INTEGRATING REMOTE SENSING AND GEOGRAPHICAL INFORMATION SYSTEMS FOR URBAN FLASH FLOOD SUSCEPTIBILITY MAPPING IN RAWALPINDI AND ISLAMABAD, PAKISTAN

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A thesis submitted to International Islamic University, Islamabad, in partial completion of the requirements for the degree of Doctor of Philosophy in Environmental Science.

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A thesis submitted to fulfill the requirements for the award of degree of the Doctor of Philosophy in Environmental Science from International Islamic University, Islamabad

We accept this dissertation as conforming to the required standard.

1. External Examiner **2. Internal Examiner**

3. Supervisor **4. Chairman**

Dedicated to My Beloved Brothers and Family members

For their unending love, support, and inspiration

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List of Abbreviations

Acronym	Abbreviation
ADP	Annual Development Plan
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AJK	Azad Jammu and Kashmir
ANN	Artificial Neural Network
AUC	Area Under the Curve
AVHRR	Advanced Very High-Resolution Radiometer
BRT	Boosted Regression Tree
CA	Climate Adaptation
CBDRR	Community-Based Disaster Risk Reduction
CCP	Cloud Computing Platform
CFDDB	China Floods and Droughts Disasters Bulletin
CI	Consistency Index
CR	Correctness Rate
CT	Classification Tree
DD	Drainage Density
DEM	Digital Elevation Model
DT	Decision Trees
DTR	Diurnal Temperature Range
EE	Earth Engine
EL	Elevation Level
ENA	Energy and Nutrient Analysis
ENSO	El Niño-Southern Oscillation
EWS	Early Warning Systems
FA	Firefly Algorithm
FAHP	Fuzzy Analytic Hierarchy Process

FAO	**Food and Agriculture Organization**
FDM	**Finite Difference Method**
FEM	**Finite Element Method**
FP	**Flood Prone**
FR	**Frequency Ratio**
FRM	**Flood Risk Mapping**
FSM	**Feature Selection Method**
FURIA	**Fuzzy Rule-Based Algorithm**
GA	**Genetic Algorithm**
GARP	**Genetic Algorithm Rule Set Production**
GCM	**Global Circulation Model**
GCRI	**German watch’s Global Climate Risk Index**
GEE	**Google Earth Engine**
GIS	**Geographical Information Systems**
GLOFs	**Glacial Lake Outburst Floods**
GMDH	**Group Method of Data Handling**
HAZUS	**Hazards U.S. Multi-Hazard Loss Estimation Methodology**
HEC	**Hydrologic Engineering Center**
FDA	**Flood Damage Analysis**
RAS	**River Analysis System**
HKH	**Hindu Kush Himalayas**
HSG	**Hydrological Soil Group**
ICCCAD	**International Center for Climate Change and Development**
ICIMOD	**International Centre for Integrated Mountain Development**
IDMC	**Internal Displacement Monitoring Centre**
IDW	**Inverse Distance Weighting**
IFRC	**International Federation of Red Cross and Red Crescent Societies**
IFWS	**Integrated Flood Warning System**
IPCC	**Intergovernmental Panel on Climate Change**
JICA	**Japan International Cooperation Agency**
JUPEM	**Directorate of National Mapping Malaysia**

KPK	**Khyber Pakhtunkhwa**
LID	**Low Impact Development**
LIDAR	**Light Detection and Ranging**
LM	**Liebenberg-Marquardt**
LMT	**Logistic Model Tree**
LR	**Logistic Regression**
LU	**Land Use**
LULC	**Land Use/Land Cover**
MCDA	**Multi-Criteria Decision Analysis**
MIDP	**Maximum One-Day Precipitation**
ML	**Machine Learning**
MSA	**Multivariate Statistical Analysis**
MWR	**Ministry of Water Resources**
NASA	**National Aeronautics and Space Administration**
NDMA	**National Disaster Management Authority**
NDVI	**Normalized Difference Vegetation Index**
NDWI	**Normalized Difference Water Index**
NHC	**National Hurricane Center**
NIR	**Near Infrared**
NOAA	**National Oceanic and Atmospheric Administration**
NRCS	**Natural Resources Conservation Service**
OA	**Overall Accuracy**
PC	**Principal Component**
PDMA	**Provincial Disaster Management Authority**
PKR	**Pakistani Rupee**
PNDA	**Pakistan National Disaster Authority**
PR	**Prediction Ratio**
PRB	**Panjkora River Basin**
RD	**Risk Density**
REPT	**Reduced Error Pruning Tree**
RF	**Random Forest**

ROC	**Receiver Operating Characteristic**
SFWV	**Surface Flow Weighting Value**
SCWV	**Stream Channel Weighting Value**
SL	**Sea Level**
SM	**Statistical Model**
SPI	**Stream Power Index**
SPA	**Set Pair Analysis**
SRTM	**Shuttle Radar Topography Mission**
ST	**Sediment Transport**
SUDS	**Sustainable Urban Drainage Systems**
SWAT	**Soil and Water Assessment Tool**
TAR	**Third Assessment Report**
TP	**True Positive**
TWI	**Topographic Wetness Index**
UN	**United Nations**
UNDP	**United Nations Development Programme**
UNDRR	**United Nations Office for Disaster Risk Reduction**
UNFCCC	**United Nations Framework Convention on Climate Change**
UNISD	**United Nations Inter-Agency Secretariat of the International Strategy for Disaster Reduction**
USD	**United States Dollar**
USGS	**United States Geological Survey**
WI	**Weight Index**
WHO	**World Health Organization**
WMO	**World Meteorological Organization**
WofE	**Weights of Evidence**
WRD	**Waterway and River Density**

ABSTRACT

Urban flash floods are among the most catastrophic natural disasters because of their rapid onset and potential for destruction, especially in places with poor drainage and ground storage systems. The study used high-resolution satellite data and geospatial tools to assess eight important factors: elevation, slope, drainage density, rainfall, soil type, aspect, Normalized Difference Vegetation Index (NDVI), and land use/land cover (LULC). A flood inventory map was made using 110 recorded flood locations. The datasets were split into 70% training and 30% testing to guarantee accurate analysis. By incorporating the AHP-FR model, the flood susceptibility data was divided into five susceptibility areas in order to identify and describe the flood risk zones. They were categorized as very low (4%), low (25%), moderate (32%), high (26%), and very high-risk zones (13%). These zones had respective areas of 82.45 km², 650.10 km², 828.01 km², 654.23km², and 320.8 km². The results of the study indicate that the central, southwestern, and northern regions are most likely to experience flooding, with very low to low zones among them Pir Sohawa, the areas surrounding Margalla Hills, Tarnol, and Sihala being in moderate risk. High risk zones include Islamabad's suburbs, the areas surrounding Nullah Lai, and the agricultural and low-lying areas of Rawalpindi region. Furthermore, by integrating the findings from both AHP-FR and GIS-based analyses, a final integrated flood susceptibility map was created, offering a thorough visual representation of flood-prone locations. The accuracy scores for the FR and AHP models were 0.72% and 0.74%, respectively, based on field surveys and the Area under Curve (AUC) approach. Based on flood location data, the validation result demonstrated that the integrated map's forecast accuracy is 73%, falling within the acceptable range. This approach offers critical insights for urban planners and policymakers to design effective flood control measures, such as improving drainage systems, promoting sustainable urban planning, and implementing green infrastructure solutions.

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CHAPTER-1 Introduction

1.1 Background of the Study

A flash flood, also known as a rapid onset flood, is a brief period of flooding in a specific location that has a relatively high peak water output. Flash floods can happen within a few hours of intense rain, quick snowmelt, a sudden glacier lake eruption, embankment failure, or the extremely quick disintegration of an ice block brought on by a sharp rise in temperature. Flash floods, which typically happen in narrow, arid valleys, cause intense rainfall that can reach up to 100 mm in just six hours. Flash floods are characterized by an unanticipated rise in water levels in streams and rivers, as well as extremely high flow rates that result in a lot of debris, boulders, uprooted trees, and the destruction of infrastructure and built-up buildings in their path. In area like Islamabad and Rawalpindi in Pakistan, which have complicated climate and topography, flash floods are common threat and pose a major risk to the local population. Because of its distinct climate and topography, the northern part of country, this includes the Islamabad and Rawapindi area susceptible to flash floods. Area's monsoon climate is characterized by heavy rainfall during the monsoon season. Flash floods often result in property damage, fatalities, and disruptions to livelihoods due to the rugged during these periods of heavy rainfall. Despite the evident of susceptibility to flash floods in the area, there is a lack of comprehensive research. Existing research has a limited geographic and intricate scope or frequently focuses on certain factors of flash floods. Expansion of urbanization and changing in climate patterns are expected to increase the risk of flash floods, therefore it is critically important to understand and assess flash flood susceptibility in detail. By integrating, modifying, and evaluating the data, GIS and satellite remote sensing-based techniques and procedures provide a very good presentation for the quick and more efficient evaluation of likely ash danger levels. Many river basin factors, including stream ordering, basin area, drainage density, stream frequency, bifurcation ratio, basin relief, roughness number, and texture ratio, must be evaluated in order to determine flood hazards. GIS and remote sensing technology can be used to extract the drainage network of basins or sub-basins. Remote sensing and GIS can be used to monitor potentially dangerous locations and analyze the land's exposure and societal susceptibility, such as hazard maps. Considering the possible risk that flash flood may do the human safety and financial losses, a through and current study of flash flood assessment in Islamabad and Rawalpindi is soorely needed. These types of the research can help in making risk reduction strategies, effective use of early warning systems and disaster preparedness plans. By using GIS and Remote sensing techniques, this research aims to cover the existing research gap by assessing flash flood susceptibility in the region of Islamabad and Rawalpindi. Our research is to give emergency response organizations, legislators, and urban planners important insights to better understand and manage flash flood threat in this area. In order to improve well being and safety of the local community.

1.2 Problem Statement

Pakistan’s capital was shifted from Karachi to Rawalpindi and then to Islamabad. As a result of this urbanization, urban development is more prominent in semi-Lesser Himalayan region. Rapid urbanization in Islamabad and Rawalpindi has changed the topography of the region, disturbed natural hydrological systems including catchment areas, water bodies and drainage networks. Large scale infrastructure development including high rise buildings and deep foundation piling has further disturbed the ground water table and changed the surface runoff patterns. Anthropogenic activities like deforestation, soil compaction and land use changes along with climate change have increased the flood vulnerability in the region. Despite the increasing frequency of urban flash floods, limited studies have used Geographic Information Systems (GIS) and Remote Sensing (RS) to assess the flood susceptibility in Islamabad and its surrounding urban areas. Existing studies have focused on the hydrological behavior of Nullah Lai, a major drainage channel, without looking at the broader spatial dynamics of flash floods across the rapidly urbanizing landscape. In recent years Islamabad and Rawalpindi have experienced urban flooding due to land use changes and modification of natural drainage systems. The topographical and hydrological changes from Margalla Hills to Rawalpindi require a systematic and data driven flood susceptibility assessment. GIS and RS integration provides a robust tool to identify high risk flood prone areas, assess flood susceptibility and inform evidence based policies and mitigation strategies to enhance urban flood resilience.

1.3 Significance of the Study

The Study topic is important for sustainable urban planning, disaster risk mitigation, climate resilience development to evaluate the susceptibility of flash floods in Islamabd and Rawalpindi. With the help of remote sensing and GIS, this study's precise flood susceptibility maps enable accurate predictions of areas at risk of flash floods and direct timely actions to mitigate adverse impacts. By managing urban expansion, optimizing drainage systems, and building flood-resilient infrastructure, it assists urban planners in reducing the amount of impervious surface that exacerbates floods. In order to create plans for preparedness and mitigation that would ultimately reduce the amount of flood-related deaths, property damage, and economic disruptions, disaster management officials need the study's critical information. Furthermore, it advances our knowledge of how topographic, climatic, and human-induced environmental changes affect hydrological responses in urban settings. The research improves community resilience by identifying high-risk areas and implementing localized adaption strategies and increased awareness. Additionally, it gives policymakers factual data to help them create evidence-based plans and distribute funds efficiently for flood control. The use of remote sensing and sophisticated GIS technology enhances scholarly discussions on flood control and provides a reproducible approach for comparable areas. Last but not least, the study emphasizes how climate change is making flash floods more frequent and intense, underscoring the necessity of taking preventative action to safeguard urban ecosystems and adjust to shifting precipitation patterns. As an important addition to science and government, this study supports national and international objectives for catastrophe risk reduction, climate adaption, and sustainable development.

1.4 Research Objectives

The objectives of the present study are

1. Evaluate the Land Use Land Cover patterns and their relationship with flash floods.
2. To analyze the topographical features and rainfall patterns' influence and relationship with flash floods.
3. To identify the areas at high risk of flash floods using GIS and RS techniques.

4. To develop a flash flood susceptibility map for the study area through GIS and RS techniques.

Literature Review

2.1 Climate Change

Frequent famines, changed rainfall patterns, and agricultural devastation are only a few of the harmful Changes in atmospheric temperature; precipitation, pressure, and humidity are indicators of a global climatic condition known as the "climate." As a result, a change in this climatic condition caused by either natural or man-made factors is called "climate change." The effects of climate change include increasing sea levels, unpredictable weather, ice-glacier melting, and global warming (NASA, 2018). Regular natural catastrophes like hurricanes Irma, Harvey, and Maria are often interpreted by many seasoned researchers, academics, environmentalists, and members of the public as proof of climate change's consequences. The people must take part in adaptation-promoting actions to confront the ever-increasing effects of climate change (Perkins et al., 2018). Due to their abundance in nature and significant influence on the climate, greenhouse gas emissions the main contributors to climate change are greenhouse gases (GHGs) (CO_2, CH_4, N_2O, and H_2O). The gradual increase in climate-related adverse meteorological phenomena around the "underestimation" of climate change is a result of the world. Along with human activity, natural occurrences such as earthquakes, volcanic eruptions, and solar cycles also play a significant part in the ecosystem's decline (Roy, 2018). With the exception of H_2O evaporation, continuous human activities including as driving, farming, forestry, industrial development, and burning fossil fuels are causing global GHG emissions to rise more quickly. GHG emissions have historically been kept below hazardous levels by natural sinks (IPCC 2014). The environment has degraded and the natural atmosphere has become imbalanced as a result of the phenomena of growing global warming brought on by GHG emissions, which did not exist before the Industrial Revolution (NASA 2018; NASEM 2017a). Human-caused land use changes and the combustion of fossil fuels, which have been causing global warming since the mid-1900s, are the two primary causes of the increase in anthropogenic CO_2 emissions in the atmosphere (Yousaf et al., 2017b). Ten of the warmest summers since 2003 and the five warmest Septembers ever recorded were the land and ocean surface temperatures from 2014 to 2018 (CO_2.Earth 2018). The Septembers of 2018 and 2017 had the fourth-highest temperature in the preceding 139 years. Because of erratic weather patterns, ecological distortion, monetary losses, and social misery, this ongoing temperature increase poses a threat to civilization (Espeland et al., 2018). The production of greenhouse gases is one of the short-term repercussions of climate change, while the long-term effects include the impact of these gases on fundamental human activities, particularly farming and agriculture in Asia (Shaffril et al., 2018). Given that resource depletion, industrialization, urbanization, and economic expansion are preventing sustainable and ecological development in many Asian countries, Pakistan's geographic location makes it vulnerable to the consequences of climate change (Shaffril et al., 2018). The excessive waste of natural and non-renewable resources is the main cause of Pakistan's and much of the world's remarkable economic and industrial advancement. This overexploitation is causing irreversible damage to the climate. One of the most important strategies to slow down climate change and decrease the effects of environmental degradation is to implement laws that consider environmental knowledge, social responsibility, cultural obstacles, behavioral objectives, and respect for Mother Nature. Hussain et al. (2019) found that Pakistan's GHG emissions grew at a pace similar to the world's record 5.8% growth in 2010. The harsh consequences of climate change could threaten Pakistan's progress in the areas of economics, society, and the environment (Khan et al., 2016). The predicted increase in this global ranking by 2030 is anticipated to be caused by transportation, rapid urbanization, energy consumption, and waste (Zuberi et al., 2015).“The melting of the Himalayan range glaciers at a never-before-seen rate, sudden rainfall, unpredictable flooding, droughts, fluctuating temperatures, scarcity of water supplies, extreme heat waves, lake saturation, storms, hurricanes, landslides, earthquakes, pest diseases, seasonal changes, and changes in lifestyle are just a few of the severe climate change effects that Pakistan is experiencing” (Hussain et al., 2018). Adaptation, which involves adjusting to climate change, its effects, and its consequences, and mitigation, which involves preventing future greenhouse gas emissions and reducing the amount of greenhouse gases in the atmosphere, are crucial steps and actions needed to combat climate change because its effects are evident (Enríquez-de-Salamanca et al., 2017). Many people may be affected by the effects of climate change, which are mostly caused by global warming. The negative consequences of climate change are likely to worsen in the future. A number of factors, such as a lack of institutional capacity, a lack of awareness and knowledge about effective measures, a lack of resources and their improper use, and unfavorable economic conditions, contribute to the severity of climate change effects in developing countries, despite their differences globally (Ullah et al., 2019). The Intergovernmental Panel on Climate Change (IPCC) predicts that in the years to come, natural calamities, human activities, and the loss of natural resources will all suffer. Global biological systems and hydrologic reserves were impacted by both El Nino and La Nina. Between 1895 and 1995, there was a 0.4 °C increase in temperature. Extreme weather conditions caused by rising temperatures include heat waves and comparatively hotter days and nights (Rauf et al., 2017). Pakistan's rapidly melting glaciers, floods, droughts, and depleting water supplies would also make it the country most affected by climate change. Pakistan's temperature is predicted to rise by 0.9 to 1.5 degrees Celsius between 2020 and 2050. In 1998 and 2004, Pakistan saw two of its worst droughts, which killed 76% of livestock and directly afflicted 84% of the inhabitants in Baluchistan, the country's largest province. Similar to the provinces, the entire nation experienced severe flooding, which compelled many people to evacuate to the country's north and center (Ullah et al., 2018). Continued high temperatures, severe droughts, pest diseases, health problems, and shifting lifestyles are all predicted to occur in the years to come (Hussain et al., 2018). Many regions of the world will see more effects of climate change, such as elevated mercury levels (Stocker et al., 2014). Agrarian countries like Pakistan, where per capita income is already low and capacity building is inadequate, would be especially badly struck by the effects of climate change, according to Bhatti et al. (2018). More than two-thirds of Pakistan's workforce is employed in agriculture, and the country currently lacks the infrastructure necessary to adapt to and mitigate the effects of climate change (World Bank 2019). Pakistan's location, increased reliance on agriculture, increased reliance on water resources, and limited ability to manage climate emergencies make it especially vulnerable to the effects of climate change (Bhatti et al., 2018). Two-thirds of Pakistan's irrigable land gets its water from snowfall and glacier melting in the north, and the country's economy is centered on agriculture, which accounts for 80% of its exports. Furthermore, it is doubtful that climate change will have an equal impact on all regions; rather, it is concerning that it will have a more severe impact on impoverished farmers in rural areas, as evidenced by the 2010–2011 floods (Gorst et al., 2015). The majority of people in mountainous regions of developing nations rely on natural resources for their livelihood. Accordingly, the nation's economy and rural communities are seriously threatened by climate change (Mukwada et al., 2018). Even though Pakistan contributes very little to global GHG emissions, it is one of the nation’s most likely to face climate-related issues. Floods, droughts, and extreme temperatures have affected most of the population, and the average number of affected people has increased since 2010. Nearly one million individuals were impacted by floods alone in 2012 and 2014, which left the populace in disarray. Due to ongoing efforts by people, non-profits, and environmentalists to lessen and adapt to climate change, the number has decreased below one million since 2015 (Balouch et al., 2018).

2.1.1 Natural Disasters and Climate Change's Socioeconomic Effects

Food insecurity and water scarcity are two effects of climate change that lead to societal unrest and political unrest as well as global migration. Severe heat strokes and difficult availability to drinking water have impacted thousands of millions of people (Ellison et al., 2017). The interior of the continent is probably going to be impacted by rising temperatures. Reduced water resources, melting glaciers, and altered weather patterns brought on by high mercury levels are putting many planted species in danger of going extinct (Shaffril et al., 2018). However, because of sea level rise, the coastal environment is in danger of being destroyed (Phillips 2018). Temperature increases, pest diseases, health problems, and changes in seasonality and lifestyle are all stubbornly happening and are likely to continue in the future (Hussain et al., 2018). For Pakistan, insufficient infrastructure and a lack of adaptability are especially troublesome. The rapid escalation of public concerns is caused by a number of factors, including traditional consumer behavior, a lack of incentives, a lack of limitations, a lack of environmental education and knowledge, and a lack of government attention to climate change (IPCC 2013).By 2050, there could be serious consequences from a 2–3% rise in mercury and a notable shift in rainfall patterns (Gorst et al., 2015). Pakistan has suffered significant financial losses as a result of environmental and natural disasters, including lower agricultural yields, system restoration, and the reconstruction of essential infrastructure. In addition, Punjab has experienced a rise in traffic accidents because of poor visibility and eye and skin diseases brought on by smog over the last three to four years (Ali et al., 2017).

2.1.2 Effects of Climate Change on Forestry, Livestock, and Agriculture

It is anticipated that climate change would exacerbate issues facing the agriculture sector since extreme weather events, like skyrocketing temperatures and altered rainfall patterns, are predicted to occur in most parts of the world, Pakistan is among them (Habib et al., 2018). Depending on the type of practices used in the agricultural systems, the effects of measures made to increase agricultural production interact with climate change in agricultural areas in a variety of ways that affect crop yields and productivity (Abrahão et al., 2015). Since crops in tropical nations have already attained the point at which they can withstand heat and drought, the consequences of climate change, such as temperature increases, may result in decreased crop yields (Agriculture Development 2008). Rising sea levels, Lowlands are expected to be harmed by frequent floods and the salinization of subsoil water. Because there isn't enough water for crops, drought-like conditions are predicted to result from the rapid melting of glaciers and the decline in snowfall (IFAD 2013). This hot and dry climate is the primary cause of droughts and floods, can significantly affect the output of agriculture. The agriculture industry is especially susceptible to climate change, both causing and being affected by it simultaneously, claims Bhatti et al. (2018). The fresh water supply may be reduced as a result of altered rainfall patterns and rising mercury in the Indus Basin, which would have an impact on Pakistan's whole economy and agriculture industry. In the Indus Basin, native genetic crop varieties are likewise in danger of going extinct. Water waste has also resulted from the lack of contemporary methods for irrigating agricultural fields (Hussain et al., 2016). Glacial lake outburst floods (GLOF) with an exceptionally powerful monsoon in July 2015 destroyed thousands of livestock animals and hundreds of acres of crops in Khyber Pakhtunkhawa (KP) province's Chitral district (Operation 2015). People in the Upper Indus Basin also saw an increase in drought-like circumstances between 2001 and 2011, which resulted in a decrease in agrarian land, a decline in animals, and a decline in agricultural and livestock output (Hussain et al., 2016). Climate change and harsh weather have negatively impacted rural livelihoods and cash crops like cotton, wheat, rice, and sugarcane throughout time (Abid et al., 2015). In light of this, it is imperative to assess how vulnerable farmers are to the consequences of climate change. A comprehensive plan should be created to increase farmers' awareness of climate change. Pakistanis depend on livestock for their livelihood, and this sector is also being significantly impacted by climate change. Climate disruptions cause severe and sometimes fatal illnesses that severely affect livestock. The output of meat and milk has drastically decreased as a result of climate change's effects on rangeland, feed, water, and forage for livestock grazing. Diseases, animal diseases, feed quality and quantity, and biodiversity all have a major impact on cattle (Rajos et al., 2017). Many plant and animal species have gone extinct as a result of rising temperatures and abnormally high atmospheric CO_2 concentrations (Abas et al., 2017). Numerous man-made problems, including drought, floods, land sliding, and global warming, are having an effect on Pakistan's forests. Insect attacks on the dying trees were found to have left behind wood fragments and mud-mixed rubble in stem-eaten voids. Between 1999 and 2008, some tree species, like rosewood and oak, have been seen to go extinct in hot, humid regions of Punjab province, Pakistan (Abas et al., 2017).

2.1.3 Climate Change's Effects on Energy and Food Security

Like the rest of the world, Pakistan is facing serious climate-related issues with energy, water, and food security. Climate change has a number of detrimental effects on poverty and food security, and these problems will only worsen in the days ahead (Qureshi et al., 2016). With more than 300 million people living in undernourished conditions, South Asia has the greatest prevalence of food insecurity worldwide. Climate and weather change have an impact on Pakistan's primary economic sector, increasing the country's levels of poverty and food insecurity (Ali et al., 2017). Changes in air temperature and the possible threat of worldwide water scarcity are two immediate and deteriorating effects of climate change. Drier deserts, hotter summers, harsher winters, and greater precipitation and snowfall are just a few of the growing weather changes occurring in many parts of the planet. The predicted temperature increase between 2040 and 2059 was at least 1°, according to Qureshi et al. (2016), which would cause rivers to flood and ice glaciers in Pakistan's central area to melt.This temperature increase makes the southern region more vulnerable to resource shortages and droughts. Summers will be warmer due to the country's May thermal boost, but winters may be colder due to an October temperature plunge.The average temperature will rise by a catastrophic 2.5 percent between 2040 and 2059 if the nation's present rate of GHG emissions continues. Furthermore, the influence of climate change on grain output has a significant impact on Pakistan's food security. A comparison between the average crop yield from 1961 to 1990 and the anticipated change in agricultural yield from 2020 to 2080 (Ali et al., 2017). Food crops can be greatly impacted by changes in mercury levels and water availability. Pakistan's main food crops suffer greatly from unexpected rainfall during the planting and harvesting seasons. Pakistan's hilly regions are poorly managed in terms of agricultural production and activity, despite the country's abundance of natural resources. Floods, dry spells, and unpredictable rains are making farmers' problems worse. Another problem is the rise in crop pests. Due to the threat to their food security, people in mountainous regions have become increasingly reliant on plain areas (Hussain et al., 2016). To ensure the food supply and rural livelihood, effective mitigation and adaptation measures must be implemented at the farm level (Abid et al., 2015). At the local level, nevertheless, a significant obstacle is that the adaption costs will be entirely borne by farmers, who are the primary stakeholders. Reducing CO2 emissions and guaranteeing food security may require the use of efficient solar energy technologies and contemporary local water management strategies (Hussain et al., 2016). Ali et al. (2017) discovered that farmers who used contemporary farming techniques had a drop in poverty (3–6%) and an increase in food security (8–13%). According to research by Abid et al. (2016), farmers with more training and experience tended to implement more practices than those with less training and experience. The government was forced to take swift action to employ thermal energy to meet its energy needs due to the rapid urbanization, industrialization, and economic growth. This short-term approach is having a substantial impact on energy security, the balance of payments, and environmental degradation. However, due to a 3000 MW electricity shortage, the government is still having difficulty managing the energy problem (Lin et al., 2017). The demand-supply imbalance increased as a result of planning mistakes (GoP 2014). However, other analysts have noted that growing urbanization, which is generating carbon emissions, has raised the demand for energy.The problem is more severe in Pakistan because of the country's lengthy history of unrestrained development, which has had a detrimental effect on its socioeconomic structure, particularly in metropolitan areas (Hussain et al., 2018). Eventually, the environment and energy security are threatened by the rise in energy demand brought on by more people using vehicles. However, the study articles in the instance of Pakistan disregard the subject of GHG emissions and energy security from road transport. Pakistan needs to strike a balance right now between enhancing environmental sustainability, energy security, and economic growth (Lin et al., 2017). Additionally, compared to conventional renewable energy sources, Pakistan's natural renewable energy resources show much greater promise (Sheikh 2010). The country can produce 2.9 million MW of electricity from solar and wind power because it is located in a natural energy zone. To further reduce CO2 emissions and their effects, politicians must make cutting emissions a high priority. To offer energy security and lower daily greenhouse gas emissions, the concepts of smart buildings, smart cities, and smart grids have been proposed. Rice, wheat, cereals, vegetables, spices, and grains are among the crops in Pakistan that are climate-sensitive. Food security problems are caused by a combination of variables, including changing rainfall patterns, declining agricultural output, and rising temperatures (Li et al., 2011). Climate change's effects on Pakistan's urban infrastructure, transportation, energy, water, and coastal regions.

2.1.4 Impacts of Climate Change on Society

In the areas of clean air, food, water, shelter, health, and illness, society must bear the consequences of the various ways that climate change impacts the environment and socioeconomic sectors. Food, human health, and early mortality are all directly impacted by climate change in the twenty-first century (Li et al., 2011). The number of people killed each year by natural catastrophes like earthquakes, floods, droughts, and heat strokes is not an exception in Pakistan. The population's health is significantly impacted in a number of ways, particularly by the ongoing annual temperature increases that fuel global warming and the warmest temperature ever recorded in Pakistan's southern regions. Due to its proximity to the equator, the southern region of Pakistan is usually thought to be particularly susceptible to the negative heat effects of global warming. However, a slight annual temperature increase is causing waves of extreme heat and humidity in Punjab, which is located in the center of Pakistan. Additionally, heat waves lasted 31 days longer between 1980 and 2007 (Sultana et al., 2009). With potential temperature increases of up to 4% in central Pakistan, over 3% in northern Pakistan, and over 1% in southern Pakistan by 2050, it is predicted that Pakistan's center and northern regions will be more susceptible to the negative consequences of climate change. More unemployment and a smaller labor market are expected to be among the economic effects of climate change in emerging nations in the near future.Almost one billion people work in agriculture, making it one of the oldest occupations in human history and the second most human capital-intensive industry after the services sector. Unpredictable rainfall patterns, rising temperatures, frequent floods and droughts, deforestation, and unpredictable weather patterns are all predicted to pose threats to the agriculture industry in the future. It is anticipated that the hazardous condition will have a detrimental effect on the agriculture industry and its workforce (Olsen 2009). Migration, which can be described as the movement one strategy for reducing and adapting to climate change is the displacement of a race due to harmful conditions for employment and living, whether caused by natural or human factors (IOM 2014). It is clear that in addition to location, climate change has an impact on education. The brief disruption of everyday life caused by extreme weather events, such hurricanes, flash floods, and erratic rains and storms, affects the population's education. Many people believe that if the current climate changes continue, disasters like frequent flooding would become more frequent (Kara et al. 2015). Long-term impacts of climate change on education include famines, severe heat waves and droughts that cause a scarcity of food and crops (C. Change 2017). Like other nations, Pakistan is experiencing the effects of climate change, as seen by rising rates of disease, mass migration, and competition for daily-wage jobs. These effects are brought on by extreme weather events such as heat waves, droughts, floods, and storms. Migration-induced shifts in the economic balance could lead to high unemployment rates, which could exacerbate child malnutrition, increase poverty, and result in food shortages. Heat waves are one of the main dangers facing developing countries. In 2015, over 65,000 people were admitted to hospitals for treatment of heat stroke due to the widespread effects of the heat wave in Karachi (Glum 2015). Over 100 people have been killed by heat waves in Pakistan's plains, which are also experiencing extreme heat waves in the summer (Sheikh et al., 2013). The lack of adequate medical facilities in the nation is making the consequences of heat waves worse (Rauf et al., 2017). Climate change is making disasters more often and flooding more severe globally. Flooding-related disasters can have detrimental effects on health, including problems related to the skin. Following flooding, the number of infectious and noninfectious dermatological problems is rising. The primary causes of morbidity among flood victims are infectious disorders that manifest as dermatological symptoms, including leptospirosis, measles, dengue fever, impetigo, tineacorporis, malaria, and leishmaniasis. Inflammation, which includes irritating contact dermatitis, is one of the most prevalent dermatological conditions (Dayrit et al., 2018). Furthermore, weather changes and climatic conditions may increase the risk of dengue hemorrhagic fever (DHF) outbreaks (Ebi et al., 2016). Through a variety of routes, weather variations contribute to the proliferation of Aedes mosquitoes. It is highly likely that DHF will spread when there is more precipitation and a favorable temperature. DHF has additional causes, such as vapor pressure and humidity (Estallo et al., 2015). Morbidity and mortality rates were low in a number of Punjab provincial districts. In 2011, the DHF killed more than 300 residents affected 14,000 individuals in just two large towns, including Faisalabad, in the district of Faisalabad (Bakhsh et al., 2018). According to Chan et al. (2016), the latter may have detrimental implications like health problems, stress, worry, missed school days, sleep deprivation, and numerous more innumerable losses. Seismic activity and earthquake frequency have significantly increased over the last 10 years, and As a result of global warming, the temperature cycle in South East Asia, especially in Pakistan, is getting worse, going from -19°C in the winter to +53°C in the summer. Pakistani residents are suffering from a variety of illnesses, such as swine flu, dengue, and avian flu. Instead of concentrating on lowering the health effects brought on by climatic factors through media advertising, expanding access to healthcare facilities, and expanding the number of health facilities in Pakistan, health policymakers urgently need to concentrate on raising awareness about outbreaks (Bakhsh et al., 2018).

2.1.5 Impacts of Climate Change on the Weather Pattern

The average global temperature has increased by 0.6 ± 0.2 °C since 1990 due to a number of factors, including the rapid melting of glaciers and sea ice, an increase in heat waves, warming of the oceans, a nearly 10–20 cm rise in sea level, and changes in weather patterns, such as heavy rains and droughts in different parts of the world. According to reports, changed precipitation and weather patterns caused the global temperature to rise by much to 4 °C in just ten years by 2010. Species borders are generally affected by changes in temperature patterns and humidity; For instance, biological regions located approximately 160 km in latitude or longitude may be impacted by a 1 °C temperature change (Ali et al., 2011). Globally, it is anticipated that there would be more warm days and nights and fewer cold days and nights (Abbas et al., 2018). The development and production of annual crops have been put in jeopardy due to rising mercury and changes in rainfall patterns. Raining patterns, energy Degradation of the air has affected availability, agriculture, and irrigation requirements. The warming and its environmental effects are likely to affect natural water resources in hilly regions (Akhter et al., 2017). East Africa experienced food insecurity as a result of the worst drought in recorded history in the Horn of Africa, which was caused by changing rainfall patterns (Williams et al., 2011). Climate change has caused similar climate damage to the northwest of India as it has to Africa, and similar changes are occurring in Pakistan. Climate change and environmental degradation were primarily caused by spatial differences in rainfall patterns and changes in the region's regular atmospheric rotation (Rodo, 2003). Because of its location and past climate, the southern portion of Pakistan is thought to be an arid area with severe risks of water scarcity and drought. It is anticipated that certain areas may receive very little precipitation, with an estimated precipitation of less than 10 mm. Pakistan's anticipated regional precipitation change from 2011 to 2050. Less than 40 mm of precipitation is expected to fall annually on average, which will negatively impact the populace and financial system of a rural nation such as Pakistan (Asif 2010). The government of Pakistan has recognized the threats that global warming poses to future social and economic progress. The regulatory authorities have taken steps to dedicate a substantial amount of resources for climate change adaptation and mitigation, despite the fact that the nation currently lacks modern technologies, infrastructure, procedures, and rules for sustainable development. Rainfall is one of the key factors influencing agricultural development (Bakhsh et al., 2018). A natural occurrence, rainfall is essential to agricultural crop nutrition and animal output. Government representatives should concentrate on obtaining funds for the development of a dependable irrigation system to handle future precipitation fluctuations. More than 40% of the population has been affected by droughts, floods, storms, and changes in rainfall, and the frequency and severity of extreme climate changes have increased over the last 20 years (Asif 2010). Along with other climatic variables, it is anticipated that the frequency and severity of storms, cyclones, floods, droughts, and unpredictable weather would continue to fluctuate (Ullah et al., 2018). Due to atmospheric changes, cold waves from the USA to the UK switched in early 2016, whereas heat waves from India to Pakistan have been present since mid-2015. More energy is needed for both warming and cooling during heat and cold waves. All living things are impacted by these extreme waves since a man must experience hypothermia below 58 °F and hyperthermia over 53 °C (Pan et al., 2016). But each year, thousands of flights are canceled and traffic is shut down by the mix of fog and snow during the cold summer months. It will be challenging to carry out multi-billion dollar development projects in the port city of Gawadar, which serves as a gateway to the Middle East for Chinese business endeavors through Pakistan, if the same combination of hot weather and humidity persists in the coastal regions of Baluchistan for a few decades (Abbas et al., 2018).

2.2 Flood as a Natural Disaster

A disaster, according to the World Health Organization (WHO), refers to "an act of nature of such magnitude as to create a catastrophic situation in which the day-to-day patterns of life are suddenly disrupted, and people are plunged into helplessness and suffering, and, as a result, you need food, clothing, shelter, medical and nursing care, and other necessities of life, as well as protection against unfavorable environmental factors and conditions" (WHO, 1974). Despite the significant differences, natural hazards and natural catastrophes are occasionally confused. Natural hazards are unexpected, unpredictable, and relatively unusual phenomena that have a significant influence on the ecosystem on a global or regional scale, even if they may not directly affect human lives (Leroy, 2020). As a result, rather than being seen as natural risks, natural disasters are seen as such. Natural risks existed before humans. The Earth's atmosphere has changed rapidly during geological eras, the land surface has gone from being covered in molten lava to having a thick covering of ice, and temperatures have varied significantly. Human evolution has also included natural risks. Archaeological and paleoclimate evidence has connected the fall of civilizations to a number of calamities. For instance, the beginning of the Little Ice Age caused the Norse settlement in Greenland to collapse in 1540, and between 250 and 900 CE, environmental degradation and protracted drought caused the The demise of the Maya Indian civilization in Central America (Leroy, 2020). Because of its natural variability, the Earth's climate has changed dramatically over time. The Earth's natural cycle and variability due to its position and distance from the Sun, climate feedbacks, interactions between climate components, and the Sun's radiation and the global energy balance are the mechanisms behind natural climate variations, according to the Intergovernmental Panel on Climate Change (IPCC, 2013). Numerous natural disasters are influenced by the climate, and their effects can interact on a large or small scale with the components of the climate to alter it over time. For instance, by releasing aerosols into the atmosphere, volcanic eruptions might momentarily lower the global temperature. By lowering the quantity of sunlight that reaches the Earth's surface, these aerosols cause abrupt cooling. But the size of the eruption has been too large to change the planet's temperature much. The massive eruption of Mount Pinatubo in the Philippines in 1991 caused a 0.5°C drop in the global surface temperature (Parker et al., 1996). Even moderate climatic events, or those that do not fall within the extreme category, can result in natural disasters weather, can cause major catastrophes for a number of reasons, including insufficient disaster management, social vulnerabilities, and policy failure (Roth et al., 2017).

