

Flood Frequency Analysis of Multiple Catchments in Pakistan



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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

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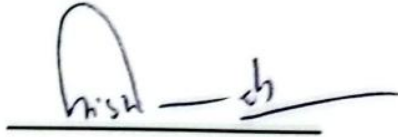
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DEDICATION

First and foremost, I thank Almighty Allah, the Most Merciful and the Most Compassionate, for His countless blessings, guidance, and strength throughout this journey. Without His grace, this achievement would not have been possible.

I dedicate this work to my beloved mother, whose unwavering love, sacrifices, and constant prayers have shaped me into the person I am today. It is her heartfelt supplications that have guided me through the toughest of times, and her encouragement has been a source of immense strength and motivation.

To my dear wife, whose love, encouragement, and understanding have been my anchor. Her patience and constant support have helped me overcome challenges and stay focused on my goals.

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This thesis is a reflection of the values of love, hard work, and dedication that each of you has instilled in me. May Allah bless you all.

DECLARATION

I hereby declare that the work present in the following thesis is my own effort, except where otherwise acknowledged and that the thesis is my own composition. No part of the thesis has been previously presented for any other degree

FAIZAN MEHTAB

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Abstract:

Flood frequency analysis is a critical aspect of hydrology, particularly in regions like Pakistan, where floods are a recurrent natural disaster, posing threats to lives, infrastructure, and agriculture. This study focuses on developing a robust predictive model to estimate the magnitude of floods expected to occur at specific return periods across major catchments in Pakistan, including Kalabagh, Kotri, Mangla, Rasul, Trimmu, and Panjnad. Previous studies have shown that while several statistical models have been applied, the Gamma (G) and Generalized Logistic (GLO) distributions provide superior performance for the dataset used in this research.

The methodology employed in this study utilized secondary data comprising annual maximum peak (AMP) flows obtained from the Federal Flood Commission, Ministry of Water and Power, Pakistan. The study period spans from 2000 to 2022, with historical data ranging from 63 to 101 years. Advanced statistical techniques, including Probability Weighted Moments (PWMs) and Maximum Likelihood Estimation (MLE), were used to estimate the parameters of the Gamma and GLO distributions. These parameters enabled the modeling of flood frequencies and the calculation of return periods for various flood magnitudes. The findings indicate that both Gamma and GLO provide accurate fits to the observed flood data, demonstrating significant variability in flood magnitudes across different return periods.

To complement the temporal analysis, the research also incorporated the Analytical Hierarchy Process (AHP) integrated with GIS for flood risk mapping in the Kalabagh and Kotri catchments. Nine flood-conditioning parameters, elevation, slope, curvature, soil type, topographic wetness index (TWI), normalized difference vegetation index (NDVI), rainfall, distance to river, and land use/land cover (LULC) were analyzed. Pairwise comparison matrices were used to derive parameter weights, which were subsequently applied in a weighted overlay analysis to generate flood susceptibility maps. The results revealed that

Kalabagh is predominantly characterized by moderate flood risk (35.83%), with only limited areas classified as high risk (0.19%). In contrast, Kotri demonstrated far greater vulnerability, with over 55% of its area falling under high susceptibility and an additional 2.51% classified as very high risk, reflecting its low-lying deltaic terrain and extensive agricultural exposure. By integrating statistical flood frequency analysis with spatial AHP–GIS modeling, this study provides both predictive and spatial dimensions of flood hazard assessment. The dual approach not only refines the accuracy of flood predictions but also identifies spatial hotspots of vulnerability, offering a comprehensive decision-support framework for policymakers, planners, and engineers. The results are expected to support the development of targeted, catchment-specific mitigation strategies and enhance climate-resilient flood management practices in Pakistan.

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Chapter 1

INTRODUCTION

1.1 The Global Threat of Floods

Floods are becoming increasingly dangerous for human life, property, and the economy all over the world. This natural disaster can be defined as the overflow of water onto land that is usually dry. Hence, floods are disastrous because of their overwhelming consequences leading to the loss of life and communities, ruining infrastructure, and setting the economy back. The World Bank states that floods are responsible for more deaths and economic damage than any other kind of natural disaster, with their effects particularly felt in low- and middle-income countries. Urbanization, inadequate infrastructure, and climate change are but a few of the factors that augment the severity of the toll [1].

Over the last several decades, floods have become not only more common but also more severe globally. The phenomenon is closely linked to human-made changes in various forms and climate change foremost. These factors include changes in the amounts of precipitation or in the pattern of its distribution as well as rises in sea levels. A changing climate has a direct effect on rainfall patterns, interrupting their normal course. Furthermore, extreme amounts of precipitation are responsible for floods, and their numbers also appear to be swelling.

Several recent studies demonstrate that the frequency of heavy rainfall increased greatly on a global scale in the recent decades. The same research scientists claim that heavy rainfall and the floods it leads to now occur more often in North America, Europe, and Asia [2]. Concurrently, higher global temperatures mean that glaciers and caps are melting, leading to increased supply of water, particularly in the regions where these resources were mainly expected to fill the rivers.

The first reason for the adverse consequences of floods is the aggravating frequency and intensity. Now, this natural disaster often causes irreparable human and environmental damage, in addition to the high frequency of torrential rain and meltwater surges, sometimes within a year. However, these puddles, both short-term and not only in the hot season, and in the cold, are truly ubiquitous. Such dynamic suspense develops under severe weather conditions, such as ice storms, thaw, and rain in the winter [3]. The consequences of this are extremely sad: increased frequency can lead to short-term recovery losses and reduce agricultural production. Overall, reported peak flow exceeded \$96 billion per year. Most concerning is the level of psychological anxiety that repeated outbreaks of fear, stress, and trauma in various cultures suggest. Due to such mental health problems, people react extremely painfully to the consequences of floods on the world and life. Overall, facial expressions, panic attacks, and insomnia have increased in disasters and floods. The psychological consequences of some of the susceptible people may become even more critical in the life everyone lived before and even after the situation was normalized. In this regard, likely and the most anxiety is the state of dissatisfaction of affected populations with no improvements. These precarious situations are a significant reason and reason against the consequences of flooding. Such emergencies amplify the impact of disasters worldwide. All the naturalists define floods as natural disasters [4, 5]. Permanent and constant flooding of lands and landfills not covered by water since the beginning of time undermines our right to life. The effects of floods lead to the loss of land, free access, and automobiles, which undoubtedly has a severe impact on the economy.

In the last decades, the tendency to emergent frequency and severity of floods at a global scale might be observed. It is caused by several factors and reasons, and one of the most vital is a climate change driven by human activities, such as deforestation and burning of fossil fuels. Certainly, alterations in land use patterns, namely urbanization and the change of natural habitats, may lead to an increase in the flooding risk. The climate change results in flooding

due to warmer temperatures creating more intensive precipitation events. So, warmer temperatures cause rivers to overflow and lead to more frequent storm surges in the case of coastal areas. The Intergovernmental Panel on Climate Change reported that the occurrence of extreme weather conditions, including floods, across different regions of the globe, is likely to be increased [6]. However, an altered pattern of land use also contributes to the flooding risk since it disrupts the capacity of the soils to absorb moisture and stimulate surface runoff. At the same time, the lack of sufficient development in flood-prone areas results in the heightened vulnerability to flooding for the population living in these territories. Different investigations showed that the incidence of the risk of floods has escalated in many parts of the world because of the combined factors. It is vital for the population of developing countries to suffer most from the destructive influence of flooding because of their limited resources and lacking infrastructure. There have been many investigations regarding the severe outcomes for developing countries in the case of the event of flood caused by worsened climate change. Smith and Ward state that developing nations often have insufficient financial resources to invest in developed management systems or infrastructure [7].

The inability of developing nations to support their populations is another vulnerability factor to floods. As [8] note, a lack of proper infrastructure in the form of sanitary sewer systems and housing has a negative effect on population exposure. In this way, flood agents contribute to setting back the development of developing nations. A comprehensive investigation by [6] points out that insufficient resources such as poverty and unequal distribution of wealth are inherently linked with socio-economic factors. Thus, the inability of developing countries to accumulate the necessary amount of money for an adequate response to and rehabilitation of people after a flood disaster during extreme weather events results in a lengthening of vulnerable periods, further deepening the poverty of the affected population. The situation is worsened by the long-term effects of flood events on developing nations. The costs that these

countries have to carry as the result of flood disaster can be significant, as emphasized by [9]. The redirecting of scarce financial resources to engage in relief efforts slows down and limits the capability of developing nations to take part in development projects. Thus, due to insufficient police capacity, floods have a negative impact on the rate of long-term sustainability and development progression of such countries.

1.2 The Case of Pakistan:

Pakistan is a country experiencing the negative impact of climate change to the fullest, which serves as a striking illustration of the consequences of this phenomenon. However, floods and heatwaves present in the region demonstrate the observable negative effects of climate change in the country. Naturally, the geographical location and climatic specifics in Pakistan create significant dependence on weather and poor abilities to resist the consequences of negative changes. As it becomes hotter globally, the effects of floods also become more frequent and aggressive. The worst floods in the region are linked to the monsoon rains, and the country is not capable of dealing with the outcomes of this natural disaster due to limited infrastructure and lack of adequate drainage. As a result of these floods, thousands of people die, communities are evacuated, and the country loses a considerable amount of money [10].

Another climate change effect in Pakistan that occurs with greater frequency is heatwaves. The country is already hot, and the spikes in temperature caused by this phenomenon threaten human health, agriculture, and overall conditions of people's life in society. High temperatures make various heat-related illnesses more likely, resulting in more deaths among the population not able to hide from the sun. However, one of the most significant problems is the effect of heatwaves on agriculture, the most important source of food and income for the local population. Therefore, it leads to more severe food security problems and increased monetary instability. Pakistan is one of the leading countries in the Global Climate Risk Index by the GCRI. The recognition highlights the immediate need for the country to start creating

opportunities for dealing with the current level of vulnerability and protecting the citizens from the disaster [11].

Pakistan is prone to a variety of climate change-related challenges due to the country's diverse geography, ranging from coastal areas to mountainous terrain. In the case of the former, the Indus River system tends to become more vulnerable to excessive rainfall and flooding, in turn affecting the country's reliance on the whole river system for agriculture and water supply. Concerning the latter, a global rise in temperature increases the intensity of the hydrological cycle, rendering precipitation more erratic and exacerbating the vulnerability of Pakistan to both floods and droughts. The melting glaciers in the Himalayas contribute to the latter challenge by increasing the unpredictability of water availability and raising the stakes for floods caused by glacial lake outburst floods (GLOFs) [12]. The impact of all these climate challenges is significantly compounded by existing social and economic vulnerabilities because of the exacerbating influence on climate calamities on the status quo. For example, rural Pakistanis dependent on rain-fed agriculture experience more frequent crop failures and loss of employment, while the residents of cities are affected by the inadequate infrastructure and informal settlements, making extreme weather events more dangerous and the risk of damages and casualties even more pronounced. The level of dangerousness of these factors is evident in the country's performance in the Global Climate Risk Index. Pakistan is consistently among the most affected nations, although the situation recently has improved somewhat due to governmental policies aimed at enhancing the local population's climate resilience [13].

The natural disaster that struck Pakistan in 2022 is a catastrophic event that has left a profound mark on the country's landscape and people's memories. The terrible flooding that happened all over Pakistan resulted in millions of people becoming refugees and caused unimaginable economic damages. However, this disaster's origins are not just in the excessive rains – it is

the culmination of a chain of events launched by a series of extraordinary climate manifestations [14].

The first element of this deadly chain was an immense heatwave striking Pakistan in March. This climate sequence needs little proof for its connection to climate change, as numerous scientific investigations have established climate change's connection to the heightened frequency and increased intensity of heatwaves. The heatwave across Pakistan during March caused the glaciers in the Hindu Kush and Karakoram ranges to melt with an unprecedented speed, feeding the Indus River system with the immense volumes of glacier water. The glaciers in these mountain ranges function as a significant natural reservoir, accumulating large amounts of fresh water that slowly leaks through the landscape. However, they were melting too quickly, filling the rivers that constitute the Indus system with massive volumes of water they never had to handle before [15].

The first element of the chain was followed by the coincidence of climate phenomena typical for June – the start of the seasonal monsoon. Ordinarily, the annual monsoon fills the desert regions of Pakistan with fresh water. However, this year, the swollen Indus overflowed with water. The 2022 floods were a testament to the reality of climate change and Pakistan's susceptibility to its effects. It is important to note that the dangerous combination of heatwaves, glacial melt, and river overflow represents a complex interplay of climatologies that cause natural disasters [16]. As Pakistan is trying to cope with their aftermath now, it is safe to say that the government should make more efforts and curb the effects of climate change. Without mitigation efforts that would be effective in reducing the toll on the environment, it is hard to believe that disasters like this are not going to reoccur with higher frequency.

1.3 Importance of Flood Frequency Analysis:

Flood frequency analysis is one of the core means of hydrology, as it allows evaluating the probability of a particular amount of floods over time. It enables predicting both the likelihood

and the frequency of a given event based on the analysis of data collected in the past for a particular area. It involves estimating the frequency with which various flood peaks may be equalled or exceeded over a period of years based on the statistical analysis of streamflow data. The process of FFA is usually based around observed discharge information, highlighting the relationship between the size and rarity of floods. To that end, the statistical techniques such as fitting a probability distribution function, with a particular form, play a major role in estimating and quantifying the likelihood of floods of certain magnitudes. Some of the common probability distributions include the Gumbel, Log-Pearson Type III, or Generalized Extreme Value distributions. As [17] explains, drafts of concrete relief spillway sections of a dam, as well as sizing of reservoir storage and sand bedding widths and gravel lining, depend heavily on the application of FFA. The same applies to the construction of bridges, which must take into consideration the estimated flood frequency to determine the proper elevation of the structure above the floodplain, specific bridge deck elevation, and the proper design of hydraulic openings. Consequently, FFA plays a vital role in the design and subsequent construction of dams, flood control works, and bridges.

Flood control infrastructure such as levees and floodwalls are designed to safeguard the built environment against potential flood events. When protecting a community from floods, the architect's first concern is to determine the frequency and magnitude of floods that will strike a given area. Flood frequency analysis enables engineers to make decisions about the design, height, and alignment of flood control structures to balance the risk of overtopping and the cost of implementing a higher level of protection [18].

In general, flood frequency analysis is a tool used to evaluate the characteristics of flood discharge at a specific site. FFA is commonly employed for the purposes of designing water-related infrastructure, including but not limited to dams, bridges, and flood control structures. Central to the concept of FFA is the employment of hydrological records stored for various

streams. Fundamentally, FFA is based on analyzing discharge data records for a specific site – discharge data is traditionally collected by hydrologists who conduct stream gauging on various streams and maintain records of streamflow that span several decades. By analyzing the records, the specialists can determine the probability of specific flood magnitudes at a site [19].

Accordingly, one of the key purposes of FFA is to estimate both the frequency and the magnitude of floods. This is typically achieved using a statistical model of data, most commonly, the Log-Pearson Type III or the Gumbel distribution. Using either of the two, or another distribution if the data indicates, hydrologists can calculate a flood's probability of recurrence. Such extended approach implies that it is possible to predict the magnitude of floods with various recurrence intervals and estimate such intervals equivalent to, for example, 2, 5, 10, 20, 50, or 100 years.

The application of FFA appears to have a great importance in a process of design and planning of different infrastructure projects vulnerable to flooding. For instance, when designing the dam's wall, the design flood shall be determined. That calculated flood represents the highest flood expected to occur in the life of the dam as an operational structure [20]. Providing data, resilient estimation of flood frequency and magnum, the engineers size spillways, and other hydraulic constructions in order to guarantee that the collection of the floodwater will escalate over them and will not put the dam in jeopardy along with the residents living downstream of the dam. Similar practice is used in constructing the bridges and overpasses. The height and velocity of the floodwater are calculated and the probability that these magnitudes exceed the certain magnitude is calculated. Then the bridge's supports size is estimated in such a way that they would resists the outrage floods with the least floodwater seeping across the bridge's surface. Furthermore, FFA is used for determination of height and the position of flood control structures such as levees and floodwalls [21]. Thus, the accurate calculating the frequency and the magnitude of floodwater will allow the planners to construct the walls in such a way that

the overpass will be able to sustain floodwater annually while protecting the bellow-built buildings and vegetation. In this way, the construction will accommodate the dwellings and reduce the potential damage of it.

In this way, FFA represents one of the inherently important tools in the set of tools applied by the engineers and planners to predict the probability of flood occurrence. As a result, the stakeholders can predict the possible scenarios of flood and build-up resilient constructions taking the valuable insight into the information the consideration. Such analysis is vital in calculation the probability of such events taking place, so the process of planning of new buildings or road thus may vary greatly [20].

Decision-makers use flood frequency analysis to assess the risk associated with different magnitudes of flood. This is crucial for designing infrastructure that can withstand extreme events without being excessively costly. For example, decision makers can use the data from FFA for designing floodplain zoning, levee, or stormwater system height for a specific level of protection. Another use of FFA is evaluating the performance of existing infrastructure and advising maintenance strategies and possible improvements for different hydrological conditions. Evaluating how frequent different magnitudes of flood occur and what different hydrological conditions may develop, overseeing flood evolution with time in other words, helps achieve this goal [22].

1.4 Flood Risk Mapping and Flood Quantiles:

Flood risk mapping is an important tool that has been used to assess and evaluate flood hazards in various regions. It is the systematic delineation and analysis of areas that are prone to floods, incorporating diverse aspects including topography, hydrography, land use, climate, and precipitation data. Through merging these data inputs, flood risk mapping achieves the assessment of potential hazards caused by flooding at multiscale levels. Through visualization, decision-makers can get a clear understanding of the areas that are prone to flood hazards and

develop appropriate adaptation and mitigation measures. Return period, or flood quantiles, are important statistical aspects that determine how frequently a specific size or flood occurs in each area [23]. For example, the 100-year flood or the 50-year flood refers to the average period that events of similar size, or flood quantiles, will occur in any specific region. In this regard, flood quantiles for large return times are less likely to occur, but in the case of a flood event, it will have extreme consequences. For example, the 100-year flood occurs once every 100 years. Through the comparison of flood quantiles for a specific return period, decision-makers can allocate resources and develop intervention measures that target the flood-prone regions.

The relevance of flood risk mapping in identifying flood-prone areas cannot be underestimated. In the era of climate change and increasing rates of urbanization, variables contributing to flooding are augmented in many areas. Accurate and up-to-date maps help governments, first responders, and the public in many regions proactively mitigate the risks of flooding through meaningful policies, construction bans, and other measures [24]. At the same time, such mapping also helps to inform the public about the risks and build more resilient communities, where people are aware of these risks and able to make informed decisions concerning their homes and evacuation plans. In addition, flood risk mapping is a dynamic tool that always evolves with the integration of new technologies and better data collection methods for better assessments and more accurate outcomes.

Given the information above, remote sensing and flood risk mapping are interrelated beyond any doubt. The process of flood risk mapping has significantly improved with the increasing use of Geographic Information Systems and remote technologies, such as remote sensing and numerical modeling. It allowed for more detailed and precise assessments and models. For instance, it is possible to increase the accuracy and precision of predictions by incorporating the information derived from the use of high-resolution satellite imagery and LiDAR data into the modeling process due to a more targeted and correct representation of terrain elevation and

land cover, the two critical variables when modeling the levels of inundation [25]. At the same time, further improvements can be made possible through the integration of different climate scenarios and the use of scenario-based models to assess the risks and predict possible changes in scenarios like exposure levels and vulnerability in relation to climate change.

Flood risk mapping is not only used for the process of disaster preparedness and response but also contributes to the assessment of economic and social vulnerabilities associated with flooding. Regarding economic vulnerabilities, the mapping process quantifies potential destructions in terms of infrastructure, agricultural lands, critical facilities, etc. In such a way, it becomes easier to define where the investments in insurance schemes and flood protection should be done first. Regarding the social side of vulnerability, given that the calculations consider social factors such as population density, income and resources, and access. [26] state that such social vulnerabilities can help to avoid or prevent the growth of social disparities in vulnerability to potential flooding among all communities. Finally, [27] suggest that flood risk mapping using multiple flood quantiles for varying return periods allows decision-makers to place flood risk estimates in a standardized manner across regions. It means that the decisions on investments in flood protection and insurance will be better justified and comparable in terms of priority between the investments.

Despite the above-mentioned benefits, such flood hazard risk mapping has its limitations and uncertainties. Some of them are well-understood and accounted for, such as those in developing regions with poor data availability, and others are not estimated, such as uncertainty regarding flood hazard and vulnerability change in the case of changing climatic conditions. [28] suggest that continuous improvement and revision, as well as validation, can help to improve the accuracy and applicability of flood risk maps. Thus, it can be concluded that flood risk mapping plays a crucial role in the assessment of potential losses and vulnerabilities related to flooding.

Flood risk maps use hydrological, hydraulic, and topographical data to represent elevations in physical form to document flood-prone areas across a region. In addition to these three layers of data incorporated, flood risk maps may estimate the area and depth of inundation, hence offering highly detailed geographical information. The probability of flood occurrences is high in areas with high flood-prone risks, the knowledge of which can be used by governments and insurers for risk assessment. With flood maps encompassing more scales of spatial detail, the risk is most informed with more precision on who or what is at the highest risk. In addition, convenient location monitoring allows for ease of execution for quick response in case of weather changes [29].

The information on flood risks is easily used as reference by local authorities for better decision-making. Using the flood risk maps, they can make feasible decisions on land-use planning. Measures proposed in land use could include granting the public use of shrub or trees to be formed as setbacks from the river's edge or set aside as a floodplain for species' conservation or controlled housing or infrastructural development. Otherwise, insurers and financial institutions make references to the flood risk maps to assess the insurance coverage risk level of property owners in these flood-prone areas. It assesses the probable extent and cost of insurable loss within an area and helps the insurance industry in establishing customized risk-based pricing with gain [30].

1.5 Integration of AHP–GIS in Flood Risk Mapping:

In recent years, flood risk mapping has increasingly benefitted from the integration of multi-criteria decision-making approaches with spatial analysis. Among these approaches, the Analytic Hierarchy Process (AHP) combined with Geographic Information Systems (GIS) has emerged as a robust framework for assessing and delineating flood risk zones. The strength of AHP lies in its ability to incorporate expert judgment in weighting diverse flood-conditioning parameters, while GIS provides the spatial environment to integrate these weights and visualize

risk across large areas. This integration not only enhances the objectivity of flood mapping but also ensures that both physical and environmental variables are represented in the analysis.

The AHP–GIS approach is particularly effective because flooding is rarely the outcome of a single factor; rather, it is the result of the interaction of multiple parameters such as elevation, slope, land use/land cover, rainfall, soil type, vegetation density, curvature, proximity to rivers, and indices like the topographic wetness index (TWI). Through pairwise comparisons, AHP enables the assignment of relative weights to these parameters based on their contribution to flooding, while consistency checks ensure that judgments remain reliable. Once the weights are derived, GIS facilitates the spatial overlay of all reclassified layers, generating composite flood risk indices that can be classified into distinct categories such as high, medium, and low risk.

By integrating AHP with GIS, flood risk mapping gains both scientific rigor and practical applicability. The method allows decision-makers to identify priority areas where interventions are most urgently required, whether in the form of structural measures such as levees and embankments, or non-structural measures such as zoning regulations, early warning systems, and community awareness campaigns. Importantly, the maps produced through this approach can be compared across catchments, making it possible to highlight differences between upstream and downstream regions and thus tailor management strategies to local conditions.

In the context of this study, the AHP–GIS framework provides a structured way to assess flood susceptibility in both Kalabagh and Kotri catchments. By evaluating nine critical parameters through expert judgment and spatial analysis, the resulting flood risk maps offer a more comprehensive perspective than traditional statistical methods alone. When combined with flood frequency analysis, this integrated approach supports evidence-based planning, enabling

policymakers, local authorities, and communities to adopt proactive strategies for reducing flood damage and building resilience against future climate-induced flood hazards.

1.6 Research Objectives:

The objective of this study can be formulated as:

- To analyze annual maximum peak flows and perform flood frequency analysis using appropriate probability distributions.
- To estimate exceedance quantiles for return periods of 2 to 100 years across the selected catchments.
- To apply AHP–GIS for multi-criteria flood risk assessment using nine hydrological and physiographic parameters.
- To generate composite flood risk maps for Kalabagh and Kotri catchments and classify them into risk zones.
- To compare spatial flood risk patterns between the two catchments for improved flood management planning.

1.7 Research Questions:

Some of the research questions which were addressed are:

- How do flood frequency characteristics vary across the selected catchments?
- What are the exceedance probabilities and return periods of major flood events?
- Which statistical distributions best fit the annual maximum peak flow data?
- How do key flood-conditioning parameters influence risk when evaluated through AHP–GIS?
- What spatial patterns of high, medium, and low flood risk zones emerge in Kalabagh and Kotri?

- How do the two catchments compare in terms of flood frequency and spatial risk distribution?
- How can the combined FFA and AHP–GIS results support improved, catchment-specific flood management strategies?

Chapter No.2

REVIEW OF LITERATURE

2.1 Escalating Flood Risk in Pakistan:

Pakistan's susceptibility to floods has increased markedly in the recent past with a notable rise in the frequency, intensity, and duration of these disastrous phenomena. The Pakistan Meteorological Department and the World Bank, among other studies, have confirmed this overall trend with the increase in the frequency of floods related to climate change-induced extreme weather and changes in hydrological cycles, and the like. Additionally, the Indus basin, is the primary river system in Pakistan that presents an elevated vulnerability to flooding, and it hosts the second-highest global population exposure to these floods. Therefore, the increase in population numbers adds to the inherent vulnerability to floods, which compounds the issues related to effective disaster management and resilience in the country [31].

Rapid urbanization and the spread and growth of settlements in hazardous flood zones further aggravate the country's vulnerability to floods. With the shift in population trends and the migration from rural to urban areas, the development of cities in the region has led to a concentrated presence of people in dangerous flood zones. Studies have examined the urban planning and infrastructure development that are largely inadequate to mitigate the impact or damage from floods, calling for the improvement of land-use planning and design of resilient urban areas. The encroachment on floodplains and wetlands and the poor design and

management of drainage systems exacerbates the socio-economic impact of floods, including loss of lives, sources of income, and facilities [32].

Apart from the exacerbating factors referred to earlier, changes in land use and deforestation contribute to Pakistan's vulnerability to floods. Deforestation in the upstream portions of river basins reduces the natural buffering mechanisms against floodwaters, increases soil erosion, and raises the risk of flooding in downstream areas. If straightforward examples are considered for the sake of the descriptive efficiency of this statement, forest vegetation serves as a suitable absorber when it is not utilized for other purposes. At this point, there are other factors that are also affected by poor land use in flooding conditions. In other words, RAS assists our understanding of NPF by being associated with the negative impacts of playground extension and the development of urban conversion on surface runoff. Moreover, research indicates that deforestation increases the risk of flooding in hilly and mountainous areas. The latter concludes that special measures need to be taken to reduce the negative impact of deforestation on water dynamics as well as land management. Their conclusions are also in line with those of in terms of the fundamental role of sustainable land management and afforestation campaigns. Socioeconomic development divides and the special conditions of the poor are increasingly recognized as amplifying factors of the multiple risk factors that contribute to high vulnerability to floods are the division between societies and the poor's specific circumstances. According to [33] floods may appear to occur due to rainfall alone, flooding may be due to inadequate infrastructure and a lack of resources to respond to and adapt to potential disasters.

The disastrous flood that occurred in 2022 in Pakistan has put the nation through an immense loss and damage that will not be easily forgotten. According to estimations, one-third of Pakistan's land, or approximately 265,365 square kilometres, was flooded, which made this disaster impact an unprecedented scale. As a result, its area became entirely declined for the nation, and even now, it has not recovered; still, many territories are lacking the necessary

conditions for life or a minimum level of comfort. Hence, the fact that a big part of the country was submerged makes this event the biggest natural disaster in Pakistan's history [34].

Only affecting one sector already means significant loss and impairment for the state; however, the devastating impact of the 2022 flood reached far further than the flooding of nearly 1 million children from their homes. Another pillar that got the most significant hit from the flooding of 2022 of the country was agriculture. A total of 3.6 million acres of land belonging to the sector was severely affected by the flood, placed inaccessible, and rendered useless. As flooding affected the rural population's only stable source of income and employment, the farmers were significantly impacted and bad after seeing all of their work be wiped out in the span of a few moments. For this sector, such disaster became a genuine threat as, without agricultural land and crops, Pakistan's food supply was in real danger and would not be secure.

