

**IMPACT OF ABRUPT CLIMATIC CHANGES ON
FLOOD SUSCEPTIBILITY IN NORTHERN SINDH
AND SOUTHERN PUNJAB, PAKISTAN**

By

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25-FBAS/PHDES/S17



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INTERNATIONAL ISLAMIC UNIVERSITY ISLAMABAD**

2022

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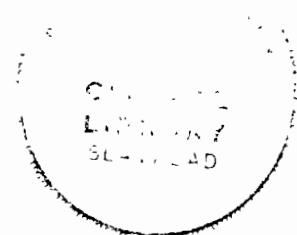
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in partial completion of the requirements for the degree of Doctor of
Philosophy in Environmental Science.*

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2022

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Date: 01-06-2022

FINAL APPROVAL

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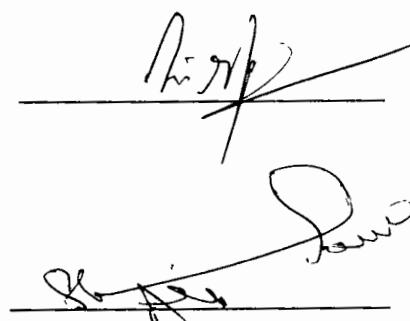
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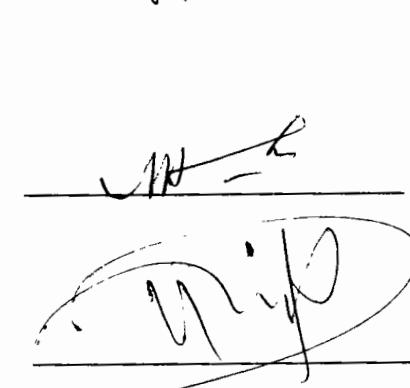
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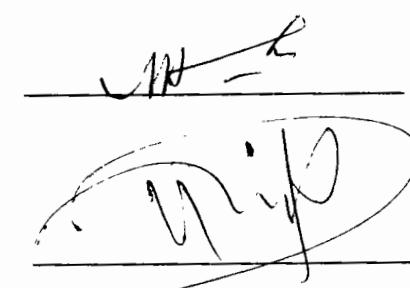
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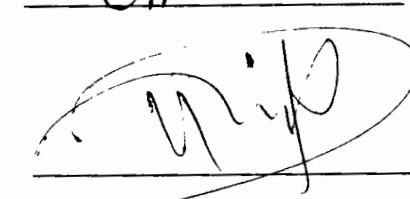
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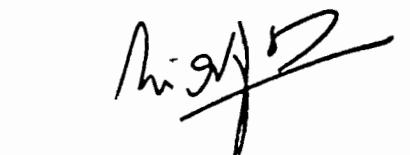
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Irfan

***DEDICATED TO MY ROLE MODEL
BELOVED PROPHET
MUHAMMAD (PBUH),
MY BELOVED PARENTS,
MY WIFE & MY CUTE SON
HASHIM BIN AWAIS***

For their unending love, support, and inspiration

DECLARATION

I, Awais Munir S/O Munir Ahmad Azad, PhD Scholar of Department of Environmental Science , Faculty of Basic and Applied Sciences, International Islamic University Islamabad, hereby declare that the entitled "**Impact of Abrupt Climatic Changes on Flood Susceptibility in Northern Sindh and Southern Punjab, Pakistan**" is my own research work carried out under the compassionate supervisions of Dr. Muhammad Asad Ghufran and Dr Syeda Maria Ali and that nothing has been incorporated in this dissertation without acknowledgment and that to the best of my knowledge and belief it does not contain any material previously published or any material previously submitted for a degree in any university; where due reference is not made in the text.

Awais Munir



Dated: 06-06-2022

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Awaiz Munir

List of Abbreviations

| Acronym | Abbreviation |
|----------------|---|
| ADB | Asian Development Bank |
| AHP | Analytical hierarchy process |
| ANN | Artificial Neural Network |
| AJK | Azad Jammu & Kashmir |
| AUC | Area under Curve |
| BSA | Body Surface Area |
| CART | Classification and Regression Trees |
| CBD | Convention on Biological Diversity |
| CCVI | Climate Change Vulnerability Index |
| CFCs | Chlorofluorocarbons |
| CITES | Conservation on International Trade in Endangered Species |
| COP | Conference of the Parties |
| CMS | Conservation of Migratory Species |
| DeO | DansgaardOeschger |
| DEM | Digital Elevation Model |
| DT | Decision Tree |
| FAO | Food and Agriculture Organization |

| | |
|--------|--|
| FATA | Federally Administered Tribal Areas |
| FFC | Federal Flood Commission |
| FR | Frequency Ratio |
| GARP | Genetic Algorithm Rule-Set Production |
| GB | Gilgit Baltistan |
| GCISC | Global Climate Change Impact Study Centre |
| GDP | Gross Domestic Product |
| GOP | Government of Pakistan |
| GHGs | Greenhouse gases |
| GIS | Geographical Information System |
| GLOF | Glacial Lake Outburst Floods |
| HKH | Hindu Kush-Himalayan Region |
| ICIMOD | International Centre for Integrated Mountain Development |
| IPCC | Intergovernmental Panel on Climate Change. |
| IFI | International Flood Initiative |
| KP | Khyber Pakhtunkhwa |
| LULC | Land Use Land Cover |
| LR | Logistic Regression |
| MCDA | Multi Criteria Decision Analysis |
| MDA | Multivariate Discriminate Analysis |
| MOCC | Ministry of Climate Change |

| | |
|-----------------|---|
| ML | Machine Learning |
| MW | Mega Watt |
| NASA | National Aeronautics and Space Administration |
| NO _x | Nitrogen oxides |
| NDMA | National Disaster Management Authority |
| NDSI | Normalized Difference Soil Index |
| NDVI | Normalized Difference Vegetation Index |
| PCRWR | Pakistan Council of Research in Water Resources |
| PDMA | Provincial Development Management Authority |
| PMD | Pakistan Meteorological Department |
| PR | Prediction Ratio |
| QUEST | Quick Unbiased Efficient Statistical Tree |
| RF | Relative Frequency |
| RS | Remote Sensing |
| SPI | Standard Precipitation Index |
| SRTM | Shuttle Radar Topography Mission |
| SUPARCO | Space & Upper Atmosphere Research Commission |
| SVM | Support Vector Machine |
| TVDI | Temperature Vegetation Dryness Index |
| TWI | Topographic Wetness Index |
| UNFCCC | United Nations Framework Convention on Climate Change |

| | |
|---------|--|
| UNDP | United Nation Development Program |
| UNEP | United Nation Environment Program |
| UNESCO | United Nations Educational, Scientific and Cultural Organization |
| UNICEF | United Nations Children's Fund |
| UN-ISDR | United Nations Office for Disaster Risk Reduction |
| USGS | United States Geological Survey |
| WCDR | World Conference on Disaster Reduction |
| WoE | Weight of Evidence |
| WMRP | Water Management and Reservoirs in Pakistan |
| WWF | World Wide Fund for Nature |

ABSTRACT

The most devastating and prevalent natural disaster is flooding. It not only threatens human health and safety, property, and resources, but it also has a severe impact on the economy of a country. As a result, in flood-prone locations, flood points must be identified in order to implement effective flood risk management. Annual rainfall graphs demonstrate that district Jacobabad contributes the most to natural disasters such as floods, while other districts contribute the least. With the use of Remote Sensing (RS) and Geographical Information System (GIS), a frequency ratio model was utilized to locate flood-affected districts in northern part of Sindh and southern part of Punjab, Pakistan (GIS). Elevation, slope, feature, profile curve, Normal Difference Vegetation Index (NDVI), Normal Difference Soil Index (NDSI), distance from road, distance from river, land use/land cover (LULC), and rainfall were all incorporated in the model. The flood inventory map was created using 230 flood spots. The data was randomly divided into two datasets, with 70 percent (161 flood points) used for training and the remaining 30% (69 flood points) for model development. The flood susceptibility map was divided into five zones: very low (19.73%), low (20.37%), moderate (20.37%), high (19.62%) and extremely high (19.88%). Flood vulnerability ratings of very high and high covered 19.88 percent and 19.62 percent of the study zone, respectively, according to the study. The resulting flood susceptibility map, which was validated using past flood sites, was validated using the range below the curve (AUC) technique. The flood susceptibility maps prediction or likelihood rate curves were generated accurately, according to the validation results. Finally, FR came up with a prediction rate that was 77.4 percent accurate. The Northern part of Province of Sindh has the most flood-prone areas. For local government managers, planners, and decision-makers, as well as for future development initiatives in Pakistan, this model's flood susceptibility study will be a very useful and efficient tool.

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CHAPTER 1

INTRODUCTION

Climate is a term that describes a worldwide long term weather state that may be measured in the atmosphere through changes in temperature, precipitation, pressure, and humidity. As a result, "climate change" denotes natural changes caused by natural processes or human activities. Global warming, unpredictable weather, melting glaciers, increasing sea levels, and a variety of different climates are all effects of climate change around the world (Lipczynska-Kochany et al., 2018). Climate variability, commonly known as climate change, is a significant environmental issue as well as a significant political issue. The temperature of the (global mean) surface air is rising all across the world (NASA 2018). More intensive water cycle processes will almost certainly reflect this rise (Huntington et al., 2006). It's unclear whether rising temperatures are always accompanied by increased runoff. Natural disasters such as hurricanes Irma, Harvey, and Maria, according to some seasoned researchers, scientists, environmentalists, and members of the general public, indicate to the effects of climate change (Hassan et al., 2016). As a result of global climate change, the frequency and amplitude of severe temperature and rainfall events are expected to rise (IPCC2013). Recent trends in extreme temperature and precipitation events, according to the Intergovernmental Panel on Climate Change (IPCC), will continue to expand in the next decades, with more frequent and longer-lasting heat waves (IPCC, 2013). Even during the "global warming hiatus," a new time series study reveals a consistent increase in the frequency of the world's most severe hot days over land (Rodo et al., 2003). As a result of continued greenhouse warming, the frequency of powerful El Nino episodes characterized by progressively extreme hot days is increasing, and heavy precipitation is predicted to increase (Carter et al., 2015). GHG emissions (CO₂, CH₄, NO₂, and H₂O) are a key contributor to climate change since they are abundant in nature and have a significant impact on the climate. GHG emissions have been kept below dangerous levels in the past by natural sinks; however, chronic human interventions like as automobile use, agricultural and forestry activities, industrial expansion, and fossil fuel use have boosted GHG emissions

chronic human interventions like as automobile use, agricultural and forestry activities, industrial expansion, and fossil fuel use have boosted GHG emissions (Huang et al., 2016; Ahmed et al. 2020). With the exception of H₂O vaporization, global GHG emissions are increasing at a rapid rate (Bousquet et al., 2006; US EPA 2016). Mounting global warming as a outcome of Green House Gas emissions has harmed the ecosystem, environment, and natural atmosphere, all of which were non-existent prior to the Industrial Revolution (IPCC 2013) and (NASEM et al., 2017). The two main sources of anthropogenic CO₂ emissions in the atmosphere, which have been contributing to global warming since the mid-twentieth century, are fossil fuel combustion or burning driven by human activity, and land-use changes (Youssef et al., 2017). With ten of the warmest summers since 2003 and the five warmest Septembers ever documented (land and ocean surface temperatures from 2014 to 2018), the Septembers of 2018 and 2017 had the fourth highest temperature in the preceding 139 years (CO₂, Earth 2018). This prolonged rise in temperature provides a challenge to civilization in the face of unpredictable weather patterns, environmental devastation, economic losses, and societal suffering (Espeland et al., 2018). Climate change has major short-term effects owing to greenhouse gas emissions, as well as the long-term effects of greenhouse gas emissions on acute human activities, mainly agriculture and agribusiness in Asia (Shaffril et al. 2018). Climate change has been blamed for extreme levels of flood hazard. Flooding is made more likely by changes in the earth's cover, such as plant clearance and climate change. Heavy rainfall, protracted rainfall, repetition near rains, or a combination of these factors can result in extreme floods. In the case of heavy rain, such as that experienced in the United Kingdom, the IPCC has made a concentrated effort to study the scientific basis for climate change in Europe, particularly in light of the recent winter floods. "While it is difficult to draw a straight link between a catastrophic event and climate change, it is apparent that we must be prepared to deal with the worst and most prevalent hydro-meteorological disasters that climate change has brought about" (UNEP).

We have greater power in the Earth system because of rising global temperatures, which means more rainfall with higher temperatures. High seawater and air temperatures enhance the likelihood of evaporation and, as a result, cloud formation.

The air may absorb more moisture at higher temperatures. Increased rainfall, duration, and frequency may result as a result of this. At greater latitudes than the equator, temperatures rise quickly. It causes a small temperature difference between latitude and polar temperatures, which might interfere with jet propagation. According to research, extreme hydro-meteorological phenomena, such as severe winter storms or extended drought in the summer, occur frequently in the North Atlantic region. At least two areas reported that there was a high risk of flooding. Hazards will expand beyond the most risky regions recognized today as global warming raises the likelihood of catastrophic weather occurrences.

As several Asian countries struggle to fulfill sustainable development and environmental goals due to dwindling resources, industrial growth, urbanization, and economic growth, Pakistan's geography makes it sensitive to the effects of climate change (Chan et al., 2018; Shaffril et al., 2018). The unregulated use of natural and non-renewable resources is the foundation of Pakistan's and the world's economic and industrial prosperity. The negative consequences of these wrongdoings have a long-term and damaging impact on the ecosystem. Global GHG emissions climbed by 5.8% in 2010, a record high (Carter et al., 2015), and Pakistan's carbon emissions are rapidly increasing. The disastrous effects of climate change may risk economics, social, and ecofriendly development of Pakistan (Khan et al., 2016).

SIGNIFICANCE OF STUDY

The present study will be of significant importance as its focus has been the identification of the areas of Northern Sindh & Southern Punjab vulnerable to different types of flood risks, and subsequently the results of the study could be used as a vital input for the formulation of pre-flood planning strategies especially for the location of the infrastructural facilities in the Study area. According to historical records, the river has been subjected to terrible floods for millennia, many of which have wreaked devastation in terms of destruction. Riverine and flash floods occur in the research area (Southern Punjab and Northern Sindh), causing damage to infrastructure, standing crops, and revenue sources, as well as human casualties. Despite the fact that flooding occurs frequently in the Northern Sindh floodplain, flood management measures have remained limited to strengthening rehabilitation and relief measures, as well as

other post-flood mitigation measures, with no pre-flood management strategy or planning strategies in place to minimize the loss of life, property, and the environment. The government needs information about the nature of floods and their effects in order to make judgments about flood management techniques like building flood protection structures (engineering structures), developing a flood emergency response plan, and relocating people.

NOVELTY OF WORK

This study was conducted to reduce flood disasters in the Northern Sindh and Southern Punjab, as no such study has been conducted in this area before. The study's main purpose is to evaluate and observe flood-prone locations, as well as to use the frequency ratio which is known as FR model to build a flood risk or susceptibility map for designated study districts. The FR model is totally GIS-based tool for producing scientifically accurate flood vulnerability maps. Flood risk demonstrating is essential for effective flood managing. Aspects to examine include drainage, thickness, slope, land use, elevation, rainfall deviance, lithology, and land practice/cover. All of these parameters could be combined with the FR model to find susceptibility zones ranging from extremely high to extremely low. Planners and developers, researchers, and local governments will be able to use these data to conduct impact assessments in order to predict future possible flood zones and reduce flood risk through the employment of various strategies.

PROBLEM STATEMENT

Pakistan was struck by 25 natural disasters between years of 2000 to 2013, the most common of these were floods, earthquakes, and landslides. In 1942, 1956, 1957, 1958, 1973, 1975, 1976, 1979, 1992, 1994, 1995, 2003, 2005, 2007, 2010, 2011, and 2013, floods were very severe. In August 2010, one of the deadliest floods in Pakistan history struck, with an estimated 8000 people killed and \$10 billion in economic losses between 1947 and 2010. Midsummer floods in Pakistan are primarily initiated by monsoon rains. The historic 2010-2011

floods in the study district were the foulest in terms of heavy and prolonged rainfall, huge flood flows, the sum of people affected, and infrastructure destruction. Almost all of the country's metrological stations recorded unusual rainfall, and the main cause of the deadly flooding was four days of continuous rain (27-30 July). In the years 2010, 2011, and 2013, riverine floods struck Northern Sindh and Southern Punjab. Jacobabad, Larkana, and Sukkur districts in northern Sindh took the brunt of the damage. In the summer of 2010, extremely heavy rain and river breaches in the districts of Rahimyar Khan and Bahawalpur in southern Punjab created an unprecedented riverine flood. Crops and orchards were washed away, irrigation systems and connecting roads were disrupted, and structures were destroyed. There is a paucity of flood vulnerability evaluation and representing. To highlight the issue, efforts were made to investigate key factors in order to better identify and anticipate flood-prone locations. The goal of this study was to figure out how vulnerable flood disasters will be in the future in the study areas, which comprised the districts of Bhawalpur and Rahimyar Khan in south Punjab and Sukkhar, Larkana and Jacobabad in north Sindh.

OBJECTIVE OF THE STUDY

1. To assess flood susceptibility in study area in context of regional climatic extremes.
2. Modeling the impacts of climatic extreme events on flood susceptibility in study area concerning the flood-prone region.
3. Spatio Temporal Assessment of Flood in Northern Sindh and South Punjab.

CHAPTER 2

LITERATURE REVIEW

2.1 CLIMATE

Climate is most commonly defined as average weather, or more accurately, the statistical description of the mean and variability of important characteristics over time periods ranging from months to hundreds of millions of years. The conventional time for averaging these variables, according to the World Meteorological Organization, is 30 years. Temperature, precipitation, and wind are commonly significant surface factors. Climatic refers to the status of the climate system in a broad sense, which includes a statistical description (IPCC 2020).

2.2 CLIMATE CHANGE

Long-term variations in temperature, rainfall, precipitation, or wind patterns are referred to as climate change (IPCC, 2007a). The United Nations Framework Convention on Climate Change (UNFCCC) is the only organization that uses the term "climate change" to refer to changes caused by human activities. Scientists examine earlier climate change in particular, as well as the tough issue of differentiating between natural and human factors in current changes (Houghton, 1990). Climate change is a real and important problem that is already affecting people and the environment all around the world (Braman et al., 2010). There is now enough scientific data to show that the global climate is changing (e.g., IPCC, 2007). As a result of the three major signals of climate change: an increase in global average temperature, a rise in sea levels, and a change in precipitation patterns, changes in extremes of floods and droughts, water availability, water demand, water quality, salinity intrusion in coastal aquifers, groundwater recharge, and other related phenomena are converted into signals of regional-scale hydrologic change (MoA, 2011). There is now enough scientific data to show that the global climate is changing (e.g., IPCC, 2007). As a result of the three major signals of climate change: an increase in global

average temperature, a rise in sea levels, and a change in precipitation patterns, changes in extremes of floods and droughts, water availability, water demand, water quality, salinity intrusion in coastal aquifers, groundwater recharge, and other related phenomena are converted into signals of regional-scale hydrologic change (Sayed et al., 2014).

Changes in precipitation patterns and the frequency of severe precipitation events, as well as changes in soil moisture and evapotranspiration, will affect runoff and river discharges throughout time periods ranging from sub-daily peak flows to yearly fluctuations (Tabari et al., 2019). Flooding events are likely to cause enormous socioeconomic and environmental damage on sub-daily and daily time scales, necessitating the development of flood protection measures to adapt to the likely changes, as well as the use of robust and accurate flood frequency and magnitude projection techniques under climate change. Flood control planning and operations in the face of climate change involve hydrologic modelling and the use of global climate models (GCMs) (Mahmoud et al., 2018).

The global average surface temperature increased by 0.74 0.18C from 1906 to 2005, according to findings released in the IPCC's Physical Science Basis report (IPPC 2020). More changes in the climate system have been discovered in the last century, such as global sea-level rise, changes in precipitation patterns, and severe events. They indicate that between 1960 and 2003, global mean sea level rose at an average of 1.8 0.5 mm per year, and that precipitation patterns have altered (Mallick et al., 2011). They observed long-term increases in precipitation patterns in eastern North and South America, northern Europe, and northern and central Asia between 1900 and 2005. Droughts in the tropics and subtropics have become more severe and last longer since the 1970s. They've also noted a rise in severe events like heavy precipitation and more frequent heat waves during the previous 50 years (Füssel et al., 2006). For example, developing nations account for nearly all disaster-related mortality, and natural disaster-related losses are twenty times higher in poor countries than in rich countries (Cardona et al., 2003c0). Many factors, including changing demographics, technological and socioeconomic conditions,

industrial development, urban expansion and infrastructure construction, unplanned human settlement in flood-prone areas, and climate variability and change, are causing global concern that flood losses will rise in the near future (full report of the Scientific and Technical Committee, UN-ISDR, 2009). A large segment of the scientific community has been focusing on determining the consequences of climate change on water resources and creating adaptation solutions in recent years (McCarthy et al., 2003).

2.3. CONVENTIONS, PROTOCOLS, DECLARATIONS RELATED TO CLIMATE CHANGE

2.3.1. MONTREAL PROTOCOL

The United Nations Foundation Convention on Climate Change (UNFCCC) was signed in 1992 as a framework for international collaboration to combat climate change by limiting average global temperature rises and the resultant climate change, as well as dealing with the unavoidable repercussions. The fundamental goals of the UNFCCC were to maintain greenhouse gas emissions at levels that would prevent catastrophic human climate change. The agreement established a regulatory framework based on the concept of shared but separate responsibilities (Solomon et al., 2007).

2.3.2. UNFCCC

2.3.3. UN CONVENTION ON DESERTIFICATION

The UN General Assembly established a committee to help in the development of the Desertification Convention in 1992. According to the treaty, desertification shall be combated by national, regional, and sub-regional action plans. India hosts the agroforestry and soil conservation network. From the ground up, the treaty encourages and promotes worldwide environmental cooperation. India ratified the UNCCD on December 17, 1996, after signing it on October 14, 1994. The UNCCD's nodal ministry in India is the Ministry of Environment, Forests, and Climate Change, and the Desertification Cell is the

nodal point within the Ministry to coordinate all UNCCD-related problems (Carola et al., 2012).

2.3.4. KYOTO PROTOCOL

The Kyoto Protocol was signed in Kyoto, Japan, on December 11, 1997, and took effect on February 16, 2005. There are now 192 signatories to the Protocol. The Kyoto Protocol is an international convention that builds on the 1992 United Nations Framework Convention on Climate Change (UNFCCC) by forcing States Parties to reduce greenhouse gas emissions based on the premise that (a) global warming exists and (b) human-caused CO₂ emissions are to blame. The Protocol's main feature is that it establishes legally enforceable pledges for nations who sign it to minimize greenhouse gas emissions. The promises were made in accordance with the Berlin Mandate, which was agreed as part of the UNFCCC negotiations leading up to the Protocol (Boyd et al., 2010).

In order to meet the Protocol's goals, Parties must establish policies and actions to reduce greenhouse gas emissions in their own countries. They must also increase gas absorption and make advantage of all available processes, including

- Joint implementation
- Clean development mechanism and
- Emissions trading, in order to be rewarded with credits that would allow more greenhouse gas emissions at home.
- Minimizing Impacts on Developing Countries by establishing an adaptation fund for climate change.
- Accounting, Reporting and Review in order to ensure the integrity of the Protocol.
- Compliance. Establishing a Compliance Committee to enforce compliance with the commitments under the Protocol.

2.3.5. BALI SUMMIT ON CLIMATE CHANGE

The Bali Action Plan, also known as the Bali Roadmap, was approved in December 2007 on the Indonesian island of Bali at the United Nations Climate Change Conference (COP-13/ MOP-3) there. A formal agreement was reached in Copenhagen in 2009 after a two-year procedure. The purpose of the conference is to establish the Climate Adaptation Fund. Review of the scope and content of Article 9 of the Kyoto Protocol in order to make technology transfer and deforestation emission reduction choices. In accordance with the Bali Action Plan, negotiations are currently underway to determine the Parties to the Kyoto Protocol's quantified emission reduction targets for the second commitment period beginning in 2013, as well as to define emission reduction targets for the United States that are comparable to those of other Kyoto Parties. According to the Bali Road Map, a framework for climate change mitigation beyond 2012 was to be agreed upon at the COP 15 in Copenhagen in 2009. The same summit, as well as the COP 16 in Mexico, were unable to achieve an agreement (Solomon et al., 2009).

2.3.6 PARIS AGREEMENT ON CLIMATE CHANGE

The Paris Climate Agreement is a legally binding international treaty on the issue of climate change. On December 12, 2015, 196 Parties agreed to it at the United Nations Conference on Climate Change (COP 21) in Paris, and it took effect on November 4, 2016. Its objective is to keep global warming far below 2 degrees Celsius, preferably around 1.50 degrees Celsius, as compared to pre-industrial levels. To attain this long-term temperature goal, countries aspire to reach global peaking of greenhouse gas emissions as soon as feasible, resulting in a climate-neutral world by mid-century. The Paris Commitment is a watershed moment in the international climate change process because it brings all nations together for the first time in a binding agreement to commit to ambitious actions to combat climate change and adapt to its repercussions (Mara et al., 2020).

The following are some of the Agreement's most important features:

- Long-term temperature goal
- Global peaking and 'climate neutrality'
- Mitigation

- Sinks and reservoirs
- Voluntary cooperation/Market- and non-market-based approaches
- Adaptation
- Loss and damage

2.4 CLIMATIC CONDITION IN SOUTH ASIA

The South Asia area encompasses the high Himalayan peaks of Bhutan and Nepal, as well as the lush deltas of Bangladesh and India's peninsula, as well as the jewel-like islands of Sri Lanka and the Maldives in the Indian Ocean. Glacial melt, forest fires, rising sea levels, mountain and coastal soil erosion, and salty water intrusion are all effects of climate change in the area, which spans climatic zones as different as its physical surroundings (Kelkar et al., 2007). Natural catastrophes and the repercussions of climate change have been compounded in recent years by aberrant monsoon patterns and increasingly frequent and destructive storms (Easterling et al., 2000). The region's 600 million absolute poor—more than half of the world's overall poor—are facing the brunt of this, since they rely on climate-sensitive businesses like agriculture, forestry, and traditional fishing for the majority of their daily needs. South Asia's geography, high population density, and extreme poverty will continue to make it particularly sensitive to global climate change, which is predicted to extend long into the next water, energy, and coastal communities will all be threatened as natural catastrophes worsen and migration grows (Easterling et al., 2007).

South Asia is vulnerable to a variety of climate change difficulties and effects, which are closely tied to the region's terrain, economics, and demographic patterns. Large parts of Bangladesh, India, Nepal, and Sri Lanka are prone to floods due to heavy monsoon rainfall, obstructed natural drainage, and low elevation (Hirabayashi et al., 2013). In 2007, unprecedented monsoon rains caught South Asia off surprise, causing floods that affected an estimated 30 million people in Bangladesh, India, and Nepal. While rainfall patterns may vary in the future, present trends in tropical cyclone intensification and storm surges, which are partially related to rising sea surface temperatures, predict that the future will be far stormier (Narisma et al., 2007). In South Asia, natural

catastrophes are quite common, and a considerable portion of the nation is vulnerable to several risks (Zhao et al., 2005). Between 1990 and 2008, more than 750 million people, or half of South Asia's population, were impacted by at least one catastrophe, resulting in about 230,000 deaths and \$45 billion in damages. Landslides, windstorms, wave surges, and cyclones are all regular catastrophes in the region, aside from floods, which have accounted for more than half of the more than 900 disaster occurrences registered in the region over the previous four decades (UNEP 2007). Droughts harmed the most people, accounting for more than half of the total disaster-affected population although only accounting for 2% of all catastrophes. Bangladesh and Nepal experienced the most natural catastrophes. India, on the other hand, experienced the highest share of losses (\$26 billion), accounting for more than half of the region's total expenses (FAO 2009). Climate-related disasters will become more likely as precipitation patterns change and temperatures rise. Droughts in India and Bangladesh's desert and semiarid areas are projected to grow more severe and stay longer, while landslides and glacial lake outburst floods in Bhutan and Nepal's alpine regions are expected to become more prevalent (Cruz et al., 2007).

2.5. CLIMATIC CONDITION IN PAKISTAN/PAKISTAN PERSPECTIVE

Climate change and its impacts, particularly as a result of global warming, are easily obvious. The dangers of climate change are expected to become more severe in the future (Bhattacharya et al., 2006). Climate change has a wide range of consequences around the world; however, the consequences in developing countries are particularly severe (Hamid et al., 2011), due to a variety of factors such as a lack of awareness and information about effective solutions, institutional weaknesses, limited resources and inefficient use, and poor economic conditions. Rural inhabitants in developing countries are particularly vulnerable to floods due to their poor adaptive capacity and assets (Fahad et al., 2018). The severity and frequency of flood occurrences in developing nations are mostly governed by biological and meteorological variables. When it comes to climate change, Pakistan is one of the most intriguing countries. Climate events include temperature fluctuations, rainfall changes, and the occurrence of hazardous occurrences (IPCC 2014). Among the different environmental

challenges to which humans are exposed, floods and droughts are the primary causes of economic and social hazards for individuals, resulting to a rise in mortality. With nearly 60% of the population living in rural regions and the agricultural sector accounting for 21.9 percent of GDP and directly or indirectly employing 45 percent of the country's total Labour force, any unfavorable consequences of climate change might have an impact on their lives (GOP 2010). Pakistan was placed 12th in 2012, 8th in 2015, and 7th in 2016 among the world's most vulnerable constituencies to climate change concerns (Kreft et al., 2013). Floods and other natural disasters, such as dwindling hydrological reserves, droughts, storms, and cyclones, have recently struck havoc on Pakistan. These natural catastrophes lasted longer and resulted in more losses (Mueller et al., 2014). In Pakistan, natural calamities such as floods from 2010 to 2014 have left many rural communities perplexed (Fahad et al., 2018). Between 2020 and 2050, Pakistan's temperature would rise by 0.9 to 1.5 degrees Celsius. In 1998 and 2004, Pakistan experienced its worst droughts in history, with 84 percent of the population directly affected and 76 percent of livestock killed; similarly, to provincial effects, the entire country was severely impacted by massive floods, displacing a large number of people in the northern and central parts of the country. In the coming years, heat waves, severe droughts, pest infections, health-related difficulties, and changing lifestyles are all expected to persist (Mahmood et al., 2012).

Global warming and climate change do not respect political/geographical boundaries, and Pakistan is no exception. Pakistan's precipitation and heat patterns have evolved considerably in recent decades as global air temperatures have risen substantially. From cold ice caps in the north to hot deserts in the south, Pakistan's environment is diverse (Rasul et al., 2005). On the north, the world's highest mountains function as a barrier, preventing cold waves from reaching the south in the winter and monsoon rains from reaching the north in the summer. The Arabian Sea, which forms the country's southern border, provides a significant amount of moisture in the form of summer monsoon, which meets the water demands of agriculture, power generation, industry, and home consumption. As a result of rising temperatures, we've witnessed changes in precipitation patterns, cropping patterns, droughts, water availability periods,

the frequency and severity of heat waves, precipitation events, and weather-induced natural catastrophes (Tingju et al., 2014).

2.5.1. TEMPERATURE VARIATIONS

The mean daily temperature is the average of the day's highest and lowest temperatures. The greatest temperature, also known as the maximum, occurs in the afternoon on a bright day, while the minimum temperature, also known as the minimum, occurs shortly before sunrise under clear skies. The maximum temperature is the temperature during the day, while the lowest temperature is the temperature during the night (Trewin et al., 2010). Maximum temperatures are recorded at 5 p.m. local time in each nation, and lowest temperatures are recorded at 8 a.m. local time to be on the safe side, allowing both daily extremes to occur in the observation time domain, according to the World Meteorological Standard. When the lowest or maximum temperature is attained, the related indices or indicators stay in place until the observer resets them. Day and night patterns, rather than mean daily temperatures, should be the emphasis since each has different biological, chemical, and physical effects (Chaudhary et al., 2004).

2.5.2. ANNUAL TEMPERATURE VARIATIONS

Fifty-Six Pakistani weather stations were chosen since their records of meteorological conditions are lengthy and consistent. The criteria were created with the purpose of portraying all of Pakistan's climatic zones with a single weighting factor based on the region's surface characteristics. Inter-annual fluctuation in mean daily temperatures has existed since 1960, with alternate cold and hot spells, although the magnitude of the changes has remained steady. The most severe El Niño in history occurred in 1998 as a result of abnormally warm East-Equatorial Pacific Sea temperatures ($>40^{\circ}\text{C}$ above normal), which sent shockwaves throughout the planet and altered global weather patterns. In comparison to prior years, this year was the warmest in Pakistan. Due to the failure of summer rains, much of the nation was engulfed in drought for four years, and the atmosphere was not reclaimed to decrease the country's temperature (Rasul et al., 2012). The heat has persisted due to loss of flora, deforestation, an unpredictable rain cycle, and increased frequency/intensity of heat waves. This

decade would have witnessed an irreversible rise in temperature except for 2005, when significant summer and winter rains-maintained temperatures in the normal range (Thenkabail et al., 2004).

2.5.3. SUMMER AND WINTER BEHAVIOR

It's fascinating to note how day and night temperatures in Pakistan have been behaving while mean daily temperatures have been steadily climbing. Is there a difference in their behaviors, or are they both hot? These facts are crucial to know since they play different roles in crop growth and development, as well as flora and fauna dynamics. Photosynthetic activity is regulated by daytime temperatures and appropriate sunlight, resulting in glucose production and the synthesis of dry matter. During respiration, dry matter generated during the day is absorbed by plants and animals at night, reversing photosynthesis. The amount of respiration increases as the evening temperature rises. Net dry matter production, which provides fuel for plant growth and development, is the difference between daylight production and nocturnal consumption. The crop's net dry matter output is also a good predictor of its economic yield. As a result, higher-than-normal evening temperatures have a detrimental impact on animal and crop output (Rasul et al., 2012).

In both the summer and winter seasons, the minimum temperature, which is a measure of the lowest nighttime temperature, and the maximum temperature, which is a measure of the highest temperature of the day, have risen in almost all sections of Pakistan (Afzaal et al., 2009). The winter season has a warmer trend than the summer season, suggesting that the winter season's duration has been shortened on both ends while the summer season's length has been increased. Night temperatures have risen quicker than day temperatures as a result of heat stress, increased water consumption, and higher rates of respiration, indicating a detrimental impact on livestock and agricultural productivity. Summer maximum temperatures have had a varied trend during the previous decade. However, in certain climatic zones, such as central Pakistan, the lowest temperature in July showed a considerable warming trend, whilst the extreme north and south showed a moderate cooling trend. In the coastal region in general, and the Indus

delta in particular, there has been no worrisome warming or cooling trend. Changes in the surrounding region's thermal regime, on the other hand, will have an influence on the deltaic region's climatic state (Tank et al., 2006).

2.5.4. PRECIPITATION

Any sort of water (liquid or solid) that falls from the clouds is referred to as precipitation. Rain, snow, hail, sleet, virga, and precipitating fog are all featured. This is the yielding component of the hydrological cycle. Water evaporates from the surface of soil, plants, and water bodies when the temperature increases because moist and warm air is lighter than dry air. It then climbs to the higher atmosphere's layers (Haroon et al., 2009). Cooling causes water vapors to condense and form clouds because the temperature in the higher layers is low.

Vapors mix when temperatures decrease, forming bigger and heavier droplets or ice crystals in clouds, which finally descend as precipitation as gravity overcomes buoyancy. Precipitation falls in the form of rain or hail at low elevations, but snow falls at higher elevations, especially in the winter when surface temperatures in mountainous terrain dip well below freezing, i.e. 0°C. The three primary types of rainfall are orographic, frontal, and convective rain. Pakistan experiences all three types of precipitation, depending on the region and time of year. It's also worth mentioning that precipitation is the most changeable of all the meteorological components on both temporal and geographical dimensions (Haroon et al., 2009).

There are two primary rainy seasons in Pakistan, which correspond to winter and summer. Westerly waves from the mid-latitudes sweep through the lower latitudes in the winter, with troughs extending down to 35°N and sometimes further south. Due to the action of westerly wave troughs and well-occluded frontal systems, the northern area of Pakistan receives heavy rainfall throughout low-elevation plains and snowfall in mountainous regions during the winter season. Summer delivers Pakistan's monsoon, which contributes for over 60% of the country's annual total precipitation between July and September. May and June are the hottest and driest months of the year, with only periodic convective

showers. Similarly, autumn (October and November) is a dry season with neither summer or winter rains, although the low temperatures are not as stressful as the pre-monsoon. The total annual precipitation of Pakistan varies from 500 to 800 millimeters, with larger amounts in the north, which receives a substantial proportion of both winter and summer precipitation. The southern half of the nation receives half of what the northern half receives since neither the monsoon nor the winter precipitation reaches with severe downpours. The southern half is made up of the provinces of Sindh and Balochistan, which have dry temperatures that make farming unfeasible without additional irrigation (Chaudhary et al., 2004).