2.3 Climate Change and its Relation with Floods

Floods caused around 220,000 deaths and about $1 trillion in direct economic losses between 1980 and 2003 (Winsemius et al., 2016). The three main categories of floods are pluvial floods (including flash floods and surface water floods), river or fluvial floods, and coastal floods (such as storm surges). A river, lake, or other significant body of water overflowing as a result of prolonged, heavy rainfall or snowmelt is known as a fluvial or river flood. Extreme rainfall events generate pluvial floods, which can overflow a body of water or cause flooding. Therefore, even in the absence of a body of water, pluvial floods can happen anywhere. One type of pluvial flood that severely damages property is a flash flood. According to Waso et al. (2019), these floods happen when a lot of rain falls over a limited area in a short period of time, creating a high level of damage locally. Floods and rainfall have a nonlinear relationship, despite the fact that extreme rainfall has increased in frequency and intensity. Long-duration floods (lasting longer than 21 days) have become more frequent worldwide between 1985 and 2015; the rise is greatest in the northern hemisphere's mid-latitudes (Najibi et al., 2018). Since the 2000s, floods have become more frequent in the tropical region. However, short-term floods do not exhibit any patterns, according to Najibi and Devineni (2018). Floods are frequently predicted to rise in frequency and intensity in tandem with a notable increase in the frequency and intensity of short-duration extreme rainfall events (Yin et al., 2018). Nonetheless, there is much disagreement in the literature about the global evolution of different kinds of floods (Wasko et al., 2019; Yin et al., 2018). Global catchment statistics show that there is no relationship between rising extreme stream flow and rising extreme rainfall (Wasko and Sharma, 2017). This is mostly because severe stream flow or flash flooding is dependent on a wide range of other factors, such as the size of the catchment, the frequency of a rainfall event, and the moisture content (Wasko et al., 2019). Therefore, it is difficult to predict how climate change may affect flash floods. Flood danger has sharply grown in recent decades, despite ongoing disagreement regarding future changes in flood features based on its temporal and spatial scale (Hirabayashi et al., 2013). According to Merz et al. (2007), flood risk is the result of multiplying the probability of flooding by the number of people and property at risk of flooding. Due to increased asset exposure and the construction of infrastructure in flood-prone locations, global warming will significantly raise the danger of flooding in the future (Hirabayashi et al., 2013). Plans for future adaptation and mitigation are therefore vital to preventing significant flooding damage.

2.4 Flood Susceptibility

According to the IPCC (2012), floods occur when water flowing through small streams or any other body overflows and submerges areas that are not typically impacted by regular water flows. Flood is a complex natural hazard, and its correlation with climate change increases its scope and extent. Climate warming and other environmental factors are making flood disasters the most frequent natural occurrence. Since most nations are vulnerable to flood dangers, which can result in various forms of harm, including social, economic, and bodily harm, human life is significantly threatened worldwide (Wahla et al., 2022). Floods were responsible for about 30% of natural disasters in the last century, causing considerable damage, fatalities, and the destruction of valuable property. Floods can cause damage anywhere, but because they impact agricultural land everywhere, the infrastructure and agricultural sector closest to rivers are particularly at risk. The participation of several characteristics, such as drainage density, slope, etc., or improper mapping or preventative actions might be the cause of this (Islam et al., 2024). Floods are generally considered to be the most common and potentially destructive of the natural disasters, including landslides, tsunamis, earthquakes, volcanic eruptions, etc. (Ullah et al., 2023). According to Hapuarachchi et al. (2011), a flash flood is often described as flooding that starts within three to six hours as a result of severe rainfall. An Elkhrachy definition of a flash flood is a flood that starts quickly and typically exhibits strong peak discharges. Elkhrachy went on to say that when there is a lot of rainfall, flash floods often affects the geomorphic low-lying zones. The economy, society, nature, and human life may all suffer significantly from flood disasters, which are also likely to occur in floodplains (Rahman et al., 2021). At the same time, it was believed that floodplains are home to about a billion people, the vast majority of whom are the poorest people in the planet. Accordingly, the most destructive natural disaster in the globe right now is flooding (Rentschler et al., 2020). Due to changes in land use, climate, and the ongoing population increase in floodplains, it is anticipated that the amount of damage and fatalities caused by flood catastrophes would continue to rise significantly in many regions of the world. Additionally, floodplains are susceptible to flood disasters, which could cause serious damage to the economy, society, environment, and human life (Rahman et al., 2021). It is clear that the global flood discharge series do not exhibit a continuous trend (IPCC 2021). Flooding is one of the world's deadliest natural disasters. Inundations have become more frequent in the Global South during the last few decades. Floods are estimated to have killed 539,811 people, injured 361,974, and affected over 2.8 billion people between 1980 and 2009. Between 1980 and 2016, the damages climbed by USD 1.6 trillion. South Asia is the most affected region of the world, accounting for almost half of all deaths worldwide (UNDRR 2020). Between 1950 and 2006, According to Barredo et al. (2007), flash floods were responsible for 40% of flood-related fatalities in Europe and over 80% in Southern Europe. According to NOAA (2017), there were 74,814 flash floods in America between 1996 and 2017, which cost 37.3 billion USD and claimed 1399 lives (about 64 years). Flash floods caused an average of 786 fatalities annually between 2000 and 2020, accounting for 67% of all flood disasters in China, according to data from the China Floods Droughts Disasters Bulletin 2020. Over the past few decades, there has been an increase in the frequency of flash floods and the damage they cause, which may be related to the growth of infrastructure and population in flood-prone areas (MWR 2020). According to published studies, flooding negatively affects over 75 million people globally and results in over 2000 fatalities each year (Mensah et al., for example). Catastrophic floods are caused by a variety of natural and man-made factors. When heavy precipitation or snowmelt overflows into nearby places, flood plains form, momentarily submerging the surrounding lands (Suh et al., 2023). According to recent studies, one of the main reasons why floods occur in many places of the world is climate change (Hirabayashi et al., 2021). According to Santos 2020, alterations in land use practices that result in an impervious surface that could raise flow velocity can significantly impact flood disasters in a given area. Developing countries are particularly susceptible to natural disasters like floods because of their poor capacity for adaptation and lack of infrastructure (Shah et al., 2019). Human activities like river encroachment significantly increase the intensity of flood impacts, even though natural and climatic changes are the main causes of the rise in flood risks in developing countries (Shah et al., 2017). Pakistan suffers greatly from climate change, even though its carbon footprint is quite tiny (United Nations 2010). The German Watch Global Climate Risk Index (GCRI) ranks Pakistan as the seventh most vulnerable and eighth most affected nation by climate change (Shah et al., 2022). Riverine and flash floods are now frequent occurrences throughout the country. Every year, the nation experiences floods that are more severe, longer-lasting, and more frequent (Ali et al., 2022). Floods are consequently occurring more frequently. As capacity declines and susceptibility increases, vulnerability—whether it be social, economic, institutional, physical/infrastructural, or attitudinal—is rapidly increasing. Pakistan saw an average of one flood every three years and about 21 extreme floods between 1950 and 2011. These floods claimed the lives of 8887 individuals and had an indirect economic cost of $19 billion (Ali et al., 2022). The largest flood in Pakistan's history happened in 2010, right before the 2022 monsoon. In addition to affecting 0.2 billion people nationally, the 2010 mega floods took 1985 lives and caused a $9.7 billion measurable loss. However, the intangible economic costs remain uncertain (Shah et al., 2019). During the monsoon season of 2022, Pakistan saw significant flooding. The 2022 monsoon floods, according to the UN, devastated 2 million acres of crops and orchards, destroyed 2 million dwellings, displaced 5.4 million people, affected 33 million people, designated 72 districts as "calamity hit," and led to at least 1033 homicides. Floods are a serious disaster that requires research from the perspectives of numerous scientific disciplines and fields due to their growing occurrence, severity, duration, and effects. Development studies, biodiversity, water resources, engineering, tourism, terrorism, meteorological sciences, agriculture, and management sciences are just a few of the disciplines that have studied floods in Pakistan, either directly or indirectly, in relation to the relationship between humans and the environment (Jamshed et al., 2021). Studies pertaining to sustainable development goals, including health care, food security, environment, education, gender, and infrastructure development, includes research on floods (Ahmed 2021). Nevertheless, flood research has also noted the use of ICT, particularly machine learning, despite its infancy (Sajjid 2021). Studies on flood mapping, household vulnerability and resilience, flood hazard assessment, effective mitigation policies, flood emergency response, barriers in the rural flood management cycle, flood hazard zonation, non-structural flood risk mitigation, economic impact assessment, flood risk perception, capacity and preparedness assessment, and gaps of local institutions were found in the context of flood risk reduction (FRR). Non-technical elements of flood early warning systems, social impediments to flood risk communication, and NGO-led initiatives (Shah et al., 2023).

2.5 Factors Responsible for Flood Incidences

One of the main factors influencing floods in an area is its topography. Flooding is more likely to occur in low-lying areas, floodplains, and locations with inadequate drainage (Zhang et al., 2023). An area's soil type might have an impact on how well it holds water. Compared to sand and gravel, low-permeable soils like clay can result in higher surface runoff and greater flooding. Natural drainage patterns can be changed by paving, urbanization, and the construction of roads and buildings (Konrad 2003). More localized floods may occur in urban areas with poor stormwater management (Li et al., 2022). Deforestation and vegetation removal can decrease soil water retention, increasing runoff and making areas more vulnerable to flooding (Mazzoleni et al., 2022). Stream and riverbank overflow may happen if there is not enough vegetation. Water overflow can be improved by modifying rivers through channelization and dam construction. Flooding along the shore may result from rising sea levels (Roy et al., 2020). Natural drainage systems can be upset by human activities like mining, farming, and urbanization, which raises the possibility of floods (Mazzoleni et al., 2022). Flooding and waterlogging can also result from poorly managed irrigation. According to Band et al. (2020), flash floods can be caused by heavy rains, dam failures, or the quick melting of snow or ice. The increase in the world's population, especially in emerging nations, has altered the pattern of flash flood severity. Furthermore, the frequency and intensity of floods can be impacted by modifications to climate patterns, such as elevated temperatures and changed precipitation patterns (Fahad et al., 2021).One of the main factors influencing floods in an area is its topography. Flooding is more likely to occur in low-lying areas, floodplains, and locations with inadequate drainage (Zhang et al., 2023). An area's soil type might have an impact on how well it holds water. Compared to sand and gravel, low-permeable soils like clay can result in higher surface runoff and greater flooding. Natural drainage patterns can be changed by paving, urbanization, and the construction of roads and buildings (Konrad 2003). More localized floods may occur in urban areas with poor stormwater management (Li et al., 2022). Deforestation and vegetation removal can cause the soil to retain less water, which increases runoff and makes the area more vulnerable to flooding. Stream and riverbank overflow may happen if there is not enough vegetation. Water overflow can be improved by river modifications such channelization and dam construction. Coastal flooding is caused by rising sea levels (Roy et al., 2020). Natural drainage systems can be upset by human activities like mining, farming, and urbanization, which raises the possibility of flooding. Flooding and waterlogging can also result from poorly managed irrigation. According to Band et al. (2020), flash floods can be caused by heavy rains, dam failures, or the quick melting of snow or ice. Global population growth, especially in emerging nations, has altered the pattern of flash flood intensity. Furthermore, shifting precipitation patterns and rising temperatures are two examples of how climate change might affect the frequency and intensity of floods (Tachiiri et al., 2021).

2.6 Impacts of Floods

Human vulnerability to floods has grown due to recent changes in land use practices and faster population growth. Direct mortality and morbidity, indirect relocation, and significant damage to property, infrastructure, and agriculture are some of the severe effects of floods. Drowning and trauma or injury are the two leading causes of death during floods. Long-term increases in infectious disease-related mortality are also possible. Future flood events provide significant risks due to factors like population expansion, population density along coastlines, increased development of flood plains and coastal areas, environmental degradation, and climate change. Globally, floods are becoming more common as climate change increases (Rahman et al., 2018).To manage floods, numerous dams and embankments have been built (Ge et al., 202). However, the flooded region following dam failure is wider and the damage is more severe due to the buildup of floodwater in reservoirs and rivers. For instance, in August 2002, more than 15 billion euros were lost as a result of more than 130 dike breaches on Germany's Elbe River (Apel et al., 2009). A portion of the Sardoba Reservoir dam in Uzbekistan fell in 2020, resulting in devastating flooding that forced over 100,000 people to evacuate and claimed six lives (Xiao et al., 2022). Floods have a detrimental effect on the environment, public health, and the economy (European Parliament and Council, 2007; Ge et al., 2021; Lehmkuhl et al., 2022). Foulds et al. (2014) found that the Pb in the flood silt from a 2012 flood in a mining zone in West Wales was much higher than the standard. In an experimental investigation of the impact of dam-breach floods on riverbed morphology, Carrivick et al. (2011) verified the reciprocal relationship between flood features and sediment flow. The flood that followed the Koshi Dyke's 2008 breach had a major impact on Nepal's Koshi Tappu Wildlife Reserve's trees, birds, and mammals (Baral, 2012). Emerson et al. (2015) noted that bacteria and fungi were still found in flooded residences in central Colorado and southern Wyoming, USA, three months after the 2013 Colorado Front Range storm had passed. Water contamination (Foulds et al., 2014), erosion and deposition (Carrivick et al., 2011), and effects on organisms (Baral, 2012; Emerson et al., 2015) are only a few of the many environmental effects of floods. Additionally, flood-induced erosion and sedimentation impact plant life (Milani et al., 2020), and water pollution impacts the survival of aquatic creatures (Hrdinka et al., 2012). Although research shows that floods have a significant environmental impact, the relationship between all of the impact indicators is yet unknown. The majority of research only looks at one facet of the impact indicators or how two indicators interact. Several factors determine how much floods affect the ecology (Zacks et al., 2018; Hadravová et al., 2020). For instance, a number of point sources (PS) and non-point sources (NPS) have an impact on the water quality of floods in areas that have been inundated (Jakovljević et al., 2020). Temperature (Winkel et al., 2017), flood factors (Woodman, 2015; Zacks et al., 2018), height, plant tolerance to waterlogging, and animal migration ability are some of the factors that affect how floods affect plants and animals (Cavallaro et al., 2017; Higgisson et al., 2018). Flood velocity and sediment content are the main factors that determine erosion and deposition (Naylor et al., 2017). These factors have complicated consequences on the environment. For instance, deep floods can give aquatic species additional food and habitat (Hadravová et al., 2020), but they are detrimental to the majority of terrestrial plants and animals (Zhang et al., 2021a, Zhang et al., 2021b). High temperatures speed up chemical reactions and degrade the quality of floodwater, even if creatures can survive at a certain temperature (Whitehead et al., 2009). Floods killed 100,000 people and impacted 1.4 billion people worldwide in the final ten years of the 20th century (Jonkman 2005). The annual cost of flooding to the global economy is estimated to be between $50 billion and $60 billion. According to a United Nations (UN) research, floods kill 22,800 people on average each year and cost the Asian economy US$136 billion (UNESCO 2003). The losses suffered by poor nations are five times greater than those suffered by wealthy nations per unit of gross domestic product (UNESCO, 2006). With a population of 1.46 billion, or 25% of the world's total population, South Asia makes up 10% of Asia and about 3.2% of the world's surface area (CIA 2005). About 40% of the world's impoverished live in South Asia, which includes Afghanistan, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka. The Indus, Ganges, Brahmaputra, and Meghna are the principal rivers of South Asia. The Kabul River runs through Afghanistan after rising in Pakistan. It is among the Indus' principal tributaries. Before draining into the Arabian Sea, the Indus and its tributaries flow west and south. To get to the Bay of Bengal, the Ganges, Brahmaputra, and their tributaries run east and south. These rivers supply water for drinking, agriculture, electricity, fisheries, inland navigation, biodiversity, and wetland preservation to the region's 500 million+ inhabitants. However, these rivers also fuel several floods that impede the socioeconomic advancement of the area. The South-West monsoon, which dominates South Asia's climate, results in notable regional and temporal changes in temperature and precipitation. Mawsynram, a tiny village close to Shillong in India's Meghalaya Hills, receives the most precipitation on average per year, 11,873 mm (Bandyopadhyay 2006). Rainfall in the area declines from east to west, with some regions receiving less than 400 mm of precipitation each year. Different forms of floods, such as landslides, debris flows, flash floods, and glacial lake outburst floods, are caused by different topography, geographic positions, and weather patterns from North to South and East to West. Large populations of farmers reside in crowded rural areas in the majority of the countries in this region. Approximately 28% of people live in cities. Compared to other parts of the world, the rate of economic growth is rather slow. Afghanistan's per capita income is at least $250 USD, but the Maldives' is $2,390 USD. A bleak picture emerges when comparing South Asia's development initiatives to those of other areas. These unfavorable social and economic circumstances, in addition to the natural and physical elements that already exist in South Asia, increase the region's susceptibility to many calamities, including earthquakes, landslides, floods, and others. For monitoring the connections between disaster risk and development as well as for spotting patterns in the effects of disasters, disaster statistics are essential (IFRCRCS 2005). Indicators used to evaluate the impact of floods include the number of fatalities, the overall number impacted, and the economic damage. In the past, Mandira Singh Shrestha has conducted some domestic and international study on floodsJonkman (2005) used data from the OFDA/CRED Emergency Disaster Database (EM-DAT) from 1975 to 2002 to analyze the death toll statistics for various flood types and geographic locations with reference to multiple flood catastrophes globally. Using the EM-DAT database, Dutta and Heradth (2004) examined the patterns of flood disasters in Asia during a thirty-year span, from 1973 to 2002. These studies demonstrate the complexity of the mechanisms and the vast array of components impacting the environmental impact of floods, even though they did not evaluate the influencing mechanisms of each aspect or identify the influencing factors of each environmental flood risk indicator.

2.7 Urbanization and Flood Vulnerability

The effects of climate change and other environmental issues are generally acknowledged to be worsening globally. The primary causes of both natural and man-made disasters are population increase, unrestrained land use development, increasing urbanization, and the resulting effects of climate change. According to the 5th Intergovernmental Panel on Climate Change (IPCC) assessment report, flood hazards are predicted to increase in frequency and severity in large urban areas with high population densities (Jiménez Cisneros et al., 2014). The Atlanta metropolitan area and surrounding areas in northern Georgia saw devastating flash floods in September 2009, while major urban flooding occurred in Boston, Chicago, Milwaukee, Nashville, Oklahoma City, and Washington, DC, in 2010. Researchers from a variety of disciplines have created a number of ideas and tactics to better identify who is at risk and where preventive action is needed in the city in order to provide a more accurate and trustworthy assessment of flood risk. For instance, in order to comprehend flood dynamics and predict future flood implications, the field of applied research has heavily relied on hydraulic and hydrologic studies of physical exposure to flood risks.To address the unequal distribution of flood dangers in the city and neighborhood, social scientists have mostly relied on field surveys and interviews with locals and city officials. Because they typically reside in metropolitan areas with distinctive spatial characteristics that characterize them as informal settlements, the urban poor are particularly susceptible to the effects of climate change and natural disasters like floods (Baker 2012). According to UN Habitat (2011), informal settlements are residential areas where residents disrespect building codes, lack security of tenure, and lack access to basic amenities. Because of their living conditions, which are marked by a lack of basic infrastructure and facilities as well as their proximity to hazardous areas like rivers, floodplains, and other unsafe places, the majority of people living in these informal settlements are susceptible to a variety of hazards (Baker 2012). For instance, there are many overcrowded, unfit-for-habitation, poor homes in several metropolitan neighborhoods of Ibadan. Unsanitary neighborhood conditions, careless waste management, and poor infrastructure set these homes apart. More significantly, Ibadan has already experienced flood disasters. Some scholars claim that Ibadan alone has seen around 16 catastrophic flood catastrophes of various intensities, resulting in over 35,000 recorded fatalities and millions of naira in economic losses (Eguaroje et al. 2015). Urban poverty, societal resilience, and vulnerability are therefore expected to worsen as a result of urban settlements being exposed to disaster threats. Even in arid areas with little yearly precipitation, urbanization has recently raised the risk of flooding. The impact of urbanization on surface runoff has been demonstrated in numerous flood risk studies (Fernández et al., 2010). These studies demonstrate that while soil penetration is losing less water, surface runoff has increased as impermeable surfaces and metropolitan regions have grown. However, other research has linked an increase in flood frequency to the effects of climate change (Jiang et al., 2015).Droughts and floods are more likely to occur in arid regions because their precipitation fluctuates more over time than in humid surroundings. Climate change has been associated with increased temperatures, changed precipitation patterns, and more severe droughts in Africa's driest continent (Ramanathan et al., 2001; Shanahan et al., 2009; Williams and Funk, 2011). Floods have become more frequent and severe in recent decades in regions like Pakistan.

2.8 History of Flash Floods

Flash floods have affected areas all over the world because of their destructive nature and abrupt start. Comprehending past flash flood incidents is essential for preparedness and mitigation initiatives (Nagamani et al., 2024). In May 1889, a breach in the South Fork Dam in Johnstown, Pennsylvania, caused a devastating flash flood. The dam was modified for a private club's use after it was first built for a reservoir. When the dam failed, 20 million tons of water poured down the valley, killing almost 2,200 people and causing massive damage. This flash flood remains one of the worst in American history (Coleman et al., 2016). In 1931, a combination of storms, melting snow, and heavy rainfall caused massive floods in China. These disastrous floods killed millions of people and caused many more to be homeless. According to Zhou et al. (2023), it is considered to be among the most devastating natural disasters in recorded history. A flash flood struck the Devon community of Lynmouth, UK, on August 15, 1952. Severe flooding resulted from the East and West Lyn Rivers overflowing due to heavy rains. 34 people lost their lives in this incident, which also seriously damaged the community (Met Office, 2023). A glacial lake outburst and intense rains in 1998 caused flash floods and landslides in the Chamoli area of Uttarakhand, India. In the impacted area, these occurrences caused a considerable loss of life and property. Pakistan faced several river floods and flash floods in 2010. Millions of people were impacted by these floods, which resulted in extensive agricultural loss, economic hardship, and relocation (Singh et al., 2023). Colorado experienced flash floods in September 2013 as a result of thunderstorms and excessive rainfall. In addition to causing substantial property damage in the impacted areas, the flash floods took many lives (Schumacher et al., 2017). Chennai and neighboring areas of Tamil Nadu, India, experienced flash floods as a result of heavy rains in November and December 2015. A serious humanitarian disaster with extensive devastation was brought on by these floods (Panda et al., 2023). Flash floods occurred in Mallorca, Spain, in October 2018 as a result of an abrupt and heavy rainfall storm. Numerous individuals lost their lives as a result of these flash floods, which also left the impacted districts in ruins (Cárdenas et al., 2020). Unprecedented rains in July 2021 caused flash floods in portions of Germany and Belgium. More than 200 people died and a great deal of damage was caused by the devastating floods (Gascón et al., 2022).

2.9 Floods in Pakistan

In recent years, flooding has been an issue in Pakistan almost every year. Land, lives, and infrastructure are all severely damaged by floods. Flooding issues in Pakistan are a result of inadequate water resource management and an ineffective water strategy (Ishaque et al.,2023). Despite having a very small carbon footprint, Pakistan is severely impacted by climate change (UNDP, 2021). According to German Watch's global climate risk index (GCRI), Pakistan is ranked eighth in terms of climate change impacts and seventh in terms of climate change vulnerability (Eckstein et al., 2023). Across the country, riverine and flash floods are becoming more frequent. Every year, floods in the country are longer, more severe, and occur more frequently (IFRC, 2022). Therefore, floods pose a bigger risk to a larger population. A combination of declining capability and increasing susceptibility is causing the rate of vulnerability (physical/infrastructural, social, economic, institutional, or attitudinal components) to increase rapidly. Between 1950 and 2011, Pakistan had an average of one flood every three years and about 21 severe floods. Pakistan is ranked seventh in terms of climate change susceptibility and eighth in terms of climate change impacts on German Watch's global climate risk index (GCRI) (Eckstein et al., 2023). Riverine and flash floods are becoming more common throughout the nation. The nation experiences longer, more severe, and more frequent floods each year (IFRC, 2022). Floods are hence a greater risk to a larger population. The rate of vulnerability (physical/infrastructural, social, economic, institutional, or attitudinal components) is rising quickly due to a mix of deteriorating competence and growing susceptibility. Pakistan saw roughly 21 severe floods and one flood every three years on average between 1950 and 2011. In addition to 8887 fatalities, these floods resulted in indirect economic loss of nearly $19 billion (Shah et al., 2020). During the 2022 monsoon season, Pakistan witnessed significant flooding. According to the United Nations reports, millions suffered and at least 1033 people died in the 2022 monsoon floods. In addition, 33 million people were impacted, 5.4 million were displaced, 72 districts were designated as "calamity hit," 2 million acres of orchards and crops were devastated, and 2 million residences were demolished. Floods are a significant calamity that requires research from a variety of scientific disciplines due to their rising incidence, severity, length, and effects (PNDA, 2022).

Table 1: Summarizing the history and damage details of significant floods in Pakistan

S. No	Year	Economic Loss (Million USD)	Deaths	Affected Villages/Homes / People	Flood Area (Unit)
1	1950	488	2,190	10,000 villages/homes	7,250.42 hectares
2	1955	378	679	6,945 villages/homes	8,297.86 hectares
3	1956	318	160	11,609 villages/homes	30,103.05 hectares
4	1957	301	83	4,498 villages/homes	6,475.42 hectares
5	1959	234	88	3,902 villages/homes	4,219.65 hectares
6	1973	5,134	474	9,719 villages/homes	16,784.32 hectares
7	1975	683	126	8,628 villages/homes	14,141.18 hectares
8	1976	3,485	425	18,390 villages/homes	33,152.06 hectares
9	1977	337	848	2,185 villages/homes	1,884.58 hectares
10	1978	2,227	393	9,199 villages/homes	12,390.04 hectares
11	1981	299	82	2,071 villages/homes	1,696.86 hectares
12	1983	135	39	643 villages/homes	761.79 hectares
13	1984	75	42	251 villages/homes	442.56 hectares
14	1988	858	508	100 villages/homes	2,484.95 hectares
15	1992	3,010	1,008	13,208 villages/homes	5,678.52 hectares
16	1994	842	431	1,622 villages/homes	2,252.23 hectares
17	1995	376	591	6,852 villages/homes	6,755.93 hectares
18	2010	43,000	1,985	1.6 million homes; 20m people	3,728,000 hectares
19	2011	3,700	434	1.5m homes; 8.9m people	2,750,000 hectares
20	2022	15,200	1,739	2m homes; 33m people	95,00000 hectares

2.10 Types of Flood

Pakistan usually sufferers 5 major types of floods, riverine floods, coastal floods, flash floods, glacial lake outburst floods, and urban floods.

2.10.1 Riverine Floods

Riverine floods are usually caused by heavy monsoon (summer) rainfall in the catchments. The most catastrophic riverine flood in Pakistan's history, the 2010 mega flood claimed countless lives and inflicted enormous financial losses. The 2010 mega flood inflicted the most damage to the agriculture sector, which includes fields like crops, cattle, and fisheries. The anticipated amount was $5045 million USD. Riverine floods in 2013 and 2014 also resulted in significant property destruction and fatalities (Shah et al., 2021).

2.10.2 Flash Floods

Natural streams undergo massive, short-lived flash floods as a result of heavy monsoon rainfall (torrential rain) in hilly and semi-hilly areas (Lin et al., 2021). Flash floods have limited warning lead periods and are hard to forecast. Chen et al. (2024) state that flash floods occur in Pakistan in the mountainous regions that border South Punjab, Kashmir, Gilgit-Baltistan, KPK, Balochistan, and the Indus River Basin. The 2011 flash flood claimed the lives of more than 500 individuals. Damage to crops, cattle, and fisheries was one of the major effects of the 2011 floods on the agriculture industry. The anticipated total loss was $1840.31 million USD. Balochistan suffered 6% of the overall agricultural, whereas Sindh suffered 94%. There were around 571 fatalities from the 2012 flash flood as well. An estimated PKR 33.6 billion was lost in crops as a result of the 2012 flash flood (World Bank, 2011, ADP, 2011, Khan et al., 2013). The National Disaster Management Authority (NDMA) reports that in 2014, flash floods affected over 460,000 people in Punjab, Gilgit Baltistan, and AJK, killing over 200 people. The 2016 flash flood also caused a large loss of life and property in Chitral, in the KPK province (NDMA 2014). A recent study conducted by the KPK Provincial Disasters Management Authority (PDMA) found that between March and July 2016, flash floods and heavy rains killed 261 people in KPK (Chitral, Mardan, Kohat, Manshera, and Malakand). 1,101 dwellings have been completely or partially destroyed, more than 200 individuals have been hurt, and several more have suffered partial damage (PDMA, 2016).

Plate3:Impact of Flooding in the Pakistan

2.10.3 Floods from Glacial Lake Outbursts

Glacial Lake Outburst Floods, or GLOFs, are caused by the collapse of glacial lakes. The hilly areas of northern Pakistan are becoming more vulnerable as a result of these floods. In July 2015, a Glacial Lake Outburst Flood in Chitral, KPK, killed three people and left almost 300,000 stranded. Global warming is causing the glaciers in Pakistan's Himalayan Karakorum Hindu Kush (HKH) region to recede. GLOF, or catastrophic flooding, is caused by glacial lakes that accumulate behind glacial deposits bursting and releasing enormous amounts of water in a matter of hours due to glacier retreat (Bazai et al., 2021). GLOF has serious economic repercussions in the HKH region of Pakistan. The International Centre for Integrated Mountain Development, or ICIMOD, has identified and mapped 2,420 lakes and 5218 glaciers in Pakistan. About 52 lakes have a potential GLOF hazard, with an occurrence frequency of roughly every three to ten years. About 35 GLOFs have been reported in the HKH region throughout the past 200 years. In recent years, Pakistan has experienced one or two burst floods annually (Shrestha et al., 2018; ICIMOD, 2021).

2.10.4 Coastal Floods

Coastal settlements in the Arabian Sea experience coastal flooding due to cyclones formed by storm surges triggered by wind. Coastal flooding occurs in Pakistan during May, June, September, and October when cyclones hit the coastal regions of Sindh and Balochistan. Between 1971 and 2001, Pakistan experienced 14 cyclones. In 2007, Gawadar, Balochistan, had coastal flooding due to two consecutive cyclones, Gonu and Yemyin, which resulted in substantial damage (Ahmed et al., 2017).

2.10.5 Urban Floods

Towns and large cities flood as a result of cyclones, heavy monsoon rains, or cloud bursts. Pakistan is also become increasingly vulnerable to urban flooding. There have been major flooding problems recently in Karachi, Lahore, Islamabad, and Rawalpindi in Punjab; Peshawar and Nowshera in KPK; and Karachi and Hyderabad in Sindh (Maqsood et al., 2019).

2.11 Case Studies of Flash floods in Pakistan

Pakistan is vulnerable to a number of hazards, including landslides, heatwaves, GLOFs, drought, desertification, floods, cyclones, earthquakes, waterlogging, riverbank erosion, and water salinity. Of the 25 catastrophes that occurred in Pakistan between 2000 and 2015, landslides, earthquakes, and floods were the most common (NDMA, 2015, Khan et al., 2020). In the last six years, glacier eruptions have mostly taken place in Booni and upper Chitral Sonoghour.Due to unusually high rainfall, Reshun village's higher meadows saw an unprecedented flash flood on August 2, 2013. Similarly, in the higher, drier, low-altitude grassland above the village, the high rainfall in July 2015 turned the rill into a severe flash flood. Buildings were destroyed, irrigation systems and related roads were disrupted, and gardens, crops, and orchards were washed away (Gul et al., 2020). Floods occur almost every year in the Panjkora River Basin (PRB), which is in the Khyber Pakhtunkhwa province of Pakistan's eastern Hindu Kush region. Typically, these floods occur during the monsoon season (June–September) (Bacha et al., 2022). In the last ten years, the region has had multiple devastating floods that have negatively impacted infrastructure, agriculture, property, and human lives (Zia et al., 2021). The most devastating floods on record occurred in 2005, 2010, 2014, and 2016. Rahman and Dawood claim that the spatiotemporal unpredictability of rainfall has grown due to climate change, putting neighboring communities at significant danger of floods (Rahman et al., 2021).

2.12 Flash Floods in Islamabad and Rawalpindi

In recent years, flash floods have demonstrated their catastrophic potential in Pakistan. The Lai Stream, which rises in the Islamabad foothills of Margalla and empties into the center of Rawalpindi, has been the subject of debate regarding flooding for the past 60 years (Bashir et al., 2019). In the Lai Stream Basin, flooding occurs during the monsoon season, which lasts from July to September. On average, flood damage in Rawalpindi happens every three years. In 1981, 1988, 1997, and 2001, there was significant flooding. The 2001 flood was regarded as a national calamity and was the biggest event ever recorded. Tragically, 74 people lost their lives and 3,000 homes were either fully or partially damaged on July 23, 2001, when 620 mm of rain fell over 10 hours from 0600 to 1600 (Naseer et al., 2020).

Plate4: Impact of Flooding in the Islamabad and Rawalpindi

An estimated 400,000 individuals were impacted by the 2001 flood, which also damaged both private and public property and resulted in damages exceeding USD 250 million (Saeed et al., 2018). On July 24, 2001, a flash flood in the nearby watercourse Lai Nullah1 destroyed Pakistan's capital, Islamabad, and its twin city, Rawalpindi. More than 400,000 people were impacted by the flood, primarily the poorest citizens of the twin towns. 64 of the 74 flood victims perished in Rawalpindi (Khan et al., 2021). Low-lying areas are particularly vulnerable to the effects of flash floods, which can be monitored, assessed, and mapped as a proactive management tool. For a nation with an official GDP of US $60.5 billion, the financial losses were estimated to be between Rs. 15 billion (about US $250 million) and Rs. 53 billion (about US $930 billion) (Japan International Cooperation Agency, or JICA, 2002). Accordingly, the most suitable and important technique for determining flash flood susceptibility areas for upcoming decision-making processes is accurate mapping of flash flood vulnerability (Hoffman et al., 2019). A wide spectrum of actors were involved in relief, recovery, and restoration activities after the tragedy, including the government, foreign funders, local non-governmental organizations, and individual residents. This flood was not unusual because the creek has been overflowing its banks roughly every two to three years, resulting in significant property destruction and fatalities. More recently, from 1994 to 1997, the Lai Nullah flooded five times; the 1997 storm destroyed 1000 homes and killed 84 people (JICA, 2002). To collect information for a post-audit of the disaster response and its impact on the impacted villages from the 2001 flood, fieldwork was conducted in the Lai Nullah watershed during the summer of 2002 and 2003 (Mustafa et al., 2003).

2.13 Flood Susceptibility

Because it identifies the most vulnerable locations based on physical characteristics that define the possibility of flooding, flood susceptibility mapping and assessment is a crucial component of flood prevention and mitigation measures (Vojteck et al., 2019). Ali claims that although floods are the most unpredictable natural disasters, they can be minimized in terms of their severity, negative impacts, and financial losses by using susceptibility analysis, which involves forecasting possible flood sites (Kaya et al., 2023). As a result, governments and scientists worldwide are increasingly concerned about flood susceptibility analysis and precise flood modeling.Because they identify the most vulnerable locations based on physical characteristics that define the risk of flooding, maps and evaluations of flood susceptibility are a crucial component of flood prevention and mitigation measures (Vojteck et al., 2019). Susceptibility analysis, which involves predicting potential flood sites, can reduce the severity, adverse effects, and monetary losses of floods, according to Ali, despite the fact that they are the most unexpected natural catastrophes (Kaya et al., 2023). Flood susceptibility study and accurate flood modeling are therefore becoming more and more important to governments and scientists around the world. Early warning systems and emergency services must assess food susceptibility in order to create management strategies for the avoidance and reduction of subsequent food episodes (Fernández et al., 2024).

2.14 Factors of Flood Susceptibility

Sustainable flood risk management requires an understanding of flood susceptibility because it offers important insights into appropriate adaptation and mitigation strategies (Huq et al., 2022). Generally speaking, different conditioning elements that reflect the physical attributes of the area under investigation are used in flood susceptibility mapping methodologies. This category usually includes geology or lithology, morphometric features (e.g., elevation or slope), density of river networks, soil types or hydrological soil groups, land use/land cover, and related factors. The desired flood susceptibility analysis's spatial scale has a significant impact on the conditioning elements chosen. In general, utilizing fewer components appears to make sense when the researched area is vast (such as on a national size), because obtaining the same data (same scale or resolution) throughout the entire territory is more difficult (Kaya et al., 2023). However, some research contends that a small number of components could make it more likely that some factors would be overrated (Shokouhifar et al., 2022). A greater variety of location-specific data and parameters can be employed in studies conducted at a local scale (such as the watershed size), which enables a more precise characterisation of the flooding predispositions (Mishra et al., 2022). Finding and choosing flood conditioning elements, as well as their correlations and multicollinearity, are essential in the flood susceptibility evaluation in order to keep just the more independent and pertinent ones. While geomorphic and geomorphic-derived variables are used extensively in multicriteria techniques, other conditioning factors pertaining to rainfall (annual volume and intensity) and permeability (derived from soil, geology, and land use data) are also used (Lu et al., 2022). A particular place may experience flooding as a result of these circumstances. For flood susceptibility modeling, a wide range of pertinent independent factors can be employed and examined. The independent components shouldn't be homogeneous spatial information, but they should be quantifiable and gathered from the entire study area. There are four possible formats for the conditioning factors: nominal, ordinal, interval, and ratio scale (Ilderomi et al., 2022). Different element combinations drive flood risk for locations since the determining factors remain environment-specific. Since these criteria stand to be highly significant in flood research scholars have implemented them in their studies. Flood studies require an understanding of how human structures fellows like land use and transport systems lead to flooding patterns when evaluating flood vulnerability (Liu et al., 2024).