Additionally, such floods resulted in substantial displacement disaster, since submerged lands displaced approximately 33 million people in 2022. Such population being deprived of habitation undermined communities, stressed resources, and aggravated hundreds of existing vulnerabilities most severely affecting the most marginalized and impoverished populations of displaced people. The displaced were placed in overcrowded tent camps or housed with their relatives, among the distress and uncertainty of the flood aftermaths [35].

Obviously, the figures on submerged land, the debilitating agricultural catastrophe, the millions of lives, and displaced populations portray the gravity of the 2022 floods in Pakistan. The proportions of destruction and human wretchedness illustrate a clear need to take action and implement comprehensive flood risk management and invest in resilient infrastructure and community resistance to mitigate the string of future calamities.

For a significant stretch of time, Pakistan has unceasingly struggled with the dangers of brutal floods that have put them all-round disaster. The country records a repeated and growing risk

and impact of flooding since the earliest time. Due to the increase in frequency and severity of flooding over the years, the floods pose significant risks and amplified impact on the country [36].

One of the turning points in the history of Pakistan floods is the 1995 catastrophe, which was also among the least disastrous in comparison to the following ones. Although this disaster was responsible for the death of 600 individuals, it affected 600,000 people and ultimately became a wakeup call to the vulnerability of the Indus River basin and the need to develop advanced flood protection measures. The flood of 2010 was the event that manifested significant aggravation of the situation. Covering 160,000 km², this catastrophe was responsible for 1,985 persons' death and forced 20.3 million individuals to leave their homes. The disaster was an indicator of the inadequacy of existing approaches to flood management to withstand the increased pressure caused by increasingly intense extreme weather events. However, the climactic point of this tendency was the most recent major flood of 2022 [37]. Inundating nearly one third of the land of Pakistan, this catastrophe was the most disastrous, exposure multiple times higher scales of the disaster in comparison to its less catastrophic predecessors. The agricultural sector suffered the most; millions of acres of crops were destroyed, and the country's future food security significantly suffered. The impact on the victim numbers was also substantial; 1,717 persons perished, including a substantial number of children which added to the sorrow of the disaster instantiation. Finally, 2.1 million people lost their home or had to seek shelter in temporary refugee camps.

A comparison of these historical flood events signals the intensifying trajectory and increasing effects associated with them. Notably, the 2010 and 2022 disasters dwarf the 1995 flood in terms of the affected area, casualties, and socio-economic disruption. This trend reveals the dire necessity of taking proactive measures to address the cumulative flood risk in Pakistan. Thereby, it underscores the need for enhanced flood forecasting, increased investment in

infrastructure, and bolstered efforts in disaster management. Only through these comprehensive approaches can Pakistan withstand the growing threats associated with its recurrent natural calamities and protect its people from calamities of such scale in the future [38].

2.2 Flood Frequency Analysis (FFA) - A Critical Tool:

The overall increase in the frequency and intensity of floods throughout the world is among the clearest signs that accurate determination of flood magnitude and frequency is of utmost importance. With the onset of global warming, the overwhelming majority of factors that contribute to flooding have become more prevalent, thereby increasing the vulnerabilities of existing infrastructures and the frequency of hazardous events. According to [39], the lengthy process of mitigation and adaptation aimed at improving infrastructure and the safety of the local population has also been exacerbated by some of the emerging trends, such as the rising sea levels and frequent, irregular, and more severe storms. Therefore, the accurate determination of FMF has become a critical aspect of flood risk management.

As far as the use of FMF in infrastructure design is concerned, one of the most common applications is Flood Frequency Analysis. The latter is a statistical technique that uses historical data to predict the future magnitude of potential floods and the likelihood thereof over a particular time frame. By integrating the FFA tools into the infrastructure design process, the architects and engineers can create structures that will be prepared to withstand the most likely magnitudes of floods, thereby ensuring resilience and sustainability of the design. In addition, FFA can be used as a tool for determining the standard requirements for the designed structure and flooding defences, thereby facilitating its integrity and longevity. Finally, in the realm of risk assessment, FFA is essential in determining the consequences of flood impact on the downstream areas and the possible vulnerability of the area and the infrastructure therein. Ultimately, the information can be used to determine the exact vulnerabilities and develop

distributive strategies to enhance the skills and knowledge of the areas where the risk of flooding is the highest [40].

Effective flood risk management is based on informed decision-making, and Flood Frequency Analysis is an important tool for the process. Being able to provide reliable estimates of flood magnitudes and frequencies, it allows policymakers, emergency managers, and other stakeholders to make reasonable choices to protect lives, property, and ecosystems. From land-use planning and zoning to emergency response planning and the investments in infrastructure, the analysis is involved in a variety of decisions meant for reducing vulnerability and enhancing resilience in the context of increasing floods. The integration of Flood Frequency Analysis with the design of infrastructure is critical for the long-term sustainability and resilience of built environments [41]. In particular, by allowing to reasonably estimate the magnitudes and frequencies of floods, it helps design the necessary infrastructure that is capable of lasting through projected floods and surviving them, which ultimately provides for the reduction of potential damage and disruption. As a result, safety is enhanced while economic and social costs related to floods as disasters are reduced. Additionally, it allows to optimize resource use and ensure that infrastructure investments are made where most needed.

FFA is used in risk assessment and is regarded as a starting point for determining the links between various types of natural hazards and people's vulnerability. It includes the examination of the existing flood events and the prediction of similar incidents in the future and makes it possible to determine regions with the highest risk that require active measures to be taken. In addition to this, FFA contributes to the development of different risk models, the formulation of their components, the estimation of various influences, and the incorporation of such factors as land use, population concentration, and future climate changes. In other words, FFA is closely associated with making predictions and establishing conceptual models and models

driven by data to guarantee that all risks are considered, and every possible impact evaluated [42].

It is not always easy to make the right decision in flooding risk management as many points need to be taken into consideration. FFA provides people with an opportunity to think critically, evaluate various activities conducted in the target area, and realize what activities should be paid closer attention to. At the core of the at-site flood frequency analysis is the need to use some of the probability distributions such as Gumbel, Log-Pearson Type III, or Generalized Extreme value distributions and analyze the ways in which probability is used to model flood occurrence. These possibilities prove that with the help of FFA, it is much easier to focus on making certain decisions, interpreting relevant data, and realizing what concepts or theories require the most of attention or development [43].

However, in the context of FFA, at-site conventional engineering methods refer to a wide variety of approaches that are adopted at the physical construction site. In general, most conventional engineering methods involve the collection and analysis of hydrological data. In the case of at-site engineering methods, it is particularly important to collect relevant hydrological data, including details of streamflow and rainfall, as well as relevant topography, to understand and characterize the hydrological processes that control flooding at that site. The application of a series of statistical techniques can also be considered a conventional engineering method as these methods allow for the likelihood of different magnitudes of floods to be determined over a specified period of return [44].

There are several factors that contribute to the end of the era of at-site FFA and the limitation of the widespread use of conventional engineering methods. Firstly, in many situations practitioners are lacking long-term and high-quality hydrological data. The monitoring network can be of poor quality, may have gaps, or not cover the areas requiring the estimation of

flooding frequency. As a solution, several hydrologists will turn to a range of technical approaches, including interpolation, regionalization, and recourse to hydrological models. Another obvious limitation is the fact that there are many external factors that can impact the magnitude of flooding in any one location. This requires a multidisciplinary approach that considers such areas as soil and land erosion and sediment, land use changes that take place in the catchment, and the alteration of hydraulic systems. It is also frequently assumed by conventional engineering methods that flooding is stationary, which may not be the case. Ways in which the estimation of return intervals could be limited are also the need for an interdisciplinary collaboration and the non-stationary nature of flooding, and various factors that may impact flooding on the ground [45, 46].

2.3 Statistical Distributions in FFA:

The selection of the proper statistical distribution for the analysis of flood peaks is critical for the accurate description and prediction of flood events. It allows for effective risk management and infrastructure planning. Several statistical distributions are used to model flood peak data, each of which relies on a different set of assumptions and characteristics that must coincide with the hydrological processes of a given region. The selection of appropriate distribution must consider the climate, geography, land use, and other watershed characteristics, as they must model the flood peaks accurately. The incorrect choice of a distribution can lead to bias in estimations of flood magnitude and frequency of occurrence, which may result in flooding damages and inadequate flood protection measures or unnecessary expenses for infrastructures. For this reason, the AMS method of analysing flood data stands out as a typical approach to flooding, owing to its simplicity and practicality. The AMS method is based on selecting the highest flood peak each year from a stream flow record, creating an AMS series [47]. Using AMS data, a Gumbel-type distribution can be fitted to estimate the flood peak frequency and magnitude. That Gumbel distribution belongs to extreme value theory, which holds that annual

maximum flood peaks distribution follow a generalised extreme value distribution. The process of fitting the GEV distribution to the AMS series of data allows hydrologists to predict the return period of a selected magnitude of flood peak.

The next major benefit of the AMS method is that it allows for non-stationarity. In other words, flood data may be observed to change over time due to climate change, changes in land use, and urbanization. If this was not considered, the estimate and risk would not be accurate as the AMS analysis would lead one to believe that the occurrence of floods does not change over time. To account for non-stationarity, the AMS analysis uses time-varying distribution fitting or incorporates covariates [48]. Thus, the method is sophisticated enough to estimate the probability of the occurrence of different floods over time, which is extremely useful for policymakers and engineers. The final benefit is that the AMS analysis can be used to quantify uncertainty in the flood frequency estimates. This is especially useful for decision-makers who are interested in how dependable a flood risk estimate is to base further construction or measures on these data. Thus, the arrival model's analysis is chosen because it allows calculating the probability of different floods adequately and with confidence, accounting for non-stationarity and uncertainty.

Overall, an appropriate statistical distribution should be chosen to characterize flood peak data and estimate flood risk effectively. Researchers have comprehensively studied different statistical distributions and their appropriateness to different conditions, including the geographical location, climatic conditions, and watershed characteristics. However, a failure to do so may lead to the application of a biased method that incorrectly estimates the probability of floods, exposing communities to the risk of floods, or overprotect them and waste resources on ineffective infrastructure [49].

Annual Maximum Series method refers to the most common way to analyze the flood data. This method presupposes that by using the analysis of the annual maximum flood peaks for the specified range of time, it is possible to define the probability of some flood magnitudes. To start the analysis, these annual maximum flood peaks should be identified. At the same time, this method presupposes that these maximum flood peaks follow a certain statistical distribution, usually the Generalized Extreme Value distribution. Also, it can be applied to another distribution, the Log-Pearson Type III distribution. For the objectivity of the data analysis, both distributions should be fitted to the annual maximum flood peaks. The purpose of this method is to help specialists model a certain distribution along with flood statistics. The last include the value of peak discharge of a certain return period [50].

In addition, the AMS method helps to identify trends and changes in floods over time, making it possible to assess how climate change and changes in land use can contribute to the flood risk. By analyzing long series of AMS data, it is possible to identify changes in the frequency of floods or their magnitude, which will contribute to the adaptation of politicians and engineers to changes. It should be noted, however, that when interpreting the outcomes of AMS, one should also consider potential biases related to changes in human activities, such as measurements, land use practices or urbanization. Thus, the combination of AMS with the uncertainty analysis approach using Monte Carlo simulations can help to ensure a more reliable estimation of the frequency of floods, which can provide politicians with the relevant data [51]. Overall, the AMS is considered the foundation of the analysis of flood data that can help to determine the specific characteristics and behaviour of the so-called rare, extreme hydrological events, which is necessary for the resilient water resources management given the current climate changes.

One of the key problems is that the choice of distribution and method of parameter estimation largely affect the results of FFA, the concept that is vital for neuroimaging. Neuroimaging

heavily relies on the accurate capturing of the statistical dependencies between the brain regions. A distribution is extremely important in determining one's beliefs about how data behaves. For instance, a Gaussian distribution is only applicable when dealing with the sensitive data, that is, when the data assumes a symmetrical form, but it is not the case with neuroimaging, which has also complex and multimodal non-normal distributions. On the other hand, the main strength of non-gaussian distributions is that they are flexible and may capture the data's heavy-tailedness and the skewness, such as attained with the gamma or inverse gaussian distributions [52].

Input to the FFA process has several sources, with the choice of distribution and parameter estimation being among the most prominent ones. To begin with, different distribution options can be used to model functional connectivity, each associated with different properties. Distribution options include, but are not limited to, the Gaussian and t -distributions. As different types of neurobiological networks have different statistical properties, the choice of distribution will affect the FFA results. Parameter estimation is another process that plays a role in shaping the FFA results, as it helps to find the best-fitting of the chosen distribution to the data.

It is important to account for the effects of parameter estimation in combination with the choice of distribution, as they have an impact on the meaning that can be derived from FFA results [53]. For example, maximum likelihood estimation, a common parameter estimation method, assumes that the data are identically and independently distributed-the assumption, which is violated in the case of neuroimaging data, as the data tends to carry dependencies both in space and time. Regarding parameter estimation methods, some other forms of parameter estimation, including the Bayesian estimation, allow the use of the prior information about the parameters. The results of this research show that different combinations of distribution and parameter estimation methods have different effects on FFA results, as reflected in different patterns of

Type I error. In terms of the application to neuroimaging studies, proper consideration of these effects is important as it will ensure the accuracy of the results in terms of statistical significance [54].

2.4 Common Probability Distributions in FFA:

Probability distributions are widely used in the study and management of water resources as they offer a mathematical tool to describe and predict various hydrological phenomena. They are paramount tools used by hydrologists, water resource engineers, and policymakers to elucidate the uncertainties inherent in these natural systems and enable decision-making related to water allocation, flood, and drought management. Specifically, ‘probabilities are used to describe the variability of quantities relevant to hydrology, for instance, in modelling precipitation, streamflow, evaporation, and groundwater recharge’. For example, probability distributions can be fitted to historical data to assess the frequency and magnitude of extreme events, such as floods and droughts, which have measurable and severe impacts on these natural systems [55]. In this regard, past research has demonstrated that climatic conditions and associated hydrological processes vary by region; as a result, a relevant probability distribution must be used to study historical data. These approaches enable researchers to understand the likelihood of rare events with significant impacts and guide the water management policy accordingly. Regarding stochastic hydrology, ‘random variables are used to account for uncertainties in stochastic hydrology and are used to perform Monte Carlo simulations of synthetic samples representing alternative realizations of future input’. These synthetic samples are generated by probabilistic models and represent ensembles of possible outcomes that can be used to assess risk and better understand how water infrastructure systems will perform under different conditions and scenarios. As the associated probability distributions represent a wider concept or class of potential events or outcomes, their precise values depend on the realizations of future hydraulic conditions [56].

Probabilistic approaches in water resources management are becoming increasingly popular as climate change and anthropogenic pressure introduce additional uncertainty about water availability. Climate models predict changes in precipitation regimes, temperature access, and the frequency of extreme weather events; this probability information can apply to water resource assessments. The classical example of probability application implies the use of adaptive strategies. Probability distributions may also be used within probabilistic risk analysis techniques to ensure that investments in infrastructure and adaptation measures proceed to reduce exposure and vulnerability of water supply systems. Within the field of agricultural economics, many phenomena related to farm finances and agricultural risk management can also be modeled using probability distributions. For example, the Log-Normal distribution is commonly used to represent and analyze the distribution of crop yields and prices: as a distribution that can adequately process positively skewed data, the Log-Normal distribution is a good reflection of reality. Some studies, for example, [57], confirm that the Log-Normal distribution can be used to analyze and draw conclusions about agricultural commodity prices. At the same time, the Weibull distribution is often used in agricultural finance to model extreme events, such as droughts and floods, and attribute the likelihood of their occurrence to the corresponding probabilities of farm income change. Recent research by [58] can be seen as typical of the studies that use probability information and the Weibull distribution in the realm of agricultural finance.

The Normal distribution is less common in an agricultural setting, mainly due of its symmetric nature. In some cases, this distribution can still be adopted, such as modeling the distribution of errors in regression analysis. The parameters of this distribution can also be used to assess the variability of given financial indicators, such as farm incomes. Some studies have applied the Normal distribution: for example, [59] used this type of distribution to analyze agricultural production data and assess the strategies of financial risk management.

In turn, the Log Pearson Type 3 distribution can be applied in the context of agricultural studies to model hydrological variables. [60] used this type of distribution to model the hydrological data needed to assess the risk of shortages of water for agricultural irrigation in the San Juan River, among other applications.

Finally, Pearson Type 3 distribution, along with its log-transformed alternative, can be used to model the distribution of a wide range of variables: from counts of livestock, quality measures of lucerne hay, and sizes of hog operations to returns from farming incomes, cash receipts from farms, price received for hogs and the price animal droppings. The application of the distribution in Agriculture has been covered in papers, such as [61], which investigated the Pearson Type 3 distribution in the context of agricultural production and the development of risk management strategies.

The Gamma distribution finds wide applications in agricultural economics to model skewed distributions of a variety of variables, such as farm incomes, the number of pesticides applied, or the number of cases of liver abscesses. For example, [62] used this thing to model farm-level data and get insights on the distribution of agricultural incomes and effectiveness of government programs.

2.5 Past Research on Distribution Selection:

Many past studies have explored and extensively evaluated a wide range of probability distributions for performing flood frequency analysis. For example, a study by [63] conducted such an investigation, targeting the Narmada River, for the purposes of analyzing flood occurrences. The distributions that were likely explored during that study include the Log-Pearson Type III LPT III and Generalized Extreme Value GEV distributions, among others. The study by [63] assessed the effectiveness of these distributions in characterizing the flood frequency patterns of the targeted river by fitting them to the available flood data from the past. In a similar manner, a past study by [64] explored flood frequency analysis, targeting the river

ZAB. The different probability distributions that were likely explored include the Log-Normal and Gamma distributions, among several others. [64] probably conducted an evaluation by comparing various sectional CDF goodness-of-fit statistics and focusing on other relevant metrics for determining the most suitable distributional weight of fits. In addition to these studies, another study by [65], which assesses many meteorological stations in Pakistan, evaluated the best fit probability distributions for analyzing floods.

The distributions that may have been explored include Weibull and Gumbel, alongside other distributions that are widely used in analyzing increasing precipitation patterns. It is likely that fitting these distributions to the past data using maximum likelihood methods produced valuable insights into the variation patterns of flood magnitude, and its frequency from different sites. In conclusion, past studies have evaluated a wide range of probability distributions for performing flood frequency analysis. These studies included a study conducted by [63], which targeted the Narmada River, and assessed the LPT III and GEV distributions. Similarly, there was a study by Wisam that targeted the river ZAB and explored the Log-Normal and Gamma distributions. [64] also conducted an evaluation focusing on the suitability of Weibull and Gumbel distributions for analyzing floods.

Notably, apart from assessing the performance of different probability distributions in flood frequency analysis, the above studies have focused on understanding regional hydrological systems and the ways in which they respond to extreme weather conditions. Thus, [66] have considered the effect of watershed morphology, land use changes, and climate variability on the principles of flood generation and flood frequency distribution patterns. By combining the knowledge of hydrology with that of statistics, the studies aimed at improving the accuracy and validity of flood frequency details and, thereafter, supporting sound insights into water resources management and natural disaster risk reduction. The methodologies, in this case, were likely to involve a wide range of statistical techniques, including but not limited to

maximum likelihood estimation, moment-based modelling methods, and goodness-of-fit tests to evaluate the suitability of the distributions to represent the observed patterns of flooding. On this basis, the sensitivity analysis would likely have followed to test whether the results of modelling methodologies are consistent in their representation of the distribution, regardless of the model used and the assumptions made.

Overall, a few studies have focused on determining the most suitable probability distributions in specific cases, offering references for other types of studies in the same area. For instance, in their 1994 study, [67] have demonstrated a comprehensive evaluation of the extent to which different families of distributions are applicable. They state that the Johnson family of distributions encompasses numerous shapes and, therefore, supports the representation of different types of distributions. Correspondingly, researchers who hope to improve the quality of modelling and ensure that their methodologies fit the data from different fields are encouraged to use Johnson distributions.

Furthermore, the research of [68] highlighted the importance of learning the underlying properties of data before selecting a distribution. The author emphasized that when deciding on the type of distribution, skewness, kurtosis, and tail behavior should be taken into account to choose the most appropriate model. Inspecting these characteristics will enable the researchers to choose a distribution that best fits the shape of the data, contributing to the production of more reliable results using appropriate statistical methods. In addition, [69] reported that power-law distributions are heavily over-represented in empirical data from a wide range of fields, including social sciences, economics, and biology. Hence, considering that power-law properties are average and typical for many events represented in life and social spheres and a non-exotic option for a distribution, the option becomes a considerable alternative. The correctly recognized power-law distribution will be a stimulus to a successful use of proper statistical methods and evaluation of the data in a chosen research area.

Moreover, the study by [70] indicated that Bayesian methods are crucial in statistics, and not applying them is illogical when using traditional approaches can be unsound. The authors underlined the flexibility and ability of Bayesian methods to implement prior knowledge for the stages of updating the prior beliefs based on the evidence from observed data. As a result, the conclusion can be made that adopting Bayesian approaches can help researchers gain more value if currently applied methods and models are not able to meet the challenges.

2.6 Role of GIS and AHP in Flood Risk Mapping

In addition to conventional hydrological and statistical techniques, Geographic Information Systems (GIS) have revolutionized the assessment of flood hazards by providing a spatial platform to integrate diverse data sources. GIS enables the processing and analysis of multiple flood-conditioning parameters such as elevation, slope, land use/land cover, soil type, rainfall, vegetation indices, curvature, and proximity to rivers. By converting these heterogeneous datasets into thematic layers and integrating them spatially, GIS produces detailed flood susceptibility maps that highlight vulnerable zones with high precision. This capability is particularly valuable for large catchments, where variability in topography and land use requires a spatially explicit approach. The visual outputs generated through GIS not only enhance the understanding of spatial flood risk but also serve as decision-support tools for urban planners, policymakers, and disaster managers in prioritizing interventions.

Complementing GIS, the Analytic Hierarchy Process (AHP) provides a structured multi-criteria decision-making framework that incorporates expert judgment in assigning relative weights to flood-conditioning parameters. The strength of AHP lies in its capacity to translate subjective assessments into consistent, quantifiable measures, allowing for the prioritization of factors based on their influence on flooding. Through pairwise comparisons and consistency checks, AHP ensures that the weightage assigned to variables such as slope, rainfall, or land cover is both systematic and reliable. When integrated with GIS, these weights are applied to

spatial layers, resulting in composite flood risk indices that delineate zones of high, moderate, and low susceptibility. The combined AHP–GIS methodology has been widely applied in flood-prone regions worldwide due to its balance of scientific rigor and practical applicability. It not only enhances the objectivity of flood risk mapping but also ensures that decisions are rooted in both quantitative data and expert knowledge. Within the context of Pakistan, where data scarcity and climatic uncertainties pose challenges, the AHP–GIS framework represents a particularly effective approach to generate reliable, context-specific flood risk maps that can guide disaster preparedness, infrastructure planning, and community-level resilience.

2.7 Application of AHP in Flood Risk Assessment

The Analytic Hierarchy Process (AHP), introduced by Saaty (1980), has emerged as one of the most widely applied multi-criteria decision-making (MCDM) techniques in environmental and water resources research. Its primary strength lies in decomposing complex problems into a structured hierarchy of criteria and sub-criteria, followed by pairwise comparisons to derive relative weights. In the context of flood risk assessment, AHP has been extensively employed to assign priority to parameters such as slope, elevation, rainfall, land use/land cover, drainage density, and soil characteristics. By converting subjective expert opinions into quantitative weights, AHP ensures consistency, transparency, and reproducibility in the evaluation process. Several studies have demonstrated the utility of AHP in mapping flood susceptibility zones. For instance, researchers in South Asia, including India, Nepal, and Bangladesh, have successfully applied AHP–GIS frameworks to delineate hazard-prone regions, with results validated against historical flood records. These applications highlight the capacity of AHP to account for both physical and socio-economic parameters, thereby providing a holistic view of flood vulnerability. Similarly, studies in African and European catchments have emphasized the flexibility of AHP in accommodating local hydrological conditions and data availability constraints. Compared with purely statistical or hydrological models, AHP offers the advantage

of integrating expert knowledge where reliable long-term flood data are scarce, making it especially valuable in developing regions.

In Pakistan, AHP-based flood risk mapping has gained increasing attention in recent years. Researchers have applied the method in the Indus Basin and hill torrent catchments to evaluate flood susceptibility, often integrating nine or more conditioning parameters, such as elevation, slope, TWI, NDVI, soil type, and proximity to river networks. These studies underline that AHP is a robust tool for prioritizing flood mitigation measures and supporting spatial planning in vulnerable districts. When coupled with GIS, AHP enhances visualization and allows for effective communication of risk to decision-makers and communities. Thus, the growing body of literature confirms that AHP is not only a reliable but also a context-sensitive tool, bridging the gap between data-driven analysis and expert-based decision-making in flood risk management.

Chapter No.3

METHODOLOGY

The secondary data (in 1000 cusecs) in the form of annual maximum peak (AMP) flows for Kalabagh, Kotri, Mangla, Rasul, Trimmu and Panjnad catchments have been obtained from the hydrological department at Federal Flood Commission Ministry of Water and Power Pakistan. Data are available in the range of 63 to 101 years. We used flood data from 2000 to 2022.

This data is crucial for developing predictive models that can be used for future flood management and planning. Specifically, from a hydrological perspective, there is a need for a procedure that can utilize the observed annual maximum flow data to estimate the magnitude

of floods expected to occur once in T years, denoted as $Q(T)$. This estimation is vital for designing flood control infrastructure, risk assessment, and creating effective flood mitigation strategies [71].

Kalabagh and Kotri are significant locations along the Indus River, each holding strategic and geographical importance. Kalabagh is situated at the point where the Indus River exits the majestic Himalayas. This position marks a crucial transition from the mountainous terrain to the plains, influencing the river's flow and its potential for hydroelectric projects and irrigation systems. On the other hand, Kotri is located near the head of the Indus River delta in Sindh. This area is vital for agriculture and the management of water resources, as it represents the river's final journey towards the Arabian Sea, distributing water across one of the most fertile regions in Pakistan.

3.1 Study Area: Kalabagh and Kotri Catchments

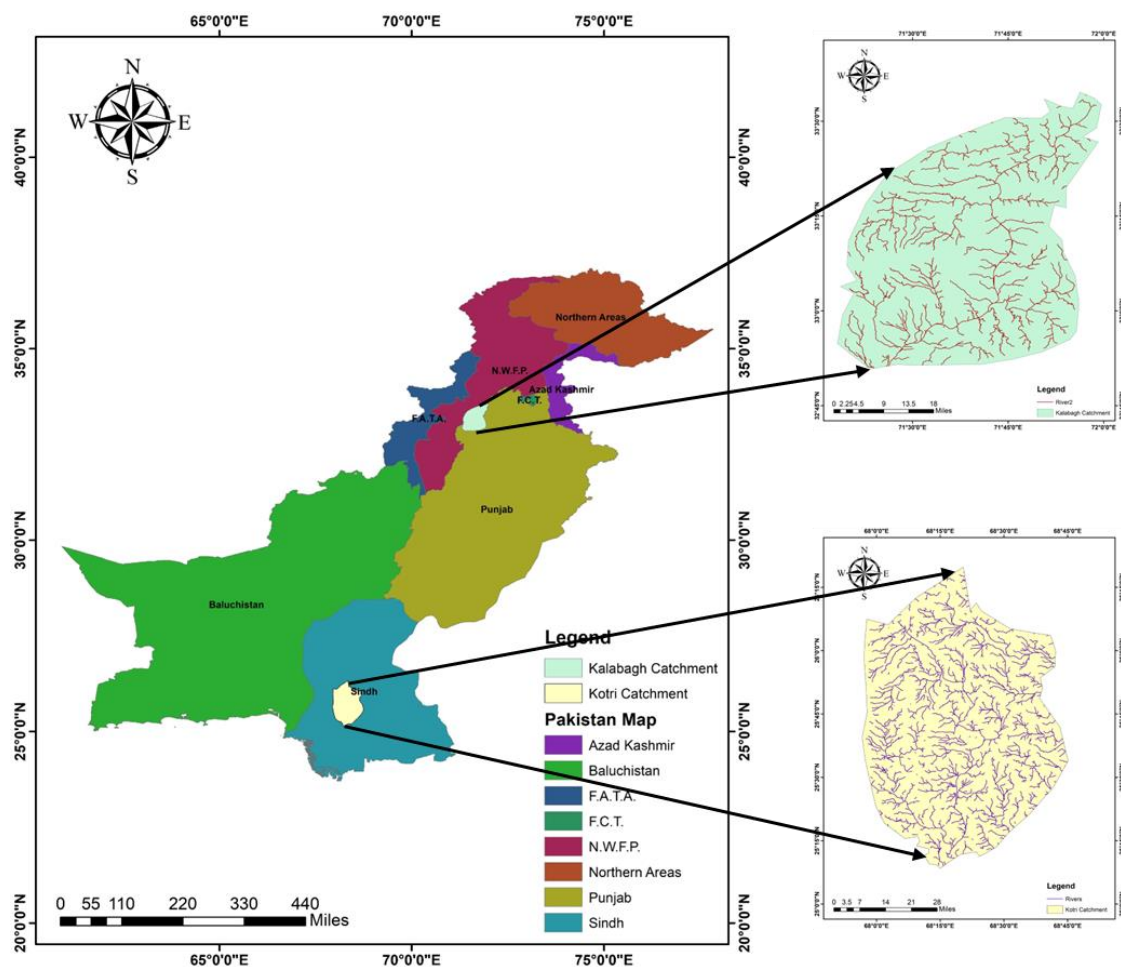
The study focuses on two major sites along the Indus River system: Kalabagh in the upstream zone and Kotri in the downstream deltaic region. Together, these catchments provide a contrasting hydrological and geomorphological perspective on flood risk in Pakistan.