Balochistan receives very little annual total precipitation (50-500 mm), as precipitation seldom reaches the region in both summer and winter. In the winter, high mountains in northern areas receive very little snow, which seldom lasts until spring, leaving insufficient reserves to ensure a regular water supply throughout the hot summer months. Lower Sindh, which is near to the coast and covers the Indus Delta, receives more rainfall than higher Sindh due to monsoon intrusion and southwesterly winds from the north Arabian Sea (Rasul et al., 2012). River flows in the summer are fed by solid precipitation deposited over the northern highlands in winter, along with glaciers, especially when the weather is dry and hot during the pre-monsoon season. The most important characteristic of precipitation is its unpredictability across time and location, which needs a detailed investigation of its dynamic behavior. Although this meteorological parameter has always been vulnerable to large-scale fluctuation, the consequences of global warming and climate change in Pakistan have been demonstrated in recent decades by prolonged dry and wet periods extending several years (Mahmood et al., 2012)

2.5.5 Summer and Winter Behavior of precipitation.

Summer precipitation is concentrated during the monsoon season, which spans from July to September, and is frequently associated with monsoon depressions (low pressure systems) that form over the Bay of Bengal and move westward over India. They have a range proportionate to their strength; otherwise, they disperse over central India. Another cause of summer monsoon

precipitation is the southwesterly flow of moisture from the Arabian Sea, which is triggered if a depression persists. Both processes combine and promote the precipitation process, resulting in high intensity rainfall, or a great volume of water falling in a short period of time (Das et al., 2003). During periods of high activity, however, the troughs of westerly waves travel far enough south to deliver good precipitation to Balochistan and Sindh. It's important to note that winter precipitation is often less intense than summer precipitation, hence winter floods are uncommon. As can be seen from the above, the northern half of Pakistan receives the bulk of yearly precipitation, particularly during the summer monsoon season, and the southern half receives relatively little precipitation throughout both seasons.

Pakistan has also been feeling the flavor of such changes at various scales in diverse climatic zones in the form of severe climatic anomalies (Rasul et al., 2004). Summer and winter seasons in different climatic zones of Pakistan indicate an average shift in precipitation amount for the decade 2001-2010 when compared to the long-term normal of 1971-2000. Precipitation in northern mountainous regions has declined dramatically over the last decade, whereas the rest of the country has seen average weather. Summer precipitation totals have decreased in the northern part of the nation, but inter-annual variability has grown considerably. The lower portion of Pakistan, notably the Indus Delta, has witnessed a significant increase in total rainfall due to numerous localized heavy rain periods throughout the summer monsoon season. This growth in the Indus Delta is not due to socioeconomic activity; rather, it is due to catastrophic downpours that are creating long-term development issues to the region. Large volumes of rain water stagnate in heavy soils with poor drainage, causing standing crops to rot and impeding timely planting of the following season's crops (Berthier et al., 2010).

2.5.6. EXTREME PRECIPITATION EVENTS

Areas in the active precipitation zone used to regularly get up to 200 mm of rain, but such events now appear to be a tragedy when this much rain happens in a single year. The bottom half of Pakistan, including Balochistan and Sindh, is

in the latter zone, with annual total rainfall in the hundreds of millimeters, most of which falls during the summer and lasts for 15-20 days. During the active monsoon season, a few big precipitation events can produce a lot of rain, wreaking chaos rather than offering benefits. Climate change would most certainly increase the frequency and intensity of catastrophic events in the twenty-first century, according to the IPCC's 4th Assessment Report (2007). (with greater than 90 percent certainty). The degree of the rise, however, will differ by location (IPCC 2007). The change in the tendency of severe precipitation occurrences is shown in pentad intervals from 1965 to 2009, including the latter two years of 2010 and 2011. Because the quantity of rain that falls over a certain period of time can range from a gift to a calamity, and because endurance varies by instance, three thresholds (50, 100, and 150 mm per day) were chosen for study of 47 years of data sets from 12 meteorological observatories in Sindh. The data analysis shows a definite rise in the frequency of severe precipitation occurrences in Sindh across all three thresholds; rather, the height of bars at 100 mm and 150 mm or more per day has been raising considerable worry for planners and policymakers over the past seven years. The province of Sindh was embroiled in the world's worst drought during the first pentad of the twenty-first century, as the summer monsoon failed to reach its active phase on multiple occasions, but the second pentad triumphed with more intensity. Between 2005 and 2009, there were 19 days with more than 100mm of rain in a single day (highest frequency 1931-2009). This recently set record was beaten by a total of two years (2010 and 2011); the pentad still has three years to complete. The situation is same on a day with a threshold rainfall of more than or equal to 150 mm (Maida et al., 2011).

2.6. ABRUPT CLIMATE CHANGE

When the climate system is forced to cross a threshold, a transition to a new state occurs at a rate determined by the climate system itself, which is quicker than the cause (Hodell et al., 1995). Even a small amount of force can result in a significant alteration, and the forcing itself may be chaotic and hence unnoticeable. Chronic changes that affect subcontinental or larger regions, and for which ecosystems and economies are unprepared or unable to react, attract

significant attention in terms of human issues. According to climatic records, large, broad, and abrupt climate alterations have happened on a regular basis throughout the geological record. Although some explanations for these shifts have been identified, and model simulations of these changes are improving, the models currently used to study human influences on climate do not yet accurately replicate past changes (Perrott et al., 1990). Although the public debate over climate change has focused on the climatic consequences of greenhouse gas emissions and their consequences for the world and human civilization, scientists and policymakers have paid less attention to the possibility of large-scale climate change occurring soon. Such abrupt climate fluctuations might be caused by natural or human-induced factors, making them one of the "dangerous anthropogenic interferences" listed in the UN Framework Convention on Climate Change (Alley et al., 2003). During the most recent glacial epoch, the North Atlantic area saw a series of dramatic climatic swings known as Dansgaard Oeschger (DeO) episodes, in which oceanic and atmospheric conditions alternated between full glacial (so-called stadial) and comparatively mild (interstadial) conditions (Laird et al., 1996). In ice-core records, the most recent DeO episodes are resolved in sub-annual detail, and analysis of these high-resolution data indicates that major atmospheric circulation changes happened in only a few years. During the Last Glacial Period, around 25 rapid shifts from stadial to interstadial conditions occurred, with amplitudes ranging from 50 to 160 degrees Celsius and each occurring within a few decades (Alley et al., 2010).

2.7. RECENT ABRUPT CHANGES IN THE EARTH SYSTEM

2.7.1. STRATOSPHERIC OZONE DEPLETION

In the early 1970s, scientists worried that nitrogen oxides (also known as "NO_x") from a proposed fleet of supersonic planes flying in the stratosphere, as well as industrially produced halocarbon gases containing chlorine and bromine (CFCs or chlorofluorocarbons and chlorofluorobromocarbons), would deplete the amount of ozone in the stratosphere (Beckmann et al., 2003). Halogen oxide radicals were predicted to be produced by the decomposition of halocarbons in

the stratosphere. Increased amounts of CFCs and halons in the atmosphere, as well as halogen oxide radicals in the stratosphere, have been discovered after a decade of rigorous stratospheric study (Broecker et al., 2000). The Montreal Protocol was agreed in 1987 after international debates, mandating industrialized nations to cut CFC production by 50% and halon production by 100% by the year 2000. Scientists determined two years before to the agreement that the amount of ozone in the stratosphere above Antarctica in the austral spring had been declining since the late 1960s, and had decreased by roughly a factor of two by the mid-1980s (Huybrechts et al., 2004). Satellite data and observations from other sites supported this pattern on a continental scale in Antarctica. Despite a rapid shift in the timing of human activity and the scale of the whole polar area, satellite observations failed to identify the change due to a lack of continuity and the rejection of data deemed abnormal (Rasmussen et al., 2014). According to the Montreal Protocol, most ozone-depleting CFCs must be phased out completely by 1996 in developed nations and by 2010 in the rest of the globe. Furthermore, the Protocol has been revised or altered multiple times in order to reduce ozone-depleting chemical emissions. Because of the Montreal Protocol and its modifications, stratospheric ozone is expected to return to pre-1980 levels when atmospheric abundances of ozone-depleting chemicals decline in the next decades (Yasuhara et al., 2014). Column worldwide ozone levels estimated in the early 1970s should be regained by the mid-twentieth century, whereas stratospheric cooling due to increases in greenhouse gases would alter the restoration's trajectory. By the late twenty-first century, the Antarctic ozone hole is expected to be gone, and its recovery will be less impacted by climate change than world ozone levels (UNEP 2000). The Antarctic ozone hole formed within a few years after a threshold was crossed when inorganic chlorine concentrations in the lower polar stratosphere exceeded nitrogen oxide concentrations, and it affected a huge area of the planet. As a result, it demonstrates the breadth and severity of the global consequences of rapid changes in human activity (Andersen et al., 2004). The Montreal Protocol against substances that degrade the ozone layer was signed by the world community thirty years ago. According to the convention, use and production of ozone-depleting chemicals should be limited. The pace of depletion has decreased as a result of the ban on the use of chlorine-containing synthetic goods, and scientists project that by 2070, the level

of depletion will have returned to 1980 levels. Since 2000, the stratosphere has returned at a pace of 1–3% every decade, according to scientific study published in 2018. After the lockdown began on January 23, particulate matter pollution fell by an average of 35% and NO₂ pollution decreased by an average of 60%. Scientists observed that the average surface ozone concentration increased by 1.5–2 times within the same time period. Chemicals that deplete the ozone layer can be released naturally or intentionally. All man-made emissions are now restricted as a result of COVID-19's closure. Production and consumption of ODS have both dropped. According to the World Meteorological Organization (WMO), economic activity was reduced during COVID-19, leading in lower CO₂ emissions. In the coming year of 2019, Warm temperatures in the upper atmosphere in the south pole area of Antarctica, according to NASA and NOAA, have resulted in a tiny ozone hole since 1982. On April 23, 2020, the Copernicus atmospheric monitoring services (CAMS) announced that the largest hole in the ozone layer ever seen over the arctic has been filled. On the 23rd of April, 2020, the. Despite the fact that lockdown is clearly displaying a crucial signal of natural balance restoration, the ozone layer is unrelated to COVID-19. This is due to a strong and long-lasting polar vortex, according to Copernicus Atmosphere Monitoring Services (CAMS) scientists, and is unrelated to changes in air quality (Arora et al., 2020).

2.7.2 BARK BEETLE OUTBREAKS

Bark beetle infestations are a normal part of woody ecosystems and occur on a regular basis. However, the bark beetle infestations that have raced through most of North America in the last two decades have been the largest and most devastating in recorded history, destroying millions of trees across millions of hectares of forest from Alaska to southern California (Petit et al., 1999). Climate change is thought to have had a role in these recent outbreaks by maintaining temperatures above the point when cold-induced death occurs. Higher temperatures in a warmer location can speed up reproductive cycles and increase the chance of outbreaks in general, especially when multiple warm years follow

one another (Kleinen et al., 2004). Other human activities, such as forest history and management, as well as climate change, have a role in these sorts of sudden climatic effects (Jeffers et al., 2011).

2.8. IMPACTS OF ABRUPT CLIMATE CHANGE

Understanding the distinction between climate change and climatic variability is crucial. Climate change, as opposed to climatic variability, refers to fluctuations in the mean state and other climate data on all geographical and temporal scales. Variations in rainfall from year to year, for example, show climatic variability, but a shift in long-term mean rainfall over several decades denotes climate change. Climate change is expected to increase flood intensity (flood flows) and duration. Different areas' hydrology, on the other hand, will respond to climate change signals in a variety of ways. As a result, regional climate change impact assessments are crucial (Ahmed et al., 2014).

2.8.1. AGRICULTURE

Climate change is wreaking havoc on agriculture, which is the most essential sector of any economy. Climate variability's impacts have gotten increasingly deceptive over time (Patt et al. 2009). The dimensions required to adjust to such threats have a significant impact on the impact of climatic disasters (O'Brien et al. 2006). In certain locations, climate change has already increased the frequency and intensity of climatic disasters such as floods, droughts, extreme heat, water scarcity, and pest and disease outbreaks (Smit et al., 2002). According to the Global Climate Change Vulnerability Index (CCVI) research, Pakistan was ranked 29th among the most susceptible areas in 2009–2010, and 16th in 2010–2011. (Khan et al., 2014). More common climatic occurrences include floods in Pakistan in 2010, 2011, 2012, and 2014, as well as a severe drought from 1999 to 2003. Pakistan is one of the regions with the least adaptation capacity due to a high degree of poverty and a lack of financial and physical resources (Abid et al., 2015). Farmers' management and adaptation decisions to climate change and its accompanying dangers are influenced by

these various experiences, either directly or indirectly (Abid et al., 2015). Climate variability influences the intensity and frequency of natural occurrences; some indirect consequences of climatic variability include changes in insect infestation frequency, soil moisture, and disease dispersion. Temperature increases, precipitation unpredictability, and losses in crop yield all have a direct influence on food security in emerging and agro-based countries (Edwards-Jones et al. 2009). According to the FAO (2011), climate variability has a substantial influence on agriculture by altering or worsening productive dimensions and increasing direct and indirect production risks (FAO 2011). Climate change affects the environment as well as socioeconomic and associated sectors such as agriculture and food security, water resources, terrestrial ecosystems, human health, and biodiversity. Changes in precipitation patterns are anticipated to exacerbate water shortages and flooding. Temperature rises also influence agricultural growth seasons, affecting food security, as well as disease transmission patterns, placing people at danger of illnesses like malaria. The pace of destruction for many habitats and species increases dramatically as the temperature rises (UNFCCC 2008).

2.8.2. HEALTH

Climate change has the potential to alter both environmental and social determinants of health, such as clean drinking water, adequate food, and safe shelter. Extreme heat events, natural disasters, and erratic rainfall patterns might all have a role. Heat waves are expected to become more frequent and last longer. In June 2015, a heat wave in Karachi claimed the lives of over 1,200 people, with another 200 people dying in other parts of Sindh Province (Chaudhary et al., 2015). A maximum temperature of 44.8°C was recorded in Karachi, which is the second highest after 1979. Heat waves are widespread in the plains of Pakistan during the premonsoon months (May–June). Rainfall and temperature changes were linked to the spread of several infectious illnesses and food security (Malik et al., 2011). In a preliminary UNDP survey conducted after the 2010 floods, it was discovered that the fraction of the population below the minimal level of dietary energy consumption rose by 3%, resulting in an extra 5 million undernourished persons. The United Nations Children's Fund (UNICEF)

published a report in 2010 that. Similarly, severe events were linked to the afflicted population's mental health, i.e., extreme events are known to generate despair, distress, anger, and other negative emotions (Save the Children. 2011). As the temperature rises, the danger of water-borne and vector-borne illnesses rises as well. Changes in temperature and heavy precipitation may be contributing to an increase in the number of mosquito breeding sites, leading in a rise in dengue and malaria cases (Khalid et al., 2013).

2.8.3. POVERTY

Pakistan is very vulnerable to climatic risks such as floods and droughts in poor countries, particularly in Southeast Asia. Floods in the years 2010 to 2014 resulted in a large number of deaths and property losses, as well as a large number of people fleeing their homes. Pest assaults, seasonal and flash floods, and droughts are some of Pakistan's other climatic occurrences (Schilling et al., 2013). Pakistan's farming industry has been hit by three big floods in a row, wreaking havoc on the country's economy and agriculture. Agriculture is the country's only substantial industry, accounting for 21% of total national income; its proportion has declined over time, and it now employs 45 percent of the workforce. Almost 70% of the population lives in rural regions, and the majority of them are directly dependent on the agricultural industry (Fahad et al., 2018). Agriculture accounts for 21.4 percent of Pakistan's GDP, 24.5 percent in the 1990s, 32 percent in 1977–1978, 53 percent in 1959–1960, and 64 percent in 1947–1948. (Fahad et al., 2018b).

2.8.4. FOOD SECURITY

Climate change is having a substantial impact on Pakistan's energy, water, and food security (Imran et al. 2016), which is comparable to the worldwide situation. Due to the effects of climate change, a variety of variables are hurting food security and poverty, and these challenges will become more common in the future days (Panel et al. 2007). With approximately 300 million undernourished people living in the region, South Asia is home to the world's most food insecure people. Climate change and weather changes are to blame for Pakistan's rising poverty and lack of food security, since they affect the country's

major sector of the economy (Ali et al., 2017). Water availability and mercury changes can have serious consequences for food crops. Unexpected precipitation at sowing and harvesting times has wreaked havoc on Pakistan's primary food crops. Farmers' woes are exacerbated by dry periods, irregular rains, and floods. Another concern is the rise of agricultural pests (Hussain et al., 2016). Farmers, as the key components, will have to bear the adaptation expenses on their own, which is a major issue at the grassroots level. Modern water management techniques at the local level, as well as efficient solar energy technologies, may be critical measures to assure food security and reduce CO₂ emissions (Hussain et al. 2016). Farmers that implemented contemporary farming methods had a higher degree of food security (8–13%) and a lower level of poverty (3–6%) as well (Ali et al., 2017).

2.8.5. BIODIVERSITY

The variety among living species from all sources, including, *inter alia*, terrestrial, marine, and other aquatic ecosystems and the ecological processes of which they are part," according to the 1992 Convention on Biological Diversity (CBD) Rio de Janeiro definition (Ali et al., 2011). This encompasses genetic variety among species, species diversity across species, and environmental diversity. The essential purpose of biodiversity is to sustain and improve people's well-being by providing livelihood security, agriculture, energy, and health, as well as additional services like as nutrient cycling and soil formation, pest and disease management, flood regulation, and so on (Ali et al., 2005). Temperature and rainfall are important factors in determining where plants and animals may survive, thrive, and reproduce. Temperature has been shown to have a direct impact on organism physiology (WWF 2005). Climate change has both direct and indirect effects on species and ecosystems. Climate change has a variety of direct effects on species and ecosystems (Siddiqui et al., 1999). Systematic data on bird nesting collected over a 60-year period in the United Kingdom revealed that 78 percent of the 65 species of birds surveyed began breeding earlier. Twenty-five percent of Australian eucalypts have temperature distributions that cover less than one degree Celsius (Hughes et al., 1996), making them more sensitive to even minor climate changes. With just 0.5°C of warming in Western

Australia, a large number of frog, animal, and plant species can be confined to smaller habitats or become extinct (Poulique et al., 2000). Marine turtles are a vital species of reptiles that may be found on nearly every sandy beach from Sindh's coast to Baluchistan's coast. They move from deeper oceans to coastal locations to deposit eggs during their breeding or egg-laying season. The Sindh Wildlife Protection Ordinance of 1972 protects turtles under regulatory provisions; as a signatory to the Convention on International Trade in Endangered Species of Wild Fauna and Flora, Sindh is a signatory to the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES). Climate change's impact on bird diversity in a Ramsar-designated wetland complex in Pakistan, as well as management strategies, were investigated (Ali et al., 2005). This significant migrating route of migrating birds is supported by all rivers in Pakistan, and it is ranked as the fourth most important bird migration flyway in the world. The Uchalli Wetland Complex, which includes the marshes of Uchalli, Khabbaki, and Jahlar, was designated as a Ramsar site in 1996. These wetlands are home to a variety of globally endangered bird species (Ali et al., 2005). Year to year, the weather conditions change. However, drought conditions remained after 1997, with rainfall dropping by more than half. The morphology of the Uchalli Wetlands Complex revealed a negative alteration, with just 336 hectares of water area compared to 1,243 ha, which had a significant influence on the migratory bird population (Ali et al., 2005).

2.8.6. WETLANDS

Pakistan's wetlands are critical for maintaining and sustaining regional biological processes that support globally significant biodiversity, such as bird migratory routes and wintering grounds. However, a major portion of Pakistan's wetlands-dependent biodiversity is designated as endangered or fragile. In Pakistan, the ecosystem of wetlands has changed dramatically in the last 10 years, reducing their capacity to serve as a home for ducks, shorebirds, and migratory birds (Abbas et al., 2018).

2.8.7. DEFORESTATION

Deforestation occurs when forests are destroyed for other land uses such as farming or ranching, resulting in the loss or removal of tree cover. Deforestation is defined by some as the permanent transfer of forests to another ecosystem. Deforestation causes environmental deterioration, carbon emissions from plant breakdown on the forest floor, albedo impact, and an increase in hydro-meteorological dangers. Forests cover over 30% of the Earth's land mass (Percy et al., 2003). Forests impact the global climate pattern by regulating the hydrological cycle, temperature stability, and air composition through physical, chemical, and biological activities. Since 1990, the extent of primary forest has decreased by 300 million hectares. Approximately 13 million hectares of forest were converted to other uses or naturally destroyed between 2000 and 2010, compared to 16 million hectares each year over the previous decade (Joseph et al., 2004). The majority of Pakistan's woods are found in the northern highlands of Khyber Pakhtunkhwa, Gilgit-Baltistan, and Azad Kashmir. Annually, almost 39 thousand hectares of forest are lost, with a depletion rate of more than 1.5 percent (Schweikert et al., 2014). The growing trend of deforestation has significant consequences for forest productivity and conservation, as well as the livelihoods of individuals who live near forests. Forest cover is declining at a catastrophic rate across the country due to unlawful exploitation and inadequate execution of regulations. Landslides, slope instability, floods, increased surface runoff, and soil erosion are all risks associated with deforestation. Because of the exploitation of forests after the Kashmir earthquake of 2005, there was an increased danger of landslides and debris flow. Pakistan was hit by the greatest flood in its history in 2010. The unusual pace of monsoon rains has been attributed to climate change in the region by scientists. Deforestation exacerbated the situation during the disastrous occurrence. The combination of natural and artificial factors contributed to the disaster. Increased surface runoff and soil erosion occurred from soil deterioration and deforestation (Hussain et al., 2019a).

2.8.8. WATER RESOURCES

Water covers around 75 percent of the Earth's surface. However, because of the dynamic nature and constant transportation of water, it is impossible to accurately measure the earth's overall water stock/store. According to current estimations, the earth's hydrosphere contains around 1386 million km³ of water. However, because freshwater is required by the agriculture sector, industry, and home and recreational users, not all of these resources are theoretically available to humanity (Lui et al., 2011). Oceans contain 97 percent of the Earth's water, which is saline. Fresh water makes up around three percent (3%) of all water on the planet, and its physical state can range from liquid to gas to solid. In the Polar Regions, glaciers, ice caps, and permanent snow cover store around 69 percent of the Earth's fresh water. Only 0.3 percent of all freshwater is contained in river systems, lakes, and reservoirs, but groundwater accounts for 30% of all freshwater on the planet (Cassardo et al., 2011). In Pakistan, over 44% of the population does not have access to safe drinking water, and the situation is even worse in rural regions (PCRWR 2010). Water availability per capita in 1951 was 5,800 m³, dropped to 1,100 m³ in 2006, and is expected to drop to fewer than 1,000 m³ in the following decade (WMRP 2008). Pakistan's economy is built on agriculture and is heavily reliant on the massive Indus irrigation system (Snow and Ice Hydrology Project, 1990). Water concerns occupy a unique position in Pakistani policymaking. For a long time, it has sparked intense discussion and controversy, as evidenced by problems such as the construction of the Kalabagh Dam and the uneven allocation of water resources across provinces (Ghazanfar, 2007). Climate change and variability's effects on water supplies are projected to have an impact on irrigated agriculture and installed electricity capacity.

2.8.9. ECONOMY

Climate change's implications on economic development are no longer a secret; they're quickly becoming a harsh reality. Increased greenhouse gas (GHG) emissions in developing nations, particularly rising economies, have prompted major concerns about the link between climate change and economic growth (Parry et al., 2007). Some sectors of the economy expand faster than

others as a result of climate change, resulting in changes in the size and composition of GDP. These changes have an impact on the country's long-term development potential (Scheraga et al., 1993). According to Nordhaus (1994), a 3°C increase in global warming would cost the United States 0.25 percent of its GDP. If unmeasurable warming consequences are factored in, damage might reach 1–2% of GDP, according to Stern (2006), and global temperatures could rise to 2–3°C in the next 50 years (Nordhaus et al., 1991). Climate change has a number of socioeconomic consequences, including effects on water, agricultural production (food), health, and so on, and will result in a loss of at least 5% of global GDP every year. The Global Climate Change Impact Study Centre (GCISC) looked examined temperature and precipitation patterns in Pakistan from 1951 to 2000 by agro-climatic zones. The average annual temperature in Pakistan is expected to rise by 4.3–4.9°C by 2085, with the increase in temperature being lower in the southern parts of the country than in the northern parts. UNEP (2000) developed an integrated scenario to explain the impacts of climate change on various sectors of the Pakistan economy, including energy, agriculture, water resources, forestry, and others. The above analysis reveals that the majority of climate change research in Pakistan are focused on the impact of climate change on agriculture, water, and the country's natural resource base. There hasn't been a comprehensive examination of the overall consequences of climate change on economic growth (Stern et al., 2006).

2.8.10. ENERGY SECURITY

Climate change is putting a strain on Pakistan's energy, water, and food security (Imran et al. 2016). Quick urbanization, rapid industrialization, and economic development forced the government to take short-term measures to meet its energy need with thermal energy. The administration is still attempting to deal with the energy issue, which has resulted in a 3000 MW electrical shortfall (Lin et al., 2017). Vehicle use is expanding, which is boosting energy consumption and presenting a danger to the environment and energy security. It is also true that natural renewable energy resources have a far higher potential in Pakistan than conventional renewable energy resources (Sheikh 2010), since Pakistan is located in a natural rich energy zone with the capacity to create 2.9

million MW of power from wind and sun energy (Sheikh et al., 2010). Climate change impacts on floods are primarily examined in the planning context by addressing the probable changes in the frequency of certain flood discharge magnitudes. Climate change is thought to be increasing the frequency of floods. For analyzing such implications on flood frequencies with adequate confidence, high-resolution regional climate predictions are required. Because of the enormous economic ramifications of the adaptation strategies, quantifying uncertainty in expected outcomes is especially important in the context of flood control (Li et al., 2011).

2.9. FLOOD

Flooding is a typical hydrological occurrence that disrupts society's normal cycle and results in calamity. Flooding causes loss of life (people and animal injuries and deaths), damage to resources (crops, agricultural land, and dwellings), and disruption of connectivity (bridges, highways, and trains) (Szewraski et al., 2015). Floodplains are one of the most important ecosystems in terms of supplying goods and services to the environment as well as maintaining biodiversity. Simultaneously, it is projected that almost one billion people, the bulk of whom are among the world's poorest population, live in floodplains. As a result, flooding is now the most dangerous natural hazard on the planet. Because of continued population development in floodplains, as well as changes in land use and climate, flood damage and mortality are predicted to rise drastically in many regions of the world. Floodplains, on the other hand, are vulnerable to flood disasters that may inflict significant damage to society, the economy, the environment, and human life (Abdullah et al., 2013). When an extreme occurrence occurs in a susceptible physical and socioeconomic context, society's capacity to regulate or endure the repercussions is considered to be a flood disaster. Flood disasters currently account for half of all deaths caused by natural disasters (Cloke et al., 2009). In 2010, floods claimed the lives of more than 8,000 individuals and impacted over 180 million people (NDMA 2012). The favorable temperature trend, according to Huntington, has not yet resulted in an increase in the number of tropical storms and floods (Huntington et al., 2006). According to Labat, a 1°C increase in global temperature correlates to a 4%

increase in worldwide runoff; however, the runoff trend varies from region to continent. North America, Asia, and South America all showed a strong positive discharge trend, whereas Africa showed a negative trend. There were no major increases or decreases in discharge patterns across Europe (Labat et al., 2004). Clearly, no global pattern for (flood) discharge series has been discovered (Robson et al., 1998). Flooding is the world's worst water-related natural calamity, with severe human, material, and ecological consequences for long-term development. Floods affect an estimated 520 million people worldwide each year, killing up to 25,000 people. They damage the global economy between \$50 and \$60 billion each year, together with other water-related calamities. In the last ten years, an estimated 96 percent of deaths from natural catastrophes happened in poor nations with little capacity to foresee and handle severe calamities (NDMA 2012). Due to large-scale urbanization, population increase in natural floodplains, ever-increasing rates of deforestation, climate change, and rising sea levels, the number of people exposed to a disastrous flood is likely to climb (Khan et al., 2011). New catastrophe risk reduction techniques are urgently needed to enhance the ability needed to confront the issues that some of the world's poorest people face. Floods, on the other hand, are natural occurrences that contribute to ecosystem biodiversity and sustainability, as well as too many human activities (Rafiq et al., 2012). Economic growth in flood-prone areas has helped both developed and developing countries. Nearly a billion people – one-sixth of the world's population, the bulk of whom are among the poorest people on the planet – currently live in floodplains (Cunderlik et al., 2009). Food security and poverty reduction are heavily reliant on fertile floodplains in developing nations with mostly agricultural economies. Many river systems' nutrient-rich deltas promote low-tech agriculture techniques and support millions of people. Wetlands in floodplains support biodiversity while also providing job possibilities (Teegavarapu, R.) (2012). Floods harm more people than any other natural catastrophe, and yearly damages are estimated to be over 104 billion US dollars, accounting for 33 percent of global losses (Kundzewicz et al., 2005). The flood affected around 196 million people in over 90 nations throughout the world (UNDP, 2004). However, the devastating floods of 2010 (for example, in Pakistan and China) are simply the most recent evidence of the world's escalating flood devastation. Over the last several

decades, the number of individuals impacted by floods on the African continent has expanded considerably (WCDR 2005). Floods have always been a component of the hydrological cycle; but, in recent decades, there has been an increase in the frequency and volume of floods (Kundzewicz et al., 2013). As a result, many countries, including Pakistan, have struggled to establish efficient flood protection methods. Flooding is becoming more common as a result of continuous climate change and land use changes caused by human activities (Sofia et al., 2017). Floods are often triggered by a confluence of adverse climatic, hydrological, and physical circumstances. The Convergence Zone of Rivers is a region of rivers that is prone to floods. Increased population and the pressures of population expansion on the environment have affected the flood intensity in the last decade (Khosravi et al., 2016). Flooding was caused by heavy monsoonal, cyclonic, cloud burst rains, and an inefficient drainage system in Pakistan. Many floods have occurred in recent years as a result of man-made factors such as massive dams and river bed siltation. Forecasting these sorts of severe risks has grown critical since the socioeconomic and environmental implications of flooding have gotten more severe in recent years (Hirabayashi et al., 2013). Flooding in downstream areas is frequently caused by high-intensity downpours in a region. Floods occur when water flows overland and inundates land (Merz et al. 2010). Natural calamities such as floods are wreaking havoc on natural and human resources. Flooding affects an average of 140 million people each year (WHO 2003). The yearly average fatality from floods in recent decades (2006-2015) has been 5709, although floods claimed 4731 lives in 2016. (Douglas et al., 2000). The majority of flood risk is borne by poor countries, such as Pakistan. The terms flood hazards, risk, and vulnerability are similar but distinct; hazard refers to the degree and likelihood of loss and damage caused by a flood disaster, while vulnerability refers to the likelihood of loss and damage caused by the disaster in terms of time over a location where flood risk is caused by hazard and vulnerability associated with natural and social prominence (Zhang et al., 2001). Flood risks methodologies are traditionally split into three categories: geomorphological, hydrological, and historical (Liu et al., 2005). Flood frequency is a hazard metric that is used to historical flood data such as discharge, rainfall, and runoff to forecast future floods (Das et al., 2018). The first stage is to determine the flood-affected area or flood forecasting in a region,

therefore flood susceptibility or vulnerability assessment is determined as the flooding sensitive areas by evaluating and changing various flood components using enumerating, weighted, and interpolating techniques (Kundzewicz et al., 2005). In flood susceptibility or hazard mapping, several geographically and flood-related parameters are required, and the various components are explored in various case studies (Poussin et al., 2014). To combat the ever-increasing flood danger, integrated flood management (which focuses on 'living with floods' rather than 'fighting floods') has been advocated as a replacement for the more traditional flood defense technique ('fighting floods'). This strategy strives to reduce flood-related human, economic, and ecological losses while maximizing social, economic, and ecological gains (UNESCO-IFI, International Flood Initiative). As a result, flood managers should be concerned not just with reducing the potential damage from major flood occurrences, but also with protecting floodplains, which are among the most significant ecosystems for delivering goods and services to civilization as well as maintaining biodiversity (Costanza et al., 1997). However, in an ever-changing environment, how to execute integrated flood control schemes, including the necessary capacity building activities, is frequently unclear, necessitating study and reassessment of present techniques. This appears to be especially true in the developing world, where effective flood control is critical to limiting flood-related social consequences (Fahad et al., 2018).

2.10. HISTORY OF FLOOD

Humans have chosen to reside in flood-prone locations because they offer good circumstances for economic growth since the earliest known civilizations, such as those in Mesopotamia and Egypt that formed in the rich floodplains of the Tigris and Euphrates and Nile rivers (Pradhan et al., 2011). The floods assessed during this time period were extraordinarily enormous, with a magnitude of 100,000 m³/s. The lack of meteorological floods in the list of biggest Quaternary floods does not imply that meteorological floods are less important. Indeed, meteorological floods are by far the most prevalent form of flood in human history, impacting regions of the world on a yearly basis (Wu et al., 2010).

Natural dam breaches or huge ice-dam failures at the borders of continental ice sheets caused the majority of the greatest known floods in the past 100,000 years. Large-scale floods in tropical basins are generally caused by rainfall in places impacted by tropical cyclones or strong monsoonal airflows (Yalcin et al., 2011). Tropical regions have seen the most severe meteorological floods, especially when monsoon rainfall falling on huge and high-relief drainage basins causes massive amounts of runoff. Almost all of the greatest rainfall-related floods have happened south of 40 degrees north latitude. Floods caused by snowmelt and ice jams have dominated north of that line. Extreme rainfall occurrences are the primary source of the biggest meteorological floods from river basins bigger than 500,000 square kilometers (Messner et al., 2006).

2.11. VULNERABILITIES OF THE INDUS DELTA

The rich Indus Delta is located in a climatically desert zone with strong heat and very variable yearly rainfall. Because it is closer to the water, it has been affected by the remarkable changes that have occurred across the sea and land as a result of global warming (MOCC 2012). Pakistan has a diverse range of climates, ranging from highly dry to extremely humid, with altitudes ranging from sea level to the world's highest mountains. Whatever hydro meteorological events occur in the north, their effects will be noticed instantly over the Indus Delta. Similarly, weather events at sea have a direct impact on delta residents' lives (Rasul et al., 2012).

2.12. FLOOD IN PAKISTAN

In recent years, Pakistan has experienced floods practically every year. Floods destroy infrastructure, kill people, and destroy land. In Pakistan, inadequate water resource management and a lack of efficient water policy have resulted in flooding (Arslan et al., 2016). Pakistan is ranked sixth among South Asian countries hit by floods, according to reports (Price et al., 2016). Floods have a long history in Pakistan. Pakistan has seen 23 of the world's worst floods between 1947 and 2015. (FFC 2015). Floods of various magnitudes hit Gilgit-Baltistan, FATA (Federally Administered Tribal Areas), AJK (Azad Jammu and Kashmir), KPK (Khyber Pakhtunkhwa), Punjab, Sindh, and Balochistan during

this time. The Pakistani mega floods of 2010 were one of the worst river floods in modern history (Sayed et al., 2014). In Pakistan, 23 significant flood disasters have resulted in a financial loss of US\$ 38.165 billion between 1947 and 2015. As stated in Table 1, more than 12,000 people were killed and 616,598 km² of land were flooded. Every year, floods harm roughly 0.715 percent of Pakistan's population, and floods are expected to affect nearly 2.7 million people by 2030. (Khan, A et al., 2015).

2.13. TYPES OF FLOOD

Riverine floods, flash floods, glacial lake outburst floods, coastal floods and the urban floods take place in Pakistan.

2.13.1. RIVERINE FLOODS

Various variables, such as exceptional climate variability, sudden sea level rise, and heavy rainfall, have greatly increased the frequency and intensity of riverine floods during the last few decades (Dawood et al., 2017). Riverine floods have been produced by the breakdown of dams, barrages, and embankments in recent years, resulting in devastating power to damage human life and property owing to their unpredictability and intensity. Furthermore, riverine floods in the Indus Basin are caused by a variety of variables, including flat terrain, hydrology, climate, and demographic and socioeconomic catchment characteristics in the vicinity of the Indus River (Gaurav et al., 2011). Riverine flooding is particularly deadly in terms of human life loss, as well as wreaking havoc on all sectors of the economy (Zhou et al., 2000). Riverine floods are usually caused by heavy monsoon (summer) rainfall in the catchments (NDMA 2013). In Pakistan, monsoon-induced floods have created a disaster of unparalleled proportions. Riverine flooding has been an extremely devastating phenomena in Punjab and northern Sindh's flatter terrain, however with a later beginning, impacting densely inhabited and farmed areas. The continuing riverine delta flooding in lower Sindh may have longer-term consequences owing to soil saturation in these low-lying locations. The 2010 super flood was Pakistan's most damaging riverine flood in history (Kundzewicz et al., 2013), resulting in massive human and financial damage (FFC 2010). The agriculture sector (crops,

animals, and fisheries) was the worst hit by the mega flood of 2010. Table 2 shows that it was expected to be worth US\$5045 million (ASDB-2010). Riverine floods in 2013 and 2014 also claimed several lives and destroyed a lot of property.

2.13.2. FLASH FLOODS

Due to intense monsoon rainfall (torrential rain) in hilly and semi-hilly locations, flash floods of enormous scale and short duration occur in natural streams (Shabbir et al. 2016). Flash floods are difficult to forecast and have limited warning periods. Flash floods are common in Pakistan's hilly regions bordering the Indus River Basin, including Kashmir, Gilgit-Baltistan, KPK, Balochistan, and South Punjab. More than 500 people died as a result of the 2011 flash flood. The 2011 floods wreaked havoc on the agricultural sector, destroying crops, cattle, and fisheries. The entire damage was assessed at US\$ 1840.31 million. Sindh suffered the most, accounting for 94% of total agricultural, while Balochistan accounted for 6%. (ADB - 2011). A total of 571 people were killed in the 2012 flash flood (FFC-2012). The cost of crop damage caused by the flash flood of 2012 was estimated to be PKR 33.6 billion (SUPARCO 2012). According to the NDMA (National Disaster Management Authority), flash floods in 2014 killed over 200 individuals and displaced over 460,000 people throughout AJK, Gilgit Baltistan, and Punjab. The 2016 flash flood in Chitral, KPK, claimed several lives and destroyed a lot of property (NDMA 2014). The PDMA (Provincial Disasters Management Authority) in KPK has stated that heavy rains and flash floods killed 261 persons in the province from March to July 2016. (Chitral, Mardan, Kohat, Manshera and Malakand). Over 200 people have been injured, 1,101 homes have been entirely demolished or swept away, and many more have been partially damaged (Yaqub et al., 2015).