2.14.1 Elevation

Digital Elevation Model (EDM) are essential tool for forecasting and assessing flood risk, particularly in metropolitan areas where flash flooding is a major problem. A thorough snapshot of land characteristics can be obtained by using DEM, which display the elevation and topographic variations in the area that impact the water distribution in floodplains. Topographical elements such as slopes, depressions and drainage systems are evaluated by models and the zones at higher risk for flash flooding are revealed, from these models (Oprea et al., 2023). DEMs' primary function for flood simulation is that they replicate water movement in the landscape, so accurate flood modeling depends on this. Digital Elevation Models (DEMs) are useful to study flash flood patterns and are required for the computational prediction of flood risk in metropolitan areas. Digital Elevation Models (DEMs) are highly detailed representations of the ground level that represent the height variations and terrain features that determine how floods flow across the landscape. Digital Elevation Models analysis of slopes, depressions and drainage patterns become critical tools for identifyingthe areas vulnerable to flash floods (Oprea et al. 2023). DEMs have become extremely important in flood modeling because they can reconstruct water flow in the landscape, an act that is critical to understand in evaluating the dynamics of floods. When calculating flood prediction in urban areas, we take into account how buildings and roads interruptate natural water streams causing local flooding. DEMs can also assist in topographical analysis, and that should be used by planners to develop better drainage systems that reduce associated risks (Falah et al., 2019). Using DEM analysis techniques defining and mapping watershed boundaries along with the drainage path identification predict water flow during flood. Watershed borders DEM defines which region is contributed to any given drainage point. This information is used to analyze collected water volumes in specific urban or natural areas during heavy rain (Mazzoleni et al., 2022). They found that Falah et al. (2019) that used DEM data research showed that areas with less drainage were more vulnerable to the flash flood based on their findings. Rawalpindi and Islamabad can be under vulnerable stormwater pooling sites as shown through low elevated lenh Nullah bordering districts that always experience frequent flash Flood. Ogden and Tarboton (1998) showed, using elevation data, that DEMs are capable of being used in hydrologic modelling to generate complicated drainage basin maps. Establishment of proper flood control systems that predict water movement path in case of heavy rainfall results to a viable flood risk reduction solution (Müller et al., 2020). DEM technology is analyzed for regions of low elevation, that are at high risk of flooding in conditions of strong rain events. At slow speeds, water evacuation is very much risk due to flash floods for such regions (Tehrany et al., 2015). A better interface prediction accuracy is anticipated from urban water collection if high resolution DEMs serve as the analyte. Early detection tools are necessary for Rawalpindi and Islamabad as development work has disrupted natural water drainage pathways and the two remain very high risk places for flash flood events. According to Zhou et al. (2023), separate DEMs can reveal micro topographical differences crucial for urban flood simulation. Schumann et al. (2008) and Han et al. (2022) find that small topographical changes significantly alter flood risks in metropolitan areas with flat to modest slopes. By integrating DEM with hydraulic and hydrological models, researcher may predict flood responses to different rainfall events. Through simulation of floodwater collection and water speed in specific areas (Qi et al. 2020), using this combination researchers are able to gain an important understanding of the behavior of a flood. Through integration of hydrological models and DEM data samples, Lin et al.(2006) were able to simulate urban flash flood scenarios. Results showed that DEMs with higher resolution improved flood depth and velocity prediction precision which supports key operations necessary for urban planning as well early warning systems (Su et al.,, 2022). Liu et al. (2014) had studied floodplain inundation simulations based on DEMs with the use of the Hydrologic Engineering Center's River Analysis System (HEC-RAS) technology. Through their research, they determined that the DEM produced elevation information allows for the reliable identification of flood boundary which is fundamental to them being able to rely so heavily on flood mitigation strategies (Rahmati et al., 2021). Topographical DEM technologies find use as a first order application in the measurement and mapping of flood risks. Elevation data is used to develop the flood susceptibility maps and they represent how various places would be ill prepared for flash floods in their worst situations. DEM is shown to give out a lot of topographical information which allows the analysis of flood risk for different areas by Chen et al. (2022). That said, DEMs (Tehrany et al., 2014) created flood hazard maps of Kuala Lumpur, and were able to accurately identify potential flash flood locations. This method can be applied to Islamabad and Rawalpindi as changes in urban structures and geographic features heighten flood risk to selected communal areas. Rahmati et al. (2019) indicate that it is necessary to enhance the accuracy of flood hazard mapping by using machine learning methods with DEMs. Stronger results from predictive models in flash flood prone regions (Rahmati et al., 2019) were obtained through the integration of DEM derived parameters such as elevation slope and flow direction. DEM's become important for flood risk assessment role for several reasons: floods risk cannot be assessed under climate change conditions without better predictive models due to expected increases in the frequency and intensity of rainfall. DEMs are tools that simulate under what conditions water flow dynamics will change and what pore space capacities per location increase to detect geographical locations where new precipitation behaviors could manifest into flash flood incidents (Vennix et al., 2023). With climate change, making DEM-based flood modeling even more critical, the IPCC (2014) states that flooding will also be worse in many regions. In the face of extreme weather conditions, data from DEMs is used by urban officials and city planners to recognize key infrastructure zones that require development to prepare for aging flood risks confronting Rawalpindi and Islamabad (IPPC 2014).

2.14.2 Slope

The primary determinant of flash flood risk assessment is terrain slope, which has a direct impact on the location, manner, and rate of water accumulation and flow across land surfaces. Water flows across surfaces based on slope, which characterizes the gradient and steepness of the terrain. According to Lu et al. (2022), steep areas have quick surface water drainage after precipitation, however, stored water induces potential flooding risk on flat and gently sloping areas. Thus, it remains important to understand slope effects on water flow patterns in order to accurately forecast and manage floods particularly, at flood susceptible locations like Rawalpindi and Islamabad in which the frequency of flash floods is quite high (Costache et al., 2019). In any terrain, surface water movement patterns for rain are strongly dependent on slope characteristics. On steeper slopes, increased rainfall surface flow velocity reduces soil infiltration time. Duan et al. (2022) indicate that quick drainage runoff from lower terrains threatens drainage network capacity and elevates the hazard of flash floods. Tehrany and their team (2014) discovered that terrains with steep slopes increased water flow rate resulting in greater flash flood exposure at base of slope. Hilly regions depressions and valleys keep standing water which increases flood risks (Tehrany et al., 2014). Borga et al. (2011), in their hydrological simulations of flood events indicate that hydrological simulations on flood events are critically slope gradient dependent. Fast water runoff from steep faces allowed little absorption time, leading to steep mountainous areas experiencing flash floods most often (Song et al., 2022). Slope also influences erosion mechanisms, and therefore surface runoff, as well as processes of water flow. Fast moving water flow and soil erosion on steep slopes lead to poor drainage system at the downstream across studies by Ren et al., 2023. Because stronger surface runoff is produced on steeper slopes, water erosion increases (Morgan 2005). In urban areas after vegetation cover removal, the soil erosion contributes drainage obstruction and elevated flood risk. Raw water accumulation and soil diffusion reduction along with development activities and steep inclines heighten flash flood dangers in Rawalpindi and Islamabad (Halama et al., 2023). In a study performed by Duan and colleagues (2016), the differences of surface runoff, soil erosion among different terrain types were considered under different slope conditions. According to the research, sites with slopes above 20% experience a greater amount of soil erosion and water runoff increasing their likelihood of flash flooding after heavy rains (Ran et al., 2019). The soil infiltration capacity and how runoff is generated depend on the slope of a landscape. Because they last time lengths across slowly sloped areas reduced surface runoff levels are observed. Fast moving water across the surface on steep angles causes increased flood danger with limited ground penetration time

(Song et al., 2022). Sharma et al. (2017) investigators report that infiltration rates vary with slope gradient because in steeper topography, faster water flow results in rate of infiltration reduced. Surplus water is faced into absorbing in steep terrain that surrounds Rawalpindi and Islamabad, and already there are impermeable surfaces that prevent any water for entering. Steeper slopes are less amenable to infiltration and they intensify vulnerability to sudden flash flooding events. In Tehrany et al. (2015) research, slope combines with water accumulation at flooding prone locations and affects water infiltration. Their model found that flood vulnerability analysis exposed areas with high slope as they are more susceptible to flash floods since water will naturally flow downhill to lower elevations (Brahim et al., 2024). In Geographic Information Systems (GIS) analysis of flood hazards, recognizing slope is important. Flood susceptibility models use slope information from Digital Elevation Models (DEMs) to identify areas at high flash flood risk based on steeper terrain (Parsian et al., 2021). Pradhan and Youssef (2010) in their 2010 study indicated that terrain was characterised of poor infiltration capacity and rapid runoff, which characterized steep areas, thus affording those steep areas to have higher risk of flash flood. Youssef et al. (2010) found that mapping flood hazard based on slope as a primary factor was effective at allowing the effective detection of high risk areas for targeted action in purchasing flood protection buildings. The team of Zhao analyzed urban flood risk by studying slope information from DEM data. Zhao et al. (2018) research shows that the steep areas are not usually suited for flash floods except where these areas have consolidated and non porous materials that intensify surface water runoff. Natural drainage patterns have been changed by urban development in Rawalpindi and Islamabad which makes slope analysis important for flood vulnerability assessment. Rainfall drains downhill from steep city hills to congested areas filling drainage systems so full that they flood in a flash. Tingsanchali (2012) demonstrates that urban development on steep inclines raises surface water flow and suppresses natural absorption capacities, creating higher flood risks. Natural landscapes are replaced with impermeable surfaces, urban development increases flood risks and stops water infiltration operations in these environments (Alshammari et al., 2023). In their 2008 finding about flood risks in the developing urban setting, Douglas et al demonstrate that steeply sloped areas are especially vulnerable to flash floods. This resulted in difficulty with water management during intense rainfalls due to a strong combination of quick surface water flow (too much water, too quickly) plus relatively inadequate drainage systems. An unabated growing urbanization has hence disturbed the natural waterflow pattern in Islamabad and Rawalpindi. Because climate changes result in storm events that are stronger and of increasing frequency, slope becomes an increasingly important factor to flooding susceptibility. Increased slope runoff velocity and volume due to heavier rains increases the severity predicted of floods in areas with steep topography (Hanif et al., 2020). Anticipating stronger and more frequent flash floods elsewhere in the world, with a key impact in steep areas, the IPCC (2014) points out that climate change will also result in prolonged periods of downpours, increased volume of rainfall, and a reduction in soil penetration capacity. Researchers have found that the risk of flash floods becomes more urgent the moment steeper terrains couple with ever more severe weather patterns (García et al., 2018). Research by Meehl et al. (2007) illustrates that flash floods made worse due to climate changes pose greater risks over terrain where mountainous and hilly slopes predominate. In these areas, where precipitation is becoming more intense these areas experience faster runoff, increasing peak flood levels, and decreasing reaction time for flood control operations (Mastrorillo et al., 2016). Analysis of the slope effect on water dynamics is required for effective flash flood mitigation strategies. However, effective sustainable urban designs, reducing the risks of slopes induced floods, communities should practice engineering techniques like terracing, slope stabilization and good drainage systems to manage runoffs in steep elevated areas (Zhao et al., 2018). De Roo et al. (2001) state that actions such as tree planting and the building of retention basins reduce water runoff on steep gradient terrain. The decrease in flash flood risk (Huang et al., 2021) can be realized through water flow reduction and increased infiltration. According to Chow et al. (2012), steep slopes result in rapid runoff and so must be able to handle rapid runoff, therefore analysts design metropolitan drainage systems for it to pass and not accumulate. In order to provide effective flood risk management in areas prone to flash flood, the analysis of urban slopes has to be part of city planning (Duncan et al. 2020).

2.14.3 Aspect

The aspect of slopes plays a central role in controlling hydrological behavior of landscapes due to its significant effect on flash flood susceptibility. The direction which a slope faces determines many environmental functions including how runoff operates along with vegetation development and levels of soil moisture retention together with exposure to sun rays (Huq et al., 2022). Sunshine exposure varies with slope orientation which consequently alters temperature balance and water evaporation rates. Southern orientation makes slopes receive more sunlight and heat in the Northern Hemisphere because it makes water evaporate more quickly and keeps less moisture compared to shaded northern slopes (Win et al., 2024). Hansen et al. (2007) demonstrated that the amount of moisture that vegetation is capable of holding changes alongside different environmental variables. The study conducted by Hansen et al. in 2007 found that soil moisture levels in south facing slopes was lower than other slopes, which caused more runoff during a rainstorm and heightened vulnerable of the place being flooded. When investigating aspect effects on soil moisture and runoff patterns, Kirkby et al. (2013) research found that shaded slope retain moisture better than the sun exposed slopes. It showed that assessing flood risks in mountainous regions requires some particular conditions (Kirkby et al., 2013). Vegetation form and abundance are dependent on slope direction to control where water flows at ground surface and how fast rainfall is absorbed. In temperate zones Leng et al. (2024), dense plant life on north facing slopes soaks rainfall better and reduces flash flooding risks. In an exploration of mountain side vegetation patterns (Li et al. 2015), Li et al. found that because south facing slope has fewer plants, they have greater storm water runoff. Li et al. (2015) found that multiple important factors on flood risk and land management need to be evaluated. In 2013 Pérez- Harguindeguy and colleagues show that patterns of plant species are dictated by the sun facing side of land and how that in turn affects how water behaves in that area. Research demonstrates the vegetation maintenance on non-sunny slopes has an important role in decreasing flash flood occurrence risk. Slopes solar orientation controls soil features and the moisture retention capacities that affect water penetration depth and runoff generation. The main factors that control flash flood vulnerability are aspect grounded on soil properties (Al Aizari et al., 2024). Shang et al. (2018) research shows that aspect and soil parameters explain a lot of soil moisture variation between exposed and shaded slopes. Schaefer et al. found that south facing slopes lose more moisture because their capacity for retaining that moisture stay lower (Schaefer et al., 2024). According to Rogers et al., (2017), soil characteristic differences based on slope aspects produce different effects during episodes of heavy rainfall. When hydrological models incorporate the slope aspect, Kaya et al. (2023) found that flood susceptibility is better predicted.

Physical aspects that change climate and rain patterns over mountainous areas are the changes in flash flood vulnerability. Kaya (2023) presents rain patterns across different slope directions affected by both primary wind patterns and mountain terrain effects. During their 2014 analysis of mountain rainfall distribution based on aspect variability, Smith et al. discovered that windward slopes received more precipitation than leeward slopes. In 2016, Teixeira and colleagues analyzed that a flood hazard is analyzed multifaceted in terms of multiple elements in a complex topographical area. Aspect and rainfall intensity and the impact these have on flash floods were examined by Hewitt et al. (2018). Geographic feature changes present various flash flood hazard patterns, and such open terrains require robust hazard evaluations (Hewitt et al., 2018). The hydrological behaviors and surface water flows in the process are subject to the combined effect of terrain forms and orientations. Wang et al., 2017 report that flash flood vulnerability is not uniform across regions because steep slopes lead to rapid runoff, while gentle slopes result in higher infiltration rates. Topographic elements and aspect determine hydrological patterns, according to Rinaldo et al. (2019). Yang et al. (2022) found that adding new components in flood susceptibility models improves predictive performance of flood susceptibility models. Working with Wang et al. 2021, an aspect model was created and combined with element topography. Hydrological studies in complex terrain find aspect informs the aspect of flood vulnerability through distinutes hydrology changes (Huang et al., 2022). When certain crucial elements are integrated into improved specific integrated flood risk assessments, reduced risks from flash floods become possible. With respect to land use planning and flood control directives from policymakers, it is more informed when elements involved in hydrological processes are considered (Hang et al., 2022). Studies by Zhou et al. (2020) indicated effects of aspect on runoff behavior and that those effects are beneficial due to vegetation management as highlighted even in flood risk management frameworks described by Kumar et al. (2021). A digital combination of aspect with remote sensing and GIS capabilities was called for by Mokarram et al. (2022) when demonstrated the vital role of aspect in the evaluation of the flood risk (Cheng, et al., 2021)

2.14.4 Rainfall

Rainfall stands as a principal trigger for flash floods which gets exacerbated in urban environments because their hard surfaces combined with poor drainage lead to dangerous runoff after heavy rains (Creutin et al., 2013). Flash flood occurrence depends largely on both how intense and persistent rainfall events last. Through cities where drainage pipes exceed capacity, intensive rainfall conditions temporary in duration direct to quick-water movement along with specific area flooding (Smith et al., 2011). Miller et al. (2019) discovered that steep landscapes alongside urban regions are extremely vulnerable to rapid and intense flash floods resulting from strong rainfall events at or above 25 mm/h intensity. Miller et al. (2019) show rainfall episode duration matters because longer rainfall duration means more continuous rainfall which can increase soil saturation, leading to more severe flooding and rising flood risk. In 1970 Nash and Sutcliffe found rainfall intensity directly related to runoff production. In addition, Brunner et al. (2020) show that the likelihood of flash floods will increase when rainfall exceeds soil infiltration capabilities. Flash flooding occurs most often in areas susceptible to heavy rainfall events when atmospheric conditions already contain high levels of moisture (OchoaRodriguez et al., 2015). Areas of higher rainfall frequency within metropolitan areas are shown by Zhang et al. (2021) to be more susceptible to flash flood events due tocumulative runoff impacts. Study directly demonstrated from above, and historical rainfall trends must be investigated for assessing flood risk, (Li et al., 2020). Fletcher et al. (2013) determined how geographical distribution and rainfall variability impacts the flood systems dynamics. The studies indicate that isolated storms result in short life span flash flood hot spots and these are exacerbated in the towns without good drainage (Baker et al., 2021). How an area hydrologically responds to new precipitation is determined substantially by pre rain fall soil conditions. After subsequent downpours, the same soils are less absorbent thus more and the contributing factor to both runoff and subsequent flash floods (Cohen et al., 2020). According to Gunderson et al. (2017), who performed the research, saturated soils at the time of the first storm generate a great deal of runoff when subsequent rains occur, which greatly contributes to the level of the flood. The study reveals that critical to understanding antecedent conditions is the need to build historical rainfall into flood risk estimates. A study by Jia et al. (2019) that in the Yellow River basin, during heavy rain events, the significant flood risk happens when the prior soil moisture level is high. According to Davis et al. (2021), antecedent conditions have to be evaluated for accurate flash flood prediction. Flash flood prediction depends on hydrological and rainfall models. These models are effective in accurately estimating the conversion of rainfall to runoff, by considering rainfall duration and intensity, with regard to soil properties and land use, and drainage conditions (Khan et al., 2022). The top model is a surface hydrological system represented by Beven and Kirkby (1979) that analyzes terrain based movement of water due to rainfall inputs and landscape features. From experiments, they found that predicting runoff and flood occurrences requires accurate rainfall input calculations. An urban flash flood rainfall-runoff model comparison study is conducted by Gharakheili et al. (2020) to discuss the efficiency of urban flash flood models. According to their study, water movement predictions must be based on those that use hydrological models which incorporate rainfall characteristics specific to each geographic area (Khan et al., 2022). The increase in frequency and severity of heavy rain episodes drive the observed flash flood risk induced by climate change. Climatic variability rainfall pattern changes have a substantial impact on flood vulnerability levels. Rising risk of floods from a climate change perspective is also the product of increasing and intensifying extreme precipitation events as suggested by the research done by Kundzewicz et al. (2014). According to the researchers, planning the responses and adaptation to future flood risks requires the use of climate projection data in models used to assess these risks. According to the 2012 Tebaldi et al. research, which shows that rising extreme rainfall frequencies projected by climate change will present major challenges to successful flood control systems. Adaptation approaches such as those recommended by the researchers that reflect changing rainfall trends in susceptible flood locations, are needed. Data supplied by rain gauges in conjunction with radar and remote sensing systems are the basis of rainfall pattern assessments and flood risk evaluations (Petersen et al., 2021). They found that in order to quantify risks from flooding comprehensively, multiple rainfall data sources need to be combined. Instead, the WMO 2019 report said, effective flood preparedness and response requires dependable rainfall monitoring networks and advanced forecasting methods. To their research based on, Petersen et al. (2021) discovered that rainfall measured using technology improved holds a vital role in flood risk management. Landslides and surface runoff results from too much rainfall in steep terrain areas and mountain ranges. Flash floods intensify when rivers and streams become blockages creating both localized flooding and increased sedimentation (Malamud et al., 2020). According to Guzzetti et al. (2012) research, landslides occur much more during times with heavy rain. The research had clearly demonstrated that there is a direct correlation between the landslides as well as the flash floods that follow in regions where vulnerability of these natural disaster exist. In 2014, Fuchs and his team found evidence that rainfall can trigger landslides, which temporarily block waterways and then rupture, sending downstream floods. In regions, landslide hazards should be integrated into flash flood vulnerability assessment (Malamud et al.,2020).

2.14.5 Normalized Difference Vegetation Index

Since its calculation is the difference between near infrared (NIR) and red light reflectance, it is a widely used remote sensing metric that measures vegetation density and health. With respect to flash flood vulnerability, the analysis of how the vegetative cover affects the variations in hydrologic processes is highly dependent on NDVI (Ilderomi et al., 2022). A reliable estimator of vegetation density and plant health, the Normalized Difference Vegetation Index also impacts the hydrological processes of a region. The research conducted by Zhang et al. (2021) concluded that the healthy cover of vegetation increases infiltration rates and increases the capability to retain water to avoid flash flooding and to reduce surface runoff. As a remote sensing technique, the Normalized Difference Vegetation Index (NDVI) is calculated from near infrared and red lightm reflectance data and indicates vegetation coverage and plant health. However, according to Ilveromi et al. (2022), NDVI is needed to evaluate the relationship between vegetation cover and hydrological dynamics related to flash flood vulnerability. Vegetation density and health have changed the way we model water flow because bands associated with the Normalized Difference Vegetation Index provide reliable data. Better ground infiltration rates and higher moisture storage capacities, found in vegetation health, assist protect towards flash floods and surface water runoff (Zhang et al., 2021). According to Yuan et al. (2021), the plant cover that helps to retain more soil moisture and suppresses floods through rapid runoff is high NDVI readings. Bajgiran et al. (2017) found that within semi arid territories, superior moisture storage and reduction of surface runoff following a rain period was facilitated by the presence of vascular plant biomass, as identified by high NDVI scores. According to the study, the regular NDVI monitoring can point out high flood risk areas. Research has been conducted by Liu et al.,

(2020) to utilizing NDVI for soil moisture prediction and flood susceptibility detection. Similar to this, findings of Yuan et al. (2021) informed us how analyzing soil moisture levels using NDVI can help researchers identify flood risk assessment methods. Vulnerability to flash flooding is highly sensitive to NDVI values which are strongly affected by land cover and land use changes. A study published by Hu et al. (2023) reveals that with urbanization and deforestation and agricultural expansion, plant cover is reduced, which further raises both risks of flooding and potential for water runoff. Meyer et al. (2018) also show how urban land use changes lead to a significant reduction of NDVI values, how would this impact speed of urban expansion. Research showed that a decrease in vegetative cover leads to increased flood risks. Reduced vegetative cover will raise flooding hazards because it will pump water through a non forested river basin with less surface water flow when the basin is deforested, as was noted by Mouton et al. in 2021. Tree-planting projects to control flooding hazards were something the researchers endorsed, as mentioned by Hu and colleagues in 2023. Including critical cover data (measured through NDVI) into hydrological models leads to better precision of flood risk assessment (el-Bagoury et al., 2024). Using hydrological modelling during 2017, Zhang and colleagues were able to analyze flood susceptibility pursuit in urban regions using NDVI data. The study also found that adding vegetation impacts on runoff and permeability coupled with NDVI generally increased the predictive quality of the models. However, Zhou et al. (2019) developed a model of watershed flood risk forecasting by merging NDVI data with supplementary environmental parameters. Investigation by El-Bagoury et al. (2024) found that NDVI significantly enhances the accuracy of mapping the potential flood hazards. Climate change is likely to lead to changes in newly emerging patterns of plant distribution and altered NDVI measurements that enhance flash flood vulnerability. Fluctuations of temperature and precipitation cause negative effects on plant density and plant health and generates cascading effects on hydrological responses (Wang et al., 2021). Zhou and his team (2020) analyze both NDVI variation as a consequence of climate change and corresponding implications for flood risk. They demonstrate that climatic variability roots changes in plant cover which lead to enhanced risk for flash floods in some areas. González and team's research revealed that vegetation losses resulting from climatic shifts render flood susceptibilities to the affected area greater. The challenges themselves have been identified through research with research establishing the indispensable need for adaptative management methods to address these challenges (Bates et al., 2023). Including NDVI into the mechanics of early warning systems can be used to fortify them and improve flood preparation. By analysing NDVI patterns, decision makers can evaluate vegetation health as well as the potential dangers of flood and support the early intervention efforts (Fernández et al., 2024). In their study, Baccini et al. (2017) proposed NDVI data (vegetation greenness index) as a tool to be used in flood early warning systems, also showing that the vegetation health other monitoring can be used to predict flood risk potential under appropriate scientific interventions. The incorporation of NDVI metrics will improve readiness for early warning systems of floods. Through persistent NDVI pattern surveillance one can take proactive actions based on information these NDVI patterns give out on vegetation health conditions and potential flood hazards. Baccini et al. (2017) showed that vegetation health monitoring for flood early warning combined with data from NDVI systems is an actionable approach towards developing flood early warning systems. In order to improve the flood preparation Ma et al. (2021) designed a NDVI integration paradigm in the scale of flood risk management to highlight the importance of real time monitoring. According to the research conducted by Ma et al. (2021), NDVI was significantly important in complete flood risk management systems.

2.14.6 Soil Type

The topographic functions of infiltration together with permeability and retention are then made up of soil properties, which in turn significantly influence regional hydrological responses. According to research provided by Majeed et al. (2023), information about the spatial distribution with types and properties of soils is extremely helpful in determining the vulnerability of landscape topographies to flash floods. Water interaction with various soil profiles are therefore analyzed from the soil map data. Rapid percolation accompanied by little surface runoff ensues from sandy and loamy soils which permit water to come in evenly, and quickly. Clay content or compacted material dominated soils have insufficient infiltration rates and low absorption rates, together resulting in more surface runoff and increased risk of flash flood. According to Baum et al. (2020), the ability of the soil to absorb the water has emerged as one main variable that determines flood development. According to Lechner et al. (2021), low permeability soils naturally repel water, and become ineffective barriers, and promote overland flow, making them more likely to fail under flash flood events. Niehoff et al. (2002) found that poorly infilitrating clayey soils contribute to greater watershed runoff production through soil type driven watershed runoff production processes. In their research, Olsson et al. (2020) demonstrated that while detailed soil maps are important tools for determining and predicting flood hazards in both agricultural and urbanised regions, a statement which I agree with. Different amounts of sand, silt and clay results in different soil texture, which in turn determines how much water a soil can drain and hold. Soils coarse textured and/or sands drain rapid, producing solid drainage and reducing the statistically of flooding. Reduced permeability, and larger water retention capacity, are associated with fine textured clay soils release more runoff in heavy raining. In support, Zhang et al. (2021) argue that hydrological processes in landscapes vary primarily according to soil texture with lower infiltration rates and greater rates of surface runoff on finer soil textures. Soil texture information available in mapping data has to be included in flood risk evaluation models according to Garnier et al. (2020). Flood danger is intensifying due to increasing rainfall during which the clayey soils maintain higher water levels and allow less infiltration which saturates soil quickly (Lal and Shukla, 2021). Kaya et al. (2023) also research results showed that soil maps are an important indicator in detecting flood prone area using soil texture information. Urban environments not only compact soil during infrastructure construction but also reduce the capacity of the earth to absorb water severely. In turn, building structures, alongside roads and parking lots, become impervious materials for more flash floods with the increase of runoff and impeded infiltration. To characterise flood hazards, urban areas require detailed maps of the soils they develop over, land use patterns and compaction measurements. Souza et al. (2016) concluded that when regions experience urban development, urbanization leads to compacted soils, which in turn reduces water absorption, and therefore increases magnitude and speed of runoff water on the surface. Assessments of city flood risk, Davis and colleagues argued in 2018, would need to include soil compaction data from up- to-date soil maps. The impact of soil compaction coupled with impermeable surfaces on flood production was studied by Paul and Meyer (2001) in urban locations. Zhang et al. (2021) show urban soil maps, coupled with land use data, provide important insights on urbanization effects to flood hazards from the hydrological perspective. Soils are divided into four Hydrological Soil Groups (HSG) by the U.S. Natural Resources Conservation Service (NRCS) based on soil infiltration capability and susceptibility to runoff. The soils in these categories (A, B, C, and D) range in infiltration rate from high (Group A) to extremely low (Group D). Soil maps stratified according to Hydrological Soil Group (HSG) classification are employed in hydrological models that estimate flood and runoff risks. The maximum runoff capacity and dominant flood generators are found to be the clayey soils (Group D), though Arora et al. (2020) also showed that hydrological soil groups assist in providing flood generation information. The necessity of HSG data inclusion in flood hazard maps mainly regarding mixed land use areas was also demonstrated in a defect research (Zhao et al., 2023). HSG group classification of soils was required to adequately map soils (Ponce and Hawkins, 1996), as group A soils (includes sandy soils) possess high infiltration rates with very low surface runoff potential during intense storms. Group D soils are vulnerable to flash floods and surface runoff, at high risk of such per Li et al. (2020). Flood vulnerability is defined by the soil texture and soil saturation status before rain. When soils are already full from prior rainfall or defective drainage, water absorption is prevented – flash floods become a great concern. Soil maps have great utility as predictive tools for flood episodes if soils themselves are mapped with indicators of soil moisture at varying time periods. Brocca et al. (2017) studies indicate that the dynamic behavior of the flash flood is dictated mainly by the initial soil moisture conditions. When considering maps that also contain soil moisture information, with saturation levels figured out, the flood model distribution capability is made more accurate (Bai et al., 2023). Research by Schneider et al. (2017) finds moderately permeable soils become flash flood generators under flood conditions if they are already saturated. Based on good soil maps and realtime soil moisture data, they suggested, it is possible to better forecast flash flood risks in such high risk areas. Soil erosion that forestry operations and agricultural practices and construction development tend to amplify severely alters hydrological patterns in particular terrains. Under normal circumstances, soils to help retain water by controlling where it flows (i.e., storing and releasing water slowly); when soil erodes and the natural structure is broken down, runoff rises. The analysis of areas at risk of flash flood depends on a soil map showing areas of land degradation. Soil erosion, according to Zhou et al. (2020), increases water runoff in mountain landscapes as well as cultivated fields and elevates flash flood risk. Research data supports that flash floods are occurring more often than in soils with an undegraded soil structure displayed in soil maps resulting from soil unable to infiltrate water (Fey et al., 2020). As Pangos et al. (2015) found soil erosion has a significant effect on soil permeability and structure, this utility of soil properties to modern flood risk assessment strategies. However, Mannion et al. (2022) favored the combination of maps of erosion susceptible zones and soil maps to find where flash floods can occur. Fundamental data required to develop successful flood protection strategies are provided by soil mapping. By identifying low permeability regions where excess compaction or degradation of soil has led to flood, land managers can control floods through reforestation strategies, soil conservation practices and urban permeable surfaces construction. Accurate soil maps can be utilized as a guiding tool for sustainable land use practices that increase water absorption and run off reduction. Marfai and King (2008) research shows that soil maps need to be included in the city's flood control strategies, as soil compaction combined with lower permeable surfaces increase flood risks. Green infrastructure and soil conservation methods together with the green infrastructure lower the problems caused by impermeable soils (López-Fernández et al., 2021). Urban Soil Maps are shown to be necessary in creating sustainable urbandrainage systems by Schwab et al. (2021). Soil mapping information should be used to guide the placement of bioswales in combination with green roofs and permeable pavements to control surface runoff to prevent rapid flood conditions, based on Schwab et al. (2021).

2.14.7 Drainage

In direct control of the drainage is the amount surface water moves through the watershed. When drainage density is high, rapid surface flow is attributed to stream channels elevating flood risk and fast tracking water level elevation. There are areas of lower drainage density where water has periods to seep downward before becoming a flash flood condition. As researchers Ouma and Tateishi (2022) found, the drainage density affects the rate of watershed reaction to rain events. Due to higher drainage densities and more extreme weather (Liu et al., 2023), more flash flooding during intense events is possible owing to increased runoff speed. According to Sharma et al. (2021), higher drainage density in watersheds causes these watersheds to be flash flood prone since they channel water quickly to minimize peak flow lag time in rain events. That's why drainage density is important when assessing risk and creating maps of flood vulnerability, according to the research that Sharma and colleagues conducted in 2021. Drainage density values are strongly controlled by the structure of topography. If less steep a flatter area will show less drainage density as water moves slower and will infiltrate better yet if steeper it will have channels develop faster and produce a higher drainage density. The foothills of these mountains near Rawalpindi and Islamabad have an enormous drainage network and, as a result, terrain with steep mountainsides generates conditions conducive to frequent flash floods (Masoudian et al., 2011). Moges et al. (2022) shows that there is a relationship between slope gradients and drainage density. Steep slopes are observed to generate a denser drainage system, accelerate runoff, and enhance flash flood hazard detected by metered observations only from mountainous terrains. Sparse network systems that enable long infiltration duration but low in flood risks, are more common in lower gradient regions (Ali et al., 2021). Furthermore, Erena and Worku (2019) study demonstrated that areas with a high drainage density contain steep and rough topography that converge surface runoff into channels very quickly, escalating flash flood risks. According to Hassan et al., (2022), research reveals that the infiltration rates in these areas are poor, resulting in faster surface runoff and further increase in flood risks. Specific patterns of land cover along with land usage influence drainage density. Urbanization, deforestation, and agriculture combine with construction of artificial channels with storm drains and culverts to cause great changes in natural drainage patterns and increase drainage network density. According to Rao et al. (2020), the outcomes of these modifications usually result in an increased flooding vulnerability, as well as speedier water movement systems. Miller and Hutchins (2021) showed that as urban development through road building, building and stormwater systems expand, so too does the expansion of artificial drainage networks. Because factors lead to more runoff, and faster water speeds, the danger of urban flash floods rises. Chen et al. (2020) research examined flash flood risks alongside drainage density patterns that emerged as land used altered. It was found that higher drainage density is caused by increasing impermeability of urban surfaces, which decrease infiltration capacity and raise the surface runoff, increasing thus flash flood vulnerability in developed areas. Drainage density is so affected by soil type and characteristics. Because the water will still go to surface waters instead of entering the ground in places with soils that inhibit water penetration, there will be advanced surface drainage systems. Research at Ghadiri et al. (2019) suggests that infiltration rates are higher in permeable soils leading to them having decreased drainage densities over various regions due to widespread infiltration. Using data from mainland China, Liu et al. (2021) showed that soil permeability is the dominant factor determining drainage density. In their research, they show that while areas dominated by clay and other types of soils with poor permeability are more likely to chaper desertification, regions with similarly poor soils foster denser drainage network formations under that regime as reduced water infiltration increases the likelihood of surface runoff and flood events. Ahmad et al. (2020) show how soil types, which determine flood risk zones, correlate with the drainage density. Impermeable soils cause more extensive drainage networks, increase flash flood risks, and are found in heavy rain prone areas, according to Benavides et al. (2023). As an important criterion in flood hazard models flash flood areas at risk are depicted by drainage net works. This results in flash flooding of many high drainage density locations that are seen to gradually accumulate during extreme rainfall events due to the faster water flow in densely connected drainage systems. Research by Abebe et al. (2022) indicates that GIS-based flood models produce more accurate flood risk assessments as a function of drainage density within the urban environment. Drainage density was found to be a key component of the flash flood susceptibility model by Tehrany et al. (2019) to Malaysia. It was found that drainage density is critical in flood risk mapping because high drainage density areas are more susceptible to downstream flood condtions. Drainage density is an analytical criterion integrated in flood hazard mapping in Bangladesh by Pradhan et al. (2022). Using their model, they demonstrate that as runoff accumulates faster, these dense locations become ideal for flash floods (Akhter et al., 2023). Climate change predictions indicate that intensified storm events will produce more dangerous flash flood conditions. Because high drainage density areas have poor water absorption abilities they face increased flood risks with swifter and stronger flood occurrences (Nash et al., 2023). The IPCC report from 2021 suggests that climate change will drive both more frequent and intensified severe rain patterns especially in regions recognized by their high drainage densities. The expected increase in flash floods depends upon drainage systems failing to manage excessive runoff. In their 2022 study Feng et al. researched how climate change affects drainage systems across Southeast Asia. Research by Gao et al. (2023) indicates locations with dense drainage systems that show current vulnerability to flash flooding will face higher risks when more intense storms induced by climate change overwhelm such systems leading to flooding. All mitigation strategies dealing with flash floods need to evaluate drainage density levels. High-density regions will experience lower flood risks when we build retention basins along with restoring natural vegetation and improving stormwater management. The application of green infrastructure through permeable pavements along with green roofs diminishes high urban drainage density impacts caused by artificial drainage systems that make populations more flood-prone according to McPherson et al. (2019). For areas experiencing high drainage system the authors Kourgialas and Karatzas proposed implementing retention ponds and detention basins which could effectively manage additional runoff while decreasing peak water flow volumes. The investigation revealed that these actions produce maximum effectiveness in metropolitan areas with developed drainage structures. Kocornik-Mina and his team (2020) encouraged the implementation of green infrastructure methods for urban flood control in areas that exhibit increased drainage density. Research evidence shows green spaces together with porous land help reduce both runoff quantity and velocity thereby reducing flash flood risks (Nascimento et al., 2021).

2.14.8 Land Use Land Cover (LULC)

Hydrological process and local flash flood vulnerability depend on land use and land cover pattern (LULC). Patterns of land utilization and their distribution in the area determine the water dynamics of a watershed, including its surface runoff, total water balance, and rainfall infiltration (Bakri et al., 2022). Urbanization together with deforestation and agriculture growth represent examples of major land use changes that have substantial effects on hydrological responses. The rise in impermeable surfaces, through conversion of land to urban areas, in turn increases runoff and reduces surface water infiltration capacity (Ciucci et al., 2023). Urban regions are defined by both Alberti (2005) as impermeable surfaces, when these impervious surfaces build buildings and roads, thus preventing water from reaching the ground. At times, when atmospheric water impacts soil impermeable extents, they become flash flood generators along with high surface runoff. In this research, Zhao et al. (2019) used land use alteration analysis in a rapidly urbanizing area and found that urban development caused pronounced increases in both in increased runoff and vulnerability to flash flooding. According to their findings (Ding et al., 2023), their analysis underscored the necessity of integrated land use planning to minimize flood hazard. Vegetated areas help control flood danger as evapotranspiration capacity and increased infiltration to slow runoff peak help regulate runoff in and through rainstorms. Higher water absorption, therefore, slower water speed channels towards streams and rivers in places that host dense vegetation (Brouwer et al., 2022). In 2020, Boretti and his colleagues found that the less urbanized areas also have lower amount of runoff when compared to urbanized areas. In turn, the research findings demonstrate that protection of natural landscape is a fundamental approach to reducing flood risk. Parker et al. (2016) research shows that with urban green areas, water retention and infiltration work to lower flooding risks. Their study discovered that green infrastructure strategies should be implemented during urban development to combat flash flooding within city boundaries. In certain areas, identified key factors for flash flood susceptibility include certain farming approaches. The sustainable land management approaches shown by Feng and colleagues to retain more moisture and make flooding risk less likely don't make for good land use if they also lead to soil compaction or loss of plant cover. Meyer et al. (2018) research discovered that due to the conventional practices of farming associated with increased erosion and surface runoff resulting in flash floods, rural methods of farming were associated with flood risks. They thought these environmental effects could be reduced through conservational farming practices, so the experts advocated for those. According to Damanski (2015) land management techniques that increase soil permeability and strengthen soil structure not only reduces surface water runoff but also flash flood risks. According to Abson et al. (2018) their research proves as well that practices of sustainable agriculture really aid in flood prevention. Urban areas are growing and developing impermeable surfaces, which is one of the fundamental elements which increase the vulnerability of regions to flash floods. Boretti et al. (2022) find that rainwater cannot soak into the ground making impervious structures such as parking lots along with rooftops and roadways produce more surface runoff. Arnold and Gibbons (1996) research showed that a larger pervious surface percentage within a watershed means higher runoff potential as a means to increase the frequency and severity of flash floods. Better stormwater systems will need to be adopted by metropolitan regions to tackle these challenges, the research demonstrates. According to Hatt et al. (2004) research, urban expansion resulting in higher impervious surfaces means that both the magnitude and the regularity of the flood events advance together. These findings show the vital importance of impermeable surface management on a reduction of flood probability outcomes (Koutroulis et al., 2021). Land cover mapping capability of GIS with remote sensing technique is used to analyze the levels of flood hazard. Finding by Gao et al. (2023) discussed that land covers maps can provide a means to spot risk areas and formulate management strategy to check flooding, among other things. As reported by Huang et al. (2015), remote sensing proved to be essential in monitoring land cover shifts and in assessing the effects of these changes on flood risk. Their research shows that the combination of remote sensing data and hydrologic modeling yields more precise flood forecasts. Wang et al. (2018) were able to use land cover data to examine flood vulnerability across a river basin and identify how areas highly urbanized were more likely to flash flood. (Sahu et al., 2022). Their research found that even though land cover data is important as part of flood risk management systems they are not incorporated in some of the current approaches. Climate change in combination with spatial land use changes increases flash flood threats. In regions of land use changes, modified precipitation patterns due to climate change had more enhanced effects as well as more frequent intense rainfall events (Lamsal et al., 2023). In an effort to understand the role of climate change on flood risk, González et al. (2020) found that flood risks tend to be greater in rapidly urbanizing regions if climate change impacts interact with land use transitions. Thus how the land is used is the main problem that researchers claim can be overcome by flexible land use design. Rojas et al. (2019) find that the interplay between land use change and climate change results in higher flood risks at urban areas with their findings helping inform flood risk management plans. Lentz et al. (2023) showed that coordinated approaches are needed for prospective flood management.