Kalabagh is located at the transition point where the Indus River exits the mountainous northern terrain and enters the plains of Punjab. This unique setting creates conditions for flash floods, as steep slopes and high-intensity rainfall rapidly generate surface runoff. The surrounding region also plays an important role in hydroelectric potential and irrigation distribution, making Kalabagh a strategic site for water management. Flood events here are typically localized but can be highly destructive, threatening infrastructure, agriculture, and downstream settlements.

On the other hand, Kotri represents the downstream extent of the Indus River, situated near Hyderabad in Sindh province, close to the river's final discharge into the Arabian Sea. Unlike Kalabagh, Kotri lies in a flat deltaic environment characterized by low gradients, extensive

floodplains, and a dense population dependent on agriculture. Flooding in Kotri is often widespread, prolonged, and exacerbated by inadequate drainage and heavy monsoon inflows from upstream. As the last major control point on the Indus, Kotri Barrage also serves as a critical regulator for irrigation supplies to lower Sindh, making flood management here a national priority.

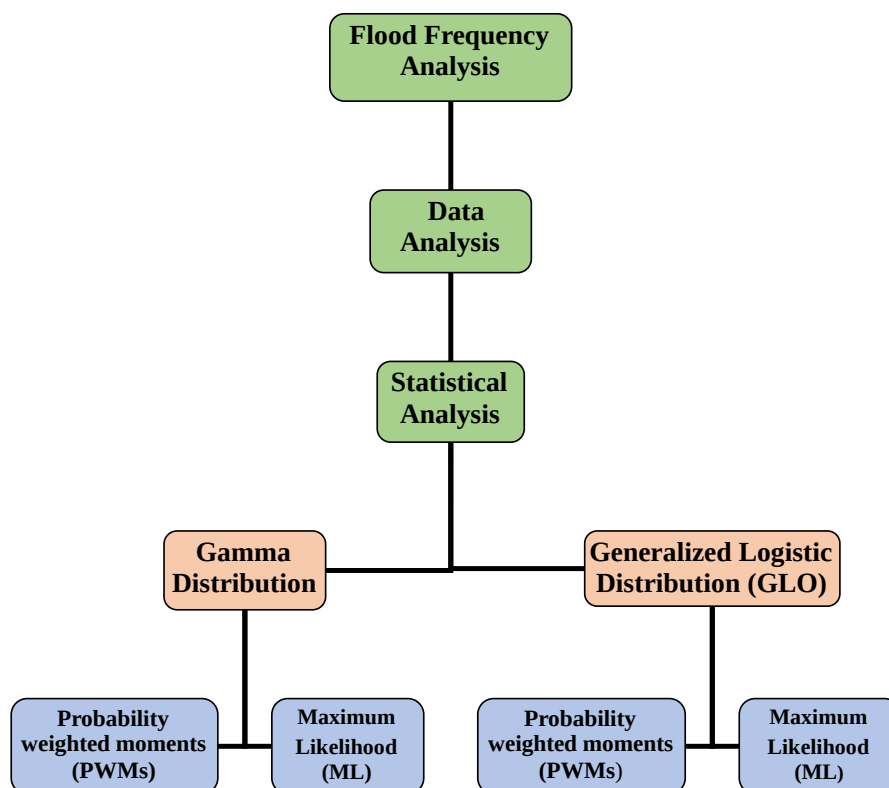
The selection of Kalabagh and Kotri catchments allows this study to capture both upstream flash flood dynamics and downstream riverine inundation risks within the same river system. Their contrasting physiographic and climatic settings provide valuable insights into the spatial variability of flood susceptibility across Pakistan.



Location of Kalabagh and Kotri catchments within the Indus River Basin

The Mangla, Rasul, and Trimmu dams are all established on the Jhelum River, one of the major tributaries of the Indus. The Mangla Dam, one of the largest in Pakistan, plays a crucial role in water storage, flood control, and electricity generation. Rasul and Trimmu, while smaller in scale compared to Mangla, also contribute significantly to irrigation and flood management, ensuring that the agricultural lands in the region remain fertile and productive [72].

The Panjnad, which means "five rivers," is a noteworthy point below the confluence of the Jhelum with the Chenab River. This convergence creates a significant hydrological feature as the waters of the Jhelum and Chenab, along with input from the other three rivers of Punjab - the Ravi, Beas, and Sutlej - merge to form the Panjnad. This area is crucial for the distribution of water resources to the southern parts of Punjab and northern Sindh, supporting both agricultural activities and local ecosystems. The integration of these river systems highlights the intricate network of waterways that sustain life and livelihoods in the region [71].



3.2 Probability weighted moments (PWMs):

Probability Weighted Moments (PWMs) are a suite of statistical measures which qualify as the expected values of particular functions of a random variable. Most of these measures can be similarly defined for any random variable for which the mean exists, providing it with an additional level of utility in statistical analysis and application. Other methods include the Log-Pearson Type III, Generalized Extreme Value (GEV), and Weibull distributions. These methods were considered, but the gamma and GLO methods demonstrated superior performance for the specific dataset used in this study.

Consider a real-valued random variable X with a distribution function $F(x)$. The concept of PWMs was introduced by [73], offering a method to capture information about the distribution of X through certain weighted expectations.

$$M_{p,r,s} = E[X^p \{F(X)\}^r \{1-F(X)\}^s]$$

$$= \int x^p \{F(x)\}^r \{1-F(x)\}^s dF(x)$$

where p , r , and s are any real numbers. Observe p , r , s if $E|X|^p$ exists. The quantities $M_{p,r,s}$ may refer to anything that describes and characterizes the probability distribution. I think one way could be to just go along $M_{p,0,0}$ where $p=1, 2, \dots$. ‘These are simply the noncentral moments of X [72]. What we actually use, as moments $M_{1,r,s}$ into which X enters linearly is in fact expressible only by the quantities

$$\alpha_r = M_{1,r,0} = E[X(1-F(x))^r], \quad r=0,1,\dots$$

$$\beta_r = M_{1,r,0} = E[X(F(x))^r], \quad r=0,1,\dots$$

PWMs do not provide a fully-fledged summary of the distribution but are instead placeholders so as to define functions over PWMs, although these single function embeddings indeed serve as descriptions of location-scale-shape properties based on any probability distributions [71]. The L stands for the linearity of λ_r in expected order statistics. where an L-statistic in terms of the previously defined α_r and β_r is given by:

$$\lambda_{r+1} = (-1)^r \sum_{k=0}^r p_{r,k} \alpha_k = \sum_{k=0}^r p_{r,k} \beta_k$$

where,

$$p_{r,k} = (-1)^{r-k} \binom{r}{k} \binom{r+k}{k} \quad r=0,1,2,\dots \quad (3)$$

The first few L-moments are:

$$\lambda_1 = E(X) = \alpha_0 = \beta_0$$

$$\lambda_2 = \frac{1}{2} E(2X_{2:2} - X_{1:2}) = \alpha_0 - 2\alpha_1 = 2\beta_1 - \beta_0$$

$$\begin{aligned} \lambda_3 &= \frac{1}{3} E(3X_{3:3} - 2X_{2:3} + X_{1:3}) = \alpha_0 - 6\alpha_1 + 6\alpha_2 \\ &= 6\beta_2 - 6\beta_1 + \beta_0 \end{aligned}$$

The probability distribution is summarized by the following measures:

1. the mean or L-location, λ_1 ;
2. the L-scale, λ_2 ;
3. the L-skewness, $\tau_3 = \lambda_3/\lambda_2$.

3.3 Generalized logistic distribution:

The generalized logistic distribution is referred to as a versatile probability distribution in a set of statistical models to represent a variety of data behaviors, such as skewness and kurtosis. It can be viewed as a generalization of the standard logistic distribution, which makes such distribution more productive for fitting diverse data. The generalized logistic distribution is characterized by the probability density function. PDF can take various forms and be expressed through different parameterizations. Parameters were calculated using Maximum Likelihood Estimation (MLE) and Probability Weighted Moments (PWM), which are robust statistical techniques for parameter estimation in flood frequency analysis. ML and PWM were chosen for their robustness and accuracy in parameter estimation. Other methods were considered but did not perform as well for the specific data characteristics in this study. The distribution is generally characterized by several parameters, which determine its shape, location, and scale. The most typical parameters include the location parameter, which shifts the distribution along the x-axis, the scale parameter, which stretches or compresses the distribution, and the shape parameters that adjust the skewness of the data and the tail behavior. The typical parameterization includes the location μ , the scale σ , and two shape parameters, which are commonly shape α and shape β . The location parameter determines the center of the Generalized Logistic Distribution, while the scale parameter introduces the effect of the spread. The shape α affects the tail heaviness of the distribution, while the shape β controls the skewness or symmetry of the shape of the distribution. Scales and shapes Monti described the relationship between the parameters of the Generalized Logistic Distribution. The parameters were derived from the actual flood data using statistical estimation techniques. This ensures that the values accurately reflect the observed data, enhancing the reliability of the analysis. The characteristics of the generalized logistic distribution reveal its ability to model a range of shapes from heavy tail to light tail. The CDF of the Generalized Logistic Distribution, which

can be complex and described in more generalized terms but is crucial for applications in statistical inference and hypothesis testing. The advantages and specific characteristics of the generalized logistic distribution make it particularly useful in finance, hydrology, and data on life to model the behavior of data that do not follow the normal or exponential distribution pattern.

The probability density function of the GLO distribution is

$$f(x) = \frac{e^{-(1-k)y}}{\alpha(1+e^{-y})^2} \quad (5)$$

where

$$y = -\frac{1}{k} \log_e \left(1 - \frac{k(x-\mu)}{\alpha}\right) \quad k \neq 0$$

$$y = \frac{(x-\mu)}{\alpha} \quad k=0$$

μ , α and k are location, scale and shape parameters respectively. For $k = 0$, GLO Distribution reduced to logistic distribution [72]. The distribution function is;

$$F(x) = \frac{1}{1+e^{-y}}$$

The quantile function for the GLO distribution is;

$$x(F) = \mu + \alpha \frac{1 - \left(\frac{1-F}{F}\right)^k}{k} \quad k \neq 0$$

$$x(F) = \mu - \alpha \log_e [(1-F)/F] \quad k=0$$

The GLO reduced variate is

$$y = -\ln \left(\frac{1-F}{F}\right)$$

[75] showed that point estimates of the parameters of the GLO distribution can be obtained via L-moments by:

$$\hat{k} = \frac{6b_2 - 6b_1 - b_0}{b_0 - 2b_1}, \quad \hat{a} = \frac{2b_1 - b_0}{\Gamma(1 - \hat{k})\Gamma(1 + \hat{k})},$$

$$\mu = b_0 - \frac{a}{\hat{k}} [\Gamma(1 - \hat{k})\Gamma(1 + \hat{k})]$$

where

$$b_r = E(xF^r) \text{ and } \Gamma(1 - \hat{k})\Gamma(1 + \hat{k}) = \frac{\pi k}{\sinh \pi k}$$

3.4 Quantile estimation;

Random variable describing the time lag between two successive peak flows exceeding Q (given that such events occur) with its average value, typically known as the return period T of Q ; determination of the distribution in question by estimating the parameters of this distribution using our sample and deriving thereafter an estimate for, i.e. function quantile $Q(T)$ [71]. If T is specified in years, and the probability of Q being exceeded at least once within that designated year is equal to p , then the return period T for one standard year may be defined as:

i.e. $T = p^{-1} = (1 - F)^{-1}$ where F is the distribution function. The return period of gamma distribution is calculated by using the table 1.3 (p 36) in [72]. The gamma and GLO methods were selected because they better fit the distribution of the flood data observed in this study. These methods are known for their flexibility and ability to model extreme events more accurately in certain hydrological contexts. While the Gumbel method is widely used, it was not chosen because preliminary analysis indicated that the gamma and GLO methods provided a better fit for the data. The statistical properties of the flood data align more closely with the gamma and GLO distributions. The quantile function of the GLO distribution in terms of return period is

$$X(T) = \mu + \frac{\alpha}{k} \left(1 - \left(\frac{1}{T-1}\right)^k\right) \quad (8)$$

3.5 Peaks over threshold (POT) model:

Selected q_0 as the threshold flow at which two, three or (approximately) four peaks per decade are likely to be surpassed on average. Suppose each instantaneous independent peak flow where is selected set as the threshold (arbitrary number). Then all above-threshold, instantaneous peak flows are extracted [71]. If we count the number of peaks greater than a certain level, and divide these by the number of years for which we have rainfall data, (this gives us a rate at which floods are exceeded λ) then it is simple to find how many times one may expect this event to happen within a particular period $N\lambda$. We consider that the occurrence rate per decade is $\lambda = 2$, and obtain the parameters' estimation and quantile estimation [72].

3.6 Data Analysis:

I used Excel software for analysis of data. Analysis of the data for the thesis using Excel was a comprehensive process. It implies a series of steps used to extract assumption and conclude the provided dataset on annual maximum peak flow for different catchment in Pakistan. I took advantage of the explicative data given to make necessary calculations and visualize the data. Since the dataset provided by the explicit has the AMP flow for different catenates, the student needs to make calculations in Excel. Describing data, I firstly imported data to understand the nature of the data. Using standard Excel functions, AVERAGE, MEDIAN, MIN, MAX, And COUNT, data such as peak data points' mean, median, minimum value, maximum value, and data counts were calculated. From this calculation, it was evident how many data points were used, and descriptive data for each catchment was calculated. Caution was needed to remove atypical points or explore outliers to navigate the nature of the system. In addition, to examine the plumbing of the occurrence of AMP flow, I imported the dataset and viewed the following table. After calculating data and understanding its nature, I concluded it necessary to make calculations to model the pumping. I used probability-weighted moments with the given

formulas and explanation to calculate it manually. I also modelled a generalized logistic distribution. In short, data analysis was a comprehensive process, including importing the data, calculating descriptive data, and modelling the data using PWM and Generalized Logistic Distribution. In addition, in the provided PS5 task, POT data was calculated, and POT model was implemented. After calculating POT and modelling the explanation, the student may use the chart to visualize the obtained information. The process of analyzing the data set helped me retrieve valuable findings to manage floods, assess risk, and plan the needs of irrigation systems in Pakistan using explicit data and Excel software.

3.7 Methodological Framework for AHP–GIS Based Flood Risk Mapping

The methodology adopted for flood risk mapping in this study is based on the integration of the Analytic Hierarchy Process (AHP) with Geographic Information Systems (GIS). The framework begins with the identification and preparation of nine flood-conditioning parameters, including elevation, slope, land use/land cover (LULC), normalized difference vegetation index (NDVI), topographic wetness index (TWI), rainfall, soil type, curvature, and distance to river. Each parameter was processed into a spatial raster layer using DEMs, remote sensing products, and ancillary hydrological datasets.

Subsequently, the AHP was employed to derive the relative importance of these parameters through expert-based pairwise comparisons. The resulting parameter weights were then integrated into the GIS environment, where the reclassified raster layers were combined using a weighted overlay technique. This process produced composite flood risk indices, which were further classified into zones of high, medium, and low susceptibility.

This methodological framework ensures that spatial heterogeneity of the catchments is explicitly represented, while expert judgment is systematically incorporated into the modeling process. The integration of AHP and GIS provides a robust and transparent tool for delineating

flood-prone areas and supporting decision-making for disaster preparedness, land-use planning, and resource allocation.

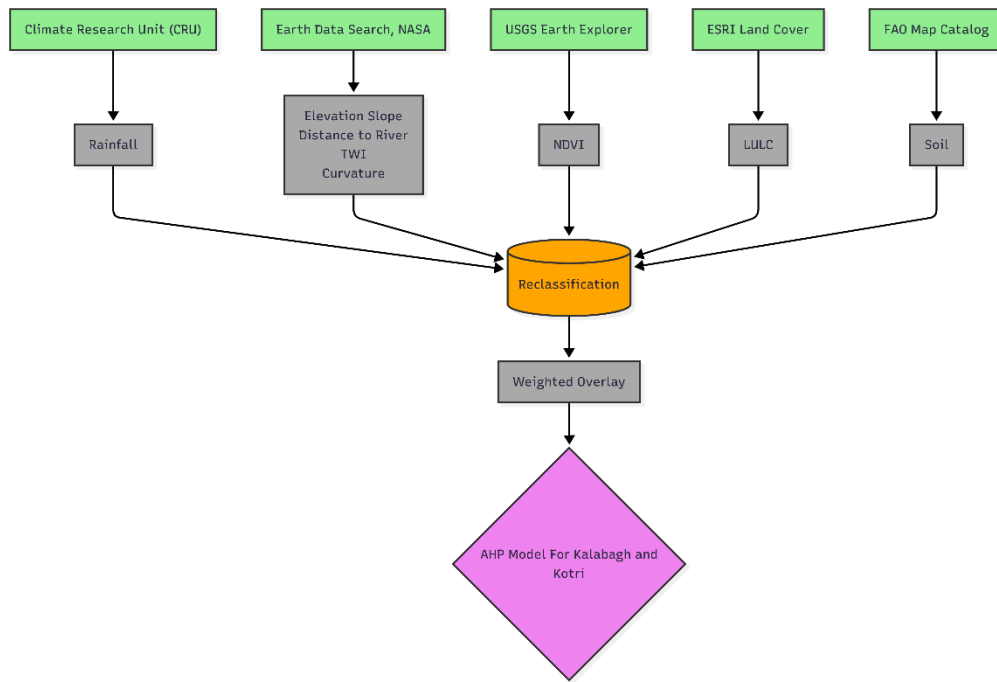
3.8 Flowchart of the Methodology

The overall methodology for flood risk mapping is illustrated in Figure given below, which presents the logical sequence of the study. The flowchart begins with the collection and preprocessing of spatial datasets, including DEM, rainfall, soil, land use/land cover (LULC), NDVI, curvature, slope, TWI, and distance to river. These nine parameters were selected as key flood-conditioning factors based on hydrological significance and literature support.

The next step involves the application of the Analytic Hierarchy Process (AHP), where expert-based pairwise comparisons were conducted to derive the relative importance (weights) of each parameter. A consistency check was performed to validate the reliability of judgments using the Consistency Ratio (CR).

Once the weights were finalized, each parameter layer was reclassified into ranked categories (e.g., very low to very high susceptibility) within the GIS environment. Finally, a weighted overlay analysis was carried out to generate composite flood risk indices, which were then classified into high, medium, and low flood risk zones.

The outcome of this framework is a set of spatially explicit flood risk maps for the Kalabagh and Kotri catchments, providing valuable insights for flood management and mitigation planning.



Flow Chart For GIS-AHP

3.9 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Saaty (1980), was used to determine the relative importance of flood-conditioning parameters. In this study, nine parameters were selected based on hydrological relevance and literature support: elevation, slope, land use/land cover (LULC), normalized difference vegetation index (NDVI), topographic wetness index (TWI), rainfall, soil type, curvature, and distance to river.

The first step of AHP is the construction of a pairwise comparison matrix. Each parameter is compared with every other parameter using Saaty's 1–9 scale, where 1 represents equal importance and 9 represents extreme importance of one factor over the other. The reciprocal values are automatically assigned to the lower diagonal of the matrix.

An example of a pairwise comparison matrix for n parameters is expressed as:

$$A = [a_{ij}] = \begin{pmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & & a_{2n} \\ & & \ddots & 1 \\ 1/a_{1n} & 1/a_{2n} & & 1 \end{pmatrix} \quad (9)$$

3.10 Derivation of Weights

Once the pairwise comparison matrix is constructed, the relative weights (W) of the parameters are calculated using the normalized principal eigenvector method. The normalized weight W_i for parameter i is given as:

$$W_i = \frac{\sum_{j=1}^n \frac{a_{ij}}{\sum_{i=1}^n a_{ij}}}{n} \quad (10)$$

The derived weights represent the proportional contribution of each parameter to flood risk. For instance, slope and elevation may receive higher weights in mountainous catchments, while rainfall and soil type may dominate in deltaic regions.

3.11 Consistency Check

Since the weights are derived from expert judgment, consistency of the pairwise comparisons must be tested. The Consistency Index (CI) and Consistency Ratio (CR) are calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (11)$$

$$CR = \frac{CI}{RI} \quad (12)$$

where $\lambda_{\max}$ is the maximum eigenvalue of the comparison matrix, n is the number of parameters, and RI is the Random Consistency Index provided by Saaty (1980). A **CR ≤ 0.1** indicates acceptable consistency, ensuring that expert judgments are reliable. If CR exceeds this threshold, the pairwise comparisons are revised until acceptable consistency is achieved.

3.12 Weighted Overlay Analysis in GIS

The final stage of the AHP–GIS integration is the weighted overlay analysis. Each parameter was first converted into a raster layer and reclassified into five categories ranging from very low to very high flood susceptibility. The reclassified layers were then multiplied by their respective AHP-derived weights. The overall Flood Risk Index (FRI) was computed as:

$$FRI = \sum_{i=1}^n (W_i \times X_i) \quad (13)$$

where W_i is the weight of parameter i and X_i is the standardized rank score of the parameter in raster form. The composite flood risk index map was subsequently classified into three categories: *high risk, medium risk, and low risk zones*.

3.13 Data Collection and Sources

For the flood risk mapping framework, multiple datasets were collected from reliable global and national repositories to ensure accuracy and consistency. Each dataset corresponds to a flood-conditioning parameter identified in the AHP–GIS framework. The datasets include terrain attributes (DEM, slope, curvature, TWI), hydro-meteorological inputs (rainfall and distance to river), land surface characteristics (LULC and NDVI), and soil properties. These data sources were selected for their high resolution, global coverage, and compatibility with GIS-based analysis. The detailed description of each dataset and its source is provided in **Table 3.1**

Table 3.1: Datasets used for AHP–GIS Based Flood Risk Mapping

Data Type	Description	Source
DEM Data	Digital Elevation Model (DEM) with 30 m spatial resolution for terrain and slope analysis	NASA Earth Data Search

Soil Data	Soil type, permeability, and texture characteristics for infiltration assessment	FAO Soil Map Catalog
Rainfall Data	Annual and seasonal rainfall distribution for hydrological assessment	Climate Research Unit (CRU) – UAE Data
Land Use/Land Cover (LULC)	Classified satellite imagery for land cover and land use distribution	Esri Land Cover – ArcGIS Living Atlas
NDVI	Vegetation density and health index for runoff and infiltration estimation	USGS Earth Explorer
Curvature	Terrain convexity/concavity derived from DEM for flow accumulation	Derived from DEM in ArcGIS/GRASS GIS
TWI (Topographic Wetness Index)	Index for soil moisture and runoff potential estimation	Derived from DEM using SAGA GIS tools
Distance to River	Euclidean distance from river channels to identify flood-prone zones	Digitized from Survey of Pakistan river network maps

3.14 Outputs of the AHP–GIS Framework

The integration of AHP with GIS in this study provides a systematic and transparent procedure for translating multiple flood-conditioning parameters into spatially explicit flood risk maps. The resulting outputs are high-resolution maps that delineate areas of high, medium, and low flood susceptibility within the Kalabagh and Kotri catchments. These maps highlight zones where combinations of topographic, hydrological, and land surface factors converge to create elevated flood risks.

The methodology ensures that the relative influence of each parameter (e.g., slope, elevation, rainfall, or distance to river) is objectively quantified through AHP weights and consistently applied in the GIS environment. This allows the flood risk maps to capture the inherent spatial

variability across the two catchments. For example, in mountainous upstream areas, slope and elevation may exert greater control on flood susceptibility, whereas in the downstream plains, soil type, land use, and proximity to river channels become more dominant factors.

By combining expert judgment with geospatial analysis, the outputs are both data-driven and decision-oriented. The classification of the catchments into susceptibility zones not only identifies the most vulnerable areas but also supports targeted flood mitigation strategies such as the reinforcement of embankments in high-risk zones, controlled land-use planning in floodplains, and prioritization of early warning systems for vulnerable communities.

Although this section focuses on the spatial dimension, these outputs are complementary to the statistical flood frequency analysis presented earlier. Together, the two approaches provide a dual perspective on flood risk:

- Flood Frequency Analysis (FFA) quantifies the probability and magnitude of future flood events.
- AHP–GIS Mapping spatially identifies where these floods are most likely to have critical impacts.

The combination of these methods offers a more holistic decision-support framework for policymakers, disaster management authorities, and water resource planners in Pakistan. It enhances the capacity to allocate resources efficiently, prioritize interventions, and develop region-specific adaptation strategies in response to the growing challenges of climate change and rapid urbanization.

Thus, the AHP–GIS framework not only generates scientifically robust maps but also translates them into practical tools for sustainable flood risk management, marking a significant methodological advancement for the study region.

Chapter 4

Results and Discussion

Floods are one of the major and recurring natural disasters in different parts of the world, also many sub-basin catchment areas in a particular river basin. It is necessary to understand the statistical properties and hydrological parameters in these regions for better management and control of flood risks. In this chapter, a thorough investigation in terms of parametric estimation on hydrological data of sub-catchment area, justification to randomness of data and further

Variable	Kalabagh	Kotri	Mangla	Rasul	Trimmu	Panjnad
N	75	102	81	81	64	81
$\bar{X}$	530	440	198	220	320	330
$X\sim$	510	420	135	145	260	315
S	130	170	200	210	195	160
C.V	0.25	0.38	1.01	0.96	0.61	0.50
$s\bar{X}$	15.0	16.5	22.0	24.0	25.0	18.0
Min	270	70	20	22	80	50
Max	920	980	1105	950	890	800
g	0.82	0.55	2.85	2.09	1.00	0.69
S. Eg	0.30	0.25	0.30	0.25	0.30	0.25
β_2	0.70	0.60	8.70	3.70	0.00	0.15

quantification into the return period for POT series are analyzed. This study tries to assess flooding dynamics in these regions with a retrospective analysis based on the statistical distributions such as Generalized Logistic (GLO). The information garnered from this analysis is crucial in developing robust flood forecasting models, supporting water resource management strategies and promoting the resiliency of communities affected.

Table 1: Basic Statistics (10³ cusecs feet)

Table 1 presents summary statistics of water flow in six locations, with the flow represented in 10³ cubic feet per second. These locations are Kalabagh, Kotri, Mangla, Rasul, Trimmu, and Panjnad. Each location is based on a set of variables associated with different measures of statistical analysis, providing a clear comparison of the characteristics of water flow in these areas. The table presents N which is the number of samples in each location, with observations on water flow ranging from 64 to 102 in each location. Other characteristics include the mean $\bar{X}$ and median $X_{\sim}$, which provide the central tendency of the flow. For instance, Kalabagh has the highest mean of 530 and median of 510, while Mangla has the lowest values 198 and 135, respectively. The standard deviation S, which shows the level of variation from the average, is a measure of the variability of each location, and is shown as being the highest in Mangla and Rasul at 200 and 210, respectively. The coefficient of variation C.V, indicates the relative variability among the locations, with Trimmu and Panjnad showing moderate variation. The range provides the spread, with minimum and maximum values for each location. Mangla shows a wide range of flow from 20 to 1105, which indicates high variation. Additional variables include skewness, the standard error of the mean S. Eg and beta-2 COEFFICIENT β_2 that show the distribution characteristics and asymmetry. Rasul, for example, shows high skewness of 2.09, indicating a right-skewed distribution. The beta-2 coefficient for Trimmu flow is 0, indicating symmetry. The table provides a good comparison measure of various characteristics of water flow in different locations.