2.13.3. GLACIAL LAKE OUTBURST FLOODS

Glacial Lake Outburst Floods (GLOF) are caused by the collapse of glacial lakes. Floods in northern Pakistan's hilly terrain are becoming more common. In July 2015, a Glacial Lake Outburst Flood in Chitral, KPK, killed three persons and trapped approximately 300,000 people. "Global warming is

causing the glaciers in Pakistan's HKH (Himalayan Karakorum Hindu Kush) area to recede. Glacial lakes form beneath glacial deposits as glaciers recede, rupturing and releasing massive amounts of water in a matter of hours, triggering disastrous floods known as GLOF (MOCC 2012). In Pakistan's HKH area, the GLOF has caused considerable socioeconomic devastation. In Pakistan, the International Centre for Integrated Mountain Development (ICIMOD) has discovered and documented 5218 glaciers with 2,420 lakes. A possible GLOF hazard exists in 52 lakes, with an incidence frequency of once every 3-10 years. Approximately 35 GLOFs have been documented in the HKH area during the last 200 years. The frequency of burst floods in Pakistan has lately climbed to 1-2 per year" (Qureshi et al., 2012).

2.13.4. COASTAL FLOODS

Cyclones caused by storm surges induced by wind in the Arabian Sea cause coastal flooding in coastal communities. Coastal flooding occurs in Pakistan throughout the months of May, June, September, and October owing to cyclones in the coastal regions of Balochistan and Sindh. Between 1971 and 2001, Pakistan was hit by 14 cyclones. Two successive cyclones, Gonu and Yemyin, caused coastal flooding in Gawadar, Balochistan, in 2007, causing massive damage (Tariq et al., 2012).

2.13.5. URBAN FLOODS

Cloud bursts, severe monsoon rains, and cyclones cause flooding in the major cities and towns. The risk of urban floods has also grown in Pakistan. Karachi, Lahore, and Rawalpindi in Punjab, Karachi and Hyderabad in Sindh, and Peshawar in KPK have all seen significant floods in recent years (Aslam et al., 2018).

2.14. FACTORS OF FLOOD

Floods, according to Zahran, are the worst type of hydro-meteorological and anthropological calamity. Extreme, strong, and long-duration floods are generated by weather phenomena such as prolonged and intense

rainfall/precipitation, cyclones, storms, tidal surges, and drainage alterations when paired with heavy rain (Toriman et al., 2009). Floods caused by rainfall are caused by thunderstorms, according to Doswell, and a single thunderstorm cell can deliver enough rainfall to trigger a flash flood. Floods can be produced by increased runoff owing to ice and snowmelt, impermeable land surfaces with saturated water, inadequate infiltration rates, and land degradation in terms of hydrological reasons. Similarly, even a tiny quantity of rain can cause flash floods on steep slopes, rocky terrain, or in densely populated areas. Weather patterns, it turns out, have a role in determining the amount and location of rain and snowfall. Unfortunately, the volume and duration of precipitation in any particular place is not consistent (Straits et al., 2019). Nott (2006) divides flood causes into two categories: physical (climate factors) and human-influenced (urban development and vegetation clearance). The majority of floods are caused by natural forces all over the world, and the majority of them are caused by persistent rainfall. Cutting down trees has altered flood patterns caused by human activity. Flooding isn't considered a natural catastrophe until it results in the loss of human life or property (Tsakiris et al., 2014). A flood is defined by the European Union (EU) Floods Directive (2007) as a temporary coverage of land by water that is not regularly covered by water. In the meaning of "flowing water," the term can also refer to the tide's influx. This water is collected from the sea, lakes, rivers, canals, and sewers, as well as rains. Natural weather phenomena such as significant rainfall and thunderstorms during a short period of time, protracted rainfall, or extended rainfall are common causes of flooding. It can also be triggered by a combination of high tide and severe weather. Human activities have a significant impact on the severity and frequency of floods in a variety of ways. Flooding has a significant detrimental influence on humanity, but it is also a natural process that shapes the Earth. Anthropogenic and natural causes such as environmental deterioration, deforestation, intensive land usage, and population growth have all been linked to them (Rahman et al., 2019). Flood damages have doubled in the last two decades, according to Termeh et al, with a very quick increase worldwide. The number of individuals exposed to disastrous floods is predicted to continue to double in the future unless proper preventative measures are adopted, according to T.De Groeve and B.Schultz (Chowdhuri et al., 2020). Human activities such as unplanned settlement growth, unregulated

building construction, and substantial land use changes, according to M.T. Dalu, impact the geographical and temporal structure of the danger. This is because unplanned and uncontrolled settlements, as the phrase indicates, are frequently not subject to land use limitations, master plan rules and regulations, or the enforcement of construction and drainage requirements (Abu El-Magd et al., 2020).

2.15. IMPACTS OF FLOOD

Floods, according to research done by the International Flood Initiative (2003), are responsible for the majority of water-related natural disasters, destroying not only people and material assets but also cultural and ecological resources (Tehrany et al., 2019a). Women are more impacted than males, according to Ariyabandu and Wickramasighe (2005), because of their household duties. Furthermore, women have more expertise and abilities to deal with natural catastrophes, yet they are frequently overlooked in policy development (Tehrany et al., 2019b). Flood happens when there is an overflow of urban drainages over the streets to the point that it cannot be absorbed by the soil surface, resulting in property damage, traffic obstruction and nuisance, as well as health problems," according to Odunuga (2012). (Costache et al., 2020). Floods cannot be averted, but their consequences can be reduced by using early warning systems, according to Sinclair and Pegram (2003). Furthermore, many impoverished people live near river banks since these are the only undeveloped regions available to them (Charlton et al., 2006). These people are more vulnerable not just because of their location, but also because of their lack of financial means. Flooding can also be caused by a large body of water overflowing onto land, exceptional hydrological events, or an unexpected presence of water on land to a depth that interferes with routine activity (Caruso et al., 2017). According to Theron (2007), these destructions lead to a long-term food deficit. The impact of the flood on man cannot be overstated since it affected every aspect of his life. This encompasses man's physical surroundings, health, and agricultural goods, among other things. Floods may harm any form of construction, including bridges, automobiles, buildings, sewage systems, motorways, and canals, depending on their volume and pace. It can also lead to

water pollution (Yalcin et al., 2004). Food shortages are typical in the aftermath of floods, according to Parker, because floods usually damage crops and cattle. Businesses might feel the consequences of the loss of livelihoods, and as a result, commercial activity can come to a standstill. (Chen and colleagues, 2009). Long-term consequences of infrastructure damage include disruptions in clean water and electrical supply, transportation, communication, education, and health care¹¹. The loss of a loved one may have a profound effect on children. Furthermore, large relief and recovery costs may deter investment in infrastructure and other development initiatives in the region, and in certain situations, may cripple the already-fragile economy (Fernandez et al., 2014). Loss of resources might result in higher prices for products and services, postponing growth plans. This implies that floods frequently disrupt drinking water supplies, resulting in short-term shortages of potable water as well as significant long-term expenditures associated with restoring drinking water supply to flood-affected households (Aggarwal et al., 2008).

2.16. FLOOD SUSCEPTIBILITY

The mapping and evaluation of flood susceptibility is an important part of flood prevention and mitigation techniques because it identifies the most vulnerable locations based on physical parameters that impact the likelihood of flooding (Teegavarapu et al., 2012). Flood, according to Ali, is the most dynamic natural catastrophe that cannot be completely avoided. However, the magnitude of the repercussions, adverse impacts, and quantity of losses may be reduced by susceptibility analysis, which involves forecasting possible flood regions (Merz et al., 2010). As a result, scientists and governments throughout the world are increasingly concerned about flood susceptibility study and reliable flood modeling. Assessment of flood potential zonation, according to Buchele and Vahidnia, is a proactive work that is regarded a pre-hazard management and planning exercise (Du et al., 2013). Because it is able to recognize Flood susceptibility mapping is an important stage in flood mitigation because it identifies the most vulnerable areas and offers enough lead time for people to adapt to floods in an anticipatory rather than reactive way (Youssef et al., 2011). Flood analysis is extremely important in terms of economic and environmental

effects. To minimize possible harm to natural resources, agriculture, and infrastructure, flood control and preventive techniques are required (Billa et al., 2006). As a result, assessing flood vulnerability is a critical responsibility for early warning systems and emergency services in developing preventative and mitigation methods for future flood events (Markantonis et al., 2013).

2.17. FACTORS OF FLOOD SUSCEPTIBILITY

Flood susceptibility is a requirement for long-term flood risk management since it gives essential information about the best mitigation and adaptation strategies (Jacinto et al., 2016). Flood susceptibility mapping procedures, in general, rely on a number of conditioning factors that describe the physical features of the region being studied. Geology or lithology, morphometric features (e.g., elevation, slope), river network density, soil types or hydrological soil groups, land use/land cover, and other aspects are commonly considered. The spatial size of the desired flood susceptibility study has a big impact on the conditioning factor selection. Basically, if the researched region is big (e.g., on a national size), employing fewer components appears reasonable because obtaining the same data (at the same scale or resolution) for the entire territory is more difficult (Kourialis et al., 2017). Certain research, on the other hand, claim that a small number of factors may improve the chances of receiving some over-rated factors (Zhao et al., 2018). A greater variety of location-specific data and characteristics may be employed in local scale research (e.g., watershed size), allowing for more precise characterization of flooding predispositions (Mahmoud et al., 2018).

The identification and selection of flood conditioning elements, their correlations, and multicollinearity are critical in the flood susceptibility evaluation so that only the most important and independent ones are retained. Multicriteria techniques heavily rely on geomorphic and geomorphic-derived variables, but they also factor in rainfall (annual amount and intensity) and permeability (inferred from soil, geology, and land use data) (Santangelo et al., 2011). These elements may have a role in the occurrence of floods in a certain location (Youssef et al., 2016). For flood susceptibility modeling, several

significant independent factors may be employed and assessed. The independent variables should be quantifiable and gathered over the whole research region, but they should not reflect homogenous geographical data. Nominal, ordinal, interval, or ratio scale conditioning factors are possible (Kourgialas et al., 2013). Many elements may have a role in the occurrence of floods in a certain location, but the same ones may not be sufficient in other situations. Several researchers employed some of these parameters in flood studies because of their usefulness and importance. In determining flood vulnerability, anthropogenic elements associated to flood occurrences, such as urban areas, road networks, and land use, should be considered (Vahid et al., 2018).

2.18. REMOTE SENSING (RS) & GEOGRAPHIC INFORMATION SYSTEM (GIS) ROLE IN FLOOD SUSCEPTIBILITY

2.18.1. REMOTE SENSING (RS)

Remote Sensing (RS) is a term that refers to the use of satellites to In the broadest sense, the measurement or acquisition of information about some property of an object or phenomenon by a recording device that is not in physical or intimate contact with the object or phenomenon under study; e.g., the use of any device and its attendant display for gathering information pertinent to the environment from a distance (as from an aircraft, spacecraft, or ship), such as measurements of force fields, electromagnetic radiation, or acoustic enemas (Das et al., 2019).

The art and science of acquiring information about an object or feature without physically coming into touch with that object or feature is known as remote sensing (RS). It's the method of inferring surface properties from observations of the Earth's electromagnetic radiation (EMR). From the Earth's surface, this EMR can be reflected or released as radiation. To put it another way, RS detects and measures electromagnetic radiation emitted or reflected by distant objects made of diverse materials in order to identify and categorize them by class or kind, substance, and geographical distribution (American Society of Photogrammetry, 1975). Cameras, lasers, and radio frequency receivers, as well as radar systems,

sonar, seismographs, gravimeters, magnetometers, and scintillation counters, are used in the technique. The process of collecting data at wavelengths ranging from ultraviolet to radio. This limited sensation is a practical result of aerial photography (Bui et al., 2019).

2.18.2. GEOGRAPHICAL INFORMATION SYSTEM (GIS)

The tools for producing, maintaining, analyzing, and displaying the data connected with constructing and managing infrastructure are provided by geographic information system (GIS) technology (Tien et al., 2019). A geographic information system (GIS) is a hardware and software system for storing, retrieving, mapping, and analyzing geographic data. A latitude/longitude or UTM coordinate system, which refers to a specific location on the Earth, is used to record spatial characteristics. Spatial characteristics are linked to descriptive information in tabular form. For mapping and analysis, spatial data and related properties in the same coordinate system can be stacked together. Geographic information systems (GIS) can be utilized for scientific research, resource management, and development planning (Khosravi et al., 2018). GIS is a term that encompasses all elements of organizing and utilizing digital geographic data. In the last two decades, GIS technology has been used in a wide range of geographic, engineering, planning, and environmental applications (Pradhan et al., 2009).

Natural hazard assessments have benefited greatly from remote sensing (RS) data and geographic information systems (GIS). For example, these technologies have been used in flood inundation modeling (Cao et al., 2016); flood hazard assessment of cloud prone rainy areas in a typical tropical environment (Pradhan et al., 2009); finding an ideal location for flood shelter (Lee et al., 2012); public engagement in flood risk management through participatory GIS (Chen et al., 2011); flood delineation techniques (Lohani et al., 2012 (Ali et al., 2019)). Remote sensing (RS) methods and Geographic Information Systems (GIS) have been more important in the assessment of geo-environmental risks in recent years (Tiwari et al., 2011).

RS is used for a variety of objectives, including a) analyzing the land's susceptibility and society's vulnerability, b) creating hazard zoning maps and possible damage maps, c) monitoring prospective hazards, and d) dealing with emergency conditions following a catastrophe. Every year, catastrophic floods in Northern Sindh and Southern Punjab inflict mortality and property damage, necessitating the creation of a flood susceptibility approach for detecting flood sensitivity regions and minimizing the losses. Remote sensing (RS) and Geographical Information Systems (GIS) techniques can assist in flood susceptibility modeling by collecting and evaluating large amounts of data in a short amount of time.

2.19. TECHNIQUES/METHODS USED FOR FLOOD ASSESSMENT

It has been demonstrated that the use of remote sensing data in conjunction with Geographical Information System (GIS) tools for analyzing multidimensional events such as landslides and floods, as well as its spatial analysis functioning system, allows all related information to be processed in a sequential manner to demarcate vulnerability zones (Tehrany et al., 2016b). Many research has used remote sensing and GIS-based flood vulnerability analyses and zonation mapping (Pradhan et al., 2010). Various quantitative, knowledge-based, and data-driven methodologies have been used over the years to determine the spatial distribution of flood likelihood; these techniques are divided into three categories: heuristic or index-based methods, process-based approaches, and statistically-based models.

The analytical hierarchy process (AHP) is a traditional approach for analyzing many components that arranges them in a hierarchical order (Samanta et al., 2016). The AHP approach has been widely utilized in hazardous risk management, such as flood risk and vulnerability assessment and mapping. With the use of GIS technology, the AHP method was used to determine the flood hazard risk zone of the Kosi River basin (Chen et al., 2011).

For such forms of catastrophe analysis, researchers have created Multi Criteria Decision Analysis (MCDA) and numerous knowledge-driven approaches since these methods allow them to overcome the difficulties of any previous inventory

data (Rahmati et al., 2016a). For flood susceptibility, a variety of statistical approaches have been used, taking into account the link between historical flood inventory and key geohydrological parameters for flood susceptibility (Tehrany et al., 2014b).

This approach is divided into bi-variate and multi-variate categories, such as Frequency Ratio (FR), Weight of Evidence (WoE), and Logistic Regression (LR) and Artificial Neural Network (ANN) (Jabbari et al., 2018). The Frequency Ratio (FR) approach is a well-known and very easy statistical tool for predicting hazards such as landslides, and it is currently being applied for flood hazard zonation (Rahmati et al., 2016a). The WoE model is a Bayesian probability-based quantitative data-driven strategy that has been expanded to various bi-variate techniques (Tehrany et al., 2015). Multiple linear regressions between dependent and independent variables are referred to as logistic regression (LR). Flood episodes are treated as dependent variables, whereas flood regulating factors are treated as independent variables in many flood risk analyses (Pradhan et al., 2010).

ANN is a mathematical approach that has been employed in all aspects of risks analysis (Pradhan et al., 2010) and has also been used in flood mimicking zones that have been delineated. For flood risk zonation of the KaluGanga river basin in Sri Lanka, Nandalal and Ratnayake (2011) used a conventional technique and a fuzzy logic approach, and the fuzzy based risk map outperformed the others. Machine Learning (ML) technologies provide cost and time saving improved prediction and performance to hydrologists for flood susceptibility and flood prediction, avoiding the troublesome statistical expression from the previous two decades (Huang et al., 2008).

For urban flood susceptibility and risk mapping, the ML approaches Genetic Algorithm Rule-Set Production (GARP) and Quick Unbiased Efficient Statistical Tree (QUEST) were used (Darabi et al., 2019). For flood modeling, Decision Tree (DT) analysis is a machine learning approach that produces verified results (Tehrany et al., 2014a). Khosravi et al. (2018) tested four tree-based approaches for flash flood susceptibility assessments and found that the Advanced Decision Trees method is more accurate.

The Support Vector Machine (SVM) is a novel supervised method for determining flood susceptibility zones that is based on the structural risk reduction principle (Tehrany et al., 2014b). Machine learning methods and their ensemble methods, such as the ensemble of Multivariate Discriminate Analysis (MDA), Classification and Regression Trees (CART), and the Support Vector Machine (SVM) have been used for flood susceptibility in northwestern Iran, have covered up the weaknesses of individual machine learning techniques and are frequently used in flood susceptibility (Billa et al., 2006). Many researchers have contributed to flood susceptibility or hazard mapping by combining two or more methodologies and doing comparative analyses. Rahmati et al. (2016a) used two bi-variate approaches, FR and WoF, in Golestan Province, Iran, and found that the susceptibility map produced by the FR model was more accurate than the WoF model. WoF (Youssef et al., 2015) employed FR, LR, and a combination of FR and LR methods to map flash flood susceptibility in Jeddah, Saudi Arabia.

The results reveal that the FR model outperformed the ensemble technique. Bi-variate and multi-variate techniques, in general, are sophisticated methods for flood susceptibility modeling, and writers prefer them over FR and WoF methods. Because these two natural disasters occurred as a result of several geo-environmental causes, there are no significant differences between the studies of landslide and flood vulnerability. Many landslide susceptibility studies have employed the methods listed above.

For landslide susceptibility analysis, the fuzzy AHP approach, also known as fuzzy extraction of AHP, involves generating fuzzy numbers in place of AHP numbers. Multi-criteria decision analysis (MCDA) is concerned with developing and clarifying judgements and predicting issues using multiple criteria analysis and the determination of the number of options and decision criteria using mathematical methods (Hong et al., 2018). Geographical or spatial decision issues are decision problems that include geographical data (Aragonés et al., 2017).

MCDA has been recognized as a valuable tool for assessing complicated decision issues including incommensurable data or criteria (Balogun et al.,

2015). To handle complicated decision issues, MCDA approaches might be used to incorporate geographical, spatial, environmental, and socioeconomic objectives. Multi-criteria decision analysis may be done in a variety of ways, and many scholars have used it to analyze natural hazards (Termeh et al., 2018). Natural catastrophes such as floods and droughts have been monitored, controlled, and assessed using remote sensing technology. It has aided in the monitoring and mapping of changes in land use and land cover (LULC) (Liao et al., 2009).

Only climate data was previously utilized to understand changes, but satellite observations have recently shown to be a useful source for geographical monitoring.

The current scenario necessitates quick collaboration in order to monitor and mitigate the effects of global climate change (Brouder et al., 1994). A well-coordinated national drought strategy is required in developing nations, which must include monitoring, early warning systems, risk management, impact assessment methods, and a drought preparedness plan (Richards et al., 1999). Adapting to changing climatic circumstances is also an effective method for reducing the effects of any calamity caused by climate change. Adaptation strategies may refer to the measures that are undertaken to reduce and control the expected impacts of disasters (IPCC 2014a).

In Pakistan, the National Disaster Management Authority (NDMC) is keeping an eye on the water situation, particularly in the country's dry regions. SPI, NDVI, TVDI, and a variety of additional technologies are used in their evaluation strategy. According to an NDMA advisory, these tools are useful for assessing the area's dry and rainy periods, and if correctly maintained, they may be utilized as an early warning system (Yahaya et al., 2010). Flood susceptibility analysis is now a tool for overcoming flood threats by statistical study of flood determining elements in an RS and GIS setting (Aina et al., 2014).

The purpose of this research was to determine the future vulnerability of flood catastrophes in the study regions, which included Bahawalpur and Rahim Yar Khan in southern Punjab and Sukkur, Larkana, and Jacobabad in northern Sindh.

The study's main purpose is to look into flood-prone locations and use the frequency ratio (FR) model to develop a flood vulnerability map for specific areas. The FR model is a GIS-based tool for producing scientifically accurate flood susceptibility maps.

CHAPTER 3

MATERIAL AND METHODS

3.1 STUDY LOCATION

3.1.1. SOUTHERN PUNJAB

South Punjab climate is fragile due to its geographic location, lower adaptability and a strong dependency on the natural surroundings. It has a population of approximately 40 million people. In this report, two cities in Punjab's interior witness severe flood conditions (i.e., Bahawalpur and Rahimyar Khan) (Khalid, et al., 2009).

3.1.1.1. BAHAWALPUR

The Bahawalpur district is found in Pakistan's Punjab province. Bahawalpur is Pakistan's 11th most populous city, with a population of 762,111 according to the 2017 census. According to Pakistan's 2017 Census, the city's population increased to 762,111 people from 408,395 in 1998. Bahawalpur District is located at an elevation of 117 meters above sea level. "Desert" is how the local climate is described. Bahawalpur receives almost minimal rain throughout the year near the location. This type of climate is defined as BWh by Köppen and Geiger. The average annual temperature of Bahawalpur is 25.7 °C | 78.3 °F. The average annual rainfall is 143 mm | 5.6 inches (PDS- 2011). The surface geology of Bahawalpur is mainly composed of Alluvium & Extrusive Mud, Older Eolian, Deposits and Stream Deposits. The alluvial plain is located adjacent to the Indus River, whereas the rolling sand dunes cover the Eolian plain of the Cholistan desert. Within this part of the desert the dunes-increase towards the northwest. Other geological composition of the district includes Deposits of Extinct Streams, Older Terrace Deposits, Alluvium, Bedrock, Stream bed and Meander-Belt Deposits. Geologically, Bahawalpur is underlain by a thick sequence of sediments consisting of sand, silt and clay deposits of fluvial and Aeolian origin, ranging in age from Pleistocene to most Recent (Geological Survey of Pakistan).

3.1.1.2. RAHIMYAR KHAN

Rahim Yar Khan, in the Punjab region of Pakistan, is the country's 17th most populous city. Rahim Yar Khan Tehsil is the district capital of Rahim Yar Khan. The city government is organized into nine Union Councils. The population of the city was 233,537 in 1998, however according to the 2017 Pakistan Census, the population increased by 80.02 percent to 420,419 in 19 years. The summers in Rahim Yar Khan are extremely hot and dry, while the winters are nice but often dry and frigid. The average annual temperature in RYK is 26.2°C. The average rainfall in this area is 101 mm. Summer lasts about a month longer than winter. Summer season happens from April and ends in October, and winter exist from November and ends in March. The months of March and November, on the other hand, are especially attractive. Dust storms are a common occurrence during the summer. The average rainfall in the city core is roughly 100 mm (PDS- 2011).

The surface geology of Rahim Yar Khan is mainly composed of Alluvium & Extrusive Mud (28.041%), Older Eolian Deposits (20.580%) and Stream Deposits (17.703%). The alluvial plain is located adjacent to the Indus River, whereas the rolling sand dunes cover the Eolian plain of the Cholistan desert. Within this part of the desert the dunes-increase towards the northwest. Other geological composition of the district includes Deposits of Extinct Streams (13.240%), Older Terrace Deposits (13.552%), Alluvium (1.040%), Bedrock (3.058%), Stream bed and Meander-Belt Deposits (2.786%). Geologically, Rahim Yar Khan is underlain by a thick sequence of sediments consisting of sand, silt and clay deposits of fluvial and Aeolian origin, ranging in age from Pleistocene to most Recent. Both lateral and vertical lithological variation may be found in the sediments, which were created as channel infills, levees, and overbank flood plain deposits. The sediments were put down due to cyclic shifts in the course of the Indus River and its tributaries. The grain size decreases laterally from northeast to southwest, indicating heterogenic deposition circumstances and a reason for differences in layer permeability values. In

general, the absence of continuous clay layers in river deposits indicates the presence of unconfined aquifers (Geological Survey of Pakistan).

3.1.2. Northern Sindh

Sindh borders the Arabian Sea on the north and the Rann of Kutch on the south. Punjab is located in the north, Balochistan is located in the west, and India is located in the east. Sindh has a basic surface configuration. Sindh's climate is usually arid, with the exception of the south, where coastal influences are more noticeable. Strong summer temperatures and poor and erratic rainfall are the most important aspects of the climate. Summertime is when it rains the most. However, both in terms of quantity and time, the uncertainty is extremely high. Winter rainfall, despite its scarcity, is beneficial to crops, especially wheat (Ahmed, et al., 2012). Sindh is Pakistani most populated and urbanised region, accounting for 24.1% of the country total population. Sindh population increase from 41.25 million persons in 2011 to 45.99 million people in 2016 (SPP-2016).

3.1.2.1. Larkana

Larkana is located between the longitudes of 67 56" 20' and 68 29" 34' east and the latitudes of 27 7" 31' and 27 56" 2' north. The district is bordered on the east by Shikarpur and Khairpur states, on the north by Jacobabad, on the west by Kamber Shahdadkot and Dadu, and on the south by Naushero Feroz. Summers are hot and humid in the region, while winters are pleasant. In the summer, the irrigation system and worldwide erosion provide more moisture to the heat. The tropical environment lasts until mid-October, when the evenings grow cooler and the daytime temperatures begin to drop. In the summer, the average and lowest temperatures are around 43°C and 33°C, respectively, and in the winter, they are 21°C and 11°C. The annual rainfall averages between 100 and 125 millimetres. Dust storms are regular, and each year in mid-May, hot winds blow for around 40 days (SPP-2016). Extinct stream deposits from the Quaternary and older terrace deposits cover the area's surface. The streambed and meander belt deposits are the most common types of stream deposits. The loess and flood plain deposits of the middle terrace make up the ancient terrace deposits.

3.1.2.2. SUKKUR

Sukkur lies amid the longitudes of 68 35" 30' and 69 48" 0' east and the latitudes of 27 04" 0' and 28 02" 15' north. To the east is Ghotki district, which borders India, to the northern side is Kashmore district, to the north-west is district Shikarpur, and to the western side and south is district Khairpur. Summers in Sukkur are extremely hot, and winters are extremely dry. Temperatures range from 7 to 22°C in January. The average summer temperature is 35°C, with highs of 52°C on rare occasions. Summer often begins in March or April and lasts until late October. The region receives an average of 88 mm of rain per year (monthly rainfall ranges from 0.59 millimetres to 25.62 millimetres) (PESA-USAID-2014). The district is bisected by the Indus River, which is flanked on both sides by lakes. The district's eastern portion, which includes a portion of Taluka Rohri, juts out east of the Nara as far as Mirpur. The Taluka Mathelo is located to the south and east of the Dahir Canal. Registan is the name of the region. The District's most prominent geographical feature is a flat and level plain. The majority of Sukkur District is covered in Indus alluvium. It is a reasonably level alluvial floodplain developed during and after the Pleistocene period, deposited over a base of tertiary shales and limestone by the river Indus and its tributaries (SMEDA).

3.1.2.3. Jacobabad

The district of Jacobabad is located between 27 55' and 28 29' northern latitudes and 68 00' to 69 44' eastern longitudes, and is bordered on the east by Kashmore area, north by Baluchistan province, south by Shikarpur district and Larkana, and west by Shahdad Kot province. Jacobabad is a popular tourist destination in South Asia. During the second half of July and August, temperatures often rise. In mid-June, the average temperature is 44.33°C, while in January, it is 29.38°C. The coldest month is 22.60°C, and the warmest month is 7.68°C (PESA-USAID-2014).

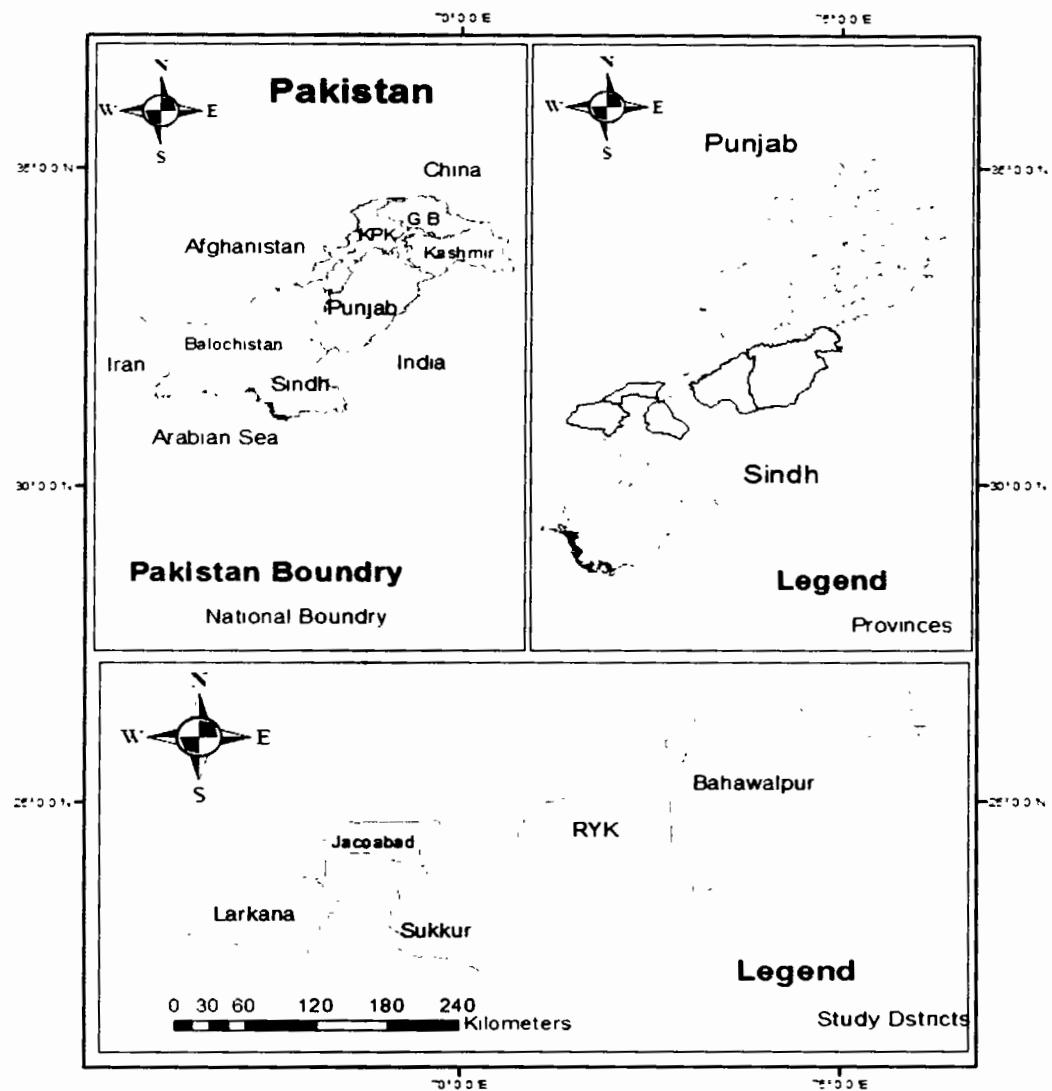


FIG. 1. LOCATION OF THE STUDY AREA.

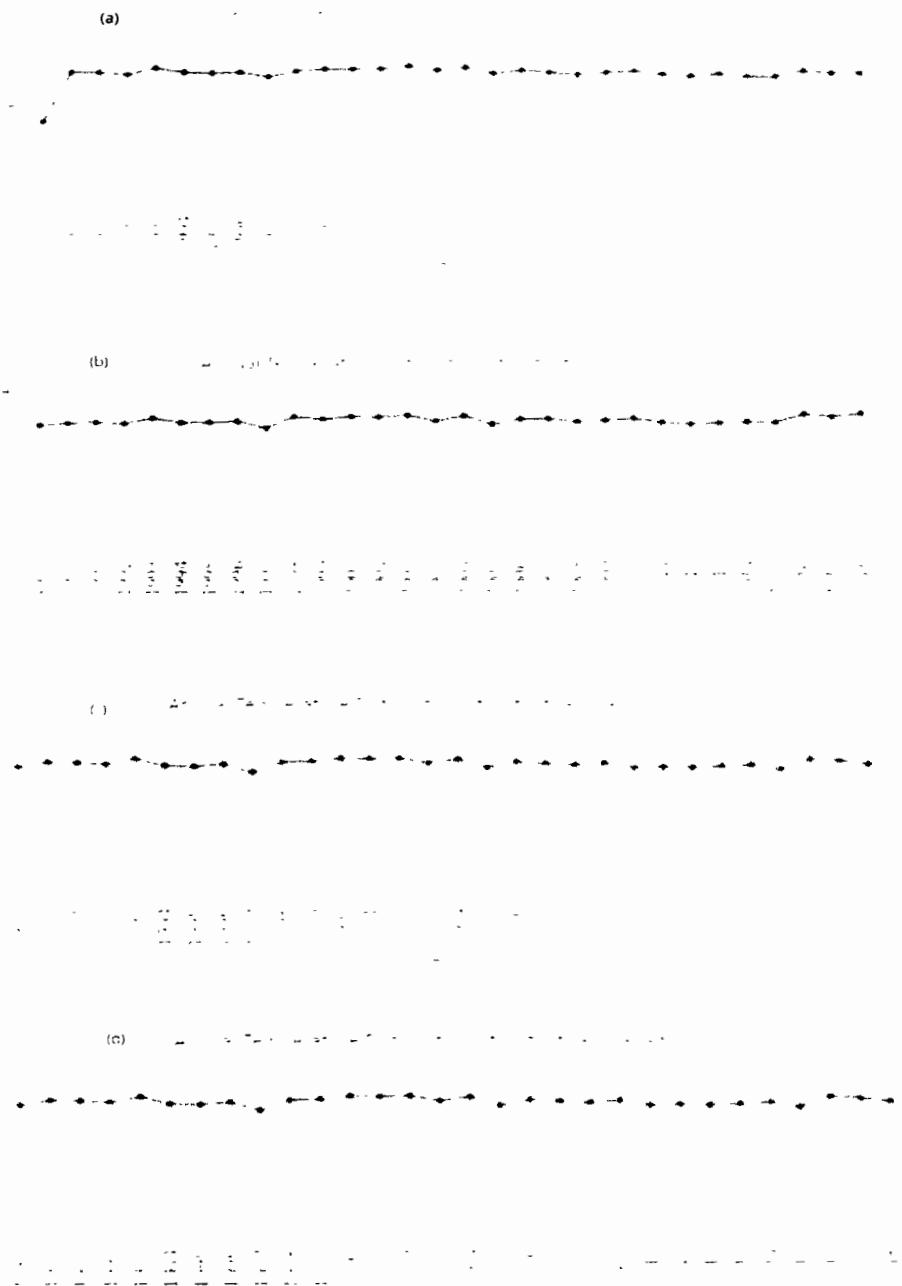


Fig.2. Annual Average Temperature of Study area

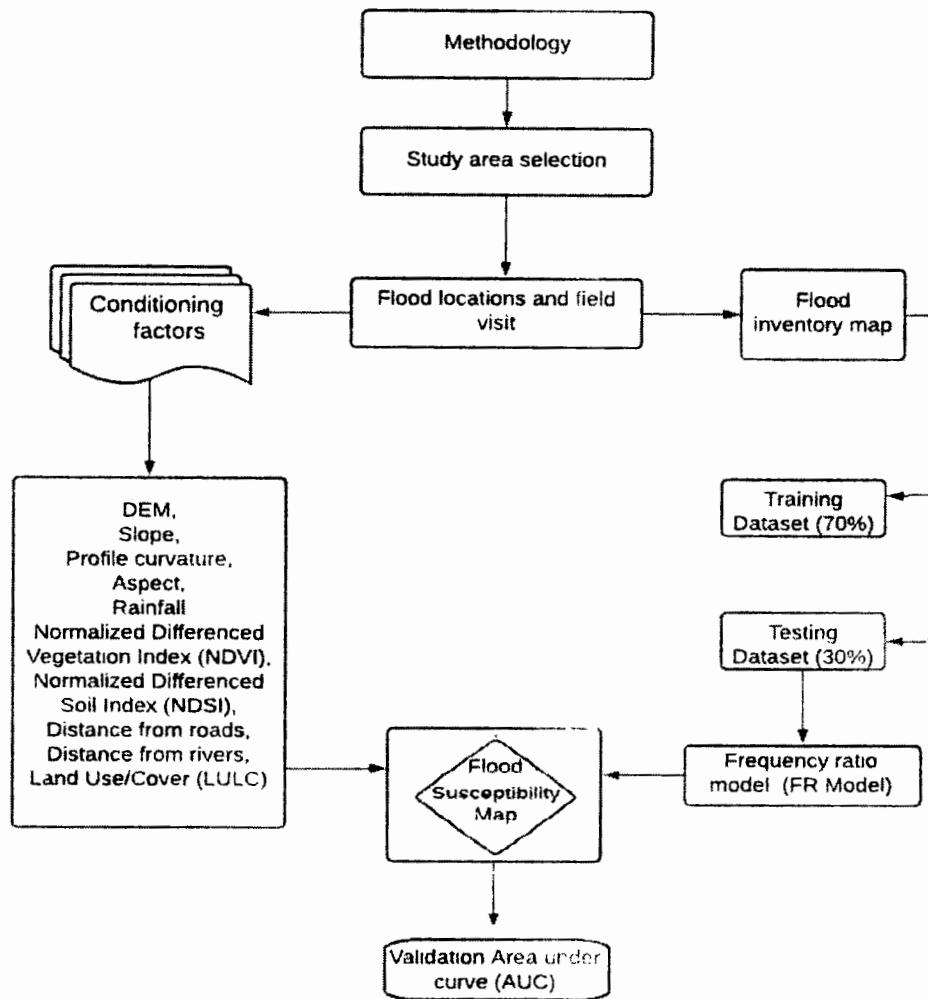


FIG. 3. FLOW CHART SHOWING METHODOLOGY FOR PREPARING FLOOD SUSCEPTIBILITY MAP

3.2. FLOOD ZONE

The floodplain is a low-lying area surrounding a stream or river that flows from the canal's edge to the bottom of the valley walls and is subject to flooding during big storms. A flood area map is a map that shows regions that have been recognized as flood-prone. These so-called flood zones are assigned a numerical value based on the risk of flooding. The flood area's elevation will decide how much damage can be done during the floods and what procedures must be taken to effectively manage them. The main advantage of such maps is to communicate and manage flood-related data (Manjare et al., 2017). Punjab and Sindh are the worst-affected provinces in Pakistan. In numerous sections of these provinces, flooding is a severe hazard. Flood zones are divided in five classes or categories: very low and low, medium, high and very high. Data from the Global Surface Water Explorer was used to alter flood levels in ArcGIS software. Flood zone of northern Sindh and southern Punjab have shown in below fig 4.

