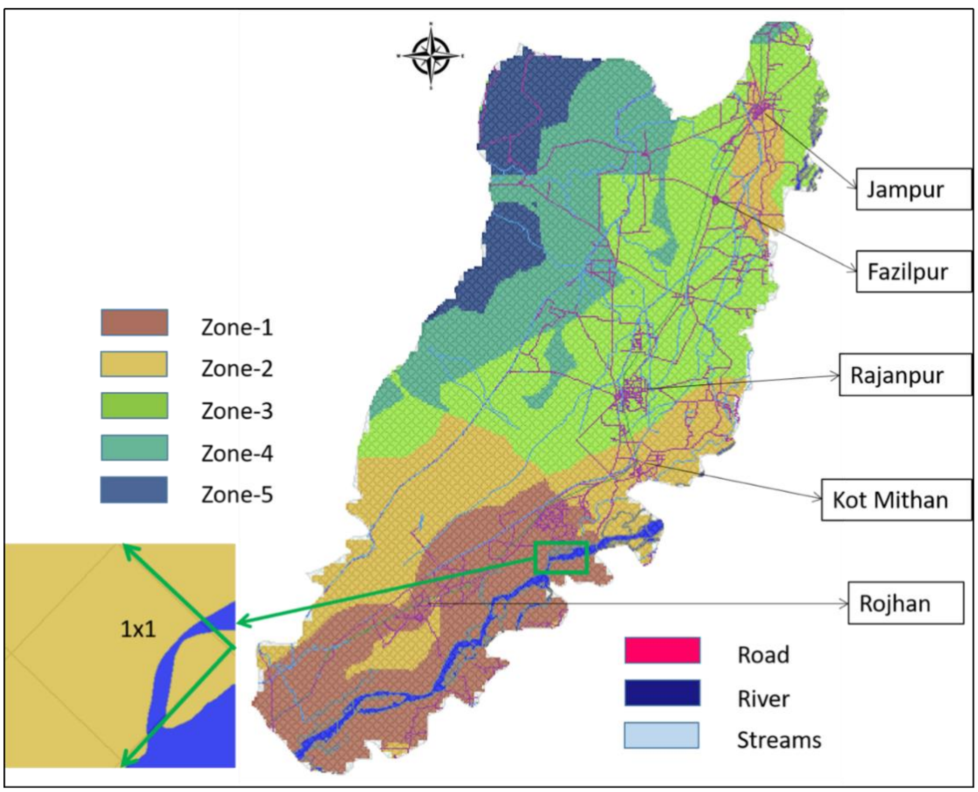



*Fig 2.13 Drone optimized flood risk map, distributed in five equal zones varying with high to low flood susceptibility while incorporating drone optimized grids.*

how to effectively utilize group of drones to survey flood area based on their performance parameters.

## 2.9 Stakeholder's Survey

Stakeholder surveys are a practical and beneficial way to collect data for assessments, giving researchers and decision-makers relevant information. It is imperative to consider stakeholder viewpoints for effective evaluations. Stakeholder evaluations facilitate the gathering of diverse viewpoints and information sources, which enhances the overall comprehension of the social intervention under investigation. To resolve differences, the stakeholder survey approach permits the addition of new research questions and helps prevent conflicts between stakeholder perceptions (Lawrence & Cook, 1982). Leach, (2002) emphasized that research lacking broad sampling may result in an inaccurate or incomplete understanding of the success and dynamics of stakeholder collaboration.