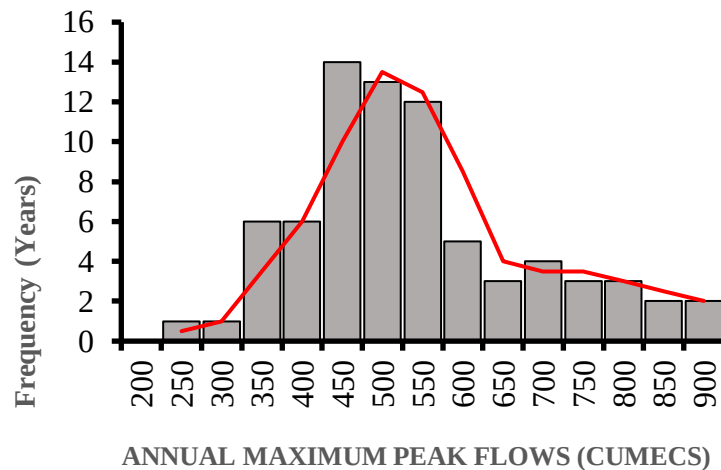


Figure 1: Histogram of flows at Kalabagh

This frequency distribution of recorded flow values is shown in Figure 1. The preceding output shows the results for this question at the Kalabagh location from the shape of the histogram, we can see that it is a positively skewed distribution, indicating that most values of flow lay on the lower end in numbers with fewer and fewer cases where they lie at high points. 77 This implies that the smaller flow events (less than mean) are more frequent to the Kalabagh, while larger flow events ($>$ mean flow), are lower in frequency. These datasets were clustered around relatively smaller values because extreme high flow events do not occur as frequently at this location but can potentially have catastrophic impact.

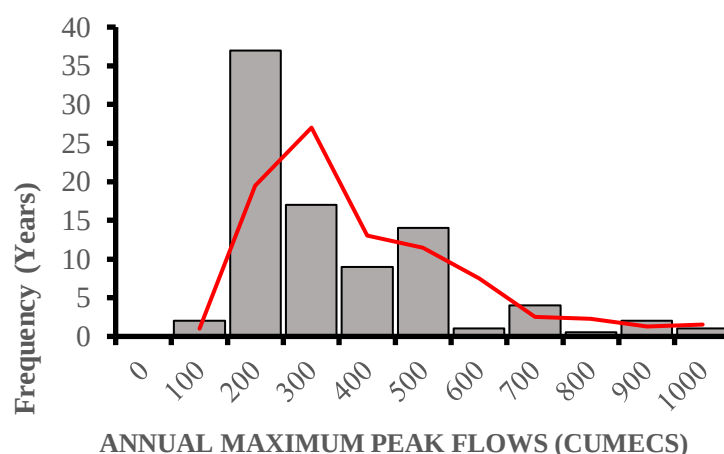


Figure 2: Histogram of flows at Trimmu

Figure 2 shows the distribution of flow values which are similar to Figure 1. Similarly, the histogram for Trimmu also presented a positively skewed distribution which indicated that this

site has frequent smaller flow events whereas larger flow is rare and less observed at this study location. it appears to be a regional behaviour related pattern as the low magnitude flow event are also witnessed on Kalabagh. The decreasing frequency with increasing flow value indicates that high flows do happen, but not nearly as often as lower flows.

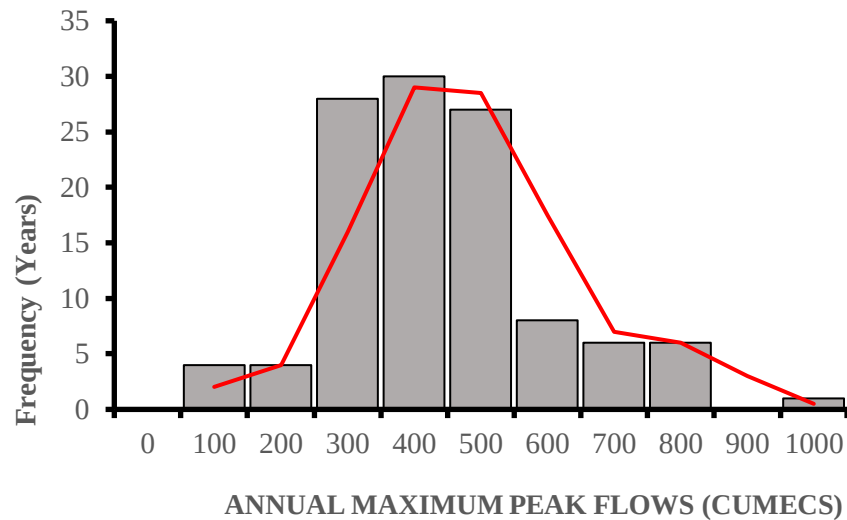


Figure 3: Histogram of flows at Kotri

From the above Figure 3, a flow distribution at Kotri location is glimpsed. The histogram shows a distribution format similar to that in Kalabagh and Trimmu, which is positively skewed. the skew of this histogram again shows, frequently most smaller flow events at Kotri and less frequently followed by the larger flows. As seen, the observed pattern support what is already determined for the other locations and that most flow values are rather on the lower side. In turn this implies that many minor events generally dominate hydrological behavior in the region.

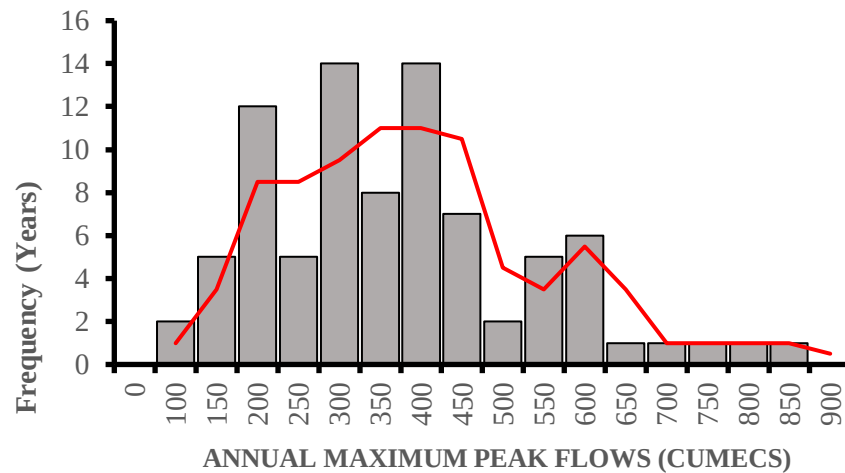


Figure 4: Histogram of flows at Panjnad

Figure 4 shows Frequency distribution of flow values at Panjnad. This dam's histogram is showing a positively skewed distribution, which is following Kalabagh, Trimmu, and Kotri locations. This means, even at Panjnad the smaller flow events are more intense and as we move toward right side of distribution curve, frequency decreases with increase in flows values. It illustrates a common skewness across all sites in recognition of broader regional hydrological behaviour, where lower flows are relatively more frequent and higher flows considerably less so.

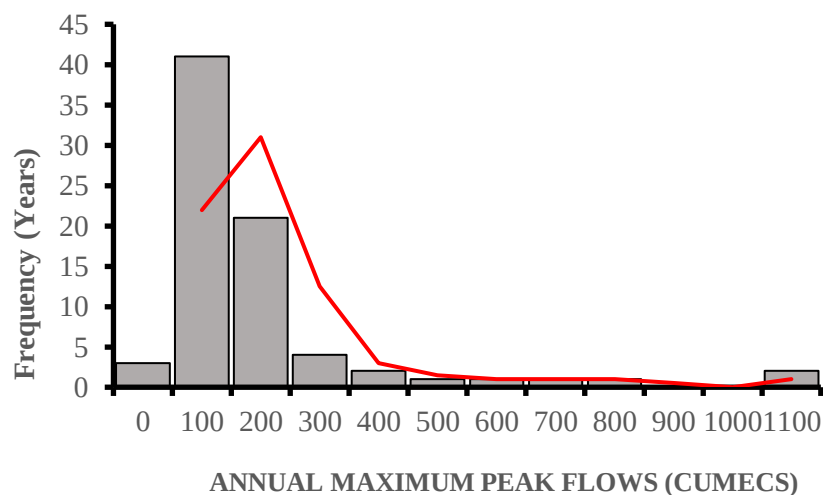


Figure 5: Histogram of flows at Mangla

Figure 5 is about Flow values frequency distribution showing a more pronounced, positive skewed compared to the rest of the locations This histogram tells us that most of the mean flow

values are centered towards lower end of the scale at Mangla, however there is wide spread that stretches to higher flow values. Furthermore, increased skewness at Mangla implies that not only the smaller flow events have relatively greater frequency of occurrences but also the possibility of wider spectrum higher flows that in turn address a unique pattern and variability to be observed in case of flow phenomena at this site. This potentially indicated some unique hydrological or geographical factors that affect flow characteristic at Mangla, which makes it somewhat different from the other locations mentioned.

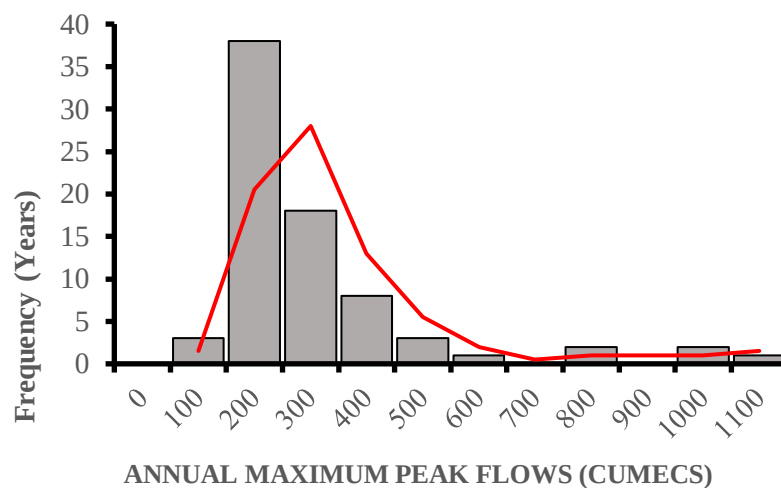


Figure 6: Histogram of flows at Rasul

Figure 6 shows the frequency distribution of flow values recorded at Rasul. There, we get a picture of how many times during this time period did each particular level of flow occur. This is what they describe as highly skewed, which means that there are many small magnitude flows (shown on the far left) and very few large events (far right). This is similar to the flow distribution pattern that we saw at Mangla which also falls under the same river basin. The asymmetry of histograms indicate that the flow regime is dominated by low-flow events at Rasul. Additionally, it may reflect some of the local modes in the hydrology within the Jhelum River basin. These factors included the fingerprint or signature, the disposition or location of precipitation at various frequency magnitudes (e.g., climate factors that may increase smaller

more frequent rainfalls), basin geography which may direct water in a manner not supportive of larger flow events and human influences such as dam operations and large extractions where we regulate out larger flows. Climate change was not considered in this analysis as the focus was on historical flood data to establish baseline conditions. However, future studies should incorporate climate change projections to assess potential impacts on flood frequency.

The histograms provided in Figures 1–6 show more explicitly the spread of flows on the X-axis. One commonality noted across all histograms was that they were all positively skewed, meaning the observations around which they clustered were at smaller flow values, with the spread gradually increasing to the larger values. Specifically, while Kalabagh and Kotri shared similarities in their histograms, it was evident that since they were located on the Indus River, the histogram could be more or less the same, no matter the actual location of a gauge. Kalabagh shares a starting point from the Himalayas, while Kotri is located near the head of the delta in Sindh. The nature of their histogram indicated the two's uniqueness in flow patterns compared to the others, illustrating the uniqueness of this streamflow. Mangla, Rasul, and Trimmu had similar histograms mainly because they have readings from River Jhelum and are therefore geographically close. The other commonality was that their histograms were more skewed than Kalabagh, Kotri, and Panjnad, which implied their mean values were closer to the smaller values, the spread smaller, and the large values further on the right than the other groups. It could have been affected by more local factors in the River Jhelum basin, especially the type of terrain possibly affecting the discharge variability. Panjnad had a more similar histogram with Kalabagh, and Kotri than it did Mangla, Rasul, and Trimmu. Although it is still unique from the former two, its similarities might be because of it not being largely influenced by River Jhelum. Hence, the regional variations in streamflow sources might have played a role in determining streamflow pattern. Histograms illustrate the frequency distribution of

flood events over the study period. Parameters such as bin width and range were set based on the data characteristics to ensure meaningful representation of the distribution.

Table 2: Randomness of Data

Catchment	Rcal	p-value	dw	α	r1	g
Kalabagh	29	0.115	2.010	0.053	0.065	0.845
Kotri	47	0.445	1.700	0.051	0.158	0.560
Mangla	31	0.085	1.460	0.049	0.290	2.900
Rasul	37	0.190	1.450	0.052	0.305	2.110
Trimmu	28	0.150	1.690	0.048	0.170	1.020
Panjnad	43	0.980	1.770	0.054	0.130	0.705

Table 2 presents a thorough analysis of data randomness within different catchment areas. For each location, it reports several statistical parameters that describe data properties. First of all, the Rcal column demonstrates the calculated R statistic for each catchment area. In this case, two of them, Kalabagh and Trimmu, were the same, 29 and 28, which means that data had a similar level of randomness. In turn, the other catchments indicated other values, with Kotri and Panjnad being higher, which implies potential differences. Second, the p-value column indicates that for each of these catchments, there was the testing of the hypothesis of randomness. Thus, the values were from 0.085 for Mangla to 0.980 for Panjnad. A lower figure means more evidence against the null hypothesis of randomness, which implies that the first one may have more structured data, whereas then second one might have data much closer to being random. Additionally, the Durbin-Watson factor is important when assessing the possibility of autocorrelation. If the value is about 2, it means that there is no autocorrelation. In this case, the values were also different and varied from 1.45 to 2.01, which means that all the conditions were different. The α value indicates the significance level in the data. For Kalabagh, it was 0.053, and for Trimmu, it was 0.054, which means that the data in these two areas may not be very significant statistically. The r1 demonstrates the first-order autocorrelation factor and reveals the strength of the linear relationship between two

consecutive measurements. Hence, data in Rasul or Mangla is more strongly correlated linearly than Munda or Sukkur. Lastly, the value of the coefficient of variation expresses the relative variability of the data. Thus, for Kotri, it was 0.560, and for Mangla, it was 2.900, which means that variability in these two spaces was different, and Mangla had either more or less stable data. Overall, the table provides a thorough analysis of possible data randomness and statistical properties in various catchment areas.

Table 3: Parameter estimates for G (2) and GLO distribution

Catchment	G (2)				GLO			GLO		
	PWM		ML		PWM			ML		
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\mu}$	$\hat{\alpha}$	$\hat{k}$	$\hat{\mu}$	$\hat{\alpha}$	$\hat{k}$
Kalabagh	14.6	36	28.5	18.4	506	67.3	-0.161	507	66	-0.157
Kotri	62.4	7	69.5	6.2	417.5	91.4	-0.095	419	88.8	-0.101
Mangla	116.3	1.7	109.1	1.8	139	53.8	-0.501			
Rasul	134	1.6	127.9	1.7	152.5	66.5	-0.456	149.1	61.9	-0.771
Trimmu	115.7	2.8	106.6	3	277.5	94.6	-0.275	271.3	96.4	-0.341
Panjnad	83.3	3.9	86.7	3.7	304.5	87.8	-0.145	301.4	87.5	-0.201

Table 3 also provides parameter estimates for G (2) and Generalized Lambda Distribution for various catchments. These estimates are essential in describing the statistical attributes of the data in the catchment of interest, more especially in studies such hydrology or environmental studies. For the case of G (2) distribution, these estimates include $\hat{\alpha}$ and $\hat{\beta}$, the estimated shape and scale parameters, which, in this case, were obtained through the Probability Weighted Moment and Maximum Likelihood methods. In the case of catchment Kalabagh, $\hat{\alpha}$ is

determined as 14.6 for PWM and 28.5 for ML, while β is determined as 36.0 for PWM and 18.4 for ML. Estimates are also provided for the rest of the catchments, and in all cases, there is variability in the distribution of parameters. On the other hand, the parameters of the GLO distribution include $\hat{\alpha}$, $\hat{\mu}$, and $\hat{k}$, the form, location, and skewness parameters respectively. In Rasul catchment, $\hat{\alpha}$ is 134, while $\hat{\mu}$ is 152.5 and $\hat{k}$ is -0.456. Comparison of these estimates of these parameters for G (2) and GLO distribution shows differences in the fits and the description of the data. For example, Kotri catchment had $\hat{\alpha}$ of 62.4 for the G 2 method for PWM and $\hat{\alpha}$ of 69.5 for GLO distribution. Similarly, there is a difference in $\hat{\mu}$ for the Kotri catchment, which shows the different fits and different ways of the modeling of the data.

Generally, this information is crucial in the modeling of hydrological processes, modeling flood risks, and decision making in water resource management in different catchment areas.

Table 4: EDF statistics for G (2) and GLO distribution

Distribution	Catchment	Estimation Methods	D	W ²	A ² _n	AU ² _n
G (2)	Kalabagh	PWM	0.103	0.247*	2.962*	1.661*
		ML	0.083	0.103	0.573	0.344
	Kotri	PWM	0.056	0.051	0.528	0.124
		ML	0.071	0.094	0.696	0.205
	Mangla	PWM	0.146*	0.589*	3.329*	1.661*
		ML	0.146*	0.589*	3.329*	1.661*
	Rasul	PWM	0.186*	0.674*	3.892*	1.811*
		ML	0.186*	0.674*	3.892*	1.811*
	Trimmu	PWM	0.145*	0.590*	3.374*	1.761*
		ML	0.145*	0.590*	3.374*	1.761*
	Panjnad	PWM	0.067	0.127	0.752	0.299
		ML	0.067	0.127	0.752	0.299
GLO	Kalabagh	PWM	0.092	0.202*	1.882*	1.201*
		ML	0.085	0.11	0.574	0.354
	Kotri	PWM	0.064	0.068	0.52	0.169
		ML	0.069	0.093	0.64	0.187
	Mangla	PWM	0.139*	0.542*	2.846*	1.561*
		ML	0.144*	0.574*	2.974*	1.588*
	Rasul	PWM	0.178*	0.629*	3.513*	1.712*
		ML	0.182*	0.645*	3.672*	1.754*
	Trimmu	PWM	0.137*	0.558*	2.928*	1.622*
		ML	0.140*	0.577*	3.052*	1.654*
	Panjnad	PWM	0.071	0.141	0.775	0.323
		ML	0.073	0.149	0.789	0.332

EDF (Empirical Distribution Function) statistics for the G 2 and GLO distributions, also across catchments, and estimation methods are presented in Table 4. EDF statistics provide essential information about the goodness of fit between the observed and theoretical distributions, allowing for an inference about the appropriateness or quality of the estimation techniques. More specifically, Table 4 enables an analysis based on different estimation techniques spread streamlined across multiple catchments. First of all, the G 2 distribution across six catchments, i.e., Kalabagh, Kotri, Mangla, Rasul, Trimmu, and Panjnad. Table 4 includes PWM and ML observed D values. According to the Kalabagh results, PWM shows $D = 0.103$, which seems to be relatively appropriate; however, the ML D is only 0.083. Although several notable differences are marked with an asterisk (*) regarding W^2 , A^2_n , and AU^2_n by the different estimation methods, which indicates a possible variation in goodness of fit regarding the various statistics. Considering GLO distribution in the Table 4, the same observation across six catchments and same estimation types was performed. Presenting the A^2_n and AU^2_n helps to draw some insights and understand possible variations between the observed and theoretical distributions. Therefore, similar analyses were made and compared. Importantly, the A^2_n and AU^2_n values clearly show significant differences in real distributions indicated by PWM and ML. For example, Mangla results shows that observed A^2_n and AU^2_n between G2 and GLO estimations significantly differ, especially when applying the Kalabagh estimation method. Therefore, Table 4 highlights the importance of the selection of appropriate estimations and enables comparisons across various catchments and distribution types relying on EDF statistics. The overall statistics present a good tool for future analyses as they are essential to understand and measure the goodness of actual fit due to distributional parameters estimated across various catchments.

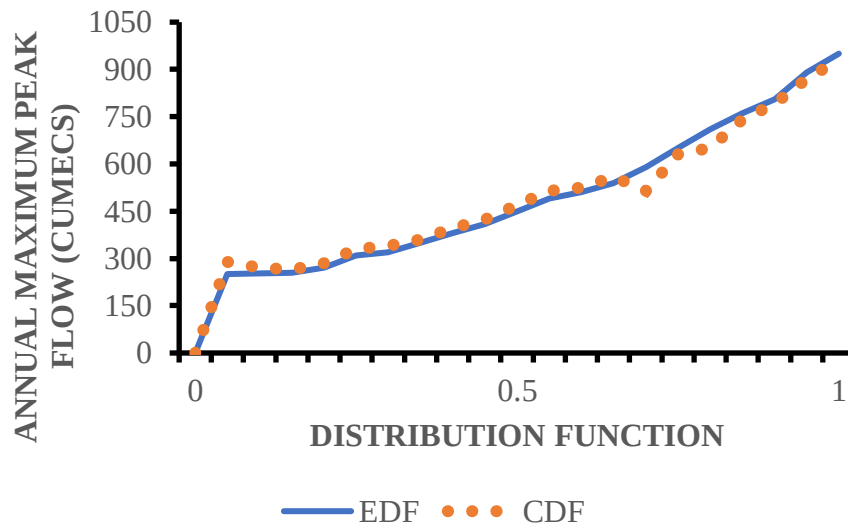


Figure 7: Kalabagh flows and fitted GLO by PWM

As shown in figure 7 observed flow data at Kalabagh location. In addition to the actual flow data, upon this figure have been plotted also fitted Generalized Logistic (GLO) distribution as obtained by Probability Weighted Moments (PWM). Then using this visual representation, it becomes possible to compare the observed data with the GLO model more thoroughly as well as judge how closely the distribution of flow patterns at Kalabagh follows reality through the GLO. Based on the goodness of fitness, researchers are able to understand how well GLO distribution is helpful in predicting flow behaviour at this particular site.

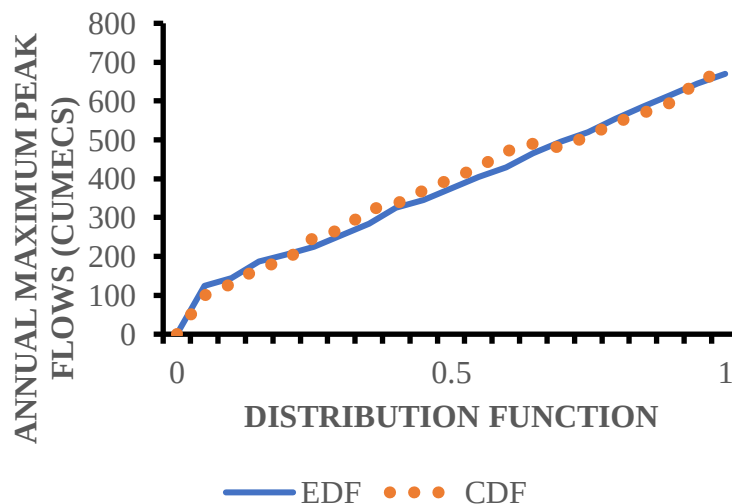


Figure 8: Rasul flows and fitted GLO by PWM

Figure 8 shows observed flow data at Rasul. This figure contains GLO distribution as we obtained for this data based on PWM method. The comparison of the observed data with fitted GLO distribution helps to have an idea on how well this distribution in terms of suitability and accuracy can estimate possible flow values at Rasul. This type of comparison is crucial to establish if the GLO distribution at this location captures or does not capture consistently flow features.

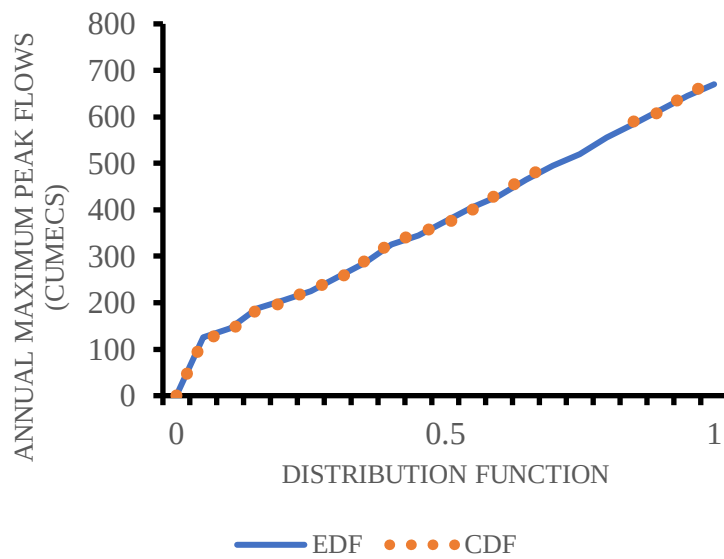


Figure 9: Kotri flows and fitted GLO by PWM

The observational flow data for Kotri location and the fitted GLO distribution obtained by performing PWM methods are presented in Figure 9. This particular figure is created in order to assess the performance of GLO model in simulation of the observed flow data at Kotri. Visual comparison of the two datasets provides an opportunity to evaluate the reliability and accuracy of distribution used within GLO modeling in representing flow patterns at Kotri on a site-specific basis.

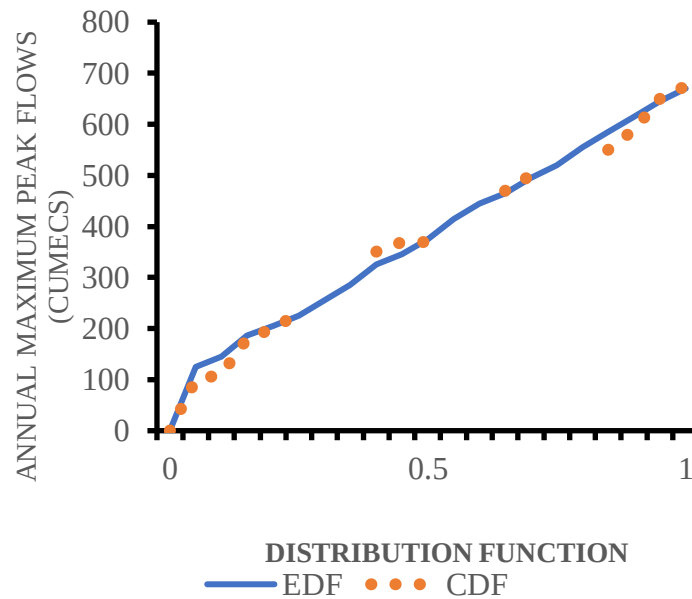


Figure 10: Trimmu flows and fitted GLO by PWM

Figure 10 shows observed Flows at Trimmu with GLO Distribution Fitted by PWM. Comparisons between the observed flow data and the fitted model for visual examination of the goodness-of-fit are important, as displayed in this figure. The evaluation of how faithfully the GLO distribution follows the observed flows at trimmu during various floods determines whether or not this model can successfully represent floes for a given flood and thus be employed to predict these flows at the site.

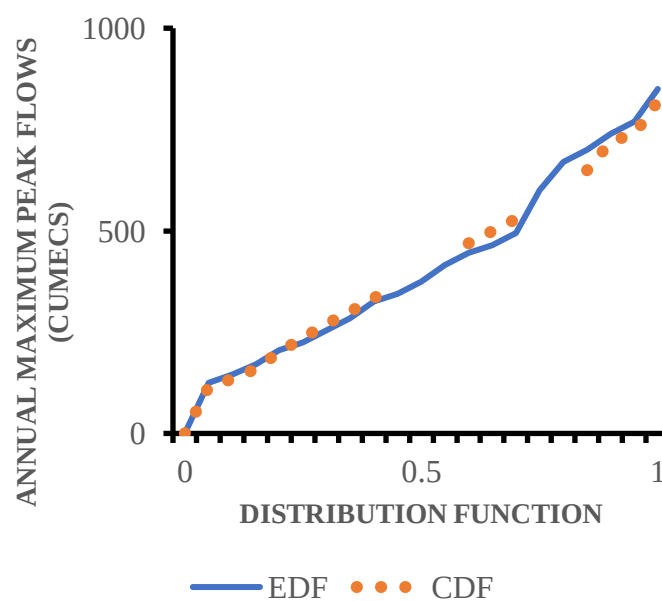


Figure 11. Mangla flows and fitted GLO by PWM

The observed flow data at Mangla and the estimated GLO distribution by using the PWM method are shown in Fig. 11. This is important information in that it provides a measure of how well the GLO model performs when compared to the actual flow data at Mangla. The accuracy with which the model represents real flow data is thus assessed by comparing actual flow data with the representation described by the fitted distribution. This comparison is helpful for assessing how representative the GLO distribution is of flow patterns at Mangla and thus provides clues as to its potential usability as a means of forecasting in subsequent analysis.