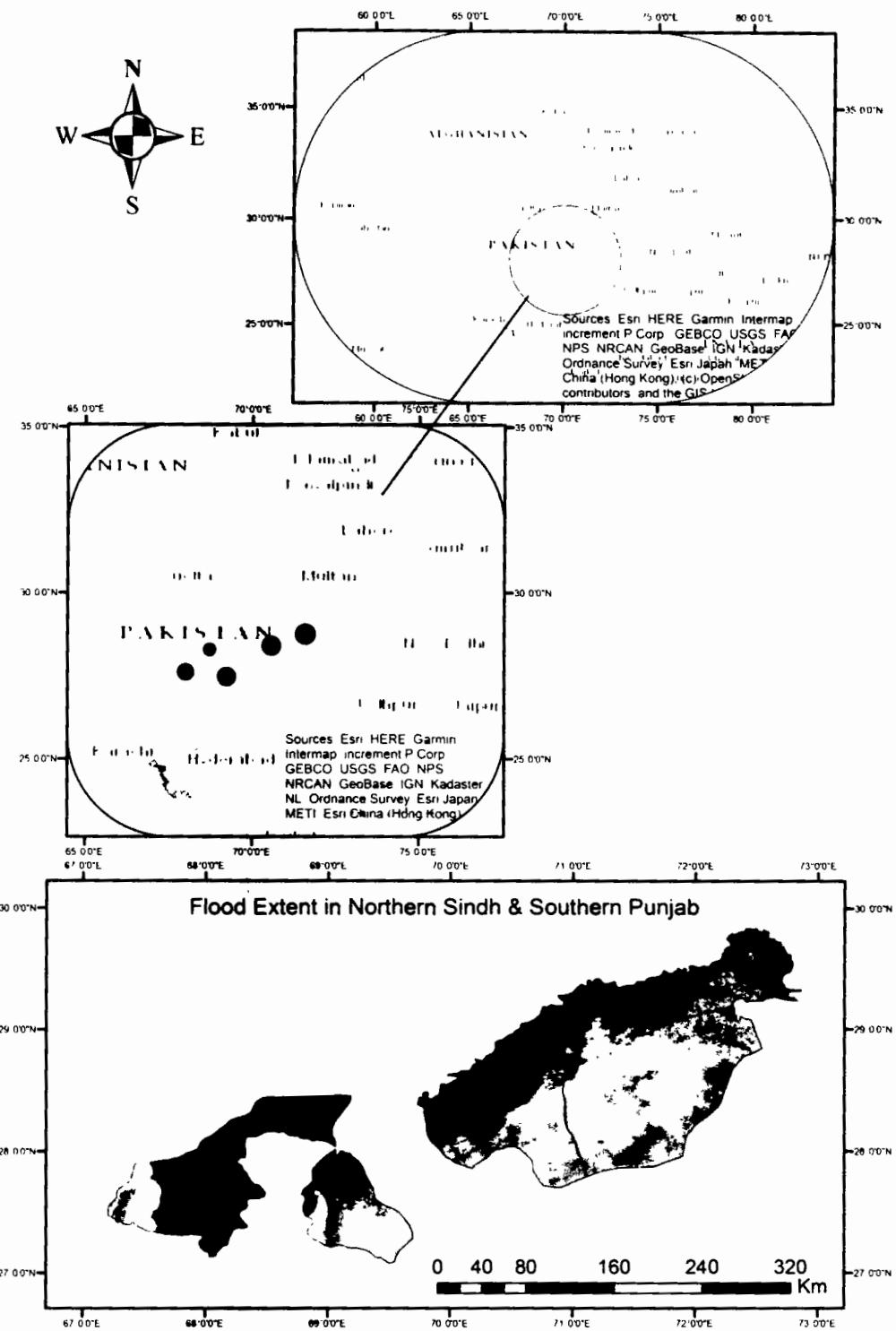


Fig.4. Flood Extent map of Northern Sindh & Southern Punjab upto 2020

Table.3.1. Detail of losses/ Damages due to Floods

DETAIL OF LOSSES/DAMAGES DUE TO FLOODS

| Sr.No | District | Year | Villages Affected | Persons Affected | Area Affected (Acres) | Cropped Area Affected (Acres) | House Damaged partially/ Fully | Persons Died | Persons Injured | Loss of livestock |
|-------|----------------|------|-------------------|------------------|-----------------------|-------------------------------|--------------------------------|--------------|-----------------|-------------------|
| 1 | Jacobabad | 2010 | 3751 | 890,000 | 455,000 | 64,230 | 156,442 | 173 | 1,235 | 9,300 |
| | | 2011 | 1 | 335 | 3,594 | — | — | — | 14 | — |
| | | 2012 | 211 | 899,878 | 29,280 | 400,124 | 48,013/ 54,596 | 53 | 226 | 31 |
| 2 | Sukkur | 2010 | 130 | 247,913 | — | — | 2,957 | 16 | — | — |
| | | 2011 | — | — | — | 16,803 | 225/560 | — | — | — |
| | | 2012 | 130 | 2,590 | 1,983 | — | — | — | — | — |
| 3 | Larkana | 2010 | 405 | 490,000 | N/A | 25,028 | 22,000 | 7 | N/A | N/A |
| | | 2011 | 115 | 54,355 | 11,793 | 5,396 | 5,794 | 6 | 1 | N/A |
| | | 2012 | — | — | — | — | — | — | — | — |
| 4 | Rahim Yar Khan | 2010 | 111 | 394,772 | 272,929 | 117,379 | 60,574/ 33,580 | 8 | 72 | 725 |
| | | 2012 | 1150 | 93,211 | 488,562 | 76,953 | 10,039/ 1947 | 20 | 9 | 552 |
| | | 2013 | 69 | 34,179 | 9,858 | — | 220/337 | — | 2 | — |
| 5 | Bahawalpur | 2011 | 60 | 3,757 | 10,887 | 7,801 | 29 | — | — | — |
| | | 2013 | 53 | 15,404 | 3,183 | — | 912 | — | — | — |

3.3. DATA

3.3.1. SPATIAL TEMPORAL ANALYSIS

3.3.1 FLOOD CONDITIONING FACTOR

In order to create flood susceptibility maps, it is vital to determine the major elements that influence flood occurrence (kia, et al., 2012). As a result, ten (10) conditioning features or factors with a pixel of 30*30 m were utilized in flood

susceptibility modeling: The following factors should be considered: elevation, slope, aspect, Normal difference vegetation index (NDVI), normal difference soil index (NDSI), distance from the river, distance from the road, land use land cover map (LULC), and precipitation/rainfall are all factors to consider. It's important to remember that data from topography has a big impact on modeling outcomes, and that a lack of correct data from topography limits a lot of research (Bates et al 2003). Landscape and derivative features play a critical part in determining flood risk (Pradhan, et al., 2009).

3.3.1.1. ELEVATION

One of the most important approaches for flood prediction is the digital elevation model (DEM), it creates a three-dimensional picture of the terrain's topography Earth Atmosphere and NASA provided a digital elevation model with a resolution of 30 metres based on the Shuttle Radar Topography Mission to the research area (SRTM) (<http://www.dwtkns.com/srtm30m>).

3.3.1.2. SLOPE

The gradient is one of the factors that directly affects rainfall intrusions into that steep slope, producing less recharge because water flows faster from the surface during rainfall, allowing surface infiltration and not giving the saturated area enough time to recharge. (Magesh, et al., 2012). Rainfall is the main source for groundwater recovery in the region. SRTM DEM data was used to get the map as a percentage using the slope function in ArcGIS.

3.3.1.3. ASPECT

The direction of the sphere's surface is indicated by an aspect map. The microclimate is greatly influenced by the direction (angle) one faces in regard to the sun. Flooding is more likely in low-slope or regional flat-surface areas, where water collects and grows. As a result, flat places may be easily identified using this characteristic. Flooding in a flat location is also affected by the direction of the monsoon wind as it hits the surface's slope (angle). SRTM DEM data was utilized to create a face map in ArcGIS using the aspect function.

3.3.1.4. PROFILE CURVATURE

The profile curve was chosen in this study because it has an impact on the rate of soil water flow. The inclusion of the curve is advantageous for accurate representations of velocity since it supports estimations on water depth and model calibration. As a result, the arc map uses the Spatial Analyst tool to measure it.

3.3.1.5. NDVI

Flood susceptibility is determined by a variety of factors in addition to vegetation and soil (Bates, et al., 2003). As a result, the NDVI was created using numerous bands after Landsat 8 which is also called (OLI) satellite images compiled through the USGS EROS database. Low concentrations favor rock, sand, or ice barren environments, whereas higher values favor rain forests with hot and humid temperatures. Low concentrations contribute to barren regions of rock, sand, or ice, as shown in NDVI fig (e), In the red and near infrared regions, there are variances in crop spectral responsiveness. Equation is used to count the number of people in the group(1).

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

3.3.1.6. NDSI

Plants and soils are also crucial elements in deciding whether or not there will be floods (Bates, et al., 2003). As a result, the NDSI was calculated using diverse bands after Landsat 8 satellite images compiled through the USGS EROS database (f). Lower numbers suggest other categories, such as green regions, and higher values imply bare soil areas. To some extent, the soil was differentiated from other soil cover forms consuming the band ratio approach in Raster calculator of Arc GIS (Regmi, et al., 2013). The Equations (2) is used to calculate the sequence.

$$NDSI = \frac{\text{Band7} - \text{Band3}}{\text{Band7} + \text{Band3}} \quad (2)$$

3.3.1.7. DISTANCE FROM ROAD

Roads and their environs serve as obstacles to entry and a source of flow that has a considerable impact on flood levels (Shuster et al., 2006). The Euclidean distance calculator is a useful tool for determining the distance between two points. The distance layer from the motorways was created using ArcMap 10.2's Spatial Analyst tool.

3.3.1.8. DISTANCE FROM RIVER

As water flows from higher terrain and collects at higher elevations, the area near rivers is prone to flooding in both typical floods and floodplains within the river. During heavy rains, these places near other groundwater sources such as lakes, dams, and lakes may be flooded as the terrain around these water sources is almost flat (Reager et al., 2016). However, depending on the weather and climate, pluvial flash floods can occur distant from water sources. The Euclidean distance tool Spatial Analyst in ArcMap 10.2 was used to compute the distance to the river.

3.3.1.9. LULC

The recharge processes are greatly influenced by the land use/cover of a location. Land usage information and a land cover map are provided via a remote sensor and a GIS processor (Soundaranayagam, et al., 2011; Selvam and Sivasubramanian, et al., 2012). Soil, human settlements, crop covers, debris, and other things are included in this feature. In this study, land use has a crucial role in groundwater recharge. Human settlements, such as concrete borders and road construction, operate as impenetrable barriers to water infiltration, preventing groundwater re-installation. Underground vegetation also plays a significant role in groundwater re-installation, as it impacts a variety of processes (Shaban, et al., 2006). To test this capability, a topical map is created using Landsat 8 ETM + satellite imagery in a controlled division. Water bodies, vegetation, landfills, and dry terrain were removed from the four primary categories of LULC. The LULC map is presented in Fig. 12 below.

3.3.1.10. Rainfall

Although it is not known how much rainfall will lead to flood progression (Segond et al., 2007), rainfall is a driver of flood production and its value is an important component in floods (Kay et al., 2006). Annual rainfall was chosen as a component contributing to the mapping of flood risk mapping in distinct regions. (Tehrany et al., 2013). The Pakistan metrological department provided the average yearly rainfall for the previous 29 years (1989-2018) (PMD).

3.3.2. Preparation of spatial database

The process of determining appropriate parameters for a spatial database is a crucial part of the flood susceptibility analysis (Papaioannou, et al., 2015). In most cases, floods are produced by a combination of factors. Despite this, the importance of various elements in determining flood susceptibility differs (Rahmati et al., 2016).

Table. 3.2. Flood predicting factors and their cell size.

| Parameters | Sub – classification | Resolution | |
|----------------------------------|-----------------------------|---------------------|--------------------------|
| | Flood record area's | Flood extent | Point coordinates |
| | Elevation (m) | 30 m | |
| | Slope angle (Degree) | 30 m | |
| | Aspect | 30 m | |
| | Profile curvature | 30 m | |
| Flood predicting factor's | Distance from Roads | 30 m | |
| | Distance from Rivers | 30 m | |
| | NDSI | 30 m | |
| | NDVI | 30 m | |
| | Mean annual rainfall | 30 m | |
| | | | |

Table 3.3. Calculation results of Frequency Ratio and Rational Fraction for all classes of factors

| Factors | Factor classes | No of Points | % of points | Class area | % of class area | FR | RF |
|---------------------|----------------|--------------|-------------|--------------|-----------------|-----|------|
| Elevation | 1 | 6220133 | 8845 | 300.41835 | 94.5 | 750 | 0.69 |
| | 2 | 443751 | 519 | 2148224 | 5.7 | 357 | 0.23 |
| | 3 | 259141 | 3.8 | 1251596 | 0.4 | 182 | 0.05 |
| | 4 | 174696 | 1.43 | 9443745 | 3.3 | 147 | 0.09 |
| | 5 | 58895 | 0.93 | 9323269 | 0.1 | 157 | 0.06 |
| Slope | 1 | 12608913 | 11.60 | 3092551 | 21.30 | 970 | 0.31 |
| | 2 | 13176643 | 19.46 | 3103423 | 24.44 | 157 | 0.24 |
| | 3 | 24461430 | 4.24 | 3115535 | 3.70 | 625 | 2.19 |
| | 4 | 15284928 | 2.08 | 3166904 | 18.43 | 412 | 0.15 |
| | 5 | 11425446 | 0.72 | 3142573 | 0.46 | 304 | 0.09 |
| Aspect | 1 | 12229735 | 12.39 | 3017666 | 21.13 | 672 | 0.23 |
| | 2 | 12609733 | 12.27 | 3167587 | 21.27 | 157 | 0.18 |
| | 3 | 14143836 | 11.77 | 3091763 | 21.62 | 719 | 0.19 |
| | 4 | 13095650 | 1.73 | 3108468 | 11.01 | 717 | 0.19 |
| | 5 | 11516541 | 0.95 | 3080646 | 11.11 | 71 | 0.19 |
| Curvature | 1 | 1344501 | 4.12 | 3107927 | 1.56 | 315 | 0.17 |
| | 2 | 2862535 | 5.7 | 3119407 | 4.58 | 610 | 0.17 |
| | 3 | 21251814 | 21.63 | 3142666 | 35.74 | 748 | 0.21 |
| | 4 | 20172308 | 21.26 | 3154552 | 36.55 | 644 | 0.24 |
| | 5 | 15570458 | 1.25 | 3099145 | 21.41 | 583 | 0.19 |
| NCD | 1 | 13404628 | 23.41 | 731404549 | 1.17 | 313 | 0.37 |
| | 2 | 11191449 | 43.79 | 23870.19214 | 44.30 | 607 | 0.22 |
| | 3 | 12722976 | 4.57 | 2904392269 | 24.46 | 106 | 0.08 |
| | 4 | 12162554 | 25.41 | 295.367359 | 14.09 | 71 | 0.06 |
| | 5 | 1197531 | 22.30 | 299.423645 | 24.44 | 616 | 0.25 |
| NDSI | 1 | 12426523 | 19.34 | 10283.65754 | 1.934 | 301 | 0.05 |
| | 2 | 1079095 | 21.13 | 11770.170437 | 21.13 | 301 | 0.05 |
| | 3 | 12640331 | 21.19 | 11376.233342 | 21.19 | 104 | 0.12 |
| | 4 | 12862422 | 16.16 | 1078.15829 | 18.38 | 408 | 0.25 |
| | 5 | 13170380 | 16.73 | 998.32925 | 18.73 | 616 | 0.52 |
| Distance from class | 1 | 13789599 | 21.83 | 313027 | 39.29 | 115 | 0.35 |
| | 2 | 11158181 | 21.48 | 3170998 | 41.46 | 129 | 0.16 |
| | 3 | 12214768 | 15.74 | 3119756 | 48.36 | 616 | 0.27 |
| | 4 | 13141057 | 14.93 | 3102122 | 21.04 | 121 | 0.07 |
| Distance from road | 1 | 1 | 1 | 3168075 | 16.08 | 203 | 0.99 |
| | 2 | 15138990 | 14.24 | 3103945 | 14.37 | 756 | 0.95 |
| | 3 | 16466134 | 15.67 | 3121.8 | 28.13 | 919 | 1.07 |
| | 4 | 15045568 | 15.41 | 3105401 | 24.92 | 149 | 2.59 |
| | 5 | 15194614 | 14.22 | 3123873 | 1.14 | 176 | 3.34 |
| JIC | 1 | 12710133 | 11.24 | 915759137.96 | 21.54 | 618 | 1 |
| | 2 | 1622170 | 13.67 | 315608358.02 | 12.51 | 619 | 0.29 |
| | 3 | 15419.36 | 31.08 | 3154498975.2 | 21.58 | 1 | 0.05 |
| | 4 | 1552258 | 17.06 | 316663140.60 | 17.06 | 410 | 0.03 |
| | 5 | 1515021 | 9.63 | 312572918.35 | 1.03 | 101 | 0.07 |
| Rental | 1 | 4065 | 1.039 | 3144736 | 10.49 | 129 | 0.13 |
| | 2 | 3478 | 11.5 | 3173151 | 42.82 | 752 | 0.31 |
| | 3 | 2127 | 1.11 | 3145817 | 11.36 | 146 | 0.04 |
| | 4 | 1129 | 1.16 | 3151601 | 11.23 | 106 | 0.01 |
| | 5 | 144.0 | 45.36 | 3110644 | 4.74 | 149 | 0.02 |

3.3.3. FLOOD INVENTORY MAP

Flood susceptibility and risk mapping are heavily influenced by the accuracy with which flood episodes are documented. (Merz, et al., 2007). For the inventory, a total of 230 flood site points were picked. Because by means of the polygon format of the inventory is problematic by the algorithm and exaggerates the outcomes, casual points were determined in the survey. The great majority of connected natural hazard models were based on point-based inventory data (Pradhan, et al. 2010). For training and assessment, the maps were divided into 70%-30% ratios (Ohlamer et al., 2003). For the production of reliant on outcomes, which contained of 0 and 1 standards, with 1 demonstrating the occurrence of floods and 0 demonstrating the absence of floods, training sites (161 points) were picked at random. Non-flooding sites were declared in the amount of 69 places.

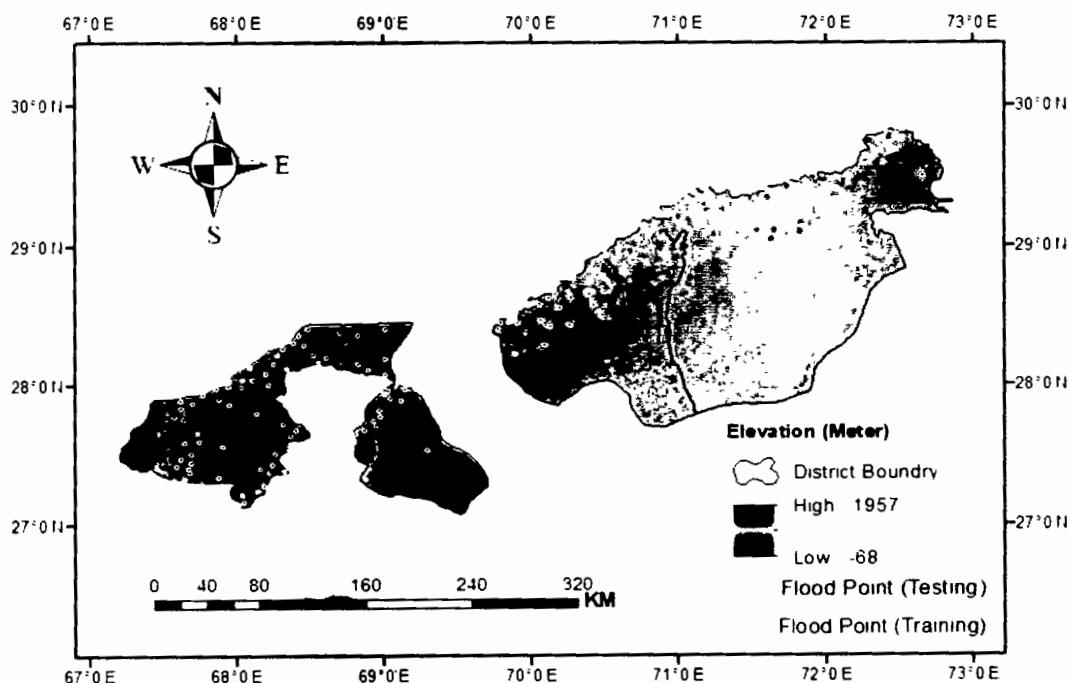


Fig. 5. Flood inventory map of study area.

3.4. BIVARIATE STATISTICAL ANALYSIS

3.4.1. FREQUENCY RATIO MODEL

When evaluating the likelihood of flooding over a specific time period and in a specific location, it is necessary to separate the conditioning elements and conditions that can cause flooding. (Yalcin et al. 2008). The flood susceptibility study was carried out with the help of GIS tools and the FR technique. FR is a particularly steadfast method for BSA because it examines the influence of each acclimatizing component on overflowing and allocates weights with high precision. The FR technique, which is calculated by the connection between overflowing spread and each training component, is using to show the association between flood sites and training elements in the study ground. If the FR value is larger than one, the proportion of floods in the region is higher, indicating a stronger association; however, if the FR value is less than one, the correlation is weaker (Akgun, et al., 2008). In order to discover flood-related factors, flood susceptibility mapping must be analysed. Past overflowing events and their activating features can be used to deduce the connection between floods and associated acclimatizing elements that can induce flooding (Pourtaghi, et al., 2014). In order to reveal flood-related features, flood susceptibility mapping must be evaluated. Past flooding occasions and their activating features can be used to deduce the association between floods and associated acclimatizing elements that can induce flooding. The Flooding Frequency Ratio is calculated by inspecting at the connection between flooding and the factors that produce it (FR). As a result, Table 2 displays the FR of each conditioning component class in connection to a past flood event. The formula (3) was used to compute and measure FR values. (Tehrany et al. 2014a, b).

$$FR = [N_{pix}(SX_i) / \sum_{i=1}^m SX_i] / [N_{pix}(Xj) / \sum_{j=1}^n N_{pix}(Xj)] \quad (3)$$

Each controlling factor incorporated all of the data to construct the final flood vulnerability map after computing the FR values for each class. The following is the formula for making a flood risk map:

Eq 4 is used to normalise the FR as the relative frequency (RF) for a range of probability levels [0, 1] (Regmi et al., 2014).

$$RF = \frac{\text{Factor class FR}}{\sum \text{Factor class FR}} \quad (4)$$

The RF has the disadvantage of giving equal weight to all causal variables after normalization. To overcome this difficulty and establish the reciprocal link between flood causative components, a prediction rate with abbreviated PR or weight was generated by assessing each flood causative component using the training data set Equation 5 (Sujatha et al., 2013).

$PR = (RF_{max} - RF_{min}) / (RF_{max} - RF_{min})$ (5) Finally, the flood vulnerability index was calculated by adding the PR of each issue or component to the RF of each class using Equation 7 (Sujatha et al., 2013).

$$FVI = \sum_{j=1}^n FR \quad (6)$$

The number of flood points in variable X's class is represented by $N_{pix}(SX_i)$, while the number of flood points in variable X's class I is represented by $N_{pix}(SX_i)$ (SX_i). The number of pixels in variable X_j is represented by $N_{pix}(X_j)$, the number of classes in variable X_i is represented by m , and the number of factors or issues in the research area is represented by n .

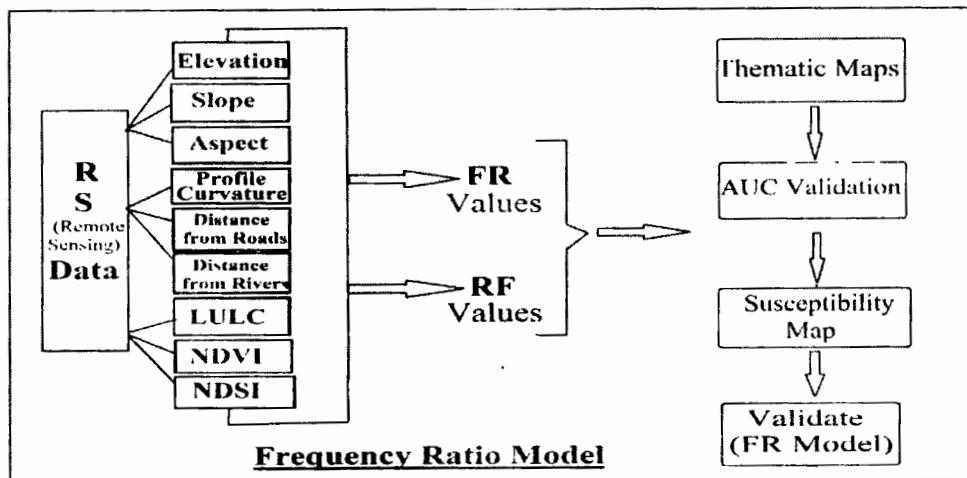


Fig.6. Frequency Ratio Model

3.5. MODEL VALIDATION

While conducting a flood susceptibility assessment, it is critical to identify places that may be impacted by possible flooding. Regardless of the validation approach employed, it is critical to validate the susceptibility maps in connection to known possible floods (Chung, et al., 2003). The AUC is a frequently used, all-encompassing accuracy metric for evaluating prediction or forecast and achievement rates (Pourghasemi, et al. 2012). AUC was used to compare defined flood data with collected flooding likelihood maps as part of the validation procedure (Tien Bui, et al., 2012a). AUC = 1 denoted a high degree of categorization, whilst AUC = 0.5 denoted a random classification. AUC has been used to assess the efficacy of susceptibility mapping in a variety of investigations (Tien Bui, et al. 2012b). One method is to divide the probability or likelihood map into the same area groups, with each probability category determined by the performance and prediction curves. From highest to lowest, the percentages of flood-prone regions are plotted on the x-axis, and flood occurrences are represented on the y-axis. When the slope is steeper, floods are more likely to occur in more vulnerable regions.

CHAPTER 4

RESULTS AND DISCUSSION

In flood susceptibility mapping, many independent variables known as conditioning factors play a key role (Pourghasemi, et al., 2012). The ten (10) conditioning components include elevation, slope, aspect, curvature, NDVI, NDSI, Distance from path, Distance from river, LULC and rainfall, each with their own spatial dissemination and statistical information.

4.1 ELEVATION

Because water moves from higher to lower land regions, elevation is an important role in flood incidence (Sahana, et al., 2019). Flooding is less likely in higher elevation places and more likely in lowland areas, according to previous study (Das, et al., 2019). In general, as the height of the region grows, the FR value decreases (Khosravi, et al., 2019).

Table 2 reveals that the study region's two lowest elevation classes (183m and 183 to 442m) both had higher FR reading of 2.5 and 8.5, revealing a high danger of flood in these locations. Flood is lesser frequent in regions where the FR value is low and the elevation is high. (Khosravi, et al. 2016).

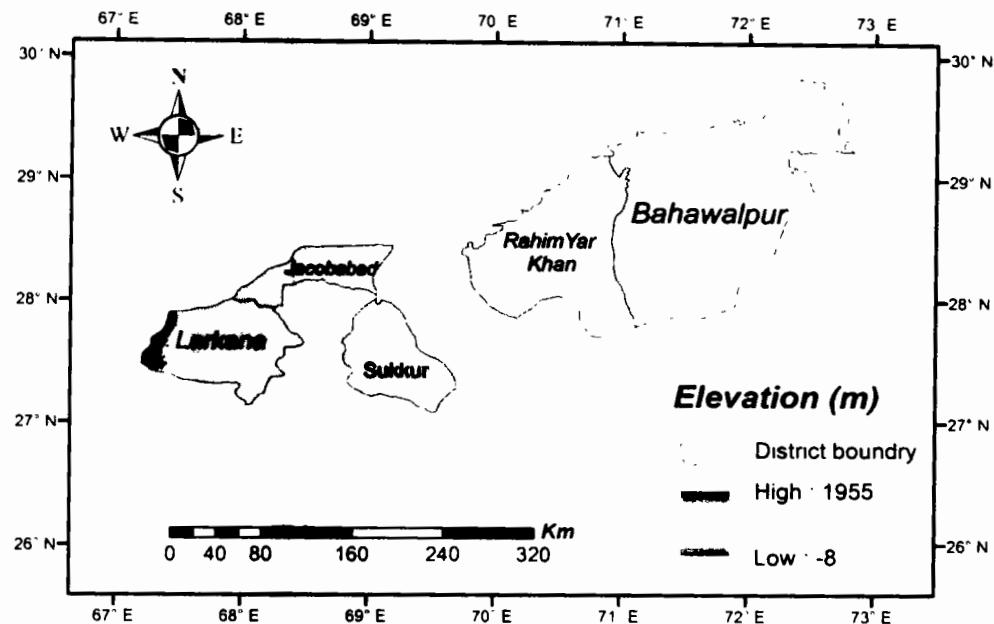


Fig 7. Map of Elevation

4.2. SLOPE

Flooding is controlled by slope, therefore lowland areas are closely linked to the flood situation during the rainy season. Flooding events are more common when the slope grade is lower. (Radmehr, et al., 2015). The gradient of the slope has a

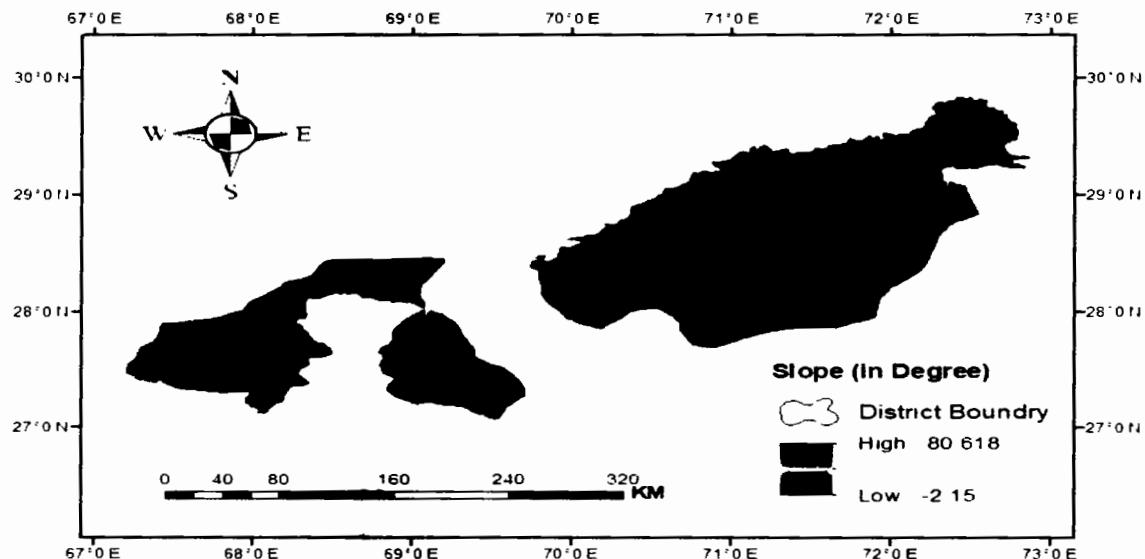


Fig. 8. Map of Slope

big impact on the infiltration process. As a result, an increased gradient delays infiltration while increasing surface runoff, a substantial amount of water becomes stagnant in locations with a steep fall gradient, resulting in flooding (Shafizadeh, et al., 2018). The lowest slope grade evaluations, 2.39° and 2.39° - 5.31°, had the greatest FR radings of 9.7 and 5.7, respectively, according to the results. The slope grade exceeding 24.7°, while has the lowest FR readings of 3.04. Around 59.3 percent of severe floods ensued in studied districts through a slope of lesser than 12.1 percent.

4.3. ASPECT

It can be valuable in hydrologic settings because physiographic tendencies and soil moisture patterns are linked to this component (Ercanoglu, et al., 2002). Floods are more common in regions where water pools and rises, such as those with a low slope or a flat surface. The results revealed that series between 65 and 283 to 359 had high FR readings of 8.9 and 7.1 in this study area. Aspect has a important impact on hydrologic procedures such as evapo-transpiration and forward rainfall direction, as healthy as weathering and vegetative growth, especially in arid regions (Sidle, et al., 2006).

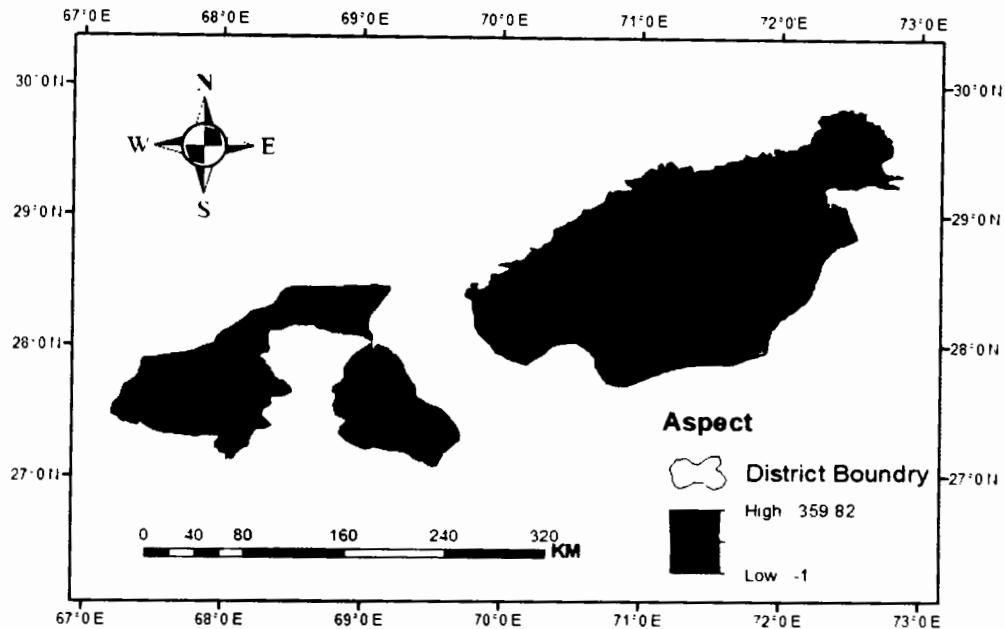


Fig. 9. Map of Aspect

4.4. PROFILE CURVATURE

Another important feature that indicates the topography's morphology is curvature (Razandi Y, et al., 2015). According to the results, the smooth apparent had the maximum RF of 0.61, while the bowl-shaped apparent had the minimum RF of 0.15. (Table 2) It was exposed that 83% of earlier floods took place on flat or convex slopes. Curvature maps are classified into three groups. A positive curvature value is found on a convex surface, a zero curvature value is found on a flat surface, and a negative curvature value is found on a concave surface (Das S, et al., 2019). Hudson and Kesal (2000) investigated the relationship between curvature and flooding in the lower Mississippi River, indicating that curvature between 1.0 and 2.0 is flood-prone (ref). Heterogeneity and hyporheic flow are influenced by curvature, which includes bed formations and water surface topography (Cardenas et al., 2004).