Stakeholder surveys have been conducted in various contexts to understand their opinions and behaviors in relation to technology adaptation. These surveys have explored factors such as intention to use new technologies, acceptance of new technology, and the use of web-based and mobile technology in various management studies. The Technology Acceptance Model (TAM) is frequently used as a theoretical framework to explain the factors influencing stakeholders' adoption of new technologies (Djimesah et al., 2022). These studies have found that factors such as perceived usefulness, ease of use, and previous experience with the technology, influence stakeholders' intention to use and their actual usage behavior. It remains important to determine that if flood risk layer is integrated with the drone's flight controller would give operators, disaster managers, GIS analyst and other concerned personnel an edge in utilizing drone in the mix of other disaster response operations. Therefore, this result was further shared with these stakeholders to see how spatial information will affect their decisions. In a study by Zhang & Zhu, (2023), a survey was conducted online using a specially created structured questionnaire. It covered a wide range of topics, from general acceptance and opinion on new technology (connected and automated vehicles) to issues pertaining to technology implementation, laws, and regulations. A survey for this study was generated in line with the Technology Adaptation Model (TAM) to (i) validate the results (ii) check the integration possibility with the current drone flight computers (iii) check how the stakeholder sees this technology for adaptation and (iv) rate the results as per stakeholder's review. Survey response was only generated from relevant people which were categorized as stakeholders, that include Drone pilots, GIS analysts, Emergency Respondents and Others category include personnel technically involved in drone operation and emergency and disaster services.

Survey was distributed in 9 sections based on the TAM Questions and their responses in stakeholder's review. The consent of research participants is of utmost importance in stakeholder surveys during any research (Parija & Mandal, 2014). Informed consent ensures that participants have a clear understanding of the research and its potential risks and benefits. It also respects their autonomy and right to make decisions about their participation (Anderson et al., 2017). Section 1 contained purpose of study, consent and confidentiality clauses, survey procedure and risks & benefits. In stakeholder surveys conducted during research, demographic characteristics and background data are crucial because they can shed light on the motivations and views of stakeholders (Ireland et al., 2019). Risk analysis and decision-making require a thorough understanding of stakeholder motivation. In situations when direct psychological evaluation techniques are not readily available, stakeholder motivational profiles can be obtained using demographic information. Aside from that, background traits like age, gender, kind of work, and level of education might affect how stakeholders feel about corporate social performance initiatives. Designing successful stakeholder-oriented policies and awareness campaigns can be aided by this information. In general, taking demographics and background data into account while conducting stakeholder surveys can help us better understand stakeholder viewpoints and increase the applicability and efficacy of study findings. Henceforth, section 2 contained background and demographic information including stakeholder’s name, organization, role in flood response operation and familiarity with flood response operations.

As highlighted in the study by (White et al., 2023), in stakeholder surveys conducted during research, the perceived usefulness of the findings is crucial because it sheds light on stakeholders' reasons for participating in the study, their objectives, and the need for more funding. It also aids in evaluating the opinions of stakeholders regarding the overall load, experience, and readiness of research. Gaining insight into stakeholders' opinions on research findings can promote cooperative research and improve participant, investigator, and stakeholder experiences (Kalibala & Nutley, 2019). Section 3 include perceived usefulness questions; these include questions on efficacy and accuracy of drone optimized flood risk map of Rajanpur District.

Stakeholder surveys during any research endeavor should consider how easy technology is regarded to utilize. In a study by (Daryanto et al., 2019), highlighted that stakeholders are more likely to adopt and use the technology in their decision-making processes when they believe it to be user-friendly. Perceived ease of use is a characteristic that influences the acceptance and usage of information technology, according to the Technology Acceptance Model (He et al., 2018). Factor that best describes consumers' use of technological systems, is its perceived simplicity of use. Thus, making sure that stakeholders approve that the technology is user-friendly and will improve their involvement and application of research findings in decision-making processes. Henceforth, Section 4 includes questions pertaining to technology perceived easier to use, incorporate into already established flood response systems, intuitive to learn and being user friendly. One important issue that must be considered is the significance of stakeholders' aspirations to use the technical features of research findings in surveys during the study process. Stakeholders have a major influence on decisions made based on the results of market research, and their choices for data gathering and analysis methods can have a subtle but important effect on the business strategies that are employed (Greenland et al., 2016). In section 5 questions related to stakeholder’s intention to use flood risk layer by integrating it with other software, their recommendation to other users for using it, their overall likeness towards this layer was gauged on a Likert scale from 1 to 10 and then this added layer’s utilization in terms of flood response stages was also recorded.