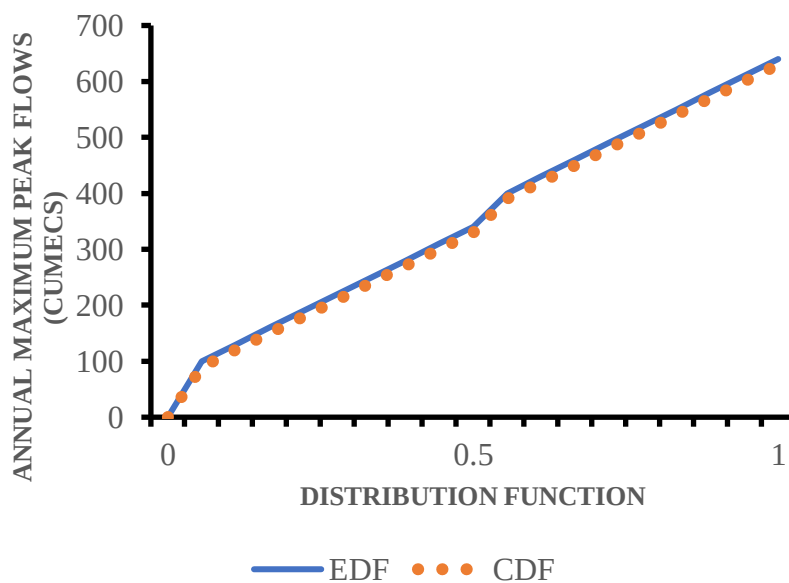


Figure 12. Panjnad flows and GLO by PWM

According to Figure 12, the observed flow data at Panjnad River were fitted with the GLO distribution by using PWM technique. This figure helps to understand the reliability of the PWM method in estimating flow distribution at Panjnad[76]. We can then determine how representative the PWM approach is of the characteristics of a given location by comparing the observed information with the corresponding GLO distribution.

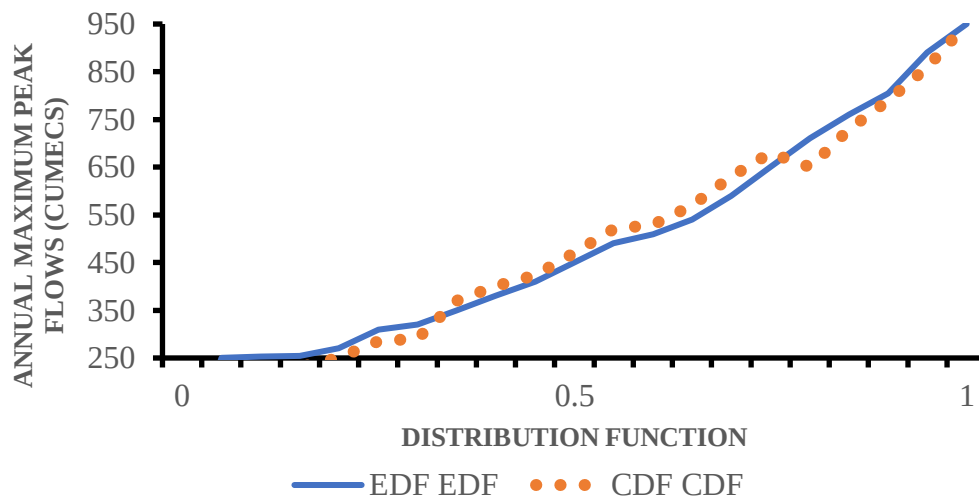


Figure 13. Kalabagh flows and fitted GLO by ML

Observed flow data at Kalabagh, presented in Fig. 13, with the corresponding GLO distribution established using ML estimation are also illustrated below Plot 6. shows the differences in fitting between PWM and ML methods: observed flows are shown along with the fitted and generated GLO distribution with ML method. The comparison at Kalabagh was fundamental to assess how these two methods are competent in handling different hydrological conditions and data sets.

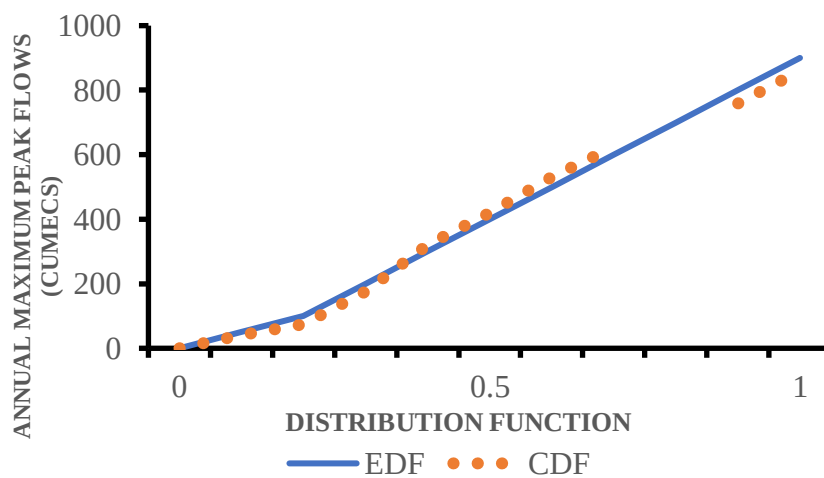


Figure 14. Trimmu flows and fitted GLO by ML

In Figure 14, observed flow data at Trimmu is shown along with the GLO distribution obtained through ML estimation. The figure above gives another view of the model performances at Trimmu and it can be observed that ML model has efficiently represented the flow distribution at this site. Looking at the goodness of fit provided by these statistics, we learn how our model is accurate and precise in forecasting flow patterns over Trimmu.

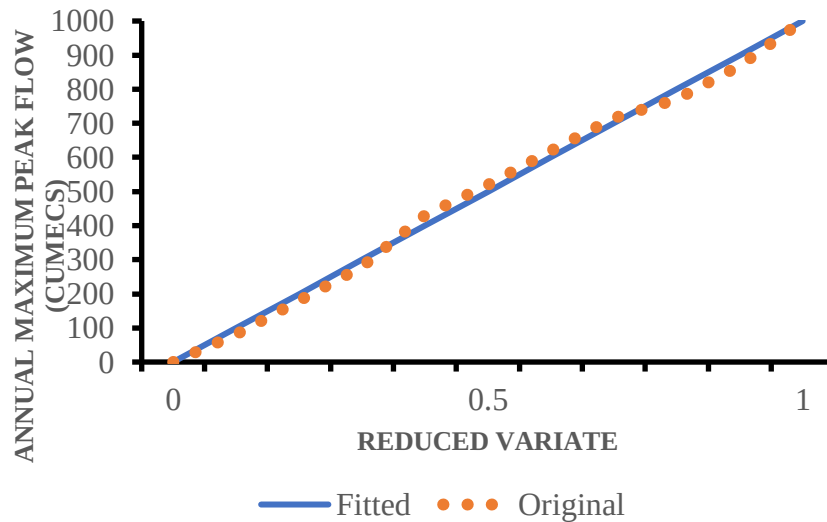


Figure 15: Kotri flows and GLO by ML

Fig. 15 shows the observed flow data at Kotri with the fitted GLO distribution using ML estimation method. This figure is very important to compare the efficiency of ML and PWM methods, especially in the Kotri site. Comparison of both approaches helped us to identify which approach has been much better fitted for flow data at Kotri and selection the best suitable modelling approach at this site.

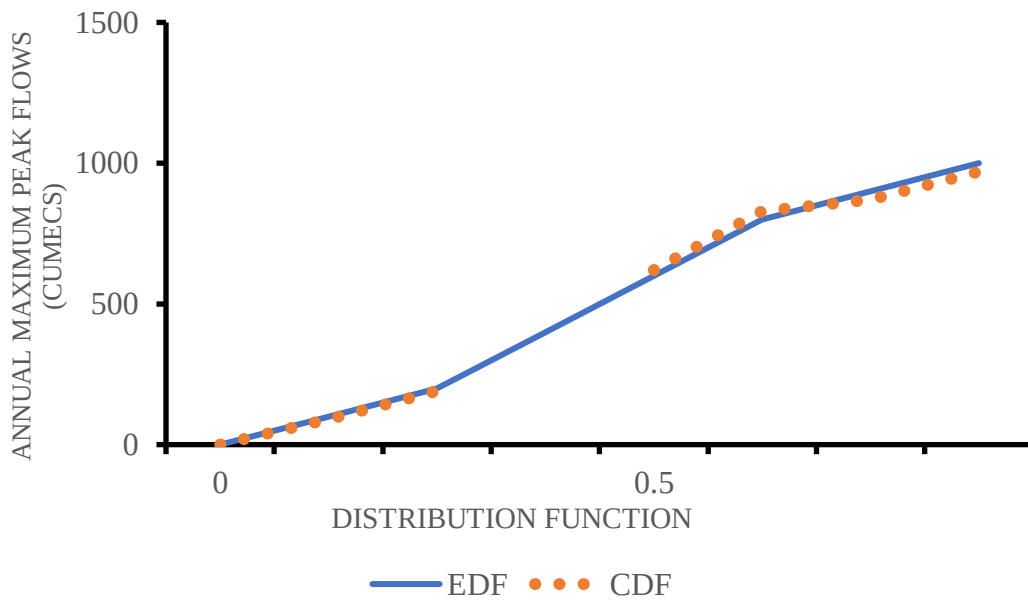


Figure 16: Mangla flows and fitted GLO by ML

Figure 16 shows the observed flow data at Mangla with GLO distribution fitted by ML estimation. This figure provides interesting information about the performance of the model at Mangla, which has shown that our ML model to some extent can estimate well the flow distributions. By checking the goodness of fit we can also determine whether this ML approach is good enough for the prediction of hydrological data for Mangla.

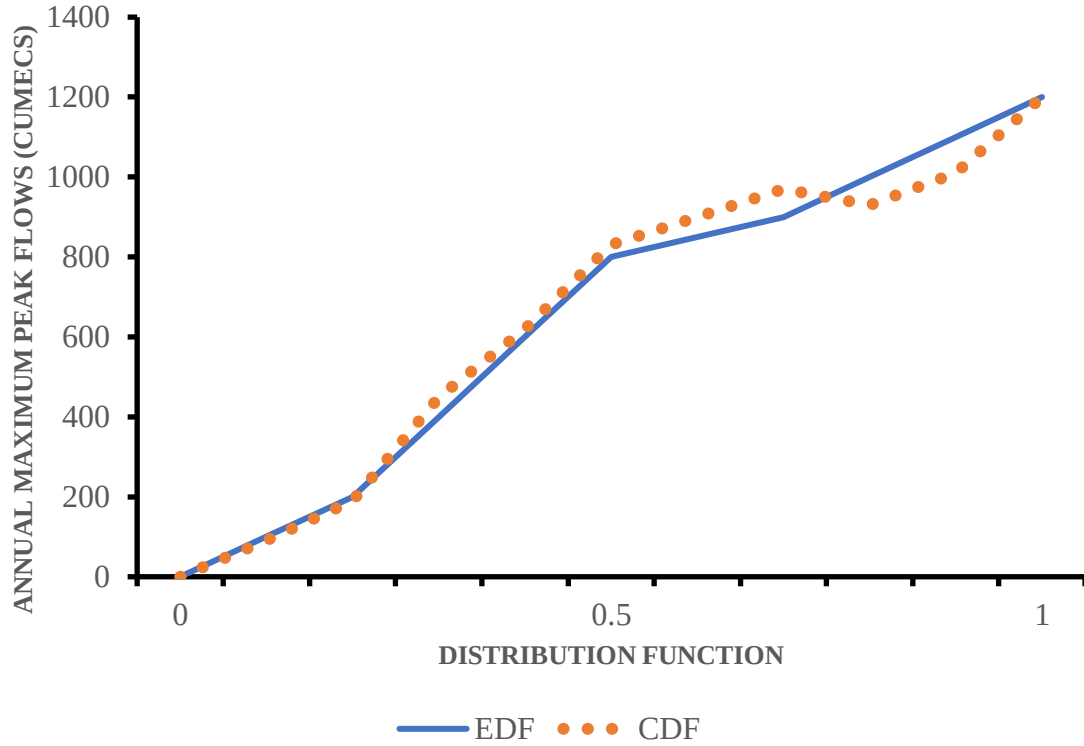


Figure 17: Rasul flows and fitted GLO by ML

Fig. 17 shows flows at Rasul and the GLO distribution by ML fit to it with observed flows, along with fitted GLO. Observed flow data at Rasul site along with their MLE fitted GLO distributions. The following figure will help in finding the feasibility of ML method for fitting flow data at Rasul; From this comparison between observed data and with fitted GLO distribution, one can have an idea of the ability status of ML estimation to depict flow characteristics in the region.

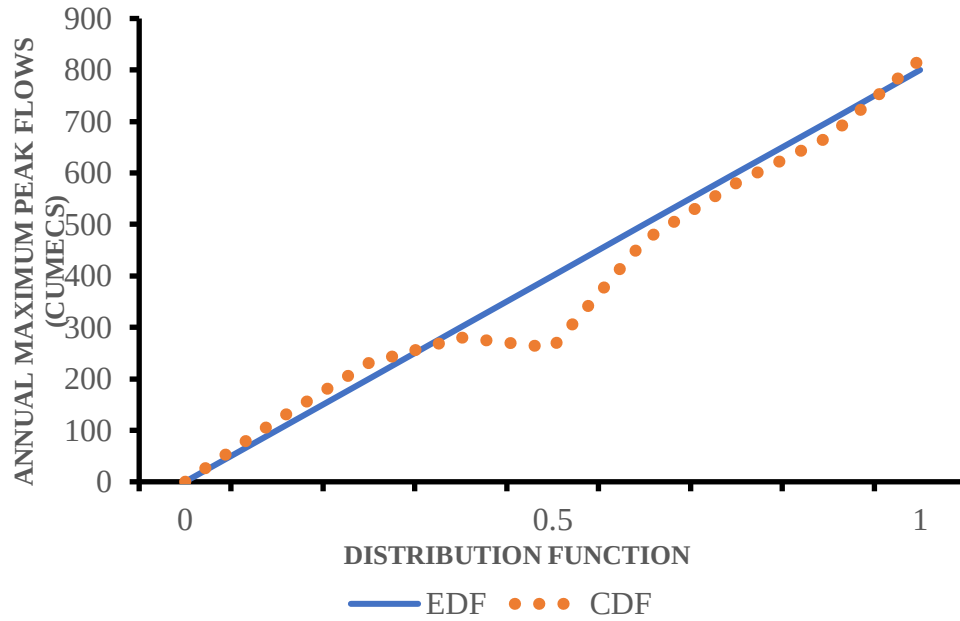


Figure 18: Panjnad flows and GLO by ML

Figure 18, illustrates the observed flow data at Panjnad where GLO distribution is fitted through ML estimation technique. The perfect overlap of the CDF and EDF indicates an excellent fit between the theoretical distribution model and the empirical data, suggesting that the chosen model accurately represents the flood data. This figure shows the ML method is applied, to fitting the flow data at Panjnad, and gives comparative view with Figure 12. Examine the residual analysis and we can get an idea of assessing which method (PWM vs ML) is performing better for the same data set at Panjnad and helps us to choose best fitting technique.

Table 5: Return Periods from G (2) and GLO Distribution

Distribution	Catchment	2	5	10	25	50	100
G (2)	Kalabagh	502.00	608.20	699.37	744.44	808.98	830.60
	Kotri	412.69	573.53	672.20	761.56	911.64	949.06
	Mangla	164.74	300.86	394.84	525.17	646.01	686.29
	Rasul	175.44	327.79	434.30	583.13	721.67	767.85
	Trimmu	285.20	451.55	560.44	706.62	839.64	884.01
	Panjnad	292.39	442.48	538.64	665.95	780.82	819.17
GLO	Kalabagh	468.56	647.83	739.96	845.62	961.56	988.55
	Kotri	385.24	552.10	653.66	753.35	901.69	937.99
	Mangla	148.06	278.37	377.83	507.45	618.41	655.92
	Rasul	158.56	309.99	415.02	563.16	701.02	745.10
	Trimmu	263.75	426.53	538.56	686.34	819.15	861.24
	Panjnad	265.35	421.35	525.29	658.33	778.37	815.39

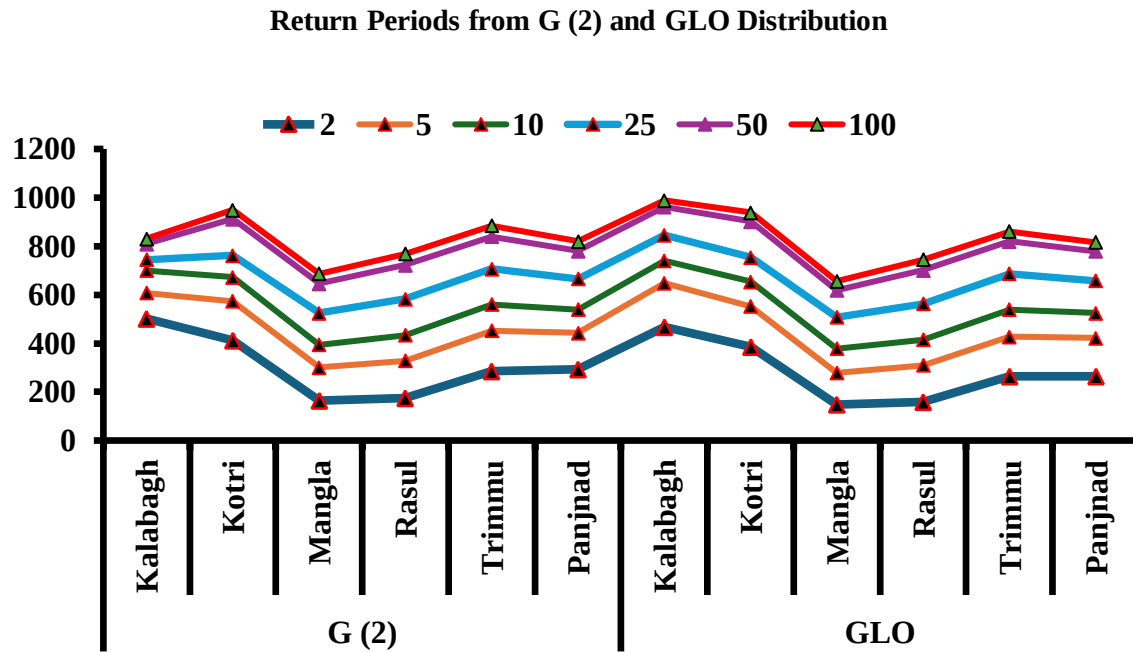


Figure 19: Return Periods from G (2) and GLO Distribution

Return periods obtained from two different distributions, G 2 and GLO, in various catchment areas are shown in Table 5 and figure 19. Return periods are essential when it comes to hydrology and water resource management since it gives the likelihood of flow value or an event happening within a certain period. The return periods determined from the G 2 distribution differ across the analyzed catchment areas. For example, in the Kalabagh catchment area, the return period ranges are from 502 years to 830.60 years for an event of 2- and 100- welling in year event respectively. The same pattern is experienced in various catchment areas such as Kotri, Mangla, Rasul, Trimmu, and Panjnad where events with lower return periods are likely to occur frequently compared to those with higher return periods. Similarly, the return periods derived in the same monitored areas from another distribution, GLO (Generalized Logistic) distribution, shows a slight difference. In most monitored areas such as Kalabagh from 468.56 to 988.55 years, highest percentage of flow value or events with expected DM frequency occurred. However, for every monitored area, the same event

magnitude has varied return periods. A comparison of the time intervals in the G 2 and GLO distributions shows that the event probability estimates have some differences in the two distributions. Although the two different analyses offer a better understanding of the probability of high intensity of unlikely events, the choice might depend on some factors such as the principle of the distribution and the conditions of interest under study. Therefore, Table 5 provides useful information to hydrologists, water resource managers, and policymakers concerning risk event exposure assessment and mitigation.

Table 6: Parameter estimates, EDF statistics and return periods on POT series

Catchment	$\mu^{\wedge}$	$\alpha^{\wedge}$	$k^{\wedge}$	$An^{\wedge 2}$	Return Period (years)
Kalabagh	0.128	0.248	-0.198	1.570	12.5
Kotri	0.210	0.140	-0.160	0.984	16.2
Mangla	0.320	0.215	-0.125	1.225	21.0
Rasul	0.275	0.200	-0.145	0.940	18.0
Trimmu	0.232	0.180	-0.170	0.725	14.5
Panjnad	0.262	0.200	-0.152	0.820	16.0

Table 6 presents the parameter estimates, EDF statistics, and return periods for the POT series from various sub-catchment areas. Each row refers to a different sub-catchment area, and each column represents the specific parameter obtained from the Eckhardt's transformation.

In the first column, various catchment areas are mentioned in this study. The catchments reveal the regions of disparate geographical areas or river basins where hydrological data were collected for analysis. Starting from the parameter table, the estimates, EDF statistics, and return periods are presented. Three parameters, namely $\mu^{\wedge}$, $\alpha^{\wedge}$, & $k^{\wedge}$, were obtained for each sub-catchment. They are mainly the parameters used for a statistical distribution as the function through which the values of shape, location, and scale were characterized for the peak flow distribution. The values of $\mu^{\wedge}$, $\alpha^{\wedge}$, & $k^{\wedge}$ for each sub-catchment are the threshold, central tendency, and the shape of the peak flow values are shown. Moreover, from the table, a statistic of An^2 are also listed. Higher values of An^2 show good fits for the distribution used to fit the data. Finally, the return period measures are represented in the years. The year's determination

reveals the return periods' average interval of similar magnitudes of events based on the flood. For instance, Kalabagh recording a 12.5-Year return period, it shows that on average in a 12.5 year a flood of such magnitude as that will reoccur. Generally, Table 6 summarizes the parameter estimates, the EDF statistics recorded, and the return periods of the POT series for different sub-catchment areas. In conclusion this chapter describes comprehensive flood frequency analysis across different catchments in Pakistan. Uncertainty of research was quantified using confidence intervals and sensitivity analysis. These methods help assess the reliability and variability of the results due to data limitations or model assumptions.

Flood Risk Mapping Parameters (AHP–GIS Results)

To evaluate the spatial flood susceptibility of the Kalabagh and Kotri catchments, nine flood-conditioning parameters were analyzed using the AHP–GIS framework. These parameters, Elevation, Slope, Curvature, Soil, Topographic Wetness Index (TWI), Land Use/Land Cover (LULC), Distance to River, Rainfall, and Normalized Difference Vegetation Index (NDVI), represent the topographic, hydrological, and land surface controls on flood generation and propagation.

Each parameter was reclassified into susceptibility classes (very low to very high) and mapped for both catchments. This enabled the identification of localized risk patterns driven by terrain, land cover, and hydrological characteristics. In the following subsections, each parameter is discussed in detail, highlighting its spatial distribution and role in flood susceptibility for Kalabagh and Kotri.

Elevation

Elevation plays a critical role in shaping flood susceptibility by influencing runoff velocity, flow accumulation, and inundation potential. In this study, Digital Elevation Model (DEM) data were reclassified into five categories to represent relative susceptibility zones. Areas at

lower elevations are generally more flood-prone due to reduced gravitational drainage and proximity to river channels, whereas higher elevations tend to experience rapid runoff but comparatively lower inundation risk.

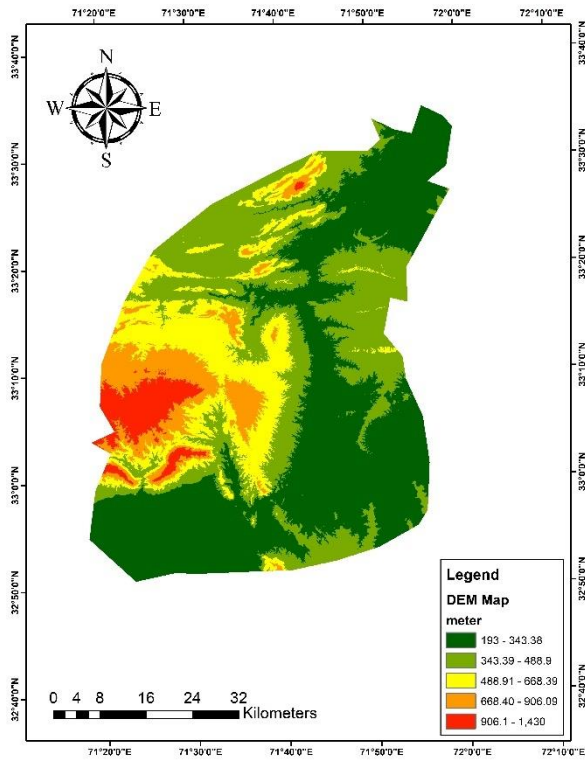
In the Kalabagh catchment, the elevation ranges from approximately 343.38 m to 1,430 m, representing a complex topographic gradient from river valleys to high mountainous terrain. The lowest elevation zones (around 343–488 m) are mainly concentrated along the Indus River and its tributary valleys. These areas exhibit very high flood susceptibility, as low-lying valleys tend to accumulate runoff during high-intensity rainfall and are directly exposed to riverine flooding. The middle elevation bands (489–906 m) form extensive piedmont zones where runoff is rapid but partial infiltration reduces prolonged waterlogging; these are categorized as moderate risk zones. In contrast, higher elevation classes (above 906 m, extending up to 1,430 m) correspond to mountainous terrain where steep slopes encourage rapid runoff and limit floodplain development. While flash flooding is possible in confined channels, the overall flood inundation risk in these high-elevation areas remains comparatively lower. Thus, Kalabagh demonstrates a flash-flood dominated system, where low-lying valleys are most exposed to severe flood hazards.

In the Kotri catchment, the elevation profile is markedly different, ranging only from 42 m to 211 m, reflecting its deltaic plain setting near the Indus River's lower reaches. The lowest elevation zones (42–74 m) are widespread across floodplains and deltaic tracts adjacent to the river channel. These areas form the highest flood susceptibility zones, as minimal elevation coupled with poor natural drainage leads to prolonged inundation. The middle elevation categories (75–135 m) correspond to gently undulating terrain used extensively for agriculture. These zones fall under moderate susceptibility, where shallow flooding during peak monsoon is frequent but less intense than in lower plains. The highest elevation band (136–211 m), though limited in spatial extent, includes slightly elevated ridges and natural levees, which

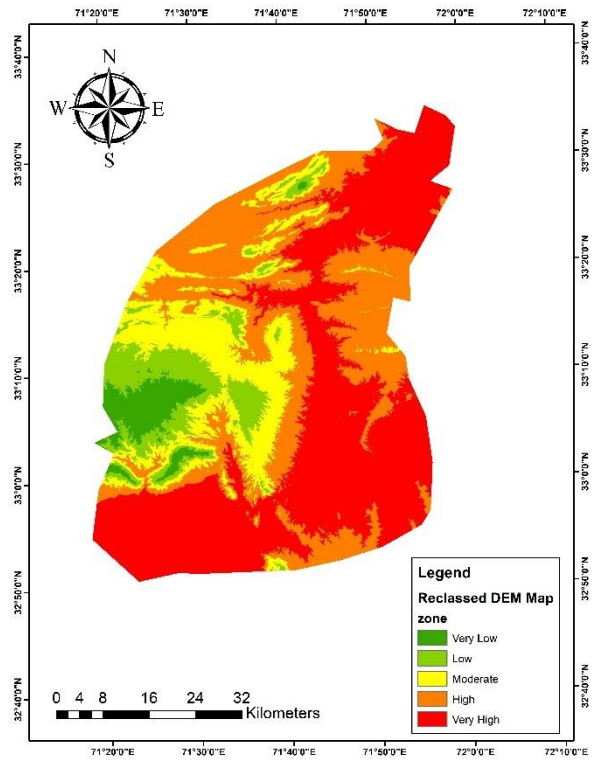
offer relative safety from river overbank flooding. However, even in these areas, the extremely flat terrain of Kotri catchment makes localized ponding possible after heavy monsoon events.