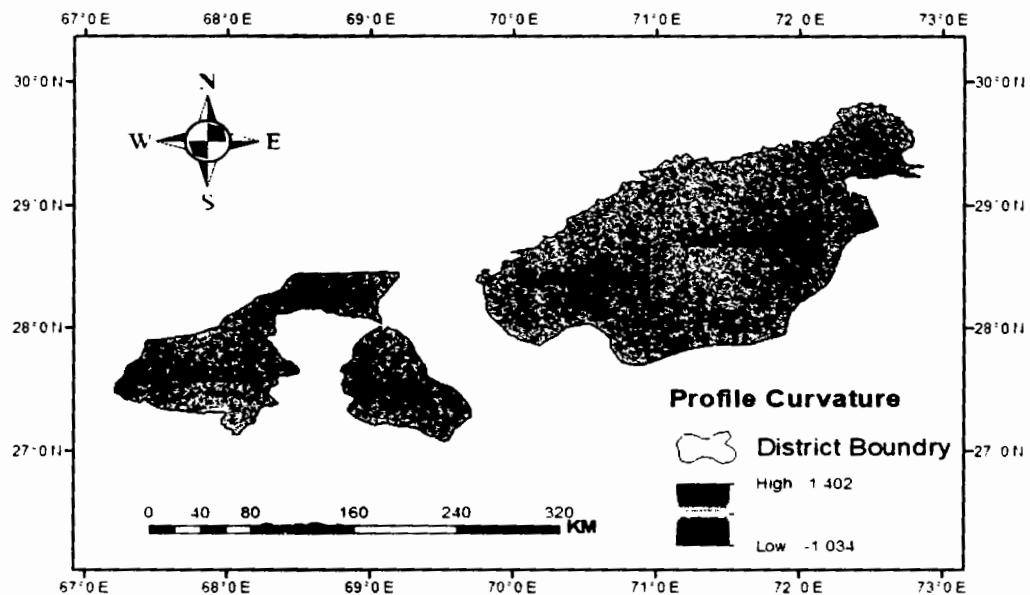


FIG. 10. PROFILE CURVATUR

4.5. NDVI

Another important flooding conditioning factor is the NDVI. The indices' values vary from -1 to +1. (Khosravi K, et al., 2016). Negative numbers suggest water, whereas positive ones indicate vegetation, according to Khosravi. The NDVI values in this sample were quantile split into five groups, ranging from -0.353 to 0.018. For the class -0.353 to 0.018, the highest FR was 0.13 (Table 2).

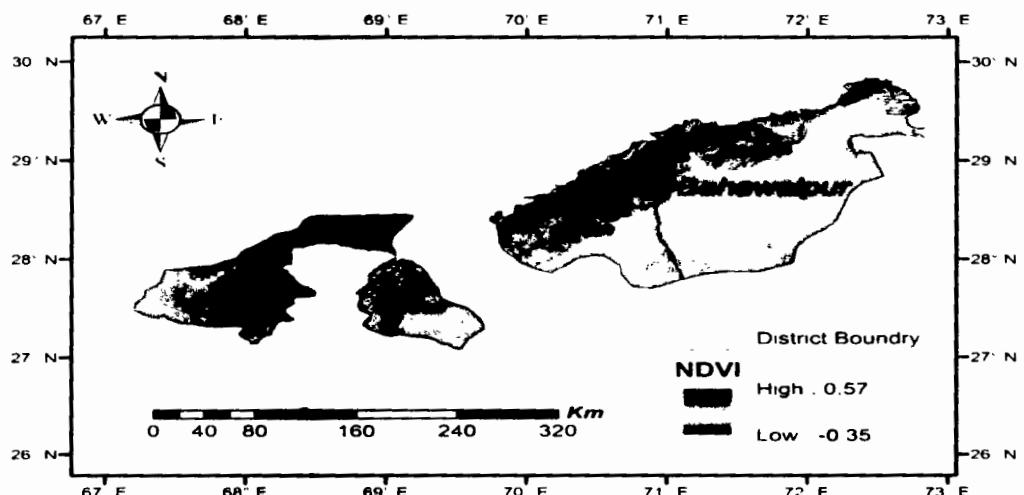


Fig. 11. Map of Normalized Difference Vegetation Index

Flooding is likely in the studied locations, according to the data (Paul, et al., 2019). As a result, the NDVI has a adverse correlation with flooding: greater NDVI degree indicate a lowest risk, whereas inferior NDVI degree signpost a larger risk.

4.6. NDSI

The results showed that in this study area, class heights of 0.135 to 0.225 and 0.225 to 0.511 had higher FR readings of 0.88 and 0.183. The normalised difference soil index (NDSI) was utilised to find signature differences in unmixing coastal marsh using satellite pictures. Deng created the normalised difference soil index (NDSI) by inverting the accustomed normalised difference water index (MNDWI), which is based on bare soil's higher reflectivity in the shortwave infrared wavelength. Despite this, the NDSI is capable of detecting big, dry bare soil parcels, although small, dispersed parcels are frequently disregarded. To detect barren terrain, the thermal infrared wavelength (TIR) has been used (Aghdam, et al., 2016).

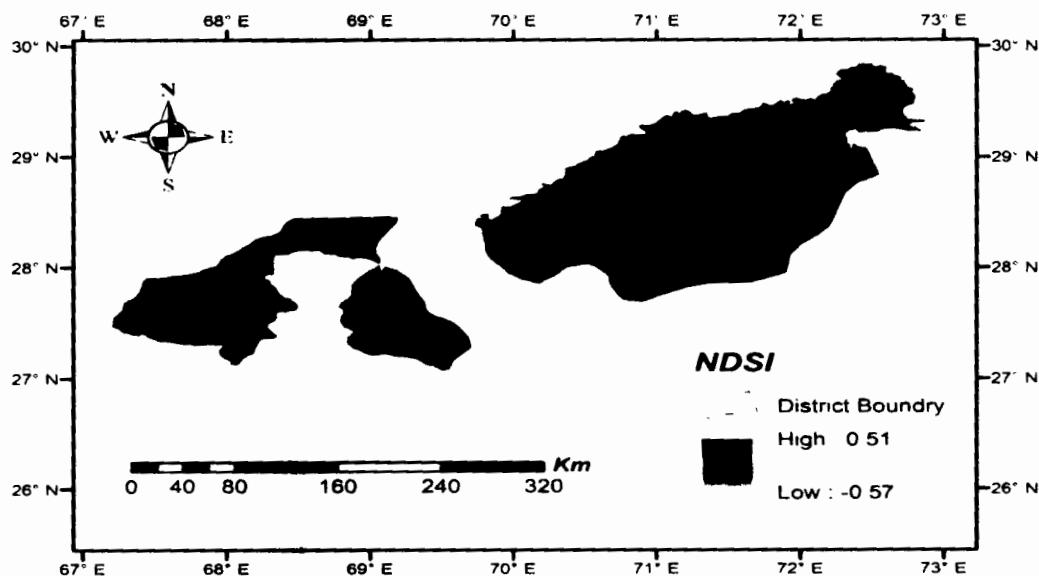


Fig. 12. Map of Normalized Difference Soil Index

4.7. DISTANCE FROM ROAD

The results show that distances shorter than 0.11 m and 0.11 to 0.18 m have high FR values of 8.1 and 7.2, respectively, when measured from the path. The distance from the road is a major consideration in flood vulnerability mapping. Impervious roadways and neighbouring urban surfaces have a substantial impact on flood levels. They serve as a runoff outlet as well as reducing the terrain's penetration potential (Shuster, et al., 2005).

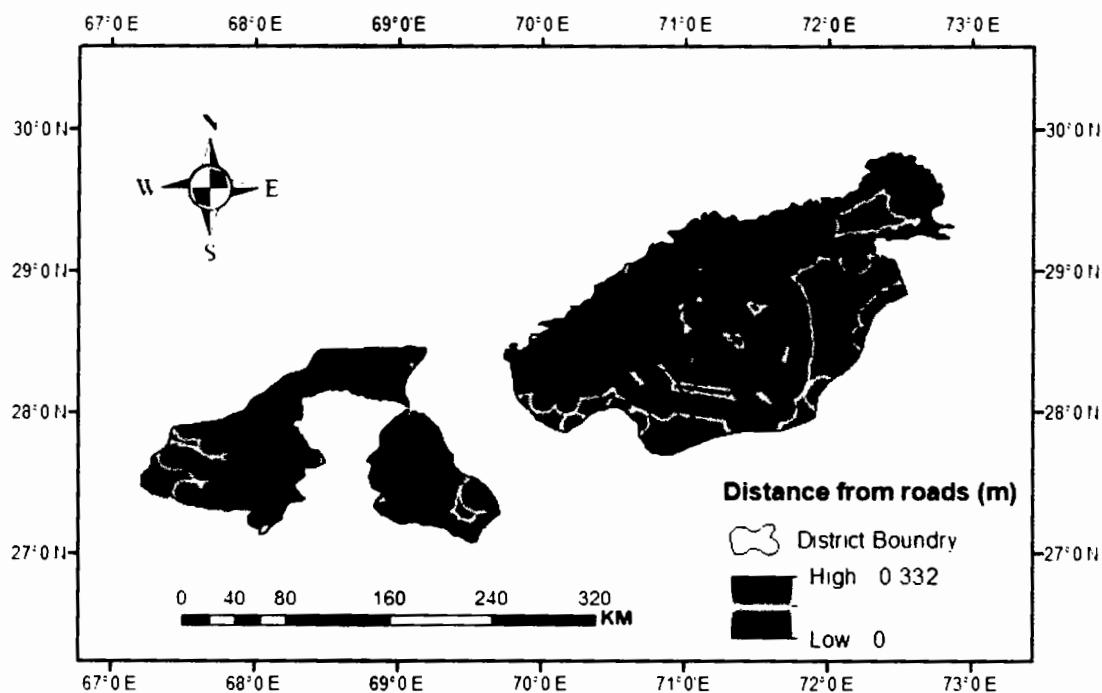


Fig. 14. Map of Distance from Roads

4.8. DISTANCE FROM RIVER

In this study area, the maximum FR values are 8.18 and 1.27, respectively, with class levels ranging from 0.45 to 0.68 and 0.68 to 1.04. Another factor to consider when evaluating flood risk is the distance from the river, as the regions closest to the river's edge are the most vulnerable to high water after a flood. Above the stream's mouth or confluence, the depth is frequently measured. Low-risk areas are those that are far from the stream's mouth or confluence, while those near the stream's confluence are considered high risk (Chapi, et al., 2017)

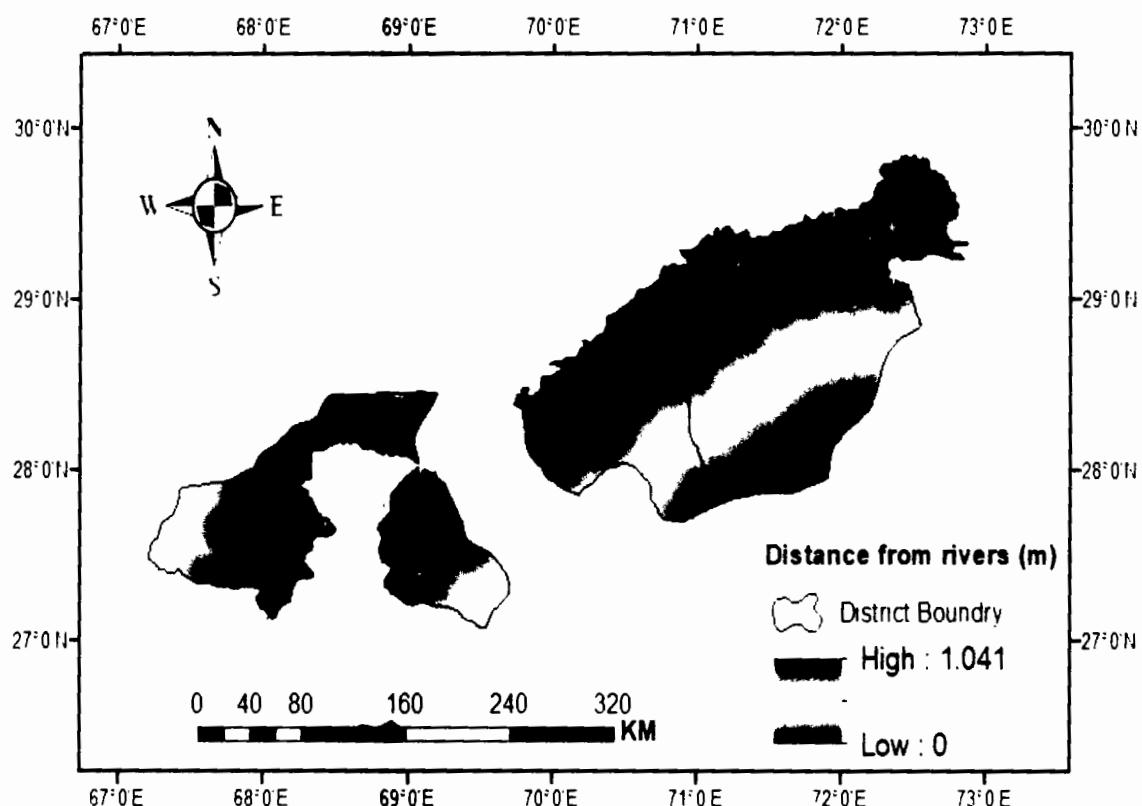


Fig. 14. Map of Distance from River

4.9. LULC

Humans and natural cycles both display patterns of land use (Khosravi K, et al., 2016). High Frequency Ratio values found in the research area in aquatic bodies and agronomic land, respectively, are 0.18 and 0.095, showing that susceptible areas are very vulnerable to floods. Because of the impermeable soil in metropolitan areas, and because there isn't enough vegetation to regulate and prevent water from rushing to the soil surface in fallow farms, runoff is higher. These are the areas that are the most vulnerable to floods and soil destruction. Due of their commercial value, living societies and higher populated, urbanized areas bordering waterways are the most vulnerable to flooding (Nandi A, et al., 2016).

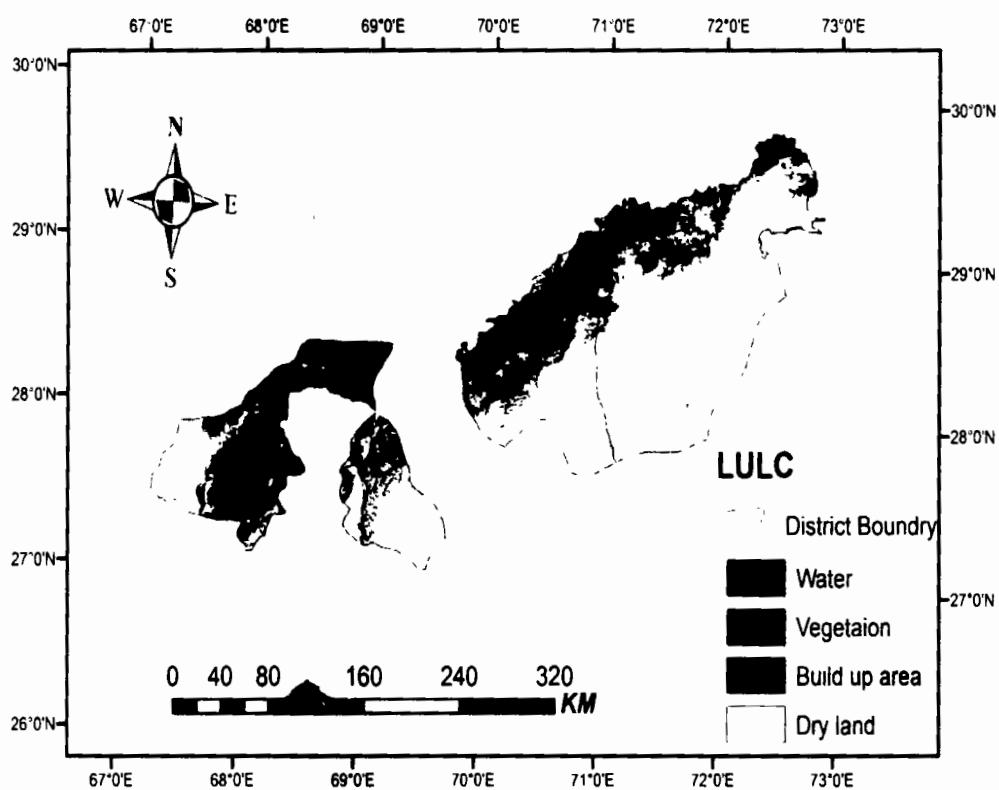


Fig. 15. Map of LULC

4.10. RAINFALL

Apart from glaciers, rainfall/precipitation is the only reason of water availability in the research districts. Flash floods can occur in semi-arid areas due to unexpected rainfall (Das S, et al., 2018). The FR value (6.4) is high in locations where there is a lot of rains in this study area (130.1 to 177.1 mm) .number of prior researchers have discovered a link between flooding and rainfall (Hong H, et al., 2018). The amount of rainfall is the most important cause of floods in every region. No one anticipates floods as a result of the rain (Sahana M, et al., 2019).

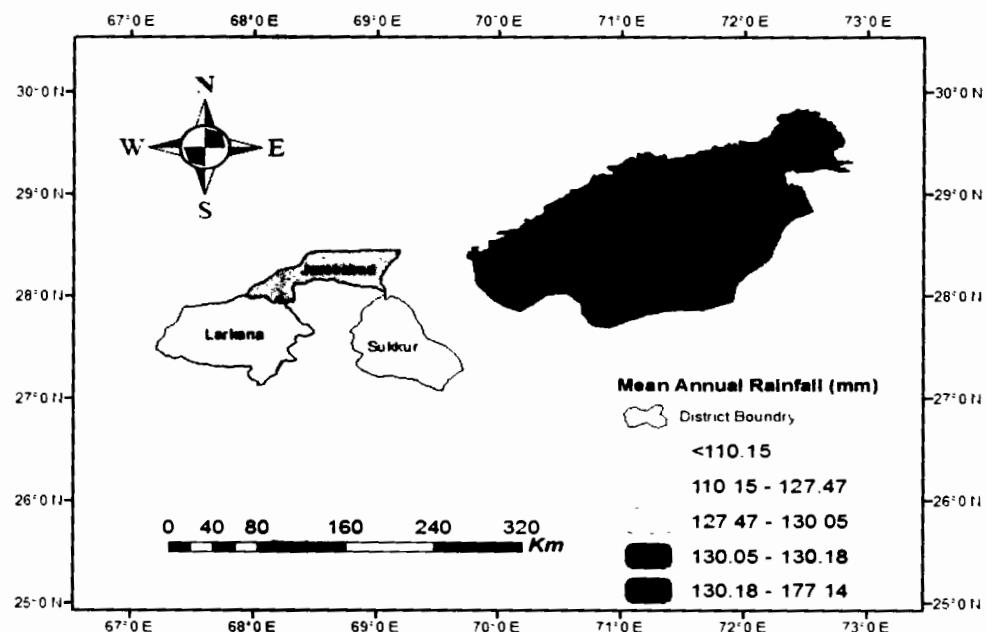


Fig. 16. Map of Rainfall

4.11. FREQUENCY RATIO MODEL

The rankings for every subclass of all acclimatizing factors are determined by the Frequency Ratio FR degrees (Table 2). Susceptible categories range in severity from tremendously higher to exceptionally higher, and they are generally focused in the research area's center (Fig.5). Advanced overflow capability, poorly to very poorly drained soil, alluvial deposits, braided flood plain, lower slope gradient, lower elevation, and earlier immediacy to the main

river characterise these higher to very higher flood vulnerability areas, all of which are important training aspects for flood vulnerability representing using the FR model. Numerous academics have produced models, but in order to evaluate a model for flood susceptibility analysis, it must be tested for accuracy and success rate. The FR model's performance has been verified in terms of success rate and forecast accuracy (Chung, et al., 2003). The model has a maximum accuracy of 1.0, demonstrating that it could reliably anticipate natural risks without bias (Pradhan, et al., 2010). The accuracy forecast was determined using the lasting 69 flood sites that were not used throughout the model building, and the realization rate was obtained using 161 workout flood sites. In the future, floods with vulnerability ratings ranging from 'moderate' to 'very high' are projected.

4.12 FLOOD SUSCEPTIBILITY MAP

The flood risk map was then distributed into 5 categories: very lower (19.73%), low (20.37%), reasonable (20.37%), higher (19.88%), and extremely high (19.88%). (19.62 percent). Further districts, including as Larkana, Rahimyar Khan, Sukkur, and Bahawalpur, are more vulnerable to flooding than Jacobabad. This area is exceedingly susceptible, and it has a very limited adaptive ability. The midsection of the study region is dominated by the high to very high zone. Advanced runoff potential, sedimentary deposits, poor to very poor exhausted soil, weaved flood plain, lowest elevation, lower slope, and immediacy to the centre level describe these reasonable to very higher flood vulnerability zones, which range from "High" to "very high".

Table 4.1. Flood susceptibility zone of study area under different subzones

| Zone | Class | Area (km ²) | Area (%) |
|------------------|-------|-------------------------|----------|
| Very low | 31-44 | 10495 | 19.73 |
| Low | 44-48 | 10831 | 20.37 |
| Moderate | 48-53 | 10835 | 20.37 |
| High | 53-59 | 10572 | 19.88 |
| Very high | 59-72 | 10434 | 19.62 |

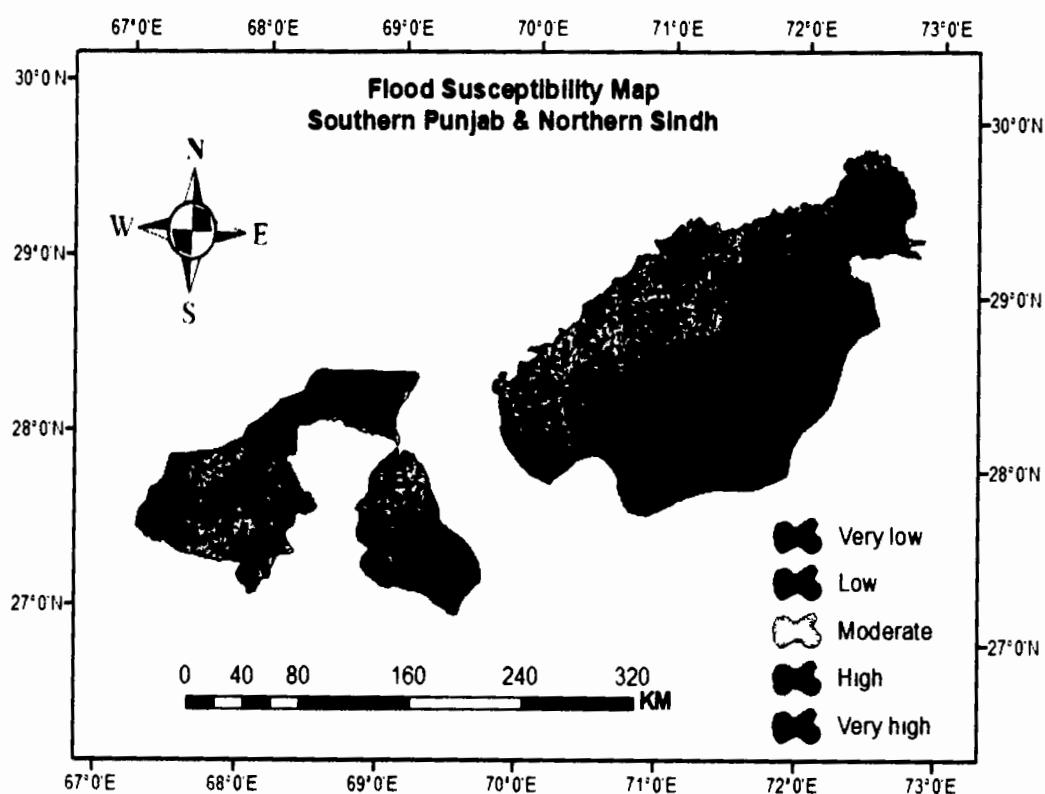


Fig. 17. Map of Flood Susceptibility

4.13. VALIDATION THROUGH AREA UNDER THE CURVE (AUC)

The likelihood and prediction curve determine the flood forecast rate. As a result, in order to establish flood susceptibility mapping performance, it must be examined as an essential result of a model. (Tehrany et al., 2015). The AUC parameter (fig 5) was derived using equation to validate the model in this study (7), The y-axis represents the true positive rate, while the x-axis represents the false positive rate.

P and N represent the total amount of floods and non-floods, respectively, whereas TP and TN represent the integer of pixels accurately categorized by TP and TN (Tien Bui et al., 2018). The validation approach utilized 30% of the whole sum of accessible flood sites. After assessment, the model's AUC was 0.774, resulting in a 0.77 percent realization rate (fig 5). Despite the limitations and precision of the data provided, this fraction was considered acceptable. It also illustrates in what way sound of frequency ratio model and its components performed in the research regions, as well as how precisely floods were predicted.

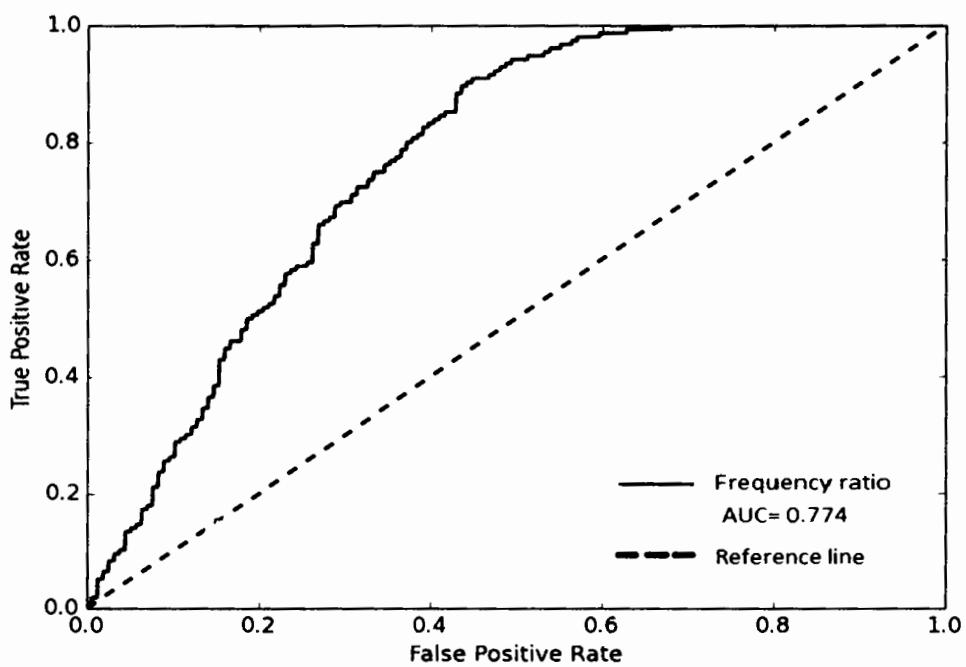
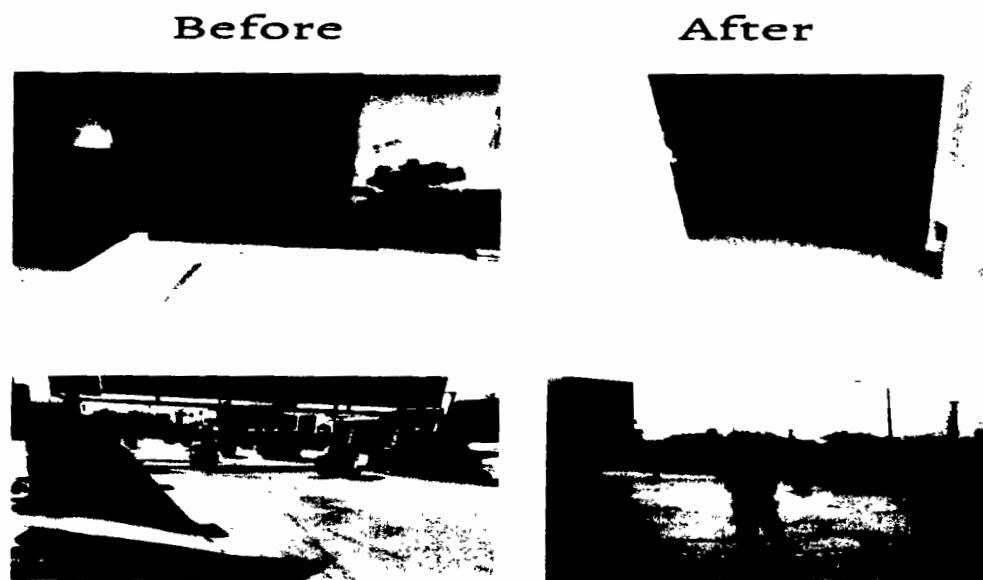


Fig. 18. Validation through AUC

4.14. FLOOD SCENARIO OF PAKISTAN (SINDH & PUNJAB)

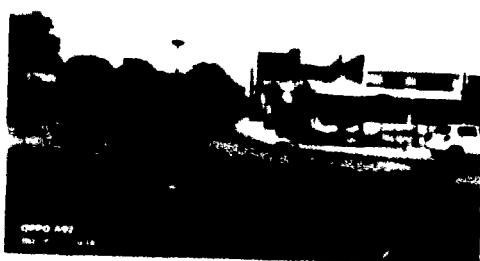
The Indus Plain's flat geography makes riverine floods the most dangerous issue. The second-worst floods in the country are flash floods (hill torrents), which endanger a large area. Floods caused by intense localized rain and cyclones are the norm in other areas. Furthermore, the bursting of tiny dams has resulted in unusually large floods (IFRCP, 2005). Rainfall of less than 200 mm falls on a major section of the country (59.3 percent of total land). The Himalaya Range, however, takes 760 millimeter to 1270 millimeter of yearly rainfall in the north of the country, providing for roughly 72 percent of the Indus River System's mean annual rainfall (Tariq, et al. 2012).



In the last 60 years, the country has had over 19 significant flood occurrences, resulting in cumulative flooding of about 594,700 km², 166,075 settlements, and a total direct cumulative cost of about US \$ 30 billion, with the loss of 10,668 innocent lives. Flooding is a typical occurrence in Pakistan during the monsoon

season, which is exacerbated by river melt. Snowmelt in the north of the country, upstream of Tarbela Dam, contributes to the monsoonal runoff. During the monsoon season in Pakistan, however, urban floods are prevalent, damaging cities such as Karachi, Islamabad, Lahore, and Hyderabad, among others. During the rainy season, various research area locations are listed below, resulting in urban and flash floods.

Before



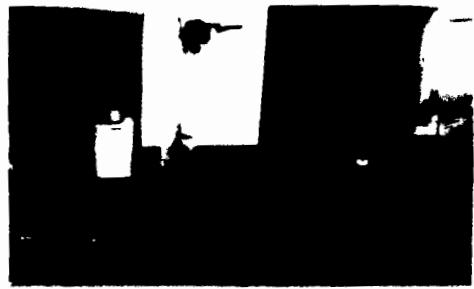
After



Before



After



Two recent examples of such storms are the Yemyin cyclone happened in 2007 and the Phet cyclone happened on 2010. During the flood of 2010, which happened in the year 2010, there was unprecedented devastation, involving the loss of around 1985 lives (Ghatak et al., 2012). Pakistan has experienced significant calamities in recent years as a result of environmental deterioration, i.e. deforestation, such as the successive floods that affected Pakistan in 2010 and 2011. Such disasters are predicted to become more common in the future

years. Pakistan's natural environment and biodiversity are being threatened by changes in environmental conditions such as urbanization and population rise. The volume of forest in the United States fell by up to 3% between 2000 and 2005, according to Federal Bureau of Statistics reports. Overgrazing, farming practices, and the use of wood as a primary basis of energy in rural areas all play a part. The rate at which deforestation is taking place in Pakistan's northern provinces is contributing to rising temperatures. (Ahmed, et al.2015).

Pakistan's hot and dry environment has undergone substantial changes in the previous few years. As a result, major rivers and streams experience severe flooding. Land sliding, on the other hand, creates temporary natural dams that, if breached, cause abnormally great flows into the main rivers, resulting in floods (FFC, 2019). Floods are most common in Pakistan between July and October. Monsoon crops, such as rice, which are planted and harvested domesticated plants, are destroyed as a result. Crops planted in the winter are occasionally affected by flooded terrain that takes too long to dry. Flood water spilling over High River banks in the upper Indus Basin (Khyber Pakhtunkhwa and Punjab) returns to the main river channel, whereas the Indus River runs at a ridge in the lower Indus Basin (Sindh), necessitating the construction of embankments on both river sides. Floodwater that breaches the embankment, on the other hand, does not return to the main river but instead inundates the fields, causing damage not only to the standing crop but also to the surrounding settlements. Due to embankment breaks, the Sindh and Punjab governments have begun repair work on the Barrages, based on a 100-year return time. The Khanki Barrage, Jinnah and Taunsa Rehabilitation, and Sulemanki Barrage have all been constructed on the Chenab, Indus, and Sutlej Rivers. Renovation and repair work on the Panjnad and Trimmu Barrages, as well as the Guddu Barrage, are now underway. In addition, once the final design is completed, restoration work on the Sukkur Barrage will begin.

Flood management planning in Pakistan is being done with three main goals in mind.

- To ensure that existing properties are not harmed.

- To reduce the risks that remain.
- To reduce the severity of future damages.

The nature of Pakistan's flood patterns vary by province. As a result, it's a challenging problem to address, especially for flood-control designers. Unfortunately, due to differing geographic, demographic, climatic, and socioeconomic factors, the catchment areas of distinct rivers have different features. According to the IPCC, one of the triggering elements that has enhanced the Asian Monsoon's precipitation rates is human-caused global warming. However, unless more extensive scientific research is done, this criterion may be illusive (Kronstadt, et al. 2010).

Some of the flood problems in Sindh and Punjab provinces are listed below (FFC, 2019).

4.15.1. SINDH

- The Indus (Sindh) River flows on a edge, with certain portions (such as those near flood embankments) flowing at a lower level than the riverbed. As a result, the river's flow rarely returns to the channel, causing low-lying areas to remain flooded for extended periods of time.
- Flood prevention measures cannot be undertaken in Sindh's upper reaches because the province's tail links to the Arabian Sea.
- A double line of flood walls has been built on both sides of the river from Guddu to a few kilometres short of the Arabian Sea. (According to the FFC).

4.15.2. PUNJAB

- Irrigation structures and headworks, as well as chosen cities and localities, have been protected by protective marginal bunds.
- In the event that flood levels surpass the expected level, pre-determined breaching sections have been provided.
- Spurs were designed to prevent erosion in crucial breach zones. (2019, FFC)

4.16. FLOOD PROTECTION INFRASTRUCTURES IN PUNJAB AND SINDH

1185 protection works have been completed in Punjab's irrigation zones of Lahore, Faisalabad, Sargodha, Multan, Bahawalpur, and D.G Khan. The Guddu Barrage, Ghotki Feeder Canal Area, Sukkur Barrage (Left and Right Bank), Kotri Barrage, and the Left Bank Canal Area Water Board are expected to require 261 protection works in Sindh, according to the report.

4.17. PRECIPITATION:

Precipitation is the most basic input unit to the hydrological cycle, influencing it directly through rainfall or indirectly through snowfall. Due to freeze-thaw action and mechanical weathering, precipitation plays an important role in the occurrence of mass-movement by acting as a medium for debris-flow transit and as a lubricant for mass-movement with slipping and sliding mechanisms (Bempah et al., 2017). Climate variability has been a major source of worry for decision makers as societal repercussions connected to climate have surfaced. Furthermore, some scientists believe that one of the consequences of anthropogenic greenhouse gas emissions to the atmosphere will be an intensified hydrologic cycle. "There is mounting evidence that a warmer climate would result in a more intense hydrological cycle, leading to more heavy rain episodes," according to the Intergovernmental Panel on Climate Change. (IPCC 1996a, IPCC 1996b, IPCC 1996c, IPCC 1996d), Recent theoretical and modeling research (e.g., Trenberth 1998) has bolstered the hypothesis, while observational

studies have bolstered the evidence (e.g., Karl and Knight 1998; Karl et al. 1995a). The association between precipitation and natural disasters varies in strength and location because localized extreme precipitation events occur within the context of large-scale air flow disturbances. Several tropical and subtropical countries are particularly sensitive to shifting precipitation patterns and the resulting hydrological hazards, which can have major implications for human life, health, food and water supplies, ecosystems, and infrastructure (Anderson et al 2015).

4.18. PRECIPITATION AND FLOOD DAMAGE IN PAKISTAN

Agricultural productivity, food production, ecosystems, climate change research, and hydrological modeling all benefit from precipitation variability. (Mir et al., 2010). Water balance, disaster management, and ecosystems are all affected by changes in precipitation patterns, shifts, and new trends. (Awan et al., 2003). Pakistan was ranked eighth most vulnerable country in 2011 and third most vulnerable country in 2012 on the Global Climate Risk Index, out of 180 countries most affected by weather-related losses (Rafiq et al., 2012). The summer monsoon system is critical for Pakistan since it contributes for more than 60% of the country's yearly precipitation. The summer monsoon system arrives from the east between mid-June and the first week of July, and its peak strength lasts until September. Even modest fluctuations in monsoon precipitation, according to studies, might have a detrimental influence on the country's Gross Domestic Product (GDP). Changes in rainfall patterns have a direct impact on water, agriculture, and disaster management (Sheikh et al., 2014). Pakistan is prone to natural disasters such as cyclones, floods, drought, excessive precipitation, and earthquakes, according to the Task Force on Climate Change report (2010). In recent decades, extreme weather events have become increasingly prevalent, frequent, and intense: over 40% of Pakistanis are extremely vulnerable to numerous disasters induced by changes in rainfall patterns, storms, floods, and droughts on a regular basis (Khan et al., 2012). Rainfall patterns have grown uneven and unexpected in most parts of the country, making it impossible for people to plan for their safety, security, crops, and animals (King et al., 2013). For example, on July 29, 2010, As severe

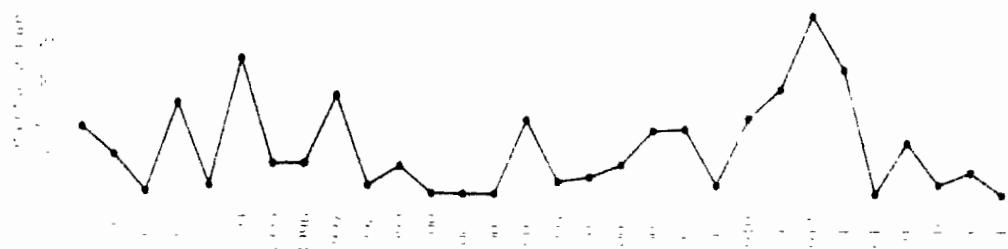
monsoon rains hit Khyber Pakhtunkhwa, Sindh, Punjab, and portions of Baluchistan, the country saw its worst flood in over eighty years. In the worst flood in history, about 2000 people were killed and 700,000 homes were destroyed. A total of 274 mm of rain fell in Peshawar over the course of 24 hours, beating the previous record of 187 mm set in April 2009. Droughts were severe in the southern and central sections of the country from 1998 to 2001. Peshawar had 274 mm of rain in 24 hours, exceeding the previous record of 187 mm set in April 2009 (NDMA 2012). In Asia, rainfall variability has grown spatially, seasonally, and annually over the last few decades. There have also been decreasing tendencies in rainfall patterns in Pakistan's coastal areas and desert plains (IPCC, 2007). The majority of Pakistan has a dry climate, with humidity dominating in a tiny region to the north, according to the Pakistan Meteorological Department. Every year, the whole province of Sindh, the majority of Balochistan, large portions of Punjab, and the core Northern Areas get fewer than 250 millimetres of rain. (Zhang et al., 2011).