In research surveys, subjective surveys are just as significant as objective questions. They offer insights on people's thoughts, feelings, and experiences that is not possible to obtain from just objective measurements. Subjective surveys give researchers a deeper understanding of the subject matter by enabling them to comprehend participant viewpoints and sentiments. They can assist in revealing underlying motives, emotions, and circumstances that could affect behavior or judgment. Subjective surveys can also be used to find possible biases or differences between participants' subjective experiences and objective facts. This data is essential for highlighting unique requirements and problems. As a result, adding subjective surveys to objective ones, improve the breadth and depth of study findings (Schork et al., 2021). In section 6 and 7, questions were related to subjective inputs from stakeholders after their informed consent, they could add any suggestion, queries, comments or any reservations related to improve findings of this study. Section 8 and 9 included contacts for follow-up and acknowledgement.

# Chapter 3 Results and Discussion

Chapter contain results obtained from various procedures undertaken during the study and discussed their implications on drone optimization for flood response. Sub sections include drone effectiveness in mitigating disasters, flood inundation extent of Rajanpur area during 2022 flood, relevance of selected factors' weight in flood risk map, DOFRM grids and their applicability on contemporary drones and analysis of DOFRM stakeholder's survey.

## 3.1 **Drones Effectiveness in Flood Imaging**

Drones have diverse applications in military, agro-based, logistics, and observation & security sectors, as well as in DIY hobby crafts, photography, and drone sports. The study by (Abdel-Fattah et al., 2017) highlights that drone, have various technical capabilities that make them versatile and useful in different applications. They are equipped with cameras and sensors that are used to obtain high-resolution images and videos from aerial perspectives. Presently there are numerous manufacturers which are developing cutting edge drones with enhanced imaging and sensing capabilities. It will be difficult to assess which drone will be best suited for disaster response in general and floods in particular. As mentioned in previous section, 178 drones from 63 manufacturers were assessed for their specifications, it is difficult to put all kinds of drone under one umbrella, as there are multifaceted drones and their capabilities. Only commercial drones were assessed, as military drones have exponentially higher specifications and could have distorted overall trend. For flood imaging, there are three major characteristics that need to be assessed, (i) drone's range / endurance, (ii) drone's altitude (iii) drone's camera / sensor resolution. Range and endurance are primarily linked to drone's battery operating time and flight controller's transmission range. Drone's altitude depends upon drone's power plant capability and most importantly regulatory issues related to drone flight within controlled or uncontrolled airspace and privacy concerns. Drone's camera / sensor ground sampling distance contribute to the overall mission parameters, 2D and 3D mapping also contributes to these parameters.  As the graphs in previous section showed that optimum range comes out to be 5-10 kms, altitude between 200-500 meters and endurance between 35-40 minutes, therefore, for a contemporary drone, aforesaid specifications were kept as minimum specs, based on the analysis. Table 3.1 highlights various requirements for a drone, to carry out flood imaging in a large-scale area. Furthermore, as a reference 03 contemporary drone models have been correlated for their performance specifications.

*Table 3.1 Based on the shortlisted capabilities in contemporary drones used in large scale flood imaging, three such drones were identified and their properties were compared.*