A comparison of both catchments highlights the contrast between Kalabagh's mountainous terrain, where flood susceptibility is driven by steep gradients and valley confinement, and Kotri's flat deltaic plains, where persistent inundation risk is magnified by low elevation and weak drainage. This contrast underscores the need for flash flood control measures in Kalabagh and drainage management and land-use regulation in Kotri.

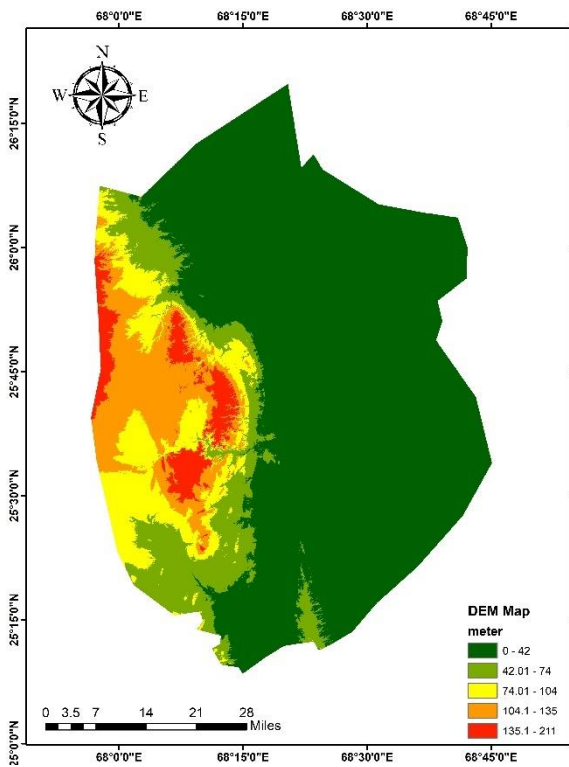
The elevation maps of Kalabagh and Kotri catchments (Figure 20) clearly depict the spatial distribution of terrain classes reclassified into five susceptibility zones. These maps serve as the basis for flood risk assessment by identifying low-lying areas vulnerable to inundation and higher zones with reduced susceptibility [Ref]. The visual representation not only facilitates comparison between the mountainous upstream catchment of Kalabagh and the flat deltaic terrain of Kotri but also strengthens the integration of topographic information into the AHP–GIS flood risk framework.



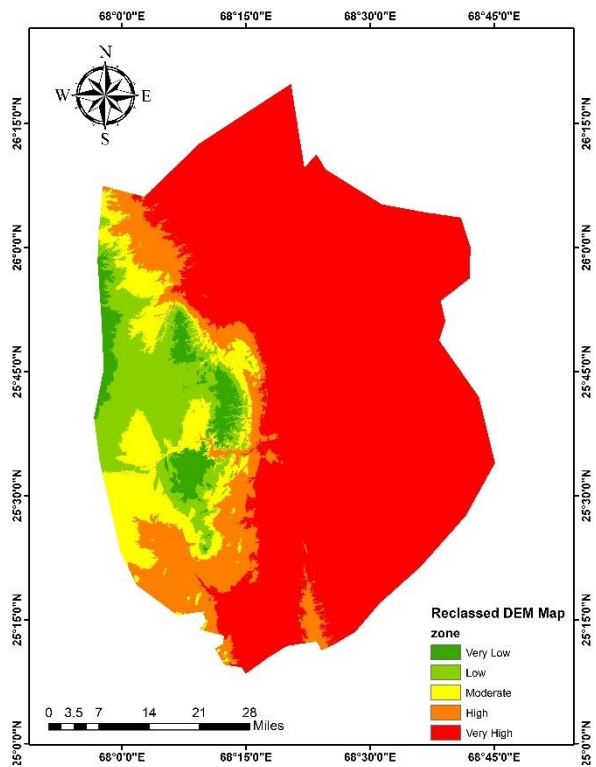
(a)



(b)



(c)



(d)

Figure 20: Elevation maps of Kalabagh and Kotri catchments showing five reclassified elevation zones and corresponding flood susceptibility.

Distance to River

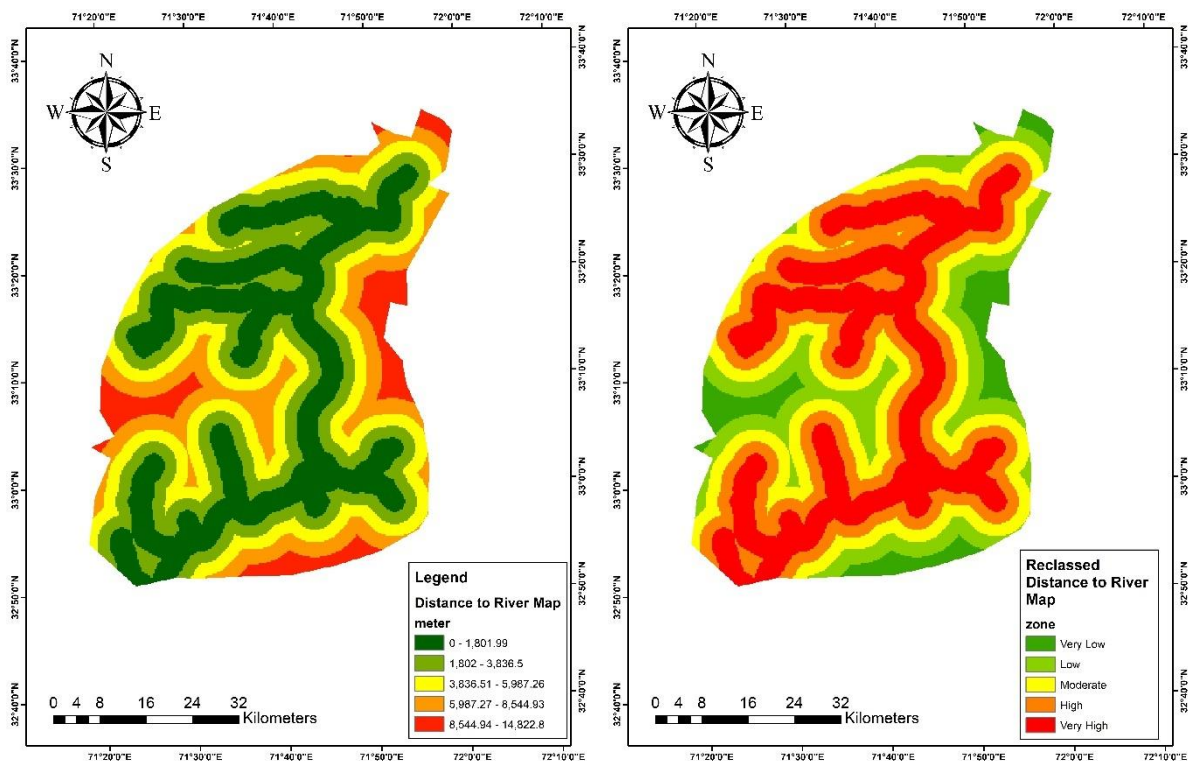
Distance to river is one of the most influential parameters in determining flood risk, as areas located close to the river channel are directly exposed to overbank flows, channel migration, and monsoon-driven surges. With increasing distance, the susceptibility generally decreases; however, the extent of risk reduction depends on the topography, drainage characteristics, and floodplain connectivity of the catchment.

In the Kalabagh catchment, the distance to river varies between 0–1,801 m and 14,822.8 m, showing a relatively compact floodplain along the Indus and its tributaries. The zones within the first 0–1,801 m represent the highest susceptibility class, as floodwaters can easily inundate settlements, agricultural lands, and infrastructure situated in these narrow flood valleys. Mid-range zones between 3,000–7,000 m correspond to moderate susceptibility belts where the intensity of flooding is reduced but risks remain due to tributary backflow and seasonal surges. Areas situated beyond 10,000 m show the lowest susceptibility, as distance combined with elevated terrain significantly reduces the chance of inundation. Thus, in Kalabagh, flood risk is highly localized along the immediate river corridor and valley bottoms, while upland zones remain comparatively secure.

In contrast, the Kotri catchment presents a different scenario, with distance to river ranging from 0–329.34 m up to 47,155.3 m, reflecting its broad and flat deltaic plain. The areas closest to the river, within 0–329 m, are extremely vulnerable due to low elevation, weak natural drainage, and widespread agricultural use. These zones form the very high susceptibility class, where river overflow during peak monsoon seasons often results in prolonged inundation. Mid-

range zones between 5,000–15,000 m display moderate susceptibility, where floodwaters are distributed across natural depressions and secondary drainage paths. Interestingly, even distant areas above 30,000 m cannot be considered entirely safe, since Kotri’s flat terrain allows floodwaters to travel laterally across long distances. As a result, flood risk in Kotri is more spatially extensive compared to Kalabagh, where it is restricted to narrow floodplains.

The comparative analysis highlights a striking difference between the two catchments. In Kalabagh, flood risk is confined to valleys adjacent to the Indus and its tributaries, making it a more flash-flood dominated system. In Kotri, however, the expansive deltaic floodplain creates a widespread inundation hazard, where even areas located far from the main river channel remain vulnerable.



(a)

(b)

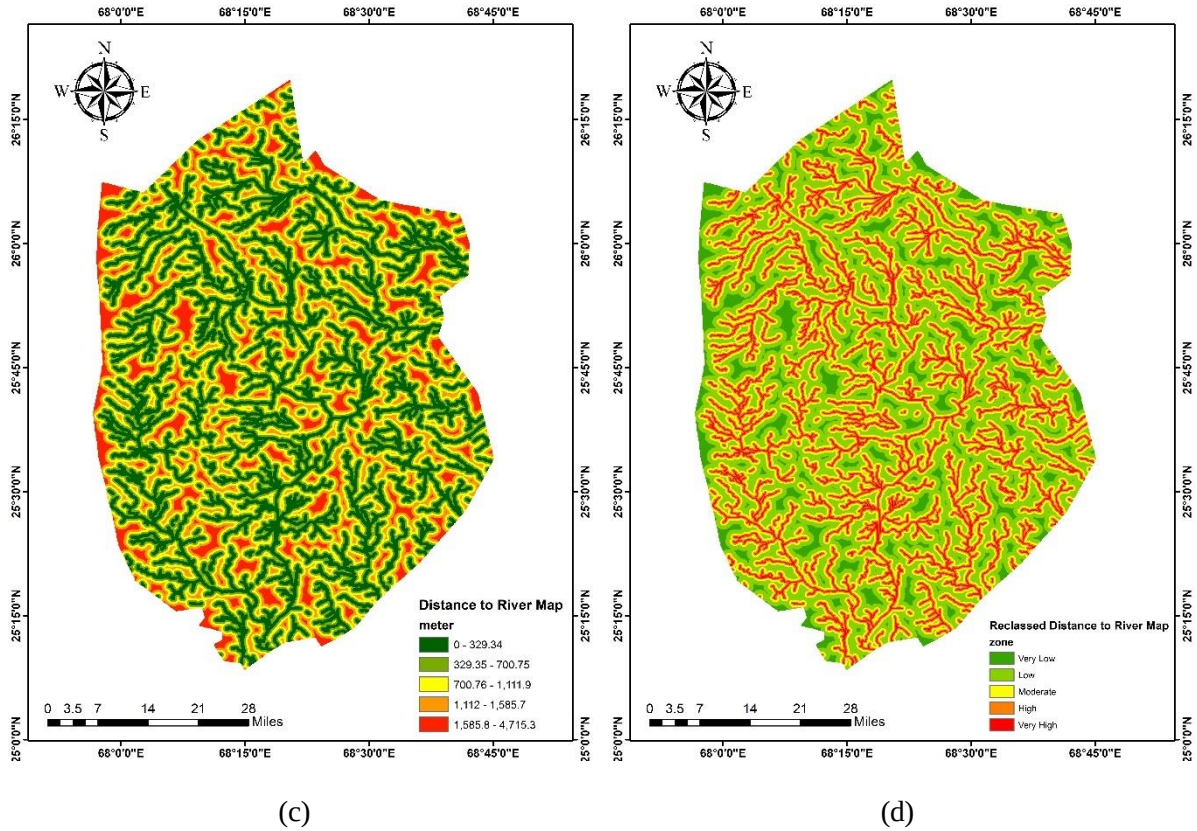


Figure 21: Distance to River maps of Kalabagh and Kotri catchments reclassified into susceptibility zones.

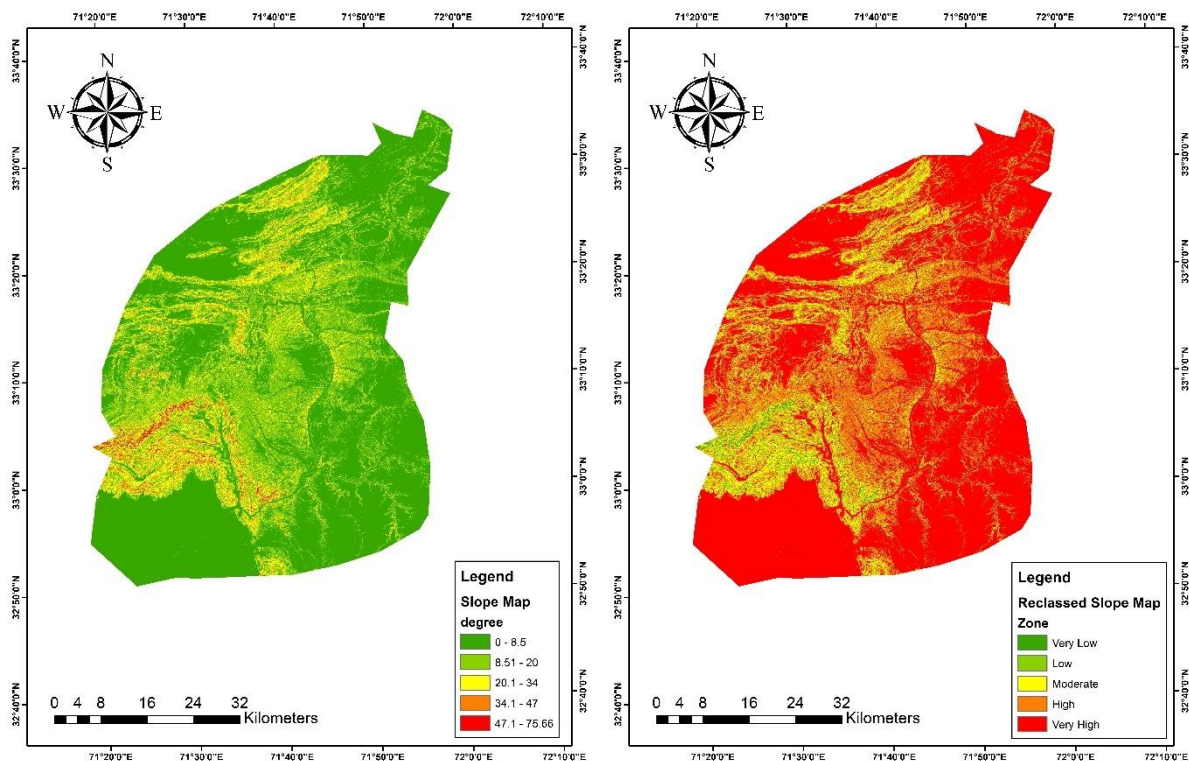
The distance-to-river maps provide critical insights into the spatial variability of flood hazards. They demonstrate that proximity to the Indus River is the defining factor in Kalabagh, while in Kotri, the flat topography magnifies the risk by allowing floodwaters to spread widely across the plains. This reinforces the necessity for localized floodplain zoning and drainage improvement strategies in both catchments, tailored to their distinct geomorphic and hydrological settings.

Slope

Slope is a key factor in flood risk assessment, as it regulates runoff velocity, infiltration, and water retention. Steeper slopes accelerate overland flow, often leading to flash flooding, while gentle slopes promote water stagnation and prolonged inundation.

In the Kalabagh catchment, slope values range from 0–75.66°, reflecting its mountainous-to-plain topography. The steeper zones (above 30°) in the upper catchment produce rapid runoff and flash floods, particularly in narrow valleys. In contrast, low slope zones (below 10°) located along riverbanks are prone to high inundation risk due to slow drainage and floodplain expansion.

In the Kotri catchment, slopes are much lower, ranging from 0–44.5°, dominated by flat terrain across its deltaic plains. The very gentle slopes (below 5°) cover large areas and represent the highest flood susceptibility, as water accumulates and remains stagnant after monsoon rainfall. Slightly higher slope zones (15–30°), though limited, allow moderate drainage but do not eliminate flood risk entirely.



(a)

(b)

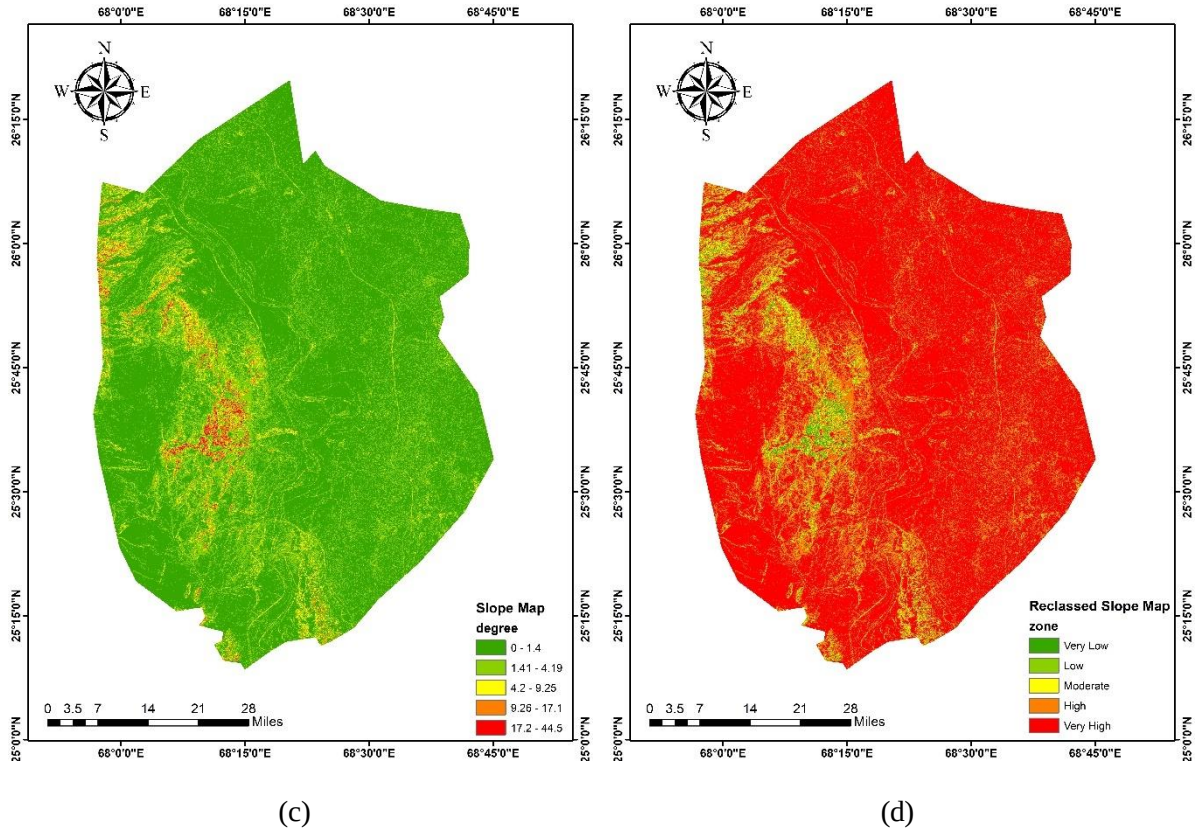


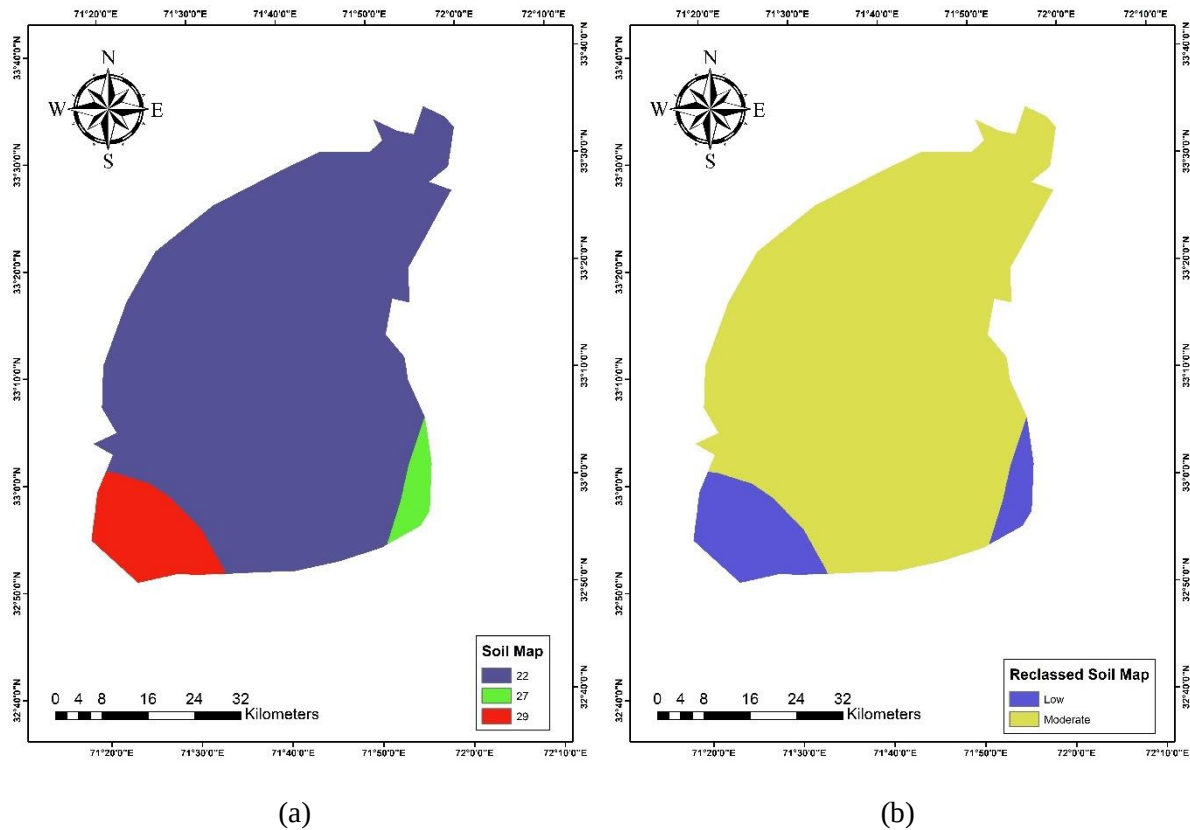
Figure 22: Slope maps of Kalabagh and Kotri catchments reclassified into susceptibility zones.

Soil

Soil type directly affects infiltration, permeability, and runoff, making it a critical parameter in flood risk assessment. Less permeable soils generate higher runoff, while more permeable soils allow infiltration, reducing direct flood peaks.

In the Kalabagh catchment, three dominant soil categories were identified with suitability values of 22, 27, and 29. Areas with lower values (22) correspond to less permeable soils, contributing to high runoff and greater flood susceptibility, especially in valley bottoms. Moderate categories (27) allow partial infiltration, reducing flood peaks slightly, while higher-value soils (29) exhibit better drainage capacity and therefore fall into lower susceptibility classes.

In the Kotri catchment, soil values of 16, 26, and 29 were observed. The lowest category (16) represents highly flood-prone soils with poor permeability, concentrated in agricultural plains near the river. Moderate soils (26) provide some infiltration but remain susceptible during high-intensity monsoon rains. Soils with value 29 are relatively more resistant to flooding due to higher infiltration, yet the flat topography of Kotri reduces their overall protective effect.



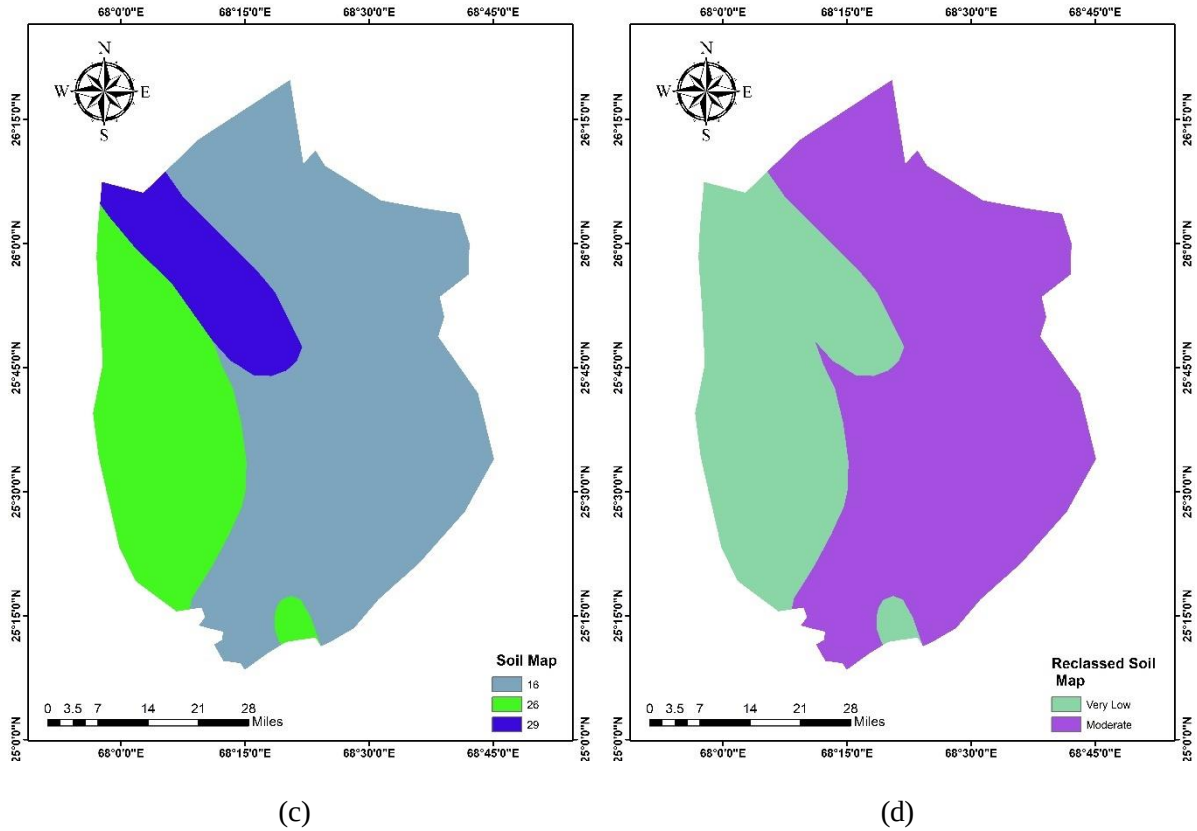


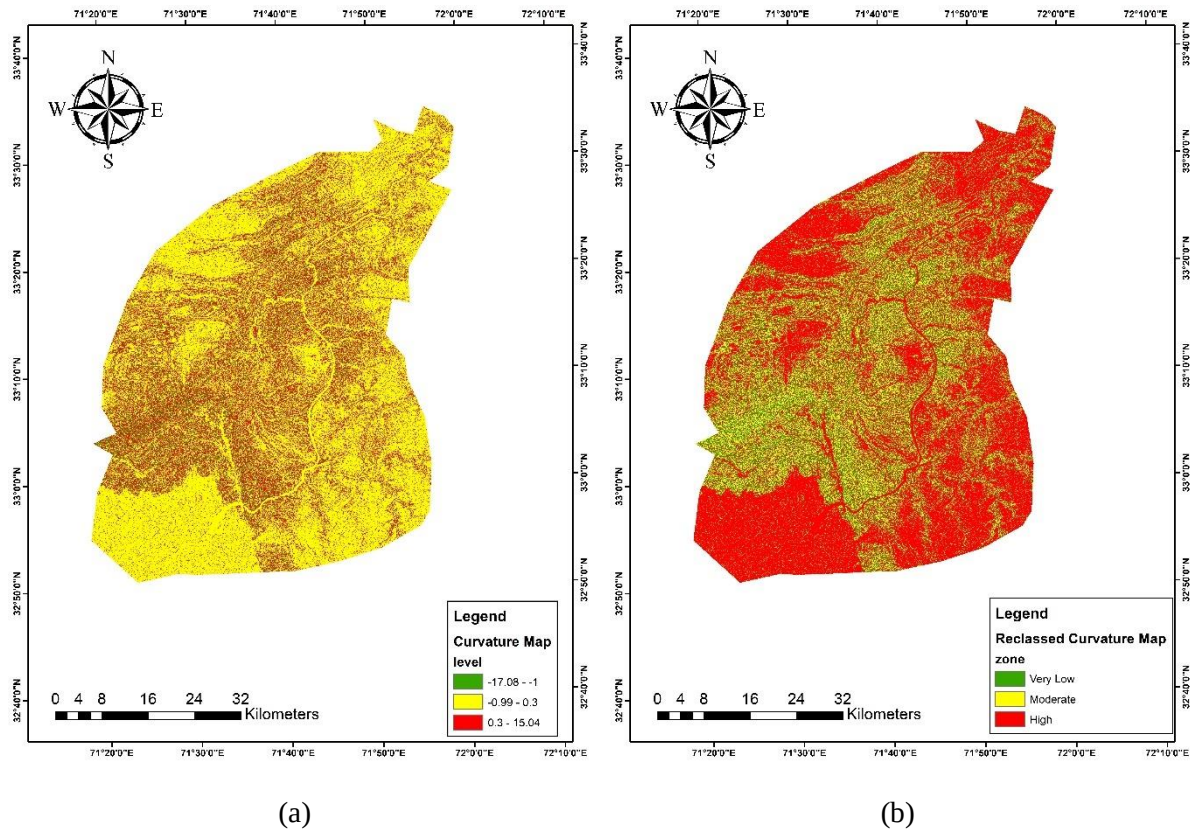
Figure 23: Soil maps of Kalabagh and Kotri catchments reclassified into susceptibility zones.