In the context of Pakistan, a populous country with an agriculture-based economy and a high susceptibility to natural disasters, it was critical to determine precipitation trends in Pakistan's various climate zones over the last three decades, as well as their significant spatial and temporal variability in the study area. There has been a slow but steady shift in the area where high rainfall occurs. The monsoon rains in Punjab were previously the most intense. Precipitation has slowly and steadily shifted north and west to Khyber Puktonkuwa in the preceding year, according to the Pakistan Meteorological Department (PMD) (Khan et al., 2014).

4.19. DISASTERS & PRECIPITATION TREND (NORTHERN SINDH & SOUTHERN PUNJAB)

4.19.1. DISTRICT JACOBABAD

The district of Jacobabad has a history of natural disasters. Droughts struck the area in 1999 and 2001. Heavy rains and flooding wreaked havoc on the district in in



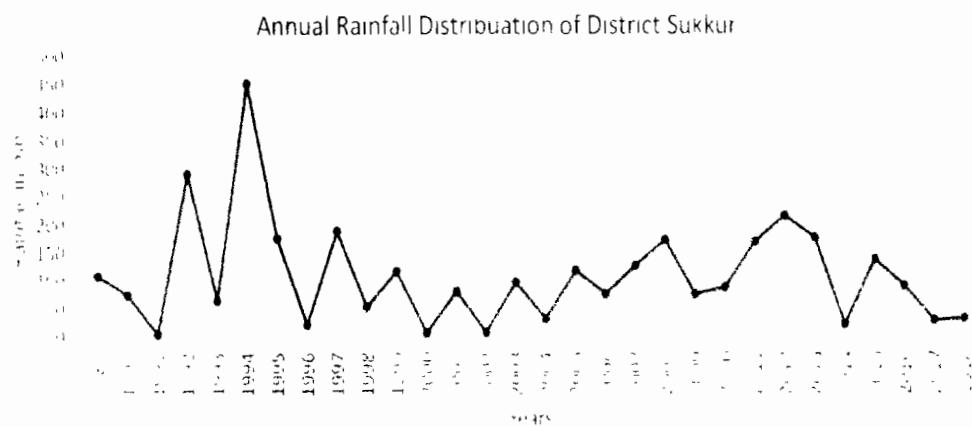
Graph. 1. Annual Rainfall of District Jacobabad

2010, when 938,659 people were affected. In the district of Jacobabad, the relative intensity of floods was assessed as high. In 2012, Jacobabad was devastated by severe floods, worse than ever before, affecting 890,000 people throughout all 40 UCs (NDMA 2012). At the right bank side of the (Sindh) Indus River, the districts of Jacobabad, Larkana, Kashmore, Shikarpur, and Kambar Shahdadkot are located, while on the left bank, the districts of Ghotki, Khairpur, Naushahroferoze, Sukkur, and Shaheed Benazirabad are located. When the River Indus is in high flood, these regions face a serious threat (NDMA 2012). Graph 1 shows that 2012 had a lot of rain, up to 500mm, and 1991, 2000, 2001, 2002, 2014, and 2018 had the least amount of rain. Previous rainfall patterns suggest that it played a role in the district of Jacobabad's flood tragedies.

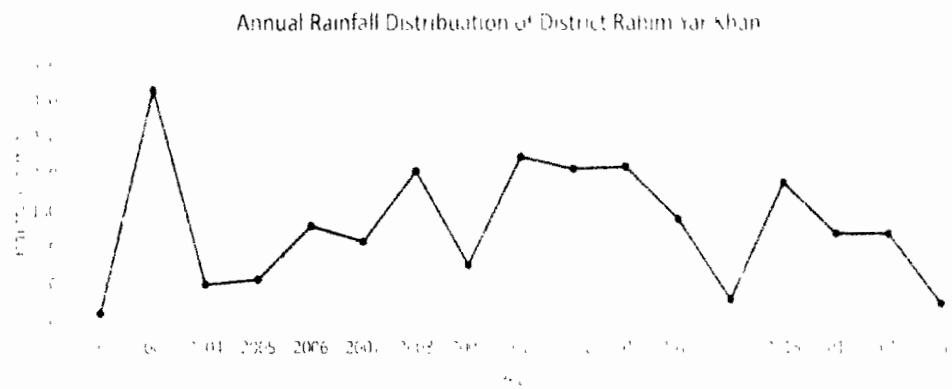
4.19.2. DISTRICT SUKKUR

Sukkur District is one of Sindh's oldest districts. Rains/floods affected it in 2010, 2011, and 2012. Despite the fact that the floods of 2010 were the worst of all, the severity of all disasters was moderate in each year. The Indus River floods the north and south of Sindh province after getting water from five of its tributary rivers (NDMA 2012). At the right bank side of the Indus (Sindh) River are the districts of Jacobabad, Kashmore, Shikarpur, Larkana, and Kamber Shahdadkot, while on the left bank are Ghotki, Sukkur, Khairpur, Naushero feroze, and

Sukkur. When the Indus River floods, these districts on the right and left sides of the river face a major threat. On the right bank of the Indus, Jamshoro, Dadu, and Thatta, and on the left bank, Tando Muhammad Khan, Matiari, and Hyderabad, are all vulnerable to riverine floods. The Indus River runs for 750 kilometres through Sindh province. Rains/floods wreaked havoc on Sukkur in 2010, 2011, and 2012. In comparison to other districts in Sindh, the severity of these floods was mild in Sukkur. PDMA Sindh has designated the district as a low-risk district. In 2010, 130 villages were destroyed. A total of 247,913 people were affected, with 16 people killed. There were 2,957 dwellings damaged in total, with 650 in the pakka area and 2,307 in the katcha area. A total of 37% and 31% of cotton and rice harvests, respectively, as well as 1% of other crops, were damaged. There were no livestock losses reported (NDMA 2012). Graph 2 shows that 1994 had a lot of rain (up to 450mm), while 1991, 1996, 2000, 2002, 2004, 2014, 2017, and 2018 had the least amount of rain. From 2010 to 2012, the district received more than 200 mm of yearly rainfall, indicating its role in flood disasters.



rains, dust storms, and diseases are a regular occurrence. During the floods of 2010, 130 of the district's 1049 villages were seriously impacted (Mazhar et al., 2015). Droughts have also been reported in the district's southern reaches. Thus, in the district of Rahimyar Khan, a lack of education, formal structures, and a variety of other host variables have exacerbated the local population's susceptibility to the aforementioned dangers and calamities (Jain et al., 2015). Punjab's 22 cities, 130 villages, and 61 union councils²³ were impacted by floods in 2010, according to the Disaster Management Authority and Board of Revenue. (Mach et al., 2014). 614,587 people were displaced, and 272,929 acres of land were flooded, according to the report. There were eight people killed and 72 people injured. In addition, 53,465 homes were partially damaged, with 26,560 homes completely destroyed (NDMA 2012). Graph 3 illustrates that the year 2003 had a lot of rain, up to 300mm, and the years 2014 and 2018 had the least amount of rain. From 2010 to 2012, the district received more than 200 mm of yearly rainfall, indicating its role in flood disasters.

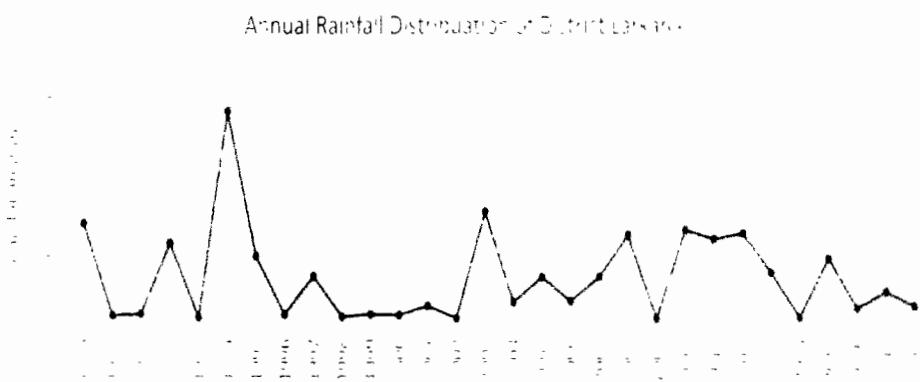


Graph.3. Annual Rainfall of District Rahim Yar Khan

4.19.4. DISTRICT LARKANA

One of Sindh's oldest districts is Larkana. In 1994, 1995, 2003, 2010, and 2011, it was inundated. After getting water from 5 tributary rivers, the Indus River floods Sindh's northern and southern regions. On the right bank of the Indus River are Shikarpur, Kashmore, Jacobabad, Larkana, and Kamber Shahdadkot, while on the left bank are Ghotki, Sukkur, Khairpur, Naushahroferoze, and

Larkana (SMEDA 2013). When the river is flooded, these districts on the right and left banks of the Indus are in grave danger. According to the PDMA Sindh data, the total number of people affected was 490,000 in 2010. The district's inundated crop area was 25,028 acres. According to the PDMA Sindh's rains/floods 2011 report, the district is classified as a low-risk district (PFDP 2010). In 2011, assessments revealed that 115 villages in seven union councils in all four talukas were affected. There were 6 fatalities and 1 injury among the 54,355 people that were affected. A total of 5,794 homes were harmed. Due to the rains/floods, 2.68 percent of the district was flooded, and 2% of the cultivated area was impacted (PBS 2017). Graph 4 shows that the 1994 has high rainfall upto 600mm and 1990, 1991, 1993, 1996, 1998, 1999, 2002, 2009, and 2014 are among the least rainfall year. In last disastrous flood 2010 to 2012 has greater than 200 mm annually rainfall which indicates its contribution in flood disasters in District Larkana.

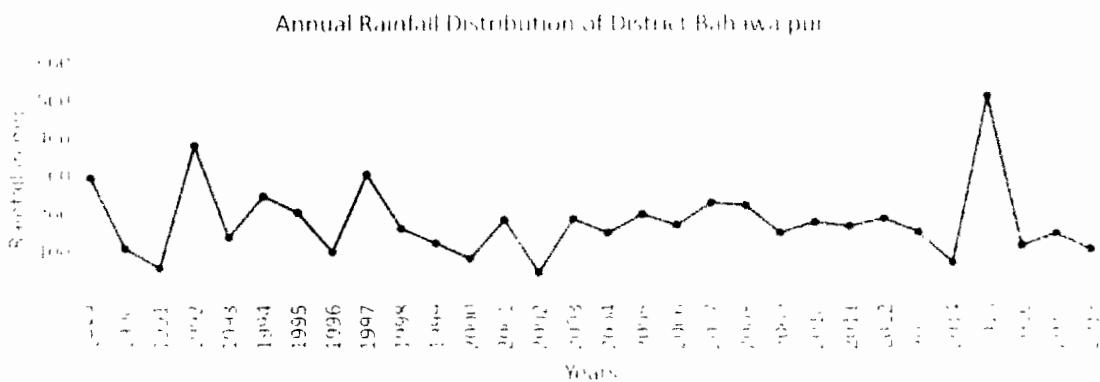


Graph.4. Annual Rainfall of District Larkana

4.19.5. DISTRICT BAHAWALPUR

According to history, floods have never struck Bahawalpur. The city's first flood occurred in 1945, when it was part of the Bahawalpur state (which was disbanded in 1954), Khanwah Khander, Goth Laskder, Jhangiwala, and Dera Bakha were among the villages along the Sutlej River that suffered devastation. The second devastating flood of the Sutlej River occurred in 1988, destroying homes, tube wells, standing crops, model villages, and small industrial estates on

both banks of the river (Khalid et al., 2009). Floods in the neighbouring areas of Goth Laskder, Jhangiwala, Dera Bakha, and other parts of Bahawalpur city were caused by heavy monsoon rainfall in the upper parts of the country, along with a considerable amount of water released by India in the river Sutlej. Erosion along the Sutlej River swamped several villages and devastated thousands of acres of crops from Minchinabad to Ahmadpur East in Bahawalpur as a result of major floods. Floods in the rivers Sutlej and Chenab submerged hundreds of acres in Mauza Kachi Shikrani near Uch Sharif, Ahmadpur East, as a result of a break in an embankment (Khan et al., 2011). As a result, Ahmadpur East has been a flood-prone area in Bahawalpur since 2010, with major flood damage occurring on a regular basis. Similar destruction was wrought by flooding in Ahmedpur East's numerous Union Councils (UCs) and Mouzas in 2013 (Khalid et al., 2010). Graph 5 shows that the 2003 has high rainfall upto 500mm and 1991, and 2002 are among the least rainfall year. Graphical trend indicates that less rainfall contribution in flood disasters in this district Bahawalpur.



Graph.5. Annual Rainfall of District Bahawalpur

4.20. ROLE AND RESPONSE OF COMMUNITY TOWARDS FLOOD SUSCEPTIBILITY

The public's perception of geo-environmental threats has influenced how society evolves and responds to disasters (MacGregor et al., 2013). Experience with the

hazard, a different historical context, and a deficiency of sufficient knowledge about the possibility of a hazard occurring in a place can all influence how the community views the danger and its effects, and determine how successful mitigation steps can be implemented. However, the inability to recognize a hazard in a timely manner may render some areas vulnerable and raise the chance of loss (Wachinger, et al., 2013). For example, due of the opportunities provided in a floodplain, public may be more attentive in living there, and as a result, they may be susceptible to poor flood risk management techniques (Lechowska et al., 2018). When a community's impression of flood is low, which is likely due to the rarity of flood events, the community may be unprepared and vulnerable to tragedy. A population with a good impression of the hazard, on the other hand, tends to be better informed and prepared as a result of their experience with varying degrees of severity (UNISDR 2019). As a result, not just physical science competence, but also a grasp of community awareness, danger perception, and risk behaviour will be required to develop successful mitigation and adaptation measures (Eiser et al., 2012). As a result, studying people's risk perceptions might help uncover susceptibility. In general, combining model findings with community perception for flood susceptibility prediction has gotten little attention, especially in flood-prone areas of Pakistan. The case studies of "Northern Sindh" and "Southern Punjab" are used to fill a gap in the research about the link between modelling findings and community danger perceptions. Nonetheless, this work will provide a solid platform for future flood modelling studies, reducing substantial flood effects in the studied region.

CHAPTER 5

CONCLUSION

Flood vulnerability mapping is critical for reducing severe floods by putting in place real remedies. Flood susceptibility data is a valuable asset for planners when it comes to adopting proper land use in flood-prone locations. The goal of this study is to investigate the interconnection of flood incidence and key factors in Southern Punjab and Northern Sindh, Pakistan, using a BSA-based FR model. Individual layers with 30 m² resolution were produced based on the flood inventory map using elevation, slope, aspect, profile curvature, NDVI, NDSI, distance from road, distance from river, LULC, and rainfall data. A random sample technique was used to choose (161) 70% of the total flood point for validation and (69) 30% for the development of the layers. The accuracy with which factor layers were created is critical for flood-vulnerable mapping authentication. The final flood susceptibility map was divided into five zones: first extremely low (19.73%), second low (20.37%), third moderate (20.37%), fourth high (19.88%), and fifth very high (19.88%). 19.88% is 19.62% of the total population. The vulnerability mapping effectiveness of the current FR model was examined and evaluated using the ROC curve. With a success rate of 77.4 percent, the approach utilized in this study produces reliable and accurate results, according to the product. Since a result, the accuracy of the conditioning factors has a substantial impact on flood susceptibility mapping, as the model's performance improves as the standard level of factors develops. The most relevant criteria and classes for flood-prone sites in southern Punjab and northern Sindh are low slope (-2.15°–2.39°), low elevation (-68–183 m), and high NDVI (-0.353–0.018). Finally, annual rainfall graphs reveal that natural disasters such as floods have the greatest impact on district Jacobabad, whereas it has the least impact on other districts. This model can help the government, planners, and decision-makers in this research districts to build effective management plans and set development boundaries by demarcating flood-prone zones.

RECOMMENDATIONS

- Dam construction appears to be the most viable answer to the flooding issue.
- Through the cooperation of telecom firms and media projection, the early warning system should be improved and an adequate warning mechanism should be established.
- Upon receiving the warning, implement an effective evacuation plan from floodplains and low-lying areas.
- Improve the ability of institutions dealing with floods, and regulate deforestation through a parliamentary legislation. While it is true that floodplains/areas across rivers are fertile for agriculture, afforestation on this alluvial plain is extremely beneficial in flood management.
- The embankments/bunds should be strengthened. The sewerage/drainage system should be improved.
- Residential areas should be relocated to safer locales. The population settlement pattern in floodplains must be revised, and susceptible places must be relocated. Construction and habitation should be avoided in low-elevation areas.
- Educate the community so that they may stay informed about weather conditions and communicate with various disaster management and rescue authorities.
- Observe the government's flood mitigation policy, which includes responding to warnings and evacuating vulnerable locations. Before and after floods, the river should be monitored and the barrages should be inspected.
- Follow the instructions in the building code. Houses with a lifted base, floating houses, or double-story houses with sturdy foundations and lifted pillars should be built.

REFERENCES

Abbas, F., Sarwar, N., Ibrahim, M., Adrees, M., Ali, S., Saleem, F., & Hammad, H. M. (2018). Patterns of climate extremes in the coastal and highland regions of Balochistan, Pakistan. *Earth Interactions*, 22(6), 1-23.

Abdullah, A. F., Vojinovic, Z., & Abdul Rahman, A. (2013). A methodology for processing raw LiDAR data to support urban flood modelling framework: case study—Kuala Lumpur Malaysia. In *Developments in multidimensional spatial data models* (pp. 49-68). Springer, Berlin, Heidelberg.

Abid, M., Scheffran, J., Schneider, U. A., & Ashfaq, M. J. E. S. D. (2015). Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab province, Pakistan. *Earth System Dynamics*, 6(1), 225-243.

Adeagbo, A., Daramola, A., Carim-Sanni, A., Akujobi, C., & Ukpong, C. (2016). Effects of natural disasters on social and economic wellbeing: A study in Nigeria. *International journal of disaster risk reduction*, 17, 1-12.

Adger, W. N., Arnell, N. W., & Tompkins, E. L. (2005). Successful adaptation to climate change across scales. *Global environmental change*, 15(2), 77-86.

Afzaal, M., Haroon, M. A., & Zaman, Q. (2009). Interdecadal oscillations and the warming trend in the area-weighted annual mean temperature of Pakistan. *Pakistan Journal of Meteorology*, 6(11), 13-19.

Aghdam, I. N., Varzandeh, M. H. M., & Pradhan, B. (2016). Landslide susceptibility mapping using an ensemble statistical index (Wi) and adaptive neuro-fuzzy inference system (ANFIS) model at Alborz Mountains (Iran). *Environmental Earth Sciences*, 75(7), 1-20.

Ahmed, K., Shahbaz, M., Qasim, A., & Long, W. (2015). The linkages between deforestation, energy and growth for environmental degradation in Pakistan. *Ecological Indicators*, 49, 95-103.

Ahmed, M., & Suphachalasai, S. (2014). Assessing the costs of climate change and adaptation in South Asia. Asian Development Bank.

Aina, Y., & Aleem, K. F. (2014). Assessing the vulnerability of an industrial city to predicted sea level rise using SRTM and GPS observations: the case of Yanbu, Saudi Arabia. *International Journal of Geoinformatics*.

Akgun, A., Dag, S., & Bulut, F. (2008). Landslide susceptibility mapping for a landslide-prone area (Findikli, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models. *Environmental Geology*, 54(6), 1127-1143.

Albritton, D. L., & Dokken, D. J. (2001). *Climate change 2001: synthesis report* (Vol. 397). R. T. Watson (Ed.). Cambridge, UK: Cambridge University Press.

Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183-194.

Ali, S., Liu, Y., Ishaq, M., Shah, T., Ilyas, A., & Din, I. U. (2017). Climate change and its impact on the yield of major food crops: Evidence from Pakistan. *Foods*, 6(6), 39.

Ali, Z. (2005). *Ecology, distribution and conservation of migratory birds at Uchalli Wetlands Complex, Punjab, Pakistan* (Doctoral dissertation, University of Punjab).

Alley, R. B., Marotzke, J., Nordhaus, W. D., Overpeck, J. T., Peteet, D. M., Pielke Jr, R. A., & Wallace, J. M. (2003). Abrupt climate change. *science*, 299(5615), 2005-2010.

Alley, R.B., 2003. Paleoclimatic insights into future climate challenges. *Philosophical Transactions of the Royal Society of London, Series a* 361, 1831–1849.

Andersen, K. K., Azuma, N., Barnola, J. M., Bigler, M., Biscaye, P., Caillon, N., & White, J. (2004). High-resolution record of the Northern Hemisphere climate extending into the last interglacial period. *Nature*, 431, 147-151.

Aragonés-Beltrán, P., Poveda-Bautista, R., & Jiménez-Sáez, F. (2017). An in-depth analysis of a TTO's objectives alignment within the university

strategy: An ANP-based approach. *Journal of Engineering and Technology Management*, 44, 19-43.

Arora, S., Bhaukhandi, K. D., & Mishra, P. K. (2020). Coronavirus lockdown helped the environment to bounce back. *The Science of the total environment*, 742, 140573. <https://doi.org/10.1016/j.scitotenv.2020.140573>

Arshad, A. (2016). Flood Warning App Developed as Part of NASA's Space Challenge. Pt: Pakistan Today,[<http://www.pakistantoday.com.pk>].

Arslan, M., Ullah, I., BAQIR, M., & Shahid, N. (2016). Evolution of flood management policies of Pakistan and causes of flooding in year 2010. *Bulletin of Environmental Studies*, 1(1), 29.

Aslam, M. (2018). Flood management current state, challenges and prospects in Pakistan: A review. *Mehran University Research Journal of Engineering & Technology*, 37(2), 297-314.

Awan, S. A. (2003). Pakistan: Flood Management-River Chenab from Marala to Khanki. *World Meteorological Organization and Global Water Partnership*.

Baig, M.A., 2008: Floods and flood plains in Pakistan. In: 20th International Congress on Irrigation and Drainage, Lahore, Pakistan.

Balogun, A. L., Matori, A. N., & Hamid-Mosaku, A. I. (2015). A fuzzy multi-criteria decision support system for evaluating subsea oil pipeline routing criteria in East Malaysia. *Environmental earth sciences*, 74(6), 4875-4884.

Bates, P. D., Marks, K. J., & Horritt, M. S. (2003). Optimal use of high-resolution topographic data in flood inundation models. *Hydrological processes*, 17(3), 537-557.

Beckmann, A., & Goosse, H. (2003). A parameterization of ice shelf–ocean interaction for climate models. *Ocean modelling*, 5(2), 157-170.

Bempah, S. A., & Øyhus, A. O. (2017). The role of social perception in disaster risk reduction: Beliefs, perception, and attitudes regarding flood disasters in communities along the Volta River, Ghana. *International journal of disaster risk reduction*, 23, 104-108.

Bernhard, G., Fioletov, V., Groß, J.-U., Ialongo, I., Johnsen, B., Lakkala, K., Manney, G., & Müller, R. (2020). Ozone and UV radiation. "State of the Climate in 2019". *Bulletin of the American Meteorological Society*, 101(8), S274–S277. <https://doi.org/10.1175/BAMS-D-20-0086.1>

Berthier, E., Schiefer, E., Clarke, G. K. C., Menounos, B. And Remy, F. 2010: Contribution of Alaskan glaciers to sea-level rise derived from satellite imagery, *Natural Geosciences*. Vol.3, 92–95, Doi: 10.1038/Ngeo737.

Betzold, C., Castro, P., & Weiler, F. (2012). AOSIS in the UNFCCC negotiations: from unity to fragmentation?. *Climate policy*, 12(5), 591-613.

Bhattacharya, S., Sharma, C., Dhiman, R. C., & Mitra, A. P. (2006). Climate change and malaria in India. *Current science*, 90(3), 369-375.

Billa L, Shattri M, Mahmud AR, Ghazali AH (2006) Comprehensive planning and the role of SDSS in flood disaster management in Malaysia. *Dis Prev Manag* 15:233–240.

Bousquet, P., Ciais, P., Miller, J. B., Dlugokencky, E. J., Hauglustaine, D. A., Prigent, C., Van Der Werf, G. R., Peylin, P., Brunke, E. G., Carouge, C., Langenfelds, R. L., Lathière, J., Papa, F., Ramonet, M., Schmidt, M., Steele, L. P., Tyler, S. C., & White, J. (2006). Contribution of anthropogenic and natural sources to atmospheric methane variability. *Nature*, 443, 439–443. <https://doi.org/10.1038/nature05132>.

Boyd, W. (2010). Climate change, fragmentation, and the challenges of global environmental law: elements of a post-Copenhagen assemblage. *U. Pa. J. Int'l L.*, 32, 457.

Braman, L. M., Suarez, P., & Van Aalst, M. K. (2010). Climate change adaptation: integrating climate science into humanitarian work. *International Review of the Red Cross*, 92(879), 693-712.

Broecker, W. S. (2000). Was a change in thermohaline circulation responsible for the Little Ice Age?. *Proceedings of the National Academy of Sciences*, 97(4), 1339-1342.

Bronstert A. 2003. Floods and climate change: interactions and impacts. *Risk Anal.* 23:545–557.

Brouder, J. A. M. (1994). Flood study in the Meghna-Dhonagoda polder, Bangladesh. Proc. Asian Institute of Remote Sensing.

Bueno Rubial, M. D. P. (2020). The Implementation Phase of the Paris Agreement: The Adaptation Provisions. In Negotiating Climate Change Adaptation (pp. 109-129). Springer, Cham.

Bui, D. T., Pradhan, B., Lofman, O., Revhaug, I., & Dick, O. B. (2012). Spatial prediction of landslide hazards in Hoa Binh province (Vietnam): a comparative assessment of the efficacy of evidential belief functions and fuzzy logic models. *Catena*, 96, 28-40.

Bui, D. T., Pradhan, B., Lofman, O., Revhaug, I., & Dick, O. B. (2012). Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS. *Computers & Geosciences*, 45, 199-211.

Bui, D. T., Tsangaratos, P., Ngo, P. T. T., Pham, T. D., & Pham, B. T. (2019). Flash flood susceptibility modeling using an optimized fuzzy rule based feature selection technique and tree based ensemble methods. *Science of the Total Environment*, 668, 1038-1054.

Cao, C., Xu, P., Wang, Y., Chen, J., Zheng, L., & Niu, C. (2016). Flash flood hazard susceptibility mapping using frequency ratio and statistical index methods in coalmine subsidence areas. *Sustainability*, 8(9), 948.

Cardona, O. D., Hurtado, J. E. and Chardon, A. C. 2003. "Indicators for disaster risk management". In *Expert Meeting on Disaster Risk Conceptualization and Indicators Modelling in Universidad Nacional de Colombia, Manizales 9–11. July 2003*.

Carter, J. G., Cavan, G., Connelly, A., Guy, S., Handley, J., & Kazmierczak, A. (2015). Climate change and the city: building capacity for urban adaptation. *Prog Plan*, 95, 1–66. <https://doi.org/10.1016/j.progress.2013.08.001>.

Caruso, G. D. (2017). The legacy of natural disasters: The intergenerational impact of 100 years of disasters in Latin America. *Journal of Development Economics*, 127, 209-233.

Chapi, K., Singh, V. P., Shirzadi, A., Shahabi, H., Bui, D. T., Pham, B. T., & Khosravi, K. (2017). A novel hybrid artificial intelligence approach for flood susceptibility assessment. *Environmental modelling & software*, 95, 229-245.

Charlton, R., Fealy, R., Moore, S., Sweeney, J., & Murphy, C. (2006). Assessing the impact of climate change on water supply and flood hazard in Ireland using statistical downscaling and hydrological modelling techniques. *Climatic change*, 74(4), 475-491.

Chaudhary, Q. Z., and G. Rasul., 2004: Agro-Climatic Classification of Pakistan. *Science Vision*, Vol.9 No. 1-2 (Jul-Dec 2003) & No. 3-4 (Jan-Jun 2004), 59-66).

Chen, J., Hill, A., Urbano, L. 2009. A GIS-based model for urban flood inundation. *Journal of Hydrology* 373: pp.184–192.

Chen, Y. R., Yeh, C. H., & Yu, B. (2011). Integrated application of the analytic hierarchy process and the geographic information system for flood risk assessment and flood plain management in Taiwan. *Natural hazards*, 59(3), 1261-1276.

Chowdhuri, I., Pal, S. C., & Chakrabortty, R. (2020). Flood susceptibility mapping by ensemble evidential belief function and binomial logistic regression model on river basin of eastern India. *Advances in Space Research*, 65(5), 1466-1489.

Chung CF, Fabbri AG (2003) Validation of spatial prediction models for landslide hazard mapping. *Nat Hazard* 30:451–472.

Cloke H, Pappenberger F (2009) Ensemble flood forecasting: a review. *J Hydrol* 375(3):613–626.

Costache, R., Pham, Q. B., Avand, M., Linh, N. T. T., Vojtek, M., Vojteková, J., ... & Dung, T. D. (2020). Novel hybrid models between bivariate statistics, artificial neural networks and boosting algorithms for flood susceptibility assessment. *Journal of Environmental Management*, 265, 110485.

Cruz RV, Harasawa H, Lal M, Wu S, Anokhin Y, Punsalmaa B, Honda Y, Jafari M, Li C, Huu N (2007) Asia. *Climate change, 2007, impacts, adaptation*

and vulnerability. In: Parry ML, Canziani OF, Palutikof JP et al (eds) Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp 469–506.

Cunderlik, J. M., & Ouarda, T. B. (2009). Trends in the timing and magnitude of floods in Canada. *Journal of hydrology*, 375(3-4), 471-480.

Das, S. (2018). Geographic information system and AHP-based flood hazard zonation of Vaitarna basin, Maharashtra, India. *Arabian Journal of Geosciences*, 11(19), 1-13.

Das, S. (2019). Geospatial mapping of flood susceptibility and hydro-geomorphic response to the floods in Ulhas basin, India. *Remote Sensing Applications: Society and Environment*, 14, 60-74.

Das, Someshwar, S.V. Singh, E.N. Rajagopal and R. Gall, 2003: Mesoscale modeling for mountain weather forecasting over the Himalayas. *Bulletin of the American Meteorological Society*, Vol. 84, no. 9, pp 1237-1244.

Dawood, M., Mahmood, S., Rahman, G., Rahman, A. (2017): Impact of rain-fall fluctuation on river discharge in Hindu Kush Region, Pakistan. – *Abasyn J Soc Sci* 10:246-259.

De Groot, T., Kugler, Z., & Brakenridge, G. R. (2007). Near real time flood alerting for the global disaster alert and coordination system. *Proceedings ISCRAM2007*, 33-39.

Dhar ON, Mandal BN, Ghose GC (1981a) The Vamsadhara flash flood of September, 1980 a brief appraisal. *Vayu Mandali* 3&4:7-11.

District Profile Jacobabad as of December 2010, UNOCHA.

Douglas, E. M., Vogel, R. M., & Kroll, C. N. (2000). Trends in floods and low flows in the United States: impact of spatial correlation. *Journal of hydrology*, 240(1-2), 90-105.

Du, J., Fang, J., Xu, W., & Shi, P. (2013). Analysis of dry/wet conditions using the standardized precipitation index and its potential usefulness for drought/flood monitoring in Hunan Province, China. *Stochastic environmental research and risk assessment*, 27(2), 377-387.

Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., & Mearns, L. O. (2000). Climate extremes: observations, modeling, and impacts. *science*, 289(5487), 2068-2074.

Easterling, W. E., Aggarwal, P. K., Batima, P., Brander, K. M., Erda, L., Howden, S. M., ... & Tubiello, F. N. (2007). Food, fibre and forest products. *Climate change*, 2007, 273-313.

Edwards-Jones, G., Plassmann, K., & Harris, I. M. (2009). Carbon footprinting of lamb and beef production systems: insights from an empirical analysis of farms in Wales, UK. *The Journal of Agricultural Science*, 147(6), 707-719.

Eiser, J. R., Bostrom, A., Burton, I., Johnston, D. M., McClure, J., Paton, D., ... & White, M. P. (2012). Risk interpretation and action: A conceptual framework for responses to natural hazards. *International journal of disaster risk reduction*, 1, 5-16.

El-Magd, S. A. A., Amer, R. A., & Embaby, A. (2020). Multi-criteria decision-making for the analysis of flash floods: A case study of Awlad Toq-Sherq, Southeast Sohag, Egypt. *Journal of African Earth Sciences*, 162, 103709.

Ercanoglu, M., & Gokceoglu, C. (2002). Assessment of landslide susceptibility for a landslide-prone area (north of Yenice, NW Turkey) by fuzzy approach. *Environmental geology*, 41(6), 720-730.

Esteves, L. S. (2013). Consequences to flood management of using different probability distributions to estimate extreme rainfall. *Journal of Environmental Management*, 115, 98-105.

Fahad S, Jing W (2018) Evaluation of Pakistani farmers' willingness to pay for crop insurance using contingent valuation method: the case of Khyber Pakhtunkhwa province. *Land Use Policy* 72:570–577.
<https://doi.org/10.1016/j.landusepol.2017.12.024>

Fahad S, Jing W, Khan AA, Ullah A, Ali U, Hossain MS, Khan SU, Huong NTL, Yang XY, Hu GY, Bilal a (2018b) Evaluation of farmers' attitude and perception toward production risk: lessons from Khyber Pakhtunkhwa Province, Pakistan. *Hum Ecol Risk Assess Int J* 24(6):1710–1722.\

Fahad S, Wang J, Hu GY, Wang H, Yang XY, Shah AA, Huong NTL, Bilal A (2018a) Empirical analysis of factors influencing farmers crop insurance decisions in Pakistan: evidence from Khyber Pakhtunkhwa province. *Land Use Policy* 75:459–467.

Fahad, S., & Wang, J. (2018). Farmers' risk perception, vulnerability, and adaptation to climate change in rural Pakistan. *Land use policy*, 79, 301-309.

FAO (2009) The State of Food Insecurity in the World 2009. Food and Agriculture Organization of the United Nations, Rome, Italy.

FAO (2011) Framework programme on climate change adaptation. Food and Agriculture Organization of the United Nation, Rome.

Federal Flood Commission Annual flood report Office of the Chief Engineering Advisor/Chairman Federal Flood Commission – Ministry of Water Resources, Islamabad, Pakistan (2018).

Federal Flood Commission, "Annual Flood Report 2010", Office of the Chief Engineering Advisor & Chairman, Federal Flood Commission, Government of Pakistan, Ministry of Water and Power, Islamabad, 2010.

Federal Flood Commission. "Annual Flood Report 2012", Office of the Chief Engineering Advisor & Chairman, Federal Flood Commission, Government of Pakistan, Ministry of Water and Power, Islamabad, 2012.

Fernández, D. S., & Lutz, M. A. (2010). Urban flood hazard zoning in Tucumán Province, Argentina, using GIS and multicriteria decision analysis. *Engineering Geology*, 111(1-4), 90-98.

FFC (Federal Flood Commission), "Annual Flood Report 2015", Office of the Chief Engineering Advisor & Chairman, Federal Flood Commission, Government of Pakistan, Ministry of Water and Power, Islamabad, 2015.

Füssel, H. M., & Klein, R. J. (2006). Climate change vulnerability assessments: an evolution of conceptual thinking. *Climatic change*, 75(3), 301-329.

Ghatak, M., Kamal, A., & Mishra, O. P. (2012, October). Background paper flood risk management in South Asia. In *Proceedings of the SAARC workshop on flood risk management in South Asia* (pp. 9-10).

Ghazanfar, M. (2008). Kalabagh Dam and the water debate in Pakistan.

Government of Pakistan, Ministry of Climate Change. (2012). National Climate Change Policy. Islamabad.

Government of Pakistan, Ministry of Planning, Development, and Reforms. (2010). Task Force on Climate Change. Final Report. Islamabad.

Govt of Pakistan (2010) Pakistan economic survey. Finance Division, Govt of Pakistan.

Guha-Sapir, D., Below, R., & Hoyois, P. (2015). EM-DAT: International disaster database. *Catholic University of Louvain: Brussels. Belgium*, 27(2015), 57-58.

Haider, N. (2006). Living with disasters: disaster profiling of districts of Pakistan. *National Disaster Management Authority Islamabad, Pakistan*, 65.