| Specification | Range/ Requirement | DJI Phantom 4 Pro V2.0 | Autel Evo II Pro | Yuneec Typhoon H Pro |
|---|---|---|---|---|
| Endurance/ Flight Time | 20-30 min or more | 30 minutes | 40 minutes | 25 minutes |
| Battery Life/Capacity | 4000mAh to 6000mAh or more | 5870mAh | 7100mAh | 5250mAh |
| Altitude/ Maximum Flight Ceiling | Exceeding 100 meters (300 feet) or more | 1968 feet (600 meters) | 9800 feet (3000 meters) | 1640 feet (500 meters) |
| **Camera Specification** | | | | |
| Megapixel (MP) Count | Higher resolution for detailed images | 20MP | 20MP | 20MP |
| Video Resolution | Full HD (1080p) or 4K capability | 4K | 6K | 4K |
| Adjustable Camera Settings | Exposure, shutter speed, white balance | Yes | Yes | Yes |
| Gimbal Stabilization | Ensures stable footage and sharper images | 3-axis gimbal | 3-axis gimbal | 3-axis gimbal |
| FPV Range | 2.4 or 5.8 G Hz | 2.4 G Hz | 2.4 and 5.8 G Hz | 2.4 G Hz |
| Motor Configuration | Quadcopter (four-rotor) for stability and redundancy | Yes | Yes | Yes |
| Obstacle Avoidance Systems | Ultrasonic, infrared, or vision sensors | Vision sensors | Vision sensors | Ultrasonic sensors |
| GPS & Positioning Systems | Accurate georeferencing and mapping | GPS | GPS | GPS |
| Durability and Waterproofing | Designed to withstand moisture and adverse weather conditions | Water-resistant | Water-resistant | Water-resistant |
| **Sensors** | | | | |
| Thermal Sensors | Detects temperature variations | Not included | Included | Included |
| LiDAR Sensors | Creates detailed 3D maps of terrain and structures | Not included | Included | Not included |
| RGB/NIR Sensors | Captures multispectral data for analysis | Not included | Not included | Not included |

## 3.2 **Flood Susceptibility of Study Area**

Floods 2022 in Rajanpur District caused inundation in lot of areas, this was validated with the flood extent calculation using GEE, more than 61000 hectares was submerged including 10396 hectares of cropland or vegetation and 298 hectares of urban area. These calculations validate that the study area is flood prone and necessitates that a flood susceptibility may be done to determine flood hot spots in terms of hazards and vulnerabilities. It is important to consider that the flood extent that was marked, mainly results from natural flood hazards like geographical locations, topography, levees breach, and substantial rains. However, hazards do not include native vulnerabilities of the study area, like population, LULC, infrastructure etc. So, it is necessary to gauge both entities as separate, to determine, (i) where the flood water can naturally flow within the study area due to natural hazards. (ii) Where are the vulnerabilities within the study area which will cause more damage to people, their belongings or croplands and general infrastructure. If flood extent marked during flood 2022 is compared with the hazard and vulnerability index maps, it can be clearly observed that hazard index is almost identical to the flood extent of 2022, whereas vulnerability index is slightly different, as it accounts for mostly man-made vulnerabilities. Therefore, when using these maps, it is important to note the objective, so that appropriate map is considered. For example, if Pre-flood survey needs to be carried out, then we may use both hazard index and vulnerability index maps separately to gauge the effects of flood in terms of both domains. During flood event, it would be appropriate to use composite map (flood risk map) to see the overall impact and extent of flood. Whereas, in post flood scenario, vulnerable areas will have priorities to save lives, precious belongings and infrastructure. Overall, it would remain the responsibility of emergency responders to clearly spell out objective for drone survey before using these layers.

### 3.3 **Drone Optimized Flood Risk Map Classification**

Most of the candidate drones were found to be quad copter, as this type leads the present drone market. VTOL is also showing promise because of its favorable characteristics, but it is still in the evolving stage. Based on the correlation between endurance and range, most of the drone fell in the 30–40-minute endurance and 5-10 kms range. Correlation between range and altitude showed a bracket of 5-10 km range and 200–800-meter altitude is where most of the contemporary drones perform. Drone's limitations of endurance and range is due to the design characteristics; however, their altitude limitation is primarily due to the flight regulatory issues. These limitations pose major challenge in terms of its field of view. When flood risk map was overlaid with 1.2x1.2 km grid, there were 5411 drone survey-able grids in total. Drone calculations were carried out utilizing the database of 178 contemporary drones: 35 min endurance, 600m altitude, 15 m/s speed and a 10 min down time after each sortie for battery replacement or repositioning etc. Parameters including 35 min endurance, 600m altitude, 15 m/s speed and a 10 min down time after each sortie for battery replacement or repositioning etc were utilized. Based on these parameters, a contemporary drone can survey 32 grids per day and if operates round the clock will take 169 days for complete drone survey of study area. This calculation is based on a single drone operated round the clock, with its launching place distance not more than 5 kms. Subsequently drone optimized flood risk map furnished that 481 grids were classified as