2.15 Flood Risk Assessment: Concepts and Methodologies

One crucial tool for researching possible flood effects is the flood risk assessment approach. Risk analysis applications are used to assess adaption choices in cost-benefit analyses with floodplain management. Without this research, it would be impossible to evaluate flood disaster mitigation strategies and to adopt workable solutions at a reasonable cost. According to Grigg et al. (2023), flood risk is perceived as the result of combining assessments of flood hazard and vulnerability.Flood hazard, which is determined by the amount, extent, and location of flooding, is defined as flooding that is anticipated to happen during a specific return period. This implies that the geographic distribution of the calculated inundation depth for different return times can be used to characterize the flood hazard. Its susceptibility to flooding is well recognized. A damage cost assessment is one way to convey the vulnerability (Olesen et al., 2017). A well-known study that offers a quantitative or qualitative classification, location, and amount of current or potential flood hazards in a specific area or on transportation infrastructure like roads, trains, or subways is flood hazard assessment (Lyu et al., 2023). Through emergency evacuation plans, the installation of protective structures, or the development of flood mitigation techniques, the resulting flood susceptibility maps are crucial for minimizing indirect losses to transportation infrastructure (Khosravi et al., 2019). If the food-prone locations are properly identified, the consequent damages can be significantly mitigated, although the phenomena cannot be totally eliminated. To comprehend the relationship between different environmental circumstances and the occurrence of flood, researchers propose a number of models and methodologies that integrate data and tools employing integrated geospatial technology (remote sensing and geographic information systems). Few studies take into account the flooding susceptibility of transportation infrastructures, whereas the majority of previous research concentrated on evaluating this phenomenon at the regional or watershed scale (Tehrany et al., 2014). The most popular models for assessing flood hazard susceptibility can be divided into four groups based on our analysis of the literature: (Colleagues and Abdulkarim, 2020) (3) statistical models (SM) or quantitative methods like logistic regression, frequency ratio, weights of evidence, and genetic algorithms; (4) machine learning methods like random forest, artificial intelligence networks, support vector machine, and decision tree; (4) hydrological and hydrodynamic models; and (5) qualitative methods like multi-criteria decision analysis (MCDA).Despite their respective drawbacks, the aforementioned techniques have proven successful in mapping and assessing flood risk (Abdelkarim et al., 2020). The lack of data hinders the application of hydrological and hydrodynamic models since they need high-resolution mapping of topographic features (Jha et al., 2020) and significant hydro meteorological data input of the research region (Cabrera et al., 2019). These methods require exact scaling procedures and are quite time-consuming when mapping flood-hazard zones (Gado et al.,2023).According to Adib et al. (2019), expert opinions influence qualitative approaches, while their assessments introduce subjectivity into assessments of flood trigger parameters. Statistical models and quantitative techniques for flood simulations are unique in hazard assessment because they offer quick and precise analysis while maintaining accuracy and richness of detail (Arabameri et al., 2019). The distribution of flood occurrence in the study area is shown by mathematical connections between different flood trigger elements, such as probabilistic and deterministic model-based approaches. Research aims to determine the probability of flooding events. The need for a flood inventory database remains the largest obstacle to applying these methods in these specific circumstances (Samanta et al. 2018; Gado et al., 2023). Machine learning techniques are the primary methods for flood assessment. Their time-consuming nature, need for specialized software, high-performance computer equipment, and strict input parameters—particularly in the absence of a regional database of past food occurrences—severely restrict their applicability to a broad range of users (Yu et al., 2023).

2.16 Role of Remote Sensing in Flood Risk Analysis

One of the most frequent natural catastrophes worldwide, floods have a very high potential for recent years in history proved how destructive floods affected the world economy along with essential resource provision plus human welfare which suffered permanent changes. The key solution to evaluating flood potential hazards for damage reduction in flood-sensitive areas remains Flood Risk Mapping (FRM) (Grigg et al., 2023). Decision-making during flood risk analysis requires current and reliable information because multiple essential factors determine the likelihood of flooding. Flood risk mapping helps control dam overflow floods together with rainwater floods for protecting both infrastructure and human lives. Heavy rainfall patterns the existence of dams combined with unfavourable environmental basic geographical parameters characterized by terrain features as well as watersheds and Land Use models produce regional flood conditions (Kundzewicz et al., 2018). Hallegatte et al. (2013) develop a qualitative and semi quantitative flood risk assessment method that considers a number of flood parameters, i.e. rainfall inputs, watershed hydrology, soil composition, usual land use patterns, etc. collectively. Accurate field measurements, on the other hand, of physical features of kinematic waves (wave height, wave velocity and flow velocity) from floodplains to restore flood episodes require considerable time and expense. A wide range of numerical models, namely Finite Difference Methods (FDMs), Finite Element Methods (FEMs), has been extensively used to solve governing equations (such as Saint Venante equation) to solve flood occurrences for 1-D, 2-D and 3-D (Costabile et al., 2021). Both FDMs and FEMs are somewhat determined totally by the hydrodynamic conditions of the flood, availability of the boundary conditions to solve the governing equations, availability of recorded data of gauged basins and the motion of the sediment (Woodruff et al., 2021). Flood equation solutions also can be impacted by appropriateness of common numerical techniques (implicit or explicit) and grid sizes to FEMs and FDMs separately. In total, there are many different factors that affect how well an area can be simulated with flood conditions. In contrast, semi empirical and semi theoretical concepts are necessary for prototype observations, physical/experimental models, and mathematical techniques that are limited to flood scales. Hence it is imperative to apply an effective method less susceptible to these influences. Remote sensing (RS) has today become an important tool that helps with the faster, cheaper data acquisition from the field without the intervention of a human (Dodangeh et al., 2020). Because of the high computational time involved, however, it is not practical to integrate these data (topography, soil texture, rainfall, water body density, vegetation situation, land use, and certain hydro-environmental indices) to model risk via Geographic Information System (GIS) software for flood monitoring. In solving this particular issue, the capabilities provided by the web based platform Google Earth Engine (GEE) at Google Company's location in Redlands CA are complete (Soltan et al., 2021). The GEE environment combines both website functionality and Cloud Computing Platform capabilities to store Earth observation satellite photographs in time series form. According to Gorelick et al. (2017) its design is intended for tackling huge amount of data volumes which enable analytic acts and took part in decision making processes. Through the GEE platform user can access raw or processed geographical data in the form of Earth Engine (EE) data stored in maps and tables which can be downloaded directly into their Google Drive or Google Cloud Storage (Google Company, CA, USA). The GEE platform provides many surface reflectance and top of atmosphere reflectance and meteorological data. Due to the various application possibilities and the capability to process data at a speed, the GEE platform has become the basis for quite a number of recent studies (Mutanga et al., 2019). The GEE platform does the work by being able to manage fast on extensive processes. It demonstrates great potential for use in solving many tasks among environmental researches (the management of natural resources, agriculture field operations and the monitoring of natural disasters) by means of the GEE platform. This platform allows quick and time efficient development and expansion of many models. A number of studies have been subsequently conducted by the scientists to explore how this platform can be leveraged to apply GEE techniques for a flood detection (Ghaffarian et al., 2020). Rapid flood response system developed by Liu et al. (2018) was built upon both radar and optical imagery as a foundation, on Google Earth Engine platform.

There are significant obstacles in synthesizing multiple flood indices comprising ecological and hydro-environmental data variables for development of flood risk mapping. The AHP presented by Yang et al. (2013) and SPA Set Pair Analysis (Guo et al., 2014) approach, and Artificial Intelligence models serve for Multi- Criteria Decision Making (MCDM) techniques and as part of the best methods of systematic approaches that professionals usually use to make the best decisions. Seejata et al. (2018) used AHP to assess different flood threat locations. Flood risk mapping was created using six physical indices (LU, Elevation (El), Slope (Sl), Rainfall, River Density (RD), and Soil Texture (ST)) and spatial analysis was performed in the ArcGIS (ESRI, Redlands, CA, USA) environment. Model analysis also showed which locations were at high overall risk. For FRM assessment in urban conditions Bourenane et al. (2020) applied hydrogeomorphological interpretation and analytical techniques. In 2019, Youssef and associates used ArcGIS software combined with the AHP technique to determine flood risk models for Egyptian territory. Mapping flood risk in the study region was based on multiple critical field emissions. The proposed model is tested by the scientists and the Overall Accuracy (OA) of the model was confirmed to be 83%. Flood risk mapping evaluation based on MCDM methods on LU, El, Sl Indices together with RS data such as Rain fall and Drainage Density (DD) together with ST Indices was carried out using GIS by Ogato et al. (2020). An integrated assessment of Lidar system data with hydrometric models led Guerriero and his colleagues (2020) to develop multiple flood risk maps. In 2020, Eini and colleagues developed a metropolitan flood risk mapping study with machine learning techniques. In their study, they produced flood risk maps using the machine learning models MaxEnt and Genetic Algorithm Rule Set Production (GARP). Flood risk was analysed to also incorporate assessment of economic and social factors, along with infrastructure features to gain a fuller understanding of flood risk. The weights of this manner were usually determined by using the FAHP (Fuzzy AHP) method by decision makers. However, the map created from the Map study performance well under evaluation through

Receiver Operating Characteristic with 98.32% and slightly less accuracy (96.76%) under the Area Under the Curve. The FAHP model showed that the performance results based on MaxEnt are higher than those based on GARP. Only with the suitable choice of weights of its chosen indices and components does SPA approach function efficiently. One of the multiple machine learning algorithms such as Group Method of Data Handling using the predictive accuracy on flood risk assessment was enhanced through multiple machine learning methods including Support Vector Machinery (SVM) along with other techniques according to Soltani et al. (2021). Random Forest stands as an ensemble based learning technique to balance classification and regression outcomes across machine learning methods. Researchers have applied RF in the analysis of physical process patterns across diverse fields like gene selection and computer-aided diagnostics in addition to tree species classification and prediction systems for rockbursts together with earthquake-induced damage classification. Research using machine learning techniques to produce flood risk maps remains underdeveloped though multiple studies demonstrate these techniques deliver excellent performance across a range of applications.Since RF modeling was initially developed for ML classification and has since gained popularity for classifying remotely sensed pictures in RS applications, it delivers greater precision when compared to other ML techniques. The RF model's parameter setup is still well-structured and maintains a sufficient operating speed (Belgiu et al., 2016).

One of the study's small differences from previous research is that it uses updated web-based data to generate flood risk indices, removing the need for powerful PC components to generate effective indices in flood risk analysis. The use of machine learning (ML) techniques in the GEE platform by upgraded web-based data does not require complicated and laborious calculations in the case of flood monitoring, in contrast to other platforms such as Python (Guido van Rossum, DE, USA), MATLAB (Mathworks, MA, USA), ENVI (L3 HARRIS, Boulder, Colorado, USA), and ArcMap (Esri, West Redlands, CA, USA) software. Additionally, the GEE platform does not require image processing or downloading. This issue could be considered one of the novelties of the research. The 11 risk indices—which are listed as follows: El, Sl, LU, RD, ST, Slope Aspect (SA), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Topographic Wetness Index (TWI), Waterway and River Density (WRD), and Maximum One-Day Precipitation (M1DP) are taken into account for flood monitoring, which is another advantage of the current study. On the Google Earth Engine cloud platform, an RF model can be implemented; however, the interactive Python and GEE interaction package is used for this procedure (Wu et al., 2020).

2.17 Geographical Information Systems (GIS) in Flood Risk Management

Floods are considered the most costly, devastating, broad, and frequent calamity due to the massive number of people killed, injured, and property ruined, as well as the economic and social disruption they cause to humanity (Merz et al., 2010). It has a special place among natural hazards; in fact, it accounts for 31% of the financial damages brought on by catastrophic disasters. Most developing countries experience river floods on a regular basis, especially those that experience monsoons. Floods such as flash floods, which are caused by heavy, continuous rainfall in a short period of time, uproot people, animals, and aquatic life, ruin infrastructure, destroy agricultural goods, and cause reservoirs and dams to overflow as a result of siltation. Recent years have seen a number of major environmental disasters, including river flooding in China in 1998, Venezuela in 1999, Eastern Europe in 1998 and 1999, and the UK during Easter in 1998 (Swiss Rei, 2022).

Thousands of inhabitants died, twenty million people suffered significant socioeconomic disruption, and an estimated twenty billion US dollars was lost due to physical damage and loss during the more than four-month-long 1998 flood in South China (Guha et al., 2019). The first stage in creating any flood management plan is identifying the regions that are most likely to flood. Due of the restricted amount of financing available for developmental operations, this is the most difficult phase for developing countries, especially those in the monsoon zone. Recording a significant flood event with a high return period with the conventional equipment currently in place at different river gauging stations is frequently extremely rare or difficult. Any flood prediction or risk model that has been assessed in affluent countries has not worked in developing countries due to a lack of sufficient ground data because of the extremely low density of gauging stations in these nations (Oladokun et al., 2023). The assessment of geo-environmental disasters has made use of GIS and remote sensing, which have proven to be reliable techniques by providing a kind of economical synoptic coverage of a very vast area. When gathering extreme hydrological data during an extreme event, this helps to get beyond the restrictions and bottleneck that traditional ground stations create. Furthermore, the researcher can trace and record the evolution of past flood episodes by using a sort of multi-date satellite imagery that is made available to them via remote sensing techniques. Recent developments in GIS and remote sensing have been included into the assessment of geoenvironmental disasters, which has significantly facilitated the creation of flood risk assessment, flood management, and flood susceptibility mapping. It is clear that planning studies and a comprehensive project in the floodplain zones might address issues related to flooding. Because GIS systems are made to integrate a wide range of environmental data and cover a wide range of applications, they may collaborate in an easily accessible manner. Furthermore, it is clear that GIS plays a significant role due to the multifaceted character of natural disasters. According to Hausmann (1988) and Clark (1998), the main goal of using GIS in flood management is not only to visualize the extent of the flood but also to generate opportunities for additional analysis of this product in order to estimate the likely damages caused by the flood (Oladokun, et al., 2023).

2.18 Flood Catastrophe Management using GIS:

For managing flood dangers and determining risk zones based on a particular geographic region, GIS has become an excellent and promising tool. Its extensive capabilities therefore made it possible to create a flood danger map by identifying the areas that are prone to flooding. This kind of map will let the appropriate authorities quickly assess the potential impact of the flood disaster and put the required control measures in place to lessen the expected impact, claim Alharbi et al. (2023). Experts can use geographic information systems to pinpoint places currently affected by flooding and forecast future areas that are likely to experience significant flooding. GIS serves as a tool that helps municipal planners and floodplain administrators identify and mark flood-risk regions in their communities.

Geographic data may now be easily accessed and studied because to its database storage capabilities. Flood-prone areas can be identified by using intersection techniques or geographic layer overlays, which makes it possible to adopt stringent floodplain management and flood mitigation measures (Afenyo et al., 2023). Safie and his colleagues' 2006 study used GIS analysis to identify the risk of floods in Segamat, Johor Bahru, Western Malaysia. The data used was initially produced by the Directorate of National Mapping Malaysia (JUPEM), including the topographical map series L7030, which has a scale of 1:50,000 and contour intervals of 20 m.

Additional information regarding land use patterns and utility layouts, as well as geological charting, may be found in the Johor Structure Plan Studies of 2002 (Afenyo et al., 2023). The authors used Autocad Map 2004 and ArcView 3.1 as their two software applications. The data for the 2009 flood water simulation of the Damansara River in Selangor was prepared, processed, and modified using AutoCAD before being transferred to GIS format. The flood volume discharge (m^3/s) over the floodplain and the water filling time were the primary focus of the simulation. According to their investigation, the flood water reached the 1.23-meter crest level in about one and a half hours. When converted to flood volume, or around 100 (m^3/s), it covers about 107 hectares of flood area.

2.18.1 Some Shortcomings of GIS Application in Flood Hazard Management

Offering a practical preventive strategy that would drastically reduce, if not totally eliminate, the negative effects of flood disasters is the aim of flood hazard management. Unfortunately, GIS and its model often fail to meet this standard. Traditional GIS applications have been hampered by a number of important issues, such as data integration, user interface, the use of cartographic modeling languages like Map Algebra, and the depiction of dynamic processes in GIS (Albrecht et al., 1997). Albrecht et al. (1997) claim that GIS structures are designed to support a variety of applications and integrate a large amount of environmental data so that they can work together in a convenient way. Because of this, basic GIS modeling still requires relatively complicated equipment and software, which greatly increases operating costs. Another area to consider is the incorporation of simulation models, which are essential instruments in environmental computer applications and might greatly expand GIS's capacity for environmental simulation and understanding (Liang et al., 2023). Burrough (1997) went on to say that this complex integration requires a significant amount of data management and programming work. Web-based GIS is therefore desperately needed, even though it is starting to become a reality. In addition to providing technological transparency, platform independence, visual engagement with data, a multimedia environment, and cost effectiveness, this will work as an interface that helps users, authorities, and local communities obtain information more readily. In a similar vein, this would facilitate local populations' involvement in environmental decisions that directly impact them (Burrough et al., 1998).

2.18.2 Flood Catastrophe and Risk Areas Delineation using GIS and Remote Sensing Tools

The hazard of flooding, a natural disaster, is demonstrated by a flood that occurred 100 years ago (Godschalk, 1991). The capacity to create a trustworthy hazard map by identifying regions that are more likely to experience floods is one of the primary challenges in flood control. Superimposing pre-flood and peak flood images to identify the inundated area is a common practice in flood mapping.Crop damage and property damage are evaluated using the current land use base map (Vrochidis et al., 2022). Nico et al. (2000) identified flooded areas using the amplitude change detection technique and multipass SAR data. Both of the previously suggested techniques, however, only make it possible to identify flooded areas when those areas are flooded during the second satellite pass rather than the first, claim Di Baldassarre et al. (2011). Nirupama and Simonovic (2002) went on to explain that the coherence two waves are said to be in Coherence, which is derived from multipass interferometry data and can be used as an indicator of changes in the surface's electromagnetic scattering behavior, can reveal all the regions affected by the overflow incident at any point between the two passes if their crests and troughs assemble at the same time and at the same location. Rejesk created three different hazard zoning strategies in 1993. The first one explains a binary model that assesses the danger of a particular raster cell. The second involves categorizing various sites within a region based on the threat level they represent. In the third and last approach, each raster cell was given a number of hazard ratings based on the findings of a multivariate model that was developed utilizing a range of parameters pertaining to river flooding and associated dangers. This strategy was later condemned by Wadge et al. (1993) (Di Baldassarre et al., 2011). In essence, how The expected flood depth, which is often determined from a variety of hydrological and remotely sensed data, determines how flood risk maps are produced. According to Popandopulo et al. (2023), the flood depth is thought to be the most accurate indicator of the level of risk. Separating the natural occurrence of river flooding into source flood and non source flood is necessary to determine the flood depth, and this has important ramifications for the GIS model. According to Kumar et al. (2023), a source flood is one that is predominantly caused by overflow of a river bank and primarily affects the locations or communities along the river channel, whereas a non-source flood is one that is caused by a widely dispersed downpour. In a source flood, the overbank flow channel from the main canal to the nearby floodplain must be modeled in order to precisely estimate the flood-affected areas; in a non-source flood, all raster cells or vector points with an elevation below the water level are presumed to be inundated. The depth of an inundation was estimated using the wetness index or topographical convergence concept (Mertens et al., 2016). The wetness index is based on the notion that the extent of the upslope region that provides water to a single cell in a raster determines the amount of water that builds up in that cell. The primary problem with using the wetness index is that it becomes undefinable when a slope is expected to be zero. As a result, this indicator is not very helpful for modeling in highly flat floodplains (Hojati et al., 2016). Townsend and Walsh (1998) used a new model to predict source flooding by assuming that the elevation difference between a site and the river at its closest hydrological link directly correlates with the chance of flooding in that area. Islam et al. (2001) undertook what is arguably one of the most creative, simple, and economical studies on flood hazard management. The scientists only used the tonal fluctuation of the inundated water to determine the depth of an inundation using NOAA AVHRR pictures. They separated the flood-affected area into different sectors according to water depth using the supervised classification. A DEM was superimposed on top of the AVHRR data in order to correctly identify the training sets. A weighted score was assigned to each of the country's land use, physiographic, and geologic divisions in order to evaluate the risk of flooding. This approach's primary characteristic is the exponential increase in weight given to the classes with deeper flood depths. In a similar vein, the weight grows gradually for low flood depths, but before a specific flood depth, it increases significantly more than for earlier flood depth categories. Using this concept, places with deeper floods will be given a high danger ranking (Munir et al., 2022). This is because flooded water becomes very important beyond a particular flood depth, and mapping a hazard area necessitates identifying this important flood level. However, the depth of a major river stage is likely to differ from one area to another based on elements such as building materials, settlement patterns, and geographic location. Due to high rainfall and rapid snowmelt, the Mississippi River in the United States saw a 100-year flood in late March 1973, the largest flood statistically predicted in a century (Deutsch et al., 1974). Solutions were devised using hydrologic modeling, GIS technologies, and remote sensing data to minimize potential losses and costs to the federal government.

2.19 Integration of Remote Sensing and GIS for Flood Susceptibility Mapping

Flooding frequently occurs downstream when a region has heavy rainfall. Floods occur when land is submerged by an overland water flow. Floods and other natural catastrophes are seriously harming both human and natural resources. Every year, flooding affects 140 million people on average. Widespread flood study is crucial in terms of the economical and environmental effects. Flood control and preventive Actions must be taken to lessen the possibility of harm to infrastructure, agriculture, natural resources, etc. (Park et al., 2024). To develop management plans for the prevention and mitigation of future flood occurrences, early warning systems and emergency services must evaluate flood risk. Many research groups throughout the world use a variety of comprehensive technologies, such as HEC-FDA, computer software that helps agricultural engineers analyze the vulnerability of flood risk reduction measures, and HAZUS, a GIS-based natural hazard analysis tool for evaluating flood danger. In order to properly establish appropriate hazard zones, RS and GIS approaches provide an appropriate platform for changing and assessing all pertinent data. When assessing flood-related damages brought on by sea wave surges in coastal locations and heavy rainfall in a catchment area, RS and GIS approaches are quite helpful. Numerous experts and scholars have estimated floods using a range of models over the last ten years (Yang et al., 2020). Alternatively, the conventional flood modeling methods may not allow for good prediction. Numerous data sources are currently accessible for flood modeling through the use of geospatial techniques. For landslide modeling applications such flood mapping and monitoring, as well as complicated issue analysis, the Analytical Hierarchy Process (AHP) is the most popular and effective approach (Swain et al., 2020). The acknowledged hazard analysis frameworks that accompanied AHP included the multi-criteria decision support method (MCDA) based on research findings by Samanta et al. (2016). The topic was covered by the 2010 research by Buchroithner and the 2010 work by Tiwari and Chatterjee. Other studies on the subject were conducted in 2012 by Lee and colleagues, in 2016b by Rahmati and associates, and in 2015 by Liao and Carin, who focused on the FR model. When using ANN techniques to anticipate floods, researchers tried to find connections between conditioning parameters and output predictions. According to research findings, artificial neural networks (ANNs) have the potential to extract valuable information from any given data, even when the input contains ambiguous information (Agarwal et al., 2021). For flood susceptibility mapping, MCDA, RS, and GIS methodologies provide accurate and reliable analysis. The MCDA technique is used by local planners to manage flood control issues in places with limited data where mapping and analysis are necessary. China used the AHP model for flood diversion, according to research by Zou et al. in 2019. Chen and colleagues found in 2011 that reliance on expert knowledge lead to significant uncertainty in the performance of the AHP model. According to a 2019 study by Abdelkebir and colleagues, the FR model provides experts who require precise flood analysis through mapping methodologies with both simplicity and efficacy. Although WofE and FR models have shown extensive use in mapping landslide susceptibility and other natural hazards, their promise for flood risk modeling applications is still in its infancy. The findings of mapping flood susceptibility using both models show almost perfect similarity. Rahman et al. (2023) predicted that the flood risk map produced by the FR model study would be used in future flood control initiatives. Since many factors must be carefully taken into account during the process, flood modeling necessitates a thorough evaluation. Flood mapping and risk assessment both benefit greatly from the RS technique. Because RS and GIS are faster and more effective, they can offer the best chance to gather, store, integrate, alter, retrieve, evaluate, and display the data for locating possible danger sites (Kumar et al., 2023).

2.20 Analytical Techniques in Flood Susceptibility Mapping

Flash floods are the deadliest hydro-meteorological disasters and their occurrences are unpredictable. Disasters involving flash floods are common as a result of global warming. In addition to often destroying property and agricultural products, floods can also claim lives (Bucherie et al., 2022). According to Elkhrachy, a flash flood is a flood that starts quickly and often exhibits significant peak discharges. Elkhrachy said that when there is a lot of rainfall, flash floods typically occur in geomorphic low-lying areas. According to Elmahdy et al. (2020), the development of flood susceptibility mapping and modeling may assist local authorities in flood management by determining the most vulnerable areas for civil protection measures, evaluating damages, and creating sound urban design. By using the notion of landslide susceptibility mapping, Santangelo et al. (2019) said that it is the likelihood that a risk event would occur in a specific location on an unknown date. The link between the conditioning elements and the distribution of prior events served as the foundation for the development of susceptibility mapping. Accordingly, susceptibility modeling is essentially a prediction of "where" natural catastrophes like floods and landslides are most likely to happen. For some populations, a susceptibility map is also referred to as a natural hazard potential map (Santangelo et al., 2019). Reichenbach et al. (2018) claim that "susceptibility" and "hazard" modeling are sometimes confused. In spite of these two names being used interchangeably, they refer to different models. Similar to Reichenbach et al. (2018), the length, width, depth, area, and volumes of a natural hazard are not taken into account by the susceptibility model. Meanwhile, a hazard model predicts "how large" a flood or landslide would be, as well as "where," "when," or "how frequently" it will occur. Reichenbach et al. (2018) state that flood susceptibility map is a crucial tool for managing and predicting future floods. There are several methods for mapping the susceptibility of flash floods, including (i) statistical, (ii) machine learning-based, and (iii) hydrological methods. However, hazard evaluations using automated and rule-based modeling techniques outperform outdated classical flood models. To improve the accuracy of forecasting areas of flooded regions (flood susceptibility), various researchers have combined a variety of approaches with GIS in recent years. These include quantitative methods like frequency ratio (FR) and weight of evidence (WoE), qualitative methods like analytical hierarchy process (AHP), and machine learning methods like artificial neural networks (ANN). Flash flood susceptibility has recently been modeled (Hinge et al., 2024), although research on flash flood modeling is still lacking. Bui et al. (2020) have used tree based ensemble approaches and feature selection method (FSM). Thus, the research area is located in Vietnam’s Lao Cai Province particularly the districts of Bao Yen and Bac Ha. Bui et al. (2020) used 12 conditioning elements of topographic wetness index (TWI), elevation, rainfall, aspect, normalization difference vegetation index (NDVI), soil type cover, lithology, stream density, toposhade, slope, curvature, and stream power index (SPI) in 654 floods. This method makes use of the fuzzy rule-based algorithm (FURIA) as the attribute evaluator and the Genetic Algorithm (GA) as the search methodology. Finding the ideal combination of conditioning elements to use when modeling evaluations is the second goal. Lastly, the FURIA-GA method for the prediction model was combined with the ensemble methods AdaBoost, Bagging, and LogitBoost. According to the test findings (Bui et al., 2020), the ensemble algorithms FURIA-GA-Bagging (93.37%) outperformed FURIA-GA-LogitBoost (92.35) and FURIA-GA-AdaBoost (89.03). As a qualitative method, Youssef et al. (2018) employed the analytical hierarchy process (AHP), among other terminology. This study's primary goal is to investigate AHP's efficacy and dependability. Ras Gharib, Egypt, is the study area. This investigation also used high resolution photos taken following earlier floods in 2016. The susceptibility model is validated using historical flood data and a slicing analysis on these high resolution images. Angle, lithological units, slope, curvature, distance from streams, elevation, and topographic wetness index (TWI) were the only seven flood factors used by Youssef et al. (2018). However, with an 83.3% rating, the study's results demonstrate that AHP produces positive outcomes (Almodayan et al, 2018). Ngo et al. (2022) employed the firefly algorithm (FA) in conjunction with machine learning to The Levenberg–Marquardt (LM) Backpropagation, a fake artificial neural network (aLm-ANN), support vector machine (SVM), and classification tree (CT) are used to assess flash floods in the Vietnamese districts of Bac Ha and Bao Yen. Using 12 flood factors—aspect, elevation, stream power index (SPI), slope, topographic wetness index (TWI), stream density, rainfall, curvature, normalized difference vegetation index (NDVI), lithology, toposhade, and soil type—Ngo et al. (2022) selected 654 flash floods to evaluate the flash flood model. (Ngo and others, 2022). Since 97.0%, LM-ANN is 92.6%, FAANN is 91.9%, SVM is 92.9%, and CT is 90.8%, it was determined that the combined FA, LM, and ANN was good. Four decision tree algorithms have been compared by Khosravi et al. (2023): The methods are Alternating Decision Trees (ADT), Naïve Bayes Trees (NBT), Logistic Model Trees (LMT), and Reduced Error Pruning Trees (REPT). The study area is close to the Haraz watershed in northern Iran. 121 streams Altitude, ground slope, curvature, river density, normalized difference vegetation index (NDVI), topographic wetness index (TWI), distance from the river, land use, stream power index (SPI), rainfall, and lithology were among the 11 factors chosen among the 201 flood locations that were discovered. (Khosreavi et al., 2023) NBT, 97.4%; ADT, 97.6%; LMT, 97.1%; and REPT, 81.1%. But first, Khosravi et al. (2021) use weighting factors, statistical index, and Shannon's entropy to compare the results of the flash flood susceptibility models. For this study, Khosravi et al., 2021 were consulted. For this study area, which included 211 flood locations, we compiled ten flash flood conditioning factors, including planned curvature, stream power index (SPI), land use, geology, distance from river, topographic wetness index (TWI), rainfall, slope angle, altitude, and normalized difference vegetation index (NDVI). According to the findings, the statistical index model has the highest prediction rate (98.72%), weighting factor (97.6%), and Shannon entropy (92.42) among the models (Khosravi et al., 2021). We use bivariate (frequency ratio) and multivariate statistical models (ensemble frequency ratio and logistic regression) to construct flash flood susceptibility modeling in Jeddah, Saudi Arabia, based on the findings of Youssef et al. (2023). Slope, elevation, curvature, geological units, land use, soil drain, and distance from streams were the seven flood characteristics that were employed in the flash flood model of the 127 flood locations in the study. Using a randomly chosen subset of the characteristics, the ensemble approach outperforms the Frequency Ratio (FR) and Logistic Regression (LR) in terms of prediction accuracy (91.3%), while the conventional Frequency Rating results come in second (89.6%). Results from Yousuf et al.'s 2023 study show the techniques used in the flash flood susceptibility model and how combining the MSA methodology with the BSA approach might improve it.

2.21 Vulnerability and Risk Assessment in Urban Areas

Since 1998, the earth has had over 7,000 natural disasters impacting over 4.4 billion people, and costing 1333,654 fatalities and over USD 2.5 trillion in losses (UN 2020). The concentration of people, resources and activities in metropolitan areas explains why most of these were disasters. These figures show the importance of disasters risk reduction to contemporary growth of societies by way of identifying what causes vulnerability and risks, defining exposed regions and increasing understanding and awareness of the most vulnerable populations about these risks (UNDRR 2019). To do this, however, it is necessary to combine quantitative and qualitative methods for long term risk reduction of catastrophes. Qualitative frameworks describe why people engage in prevention based on their assessments of how hazards occur, are severe, and how effectively a protective response ameliorates them, while quantitative such as Reischl et al. (2018) use to calculate the spatial and temporal potential impacts of disaster risks in terms of a selected set of indicators, metrics, or frameworks. Risk is the likelihood that a loss stemming from natural or man-made hazards may occur that affects environmental, economic, or social aspects. Risk is primarily determined by the intimate connections between three elements: exposure, vulnerability, and hazard. According to Birkmann et al. (2016), risk may also be thought of as a function of two variables: the hazard event and the vulnerability of the exposed elements. This is because risk links the chance of a hazard occurring with its repercussions. A catastrophe occurs when society's ability to handle the effects of risks with its own resources alone is severely disrupted, leading to significant losses in terms of people, property, or the environment (UNDRR 2021). Cardona (2003) emphasized that in order to appropriately refer to dangers, there must be a link between severity, specific location, and duration of exposure. However, Cutter (2001) views risks as a threat to people and the things they value, whereas Burton et al. (1993) claim that hazards are the product of the interplay between natural and social systems. Exposure is another aspect of disaster risk that includes everything that might be impacted at a location where a hazard event could happen (Fuches et al., 2011). According to Fuchs et al. (2011), exposure is a critical component of vulnerability and a required but insufficient risk factor. On the contrary, vulnerability requires exposure. Vulnerability depends on a number of factors, including physical, social, economic, cultural, and environmental aspects that change over time and space, even though it has historically been linked to physical fragility (Fuches et al., 2011). Various interpretations of vulnerability are based on climate change as a hazard. Vulnerability is defined as the tendency of exposed elements to be adversely affected when hazard occurrences occur (Bankoff et al., 2014). Vulnerability dictates how much climate change harm a system can withstand, according to the Intergovernmental Panel on Climate Change (2001). In order to determine future adaptation strategies, Adger (2006) defines vulnerability based on a variety of research conducted under various climatic scenarios. Vulnerability may be classified into a number of categories due to its multifaceted character, including physical, social, and economic vulnerability (Adger et al., 2006). Physical vulnerability studies how the properties that make up a physical element determine the potential harm it might experience in the event of a hazard occurrence. The capacity of a community to manage the impact of risks is constrained by social vulnerability. Social vulnerability is quite independent of the type of threat experienced, in contrast to physical vulnerability. Economic vulnerability refers to personal incapability in addressing a specific hazard that is against one’s source of survival (Noy et al., 2018). There is no universally accepted definition of an urban area since many nations have varied their labelling at various times, and urban areas are marked by economic occupation, population density, and urban functions. In terms such as the one provided by Lopez-Moreno (2017) there are different definitions of urban agglomeration which are currently in use: one of these definitions is population confined into a continuous band with urban density levels regardless of administrative boundaries. Urban vulnerability is the degree to which physical assets and socioeconomic systems in cities are susceptible to and can endure the harmful effects of at least one disaster (Diaz et al. 2020). The literature holds many research on measuring urban vulnerability. The Barbat et al. (2010) study considered seismic risk over a 15 year period. Ciurean et al. (2017) and Papathoma-Köhle et al. (2017) estimated fooding vulnerability in multi scale using hydro-meteorological risks. Tarbotton et al (2015) investigated tsunami vulnerability over the past ten years to create empirical vulnerability functions. Vamvatsikos et al. (2010) finished a review of evaluations of structure vulnerability under earthquake, fooding, and tsunami risks. This article studied the methodology of urban vulnerability assessment to examine its capability of expanding the research area of the community field vulnerability to different disaster effects. The main objective of this study was to assess future vulnerability of selected study areas (Islamabad and Rawalpindi) to flood catastrophe. The study examines the flood prone areas and uses FR and the AHP model to generate a flood risk map for particular region. FR and AHP models are a GIS based techniques recognized to generate maps of flood susceptibility that have scientific sound.

Research Methodology

3.1 Study Area

3.1.1 Islamabad

Pakistan's capital city, Islamabad, is located in the country's northern region. The approximate coordinates of Islamabad are 33.6844° North latitude and 73.0479° East longitude. It is located in Pakistan's northern region. Part of the Himalayan range, the city lies tucked away in the foothills of the Margalla Hills. The geography of Islamabad is dominated by these hills, which provide the city a breathtaking background. With its untamed landscape and varied wildlife, the Margalla Hills National Park is an important natural reserve in the area. The southern portion of Islamabad is characterized by rather flat topography, whereas the northern limit is hilly and scenic due to the Margalla Hills. Rawal Lake is an artificial reservoir that divides the city and enhances the area's scenic value. The population of Islamabad was around 1.1 million. TIslamabad has a humid subtropical climate with four distinct seasons. Summers are dry and pleasant, with average temperatures between 25°C and 35°C (77°F and 95°F). However, temperatures can occasionally increase. With cooler temperatures and less humidity, autumn offers lovely weather. With overnight lows regularly dropping below freezing, winters are severe. Temperatures during the day range from 10°C to 20°C (50°F to 68°F). Spring is characterized by blooming flowers and warmer temperatures. It is considered to be one of the most lovely seasons of the year.Islamabad serves as both the nation's capital and the hub of all government activities (Khan et al., 2022).

3.1.2 Rawalpindi

Adjacent to Islamabad, Rawalpindi is sometimes referred to as the capital's twin city. Because to their close closeness, Rawalpindi and Islamabad have virtually similar coordinates, with Rawalpindi being at around 33.6844° North latitude and 73.0479° East longitude. Compared to Islamabad, Rawalpindi has a more diverse topography. It has a variety of low-lying plains, plateaus, and higher regions. The city is located on the high, level, and somewhat dry Pothohar Plateau. Particularly in the northwest and northern areas, Rawalpindi has mountainous terrain and steep slopes in certain places. The plateau progressively slopes southward, where the ground flattens out and becomes appropriate for infrastructure and urban growth. The population of Rawalpindi was around 2.1 million. Because of their near proximity, Rawalpindi and Islamabad have similar climates. During the hot, dry summer months, the average temperature ranges from 25°C to 35°C (77°F to 95°F). The fall season in Rawalpindi is characterized by pleasant weather and milder temperatures. With overnight lows regularly dropping below freezing, winters are severe. Temperatures during the day range from 10°C to 20°C (50°F to 68°F). Similar to Islamabad, spring is a lovely season with lovely flowers and milder temperatures. Rawalpindi is an older and much larger city that serves as a center for industry, the economy, and the military (Khan et al., 2022).