Hamid, A., Akram, N., Bashir, S., & Janjua, Y. (2011). an intuitive analysis of the impacts of floods on achieving MDgS in Pakistan. *Current Research Journal of Economic Theory*, 3(4), 118-128.

Haq, M., Akhtar, M., Muhamad, S., Paras, S., & Rahmatullah, J. (2012). Techniques of remote sensing and GIS for flood monitoring and damage assessment: a case study of Sindh province, Pakistan. *The Egyptian Journal of Remote Sensing and Space Science*, 15(2), 135-141.

Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction*, 14, 256-272.

Haroon, M. A., & Rasul, G. (2009). Principal component analysis of summer rainfall and outgoing long-wave radiation over Pakistan. *Pakistan Journal of Meteorology*, 5(10), 109-114.

Held, H., & Kleinen, T. (2004). Detection of climate system bifurcations by degenerate fingerprinting. *Geophysical Research Letters*, 31(23).

Hewitt, K. (2005). The Karakoram anomaly? Glacier expansion and the 'elevation effect', Karakoram Himalaya. *Mountain Research and Development*, 25(4), 332-340.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., ... & Kanae, S. (2013). Global flood risk under climate change. *Nature climate change*, 3(9), 816-821.

Hodell, D. A., Curtis, J. H., & Brenner, M. (1995). Possible role of climate in the collapse of Classic Maya civilization. *Nature*, 375(6530), 391-394.

Hong, H., Panahi, M., Shirzadi, A., Ma, T., Liu, J., Zhu, A. X., ... & Kazakis, N. (2018). Flood susceptibility assessment in Hengfeng area coupling adaptive neuro-fuzzy inference system with genetic algorithm and differential evolution. *Science of the total Environment*, 621, 1124-1141.

Hong, H., Tsangaratos, P., Ilia, I., Liu, J., Zhu, A. X., & Chen, W. (2018). Application of fuzzy weight of evidence and data mining techniques in construction of flood susceptibility map of Poyang County, China. *Science of the total environment*, 625, 575-588.

Houghton, J. T., Jenkins, G. J., & Ephraums, J. J. (1990). Climate change: the IPCC scientific assessment. *American Scientist: (United States)*, 80(6).

Huang, X., Tan, H., Zhou, J., Yang, T., Benjamin, A., Wen, S. W., ... & Li, X. (2008). Flood hazard in Hunan province of China: an economic loss analysis. *Natural Hazards*, 47(1), 65-73.

Huntington, T. G. (2006). Evidence for intensification of the global water cycle: review and synthesis. *Journal of Hydrology*, 319(1-4), 83-95.

Hussain, A., Agrawal, N. K., & Leikanger, I. (2016). Action for adaptation: bringing climate change science to policy makers—a synthesis report of a conference held in Islamabad on 23–25 July 2015. *Food Security*, 8, 285–289. <https://doi.org/10.1007/s12571-015-0529-7>.

Hussain, M., Butt, A.R., Uzma, F., Ahmed, R., Islam, T., & Yousaf, B. (2019a). A comprehensive review of sectorial contribution towards greenhouse gas emissions and progress in carbon capture and storage in Pakistan 20, 1–20. <https://doi.org/10.1002/ghg.1890>.

Huybrechts, P., Gregory, J., Janssens, I., & Wild, M. (2004). Modelling Antarctic and Greenland volume changes during the 20th and 21st centuries forced by GCM time slice integrations. *Global and Planetary Change*, 42(1-4), 83-105.

Imran, M. Q., Usama, A., Zeeshan, A., Rasli, A. M., Zaman, K., & Khan, F. (2016). Pollution, greenhouse gas emissions and agricultural production in Pakistan: sustainable agriculture key to policy success. *Nat Hazards*, 84, 367–381. <https://doi.org/10.1007/s11069-016-2423-9>.

Intergovernmental Panel on Climate Change (IPCC) (2007a). *Climate Change 2007 – The Physical Science Basis*. Cambridge University Press, Cambridge.

Intergovernmental Panel on Climate Change (IPCC) (2014a). Summary for policymakers, *Climate Change 2014: Impacts, Adaptation, and Vulnerability, Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

Intergovernmental Panel on Climate Change (IPCC) (2020). *Climate Change and Land. An IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems; Summary for Policymakers*.20.

IPCC (2014) *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Intergovernmental Panel on Climate Change.

IPCC, Asia in Climate Change. (2007): *Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge: Cambridge University Press, 469–506.

IPCC. (2013). *Summary for policymakers. Clim. Chang. 2013 Phys. Sci. Basis. Contrib. Work. Gr. I to Fifth Assess. Rep. Intergov. Panel Clim. Chang.* 33. <https://doi.org/10.1017/CBO9781107415324>.

Jabbari, A., & Bae, D. H. (2018). Application of Artificial Neural Networks for accuracy enhancements of real-time flood forecasting in the Imjin basin. *Water*, 10(11), 1626.

Jacinto, R., Grosso, N., Reis, E., Dias, L., Santos, F. D., & Garrett, P. (2015). Continental Portuguese territory flood susceptibility index—contribution to a vulnerability index. *Natural Hazards and Earth System Sciences*, 15(8), 1907-1919.

Jain, V. K., Pandey, R. P., Jain, M. K., & Byun, H. R. (2015). Comparison of drought indices for appraisal of drought characteristics in the Ken River Basin. *Weather and Climate Extremes*, 8, 1-11.

Jeb, D, Aggarwal, S. (2008). Flood Inundation Hazard Modeling of the River Kaduna Using Remote Sensing and Geographic Information Systems, *Journal of Applied Sciences Research*, 4(12), pp.1822-1833

Jebur, MN, Pradhan B, Tehrany, MS. (2014). Optimization of landslide conditioning factors using very high-resolution airborne laser scanning (LiDAR) data at catchment scale. *Remote Sens Environ* 152:150–165.

Jeffers, E. S., Bonsall, M. B., Brooks, S. J., & Willis, K. J. (2011). Abrupt environmental changes drive shifts in tree–grass interaction outcomes. *Journal of Ecology*, 99(4), 1063-1070.

Khalid S, Gilani AH (2009) Distinctive cultural and geographical legacy of Bahawalpur. *Pak A J Pak Stud* 2:1–17.

Khalid, B., & Ghaffar, A. (2015). Dengue transmission based on urban environmental gradients in different cities of Pakistan. *International journal of biometeorology*, 59(3), 267-283.

Khalid, B., Cholaw, B., Alvim, D. S., Javeed, S., Khan, J. A., Javed, M. A., & Khan, A. H. (2018). Riverine flood assessment in Jhang district in connection with ENSO and summer monsoon rainfall over Upper Indus Basin for 2010. *Natural Hazards*, 92(2), 971-993.

Khan, A. M., & Yasmeen, S. (2010). Impact of devolution on enrolment rate at primary school level in selected districts of the Punjab. *Journal of Elementary Education*, 21(2), 35-52.

Khan, A. N. (2011). Analysis of flood causes and associated socio-economic damages in the Hindu Kush region. *Natural hazards*, 59(3), 1239-1260.

Khan, A., Mohammad, K., Ali, J., Ali, Z., Ahmad, I., & Ahmad, N. M. (2016). The challenge of climate change and policy response in Pakistan. *Environ Earth Sci*, 75, 1–16. <https://doi.org/10.1007/s12665-015-5127-7>.

Khan, F. A., & Salman, A. (2012). A simple human vulnerability index to climate change hazards for Pakistan. *International Journal of Disaster Risk Science*, 3(3), 163-176.

Khan, H., Haider, S., Saeed, K., & Ali, N. (2008). Assessment of potable water quality of Kohat division and its impact on health. *JOURNAL-CHEMICAL SOCIETY OF PAKISTAN*, 30(2), 246.

Khan, J. A., & Fee, L. (2014). Cities and climate change initiative-abridged report: Islamabad Pakistan, climate change vulnerability assessment. United Nations Human Settlements Programme (UN-Habitat)(Available at: [http://www.fukuoka.unhabitat.org/programmes/ccci/pdf/Islamabad_23_February_2015_FINAL_\(5th_revision\).pdf](http://www.fukuoka.unhabitat.org/programmes/ccci/pdf/Islamabad_23_February_2015_FINAL_(5th_revision).pdf) (Last access: 0710 2015)).

Khosravi, K., Melesse, A. M., Shahabi, H., Shirzadi, A., Chapi, K., & Hong, H. (2019). Flood susceptibility mapping at Ningdu catchment, China using bivariate and data mining techniques. In *Extreme hydrology and climate variability* (pp. 419-434).

Khosravi, K., Nohani, E., Maroufinia, E., & Pourghasemi, H. R. (2016). A GIS-based flood susceptibility assessment and its mapping in Iran: a comparison between frequency ratio and weights-of-evidence bivariate statistical models with multi-criteria decision-making technique. *Natural Hazards*, 83(2), 947-987.

Khosravi, K., Pham, B. T., Chapi, K., Shirzadi, A., Shahabi, H., Revhaug, I., ... & Bui, D. T. (2018). A comparative assessment of decision trees algorithms for flash flood susceptibility modeling at Haraz watershed, northern Iran. *Science of the Total Environment*, 627, 744-755.

Kia, M. B., Pirasteh, S., Pradhan, B., Mahmud, A. R., Sulaiman, W. N. A., & Moradi, A. (2012). An artificial neural network model for flood simulation using GIS: Johor River Basin, Malaysia. *Environmental earth sciences*, 67(1), 251-264.

King, A. D., Alexander, L. V., & Donat, M. G. (2013). The efficacy of using gridded data to examine extreme rainfall characteristics: a case study for Australia. *International Journal of Climatology*, 33(10), 2376-2387.

Kisi, O., Nia, A. M., Gosheh, M. G., Tajabadi, M. R. J., & Ahmadi, A. (2012). Intermittent streamflow forecasting by using several data driven techniques. *Water resources management*, 26(2), 457-474.

Klein Tank, A. M., Peterson, T. C., Quadir, D. A., Dorji, S., Zou, X., Tang, H., ... & Spektorman, T. (2006). Changes in daily temperature and precipitation extremes in central and south Asia. *Journal of Geophysical Research: Atmospheres*, 111(D16).

Kourgialas, N. N., & Karatzas, G. P. (2011). Gestion des inondations et méthode de modélisation sous SIG pour évaluer les zones d'aléa inondation-une étude de cas. *Hydrol. Sci. J.*, 56(2), 212-225.

Kourgialas, N. N., & Karatzas, G. P. (2017). A national scale flood hazard mapping methodology: The case of Greece—Protection and adaptation policy approaches. *Science of the Total Environment*, 601, 441-452.

Kramarova, N., Newman, P. A., Nash, E. R., Strahan, S. E., Long, C. S., Johnson, B., Pitts, M., Santee, M. L., Petropavlovskikh, I., Coy, L., de Laat, J., Bernhard, G. H., Stierle, S., & Lakkala, K. (2021). 2020 Antarctic ozone hole. "State of the Climate in 2020." *Bulletin of the American Meteorological Society*, 101(8), S345–S349. <https://doi.org/10.1175/BAMS-D-21-0081.1>

Kreft, S., & Eckstein, D. (2013). Global Climate Risk Index 2014-Who Suffers Most from Extreme Weather Events? Weather-Related Loss Events in 2012 and 1993 to 2012.

Krishnamurti, T. N. & Chang, C.-P. (1987). Monsoon meteorology. New York Oxford [Oxfordshire] : Oxford University Press ; Clarendon Press, <http://www.loc.gov/catdir/enhancements/fy0638/86018107-t.html>

Kronstadt, K. A., Sheikh, P. A., & Vaughn, B. (2010). Flooding in Pakistan: Overview and Issues for Congress, Congressional Research Service.

Kundzewicz, Z. W., Graczyk, D., Maurer, T., Pińskwar, I., Radziejewski, M., Svensson, C., & Szwed, M. (2005). Trend detection in river flow series: 1. Annual maximum flow/Détection de tendance dans des séries de débit fluvial: 1. Débit maximum annuel. *Hydrological Sciences Journal*, 50(5).

Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., ... & Sherstyukov, B. (2014). Flood risk and climate change: global and regional perspectives. *Hydrological Sciences Journal*, 59(1), 1-28.

Kundzewicz, Z. W., Pińskwar, I., & Brakenridge, G. R. (2013). Large floods in Europe, 1985–2009. *Hydrological Sciences Journal*, 58(1), 1-7.

Labat, D., Goddérus, Y., Probst, J. L., & Guyot, J. L. (2004). Evidence for global runoff increase related to climate warming. *Advances in water resources*, 27(6), 631-642.

Laird, K. R., Fritz, S. C., Maasch, K. A., & Cumming, B. F. (1996). Greater drought intensity and frequency before AD 1200 in the Northern Great Plains, USA. *Nature*, 384(6609), 552-554.

Lal, M. (2003). Global climate change: India's monsoon and its variability. *Journal of Environmental Studies and Policy*, 6(1), 1-34.

Lechowska, E. (2018). What determines flood risk perception? A review of factors of flood risk perception and relations between its basic elements. *Natural Hazards*, 94(3), 1341-1366.

Lee, M. J., Kang, J. E., & Jeon, S. (2012, July). Application of frequency ratio model and validation for predictive flooded area susceptibility mapping using GIS. In 2012 IEEE international geoscience and remote sensing symposium (pp. 895-898). IEEE.

Leichenko, R. M., & Wescoat Jr, J. L. (1993). Environmental impacts of climate change and water development in the Indus delta region. *International Journal of Water Resources Development*, 9(3), 247-261.

Li, D., & Yap, K. S. (2011). Climate change and its impact on food and nutrition security and food safety in China. *World Rev Nutr Diet*, 102, 175–182. <https://doi.org/10.1159/000327807>.

Li, X. H., Zhang, Q., Shao, M., & Li, Y. L. (2012). A comparison of parameter estimation for distributed hydrological modelling using automatic and manual methods. In *Advanced Materials Research* (Vol. 356, pp. 2372-2375). Trans Tech Publications Ltd.

Liao, X., & Carin, L. (2009). Migratory logistic regression for learning concept drift between two data sets with application to UXO sensing. *IEEE Transactions on Geoscience and Remote Sensing*, 47(5), 1454-1466.

Lin, B., & Ahmad, I. (2016). Energy substitution effect on transport sector of Pakistan based on trans-log production function. *Renew Sust Energ Rev*, 56, 1182–1193. <https://doi.org/10.1016/j.rser.2015.12.012>.

Lin, B., & Ahmad, I. (2017). Analysis of energy related carbon dioxide emission and reduction potential in Pakistan. *Journal of Cleaner Production*, 143, 278-287.

Lipczynska-Kochany, E. (2018). Effect of climate change on humic substances and associated impacts on the quality of surface water and groundwater: a review. *Sci Total Environ*, 640–641, 1548–1565. <https://doi.org/10.1016/j.scitotenv.2018.05.376>

Liu Y, & De Smedt F (2005) Flood modeling for complex terrain using GIS and remote sensed information. *Water Resour Manag* 19(5):605–624

Lohani, A. K., Kumar, R., & Singh, R. D. (2012). Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. *Journal of Hydrology*, 442, 23-35.

Mach K, & Mastrandrea, M.. (2014) Climate change 2014: impacts, adaptation, and vulnerability. In: Field CB, Barros VR (eds) Cambridge and New York. Cambridge University Press.

Mahmood, T., & Rasul, G. (2012). Predictability of summer monsoon rainfall by using high resolution regional model (HRM). *Pakistan Journal of Meteorology* Vol, 9(17).

Mahmoud, S. H., & Gan, T. Y. (2018). Multi-criteria approach to develop flood susceptibility maps in arid regions of Middle East. *Journal of cleaner Production*, 196, 216-229.

Malik, S. M. (2011). A Study of the Effects of Climate Change on Human Health in Pakistan: Evidence-Based Policy Advocacy. SightSavers. http://pk.sightsavers.org/in_depth/policy_and_research/15837_climatechange.

Mallick, S., & Masood, A. (2011). Environment, energy and climate change in Pakistan: Challenges, implications and required responses. *Mahbub ul Haq Human Development Centre Working Paper Series*.

Manjare, B. S., Jambhulkar, P., Padhye, M. A., & Girhe, S. S. (2017). Digital terrain analysis and geomorphological mapping using remote sensing and GIS: A case study from Central India. In *Sustainable Management of Land Resources* (pp. 327-345). Apple Academic Press.

Manney, G. L., Livesey, N. J., Santee, M. L., Froidevaux, L., Lambert, A., Lawrence, Z. D., ... & Fuller, R. A. (2020). Record-low Arctic stratospheric ozone in 2020: MLS observations of chemical processes and comparisons with previous extreme winters. *Geophysical Research Letters*, 47(16), e2020GL089063.

Markantonis V, Meyer V, Lien hoop N (2013) Evaluation of the environmental impacts of extreme floods in the Eros River basin using contingent valuation method. *Nat Hazard* 69:1535–1549.

Mazhar, N., Nawaz, M., Mirza, A. I., & Khan, K. (2020). Socio-political impacts of meteorological droughts and their spatial patterns in Pakistan. *South Asian Studies*, 30(1).

McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J., & White, K. S. (Eds.). (2001). *Climate change 2001: impacts, adaptation, and vulnerability: contribution of Working Group II to the third assessment*

report of the Intergovernmental Panel on Climate Change (Vol. 2). Cambridge University Press.

Merz, B., Kreibich, H., Schwarze, R., & Thielen, A. (2010). Review article "Assessment of economic flood damage". *Natural Hazards and Earth System Sciences*, 10(8), 1697-1724.

Messner F, & Meyer V (2006) Flood damage, vulnerability and risk perception—challenges for flood damage research. Springer, Amsterdam, pp 149–167.

Mindlin, J., Shepherd, T. G., Vera, C., & Osman, M. (2021). Combined effects of global warming and ozone depletion/recovery on Southern Hemisphere atmospheric circulation and regional precipitation. *Geophysical Research Letters*, 48(12), e2021GL092568. <https://doi.org/10.1029/2021GL092568>

Mir, H., Latif, S., Mahmood, A., & Hussain, S. (2010). Flood report 2010, Flood reports. Pakistan Meteorological Department, Flood Forecasting Division, Lahore, Pakistan, p. 34.

MoA (2011) Agriculture Sector Programme of Plan on Adaptation to Climate Change. In: Salehu, A., et al., Eds., Ministry of Agriculture, Federal Democratic Republic of Ethiopia (FDRE), Addis Ababa, Ethiopia, 101.

Mueller, V., Gray, C., & Kosec, K. (2014). Heat stress increases long-term human migration in rural Pakistan. *Nature climate change*, 4(3), 182-185.

Nandi, A., Mandal, A., Wilson, M., & Smith, D. (2016). Flood hazard mapping in Jamaica using principal component analysis and logistic regression. *Environmental Earth Sciences*, 75(6), 1-16.

Narisma, G. T., Foley, J. A., Licker, R., & Ramankutty, N. (2007). Abrupt changes in rainfall during the twentieth century. *Geophysical Research Letters*, 34(6).

NASA. (2018). Climate change. [WWW document]. URL <https://climate.nasa.gov/>.

National Academies of Sciences, Engineering, and Medicine. (2017). Valuing climate damages: updating estimation of the social cost of carbon dioxide. National Academies Press.

National Disaster Management Authority of Pakistan (NDMA) (2012). National Disaster Management Plan. Islamabad: NDMA. Available at <http://www.ndma.gov.pk/ex/Documents/ndmp.zip>.

NDMA (National Disaster Management Authority), “National Monsson Contingency Plan 2013”, 41p, Government of Pakistan, Islamabad, 2013.

Neelam, M., Afzal, I., Nawaz, M., and Ahmad, S.S., “Flood Damages and its Management Strategies (2010) in Layyah District, Pakistan”, International Journal of Scientific & Engineering Research, Volume 5, No. 11, pp. 375-379, 2014.

Nordhaus, W.D. 1991: To slow or not to slow: The economics of the greenhouse effect. *The Economic Journal* 101, 920–37.

O'Brien, G., O'keefe, P., Rose, J., & Wisner, B. (2006). Climate change and disaster management. *Disasters*, 30(1), 64-80.

Ohlmacher, G. C., & Davis, J. C. (2003). Using multiple logistic regression and GIS technology to predict landslide hazard in northeast Kansas, USA. *Engineering geology*, 69(3-4), 331-343.

Pakistan emergency situation analysis (PESA) –USAID (2016): Government of Pakistan.

Pakistan Floods 2010- District Profile Matiari 2010, UNOCHA <http://floods2010.pakresponse.info/DistrictProfiles.aspx> retrieved on 11/03/2013.

Papaioannou, G., Vasiliades, L., & Loukas, A. (2015). Multi-criteria analysis framework for potential flood prone areas mapping. *Water resources management*, 29(2), 399-418.

Pardhan B, Shafee M, & Pirasteh M, (2009) Maximum flood prone area mapping using RADARSET images and GIS: Kelantan River Basin. *Int J Geoinf* 5(2):49-61.

Parry, M., Canziani, O., Palutikof, J., Linden, P.V., and Hanson, C. (2007): Climate change 2007: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the

Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, p. 976.

Patel, D. P., & Srivastava, P. K. (2013). Flood hazards mitigation analysis using remote sensing and GIS: correspondence with town planning scheme. *Water resources management*, 27(7), 2353-2368.

Patt, A., Peterson, N., Carter, M., Velez, M., Hess U, & Suarez, P. (2009) Making index insurance attractive to farmers. *Mitig Adapt Strateg Glob Chang* 8:737–753.

Paul, G. C., Saha, S., & Hembram, T. K. (2019). Application of the GIS-based probabilistic models for mapping the flood susceptibility in Bansloi sub-basin of Ganga-Bhagirathi river and their comparison. *Remote Sensing in Earth Systems Sciences*, 2(2), 120-146.

PCRWR (PAKISTAN COUNCIL OF RESERCH IN WATER RESOURCES). Water quality statistics in rural areas of Pakistan. Publication no: 143-2010, 2010.

Percy K.E., Jandl R., Hall J.P. and Lavigne M., 2003, the Role of Forests in Carbon Cycles, Sequestration, and Storage, International Union of Forest Research Organizations, 1.

Petit, J. R., Jouzel, J., Raynaud, D., Barkov, N. I., Barnola, J. M., Basile, I., ... & Stievenard, M. (1999). Climate and atmospheric history of the past 420,000 years from the Vostok ice core, Antarctica. *Nature*, 399(6735), 429-436.

Pourghasemi H R, Pradhan B, & Gokceoglu C. (2012c). Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran; *Nat. Hazards* 63(2) 965–996.

Pourghasemi HR, Moradi HR, Aghda SMF, Gokceoglu C, & Pradhan, B. (2014) GIS-based landslide susceptibility mapping with probabilistic likelihood ratio and spatial multi-criteria evaluation models (North of Tehran, Iran). *Arab J Geosci* 7(5):1857–1878.

Pradhan B, Hagemann U, Tehrany MS, Prechtel N (2014) An easy to use ArcMap based texture analysis program for extraction of flooded areas from TerraSAR-X satellite image. *Comput Geosci* 63:34–43.

Pradhan, B, & Buchroithner, MF, (2010) Comparison and validation of landslide susceptibility maps using an artificial neural network model for three test areas in Malaysia. *Environ Eng Geosci* 16:107–126.

Pradhan, B. & Youssef, A. (2011) a 100-year maximum flood susceptibility mapping using integrated hydrological and hydrodynamic models: Kelantan River Corridor Malaysia. *J Flood Risk Manag* 4(3):189–202.

Price, G., & Mittra, S. (2016). Water, ecosystems and energy in South Asia: Making cross-border collaboration work.

Punjab Development Statistics (2011) Bureau of StatisticsGOP (2011): Lahore. Available at <http://www.bos.gop.pk/developmentstat> Rahimzadeh-Bajgiran P, Omasa K.

Qureshi, A. S. (2011). Managing floods in Pakistan: From Structural to non-structural measures. In Symposium on “Emerging Phenomenon of Untimely Rains/Floods-2011 in Pakistan (pp. 107-114).

Qureshi, N. A., & Ali, Z. (2011). Climate change, biodiversity Pakistan’s scenario. *J. Anim. Plant Sci*, 21(2 Suppl), 358-363.

Radmehr, A., & Araghinejad, S. (2015). Flood vulnerability analysis by fuzzy spatial multi criteria decision making. *Water resources management*, 29(12), 4427-4445.

Rafiq, L. and Blaschke, T. (2012). Disaster risk and vulnerability in Pakistan at a district level. *Geomatics, Natural Hazards and Risk*, 3(4), pp.324-341., DOI: 10.1080/19475705.2011.626083. Available at: <http://dx.doi.org/10.1080/19475705.2011.626083>.

Rahman, M., Ningsheng, C., Islam, M. M., Dewan, A., Iqbal, J., Washakh, R. M. A., & Shufeng, T. (2019). Flood susceptibility assessment in Bangladesh using machine learning and multi-criteria decision analysis. *Earth Systems and Environment*, 3(3), 585-601.

Rahmati O, Zeinivand H, Besharat M (2016a) Flood hazard zoning in Yasooj region, Iran, using GIS and multi-criteria decision analysis. *Geomat Nat Hazard Risk*. <https://doi.org/10.1080/19475705.2015.1045043>

Rahmati, O., Pourghasemi, H. R., & Zeinivand, H. (2016). Flood susceptibility mapping using frequency ratio and weights-of-evidence models in the Golastan Province, Iran. *Geocarto International*, 31(1), 42-70.

Rahmati, O., Zeinivand, H., & Besharat, M. (2016). Flood hazard zoning in Yasooj region, Iran, using GIS and multi-criteria decision analysis. *Geomatics, Natural Hazards and Risk*, 7(3), 1000-1017.

Rasul, G., & Ahmad, B. (2012). Climate change in Pakistan. *Pakistan Meteorological Department*.

Rasul, G., & Ahmad, B. (2012). Climate change in Pakistan. *Pakistan Meteorological Department*.

Rasul, G., Chaudhry, Q. U. Z., Sixiong, Z., & Qingcun, Z. (2004). A diagnostic study of record heavy rain in twin cities Islāmābad-Rāwalgind. *Advances in atmospheric sciences*, 21(6), 976-988.

Rasul, G., Chaudhry, Q. U. Z., Sixiong, Z., Qingcun, Z., Linlin, Q. I., & Gaoying, Z. (2005). A diagnostic study of heavy rainfall in Karachi due to merging of a mesoscale low and a diffused tropical depression during South Asian summer monsoon. *Advances in Atmospheric Sciences*, 22(3), 375-391.

Rasul, G., Dahe, Q., & Chaudhry, Q. Z. (2008). Global warming and melting glaciers along southern slopes of HKH range. *Pak. Jr. of Meteorology*, 5(9).

Razandi, Y., Pourghasemi, H. R., Neisani, N. S., & Rahmati, O. (2015). Application of analytical hierarchy process, frequency ratio, and certainty factor models for groundwater potential mapping using GIS. *Earth Science Informatics*, 8(4), 867-883.

Richards, J. A., & Richards, J. A. (1999). *Remote sensing digital image analysis* (Vol. 3, pp. 10-38). Berlin: springer.

Robson, A. J., Jones, T. K., Reed, D. W., & Bayliss, A. C. (1998). A study of national trend and variation in UK floods. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 18(2), 165-182.

Rodó, X. (2003). Global climate: current research and uncertainties in the climate system.

Saha, A. K., Gupta, R. P., Sarkar, I., Arora, M. K., & Csaplovics, E. (2005). An approach for GIS-based statistical landslide susceptibility zonation—with a case study in the Himalayas. *Landslides*, 2(1), 61-69.

Sahana, M., & Patel, P. P. (2019). A comparison of frequency ratio and fuzzy logic models for flood susceptibility assessment of the lower Kosi River Basin in India. *Environmental Earth Sciences*, 78(10), 1-27.

Samanta, S., Koloa, C., Kumar Pal, D., & Palsamanta, B. (2016). Flood risk analysis in lower part of Markham river based on multi-criteria decision approach (MCDA). *Hydrology*, 3(3), 29.

Santangelo, N., Santo, A., Di Crescenzo, G., Foscari, G., Liuzza, V., Sciarrotta, S., & Scorpio, V. (2011). Flood susceptibility assessment in a highly urbanized alluvial fan: the case study of Sala Consilina (southern Italy). *Natural Hazards and Earth System Sciences*, 11(10), 2765-2780.

Save the Children. 2011. Psychological Assessment Report: Psychological Problems and Needs of Children in Flood Affected Areas in Pakistan. Pakistan.
http://www.savethechildren.org.uk/sites/default/files/docs/Psychological_Assessment_Report_1.pdf

Sayed, S. A., & González, P. A. (2014). Flood disaster profile of Pakistan: A review. *Science Journal of Public Health*, 2(3), 144-149.

Scheraga, J. D., Leary, N. A., Goettle, R. J., Jorgenson, D. W., & Wilcoxon, P. J. (1993). Macroeconomic modeling and the assessment of climate change impacts. ed. Y. Kaya, N. Nakicenovic, WD Nordhaus and FL, Toth, Costs, Impacts and Benefits of CO₂, 2.

Schilling, J., Vivekananda, J., Khan, M. A., & Pandey, N. (2013). Vulnerability to environmental risks and effects on community resilience in mid-west Nepal and south-east Pakistan. *Environment and Natural Resources Research*, 3(4), 27.

Schuldenrein, J., Wright, R. P., Mughal, M. R., & Khan, M. A. (2004). Landscapes, soils, and mound histories of the Upper Indus Valley, Pakistan: new insights on the Holocene environments near ancient Harappa. *Journal of Archaeological Science*, 31(6), 777-797.

Schweikert, A., Chinowsky, P., Kwiatkowski, K., & Espinet, X. (2014). The infrastructure planning support system: Analyzing the impact of climate change on road infrastructure and development. *Transport Policy*, 35, 146-153.

Sezer, E. A., Pradhan, B., & Gokceoglu, C. (2011). Manifestation of an adaptive neuro-fuzzy model on landslide susceptibility mapping: Klang valley, Malaysia. *Expert Systems with Applications*, 38(7), 8208-8219.

Shafapour Tehrany, M., Kumar, L., Neamah Jebur, M., & Shabani, F. (2019). Evaluating the application of the statistical index method in flood susceptibility mapping and its comparison with frequency ratio and logistic regression methods. *Geomatics, Natural Hazards and Risk*, 10(1), 79-101.

Shaffril, H. A. M., Krauss, S. E., & Samsuddin, S. F. (2018). A systematic review on Asian's farmers' adaptation practices towards climate change. *Sci Total Environ*, 644, 683-695. <https://doi.org/10.1016/j.scitotenv.2018.06.349>.

Shafi, M. S. (2010). Pakistan: Pakistan Floods (2010) Damage and Needs Assessment.

Shafizadeh-Moghadam, H., Valavi, R., Shahabi, H., Chapi, K., & Shirzadi, A. (2018). Novel forecasting approaches using combination of machine learning and statistical models for flood susceptibility mapping. *Journal of environmental management*, 217, 1-11.

Sheikh, M. A. (2010). Energy and renewable energy scenario of Pakistan. *Renew Sust Energ Rev*, 14, 354–363. <https://doi.org/10.1016/j.rser.2009.07.037>.

Sheikh, M. M., Manzoor, N., Ashraf, J., Adnan, M., Collins, D., Hameed, S., ... & Shrestha, M. L. (2015). Trends in extreme daily rainfall and temperature indices over South Asia. *International Journal of Climatology*, 35(7), 1625-1637.

Shuster, W. D., Bonta, J., Thurston, H., Warnemuende, E., & Smith, D. R. (2005). Impacts of impervious surface on watershed hydrology: A review. *Urban Water Journal*, 2(4), 263-275.

Siddiqui, K. M., Mohammad, I., & Ayaz, M. (1999). Forest ecosystem climate change impact assessment and adaptation strategies for Pakistan. *Climate Research*, 12(2-3), 195-203.

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Analysis: An International Journal*, 24(2), 311-322.

Small & Medium Enterprise development Authority (SMEDA), “A Brief Profile of Larkana”, (http://www.smeda.org/index.php?option=com_content&view=article&id=78&Itemid=180) accessed on 23/03/2013.

Smit B, & Skinner, MW. (2002) Adaptation options in agriculture to climate change: a typology. *Mitig Adapt Strateg Glob Chang* 7:85–114.

Sofia, G., Roder, G., Dalla Fontana, G., & Tarolli, P. (2017). Flood dynamics in urbanised landscapes: 100 years of climate and humans' interaction. *Scientific reports*, 7(1), 1-12.

Solomon S., & Forster P, (2007) in Climate Change 2007: The Physical Sciences Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Changes in atmospheric constituents and in radioactive forcing, ed Solomon S, et al. (Cambridge Univ Press, Cambridge, UK), pp 129–234.

Solomon, S., Plattner, G. K., Knutti, R., & Friedlingstein, P. (2009). Irreversible climate change due to carbon dioxide emissions. *Proceedings of the national academy of sciences*, 106(6), 1704-1709.

Space, P. (2012). Upper Atmosphere Research Commission and Food and Agriculture Organization of the United Nations, “Rapid Crop Damage Assessment. *Pakistan: Floods/Rains*.

Stern, N. (2006): The economics of climate change, The Stern review. Cambridge University Press.

Street-Perrott, F. A., & Perrott, R. A. (1990). Abrupt climate fluctuations in the tropics: the influence of Atlantic Ocean circulation. *Nature*, 343(6259), 607-612.

Syeda, M. H., & Adnan, M. (2016). Rebuilding lives: Natural disasters and role of a social worker in Pakistan. *Journal of the Research Society of Pakistan*, 53(2).

Szewrański, S., Kazak, J., Szkaradkiewicz, M., & Sasik, J. (2015). Flood risk factors in suburban area in the context of climate change adaptation policies—Case study of Wrocław, Poland. *Journal of Ecological Engineering*, 16(2).

Tabari, H., Hosseinzadehtalaei, P., AghaKouchak, A., & Willems, P. (2019). Latitudinal heterogeneity and hotspots of uncertainty in projected extreme precipitation. *Environmental Research Letters*, 14(12), 124032.

Talei, A., Chua, L. H. C., & Quek, C. (2010). A novel application of a neuro-fuzzy computational technique in event-based rainfall-runoff modeling. *Expert Systems with Applications*, 37(12), 7456-7468.

Tariq, M. A. U. R., & Van De Giesen, N. (2012). Floods and flood management in Pakistan. *Physics and Chemistry of the Earth, Parts A/B/C*, 47, 11-20.

Teegavarapu, R. (2012). Floods in a Changing Climate: Extreme Precipitation (International Hydrology Series). Cambridge: Cambridge University Press. Doi: 10.1017/CBO9781139088442

Teegavarapu, R. (2012). Floods in a Changing Climate: Extreme Precipitation (International Hydrology Series). Cambridge: Cambridge University Press. Doi: 10.1017/CBO9781139088442

Tehrany, M. S., Jones, S., & Shabani, F. (2019). Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques. *Catena*, 175, 174-192.

Tehrany, M. S., Lee, M. J., Pradhan, B., Jebur, M. N., & Lee, S. (2014). Flood susceptibility mapping using integrated bivariate and multivariate statistical models. *Environmental earth sciences*, 72(10), 4001-4015.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2014a). Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. *Journal of hydrology*, 512, 332-343.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2015). Flood susceptibility analysis and its verification using a novel ensemble support vector machine and frequency ratio method. *Stochastic environmental research and risk assessment*, 29(4), 1149-1165.

Tehrany, M.S., Pradhan, B., Mansor, S., & Ahmad, N. (2015). Flood susceptibility assessment using GIS-based support vector machine model with different kernel types. *Catena* 125, 91-101. <https://doi.org/10.1016/j.catena.2014.10.017>.

Termeh, S. V. R., Kornejady, A., Pourghasemi, H. R., & Keesstra, S. (2018). Flood susceptibility mapping using novel ensembles of adaptive neuro fuzzy inference system and metaheuristic algorithms. *Science of the Total Environment*, 615, 438-451.

The International Federation of Red Cross Pakistan: Floods, International Federation of Red Cross and Red Crescent Societies, Islamabad (2005).

The Straits Times. Heavy Rain Causes Flash Floods in Several Parts of Malaysia. 2018. Available online: <https://www.straitstimes.com/asia/se-asia/heavy-rain-causes-flash-floods-in-several-parts-ofmalaysia> (accessed on 19 March 2019).

Thenkabail, P. S., & Gamage, M. S. D. N. (2004). *The use of remote sensing data for drought assessment and monitoring in Southwest Asia* (Vol. 85). Iwmi.

Tien Bui, D., Khosravi, K., Li, S., Shahabi, H., Panahi, M., Singh, V. P., ... & Bin Ahmad, B. (2018). New hybrids of anfis with several optimization algorithms for flood susceptibility modeling. *Water*, 10(9), 1210.

Tien Bui, D., Khosravi, K., Shahabi, H., Daggupati, P., Adamowski, J. F., Melesse, A. M., ... & Lee, S. (2019). Flood spatial modeling in northern Iran using remote sensing and gis: A comparison between evidential belief

functions and its ensemble with a multivariate logistic regression model. *Remote Sensing*, 11(13), 1589.

Tiwari, M. K., & Chatterjee, C. (2010). Uncertainty assessment and ensemble flood forecasting using bootstrap based artificial neural networks (BANNs). *Journal of Hydrology*, 382(1-4), 20-33.

Toriman, M. E., Hassan, A. J., Gazim, M. B., Mokhtar, M., SA, S. M., Jaafar, O., ... & Aziz, N. A. A. (2009). Integration of 1-d hydrodynamic model and GIS approach in flood management study in Malaysia. *Research Journal of Earth Sciences*, 1(1), 22-27.

Trewin, B. (2010). Exposure, instrumentation, and observing practice effects on land temperature measurements. *Wiley Interdisciplinary Reviews: Climate Change*, 1(4), 490-506.