Least susceptible, 956 grids were classified as Less Susceptible, 1763 as Moderate, 1286 were classified as susceptible and 925 grids were classified as most susceptible. Zone-1 which is most susceptible was extracted out and further dissected as given in Fig 3.1. Zone-1 of flood risk map revealed that 295 grids are within 1 km of active channel, 371 grids are within 1 km of major roads, 95 grids are within 1 km of major rail track, 215 grids are within 1 km of streams and 210 grids cover urban areas. Overall number of grids were reduced from 5411 to 925 (83% area reduction). Table 3.2 highlights drone calculations for surveying critical features and their surrounding within study area, these calculations and survey areas are for reference and can be made more precise pursuant to actual flood imaging requirements. These calculations underpin the necessity of DOFRM as drones can be employed smartly wherever requirement arises.

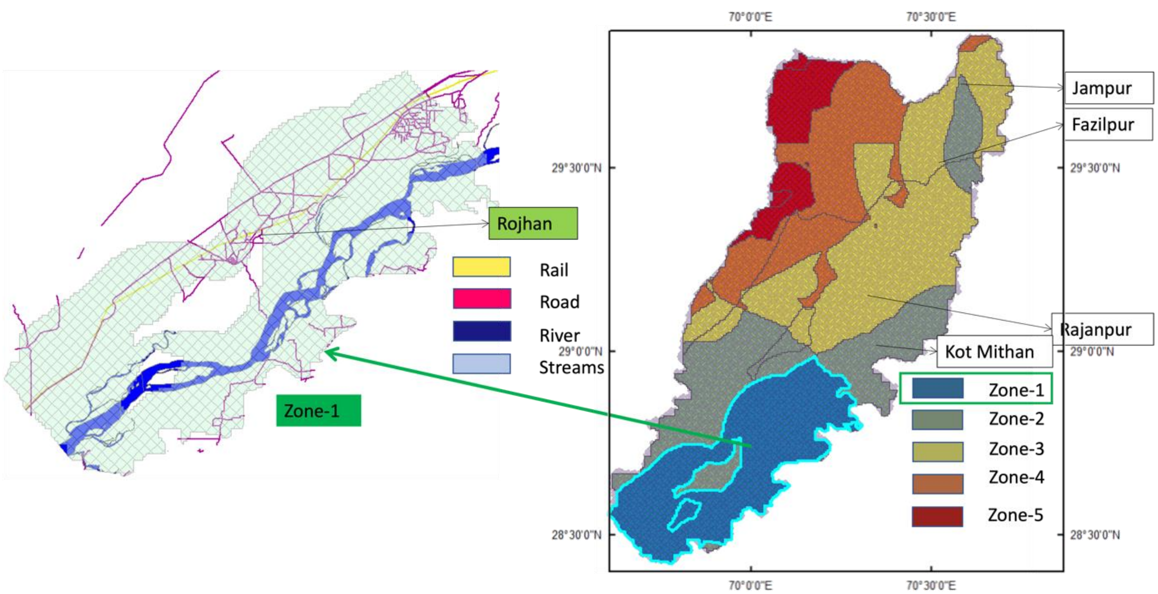



*Fig 3.1 Zone-1 of Flood Risk Map divided into equal grids of 1.2x1.2 square km, this size of grid is based on the drone's performance parameter of 35 min endurance, 600 m altitude, 15 m/s speed and 10 min down time after each sortie.*