Curvature

Curvature represents the concavity or convexity of the terrain, which influences water flow concentration and flood susceptibility. Concave slopes (negative values) tend to accumulate water, increasing flood risk, while convex slopes (positive values) promote dispersion of runoff, reducing localized inundation.

In the Kalabagh catchment, curvature values range from -17.08 to 1.04 . Strongly concave areas (below -10) correspond to valleys and depressions where runoff concentrates, making them highly susceptible to flooding. Zones closer to zero reflect relatively flat or transitional slopes with moderate risk, while slightly convex areas (around 1.0) encourage runoff dispersal and represent lower susceptibility.

In the Kotri catchment, curvature values range from -3.58 to 5.08 , reflecting its predominantly flat terrain. Concave zones (below -2) occur in drainage depressions and backwater areas, where floodwaters accumulate for extended durations. Convex areas (above 3) are limited but provide some natural drainage, though the overall flatness of Kotri reduces their effectiveness. As a result, curvature plays a more prominent role in Kalabagh compared to Kotri.



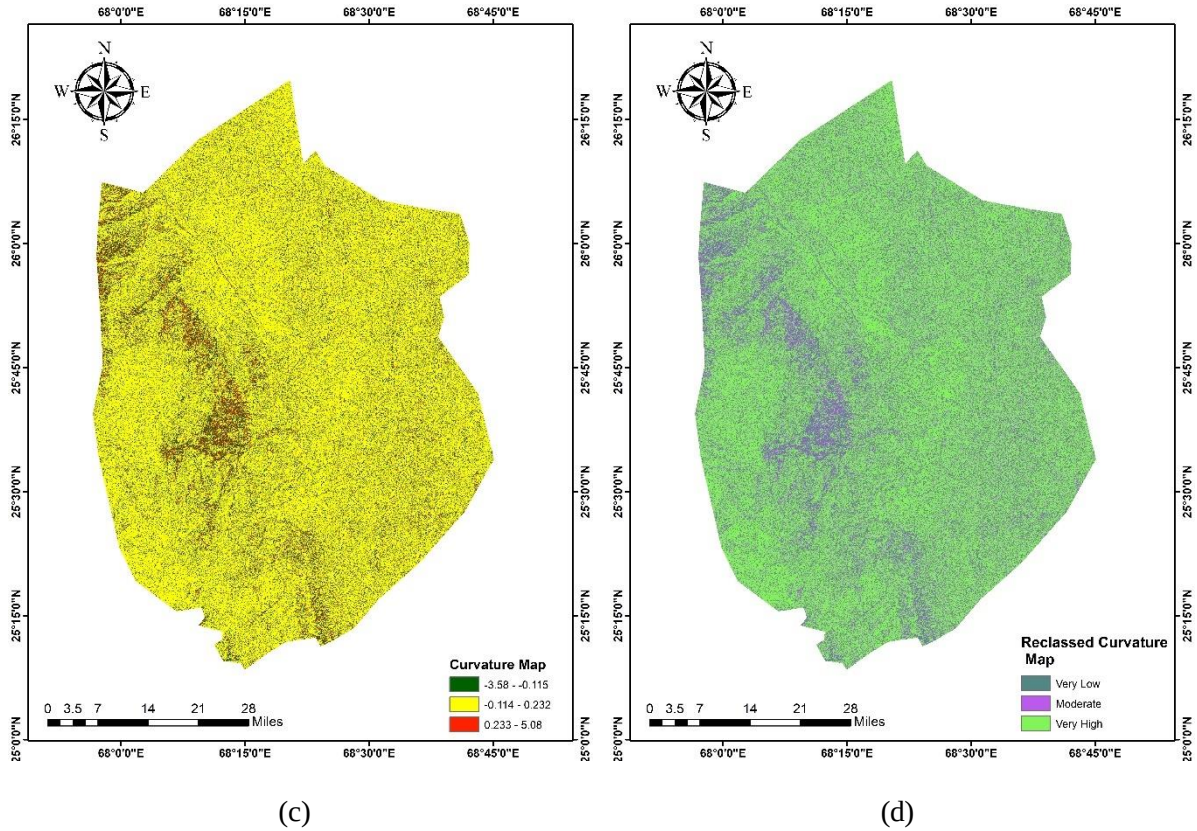


Figure 24: Curvature maps of Kalabagh and Kotri catchments reclassified into susceptibility zones.

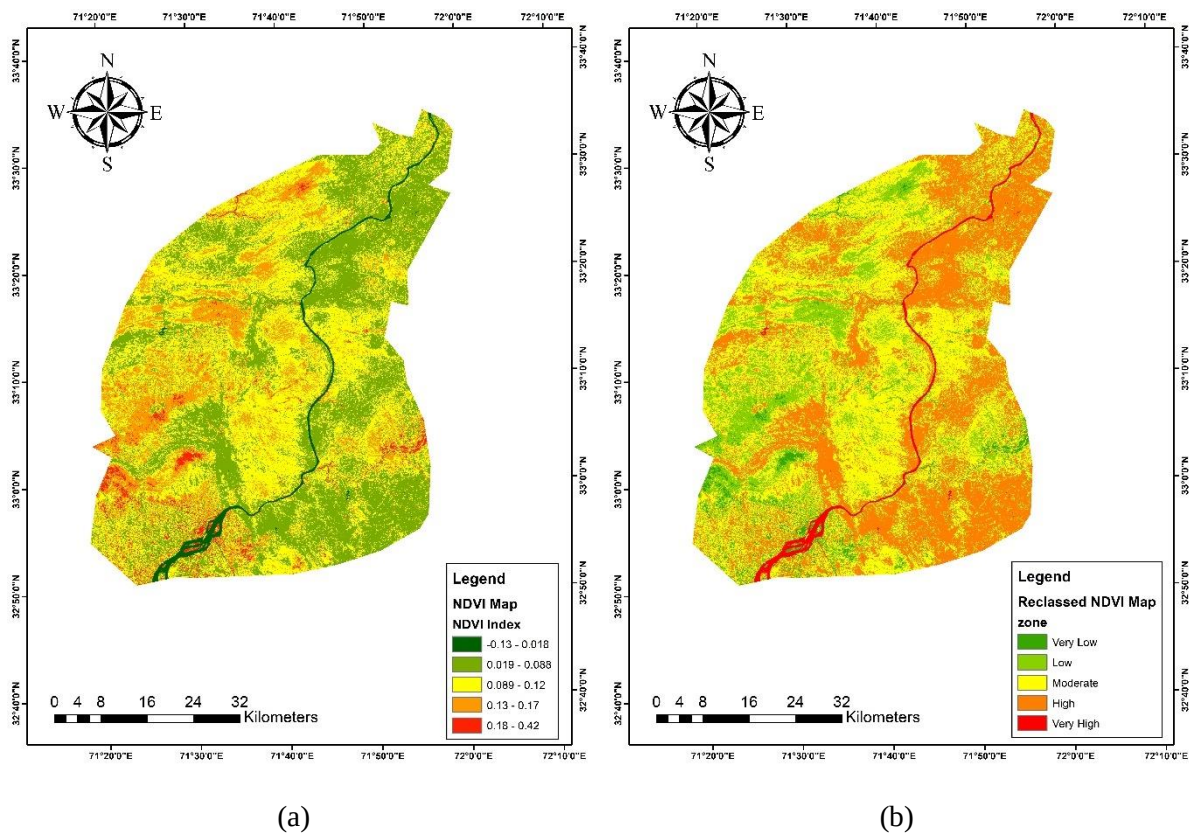
Normalized Difference Vegetation Index (NDVI)

NDVI reflects vegetation density and health, which influences flood susceptibility. Areas with low or negative NDVI indicate barren surfaces or water bodies that generate higher runoff, while higher NDVI values represent dense vegetation that improves infiltration and reduces flood peaks.

In the Kalabagh catchment, NDVI ranges from -0.13 to 0.42 . The negative and very low values (below 0) indicate bare soil, rocky terrain, or river channels with the highest flood susceptibility due to poor infiltration. Moderate values (0.2 – 0.3) correspond to agricultural lands and sparse vegetation, providing partial buffering against floods. The higher end (above 0.4) reflects

denser vegetation zones, which act as natural flood mitigators by absorbing rainfall and slowing runoff.

In the Kotri catchment, NDVI values vary between -0.171 and 0.51 , showing a broader spread compared to Kalabagh. Negative values highlight barren lands and active river channels with extreme susceptibility. Moderate ranges (0.1 – 0.3) dominate much of the catchment, representing croplands with seasonal vegetation that moderately reduces flood risk but remains highly vulnerable during monsoon periods. Higher NDVI areas (0.4 – 0.5), though less extensive, indicate dense vegetation patches that provide localized flood resistance.



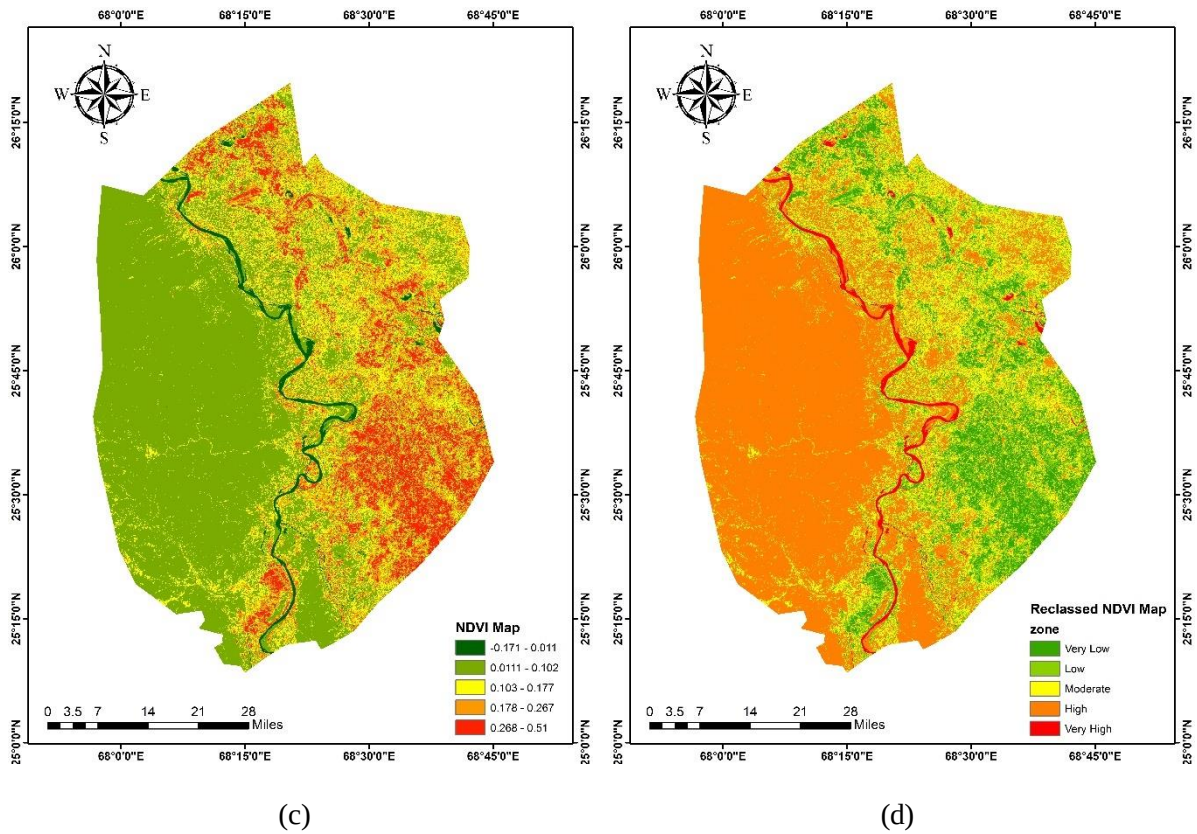


Figure 25: NDVI maps of Kalabagh and Kotri catchments reclassified into susceptibility zones.

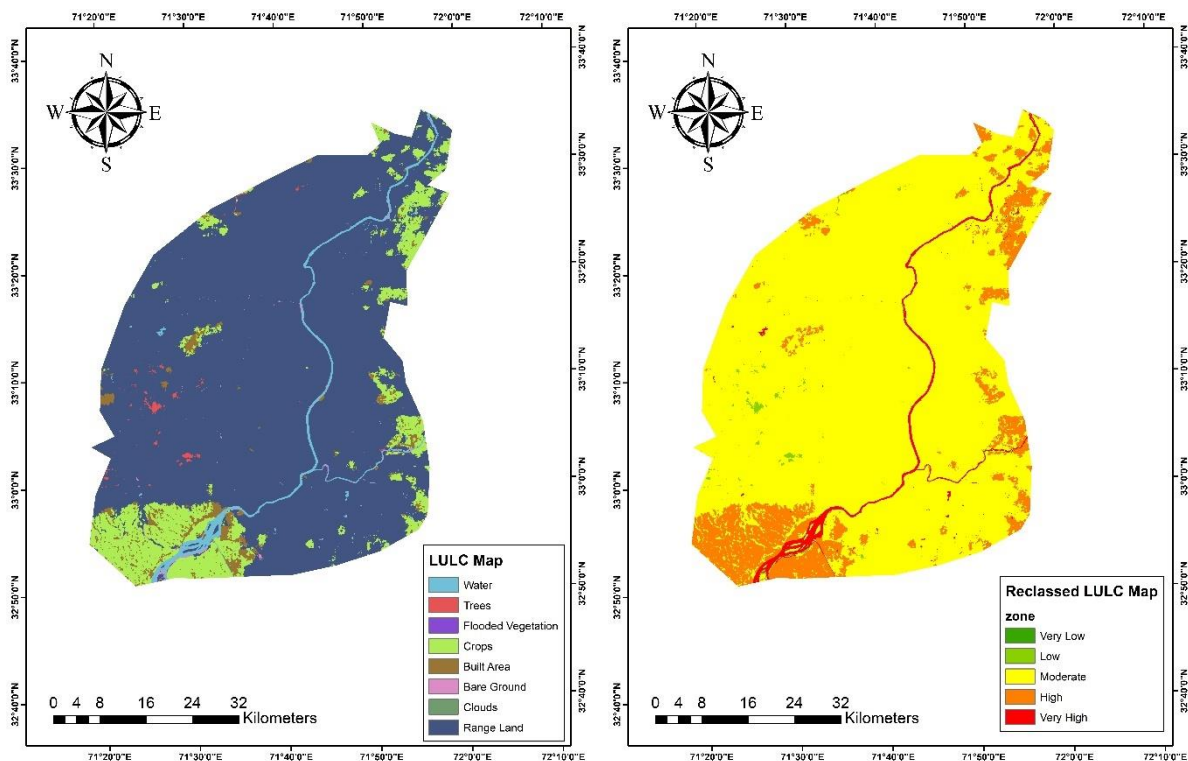
Land Use/Land Cover (LULC)

Land use and land cover strongly influence surface runoff, infiltration, and exposure to flood hazards. Different classes such as water bodies, croplands, built-up areas, and bare ground respond differently to flooding depending on permeability and land management.

In the Kalabagh catchment, LULC is characterized by water bodies, trees, croplands, built-up areas, bare ground, and rangelands. Water bodies and built-up zones fall into the very high susceptibility class, as they either accumulate or obstruct runoff. Croplands and rangelands represent moderate susceptibility, since they provide partial infiltration but remain highly exposed during intense rainfall events. Tree-covered areas reduce runoff through interception

and infiltration, placing them in the low susceptibility category, while bare ground is prone to high runoff and soil erosion, making it highly flood-sensitive.

In the Kotri catchment, LULC composition includes water bodies, flooded vegetation, croplands, trees, built-up areas, bare ground, and rangelands. The flooded vegetation and cropland areas dominate the landscape, falling under high to very high susceptibility zones because of their location in flat deltaic terrain. Built-up areas are also highly vulnerable due to poor drainage networks and population density. Tree cover provides localized flood resistance, while rangelands and bare ground exhibit higher runoff, contributing to flood hazard. Water bodies within Kotri further amplify inundation risk, as excess flow directly accumulates in low-lying depressions.



(a)

(b)

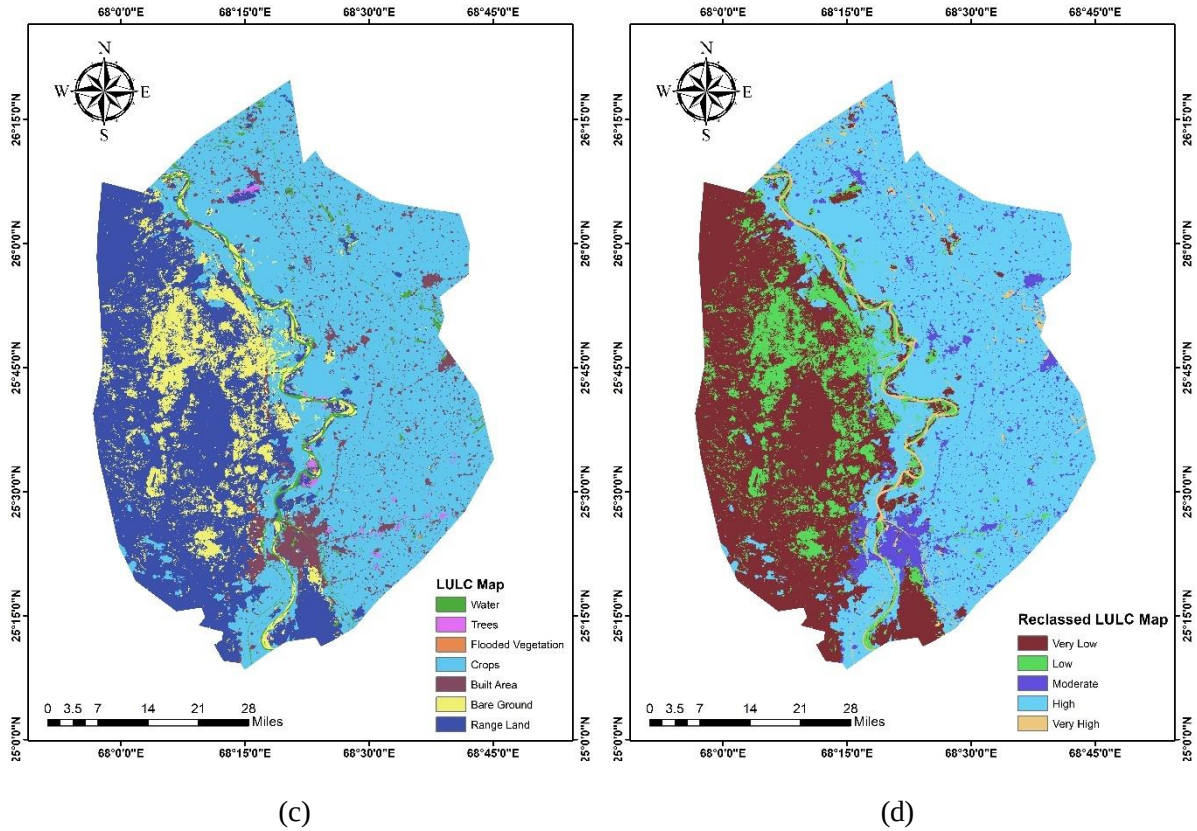


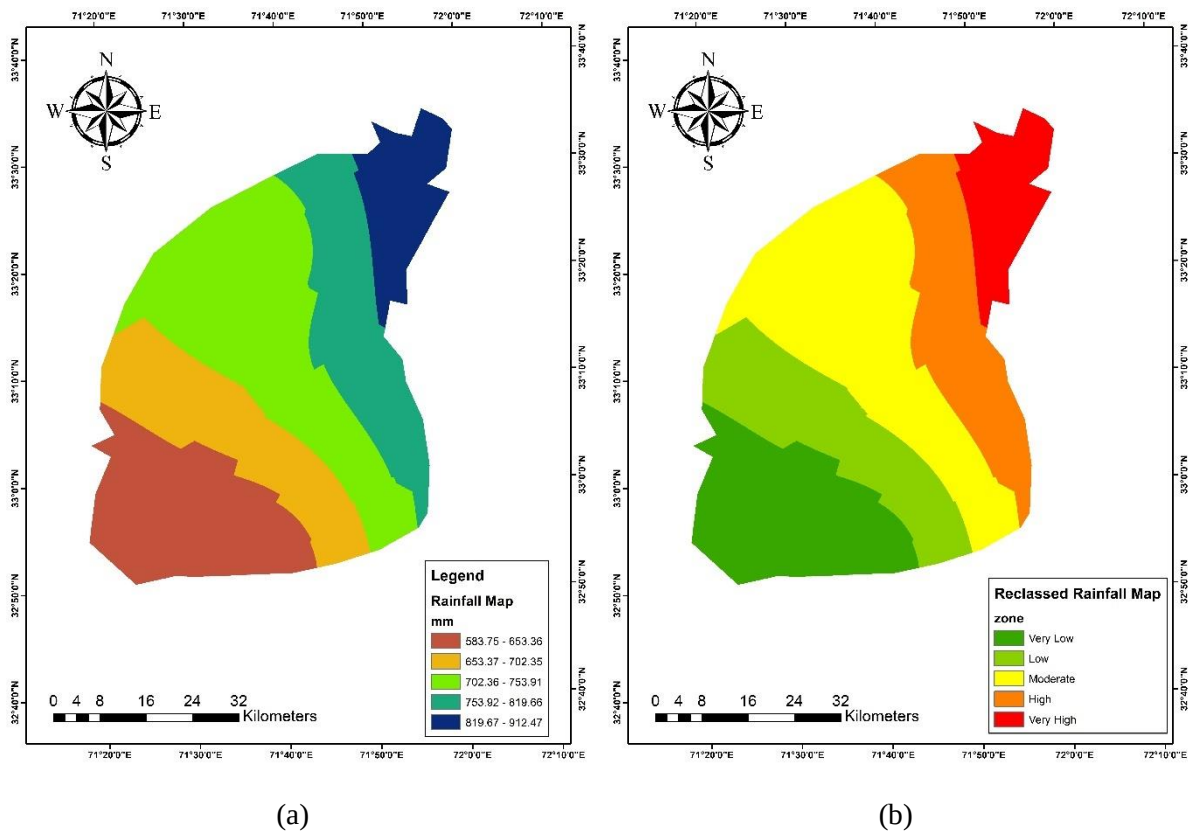
Figure 26: LULC maps of Kalabagh and Kotri catchments reclassified into flood susceptibility zones.

Rainfall

Rainfall is the primary driver of flood events, with both intensity and spatial distribution directly influencing runoff generation and flood susceptibility.

In the Kalabagh catchment, rainfall values range from 83.75 to 912.47 mm, showing strong variability between upstream mountainous areas and downstream plains. The higher rainfall zones (above 700 mm) correspond to steep mountainous regions, where intense precipitation rapidly transforms into flash floods due to limited infiltration. Moderate rainfall areas (300–600 mm) produce seasonal flooding, while the lowest rainfall zones (<200 mm) have comparatively reduced flood risk, though they remain exposed during extreme storm events.

In the Kotri catchment, rainfall varies between 398 and 484.5 mm, reflecting its relatively uniform but lower precipitation regime. Despite moderate rainfall amounts, the flat deltaic topography and poor drainage significantly enhance flood susceptibility, as even medium-intensity events result in widespread inundation. Unlike Kalabagh, where rainfall-driven flooding is localized and intense, Kotri experiences broad and prolonged flooding due to slow water recession.



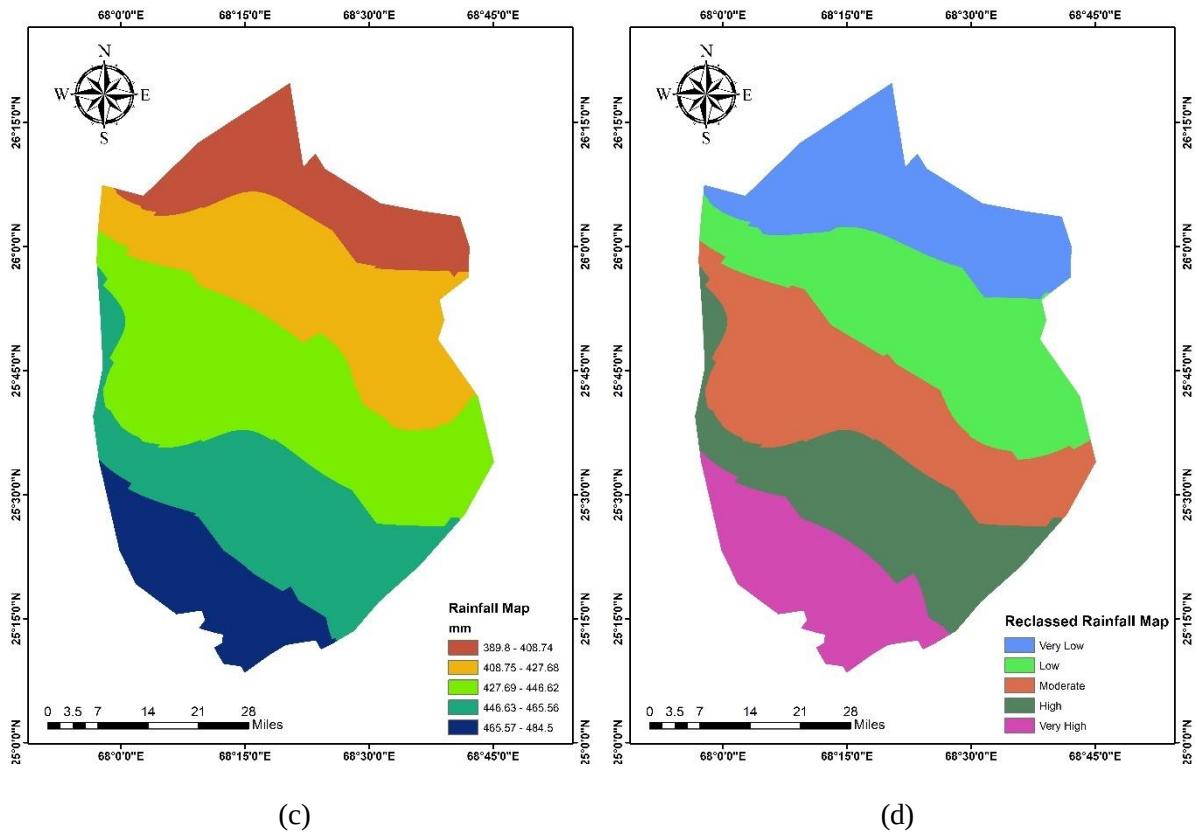


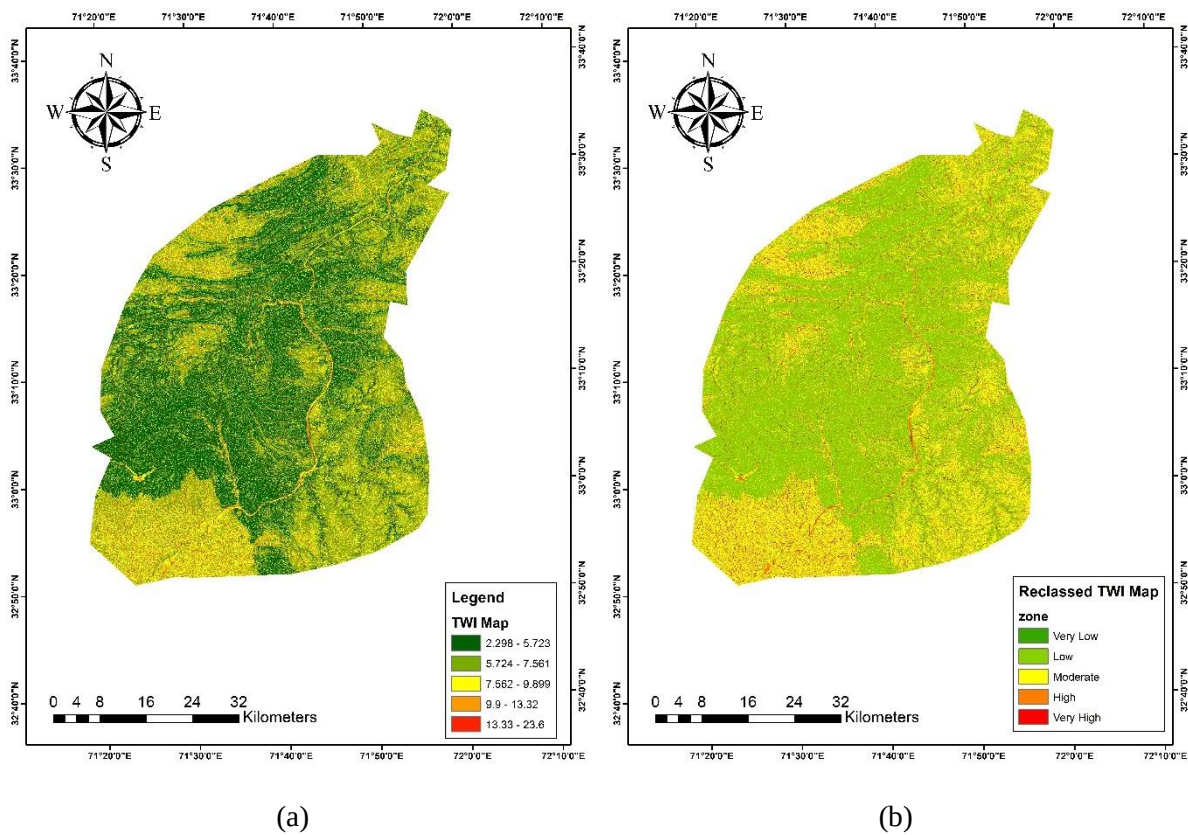
Figure 27: Rainfall maps of Kalabagh and Kotri catchments reclassified into flood susceptibility zones.