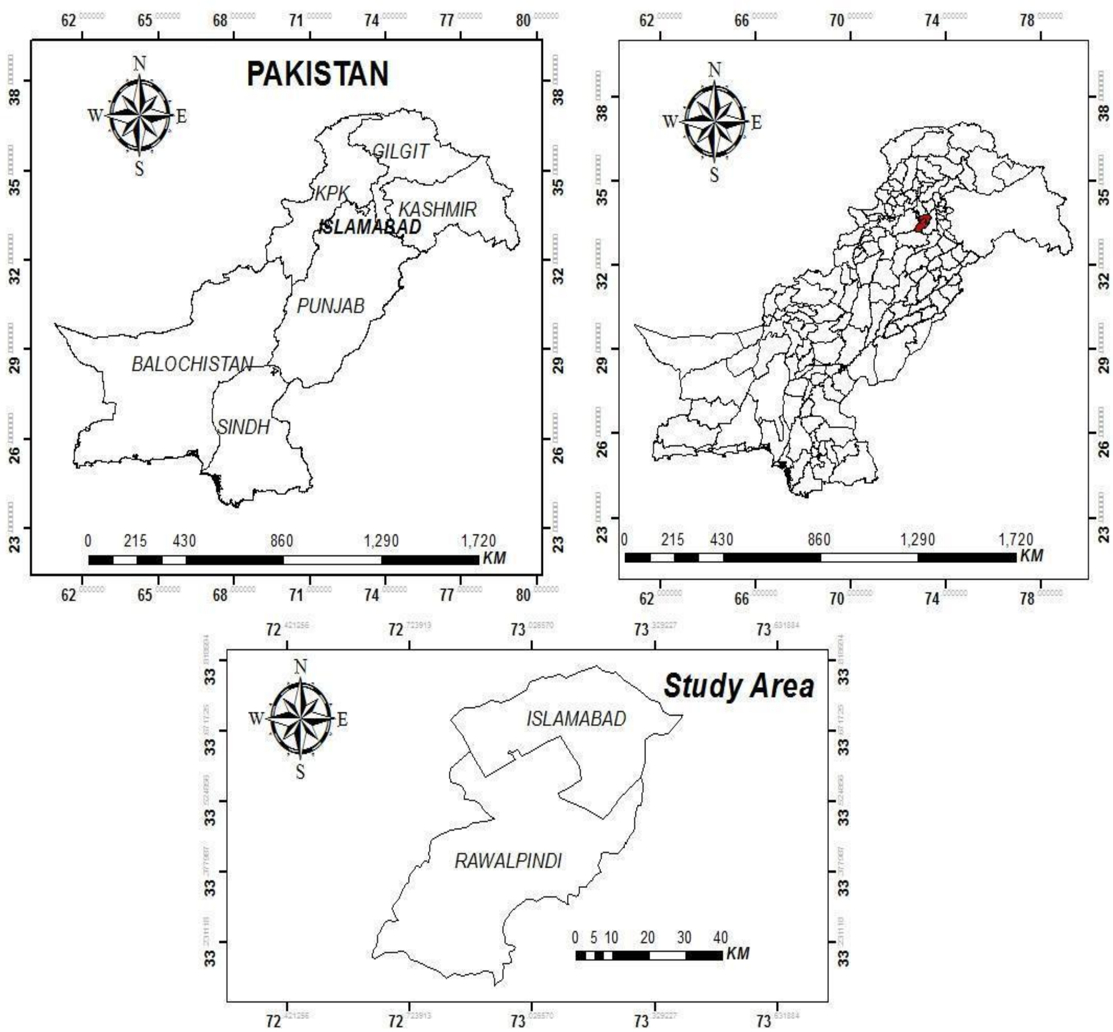


Figure 1: Location of the Study area

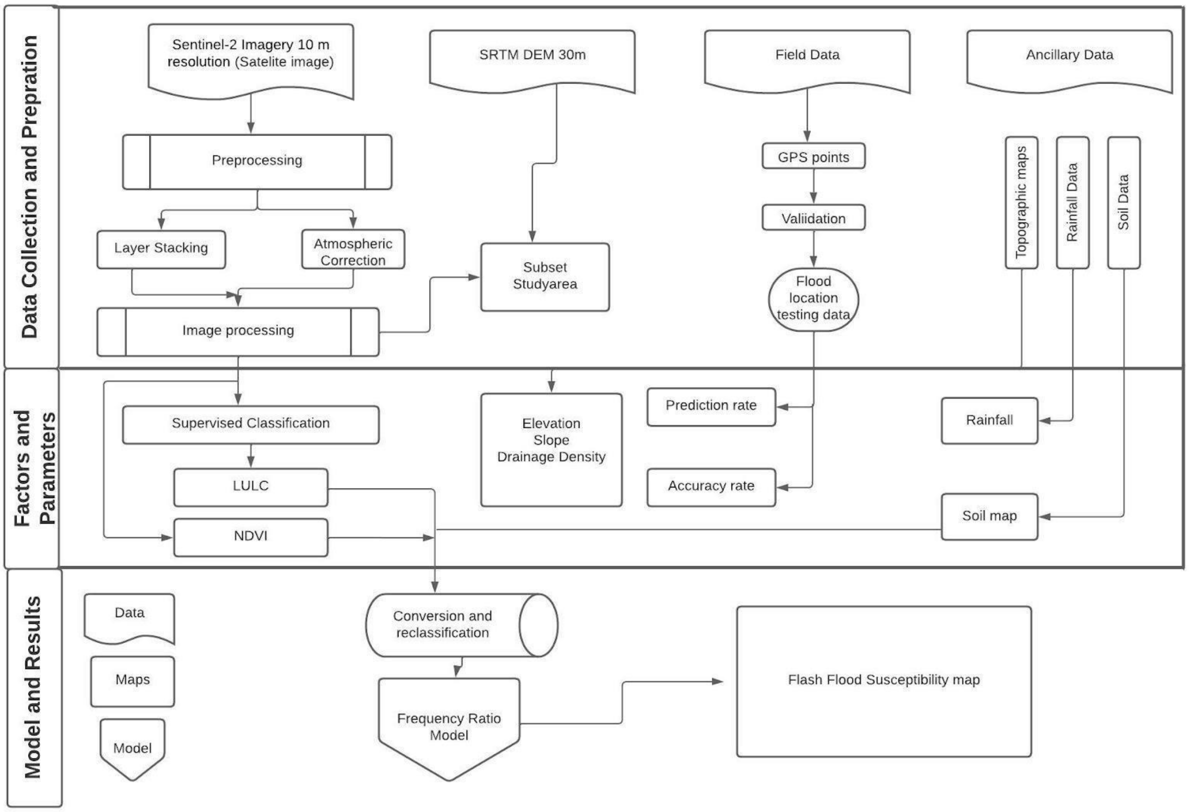


Figure 2: Flow chart showing methodology for flash flood susceptibility

3.2 Flood Zone

Rawalpindi and Islamabad are located on the Pothohar Plateau, which is bordered to the south by the scenic Rawal Lake and to the north by the Margalla Hills. Because the Margalla Hills frequently experience heavy rainfall, which causes a quick rush of water into the metropolitan areas, this topographical configuration puts the cities at danger of flash floods. In Pakistan, flash floods are mostly caused by the monsoon season, which normally lasts from July to September. During this time of year, heavy rainfall frequently causes rivers and streams to overflow, flooding low-lying regions and urban infrastructure (Sohail et al., 2019). Increased surface runoff and insufficient drainage systems brought about by rapid urbanization have made areas more vulnerable to flash floods. Rainwater is accumulating quickly as a result of the land's natural capacity to absorb water being diminished by the construction of roads and houses. A major contributing factor to the region's vulnerability to flash floods is its uneven topography, which includes a range of heights.The Margalla Hills' steep slopes can cause rapid water flows into the lowlands, overtaxing drainage systems. The risk of flash floods is also increased by inefficient land use practices, such as deforestation and building in flood-prone regions. Vegetation and trees are essential for stabilizing the soil and absorbing surplus water. One important issue is the susceptibility of residential areas, highways, bridges, and other infrastructure to flash floods. Flash floods have the potential to uproot people, interfere with transportation systems, and destroy vital infrastructure. To lessen the effects of flash floods, sophisticated hydrological and meteorological monitoring systems must be put in place, along with efficient early warning systems. These devices can give authorities and locals immediate information so they can take the appropriate safety measures and evacuate. To limit construction in high-risk locations and encourage sustainable development practices, proper zoning and floodplain control are crucial. By making sure that these rules are followed, metropolitan areas' susceptibility to flash floods can be lessened. Programs for community education and preparation can enable locals to recognize the dangers and take preventative action in the case of flash floods. This entails being aware of evacuation routes, keeping emergency supplies on hand, and adhering to safety procedures.

3.3 Collection and Preparation of Data

3.3.1 Historical Flash Flood Data

To accurately show the areas at danger of flooding, precise data on the areas that have already experienced floods must be gathered (Martinis et al., 2009). If records of previous flash flood occurrences have been kept, it is possible to predict with accuracy the likelihood of flash floods in a certain area. Some of the key factors that influence the probability of flash floods and the potential damage they could cause are land use activities, rainfall frequency, drainage, slope, elevation, NDVI, and soil map (Chen et al., 2022). Planning, inventorying flash floods, and eventually modifying the projection all need consideration of these aspects. This study examined data from 110 different zones, some of which had previously been impacted and some of which were not. Figure 2 illustrates the area's classification based on many possible danger categories.

3.3.2 Flash Flood Inventory

Flood event data accuracy has a major impact on mapping flood risk and susceptibility. For the flood inventory of this study, a total of 110 sites were chosen. Using random points rather of a polygon design, which poses challenges for the program, simplified the inquiry. This kind of inventory information is frequently used in natural hazard modeling. In order to generate dependent outcomes, 70% of the map was utilized for training and 30% was used for testing. Specifically, 110 training locations were chosen at random, with 33 points identified as non-flooding areas and dependent results marked as 0 in the absence of flooding and 1 in the presence of it (fig 5).

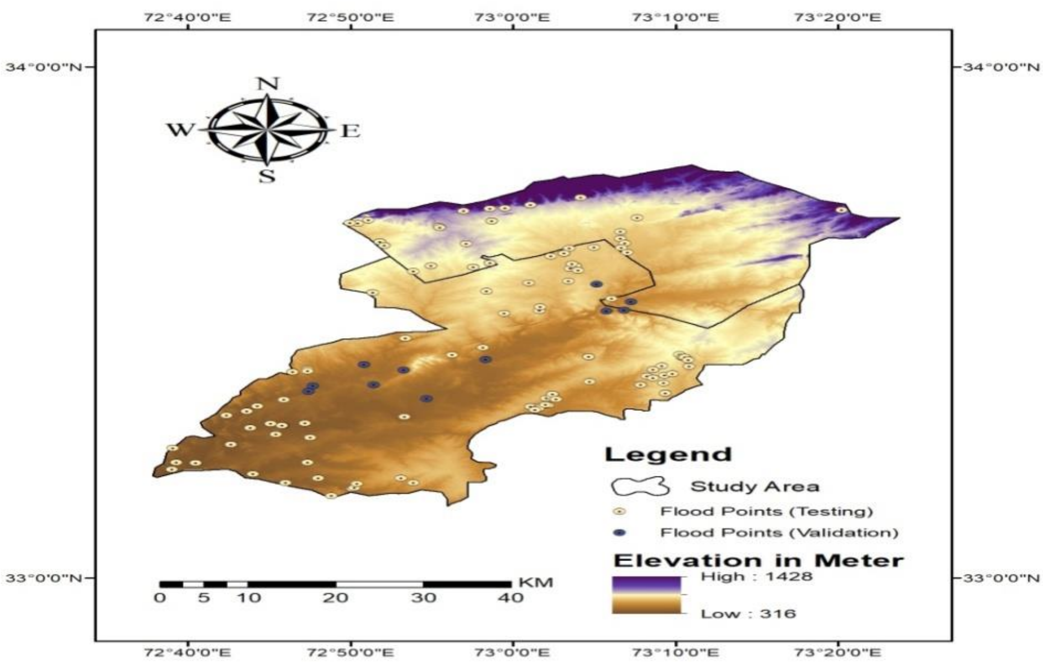


Figure 3: Flood inventory map of the study area's

3.4 Flooding Factors

This study looked at seven factors that influence flash floods: soil types, elevation, slope, rainfall, drainage density, LULC, and NDVI. Thematic maps were created using Erdas Imagine, ArcGIS 10.8, and ENVI 5.4. A soil investigation and data were gathered. Numerous variables, including as soil type, NDVI, drainage density, slope, elevation, rainfall, and land-use/cover activities, influence these occurrences. Make a list of likely flash floods and project their occurrences. These flash flood conditioning components are essential. A range of ArcGIS tools were used to create maps and flood risk estimations. Thus, flood risk was predicted using ArcGIS tools and techniques as well as geographical data from the ArcGIS database. The analysis of this study focused on the main and secondary data sources. The Google Earth Engine was used to gather a large portion of the original data. Getting the relevant information was one of the most crucial steps in fixing this problem. We acquired meteorological and hydrological data for this study from the Pakistan Meteorological Department (PMD), Punjab, Pakistan (https://www.pmd.gov.pk/en/). We received basic geology and soil data from the Pakistani soil survey agency (https://gsp.gov.pk/) in addition to meteorological data. A digital elevation model with a resolution of 30 meters was supplied to the research area by Earth Atmosphere and NASA, based on the Shuttle Radar Topography Mission (SRTM) http://www.dwtkns.com/srtm30m. Examples of natural disasters that mostly depend on several elements are floods, landslides, and cyclones. Flood susceptibility map parameter selection may be challenging (Rahmati et al., 2016). Thus, a field investigation was conducted to determine the most relevant flood-triggering elements. In 2024, a tour of the areas most susceptible to floods was conducted. The collection of residents' individual perspectives aided in the planning of the inventory map.

3.4.1 Elevation

The value of DEM cells would be greater at lower elevation. Data on elevation demonstrates how the ground's height varies over an area. This information is essential for making flood maps since it is generally acknowledged that these factors have a direct influence on flood mapping (Hawker et al., 2018). They provide us with the opportunity to explore, mimic, and demonstrate amazement. ArcGIS uses natural breaking to categorize the features, and the elevation map is created using the 30 m spatial resolution SRTM DEM.

3.4.2 Slope

The hydrologic features of catchments are influenced by a variety of variables, which in turn impact the generation of surface runoff. It controls penetration, subsurface flow length, and overland migration (Yariyan et al., 2020). The slope has a crucial role in terrain stability.The gradient of the slope affects the quantity and direction of surface runoff and subsurface drainage that reach a place. The slope significantly affects the amount of precipitation that contributes to stream flow because it controls the length of overland, subsurface, and infiltration flow. The relationship between the lithology, structure, soil type, drainage system, and slope shape is mostly determined by slope angles (Simelane et al., 2024). Compared to a smooth or flat surface that permits water to flow more rapidly, a rough surface slows down the flood response. While flat terrain is more likely to encounter water logging, steeper slopes are more likely to see surface runoff. Low-gradient slopes are more likely to flood than high-gradient slopes. In a region with a generally low slope gradient, rain or additional river water continuously accumulates. Steep slopes prevent water from building up and causing floods. Local depressions are more likely to create pluvial floods, whereas variations in DEM cell heights are more likely to trigger river-induced floods (Avand et al., 2021). This implies that the relationship between elevation and risk is crucial. In this work, SRTM DEM and ArcGIS slope creation tools were used to create a slope map.

3.4.3 Aspect

An aspect map shows the orientation of the sphere's surface. The microclimate is greatly influenced by one's orientation (angle) with relation to the sun. Flooding is more likely to happen in low-slope or regional flat-surface areas since that is where water collects and forms. As a result, this feature makes it simple to identify flat areas. The direction of the monsoon wind when it strikes the slope (angle) of the surface also affects flooding in a level area (Khosravi et al., 2021). The aspect function in ArcGIS was used to generate a face map using SRTM DEM data.

3.4.4 Drainage

The overall length of the river network per unit area is known as the drainage density. The Strahler-recommended approach was used to determine the stream order in this study field. Throughout the study, areas with superior drainage received lower weights, and areas with insufficient drainage densities received higher weights (Bui et al., 2019). The drainage density layer was further divided into five (5) grades within the five subgroups. Places with unusually high drainage. Densities received a score of 1, while locations with low drainage densities received a score of 5. The drainage density map was assessed using ArcGIS's line density feature.

3.4.5 Rainfall

High rainfall and flood sensitivity are positively correlated with the frequency of floods. Havoc flooding is the cause of flash flooding. The detection of flooding months is made possible by the rise in rainfall rate in the research region from July to September. When estimating spectacular, rapid, and short-lived flood types, the amount of surface runoff from heavy rainfall is essential (Tariq et al., 2021). Since a positive rainfall deviation may result in floods and a negative rainfall deviation may result in a scarcity of rainfall, which may cause drought, the rainfall variance was considered as a starting point for the research of flood vulnerability. The rainfall deviation map for the research area was created in ArcGIS using the inverse distance weight (IDW) interpolation method.

3.4.6 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI), which is computed and acquired by the Copernicus open-access hub, was created using Sentinel-2 satellite images. Arid regions of rock, sand, or snow are represented by low values, whilst temperate and tropical rainforests are represented by high values. To illustrate the differences in plant spectral responses in the red and near-infrared areas, the NDVI was created. To a certain degree, it was determined using the band ratio method in ArcGIS (Raster calculator), where exposed vegetation zones are indicated by big values and other categories by low values (Tehrany et al., 2014).

$$NDVI = \frac{Band5 - Band7}{Band5 + Band4} \qquad (1)$$

3.4.7 Soil Type

Soil structure and moisture are the two most important soil properties. Floods are greatly impacted by soil textures since sandy soils quickly drain water and have less runoff. This indicates that regions with clay soils have a greater impact on flooding. As soil penetration decreases, surface runoff increases, increasing the likelihood of flood danger. For this case study, the soil map was arranged according to its capacity for infiltration (Bui et al., 2017). Three broad categories were used to classify the soil types identified in the district: barely penetrated, mildly infiltrated, and heavily infiltrated. To provide a weight to each soil class, a weighted soil map was made. The soil type that had the greatest potential to produce a high flood rate was ranked number three, and the soil type that had the least potential to do so was ranked number one.

3.4.8 Land Use Land Cover (LULC)

Utilization of Land When mapping floods, one of the most important aspects is land cover. Because it reflects the land's current use, pattern, and types of use, it is essential for soil infiltration and stability. The ability of the soil to retain water is greatly impacted by land cover, including soil vegetation cover, such as permanent grassland or another crop cover (Venkatesh et al., 2020). Fields with a good amount of crop cover are much less prone to experience rainfall floods than bare fields. In other words, different land uses act as protective covers that reduce the amount of time that water is held; usually, this leads to a larger peak water flow, which results in a more precise flood forecast. As a result, LULC is essential for forecasting the likelihood of floods (Wang et al., 2019). Snow cover was rated poorly in this study, but water bodies were given an exceptionally high score. Sentinel 2 imaging data was analyzed to extract land use and land cover information, and the Erdas Imagine tool was used for supervised classification.

3.5 Preparation of Spatial Database

Choosing the appropriate parameters for a geographic database is one of the most crucial stages in the flood susceptibility analysis. Floods are frequently the result of a series of interconnected events. Nevertheless, different factors have varying degrees of significance in affecting flood vulnerability (Rahmati et al., 2016).

Table 2:The sources of data collection.

S. No	Primary Data	Spatial Resolution	Format	Source of Data	Derived Map
1	Sentinel-2	10 m	Raster	(https://earthexplorer.usgs.gov)	Land Use Land Cover Map (LULC) NDVI
2	SRTM (DEM)	30m	Raster	https://opentopography.org/	Elevation Slope Drainage Density
3	Soil Data	1:100,000	Vector	https://soil.punjab.gov.pk/	Soil Map
4	Rainfall Data	1:100,000	Raster	https://www.pmd.gov.pk/en/	Rainfall Map

3.6 Training and Testing Dataset's Generation

Mapping flood vulnerability and risk is significantly impacted by the accuracy of flood incidence documentation (Sadek et al., 2019). For the inventory, 70 flood site locations were chosen. Because the inventory's polygon structure is hard for the algorithm to use and overstates the results, random points were used in the investigation. The great majority of linked natural hazard models were built on point-based inventory data (Youssef et al., 2019). The map was divided into 70–30 percent ratios for training and assessment reasons. The dependent outcomes were built using 0 and 1 values, where 1 indicated the presence of floods and 0 indicated their absence. Training locations (70 points) were selected at random. Thirty locations were chosen to be non-flooding points. These procedures were carried out using the ArcGIS 10.8 environment.

3.7 Bivariate Statistical Analysis (BSA)

3.7.1 Frequency Ratio Model (FR)

FR is one of the main bivariate analytical techniques frequently employed in flood susceptibility research. FR is a bivariate statistical analysis that is based on the spatial relationship between the independent and dependent variables (Chakraborty et al., 2020). The selected training area Geographical links between the dependent components were established by taking into account the factors that cause floods, such as geography, climate, and local characteristics, which were examined as distinct variables in this study. The frequency ratio model on flood susceptibility and insecurity has been effectively implemented in numerous flood-prone regions across the globe (Khosravi et al., 2016).

$$FR = \frac{Floodpointsinfactorclass/Totalfloodpoints}{FactorClassArea/TotalArea} \qquad (2)$$

Once the FR values for each class were established, all of the data from each controlling factor was combined to create the final map of flood susceptibility. A flood risk map is made using the formula below:

Once the FR has been normalized using Eq 3, the relative frequency (RF) is computed across a range of probability levels [0, 1].

$$RF = \frac{Factor\ class\ FR}{\sum Factor\ class\ FR} \qquad (3)$$

Another disadvantage is that, following normalization, the RF assigns the same weight to each causal element. Equation 4, which also generated a prediction rate with a shorter PR or weight, was used to evaluate each flood-causing element in order to get around this issue and determine the reciprocal link between them (Nabavi et al., 2019).

$$PR = (RF_{max} - RF_{min})/(RF_{max} - RF_{min}) \quad (4)$$

Table 3:Calculation results for FR and RF for all classes for factors

Parameters	Class	Class Pixels	% Class Pixels	Flood Pixels	% Flood Pixels	FR	RF
Slope	< 2.8	1689576	60.2	41782	65.8	0.02	0.3
	2.8 - 7.6	794006	28.3	15812	24.9	0.02	0.241
	7.6 - 16.25	203238	7.2	4912	7.7	0.02	0.293
	16.25 - 29.15	76284	2.7	965	1.5	0.01	0.153
	29.15 - 60.94	43584	1.6	47	0.1	0.00	0.013
Elevation	< 434	816306	29	40464	63.7	0.050	0.571
	434-524	1074038	38.1	5924	9.3	0.006	0.064
	524-651	748647	26.6	15907	25	0.021	0.245
	651-883	121996	24.3	1271	2	0.010	0.12
	883-1428	56299	2	0	0	0	0
LULC	Water	26876	1	12073	19	0.449	0.865
	Forest	220589	7.8	1556	2.4	0.007	0.014
	Vegetation	1186463	42.1	21365	33.6	0.018	0.035
	Built up	832826	29.6	11402	17.9	0.014	0.026
	Bare land	550593	19.5	17167	27	0.031	0.06

Drainage Density	< 0.21	835063	29.6	6427	10.1	0.008	0.06
	0.21 - 0.57	648133	23	15524	24.4	0.024	0.187
	0.57 - 1.05	687468	24.4	18479	29.1	0.027	0.21
	1.05 - 1.71	477754	17	17597	27.7	0.037	0.288
	1.71 - 3.26	168815	6	5506	8.7	0.033	0.255
Rainfall	< 1264.60	275049	12	33521	61	0.122	0.79
	1264.60- 1316.38	521676	22.7	5643	10.3	0.011	0.07
	1316.38 - 1359.71	691283	30.1	9923	18.1	0.014	0.093
	1359.71 - 1408.32	811488	35.3	5877	10.7	0.007	0.047
	1408.32 - 1467.49	517884	22.5	8603	15.7	0.017	0.108
NDVI	-1.08	483344	17.2	19880	31.3	0.041	0.363
	0.08 - 0.17	797662	28.3	12373	19.5	0.016	0.137
	0.17- 0.26	685218	24.3	15871	25	0.023	0.204
	0.26 - 0.38	557245	19.8	11767	18.5	0.021	0.186
	0.38 - 0.72	293890	10.4	3675	5.8	0.013	0.11
Soil Map	Sandy Loam	2081	0.1	345	0.5	0.166	0.49
	Loam	153060	5.4	7035	11.1	0.046	0.136

	Sandy Clay loam	443371	15.7	56139	88.3	0.127	0.374
	Clay loam	2218064	78.8	76	0.1	0.000	0

Lastly, the flood vulnerability index is calculated using Equation No. 5 by adding the RF of each class and the PR of each class.

$$FVI = \sum_{j=1}^{n} \mathrm{FR} \qquad (5)$$

3.8 Analytical Hierarchy Processing (AHP) Method

Flood's study used Saaty's (1987) AHP methodology to score the multiple criterion decision concerns. AHP has been utilized by many researchers to evaluate urban flood-prone areas and reach multi-criteria conclusions (Negese et al. 2022). To ascertain the relative importance of flood-conditioning components, AHP analysis was employed. To do this, a pairwise comparison matrix (Table 3) had to be computed, normalized, and the entries had to be weighted. After each conditioning element was reclassified as indicated in, an additional evaluation was conducted to verify the consistency. Based on Saaty's 1–9 scale, Table 3 shows a matrix of pairwise comparisons for each flood-conditional element. The total of each element was then split by the matching pairwise comparisons matrix entry. In the end, each weight was calculated by dividing the line sum of the normalized matrix by seven (Negese et al. 2022).

Table 4: Flood-conditioning factors: their weights, ratings, and classifications

Factor	**Class**	**Flood Susceptibility**	**Class Range**	**Weight**
Elevation	< 434	Very High	5	15
	434-524	High	4	
	524- 651	Moderate	3	

	651-883	Low	2	
	883-1428	Very Low	1	
Slope	< 2.868	Very High	5	10
	2.868 - 7.688	High	4	
	7.648 - 16.252	Moderate	3	
	16.252 - 29.158	Low	2	
	29.158 - 60.945	Very Low	1	
Aspect	< 94.931	Very Low	1	5
	94.931 - 137.645	Low	2	
	137.645 - 221.116	Moderate	3	
	221.116 - 294.683	High	4	
	294.683 - 359.762	Very High	5	
Rainfall	< 1264.603	Very Low	1	20
	1264.603 - 1316.384	Low	2	
	1316.384 -	Moderate	3	

	1359.711			
	1359.711 - 1408.321	High	4	
	1408.321 - 1467.499	Very High	5	
Soil Type	Sandy Loam	Very Low	1	10
	Loam	Low	2	
	Sandy Clay Loam	Moderate	3	
	Clay Loam	High	4	
Drainage Density	< 29.690	Very Low	1	15
	29.690 - 76.163	Low	2	
	76.163 - 121.345	Moderate	3	
	121.345 - 178.145	High	4	
	178.145 - 329.182	Very High	5	
Land use/land cover (LULC)	Waterbody	Very Low	1	15
	Forest	Low	2	

	Grassland	Moderate	3	
	Built area	High	4	
	Dryland	Very High	5	
Normalized Difference Vegetation Index (NDVI)	< 0.087	Very High	5	10
	0.087- 0.174	High	4	
	0.174 - 0.269	Moderate	3	
	0.269 - 0.384	Low	2	
	0.384 - 0.721	Very Low	1	

Once the weights of each flood-proneness element were established, the accuracy of the comparison was evaluated by generating a consistency index check using Saaty's (1987) Eq. 6. where CI is the consistency index, λ max is the greatest eigenvalue of the comparison pairwise matrix, and n is the number of items under examination (Hamami et al.,2019).

$$CI \frac{\lambda_{max-n}}{n-1} \tag{6}$$

According to Senan et al. (2023), CI represents consistency index, λ max represents maximum eigenvalue of comparison pairwise matrix, and n represents the number of items being studied.

Table 5: The 1980 Saaty Scale

Intensity of importance	Degree of preference	Explanation
1	Equal importance	Both elements equally advance the objective.

3	moderate importance	Experience and discretion marginally favor one measure over another
5	The paramount or vital significance	Experience and judgment greatly favor one activity over another.
7	Extremely important	There is a strong preference for one parameter over another, and this preference is manifested in practice
9	Extreme importance	The evidence favoring one parameter over another has the strongest possible order of affirmation.
2,4,6,8	Intermediate numbers	When factors that are almost identical in significance

The maximum Eigenvalue (λ max) of the comparison pairwise matrix was obtained using the following methods (Saaty 1987).

First, assign a weight to each value in the non-normalized matrix's columns. The weighted total is then calculated by adding the values of the rows. A weighted aggregate value is then assigned to each criterion value. the total of the weighted averages of the criteria weights (Senan et al., 2023).

Next, using Eq. 7, the consistency ratio (CR), which shows that Saaty's (1987) comparison is legitimate, was computed.

$$CR = \frac{CI}{RI} \tag{7}$$

A consistency ratio of less than 0.10 indicates consistency in a pairwise comparison, per Saaty (1987). Insufficient consistency necessitates repeating the process multiple times until the CR value drops below the cutoff if it is greater than or equal to 0.10. The matrix size of the equation was subjected to the random consistency index (Taherdoost et al., 2017).

3.9 Flood Prone Map Preparation Method

All flood-conditioning elements were rated from very low to very high using an analytical hierarchy technique in order to create a map of the research region that is prone to flooding. Next, Eq. 8 was used in the weighted overlay method of the Spatial Analyst extension for ArcGIS. Numerous studies have employed this technique to map flood-prone regions and identify locations at increased risk of flooding (Negese et al., 2022).

$$FP = \sum_{i=0}^{n} Xi * Wi \quad (8)$$

where FP stands for flood-prone, Xi is the particular normalized criterion, and WI is the weight of the criterion, and n is the total number of criteria employed in the decision-making process.To illustrate the increased significance of flood susceptibility from very high to very low flood risk zones, the Flood Vulnerability Index (FVI) was also computed in the current AHP and FR model study (Taherdoost et al., 2017).

The SFWV chosen for flood occurrences and the SCWV for each class of the variables chosen were incorporated into the FVI computation using the following Eq. 9:

$$FSI = \sum_{n=1}^{n} (wi * FR) \quad (9)$$

3.10 Model Validation

3.10.1 Area Under Curve (AUC)

The Islamabad and Rawalpindi research zones were included in the flood susceptibility map, as demonstrated by the Area Under the Curve (AUC) approach. This experimentally confirmed method verifies the accuracy of the FR model by comparing it with historical flood episodes. Previous work has made substantial use of the AUC technique, which is generally regarded as the best approach for verifying the AHP model (Bui et al., 2023).

$$AUC = \sum_{i=1}^{n=100} \frac{(X1+X2}{2\,(Y2+Y1)} \quad (10)$$

Based on the AUC (Area Under the Curve) values ranging from 0.00 to 1.00, the accuracy levels are separated into the following groups: Mitra et al. (2022) state that low accuracy is indicated by values between 0.50 and 0.60, moderate accuracy is suggested by values between 0.61 and 0.70, high accuracy is indicated by values between 0.71 and 0.80, very good accuracy is indicated by values between 0.81 and 0.90, and exceptional accuracy is indicated by values between 0.91 and 1.00.

Results and Discussion

4.1 Assessment through Frequency Ratio Model

Flood susceptibility mapping specifically involves a large number of independent variables, referred to as conditioning factors (Kia et al., 2012). The following are the spatial distributions and statistical databases for each of the seven (07) conditioning factors: Along with their subclasses, maps of slope, elevation, LULC, rainfall, NDVI, drainage density, and soil were created (Table 3). Because slope affects flood frequency, low-lying land areas are closely related to the flood situation during rainy spells. As slope gradients diminish, the probability of floods and their occurrences rises (Rahmati et al., 2016).

4.1.1 Slope

The infiltration method is often influenced by the gradient of the slope. Surface runoff increases and penetration diminishes as the gradient rises. Because a significant amount of the water remains inactive, floods occur in areas with abrupt gradient descents (Muhammad Ishaq et al., 2020).The slope (in degrees) was calculated and categorized into five (5) groups using DEM data. The findings show that the two lowest slope gradient grades, < 2.8° and 2.8° - 7.6°, respectively, had the highest FR values of 0.02. The slope gradient is more than 29.1° on the opposite side, which has the lowest FR value of 0.000 (fig 6).

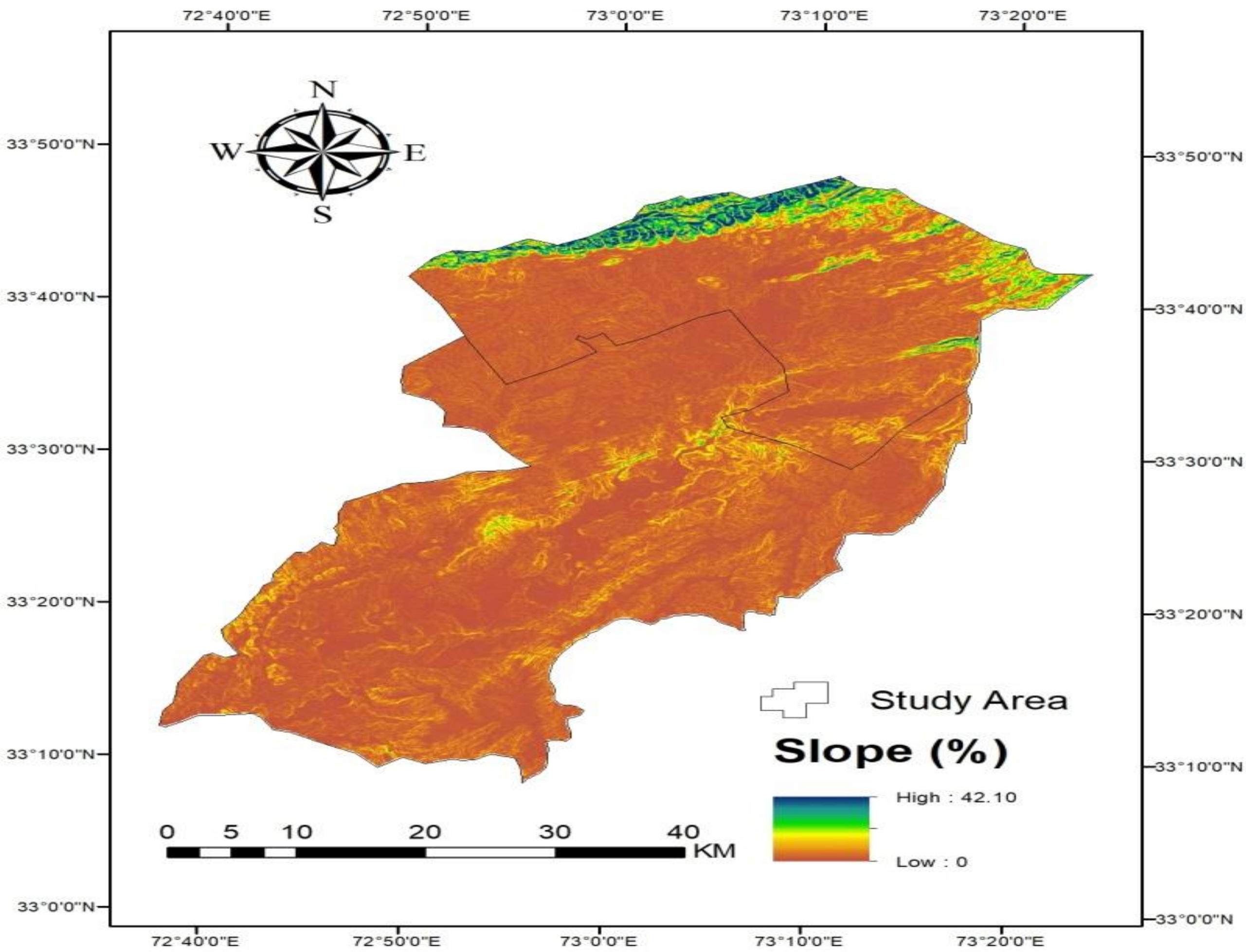


Figure 4: Spatial distribution of Slope

4.1.2 Elevation

Height significantly affects the frequency of floods since water usually moves from higher altitudes to lower land areas. A prior study found that flooding is less likely to occur in higher elevation sites and more likely to occur in lowland areas. The FR number will frequently drop as the region's height increases. High-frequency ratio values of 0.050 are found for the 1 lower raised class in the study zone < 434m. Suggesting that low elevated locations are significantly more likely to flood (Table 3). Locations with low FR-value and high altitude are less likely to experience flooding (Das et al., 2018).

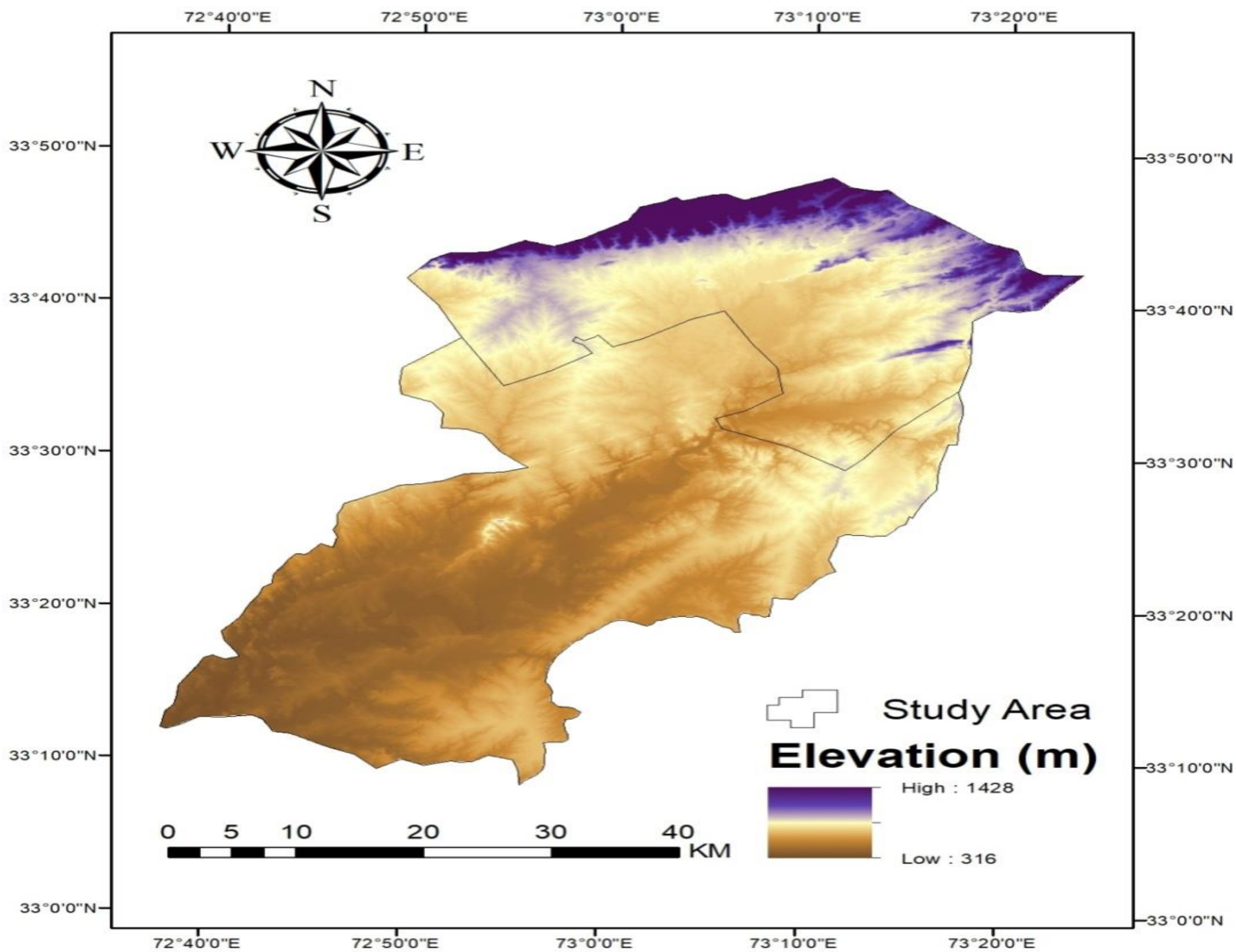


Figure 5: Spatial Distribution of Elevation

4.1.3 LULC

Human and natural cycles are both reflected in patterns of land use. Since there is less vegetation to regulate and stop the rapid release of water onto the soil surface, runoff is higher on fallow farms and higher in metropolitan areas due to the wide impermeable soil. These regions are at risk for both soil erosion and floods, and they are more susceptible to flooding. Population density, economic success, and a big housing stock make built-up communities along rivers more vulnerable to flooding (Nandi et al., 2016). Table 3 shows that unprotected places are particularly vulnerable to floods, with bare ground and water bodies in the research area having high FR values of 0.031 and 0.449, respectively.