*Table 3.2 Calculations based on performance parameters of contemporary drones and DOFRM grid for flood imaging of critical features within study area.*

| Survey feature | No of Grids | Days/Time Required |
|---|---|---|
| 1 km around Active Channel | 295(5%) | 09 days |
| I km around all major roads | 371(6%) | 12.5 days |
| 1 km around rail track | 95(1%) | 03 days |
| 1 km around all streams | 215(3%) | 6.5 days |
| All populated areas | 511(9%) | 16 days |
| Urban areas | 210(3%) | 6.5 days |
| Each populated area | 01(0.0001%) | 45 min |

## 3.4 **Analysis of Stakeholder's Survey**

To further validate results of this research, a stakeholder's survey was drafted while considering Technology Adaptation Model's key aspects like demographic and background information, perceived usefulness, perceived ease of use and intention to use this technology in future. Stakeholder were very carefully chosen considering technical details and variety of potential users of this technology. Stakeholders chosen involved GIS analysts, as this community can understand flood susceptibility layer, data and software used and the way they are applied. GIS analysts were contacted from different PDMAs, universities, housing schemes, international GIS firms etc. Other potential users include Emergency responders, which were primarily from disaster management associates, they may not have appropriate GIS skills, but they were those people who would use this technology in their drone planning and operations. Third category included drone operators or drone pilots, these are the people who will have to fly these machines onto that layer, so their response is supposed to be critical in validating this technology. Fourth category was 'others', these include technicians, involved in these organization, like drone technicians, GIS students, and software developers etc., these people will comment on peculiar issues like integration of this technology with flight computers and how to optimize controller software after integration of this technology.