Topographic Wetness Index (TWI)

TWI reflects the spatial distribution of soil moisture by combining slope and upstream contributing area, making it a strong indicator of flood-prone zones. Higher TWI values denote wetter conditions and greater susceptibility to water accumulation, while lower values represent drier areas with reduced flood risk.

In the Kalabagh catchment, TWI ranges from 2.298 to 23.6. Low values (<5) occur in steep uplands, where rapid runoff prevents moisture buildup, leading to reduced local flood risk. Moderate values (10–15) are common along mid-slopes, indicating partial saturation and moderate susceptibility. The highest TWI zones (>20) occur in valleys and flat floodplains, where water accumulation is significant, marking very high flood-prone areas.

In the Kotri catchment, TWI varies from 3.77 to 23.4, with generally higher averages than Kalabagh due to the flat terrain. Low values (<7) cover limited elevated patches, while the majority of the catchment lies within moderate-to-high ranges (12–20), representing persistent saturation risk. The highest TWI zones (>20) correspond to depressions and agricultural floodplains, where long-duration inundation is frequent during monsoon events.



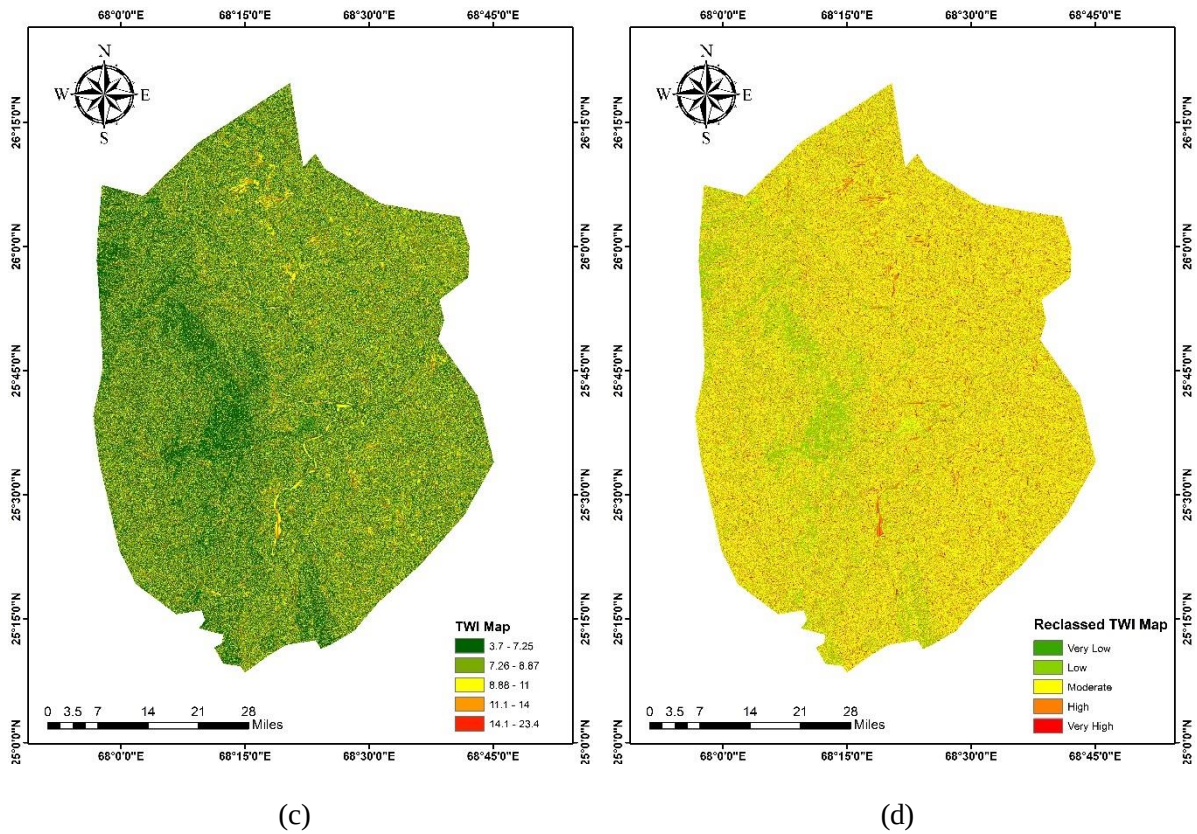


Figure 28: TWI maps of Kalabagh and Kotri catchments reclassified into flood susceptibility zones.

Pairwise Comparison and Consistency Ratio

To integrate the nine flood-conditioning parameters into a composite flood risk framework, the Analytical Hierarchy Process (AHP) was employed. A pairwise comparison matrix was constructed where each parameter was compared relative to the others based on its influence on flood susceptibility. Expert judgment and literature evidence guided the assignment of relative importance scores.

The resulting pairwise matrix was then normalized, and the principal eigenvector was extracted to derive the weights of each parameter. This weighting process ensures that parameters such as rainfall, slope, distance to river, and LULC receive higher influence values due to their

strong role in flood generation and propagation, while secondary factors such as curvature or soil type were assigned relatively lower weights.

To validate the reliability of the pairwise judgments, the Consistency Ratio (CR) was calculated. A CR value below 10% indicates that the comparisons are consistent and acceptable. In this study, the CR was found to be 5.5%, confirming that the weight assignments were logically consistent and robust.

	1	2	3	4	5	6	7	8	9
1	1	2.00	3.00	3.00	4.00	5.00	6.00	7.00	9.00
2	0.50	1	2.00	4.00	4.00	6.00	6.00	8.00	8.00
3	0.33	0.50	1	1.00	3.00	6.00	7.00	7.00	9.00
4	0.33	0.25	1.00	1	2.00	4.00	7.00	6.00	8.00
5	0.25	0.25	0.33	0.50	1	3.00	6.00	5.00	7.00
6	0.20	0.17	0.17	0.25	0.33	1	2.00	3.00	5.00
7	0.17	0.17	0.14	0.14	0.17	0.50	1	1.00	2.00
8	0.14	0.12	0.14	0.17	0.20	0.33	1.00	1	2.00
9	0.11	0.12	0.11	0.12	0.14	0.20	0.50	0.50	1

Table 7 displays the matrix of comparisons between pairs for each parameter.

Cat		Priority	Rank	(+)	(-)
1	Rainfall	27.6%	1	12.4%	12.4%
2	Distance to River	23.9%	2	11.7%	11.7%
3	Slope	15.8%	3	5.7%	5.7%
4	Elevation	12.9%	4	3.9%	3.9%
5	LULC	8.8%	5	3.4%	3.4%
6	TWI	4.5%	6	1.8%	1.8%
7	NDVI	2.5%	7	1.0%	1.0%
8	Soil	2.4%	8	0.7%	0.7%
9	Curvature	1.6%	9	0.7%	0.7%

Number of comparisons = 36

Consistency Ratio CR = 5.5%

Table 8 The decision matrix; Illustrates the comparative priority and ranking of criteria used in the flood risk assessment, with weights assigned based on their importance

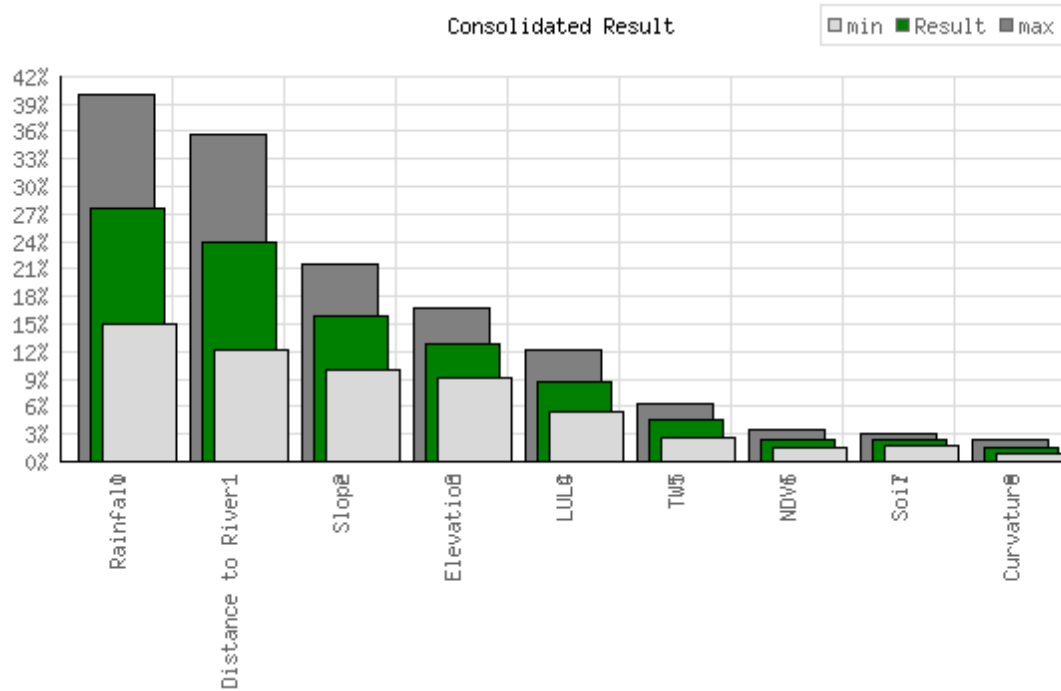


Figure 29: Consolidated Result

Flood Susceptibility Mapping (FSM)

The integration of AHP-derived weights with the nine flood-conditioning parameters in GIS resulted in the generation of Flood Susceptibility Maps (FSMs) for the Kalabagh and Kotri catchments. These maps provide a spatially explicit assessment of flood-prone zones, categorized into very low, low, moderate, high, and very high susceptibility classes.

In the Kalabagh catchment, the spatial distribution of susceptibility reveals a predominance of moderate flood-prone areas. Approximately 35.83% of the catchment falls under moderate susceptibility, reflecting the interplay between steep terrain, variable rainfall, and agricultural land use. Zones of very low and low susceptibility occupy 4.10% and 5.86%, respectively, largely corresponding to elevated ridges, well-drained slopes, and sparsely vegetated areas where runoff is quickly conveyed away. Only a negligible portion, about 0.19%, falls within the high susceptibility category, mostly confined to narrow valleys and low-lying zones

adjacent to the Indus River. This distribution highlights that while Kalabagh is hydrologically active and subject to flash floods, its rugged topography restricts the extent of widespread inundation. The concentration of risk in specific valley bottoms indicates localized vulnerability rather than basin-wide exposure.

By contrast, the Kotri catchment displays a much higher degree of flood susceptibility, owing to its flat deltaic terrain, dense croplands, and poor natural drainage. The FSM results show that more than half of the catchment, about 55.28%, lies in the high susceptibility zone. This dominance of highly vulnerable areas reflects the capacity of even moderate rainfall to generate widespread inundation, given the limited slope gradients and extensive floodplains. A further 37.20% of the catchment is classified as moderate susceptibility, indicating large areas that experience recurrent but less severe flooding. Only marginal zones are resistant to flooding, with 0.0005% classified as very low susceptibility and 4.0% as low susceptibility, located mainly on slightly elevated lands and embankments. Additionally, 2.51% of the catchment falls under very high susceptibility, primarily concentrated in low-lying depressions and agricultural fields near river channels, where prolonged inundation is common during monsoon seasons.

Overall, the FSM analysis underscores a sharp contrast between the two catchments. Kalabagh, with its steep terrain and localized valley flooding, exhibits a more contained but intense flood risk pattern. Kotri, in contrast, demonstrates widespread and extensive flood vulnerability, where large portions of the catchment are persistently exposed to inundation due to geomorphological and land use factors. This comparative understanding reinforces the importance of adopting catchment-specific flood management strategies: structural and flash flood control measures in Kalabagh, and large-scale drainage improvement, land-use planning, and delta management interventions in Kotri.

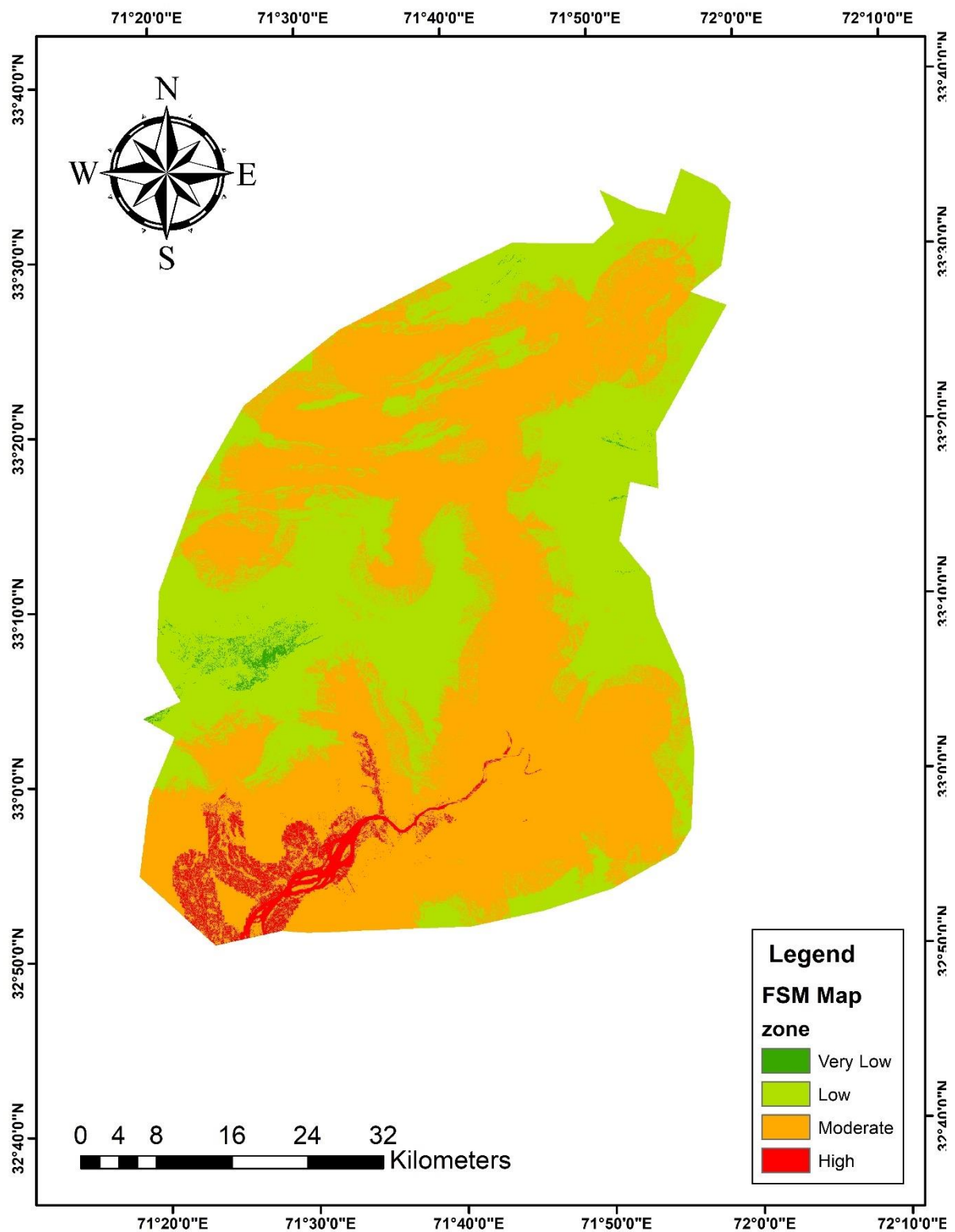


Figure 30: Flood Susceptibility Maps (FSM) of Kalabagh catchments derived from AHP–GIS weighted overlay analysis.

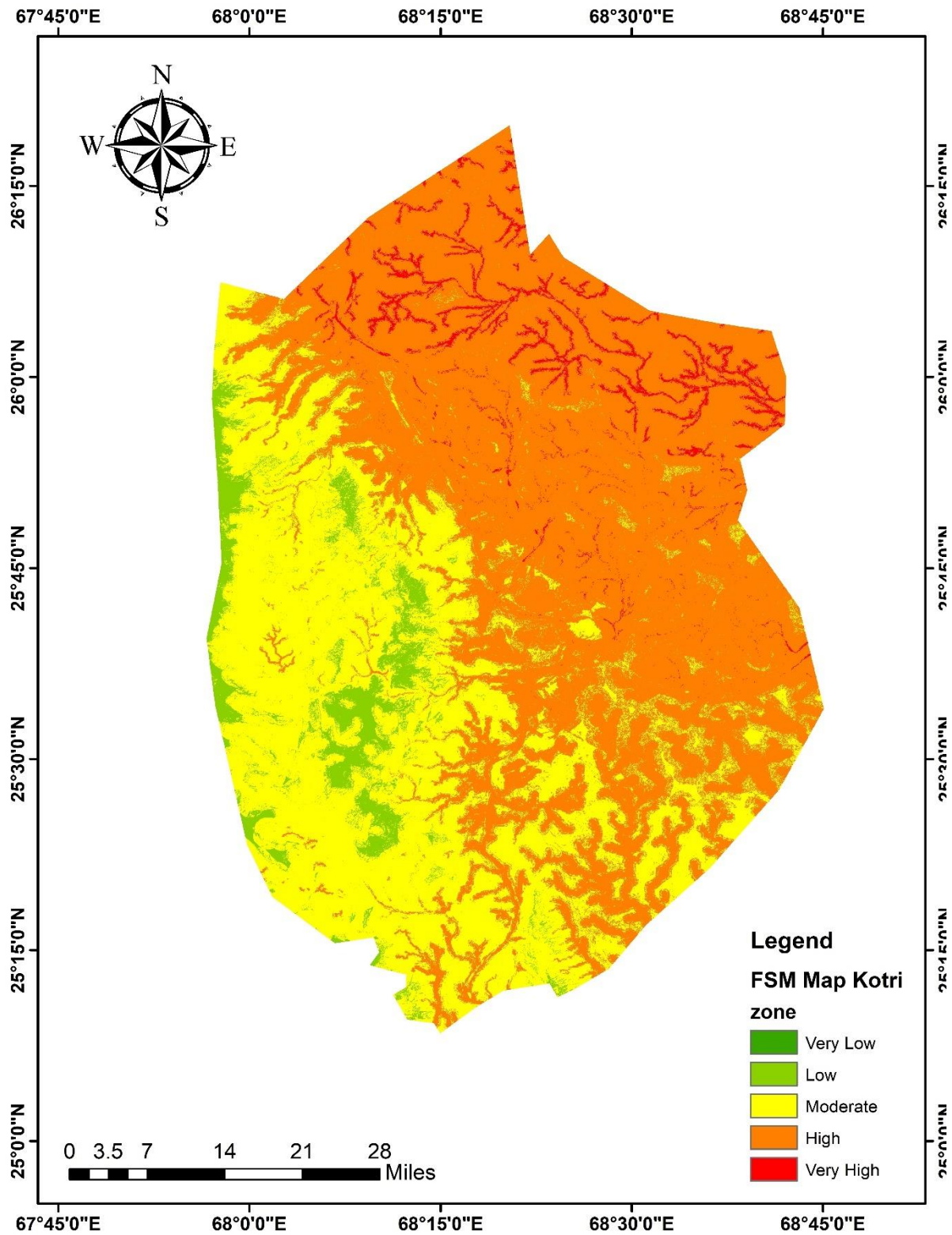


Figure 31: Flood Susceptibility Maps (FSM) of Kotri catchments derived from AHP–GIS weighted overlay analysis.

Conclusion:

The investigation into flood frequency analysis within the context of global climate variability highlights the escalating risk and impact of flood events on human settlements, economic stability, and ecological systems. The findings of this thesis underscore the pressing need for integrating advanced analytical tools in assessing and predicting flood occurrences. By examining case studies, including the recurrent floods in Pakistan, the research brings to light the multifaceted nature of flood hazards exacerbated by anthropogenic activities, climate change, and inadequate infrastructural resilience. The implications of this study extend beyond academic discourse into practical applications. It emphasizes the importance of using flood frequency analysis not only as a predictive tool but also as a foundational element in the planning and development of urban and rural infrastructure. As climate change continues to alter hydrological patterns, the historical data traditionally used in flood prediction models may no longer suffice. This necessitates the adoption of dynamic models that can accommodate evolving climatic parameters and provide more accurate flood predictions. Furthermore, the case of Pakistan illustrates the dire consequences of insufficient flood management strategies. Despite the recurrent nature of these disasters, there remains a gap in effective flood mitigation and adaptation strategies. This research advocates for a paradigm shift towards more proactive and preventive measures, underscoring the critical role of scientific research in informing policy and practice. In conclusion, the study not only contributes to the understanding of flood dynamics but also serves as a call to action for stakeholders at all levels. It underscores the necessity of robust and adaptable flood management frameworks that can withstand the test of climatic fluctuations and rapid urbanization. The integration of flood frequency analysis into broader environmental and developmental policies is imperative to safeguard communities, protect economic interests, and preserve natural ecosystems.

The investigation into flood frequency analysis within the context of global climate variability highlights the escalating risk and impact of flood events on human settlements, economic stability, and ecological systems. The findings of this thesis underscore the pressing need for integrating advanced analytical tools in assessing and predicting flood occurrences. By examining case studies, including the recurrent floods in Pakistan, the research brings to light the multifaceted nature of flood hazards exacerbated by anthropogenic activities, climate change, and inadequate infrastructural resilience.

In addition to the statistical assessment of flood frequency, this study incorporated an AHP–GIS based flood risk mapping framework for the Kalabagh and Kotri catchments. The integration of nine conditioning parameters, elevation, slope, curvature, soil, TWI, NDVI, rainfall, distance to river, and land use/land cover, enabled a spatially explicit evaluation of flood susceptibility. The results revealed a distinct contrast: while Kalabagh is dominated by moderate susceptibility zones (35.83%) with limited high-risk areas due to its rugged terrain, Kotri exhibited an alarming concentration of risk, with over 55% classified as highly susceptible and an additional 2.51% falling under very high susceptibility. These findings demonstrate that upstream and downstream flood dynamics differ markedly, demanding catchment-specific management approaches.

The implications of this combined approach extend beyond academic discourse into practical applications. It emphasizes the importance of using flood frequency analysis not only as a predictive tool but also as a foundation for infrastructural planning, while simultaneously employing spatial decision-support tools like AHP–GIS to pinpoint the most vulnerable locations. As climate change continues to alter hydrological patterns, the reliance on historical flood data alone may no longer suffice. This necessitates the adoption of dynamic and hybrid models that integrate both statistical frequency methods and spatial multi-criteria analysis for improved accuracy.

Furthermore, the case of Pakistan illustrates the dire consequences of insufficient flood management strategies. Despite the recurrent nature of these disasters, there remains a gap in effective mitigation and adaptation. The results of this thesis advocate for a paradigm shift towards more proactive measures, underscoring the critical role of scientific modeling in guiding policy and practice. By combining frequency-based predictions with AHP–GIS flood risk mapping, this study demonstrates a robust and adaptable framework capable of addressing both temporal and spatial dimensions of flood hazards.

In conclusion, the study not only contributes to a deeper understanding of flood dynamics but also provides a practical roadmap for integrated flood risk management. It underscores the necessity of flexible, science-based policies that link statistical analysis, spatial mapping, and climate adaptation to safeguard communities, protect economic interests, and preserve natural ecosystems in the face of increasing hydrological uncertainty.

Recommendations:

1. **Policy Integration and Development:** Governments and local authorities must incorporate flood frequency analysis into urban and regional planning policies. This includes updating building codes, land-use plans, and zoning laws to reflect the latest flood risk assessments. Policies should also promote the creation of flood buffers, such as green spaces and permeable surfaces, to enhance natural flood absorption.
2. **Infrastructure Resilience:** Significant investment is needed in the development and maintenance of resilient infrastructure. This involves constructing flood barriers, enhancing drainage systems, and retrofitting existing structures to withstand extreme weather events. Infrastructure projects should be guided by the latest flood frequency models to ensure they are built to last.
3. **Climate Change Mitigation and Adaptation:** Addressing the root causes of increased flooding, such as greenhouse gas emissions, is crucial. Mitigation strategies should be

complemented by adaptation measures, including the development of early warning systems and emergency response protocols tailored to local conditions. The robustness of this research can be enhanced by explicitly accounting for climate change impacts on flood magnitude and frequency.

4. **Community Engagement and Capacity Building:** Communities must be empowered with knowledge and tools to respond effectively to flood risks. This includes education campaigns, community-led flood risk assessments, and training programs that equip residents with the skills to implement local flood defenses and evacuation plans.
5. **International Collaboration and Knowledge Sharing:** Countries should engage in international partnerships to share data, technology, and best practices in flood management. Global forums can facilitate the exchange of innovative solutions and provide technical assistance to developing nations lacking resources.
6. **Continued Research and Innovation:** Ongoing research into the effects of climate change on hydrological cycles is essential. This includes refining flood prediction models, developing real-time monitoring systems, and exploring the use of artificial intelligence in flood forecasting.
7. **Resource Allocation and Financial Mechanisms:** Adequate funding must be allocated to flood mitigation and adaptation initiatives. Governments should consider establishing dedicated funds or insurance schemes to provide financial support for affected communities and to facilitate rapid recovery and reconstruction efforts.

By implementing these recommendations, policymakers, engineers, and communities can work together to create a safer and more resilient future. The integration of flood frequency analysis into all aspects of development and planning will be instrumental in reducing the vulnerability of populations to flood-related hazards and in ensuring sustainable growth in the face of climate change.

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