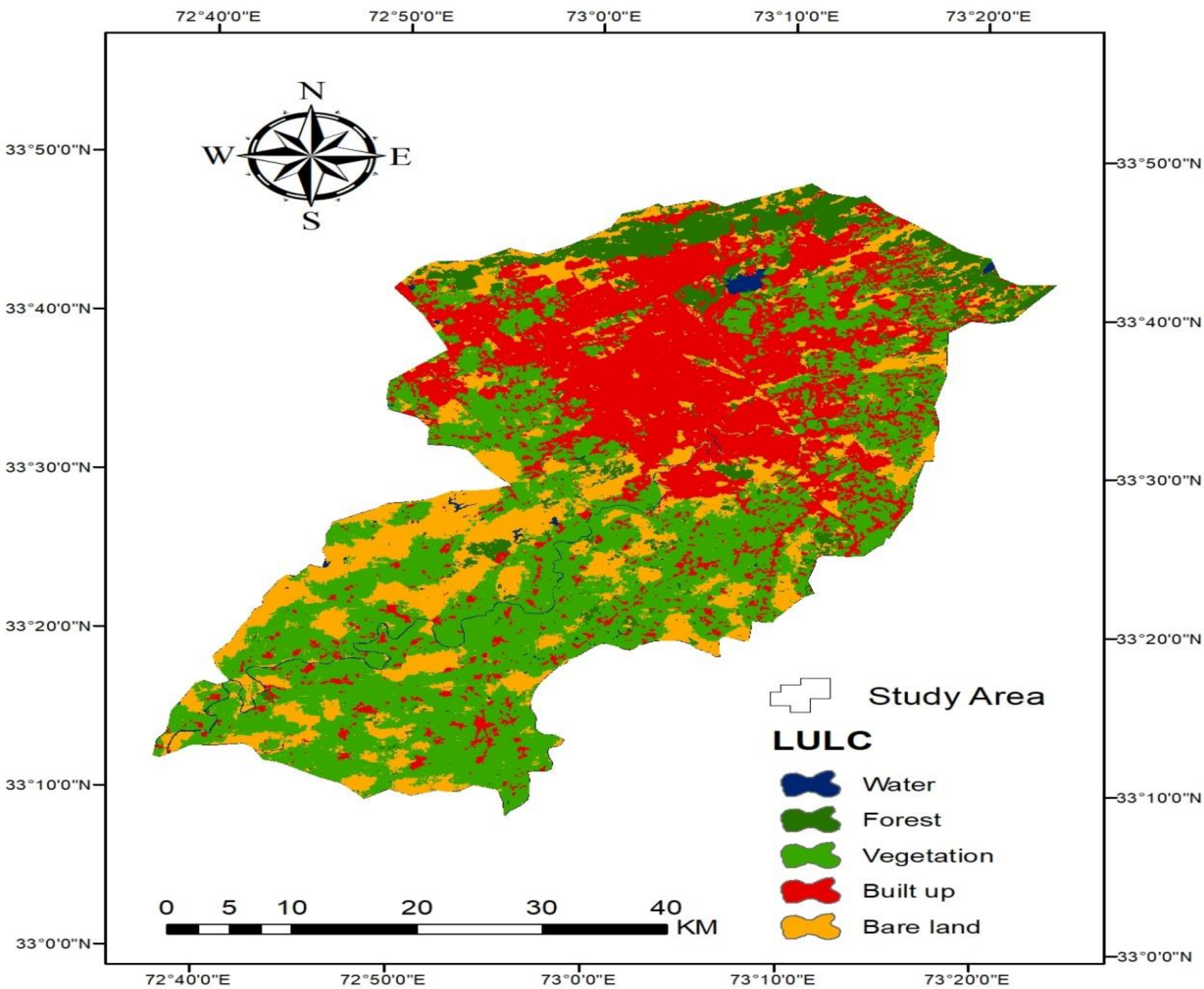


Figure 6: Spatial distribution of Land Use Land Cover (LULC)

4.1.4 Rainfall

In the study of flood vulnerability in terms of climate, rainfall remains a critical component. Rainfall variation was used to determine the risk of flooding because it is thought to be the greatest indication of flood zones (Das et al., 2018). In this study location, the FR value of 0.12 is high (< 1264.60) during periods of significant rainfall.

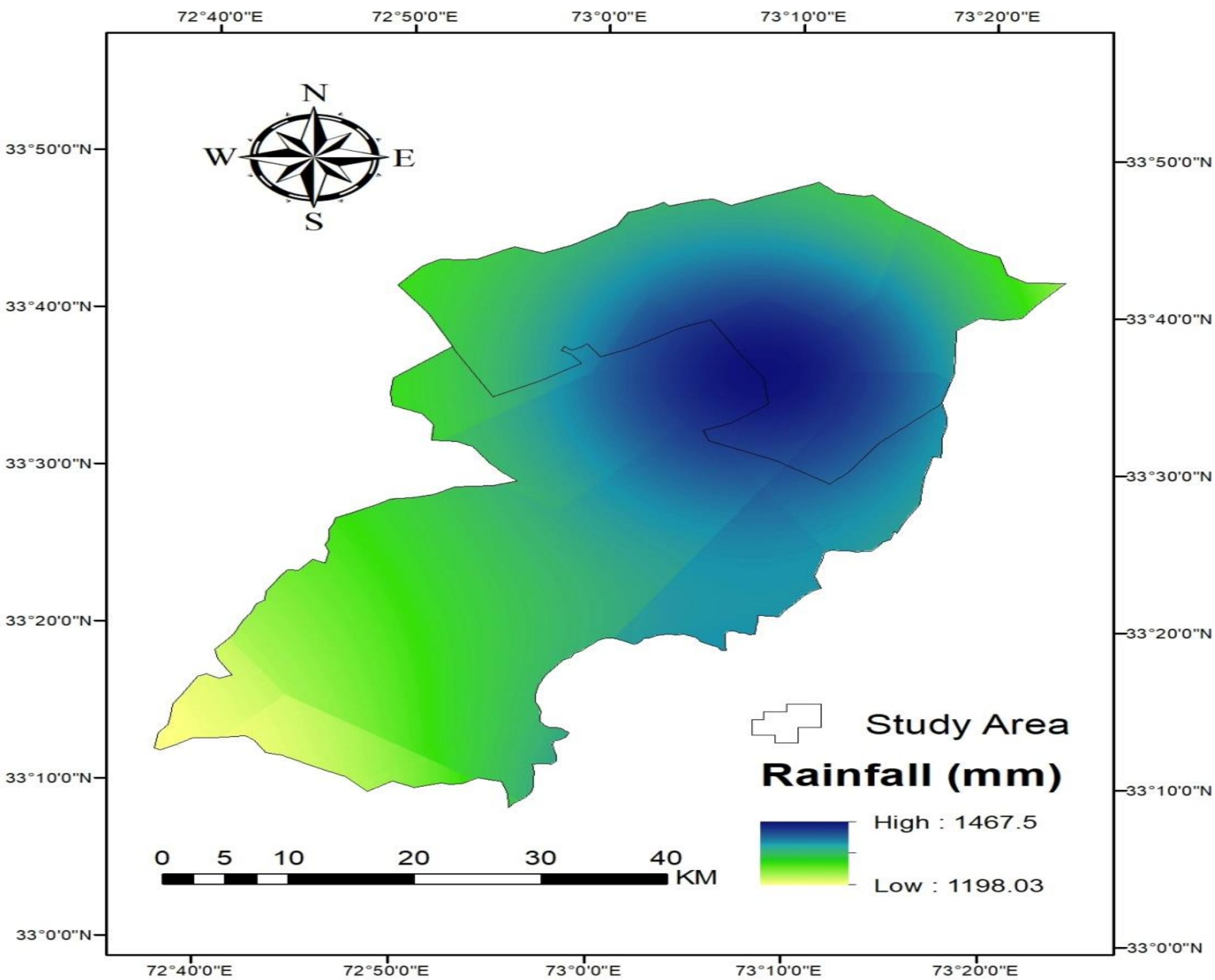


Figure 7: Spatial Distribution of Rainfall

4.1.5 Drainage

Generally, flash flood danger is higher in areas with high drainage densities. This is due to the fact that areas with a lot of streams and rivers can quickly route rainfall, which can result in sudden flooding and dramatic rises in water flow. Conversely, areas with low drainage density tend to absorb more water, which causes runoff that is less severe and occurs later (Lazarević et al., 2023). The research region results suggest that the FR values of 1.05 to 1.71 and 1.71 to 3.26 are higher, at 0.037 and 0.033, respectively. Some studies indicate that particular drainage density ranges have a higher risk of flash floods.

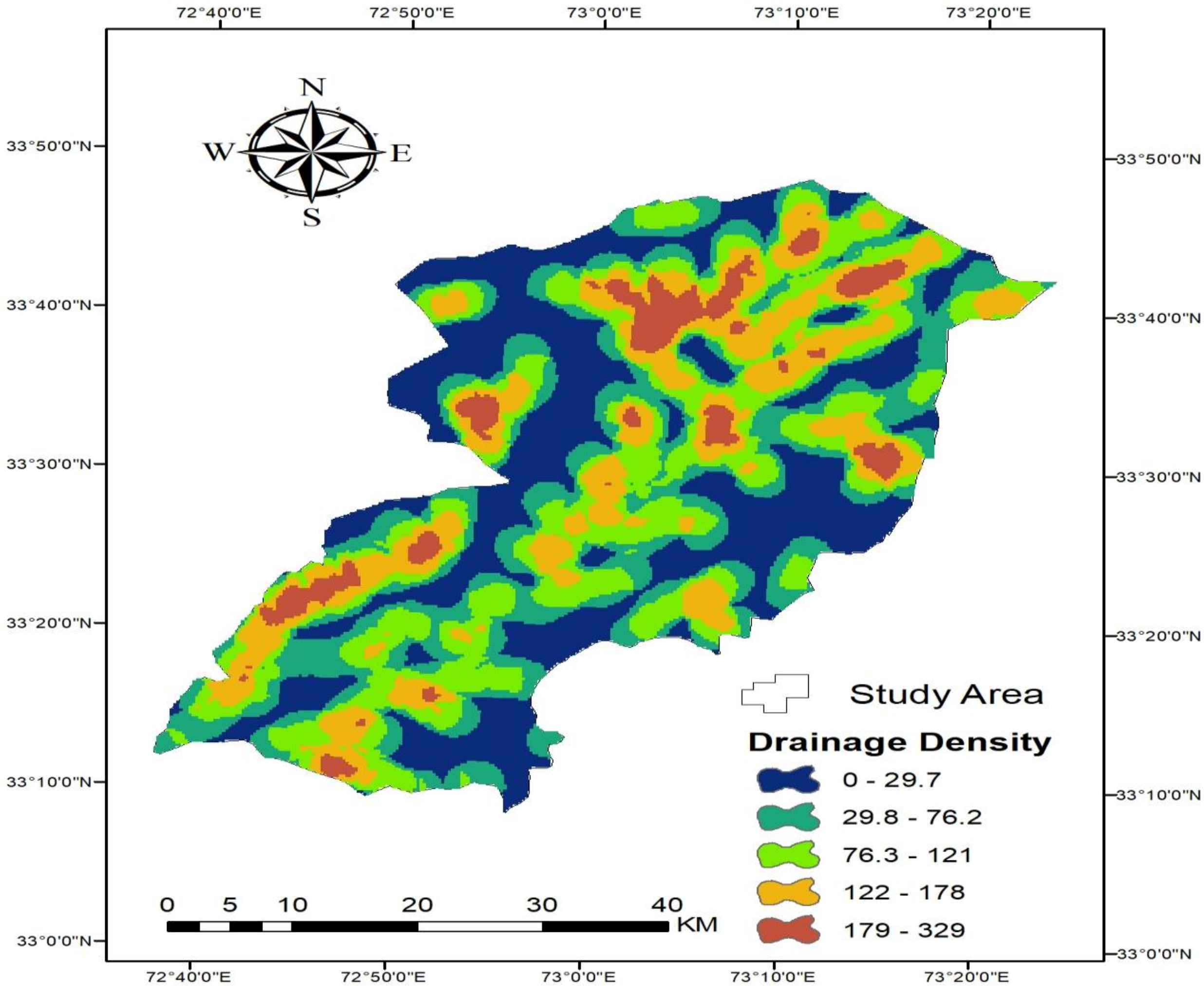


Figure 8: Spatial Distribution of Drainage Density

4.1.6 Normalized Difference Vegetation Index (NDVI)

The NDVI, an indicator with values ranging from -1 to +1, is another significant flooding conditioning element. Since Khosravi states that positive (+ve) values indicate vegetation and negative values reflect water, there is a negative correlation (-ve) between floods and the NDVI. While lower NDVI levels indicate a higher danger of flooding, higher NDVI values indicate a lower or lesser risk of flooding (Paul et al., 2019). High FR values of 0.041 and 0.023 are associated with the NDVI values in this sample, which range from -1.08 to 0.17–0.26. Because there is less infiltration and more runoff when there is less vegetation, flash floods are more common.

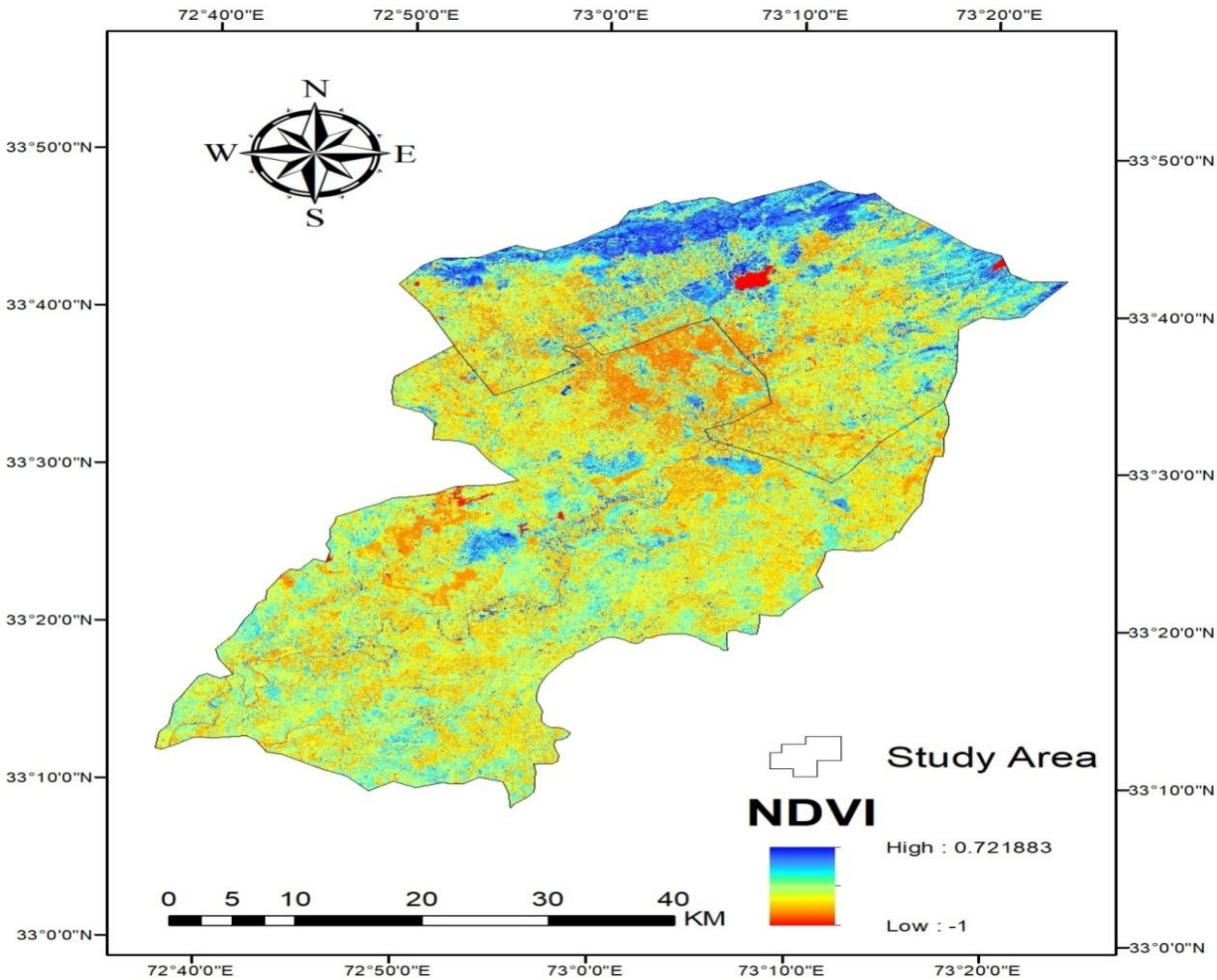


Figure 9: Spatial Distribution of Normalized Vegetation Index (NDVI)

4.1.7 Soil Type

The ability of soils to absorb water is influenced by their structure and texture, which are shown on soil maps as clay, silt, and sand. While sandy soils frequently have high infiltration rates, which reduce surface runoff, clayey soils have low infiltration rates, which increase runoff and the risk of floods (Lazarević et al., 2023). Sandy loam (0.166) and sandy clay loam (0.127) have high FR values, indicating that they are soil types that greatly increase the risk of flooding due to their moderate to high runoff capacity, variable infiltration rates, and sensitivity to erosion. A comprehensive grasp of these characteristics facilitates the accurate assessment and management of flood hazards.

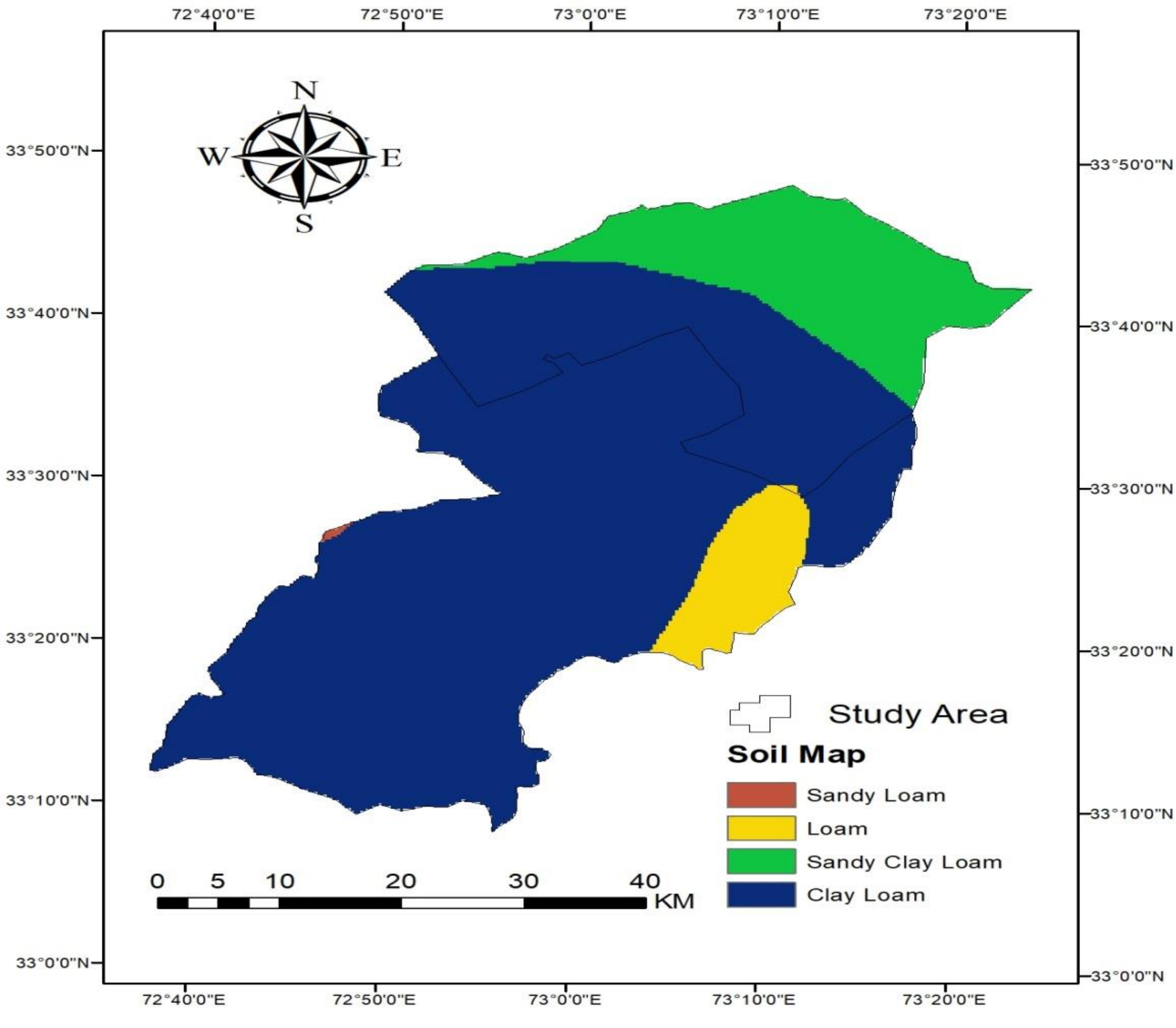


Figure 10: Spatial Distribution of Soil Type

Finally, the flood probability database was constructed using the FR model in Eq. 5. The model output's FR value ranged from 2.66 to 19.02. A larger chance of flooding was indicated by a higher FR rating. Five (5) distinct flood susceptibility zones—very low, low, moderate, high, and very high susceptibility was created using the reclassification database. 13% are classified as low, 23% as very high, 27% as extremely high, 22% as high, and 15% as moderate. The western-southern section of the region is particularly vulnerable to flooding in comparison to other regions. This region is very sensitive and lacks the ability to adapt.

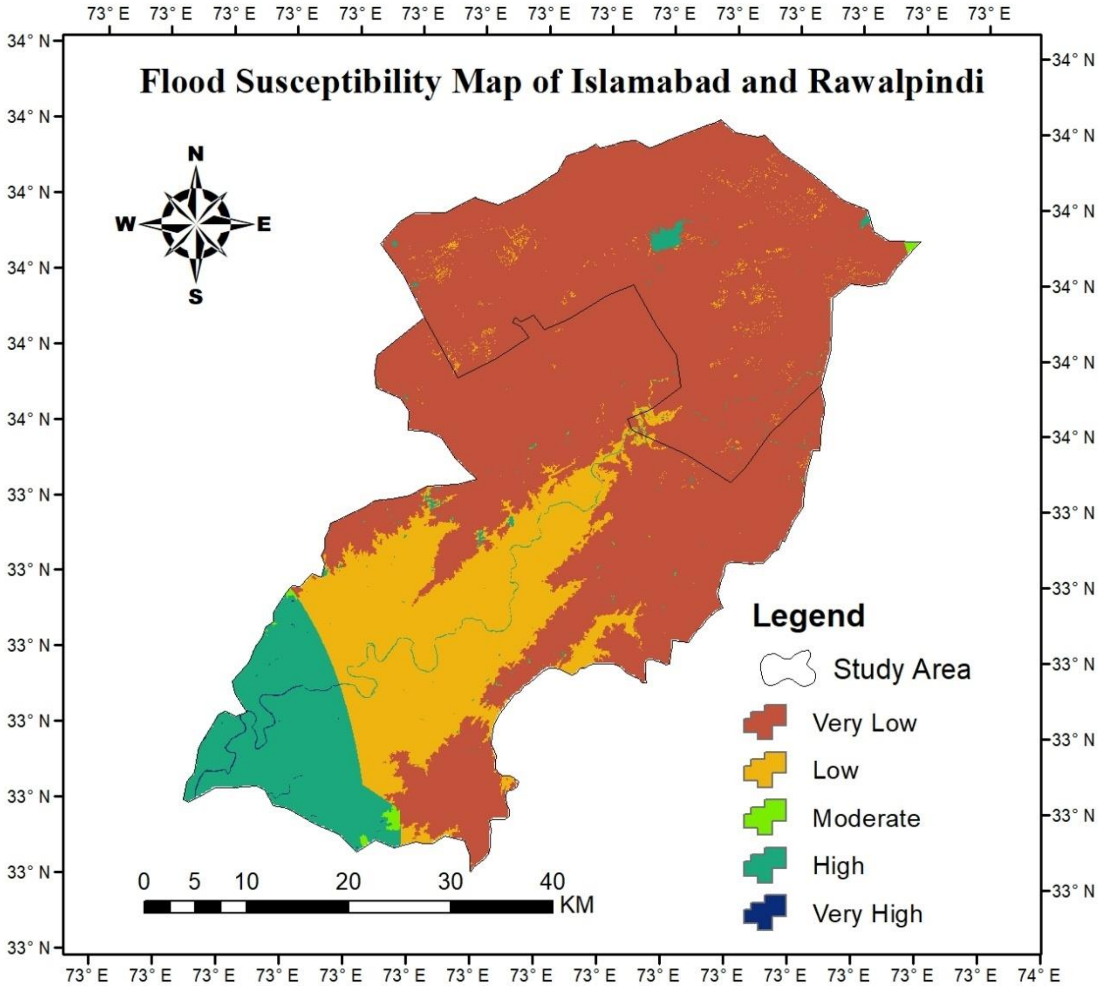


Figure 11: Spatial Distribution of FR Model

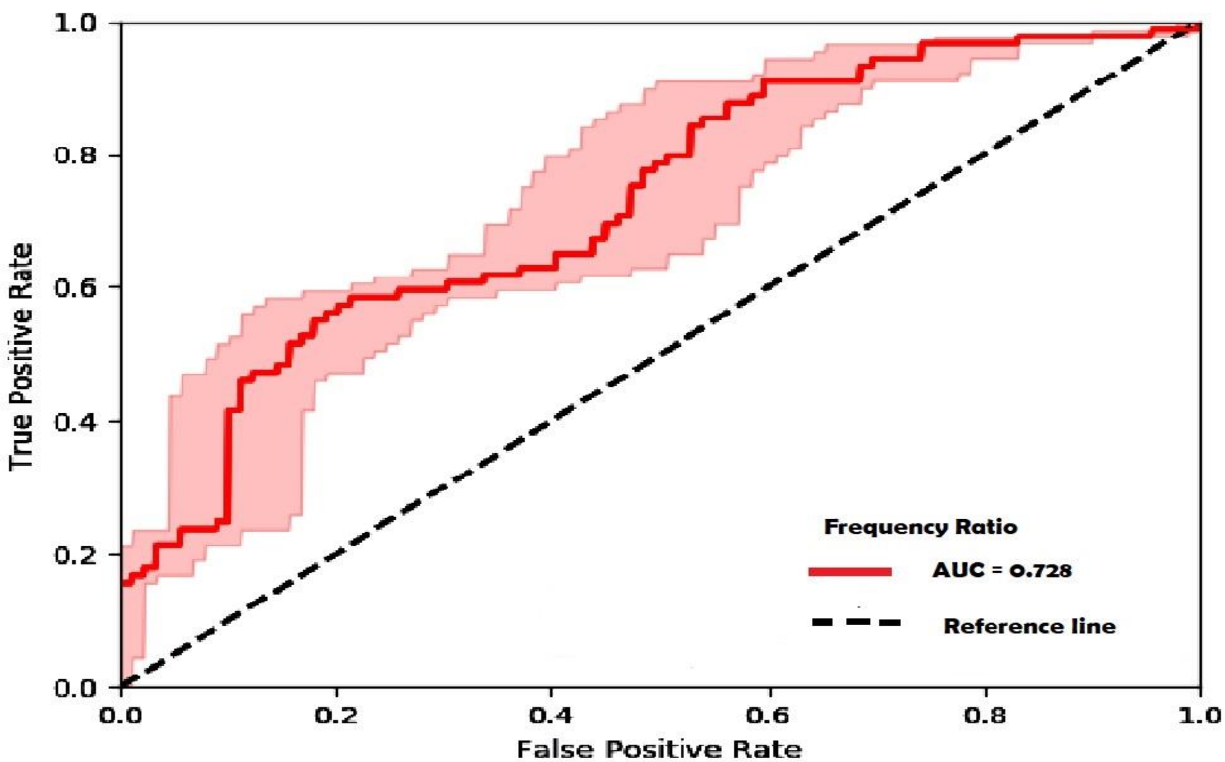
The northwestern region is showing extremely high to high levels, while the southwest region is showing moderate levels. A gradient in flood sensitivity is seen in the study area, with zones of moderate to low susceptibility giving way to areas of severe to high vulnerability, which are primarily found in the central and western regions of the study area (Fig 13).

Table 6: Classified flood zones of the area

S. No	Flood Zone	%
1	Very Low	23
2	Low	13
3	Moderate	15
4	High	22
5	Very High	27

These high to very high flood susceptibility zones are characterized by higher runoff potentiality, poorly to very poorly drained soil, alluvial deposits, braided flood plain, lower elevation, lower slope gradient, and closeness to the main river. Numerous scholars have put out a variety of models; however, in order to validate a model for assessments of flood susceptibility and vulnerability, it is essential to examine its accuracy and success rate. The bivariate statistical analysis of the FR model can be used to evaluate the relationship between the flood area and the criteria of each conditioning component (Tehrany et al., 2019; Ullah et al., 2020). The FR model simplifies the management of input data, calculation, and output processes in comparison to alternative methods (Hang et al., 2021). These features have led to the recent rise in popularity of the FR approach for making maps of flood hazard susceptibility (Trinh et al. 2022). Because it takes a different approach from expert review, its judgments are also more reliable (Thanh et al. 2020). It is predicted that vulnerable floods with values in the "moderate" to "very high" range will happen often in the future. The Area under the Curve (AUC) is used to calculate the flood forecast rate and validate the model. It needs to be evaluated as a critical outcome and result

(Fig. 13) AUC for the validation and performance of the model. Equation (10) was used to determine the AUC parameter, which was used to validate the model in this investigation. The genuine positive rate on the y-axis of the model is contrasted with the false positive rate on the x-axis. where TP and TN represent the number of pixels that were correctly identified, P represents the total integer of floods, and N represents the total integer of non-floods (Tien et al., 2018). Thirty percent of the flood points were employed during the validation phase. After evaluation, the model's AUC was 0.72, meaning that 0.72 percent of the attempts were successful. Despite the raw data's limitations and imprecision, this proportion was deemed acceptable. It also shows how well the frequency ratio model and its components worked in the study area or predicted



floods.

Figure 5: Validation through Area under Curve (AUC)

4.2 Assessment through Analytical Heirachiery Process Model (AHP)

The study's eight flood-controlling factors elevation, slope, aspect, rainfall, soil type, drainage density, adjusted differential vegetation index, and land cover and use were used to identify and map potential flood-vulnerable areas. The spatial distribution of flood vulnerability in the research region was determined and mapped by looking at and evaluating these features. Below is a more detailed display of each component's analysis.

4.2.1 Elevation

Elevation affects the likelihood of flooding. Because they suffer significantly larger water flows, rivers discharge, and flood more quickly, lower elevated locations are often more susceptible to flooding than higher elevated sites (Lee et al., 2022). The elevation of the study area ranges from 434 to 1428 meters above sea level. The low-lying (less than 1400

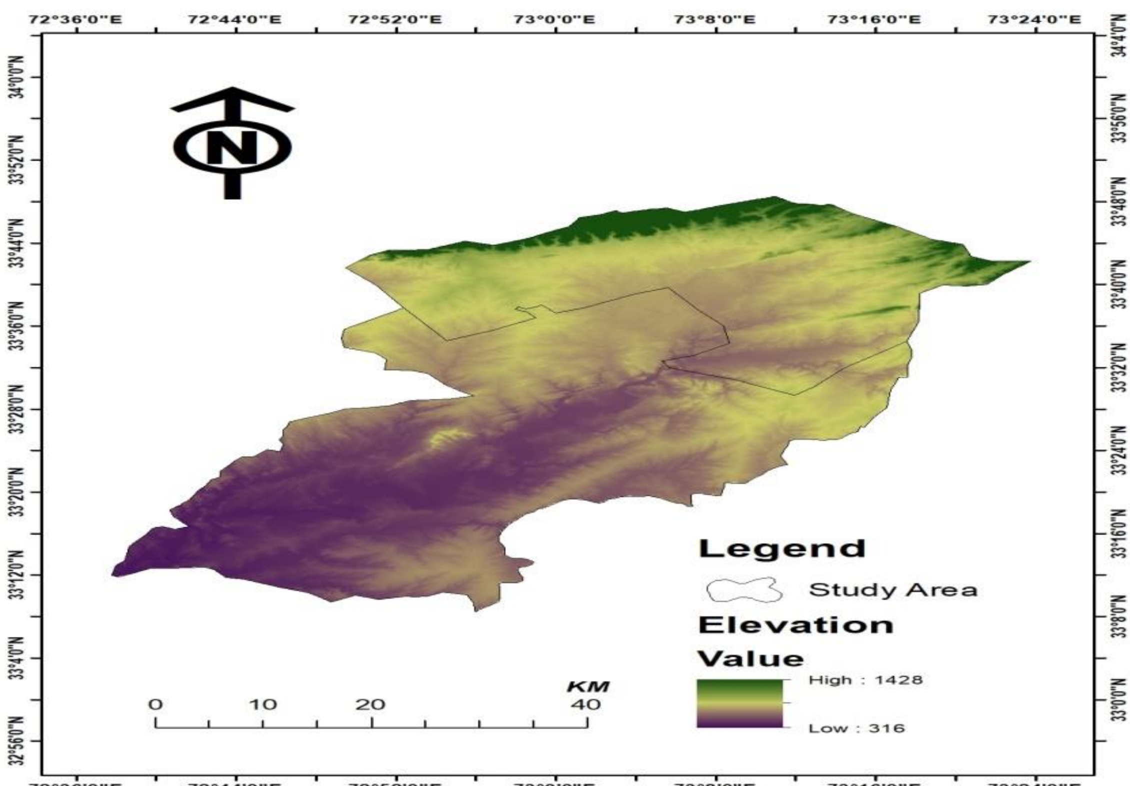


Figure 13: Spatial Distribution of Elevation

southern parts of the study region are especially susceptible to flooding, as shown in Fig. 2a. On the other hand, areas above the district center, from southeast to northwest (at 1,400m or higher above sea level), are extremely vulnerable to floods (Table 4).

4.2.2 Slope

The land's slope affects the flow rate of surface water. As the slope and surface water flow velocity drop, the amount of water covering the land and the probability of a flood rise (Das et al., 2021). In contrast to mountainous areas, which frequently have higher slopes that prevent water from pooling, lowlands and flatlands with mild slopes are more likely to have floods in 2021, according to Astutik et al. (Wang et al. 2015). The data points (Fig. 16) show that the range is 0 to 2.868°, indicating a very high vulnerability to flooding. The research region is characterized by varying degrees of sensitivity to flooding: high at 2.868–7.688° and moderate at 7.688°–16.252°, respectively. regions with very low (29.158–60.945°) and low (16.252–29.158°) flood susceptibility, respectively (Table 4).

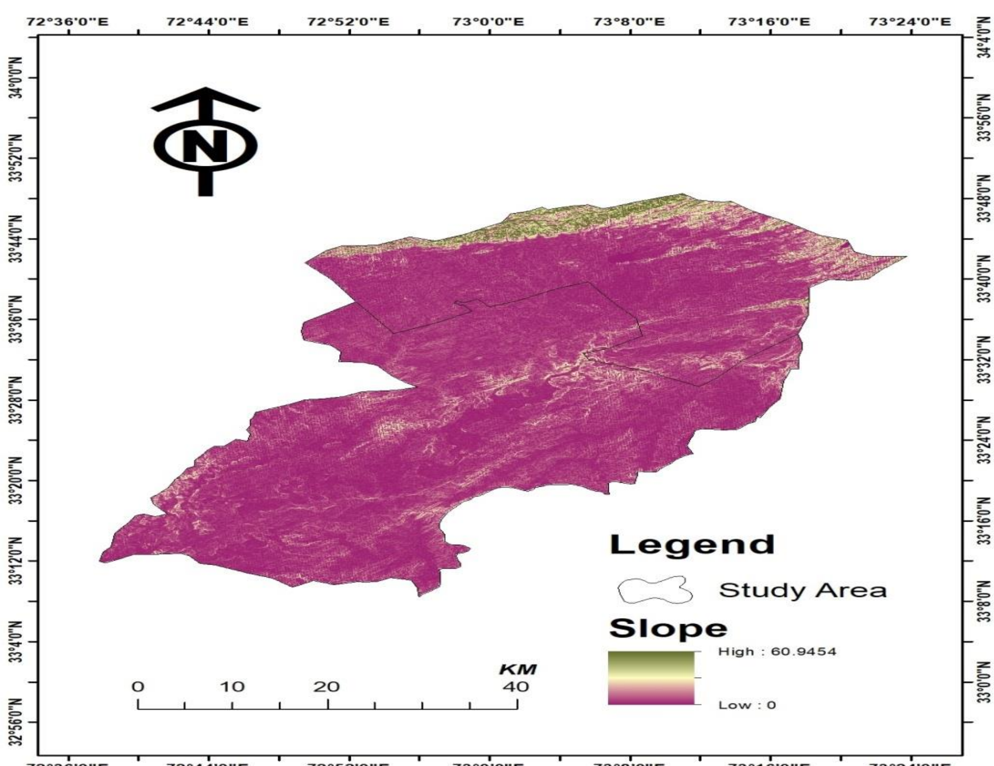


Figure 14: Spatial Distribution of Slope

4.2.3 Aspect

An important factor in urban floods is aspect, or the orientation of a slope, which influences the direction and velocity of surface runoff. Slopes that face the direction of the predominant wind and precipitation may be more susceptible to runoff buildup. There may be greater rainfall on certain hills. The risk of flooding may be increased in some urban situations due to faster water flow toward low-lying areas. Furthermore, the factor affects water evaporation rates and soil moisture retention, which might affect flood dynamics and necessitate particular flood mitigation and management strategies in urban development (Taromideh et al., 2020). The range of 0 to 49.931 in the data (Fig. 17) indicates a comparatively low sensitivity to flood inundation. The study area is classified as having low flooding susceptibility (49.931–137.645) and intermediate flooding susceptibility (137.645–221.116). Areas at high risk of flooding (221.116–294.683) and extremely high risk (294.683–359.762).