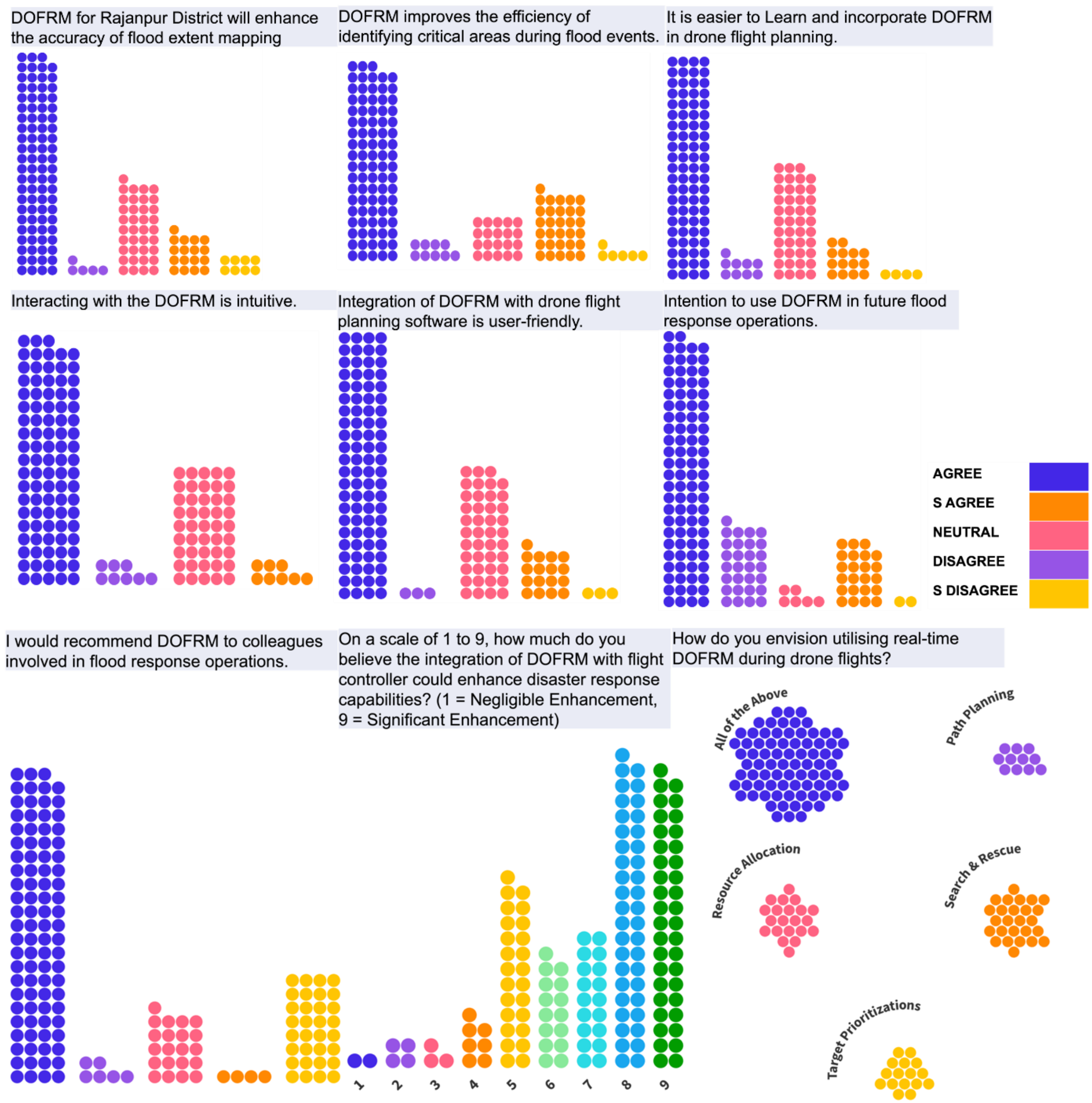



*Fig 3.2 Survey results of stakeholders TAM based questionnaire, stakeholders were shortlisted based on their association either with RS & GIS tech or disaster management responsibilities. Stakeholders from various agencies were engaged including DM organizations, drone operators, GIS specialists etc.*

Fig 3.2 illustrates survey results of stakeholders TAM based survey on DOFRM's effectiveness and ease of usefulness. Overall response was encouraging as 80% stakeholder graded this technology from 5-10 score, out of 0-10, where 0 means negligible improvement and 10 means significant improvement. This fact can further be validated from the fact that more than 50% graded it in range of 8-10. In the same section, i-e "intention to use this technology", 78% stakeholders rated that they intend to use it either ‘likely’ or ‘very likely’. In the perceived usefulness section, more than 76% either ‘agreed’ or ‘strongly agreed’ that GIS based flood risk layer will enhance the overall accuracy of flood extent mapping in study area. In the same section, more than 77% of stakeholders either agree or strongly agree that flood risk layer would help highlight the most susceptible areas within the study area. In the perceived ease of use section, more than 82% either agreed or strongly agreed that it is easier to learn and incorporate this technology.

These results of the stakeholder’s survey indicate a high yield of perceived usefulness (PU) and perceived ease of utilization (PEU), which suggests that stakeholders intend to incorporate drone optimized utilization technology with drone flight computers for disaster response operations. This research’s MCDA model may be adopted to create susceptibility or risk layers at regional or global levels and may be incorporated into drones being utilized in disaster response operation.

# Chapter 4 Conclusion and Recommendations

## 4.1 Conclusion

The present research undertook an all-encompassing exploration for improving flood susceptibility assessment through the utilization of a synergistic integration of advanced technologies and comprehensive stakeholder participation. The integration of Multi-Criteria Decision Analysis (MCDA), Geographic Information Systems (GIS), analysis of contemporary drone state of the art, and multiple geospatial datasets has facilitated the development of a dynamic DOFRM that provides decision-makers with the means to effectively employ drones in conjunction with other disaster mitigation operations, thereby strengthening flood preparedness, response, and mitigation efforts.

Integral to this research is the responses of stakeholders, represented by disaster management agencies, local authorities, and community members. The Technology Adaptation Model Survey Technique (TAMST) has enabled to systematically gather their insights and recommendations. This stakeholder engagement not only grounds this research in practical realities but also fosters a sense of ownership among those who bear the brunt of flooding events. Decision-makers can leverage its insights to develop targeted drone optimized flood preparedness plans, allocate resources efficiently, and engage communities proactively. In doing so, they can mitigate the socio-economic impacts of flooding on vulnerable populations.

In a rapidly changing climate, the need for adaptable, data-driven flood susceptibility assessment practices has never been more critical. This research exemplifies this adaptability, reflecting commitment to advancing the science of flood risk management. As the challenges of the future unfold, it is anticipated that this work will serve as a cornerstone for further research, innovation, and progress in flood susceptibility assessment and optimum drone utilization. The significance of this research is underscored by its relevance to several United Nations Sustainable Development Goals (SDGs), including SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), SDG 15 (Life on Land), and SDG 17 (Partnerships for the Goals). By addressing these global goals, this research contributes to the broader agenda of sustainable development and the well-being of both communities and ecosystems.

This research stands as a manifestation of interdisciplinary collaboration, technological innovation, and stakeholder engagement in enhancing flood susceptibility assessment. The aim is to empower communities, utilize technology resources effectively, protect ecosystems, and build resilience against challenges associated with changing climate, ultimately contributing to a more sustainable and secure future for all. Following conclusions can be drawn from this study:

a) AHP results indicate that proximity to active channel, rainfall and proximity to streams account for 58% of total criteria weight in FHI, whereas population density and urban land cover accounts for more than 50% of total criteria weight in FVI.

b) Drones are unable to undertake flood imaging of large-scale areas, and their optimized employment is essential.

c) Correlation between range and altitude showed a performance envelope of 5-10 km range, 35-40 minutes endurance and 200–800-meter altitude is where most of the contemporary drones perform.

d) Based on the drones' state of the art, Commercial drones can conduct flood imaging of 1.2 x 1.2 Km grid in a single sortie.

e) Through DOFRM, 17% of the total area was prioritized for drone employment, and further division of this 17% area was carried out to determine precise drone effort for hypothetical survey requirements. Highly susceptible area was further subdivided based on critical features including urban areas (3%), active channel (5%), road (6%), rail networks (1%), stream networks (3%) and all populated areas (9%).

f) A total of approx. 16 grids (1.2 x 1.2 km) can be surveyed by a single drone in one day by carrying out 32 sorties. Same necessitates smart drone employment within most susceptible zone to overcome precise flood mitigation requirement.

g) Response of stakeholders' survey validates that drone optimized flood risk map's adaptation with existing drone operating software would be user friendly and may assist all stakeholders to improve drones' effectiveness.

h) Integration of drone optimized grid with flood risk map provides adequate solution for drone employment in large scale areas. Drone employment can be undertaken in pre, post and active flood scenarios; however, drone employment for flood mitigation is most effective in pre-flood scenario where logistical and environmental challenges are minimal.

## 4.2 Recommendations

a) Implementation of real-time data integration, including weather, climate, river gauge data and remote sensing information, will enhance the accuracy and responsiveness of flood susceptibility assessment and early warning systems.

b) Prospective research should concentrate on the development of standardized protocols for the collection of data via drones, the integration of drone-derived data into existing systems of data management, and the exploration of the utilization of algorithms pertaining to artificial intelligence and machine learning for the analysis of such data.

c) Future research can also expand upon the methodologies developed in this study, applying them to different geographic regions and exploring the integration of additional data sources and technologies. By continuing to collaborate, innovate, and adapt, it can strengthen collective capacity to address the complex and evolving challenges of flood management.

d) Strengthen partnerships between disaster management agencies, local authorities, NGOs, and academic institutions will enable data sharing and coordinated response efforts.

e) Collaboration with drone manufacturers to promote innovation in drone technology for disaster response, encouraging designs tailored to response needs. Drone flight controllers may be enabled a provision to incorporate disaster susceptibility layers in a seamless way.

f) Continuous refinement of drone optimized grid for various disaster scenarios and dynamic adjustments based on real-time conditions.

g) It would be beneficial to Investigate advanced sensor integration into drones, such as thermal imaging, LiDAR, air quality monitoring, and communication relay equipment, to enhance their capabilities in disaster response.

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