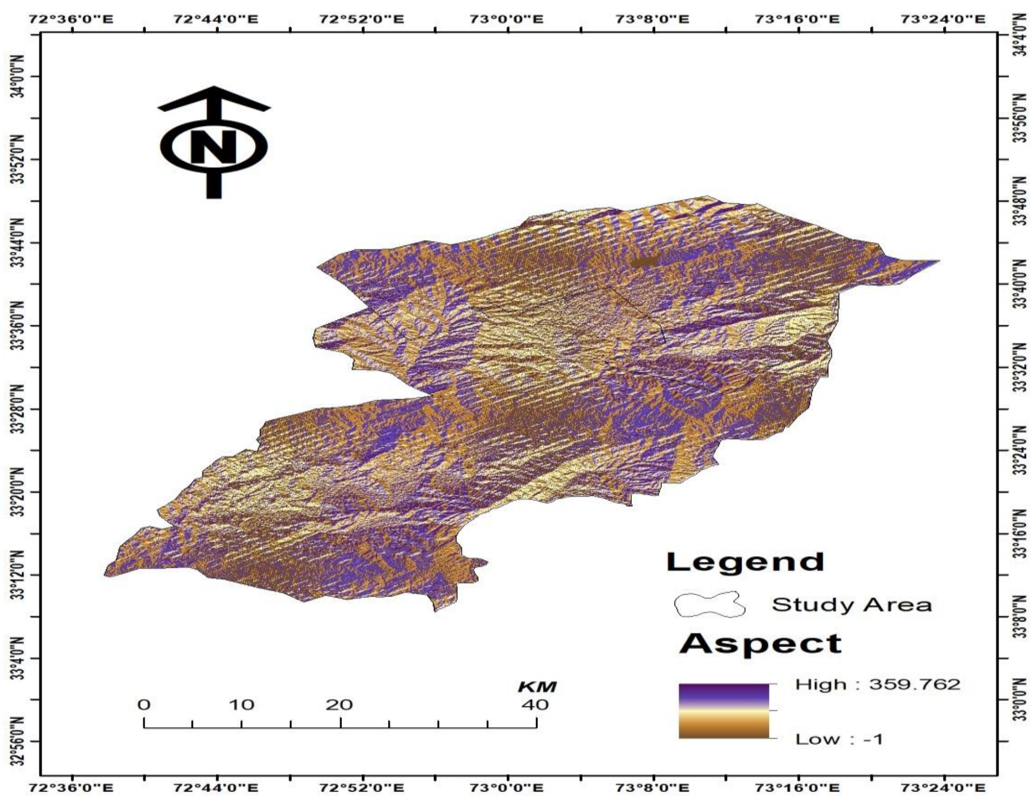


Figure 15: Spatial Distribution of Aspect

4.2.4 Rainfall

Studies on flood susceptibility must take rainfall into account since we cannot conceive a flood happening without it. Since it produces a large volume of runoff when extremely heavy or protracted rainfall causes flood inundation, it is the main cause of floods (Allafta et al. 2021). The research region receives between 1264.60 and 1467.499 mm of rain on average each year. Table 4 and Figure 18 show the new classifications for the following categories: below 1264.60 mm, 1264.60–1316.384 mm, 1316.384–1359.711 mm, 1359.711–1408.321 mm, and 1408.321–1467.499 mm. These relate to flood contributions that are very low, low, moderate, high, and very high.

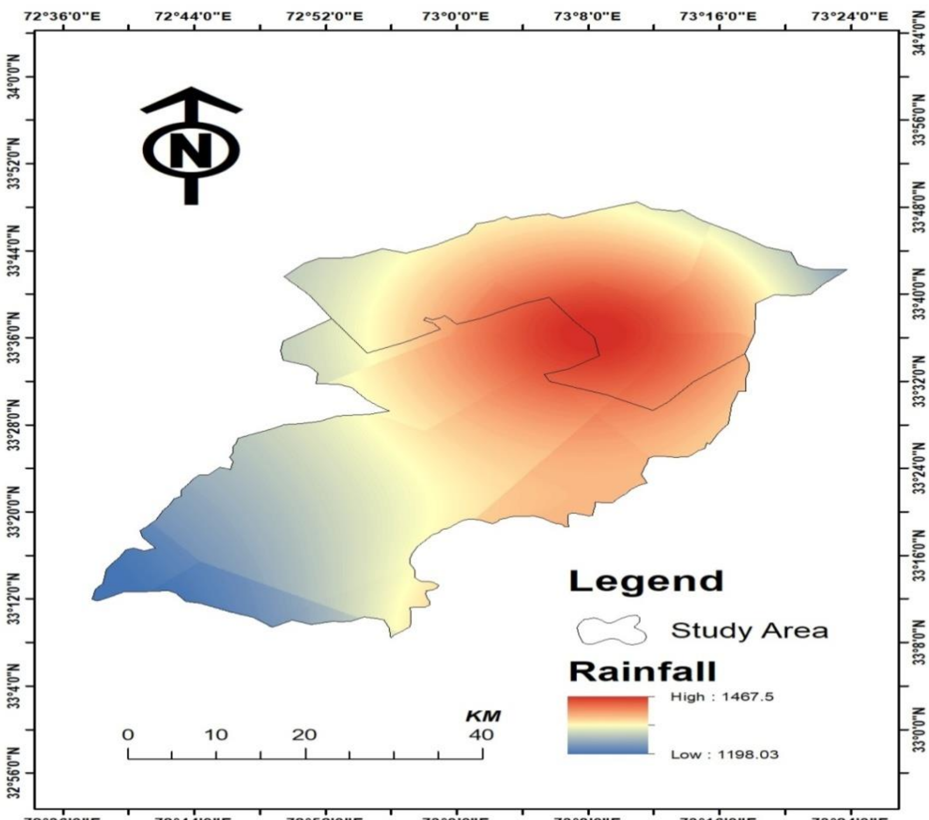


Figure 16: Spatial Distribution of Rainfall

4.2.5 Drainage

The total length of an area's streams divided by its size yields the drainage density of that area (Ogden et al., 2011). The drainage density of a given area can be determined by dividing the stream's overall length by its area (Abdulkarim et al., 2017). Drainage density values in this study are categorized into five groups, as indicated in Fig. 19 and Table 4: very low < 29.690, low 29.690 - 76.163, moderate 76.163 - 121.345, high 121.345 - 178.145, and very high 178.145 - 329.182. Areas with very high drainage densities are shown in deep blue in Figure 2e, whereas areas with low drainage densities are shown in red.

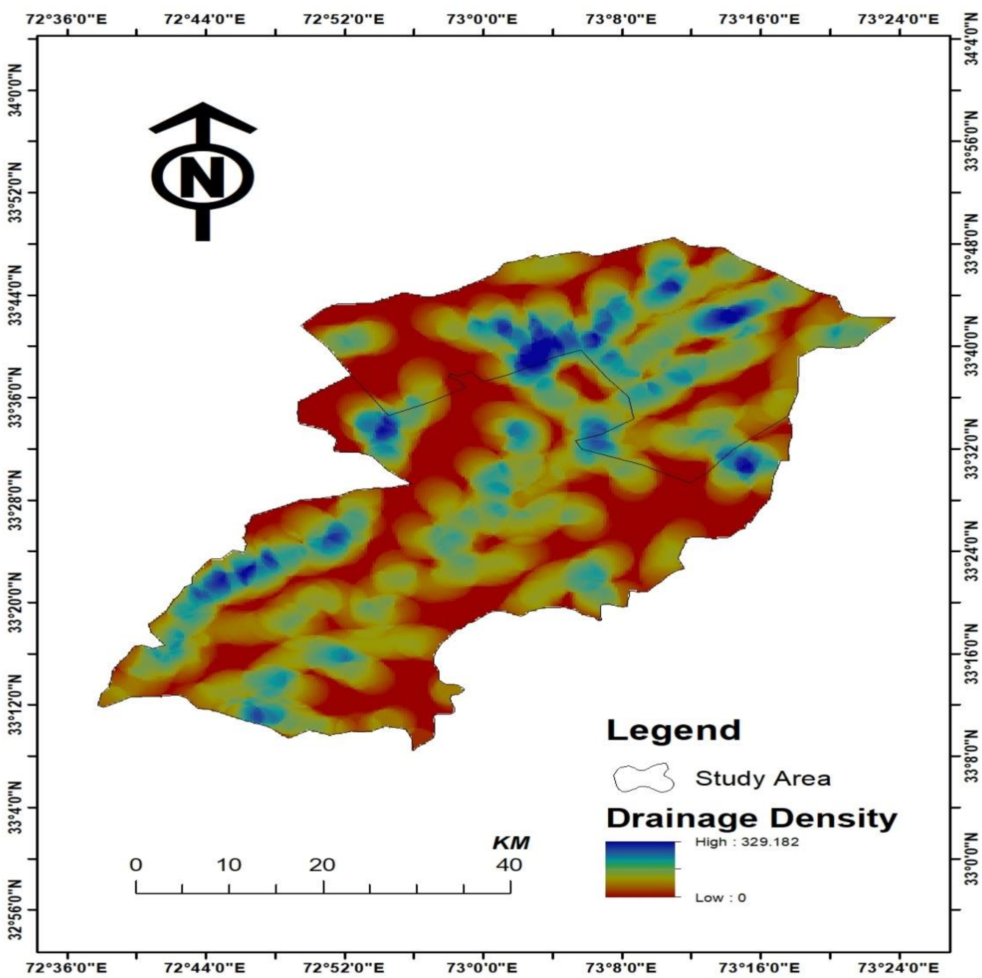


Figure 17: Spatial Distribution of Drainage

4.2.6 Land use land cover (LULC)

Land cover and use are one of the most important factors impacting the chance of flooding. High vegetation densities increase infiltration and slow down rapid water flow, making areas covered by them often less vulnerable to flooding. In contrast, runoff is higher in urban and residential regions due to impermeable surfaces and low infiltration (Rana et al., 2024). Figure 20, the LULC map, illustrates how the region's susceptibility to flooding is separated into There are five categories: low (forest), moderate (grassland), very low (water), very high (dryland), and high (built area).

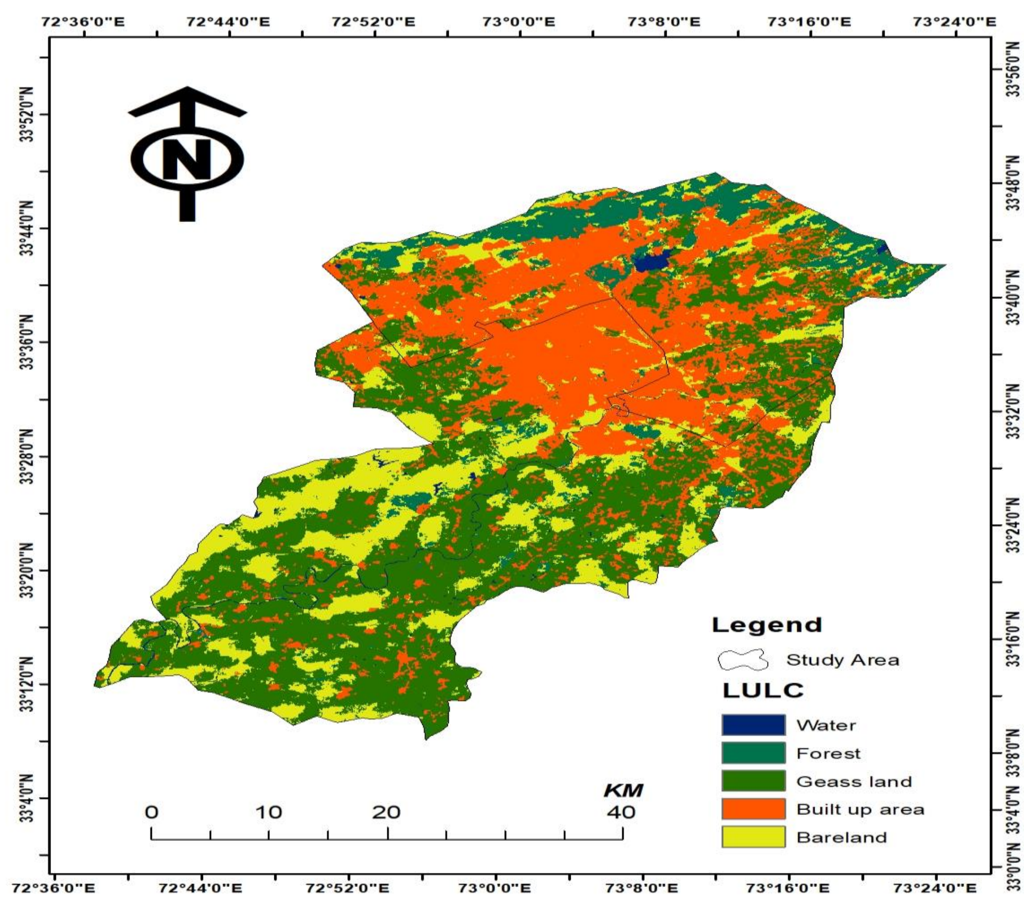


Figure 18: Spatial Distribution of Land Use Land Cover

4.2.7 Soil Type

The infiltration process is significantly influenced by the kind of soil. Because of its fine texture, the soil reduces infiltration while increasing surface runoff. Flooding is therefore more likely to occur in places with finer soil texture than in areas with coarser soil texture (Basri et al., 2022). The soil types in the study area exhibited extremely low (Sandy loam), low (loam), moderate (Sandy clay loam), and high (clay loam) flood vulnerability, based on the classification displayed in (Fig 21).

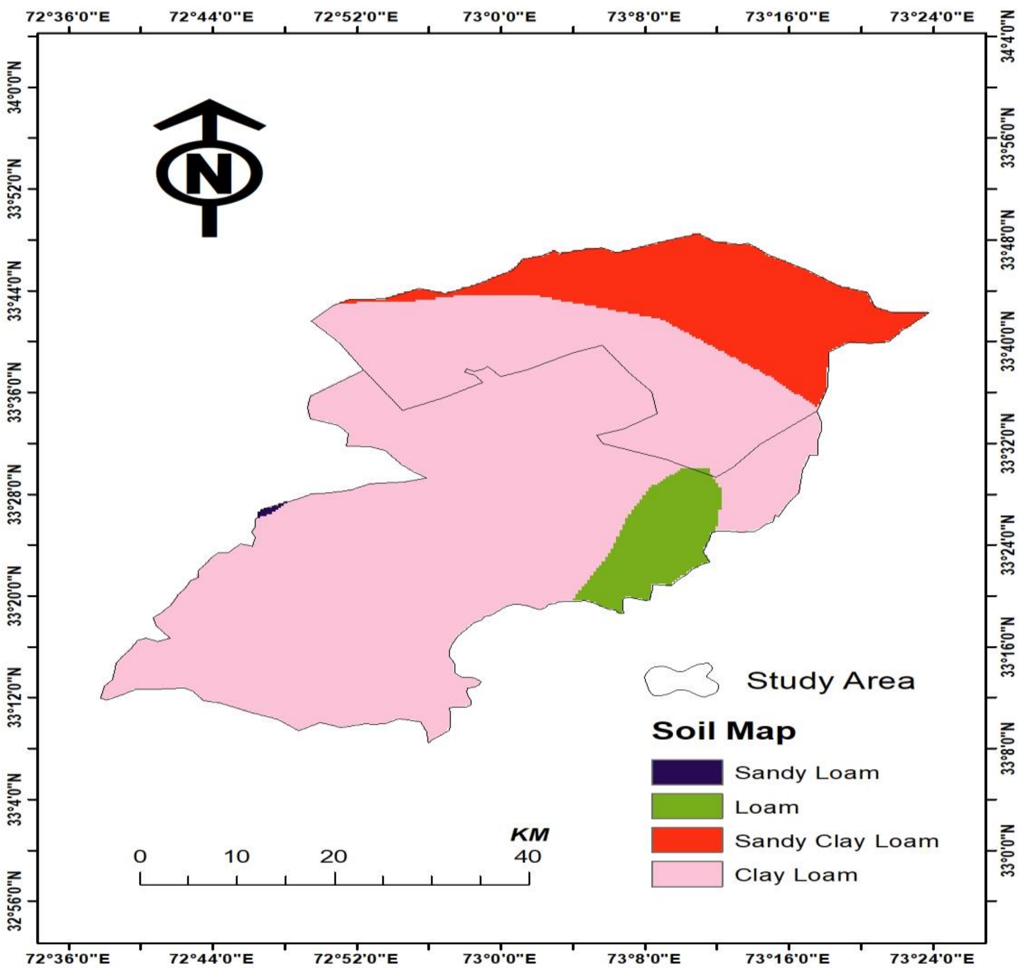


Figure 19: Spatial Distribution of Soil Type

4.2.8 Normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Index, which gauges the amount of vegetation in a given area, is one factor used to assess flood susceptibility (Ali et al. 2020). By reducing runoff, a higher vegetation density reduces the frequency of floods (Tehrany et al. 2017). Flood-risk zones were categorized as very high, high, moderate, low, and very low in this study. Less then 0.087, 0.087 to 0.174, 0.174 to 0.269, 0.269 to 0.384, and 0.384 to 0.721 are the ranges in which NDVI readings fall. As seen in Fig. 22, the NDVI values in the northern and a few central locations within the research zone were high to extremely high.

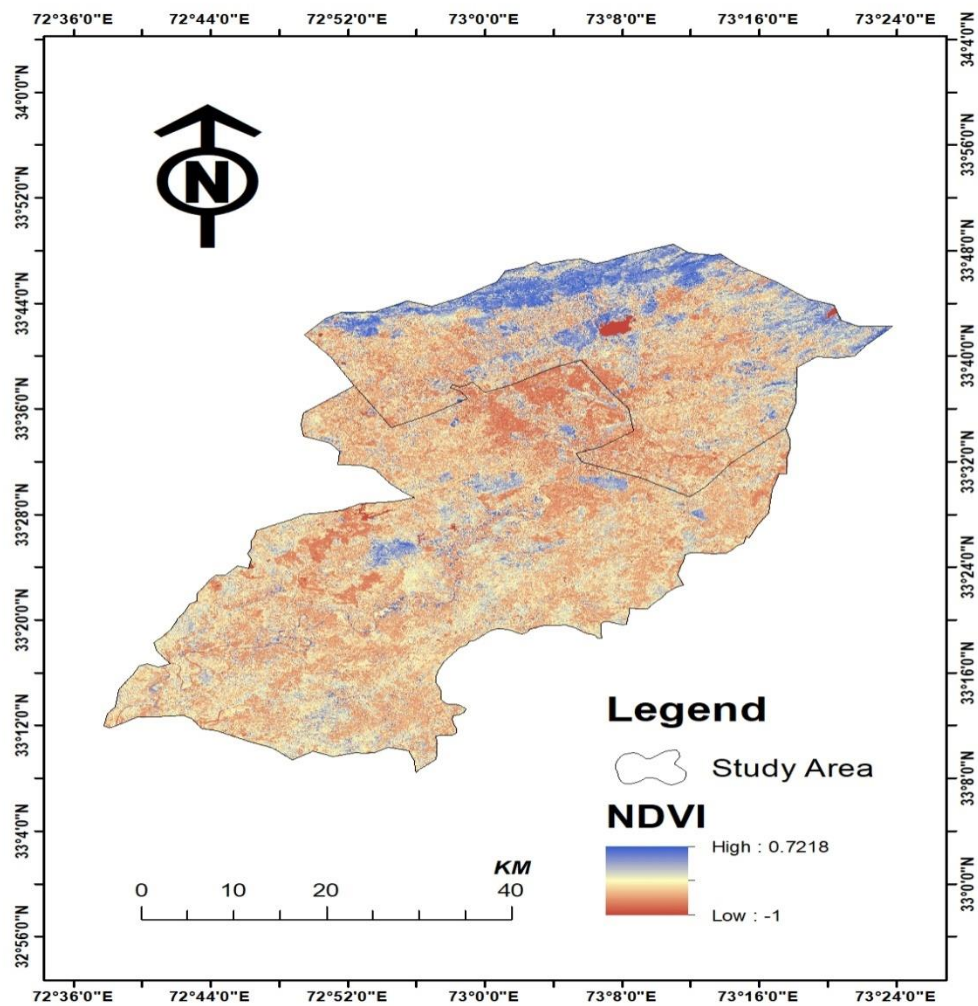


Figure 20: Spatial Distribution of Normalized Vegetation Index

Table 7: Matrix of pair wise comparisons for specific flood-control variables

Factors	Elevation	Slope	Aspect	D- Density	Rainfall	Soil Type	NDVI	LULC
Elevation	1	2	2	3	2	3	4	4
Slope	1/2	1	4	3	3	4	5	6
Aspect	1/2	1/4	1	2	2	2	2	5
D- Density	1/3	1/3	1/2	1	3	3	4	4
Rainfall	1/2	1/3	1/2	1/3	1	3	4	4
Soil Type	1/3	1/4	1/2	1/3	1/3	1	2	3
NDVI	1/4	1/5	1/2	1/4	1/4	1/2	1	2
LULC	1/4	1/6	1/2	1/4	1/6	1/6	1/2	1

Table 8: Calculated criteria weight for each item and a normalized pair wise comparison matrix

Factors	Elevation	Slope	Aspect	D- Density	Rainfall	Soil Type	NDVI	LULC	CW	CW (%)
Elevation	0.27	0.38	0.166	0.165	0.106	0.126	0.14	0.093	1.84	1
Slope	0.11	0.19	0.333	0.165	0.16	0.169	0.175	0.139	32.17	32
Aspect	0.11	0.047	0.083	0.11	0.106	0.084	0.07	0.046	2.63	2
D- Density	0.075	0.063	0.027	0.055	0.16	0.126	0.14	0.139	20.18	7
Rainfall	0.11	0.063	0.027	0.018	0.053	0.126	0.14	0.139	10.17	10
Soil Type	0.075	0.046	0.027	0.018	0.017	0.042	0.07	0.139	4.34	4
NDVI	0.056	0.038	0.027	0.013	0.013	0.021	0.035	0.046	6.87	6
LULC	0.056	0.031	0.027	0.013	0	0	0.017	0.023	21.76	21

Table 9: Determining the pair wise comparison's consistency

Factors	Elevation	Slope	Aspect	D-Density	Rainfall	Soil Type	NDVI	LULC	WSV	CW	WSV /CW
Elevation	0.1780	0.3756	0.1646	0.2457	0.1444	0.1413	0.1184	0.0772	1.4452	0.1780	8.1191
Slope	0.0890	0.1878	0.2249	0.2257	0.1916	0.1284	0.1280	0.1158	1.2912	0.1878	6.8754
Aspect	0.0890	0.0469	0.0823	0.1438	0.1244	0.0942	0.0592	0.0965	0.7363	0.0823	8.9465
D-Density	0.0590	0.0326	0.2191	0.0819	0.2166	0.1413	0.1184	0.0772	0.9461	0.0819	11.5519
Rainfall	0.0890	0.0339	0.0140	0.0112	0.0722	0.1413	0.1184	0.0772	0.5572	0.0722	7.7175
Soil Type	0.0590	0.0225	0.0116	0.0112	0.0241	0.0471	0.0592	0.0579	0.2926	0.0471	6.2123
NDVI	0.0440	0.0129	0.0113	0.0104	0.0181	0.0123	0.0296	0.0386	0.1772	0.0296	5.9865
LULC	0.0440	0.0213	0.1115	0.0104	0.0122	0.0131	0.0123	0.0193	0.2441	0.0193	12.6477

4.2.9 Analytical Hierarchy Process (AHP) Analysis

An AHP analysis was conducted after each flood-control component was classified in order to ascertain the relative weight or significance of the components under consideration for a weighted overlay (Table 7). The final criteria weights for each flood-controlling component are displayed in (Table 8) in accordance with the methods recommended by Saaty (1987). Land use and land cover (21.0%), drainage density (20.1%), elevation (1.84%), slope (32.1%), aspect (2.36%), rainfall (10.1%), soil type (4.34%), and NDVI (6.00%). Table 7 generated a pairwise comparison matrix, Table 8 computed the pairwise comparison's normalization and factor weight, and Table 9 assessed the consistency of the comparison. These weights show the estimated relative contributions of each component to the research area's risk of flooding. The consistency index (CI = 0.05) and consistency ratio (CR = 0.07) were calculated using equations (6) and (7). The computed maximum eigenvalue ($\lambda max = 8.72$) and the number of variables ($n = 8$) were used to determine the confidence interval (CI). with a random index (RI) of 1.41. Given that the computed consistency ratio (CR) is less than 0.1 (10%), the comparison is appropriate for weighted overlay. In this instance, the CR value is 0.07.

4.3 Flood Susceptibility Map

The final flood susceptibility map for Islamabad and Rawalpindi was made by integrating eight theme maps with flood-prevention components. The research area's flood vulnerability was categorized into four groups using the weighted overlay integration method: extremely high, high, moderate, and low. The expected area for each susceptibility class is displayed in Table 6. There are four levels of flooding sensitivity in the study area: low (10%), moderate (60%), high (27%), and extremely high (2%). About 90% of the study region is at moderate to extremely high risk of floods. The remaining 11% of the study area is made up of regions with little vulnerability to flooding. The flood susceptibility map (Fig. 23) shows that the areas most vulnerable to flooding are the north, central, and southern. Particularly susceptible to floods are the low-lying Margalla Hills areas, such as G-6, G-7, G-9, G11, and I-9 in Islamabad, and Alwadi colony, Kot Hatyal, and Gokina near the summit of the Margalla Hills. Additionally, areas like E-11 and F-11 that are closer to the Margalla Hills are more vulnerable to flooding. Flooding is a serious worry in Sadiqabad, Dhoke Ratta, Gawalmandi, Chakri, and the central regions of Rawalpindi, including Per Wadhai, Khyaban e Sehar, Shamshabad, Raja Bazaar, and Arya Mohalla. Flooding is a big become concerned in Sadiqabad, Dhoke Ratta, Gawalmandi, Chakri, and the central regions. These locations include Per Wadhai, Khyaban e Sehar, Shamshabad, Raja Bazaar, and

Arya Mohalla. Locations with an extremely high to high risk of flooding include those with braided flood plains, lower elevation, lower slope gradient, poor to extremely poorly drained soil, alluvial deposits, and greater proximity to the main river.

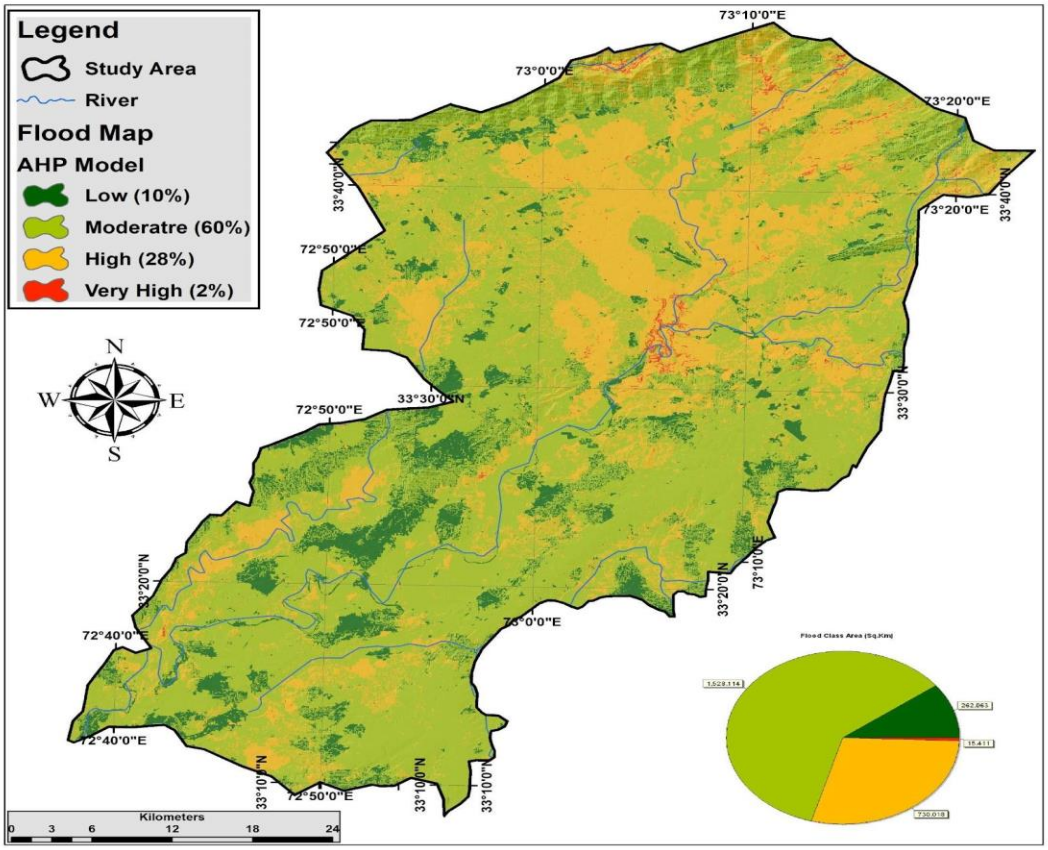


Figure 21: Flood susceptibility map using the AHP model.

Table 10: Classified flood zones of the area

S.NO	Flood Zone	Area (km²)	%
1	Low	262.063	10
2	Moderate	11528.114	60
3	High	730.018	28
4	Very High	15.411	2

4.4 Validation through AUC

A model's accuracy and success rate in risk assessments and flood susceptibility must be evaluated in order to validate it, even if many academics have suggested and endorsed certain models. The AHP model performs exceptionally well in terms of forecast accuracy, forecast and prediction accuracy, and success rate (Munir et al., 2022). The model shows that it can accurately and objectively forecast natural hazards with a maximum accuracy of 1.0. The 77 training flood sites were used to calculate the accuracy forecast, while the other 33 flood locations that were not taken into account when the model was being created were used to calculate the success rate. Risk of flooding Values in the "moderate" to "very high" range are anticipated in the future. The models are validated and the flood forecast is computed using the Area under the Curve (AUC). It must be viewed as a noteworthy outcome (Fig. 5). AUC for the validation and performanceofthe model. Equation (10), which was used to verify the model in this study, was used to compute the AUC parameter. The model's y-axis displays the true positive rate, and the x-axis displays the false positive rate. Where P is the total number of floods, N is the total integer of non-floods, and TP and TN are the numbers of pixels that were correctly identified (Tien et al., 2018). During the validation phase, 30% of all flood sites were used. Upon evaluation, the model's AUC was 0.74, meaning that 0.74 percent of the attempts were successful. Despite the limits and imprecision of the provided data, this proportion was considered good. It also demonstrates the effectiveness of the frequency ratio model's constituent parts in the research region.

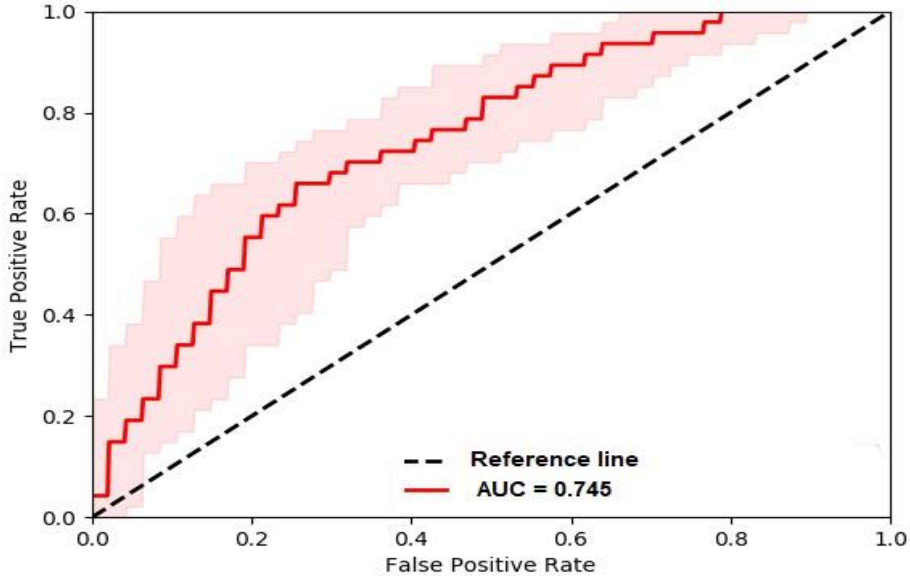


Figure 22: The AHP model's AUC graph

4.5 Integrating AHP and FR model

Based on the weight's volume and the GIS environment, final susceptibility zones were constructed using the factor weight and the class values derived from the FR and AHP investigation. All selected subgroups of the same variable were subjected to the SCWV, as seen in (Figure 25). We totaled the FR values for each of the possible reasons to assess a region's susceptibility to flooding (Tariq et al., 2020). All of the factors that have been demonstrated to cause flooding were added together to form the flood susceptibility index. A higher likelihood of flood episodes is indicated by a higher flood susceptibility score. Conversely, a lower FSI value indicates a decreased likelihood of flooding. The FSI database was divided into five susceptibility areas in order to identify and distinguish the flood risk zones (Zainab et al., 2021). With corresponding areas of 82.45 km2, 650.10 km2, 828.01 km2, 654.23 km2, and 320.8 km2, these zones were classified as very low (4%), low (25%), moderate (32%), high (26%), and very high-risk zones (13%), respectively (Table 11). Some seriously damaged locations were found on the tour of the affected districts. The following areas saw the most damage during previous floods.

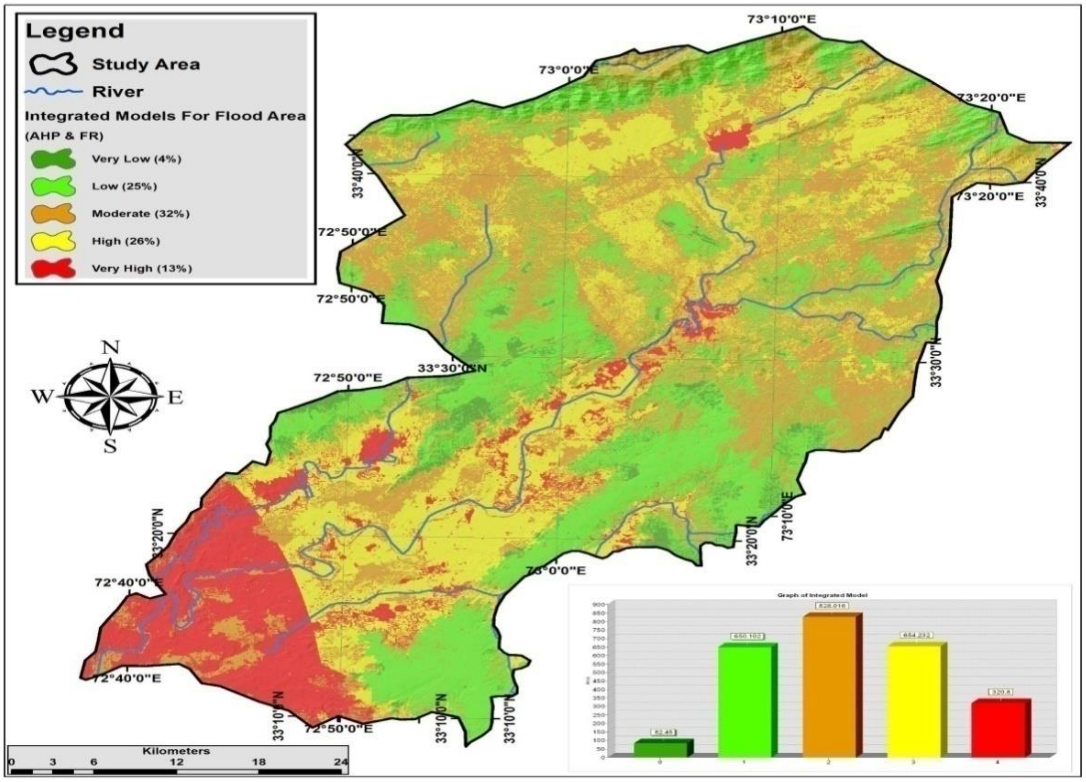


Figure 23: Integrated map of AHP and FR model

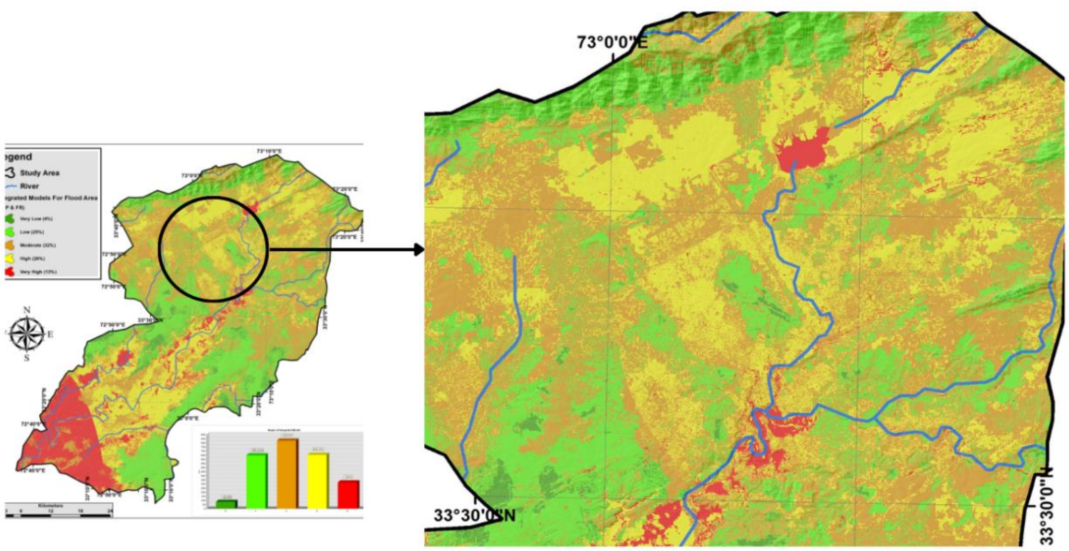


Fig 24: Spatial Enlargement of Identified Flood Susceptibility Hotspots

Table 11: Classified flood zones of the area

S. No	Flood Zone	Area (sq/km)	%
1	Low	262.063	10
2	Moderate	1528.114	60
3	High	730.018	28
4	Very high	15.411	2

Urban flash floods in the Islamabad–Rawalpindi region are influenced by an interplay of topographic, hydrological, and anthropogenic factors. Elevation plays a pivotal role, as low-lying areas such as E-11, D-12, G-13 in Islamabad, and Gawalmandi, Dhoke Hassu, and Sadiqabad in Rawalpindi are prone to flood accumulation due to their position relative to the Margalla Hills and adjoining uplands. These lower basins serve as runoff sinks, collecting water from elevated terrains where rainfall runoff accelerates down the slope. Slope gradient further regulates this behavior—steep slopes in the Margalla foothills rapidly generate overland flow that concentrates in adjacent zones like D-12 and E-11. Conversely, sectors like E-6, E-7, and F-6 are on steeper, elevated terrain with better drainage, allowing swift runoff evacuation and minimal stagnation. Soil type also significantly influences flood generation. Areas like E-11 and Rawalpindi's downtown exhibit clay-rich soils (Hydrologic Soil Group C/D) with low infiltration capacity, which enhances runoff during heavy precipitation events. In contrast, loamy or well-drained soils in other sectors promote infiltration and reduce surface water logging. Rainfall remains the dominant flood trigger. The monsoonal regime, intensified by climate change, has led to frequent high-intensity rainfall events surpassing 100 mm/hr. Such extremes, when coinciding with low-permeability soils and poor drainage infrastructure, generate instant flash floods, particularly in urbanized and unregulated zones. Drainage density both natural and artificial—is a critical flood moderator. In sectors like D-12 and Rawalpindi's inner city, drainage channels are often blocked or insufficient, leading to runoff overflow and waterlogging. Contrarily, sectors with open nullahs and planned drainage layouts show lower vulnerability. Land Use/Land Cover (LULC) changes further exacerbate flooding. Rapid urban expansion, especially in Islamabad's western sectors, has resulted in the loss of permeable and vegetated land, replaced with impervious surfaces such as concrete, rooftops, and asphalt. This sealing effect boosts runoff volume and overwhelms drainage systems. NDVI data confirms vegetation loss in flood-prone zones, where minimal green cover leads to reduced rainfall interception and infiltration. Areas like F-6 and F-7, which maintain higher green density, are less susceptible. Lastly, aspect, although less influential than other factors, contributes to soil moisture dynamics and microclimatic variations. South-facing slopes receive more solar radiation, affecting evapotranspiration and possibly influencing storm water retention in pre-monsoon phases.

Elevation significantly influences flood susceptibility by controlling surface water accumulation. In the Islamabad–Rawalpindi region, lower elevation zones, particularly E-11, D-12, G-13 (Islamabad) and Gawalmandi, Dhoke Hassu, and parts of Sadiqabad (Rawalpindi), are highly flood-prone due to their topographic depression relative to the Margalla Hills and adjoining highlands. These lower zones act as natural runoff sinks, accumulating water flowing from elevated catchments. The east-to-west elevation decline of the Margalla Hills leads to intense runoff toward these western and southwestern urban sectors. Scientific findings (Ahmad et al., 2020) validate that lower basin topography when coupled with poor drainage infrastructure increases flood susceptibility.Slope gradient regulates runoff velocity and concentration. Steep slopes in Margalla Hill foothills generate fast-moving runoff, which flows toward the adjacent moderately sloped sectors like D-12, E-11, and parts of G-13, where it accumulates. In contrast, sectors such as E-7, F-6, and E-6 are located on relatively higher and steeper slopes with well-channeled drainage, allowing for faster evacuation of surface water, thereby reducing flood susceptibility. Rawalpindi’s older urban core (e.g., Sadiqabad) sits on flatter terrain with low slope and poor gradient, which leads to water stagnation. Consistent with Rahmati et al. (2019), areas with moderate slope and urban obstruction exhibit higher runoff accumulation and flash flood potential.Soil type affects infiltration and surface runoff behavior. Much of the flood-prone zones, including E-11, D-12, G-13 (Islamabad) and Dhoke Hassu, Sadiqabad, and Raja Bazaar (Rawalpindi), are dominated by clay-rich soils with low permeability (Hydrologic Soil Group C/D). These soils saturate rapidly during rainfall events, leading to excessive runoff. In contrast, areas with loamy or mixed-texture soils such as some parts of the E and F sectors of Islamabad allow greater infiltration and mitigate surface water buildup. Literature (Das & Gupta, 2021) supports the finding that clayey soils with low infiltration potential directly enhance flood generation in urban areas.

Rainfall is the main triggering factor of flash floods. Islamabad–Rawalpindi experiences intense monsoon bursts, often exceeding 100 mm/hr during peak events. Due to climate change, the frequency and intensity of these events have increased (PMD, 2022; IPCC, 2021). High-intensity rainfall, when coinciding with urban expansion and soil saturation, causes instantaneous runoff in impervious urban zones. Historical events (e.g., the 2001 and 2021 flash floods in Islamabad) confirm that sectors with inadequate drainage especially in E-11, D-12, G-13, and Rawalpindi's downtown core—are particularly vulnerable to such extreme precipitation.Drainage density represents the efficiency of natural or man-made channels in evacuating runoff. In Islamabad and Rawalpindi, drainage networks are often encroached, poorly maintained, or covered due to rapid urban development. E-11, D-12, and G-13 in Islamabad, and Dhoke Hassu and Sadiqabad in Rawalpindi, exhibit low functional drainage density, resulting in waterlogging and channel overflow. In contrast, areas with connected nullahs and natural streams, such as sectors closer to Margalla's eastern flank, display better drainage behavior. Similar findings by Sulaiman et al. (2020) emphasize that low drainage density under urbanization causes higher flood vulnerability.LULC change is one of the most influential anthropogenic drivers of urban flooding. The unregulated urban sprawl in Islamabad (e.g., E-11, D-12, and G-13) and densely built environments in Rawalpindi (e.g., Gawalmandi, Sadiqabad) have drastically reduced natural infiltration zones. These areas show a predominance of impervious surfaces, such as roads, rooftops, and parking lots, which block infiltration and increase runoff volume. Vegetated and permeable land in sectors like E-7 and F-6 is rapidly being lost to construction. Studies (e.g., Sajjad et al., 2022) report a direct link between impervious cover expansion and elevated flood risks in the twin cities.

NDVI reflects vegetation density, which helps in intercepting rainfall, enhancing infiltration, and stabilizing soil. Flood-prone areas in both cities, such as E-11, D-12, and inner Rawalpindi, exhibit low NDVI values, confirming sparse or degraded vegetation due to construction and soil sealing. On the other hand, sectors near Margalla or public parks (e.g., F-6, F-7) show higher NDVI and natural retention potential. Scientific evidence (Jebur et al., 2015) highlights that

NDVI is inversely related to flood risk, particularly in rapidly urbanizing environments.Aspect, or slope orientation, affects solar radiation, moisture retention, and vegetation cover. In Islamabad–Rawalpindi, south-facing slopes, especially on the Margalla side, receive more solar radiation, influencing soil dryness and vegetation. However, during the monsoon, this effect is overridden by intense rainfall saturation. Therefore, while aspect plays a supporting role in microclimatic variation, it is less significant than slope, LULC, and elevation in determining flood-prone areas. However, it may influence pre-storm soil moisture, contributing to runoff behavior. Nobre et al. (2011) suggest that aspect is more significant in semi-arid settings than in monsoonal regions.

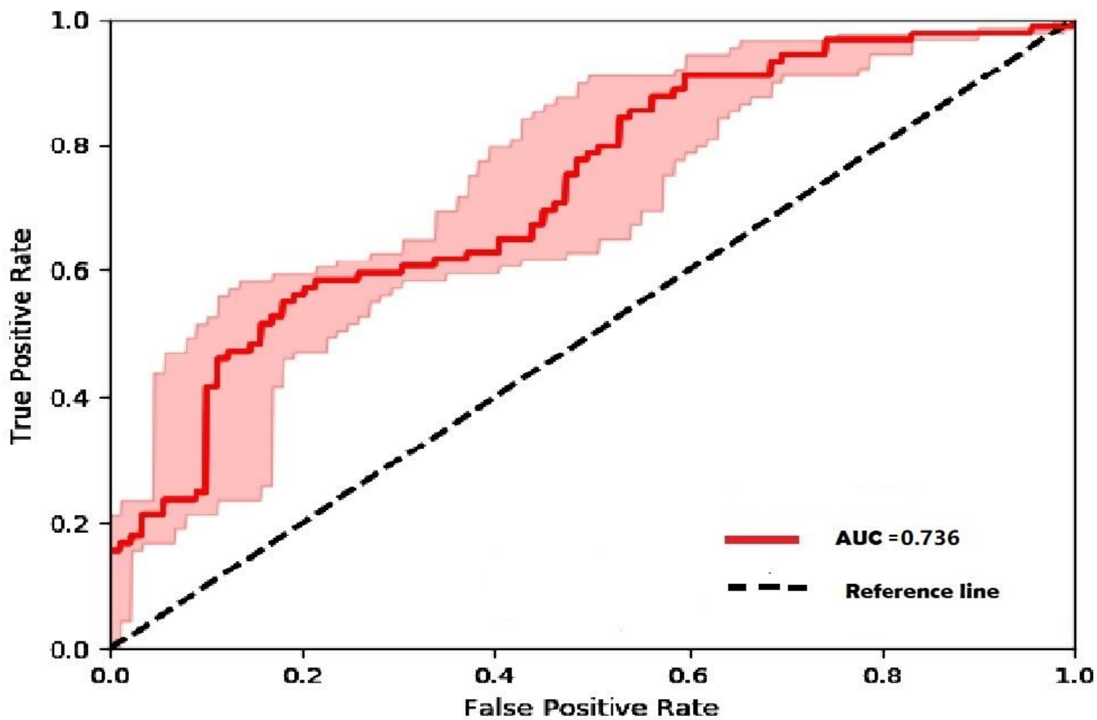
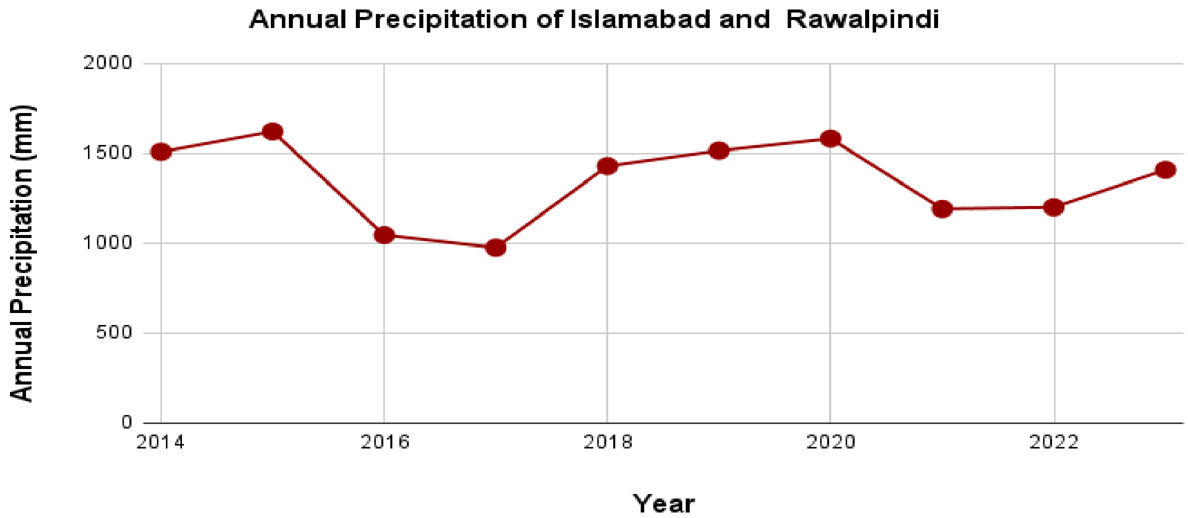


Figure 24: The integrated model's AUC

4.6 Precipitation Variability in Islamabad and Rawalpindi: Trends, Implications, and Climate Dynamics

An essential part of water cycle and a determinant in urban design, flood control efforts and city water systems, especially phenomena in Islamabad and Rawalpindi city are rainfall. The study ofannual precipitation patterns through the period from 2014 to 2023 reveals substantial fluctuations from one year to the next. Most rainfall was recorded in 2015, nearly 1500 mm, which decreased sharply in 2016 to below 1000 mm of rainfall. Variability occurs on regional climate scales influenced by both worldwide attributes such as the El Niño-Southern Oscillation (ENSO), and Western disturbances and the Indian monsoon system. While farm generated This variability is consistent with regional climate dynamics that are impacted by global phenomena including the El Niño-Southern Oscillation (ENSO), Western disturbances, and the Indian monsoon system. Anthropogenic climate change has increased the frequency and unpredictability of extreme weather events in South Asia, contributing to the region's monsoonal rainfall variability (Rahman et al., 2023). Because of their position and distinct topography, Islamabad and Rawalpindi are especially vulnerable to variations in precipitation. Rawalpindi's congested urban setting aggravates rainfall-runoff processes, while Islamabad, which is located at the foot of the Margalla Hills, frequently receives more orographic rainfall. Because impermeable surfaces enhance runoff generation and decrease infiltration, urbanization has a profound impact on rainfall patterns and hydrological responses. Urban heat island effects

intensify localized convection, leading to abrupt, heavy rainfall events, according to studies like Ahmad et al. (2020). Because drainage systems like the Leh Nullah are unable to handle excessive rainfall during monsoon seasons, this occurrence has contributed to the rising frequency of flash floods, especially in Rawalpindi (Khan et al., 2021).



Source: Pakistan Metrological Department (PMD)

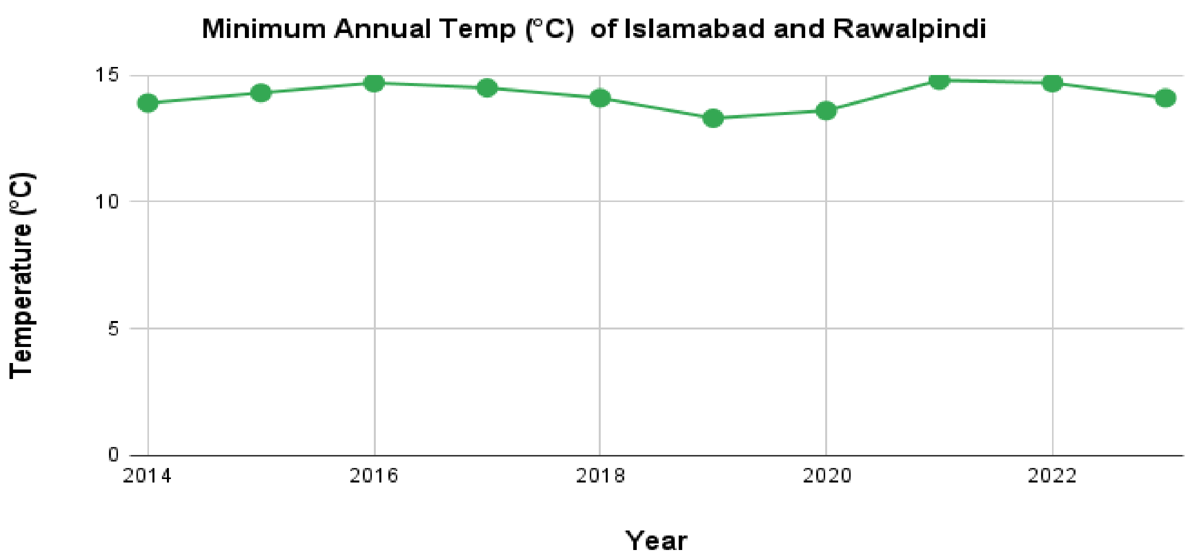
Graph 1: Annual Precipitation (2014-2023)

A changing precipitation regime is reflected in the decadal trend from 2014 to 2023, which is in line with findings from recent research on South Asia. According to climate projections, although the overall amount of rainfall each year may stay mostly constant, its distribution is becoming more erratic, with brief, intense rainfall episodes interspersed with extended dry periods (Shah et al., 2022). The main cause of this pattern is the increase in global temperatures, which raises the capacity of the atmosphere to hold moisture and causes more intense precipitation episodes. Such occurrences have frequently overloaded urban drainage systems in Islamabad and Rawalpindi, causing frequent flash floods, property damage, and disturbances to day-to-day activities. According to Hashmi et al. (2023), warmer oceans and shifting wind circulation patterns are the main causes of this trend, which is suggestive of a larger change in the South Asian monsoon system. These precipitation patterns have significant hydrological ramifications. Planning for water resources, catastrophe risk reduction, and urban flood management are all made more difficult by increased rainfall intensity unpredictability. For instance, insufficient drainage infrastructure has made Rawalpindi susceptible to frequent flash floods, and the growth of impervious surfaces has increased surface runoff (Ali et al., 2020). Despite being less urbanized, Islamabad has problems protecting its natural water recharge zones, which are essential for sustaining groundwater levels during dry spells. These problems highlight the necessity of integrated approaches to water resource management that take into account long-term water security issues as well as immediate flood hazards. Cities such as Islamabad and Rawalpindi need to implement thorough urban planning and flood risk reduction methods in order to adjust to the difficulties presented by shifting precipitation patterns. In order to decrease surface runoff and improve infiltration, Sustainable Urban Drainage Systems (SUDS) such as retention basins, permeable pavements, and green roofs have been widely advocated (Shah et al., 2022). Furthermore, two essential interventions for reducing the frequency of flash floods are the restoration of natural floodplains and the enhancement of urban drainage systems such as the Leh Nullah. Better rainfall monitoring and hydrological modeling, along with climate-resilient infrastructure planning, can further improve urban flood readiness. In Rawalpindi, where flash floods are a frequent danger, the correlation between precipitation variability and urban flooding is especially noticeable. Research shows that increased urbanization and the intensifying monsoon rains have created a cycle of vulnerability that is made worse by insufficient infrastructure (Dawood et al., 2022). One example is the monsoon season of 2020, which brought a lot of rain to the area and caused major floods in peri-urban and metropolitan regions. In order to provide early warnings and direct evacuation operations, the tragedy brought to light the necessity for real-time flood prediction systems that combine rainfall data with hydrological models and Geographic Information Systems (GIS).

4.7 Islamabad and Rawalpindi Temperature:Minimum and Maximum Annual Records

Beyond making its contribution to urban heat island intensification in cities, temperature is a critical climatic factor that determines environmental conditions and affects local water cycles. Annual temperature in Islamabad and Rawalpindi during 2014 to 2023 has also been found to be consistent with a warming trend, which represent the overall impact of the ongoing global climate change. While affecting urban development strategies the changes impact energy requirements public health quality and environmental stability. As temperatures grew, they hit what was recorded as Islamabad and Rawalpindi's lowest annual temperature between 11 and 15 degrees Celsius over the past 10 years. Before settling at 12°C plus, temperature dips between 2014 and 2016 remained consistent. However, in 2017 a slow temperature climb to the top was begun at 15°C in 2022 and had not been returning down properly in 2023. Other global data sets agree with this pattern of nighttime warmings across different regions in accord with urban development and greenhouse gas emissions. Nighttime temperatures, the minimum temperature values, are especially sensitive to urban heat retention, due to impermeable surfaces and lack of vegetation and heat trapping pollutants. Khan et al. (2021) claim that Rawalpindi's urban heat island effect has gotten worse over time, raising the city's minimum temperatures. Like other urbanized cities, comparatively similar warming has been occurred in Islamabad, which is less urbanized due to rapid urbanization and changes in land use, as noted by Ahmed et al., (2020). Rising minimum temperatures also directly affect energy use, especially for cooling, and decrease overnight relief from heat waves creating health hazards. The rise in lowest yearly temperatures is consistent with global climatic patterns as well. Studies show (Hashmi et al., 2022) that anthropogenic activities have been the main driver of 1.5°C rise in average nighttime temperatures in the South Asian region during the latter half of the twentieth century, which further reduced rainfall compared to traditional expected rainfall. Such warming worsens heat stress in densely populated urban places like Rawalpindi, where vulnerable populations are more likely to suffer from heat related maladies.

Source: Pakistan Metrological Department (PMD)

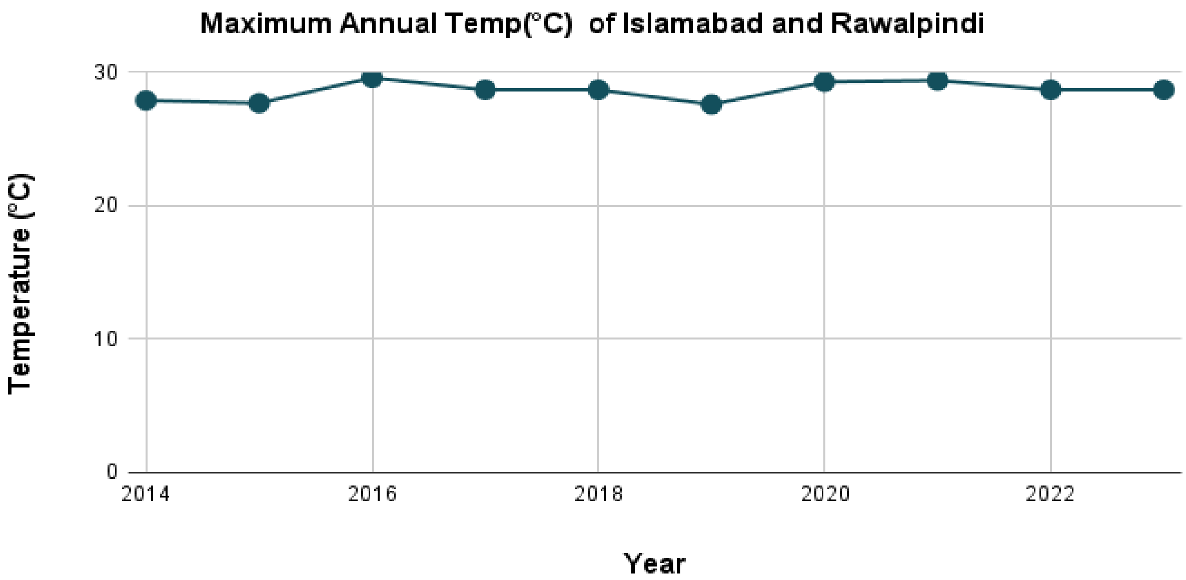


Graph 2: Minimum Annual Temperature (2014-2023)

has risen significantly, ranging from about 11°C to 15°C. Minimum temperatures fluctuated slightly between 2014 and 2016, leveling off at just over 12°C. But starting in 2017, there was a slow but steady rising trend that peaked in 2022 at about 15°C and then significantly decreased in 2023. This pattern is consistent with larger regional and worldwide observations of warmth at night brought on by rising urbanization and greenhouse gas emissions. Particularly vulnerable to urban heat retention brought on by impermeable surfaces, less vegetation, and heat-trapping pollutants are nighttime temperatures, which make up the lowest temperature values. Khan et al. (2021) claim that Rawalpindi's urban heat island effect has gotten worse over time, raising the city's minimum temperatures. According to Ahmed et al. (2020), Islamabad has also seen comparable warming as a result of fast urbanization and changes in land use, despite being less urbanized. In addition to directly affecting energy use, especially for cooling, the rising minimum temperatures also present health hazards by decreasing overnight relief during heat waves. Global climatic patterns are also consistent with the rise in lowest yearly temperatures. According to Hashmi et al. (2022), anthropogenic activities have been the primary cause of the 1.5°C increase in average nighttime temperatures in the South Asian region since the middle of the 20th century. In densely populated urban places like Rawalpindi, where vulnerable populations are more likely to suffer from heat-related ailments, this warming makes heat stress worse.

4.7.1 Maximum Annual Temperature Trends (2014–2023)

The annual maximum temperature trends from 2014 to 2023 reflect a stabilization at higher levels, consistently ranging between 27°C and 30°C. A notable increase occurred between 2014 and 2016, after which maximum temperatures hovered close to 29°C. The highest annual maximum temperature during this period was recorded in 2022, aligning with reports of extreme heat events across South Asia. Increased radiative forcing is strongly related to global warming and rising maximum temperatures: The summers get hotter and heatwave duration increases. Deforestation and urban development in Islamabad and Rawalpindi has been pushing these changes. According to research by Shah et al. (2022), this pattern is caused by peri-urban areas' diminishing plant cover, which has decreased the area's capacity to tolerate excessive heat through evapotranspiration. For example, Dawood et al. (2023) also illustrate the contribution of industrial operations and vehicle emissions to the urban warming trends. High temperature dominoes away at the urban environment and infrastructure. For instance, summer temperatures



Source: Pakistan Metrological Department (PMD)

Graph 3: Maximum Annual Temperature (2014-2023)

in Rawalpindi have risen and their higher cooling demands, along with more evapotranspiration have increased the pressure of water supplies (Ali et al., 2021). In a similar vein, Islamabad's energy infrastructures are under growing strain to handle the city's summertime cooling demands. Extended exposure to high maximum temperatures has also had an impact on public health: But during extreme heat events, we've seen more reports of heat exhaustion, dehydration, and cardiovascular disease.

Conclusion

In order to prevent flash floods and encourage organized growth in Rawalpindi and Islamabad, decision-makers and government agencies need to use precise flash flood susceptibility maps in their research on flash flood management. The purpose of this mapping analysis of flood susceptibility was to pinpoint specific regions that are vulnerable to floods. The main objective of the flood susceptibility map design was to inform the public, local government representatives, and other organizations about the risks associated with flooding. To forecast the probability of flash flood occurrences, we employed computational techniques for FR and AHP learning. The following eight conditioning elements were used: NDVI, soil map, drainage density, elevation, slope, aspect, rainfall, and LULC. 110 flood points were chosen at random and divided into 70% (testing) and 30% (training) ratios in order to validate the results. By incorporating the AHP-FR model, the flood susceptibility data was divided into five susceptibility areas in order to identify and describe the flood risk zones. They were categorized as very low (4%), low (25%), moderate (32%), high (26%), and very high-risk zones (13%). These zones had respective areas of 82.45 km2, 650.10 km2, 828.01 km2, 654.23 km2, and 320.8 km^2. The northern, southwestern, and central regions are most likely to experience flooding. The Margilla Hills are surrounded by very low to low zones, including Pir Sohawa, Daman e Koh, Sector E-7, F-10, F-11, E-11, and G-13. The agricultural region surrounding Tarnol, Sihala, and Golra Sharif, as well as urban to rural areas like DHA phase 2, Bahria Town phase 8, and PWD colonies, are all included in the moderate zone. High coverage of the zone Flooding is a risk in Nullah Lai, which includes Shamshabad, Satellite Town, Khanna Pull, Dhoke Ratta, Koral Chowk, and the surrounding suburban areas, particularly those close to the Islamabad Highway. Rawalpindi's low-lying, suburban districts particularly those around Nullah Lai, Saddar, Gawalmandi, Katariyan, Chakri, Khyaban e Sehar, and the suburbs close to the Sohan River, as well as the agricultural terrain in the south are particularly vulnerable. Alluvial deposits, lower elevation, a lower slope gradient, Factors include weak to extremely poor drained soil, braided flood plains, and a closer proximity to the main river that contribute to an area's extremely high to high risk of flooding. According to the study, the climate (rainfall), the growth of urbanization, and local-based factors all contribute significantly more than topographic factors (elevation and slope) because the Islamabd and Rawalpindi area is flat near the Margalla Hills and in urban areas near the Nullah Lai river. The reliability of the model was verified by field surveys and the Area Under Curve (AUC) method; the accuracy ratings for the FR and AHP models were 0.72% and 0.74%, respectively. The integrated map's forecast accuracy of 73%, which falls within the acceptable range, was demonstrated by the validation result, which was based on flood location data. This analysis has to be applied to additional places in order to evaluate its practical use in a variety of terrains and environments. This study also considered dynamic adjustments that can be brought about by human activity, such as climatic change, infrastructure growth, and land use changes. The regular hydrological cycle and consequently flood patterns may be impacted by these changes, particularly in populated areas where flash floods can have a major effect on the affected communities' property and livelihoods. Nonetheless, there is a great deal of promise for enhanced creation of maps of flash flood vulnerability through further study on the mapping, forecasting, and estimating of flash floods utilizing high-resolution geospatial data and various hybrid artificial intelligence model variations across several domains. The development plan frequently turns out to be a barrier in addition to public understanding. Nonetheless, a high-risk area can demonstrate significant flood preparedness if it responds well to a range of strategies,include evacuation planning, flood shelter facilities, flood emergency preparation, and flood-proofing techniques. Through the creation and deployment of practical susceptibility analysis tools, these tactics can be anticipated and recognized. Future research may therefore employ a variety of computational models based on a variety of parameters in order to lower the flood risk load.

Recommendation

Comparative Analysis and Implications

The upwards trend in both minimum and maximum temperatures has major implications for urban development and environmental management in Islamabad and Rawalpindi. A trend towards warmer evenings has been associated with reduced agricultural output, higher human and ecosystem heat stress, and reduced diurnal temperature range (DTR), the reduced gap between daily temperature extremes. Studies by Rahman et al. (2023) found that this is a pattern characteristic of urbanized areas, where the cover of vegetation is less and surface sealing is more during the night and the area will retain more heat. Rising temperatures speed snowmelt and alter monsoonal dynamics, with corresponding effects on precipitation patterns and increased risk of flooding from the hydrological perspective. In the forthcoming decades, the trend of growing minimum and maximum temperatures is expected to lead to an increased frequency and severity of severe events, such as storms and heat waves.

Strategies for Mitigation and Adaptation

To overcome the problem posed by rising temperatures, Islamabad and Rawalpindi must install energy efficient cooling systems and follow an urban planning method that is climate resilient. Expanding the green spaces in city centers, reintroducing native flora, and encouraging sustainable building plans, that incorporate passive cooling elements, will all help to lessen the urban heat island effect. Legislators must also make a priority of the creation of heat action plans, including public awareness campaigns, early warning systems and emergency response procedures during heat waves. That is we can make investments in renewable energy sources such as wind and solar which will reduce our dependence on fossil fuels and slow down urban warming. Geographic Information Systems (GIS) can map urban heat hotspots, track real time temperature trends and aid Islamabad and Rawalpindi in designing focused interventions to curtail rising temperatures and mitigate heat stress. Flash Flood Mitigation Plan for Rawalpindi and Islamabad, Pakistan Flash floods, using abrupt and powerful water torrents, are a threat to urbanized areas including Rawalpindi and Islamabad. They are located in their geography, high speed urbanizations, and climate. The flash floods are especially vulnerable as these cities continue to expand uncontrolled and with the source of flooding being the Leh Nullah. Utilizing cutting edge technology, environmentally friendly procedures, and community involvement, this mitigation strategy reduces these communities susceptibility to flash floods.

Integrated Flood Warning System (IFWS)

Early Warning Systems (EWS)

An efficient Early Warning System (EWS) is needed to reduce the impact of flash floods. Cities should establish real time rainfall and river monitoring stations outfitted with satellite based remote sensing, automated weather stations and Doppler radar to identify approaching flash floods. When combined with Geographic Information technologies (GIS), these technologies can use meteorological data to make extremely plausible predictions about how likely flooding will occur. As an instance, Younis et al. (2008) showed how GIS mapping and improved weather forecasting may increase the prediction of flash floods in Mediterranean regions. The techniques used could be applied to follow rainfall, stream water levels and the degree of soil saturation in real time in all of Rawalpindi and Islamabad's flood-affected areas. In addition, Sentinel 2 and Landsat satellite data can help evaluate the potential for runoff from different locations, and can also track land use changes. To enable for prompt evacuations, minimum of 6–12 hours' warning should be disseminated followed by public warnings through social media, radio and SMS at least 6–12 hours before the predicted flooding. Mileti (1999) contends that a multi-hazard approach would ensure that these systems tell users about other natural disasters as well as the flash floods.

Real-time Monitoring Using GIS & Remote Sensing

Geographical data for identifying flash flood vulnerable locations can be provided by flood forecasting and monitoring systems integrated with GIS and remote sensing. Hydrological models (such as HEC-RAS or SWAT models) can be created which simulate rainfall – runoff processes and relate topographical data to weather forecasts. With sources such as Shuttle Radar Topography Mission (SRTM) data, Digital Elevation Model (DEM) data can be utilized to produce detailed maps of flood susceptibility. The models allow for evaluation of water flow and buildup in cities in real time. Smith et al. (2011) demonstrate the importance of remote sensing tools and high resolution DEMs for quantifying flash flood dynamics in Appalachia. Similar applications are needed in Islamabad and Rawalpindi to know where water might flow during intense rains.

Cross-institutional Collaboration

The nature of this flash flood dictates that multiple government entities play an important role including the National Disaster Management Authority (NDMA), Pakistan Meteorological Department (PMD) and the local governments. Coordination can be secured through the institutions, so that timely distribution of informatioin and alert can be ensured. Reducing the flood danger is particularly crucial in developing areas where resources may be scarce and a multi- stakeholder approach is essential (Kundzewicz et al., 2013).

Structural Measures

Drainage System Improvement

Flash floods in Rawalpindi are caused by the Leh Nullah overflowing when it gets heavy rainfall. The Nullah Leh drainage system, which has to be ultimately upgraded and expanded to reduce the city’s vulnerability to flooding, has no corresponding future development work, detached from the city’s expanding water infrastructure. To handle high storm water volumes, the nullah will need to be cleaned channels, cleared unauthorized encroachments as well as modernize the sewer system. Kar et al. (2015) offers another instance in which one of the best ways to reduce urban flooding in developing cities is to increase drainage capacity.

Flood Retention Ponds

By constructing flood retention ponds in Islamabad, especially in low-elevation regions, stormwater can be temporarily retained during periods of high rainfall, relieving the strain on the city's current drainage systems. Additionally, retention ponds enhance local water quality and aid in groundwater recharge. Retention ponds have both ecological and flood mitigation benefits, as demonstrated by Wheater and Evans (2009) in their study on flood management in the UK.

Riverbank and Nullah Embankments

Overflow can be avoided by building and strengthening embankments around nullahs and along riverbanks. To prevent erosion and control increased water flow during flood events, embankments can be lined with concrete or gabions, which are wire meshes filled with stones. Many flood-prone communities, such as New Orleans following Hurricane Katrina, have shown that embankments are an efficient flood control measure (Kazemi, 2014).

Land Use Planning and Zoning Floodplain Zoning

Floodplain zoning must be incorporated into urban planning in Islamabad and Rawalpindi in order to limit development in high-risk areas. This can be accomplished by explicitly defining locations that are vulnerable to floods using GIS-based flood hazard maps. Strict enforcement of zoning laws is necessary to stop the encroachment of drainage systems and natural floodplains. In order to lessen flood damage in Pakistan, Rana et al. (2021) emphasized the significance of zoning and land-use limitations.

Green Infrastructure and Urban Design

Green infrastructure—drainage practices that reestablish natural hydrologic cycle, including bioswales, permeable pavement, and green roofs—will increase rainwater infiltration, reduce surface runoff and the risk of generation of flash floods. Urban wetlands should also be conserved or restored to serve as organic sponges during periods of intense precipitation; in accordance with Gill et al (2007), the key to urban flooding management is the use of green infrastructure that significantly reduces runoff.

Watershed Management and Reforestation

Reforestation in Margalla Hills and Catchment

Areas Deforestation of the Margalla Hills National Park and the catchment areas surrounding it worsens surface run off. Reforestation can stabilize the soil, enhances water retention and decrease overflowing that can start flash floods. The research of Bradshaw et al. (2007) found a strong relationship between increased frequency and intensity of flood and deforestation.

Watershed Management Programs

Two benefits of creating sustainable watershed management initiatives include: reducing runoff from sources upstream and protecting natural water retention zones. On the side of these initiatives in watershed areas, the emphasis should be on sustainable agriculture, afforestation and soil conservation. In Ntelekos et al. (2006) integrated planning was discussed as a method for the reduction of flood risks in metropolitan areas through sustainable watershed management strategies.

Community-Based Disaster Risk Reduction (CBDRR)

Public Awareness and Education

To reduce the financial and personal costs of flash floods we need the community to be aware. The danger of flooding should be publicized and people told how to react to flood warnings, and what they can do to protect their homes and families. According to Gaume et al. (2009), however, reducing the fatality rate in flash flood events involves more knowledge and preparedness by the public.

Community Engagement in Flood Response

Local community is involved in disaster response planning through community flood response teams. They can also be trained to help control flood defenses during emergencies, to help with evacuations and to provide first aid. The importance of including community participation in disaster response and mitigation was highlighted by Mileti (1999) in metropolitan areas prone to natural disasters, and is especially important in high-risk metropolitan areas. Non-Structural Measures Flood Insurance A flood insurance scheme oriented to flood prone areas can provide financial protection to vulnerable populations. This would help households recover faster from effects of flash floods. Botzen and van den Bergh (2008) note that flood insurance can be a useful non structural strategy for controlling flood risk in urban settings.

Flood Education in Schools

Incorporating lessons on flood awareness and preparedness into the curriculum will help the next generation think more resiliently.In order to organize young people, authorities must set up conferences, live webinars, and meets with social activists. Regular drills and disaster risk reduction education materials should be offered by schools. The efficacy of education-based disaster preparedness initiatives in lowering vulnerabilities in Asian nations was shown by Shaw et al. (2011).

Regular Risk Assessment and Mapping Flash Flood Susceptibility Mapping

Using GIS and remote sensing data to update flash flood susceptibility maps on a regular basis is essential to keeping up with Islamabad's and Rawalpindi's land-use changes and urban growth. Decisions on urban development should be guided by these maps, which ought to be accessible to the general public. Similar GIS-based flood hazard maps were utilized in Kuala Lumpur, Malaysia, by Tehrany et al. (2013), who discovered that they were very successful in lowering the danger of flooding.

Use of Machine Learning Models

To forecast the likelihood of flash floods, employ machine learning models like Random Forest or Decision Trees, which are trained on past flood data, rainfall trends, and land-use characteristics. These models can be visualized and hotspots for upcoming flood events can be found with the aid of GIS. Shafapour Tehrany et al. (2014) employed machine learning techniques to precisely forecast Southeast Asian regions that are prone to flooding.

Post-flood Risk Assessment

After each major flood, conduct a thorough post flood risk assessment, to learn the extent of the damage which can be used for the future mitigation tactics. GIS techniques can also be used to superimpose damage data on flood danger maps to discover vulnerabilities in the city's defenses. Kundzewicz et al. (2013) emphasized the importance of post implementation assessments as a way of improving the management of flood risk.

Climate Change Adaptation Incorporate Climate Change Projections

Urban designers must consider climate change estimates that show more frequent and strong rainfall events for Rawalpindi and Islamabad. Downscaled Global Circulation Models (GCMs) should be used in flood risk models in order to predict future flooding in locations. Meehl et al. (2007) note that flash floods in Asia should become much more frequent due to climate change. Adaptive Urban Planning, Therefore, Islamabad and Rawalpindi must redesign their urban planning codes and building laws in order to ensure new construction is resistant to the impacts of future flooding event exacerbated by climate change. We need to put in place climate resilient infrastructure like raised infrastructure and climate proof drainage systems. The IPCC (2014) focused on the importance of adaptive planning in metropolitan areas to reduce the consequences of climate change related disasters, such as flash floods.

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