Tsakiris, G. 2014. Flood risk assessment: concepts, modelling, applications. *Natural Hazards Earth System Sciences* 14: pp.1361-1369.

UNEP (United Nations Environment Programme) (2007) GEO yearbook 2007: an overview of our changing environment. UNEP, Nairobi, p 86.

UNFCCC, COP 13 (2008) "Report of the Conference of the Parties on its thirteenth session, held in Bali from 3 to 15 December 2007, Addendum part two: Action taken by the Conference of the Parties at its thirteenth session.

UNISDR, Visions of Sharing Responsibility for Disaster Resilience. 2012 20, (February 2019) Available from: <https://www.unisdr.org/we/inform/events/25044>.

United Nation Pakistan 2010. The Human Cost of Floods in Pakistan. Annual Report 2010. http://www.unicef.org/pakistan/UNICEF_Pakistan_2010_Annual_Report.

United Nations Environment Programme. 2000: Developing strategies for climate change: The UNEP country studies on climate change impacts and adaptation assessment. Report 200:2. University of Oslo and UNEP.

United Nations Environment Programme. 2000: Developing strategies for climate change: The UNEP country studies on climate change impacts and adaptation assessment. Report 200:2. University of Oslo and UNEP.

US EPA. (2016). Climate change indicators in the United States. [WWW document]. <https://www.epa.gov/sites/>.

Vahid, S., Termeh, R., Kornejady, A., Reza, H., & Keesstra, S. (2018). Flood susceptibility mapping using novel ensembles of adaptive neuro fuzzy inference system and met heuristic algorithms. *Sci. Total Environ.* 615, 438–451. <https://doi.org/10.1016/j.scitotenv.2017.09.262>.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox—implications for governance and communication of natural hazards. *Risk analysis*, 33(6), 1049-1065.

Wandel, J., & Smit, B. (2000) Agricultural risk management in light of climate variability and change. *Agricultural and environmental sustainability in the new countryside*. Hignell Printing Limited, Winnipeg, pp 30–39

Wanders N, Karssenberg D, de Roo A, de Jong SM, & Bierkens MFP. (2014). the suitability of remotely sensed soil moisture for improving operational flood forecasting. *Hydrol Earth Syst Sci* 18:2343–2357.

Wang, HB, Wu, SR, Shi, JS, Li B. (2013). Qualitative hazard and risk assessment of landslides: a practical framework for a case study in China. *Nat Hazard* 69(3):1281–1294

Water Management and Reservoirs in Pakistan, South Asian Journal, and South Asian Free Media Association, available at: <http://www.southasianmedia.net/Magazine/Journal/previousissues11.htm>, 2008.

WCDR (WORLD CONFERENCE ON DISASTER REDUCTION). (2005). A Review of Disaster Management Policies and Systems in Pakistan. Available at: <http://www.unisdr.org/2005/wcdr/wcdr-index.htm>

WMO (World Meteorological Organization) (1994) On the front-line: public weather service, WMO No. 816, WMO, Geneva.

World Bank and Asian Development Bank, "Damages and Needs Assessment Report 2011", World Bank and Asian Development Bank, Islamabad, Pakistan, 2011.

Wu, S. J., Lien, H. C., & Chang, C. H. (2010). Modeling risk analysis for forecasting peak discharge during flooding prevention and warning operation. *Stochastic Environmental Research and Risk Assessment*, 24(8), 1175-1191.

Yahaya, S., Ahmad, N., & Abdalla, R. F. (2010). Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are River basin, Nigeria. *European Journal of Scientific Research*, 42(1), 71-83.

Yalcin, A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): comparisons of results and confirmations. *catena*, 72(1), 1-12.

Yalcin, A., Reis, S., Aydinoglu, A. C., & Yomralioglu, T. (2011). A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey. *Catena*, 85(3), 274-287.

Yalcin, G., & Akyurek, Z. (2004, July). Analysing flood vulnerable areas with multicriteria evaluation. In 20th ISPRS congress (pp. 359-364).

Yaqub, M., Beytullah, E. R. E. N., & Doğan, E. (2015). Flood causes, consequences and protection measures in Pakistan. *Disaster Science and Engineering*, 1(1), 8-16.

Yasuhara, M., Okahashi, H., Cronin, T. M., Rasmussen, T. L., & Hunt, G. (2014). Deep-sea biodiversity response to deglacial and Holocene abrupt climate changes in the North Atlantic Ocean. *Global Ecology and Biogeography*, 23(9), 957-967.

Youssef, A. M., Pradhan, B., & Hassan, A. M. (2011). Flash flood risk estimation along the St. Katherine road, southern Sinai, Egypt using GIS based morphometry and satellite imagery. *Environmental Earth Sciences*, 62(3), 611-623.

Youssef, A. M., Pradhan, B., & Sefry, S. A. (2016). Flash flood susceptibility assessment in Jeddah city (Kingdom of Saudi Arabia) using bivariate and multivariate statistical models. *Environmental Earth Sciences*, 75(1), 1-16.

Zahid, M., & Rasul, G. (2012). Changing trends of thermal extremes in Pakistan. *Climatic change*, 113(3), 883-896.

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., & Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *Wiley Interdisciplinary Reviews: Climate Change*, 2(6), 851-870.

Zhang, X., Harvey, K. D., Hogg, W. D., & Yuzyk, T. R. (2001). Trends in Canadian streamflow. *Water Resources Research*, 37(4), 987-998.

Zhao, G., Pang, B., Xu, Z., Yue, J., & Tu, T. (2018). Mapping flood susceptibility in mountainous areas on a national scale in China. *Science of the Total Environment*, 615, 1133-1142.

Zhao, Y., Wang, C., Wang, S., & Tibig, L. V. (2005). Impacts of present and future climate variability on agriculture and forestry in the humid and sub-humid tropics. *Climatic Change*, 70(1), 73-116.

Zhongming, Z., & Wei, L. (2017). Climate Change Profile of Pakistan.

Zhou, C., Luo, J., Yang, C., Li, B., & Wang, S. (2000). Flood monitoring using multi-temporal AVHRR and RADARSAT imagery. *PE&RS, Photogrammetric Engineering & Remote Sensing*, 66(5), 633-638.

Zhu, T., Xie, H., Waqas, A., Ringler, C., Iqbal, M. M., & Goheer, M. A. (2015). Climate change and extreme events: impacts on Pakistan's agriculture.

Zou, Q., Zhou, J., Zhou, C., Song, L., & Guo, J. (2013). Comprehensive flood risk assessment based on set pair analysis-variable fuzzy sets model and fuzzy AHP. *Stochastic Environmental Research and Risk Assessment*, 27(2), 525-546.-546.

ANNEXURE I

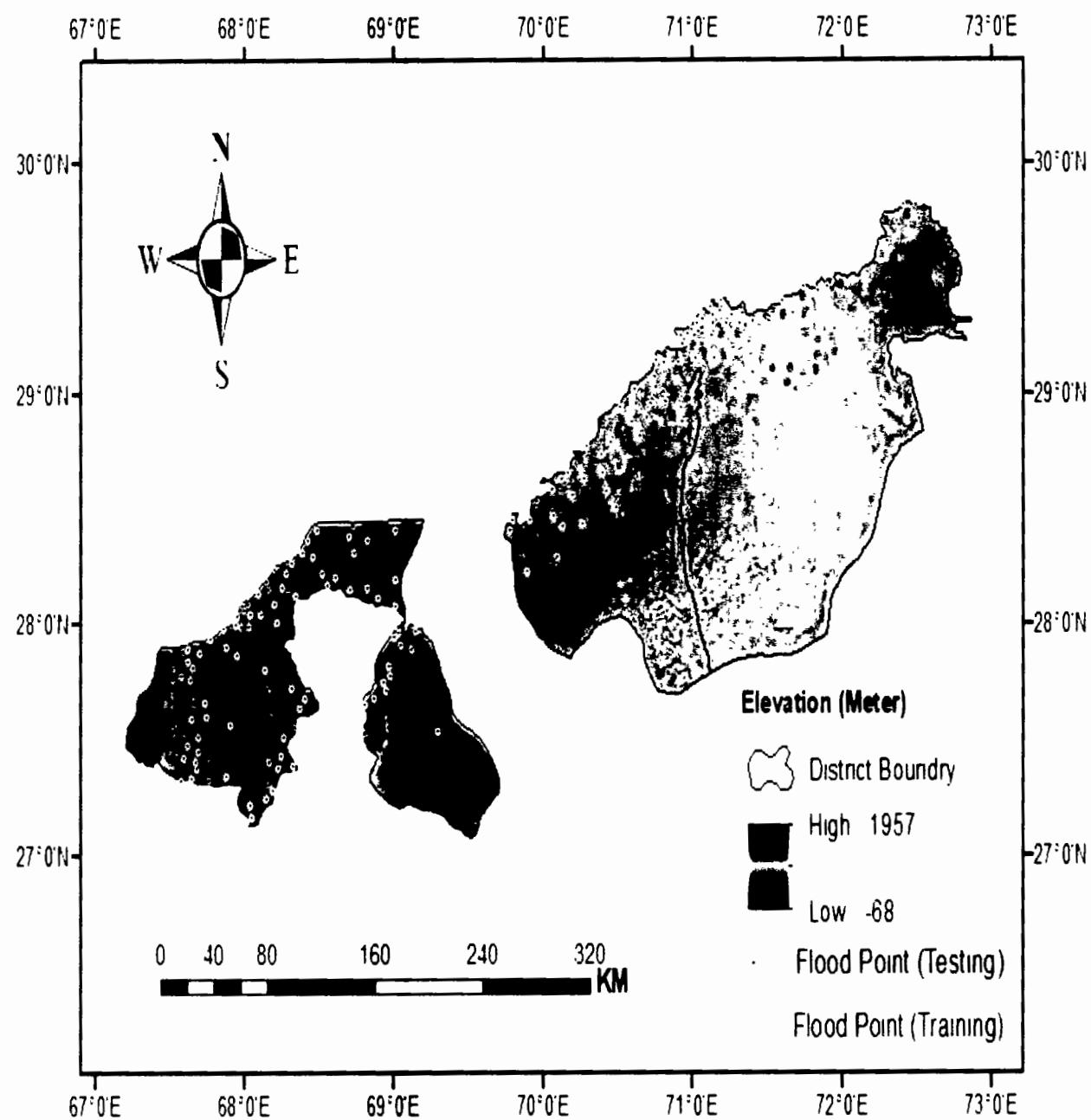


Fig. 3. Flood inventory map of study area.

Original Research

Flood Susceptibility Assessment Using Frequency Ratio Modelling Approach in Northern Sindh and Southern Punjab, Pakistan

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Abstract

Flooding is among the most catastrophic and common natural events. It not only endangers human lives, their livelihoods, and possessions but also devastates the nation's economy. Increased flooding is an inevitable consequence of climate change. Hence, Identification of flood suspectable hotspots is vital for flood risk management along with disaster handling. The primary objective of this research is to use a frequency ratio model to classify flood-prone zones in two provinces of Pakistan. The flood inventory map was developed using 230 flood location points in Northern Sindh and Southern Punjab. Aspect, profile curvature, elevation, slope, normalized difference vegetation index (NDVI), normalized difference soil index (NDSI), distance from the road, distance from the river, land use/land cover (LULC) and rainfall were among the ten (10) determining factors. The data were randomly divided into two distinct datasets, with 70% flood points (161) used for inventory formulation and the other 30% (69 flood points) for result validation. The flood vulnerability map was categorized into five different zones ranging from very low (19.73%) to very high (20.37%) susceptibility range. The area under the receiver operating characteristic curve (ROC) and area under curve (AUC) was used to demonstrate the prediction result that yielded a reasonable score of 77.4%. The study suggested that in comparison to other studied districts, Jacobabad is the most prone region with acute vulnerability and constrained resilience. The presented data can serve as a source for tracking, assessing, and predicting potential flood activity in the area and could be beneficial for planners and decision-makers involved in early disaster response planning within the country.

Keywords flood susceptibility, GIS modelling, flood inventory mapping, conditioning factors, frequency ratio modelling

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Introduction

Every year, various natural disasters such as earthquakes, floods, drought, and landslides cause a large number of deaths and property damage around the world [1]. Among all other disasters, flooding is one of the most destructive natural disasters that occur when a large amount of water exceeds its usual limits, inundating river banks and causing water retention for a short period [2]. Floods are a major factor destroying the environment, transportation systems, agriculture, sociocultural and human life accounting for almost 40% of all-natural disaster losses [3-5]. The size of the flood is one of the most significant aspects while increased harm has been attributed to urbanization and population growth along rivers and decline in forest areas. Poor infrastructure, social mentality, low resilience, and deficiency of long-term mitigation steps are also among important determining factors [6, 7]. Almost one-third of the world's land area is vulnerable to the risk of flooding [8]. Flood-related damages caused 32% of human and environmental harm between 1963 and 1992 and affected an average of 99 million people from 2000 to 2008 [9]. China is the most affected country, in terms of facing the social and economic effects of flooding [10, 11]. Failure of the dam as a result of the heavy rains has also triggered floods in downstream areas. In 1979, the collapse of the Machu dam in Marvi, Saurashtra, resulted in immense losses of land, crops, livestock, and approximately 10,000 human lives [12]. Unless appropriate flood prevention measures are taken, the number of people vulnerable to catastrophic flooding will continue to increase [13].

Between 2000 and 2013, Pakistan was hit by 25 natural disasters, the most prevalent of which were floods, earthquakes, and landslides [14]. Floods were particularly severe in 1942, 1956, 1957, 1958, 1973, 1975, 1976, 1979, 1992, 1994, 1995, 2003, 2005, 2007, 2010, 2011, and 2013. One of the worst floods in Pakistan's history hit in August 2010, while between 1947 and 2010 approximately 8000 people died and approximately \$10 billion was lost in economic losses [15]. Summer floods in Pakistan are mostly caused by monsoon rainfall. The historical 2010-11 floods in the study region were the worst in terms of severe and extended rainfall, large flood discharge, the number of people impacted and their property destruction [16]. Abnormal rainfall was recorded by almost all the meteorological stations in the country and the main cause behind this disastrous flooding was the consecutive rainfall for four days (27-30 July) [17]. During 2010, 2011, and 2013 years, there have been riverine floods in Northern Sindh and Southern Punjab areas. The Districts of Northern Sindh, Jacobabad, Larkana, and Sukkur were badly affected. Similarly, in summer 2010, unusually heavy rain and river breaches in the Southern Punjab's District Rahimyar Khan and Bahawalpur caused an unprecedented riverine flood. Structures were destroyed, irrigation channels and

linking roads were damaged, crops and orchards were washed away [18].

Flooding is a devastating natural hazard that is almost impossible to fully eradicate, modeling flood susceptibility is one of the latest strategies used for dealing with flood disasters. Remote sensing and GIS software techniques have become increasingly popular in recent decades because they add a whole new dimension to risk assessment and justification. Satellite image analysis on the RS and GIS platforms yielded adequate results for flood susceptibility and vulnerability mappings as it provides an incredible environment to run and manipulate a wide range of models to assess flood vulnerability with rational and reliable results [19]. It is critical to develop flood susceptibility mapping and flood risk assessments as it can enable government officials and planners to develop appropriate flood control plans and propose management schemes for reducing flood vandalism in the future [20].

Study Area

(Fig. 1) Punjab's climate is vulnerable, because of its geographical position, low adaptability, and a high reliance on the natural surroundings. This province has an estimated population of 93 million people.

Sindh is Pakistan's most heavily inhabited and urbanized province, accounting for 24% of the country's overall population. Sindh's population grew from 41 248 million people in 2010 to 45 998 million people in 2015 [21]. Due to monsoon and the Indus River, Northern Sindh and Southern Punjab's floodplain are susceptible to recurrent flooding during the summer season. Because it flows along a ridge, the Indus River in Northern Sindh and Southern Punjab is treacherous. It is known for its ability to change course and the outflowing water once breached cannot be discharged back into the river [15]. A considerable number of villages are existent next to the river catchment and population settlements are encroaching toward risky locations in the study area [22]. Historical data indicate that three extreme and fourteen moderate riverine and flash flood incidences occurred between 1942 and 2013 in Pakistan's northern Sindh and Southern Punjab region, which destroyed natural resources and thousands of lives [23]. There is a lack of flood susceptibility assessment and mapping. To emphasize this problem, attempts were made to research certain factors to better identify and forecast areas that are more vulnerable to flooding. This study was conducted to find out the future susceptibility of flood disasters in the chosen study areas that include Bahawalpur and Rahimyar Khan in southern Punjab and Sukkur, Larkana and Jacobabad in Northern Sindh. The main goal of the study is to examine flood-prone areas and the usage of frequency ratio (FR) model to create flood vulnerability map for selected regions. The FR model is a GIS-based method that is known to generate scientifically valid

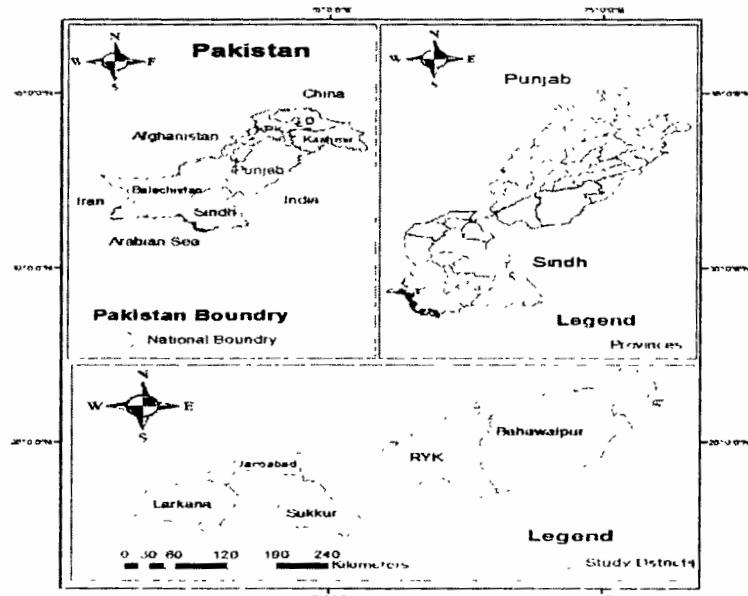


Fig. 1. Map of the study area.

flood susceptibility maps [24]. Flood risk modeling is crucial for its management [25]. It involves various relevant factors such as drainage, density, slope, land use, elevation, rainfall deviation, lithology, and land use/cover. All these factors can be used with the help of the FR model to identify very high to very low susceptibility zones. These findings will be useful to planners, researchers, and local governments for impact assessments to predict future potential flood zones and activity in the area and could be beneficial for planners and decision-makers involved in early disaster response planning within the country.

Experimental

Materials and Methods

The flood susceptibility modelling involves a number of steps. The presented flow chart demonstrates the summary of the followed methodology that consist of four main steps including spatial database preparation, flood inventory mapping, origination of flood conditioning factors and bivariate statistical analysis of the flood conditioning factors using frequency ratio modeling.

Spatial Database Preparation

The spatial database preparation is a significant step in the flood vulnerability and susceptibility analysis process, as it entails the collection of appropriate factors of floods [26]. Floods cannot be caused by

a single factor in most cases. Many parameters like climate and geomorphologic composition regularize the occasion of floods and their intensity [27]. The multi-criteria analysis MCA-based flood susceptibility and susceptibility assessment will be more reliable and authenticate instead of single criteria-based flood susceptibility analysis [28, 29]. (Table 1) (Fig. 2).

Flood Inventory Map

The precision with which flood events are recorded has a huge effect on the mapping of flood vulnerability and susceptibility [30]. A total of 230 location points for flood were chosen for the inventory. Since using the polygon layout of the catalog is challenging for the algorithm and results amplification, random points were used in the study. This format for inventory data has been used in the majority of related natural hazard modeling [31]. For training and testing, the map was divided into 70% -30% ratios [32]. Training locations (161 points) were chosen at random for the generation of the dependent results, which consisted of 0 and 1 values, with 1 indicating the presence of flooding and 0 indicating the nonexistence of flooding. As a non-flooding point, equivalents of 69 points were selected. (Fig. 3).

Flood Conditioning Factors

It is very critical to identify the important factors that influence flood occurrence in establishing flood susceptibility maps [33]. As a result, in flood susceptibility modeling ten (10) conditioning factors

Table 1. Flood predicting factors and their cell size.

| Parameters | Sub-classification | Resolution |
|--------------------------|---------------------------|-------------------|
| Flood record area's | Flood extent | Point coordinates |
| | Elevation (m) | 30 m |
| | Slope angle (Degree) | 30 m |
| | Aspect | 30 m |
| | Profile curvature | 30 m |
| Flood predicting factors | Distance from road (m) | 30 m |
| | Distance from river (m) | 30 m |
| | NDSI | 30 m |
| | NDVI | 30 m |
| | Mean annual rainfall (mm) | 30 m |

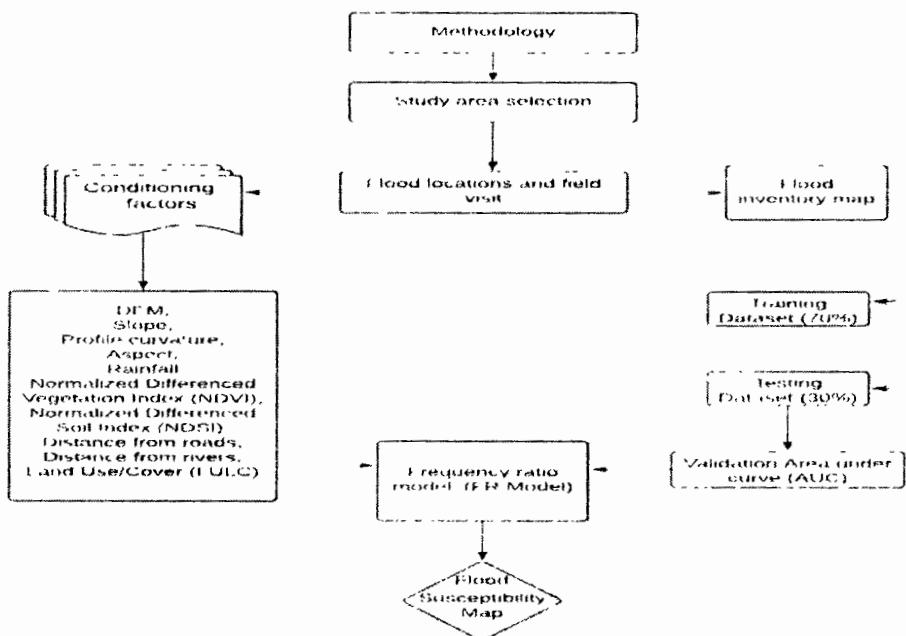


Fig. 2. Flow chart of the methodology for preparing flood susceptibility map

with 30* 30-m pixel size were used: (1) Aspect, (2) Slope, (3) Elevation, (4) Profile Curvature, (5) Normalized Difference Soil Index (NDSI), (6) Normalized Difference Vegetation Index (NDVI), (7) Distance from the river, (8) Distance from the road, (9) Land use land cover map (LULC), and (10) Rainfall. It's essential to note that topographic data has a significant effect on modeling results and that a lot of research is limited by a lack of accurate topographic data [34]. Derivative factors and topography play a significant role in determining flood susceptibility and vulnerability [35].

(Fig. 4) Previous 29 years' data of mean annual rainfall (1989-2018) was taken from the Pakistan

metrological Department (PMD). Digital elevation model (DEM) is one of the most useful techniques for flood prediction which provides a three-dimensional view of the ground surface terrain. The DEM for the study districts was obtained by the Shuttle Radar Topography Mission SRTM with a resolution of 30 m obtained from Earth Atmosphere and NASA (<http://www.dwtkns.com/srtm30m>). The Euclidean distance tool of the Spatial Analyst tool in ArcMap 10.2 was used to establish the layers of distance from rivers and distance from roads. The profile curvature (Fig. 4d) was used in this analysis because it influences the flow rate of water draining the soil ArcMap measured it using

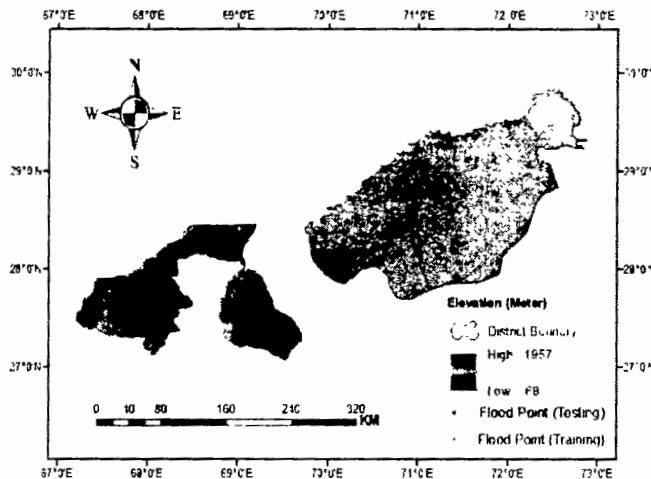


Fig. 3 Flood inventory map of the study area.

the spatial analyst tool. The vegetation and soil are also essential factors in determining flood susceptibility [34]. The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Soil Index (NDSI) were calculated and gained by using different bands from Landsat 8 OLI satellite images assembled by the USGS EROS data center by using diverse bands from Landsat 8 OLI satellite images. NDSI Fig. 4f) is an analytical method for improving soil data from vegetation and impermeable surfaces. It was calculated using the band ratio method in ArcGIS (Raster calculator) to distinguish soil from other ground cover forms to a degree, with high values indicating exposed soil areas and low values indicating other categories which also include vegetated areas [36]. NDVI Fig. 4e) was also determined to illustrate the differences in vegetation's spectral responses in the red plus near-infrared bands low values contribute to bare areas of rock/sand or snow and high values suggest temperate rainforests and tropical rainforests. Equations (1) and (2) were then used to calculate respectively.

$$NDSI = \frac{\text{Band7} - \text{Band3}}{\text{Band7} + \text{Band3}} \quad (1)$$

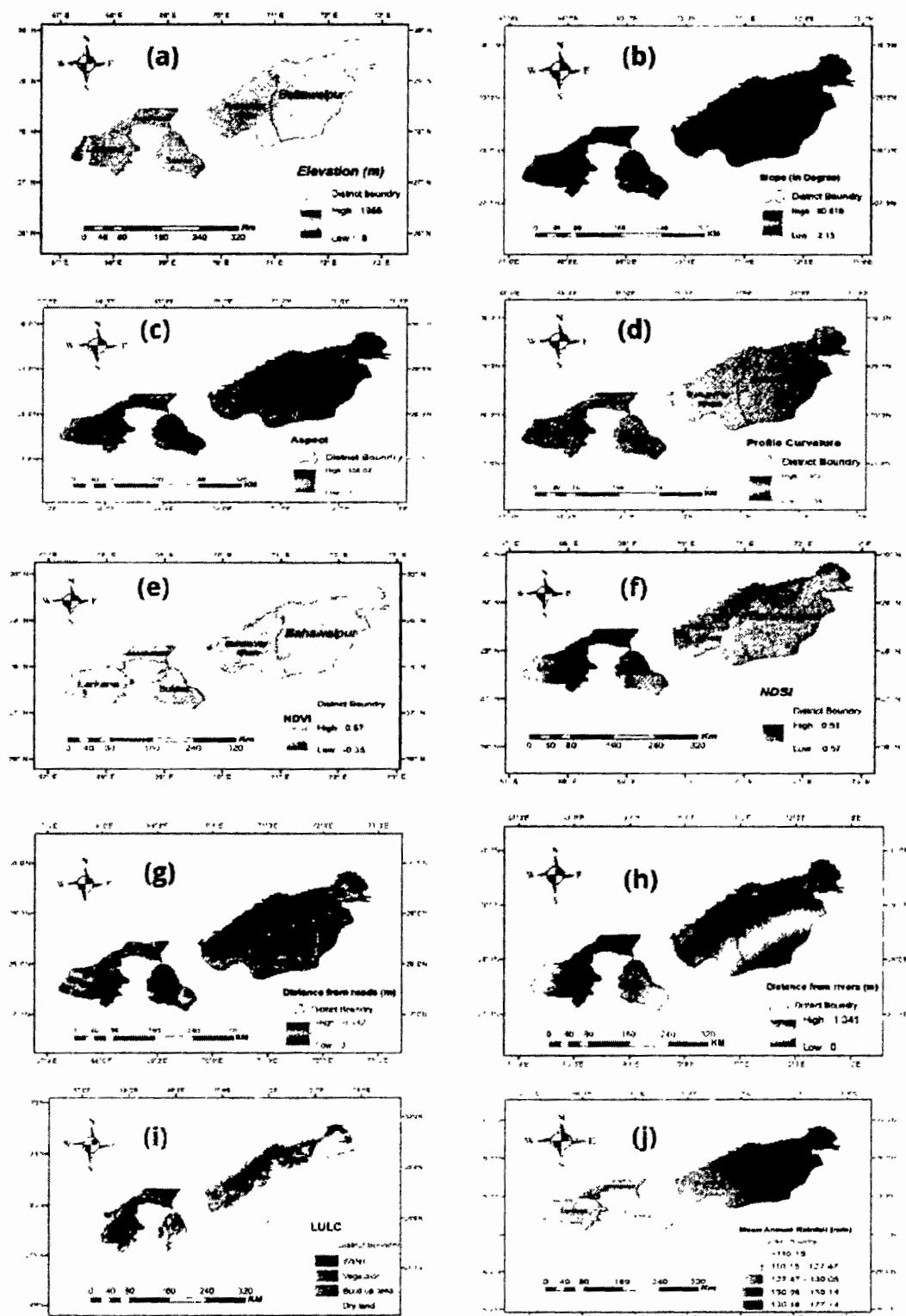
$$NDVI = \frac{\text{Band5} - \text{Band4}}{\text{Band5} + \text{Band4}} \quad (2)$$

Frequency Ratio Model

It is very critical to differentiate the conditioning factors and conditions which can trigger flooding when determining the probability of flooding over a specific period in a particular environment [37]. For flood susceptibility mapping, there are several models and techniques from which to choose. The frequency ratio model [38] is a highly suitable technique for hazards identification amid a high exactness rate.

The frequency ratio (FR) is a method of bivariate statistical analysis (BSA), in which each class of a parameter is assigned a value, and its effect on flood occurrence is assessed [39]. The FR approach was used in conjunction with GIS techniques to conduct the study of flood vulnerability and susceptibility. For BSA, FR is a very reliable method since it considers the effect of every conditioning factor on flooding and assigns weights very accurately. The FR method is determined by the relationship b/w flooding spread and every conditioning factor, and it is used to show the relationship between flood locations and floods conditioning factors in the research study field. If the FR value is greater than 1, the percentage of flooding is greater than the region, indicating a stronger correlation; however, values less than 1 indicate a weaker correlation [40]. The evaluation of flood susceptibility mapping is critical for identifying flood-related factors. Historical flooding events and their triggering parameters may be used to derive the relationship between flood and linked conditioning factors that can cause flooding [41]. The assessment of flood susceptibility mapping is critical for identifying flood-related factors. Historical flooding events and their triggering parameters may be used to derive the relationship between floods and linked conditioning factors that can cause flooding. The Flood Frequency Ratio (FR) is determined by looking at the relationship b/w flood events and the factors that provide the reasons. As a result, the FR of each class of each conditioning factor was determined concerning earlier flood occurrence as shown in Table 2. Frequency Ratio (FR) values were obtained and calculated by via following given formula (3):

$$FR = \left[N_{pix}(SX_i) / \sum_{i=1}^m SX_i \right] / \left[N_{pix}(Xj) / \sum_{j=1}^n N_{pix}(Xj) \right] \quad (3)$$



After calculating the Frequency Ratio values for each class, every controlling factor added all of the values together to generate the final flood vulnerability or susceptibility map. The flood risk map formula is given:

In the next step, the FR is normalized as the relative frequency (RF) for a range of probability levels [0, 1] using equation (4).

$$RF = \frac{\text{Factor class FR}}{\sum \text{Factor class FR}} \quad (4)$$

After normalization, the RF also has the downside of assigning equal weight to all causative variables. To solve this trouble and discover the mutual interdependence of flood contributory factors, a (PR) predictor rate or weight was determined by ranking each flood contributory factor using the training data set equation (5)

$$PR = (RF_{max} - RF_{min}) / (RF_{max} - RF_{min}) \quad (5)$$

Table 2. Calculation results of FR and RF for all classes of factors

| Factors | Factor classes | No of points | % of points | Class area | % of class area | FR | RF |
|-----------|----------------|--------------|-------------|-------------|-----------------|------|------|
| Elevation | 1 | 6220113 | 86.81 | 300.41835 | 98.5 | 2.5 | 0.69 |
| | 2 | 443751 | 6.19 | 2.143223 | 0.7 | 8.57 | 0.23 |
| | 3 | 2591941 | 3.61 | 1.251596 | 0.4 | 1.82 | 0.05 |
| | 4 | 174696 | 2.43 | 0.843745 | 0.3 | 2.47 | 0 |
| | 5 | 66895 | 0.93 | 0.323089 | 0.1 | 2.57 | 0 |
| Slope | 1 | 10608913 | 13.6 | 0.092251 | 21.8 | 9.7 | 0.31 |
| | 2 | 15176643 | 19.46 | 0.103423 | 24.44 | 7.57 | 0.24 |
| | 3 | 20461498 | 26.24 | 0.115555 | 27.3 | 6.25 | 0.19 |
| | 4 | 16284928 | 20.88 | 0.069604 | 16.45 | 4.72 | 0.15 |
| | 5 | 15425436 | 19.78 | 0.042273 | 9.99 | 3.04 | 0.09 |
| Aspect | 1 | 12219715 | 19.35 | 0.098066 | 23.13 | 8.92 | 0.23 |
| | 2 | 10909733 | 17.27 | 0.067587 | 15.97 | 6.87 | 0.18 |
| | 3 | 14383836 | 22.77 | 0.091703 | 21.67 | 7.09 | 0.19 |
| | 4 | 13095650 | 20.73 | 0.084868 | 20.05 | 7.17 | 0.19 |
| | 5 | 12536681 | 19.85 | 0.080866 | 19.11 | 7.17 | 0.19 |
| Curvature | 1 | 1342501 | 2.12 | 0.007027 | 1.66 | 5.95 | 0.17 |
| | 2 | 3602535 | 5.7 | 0.019407 | 4.58 | 6.1 | 0.17 |
| | 3 | 21251814 | 33.65 | 0.14286 | 33.76 | 7.48 | 0.21 |
| | 4 | 20372308 | 32.26 | 0.154652 | 36.55 | 8.44 | 0.24 |
| | 5 | 16576458 | 26.25 | 0.099145 | 23.43 | 6.63 | 0.19 |
| NDVI | 1 | 11404628 | 23.81 | 733.404549 | 1.37 | 0.13 | 0.37 |
| | 2 | 11391449 | 23.79 | 23878.19214 | 44.9 | 0.07 | 0.22 |
| | 3 | 12722976 | 26.57 | 12904.39117 | 24.26 | 0.02 | 0.08 |
| | 4 | 12362658 | 25.81 | 7975.387359 | 14.99 | 0.02 | 0.06 |
| | 5 | 11197031 | 23.38 | 7669.423643 | 14.44 | 0.08 | 0.25 |
| NDSI | 1 | 11426523 | 19.34 | 10283.85754 | 19.34 | 0.01 | 0.05 |
| | 2 | 13079095 | 22.13 | 11771.17044 | 22.13 | 0.01 | 0.05 |
| | 3 | 12640331 | 21.39 | 11376.28334 | 21.39 | 0.04 | 0.12 |
| | 4 | 10862412 | 18.38 | 9776.15829 | 18.38 | 0.08 | 0.25 |
| | 5 | 11070380 | 18.73 | 9953.32925 | 18.73 | 0.18 | 0.52 |

Table 2. Continued.

| | | | | | | | |
|---------------------|---|----------|-------|-------------|-------|------|------|
| Distance from river | 1 | 13789599 | 21.83 | 0.13027 | 30.79 | 1.05 | 0.35 |
| | 2 | 17358181 | 27.48 | 0.170938 | 40.4 | 1.09 | 0.36 |
| | 3 | 16254768 | 25.74 | 0.119756 | 28.3 | 8.18 | 0.27 |
| | 4 | 15743067 | 24.93 | 0.002127 | 0.5 | 1.27 | 0 |
| Distance from road | 1 | 1 | 0 | 0.068071 | 16.08 | 0 | 0.99 |
| | 2 | 15338998 | 24.29 | 0.103985 | 24.57 | 7.56 | 9.95 |
| | 3 | 16466134 | 26.07 | 0.12176 | 28.77 | 8.19 | 1.07 |
| | 4 | 16045568 | 25.41 | 0.105401 | 24.91 | 7.29 | 9.59 |
| | 5 | 15294914 | 24.22 | 0.023873 | 5.64 | 1.76 | 2.32 |
| LULC | 1 | 12730113 | 21.24 | 96.91525914 | 21.54 | 0.18 | 1 |
| | 2 | 11622270 | 19.67 | 2.835608358 | 19.67 | 0.09 | 0.29 |
| | 3 | 18839280 | 31.88 | 2.135449098 | 31.88 | 0.01 | 0.05 |
| | 4 | 10552058 | 17.86 | 60.75866314 | 17.86 | 0 | 0.03 |
| | 5 | 5335021 | 9.03 | 33.38357293 | 9.03 | 0.02 | 0.07 |
| Rainfall | 1 | 4065 | 10.09 | 0.044286 | 10.45 | 1.2 | 0.1 |
| | 2 | 5478 | 13.6 | 0.173151 | 40.87 | 3.5 | 0.31 |
| | 3 | 2727 | 6.77 | 0.143627 | 33.9 | 5.86 | 0.52 |
| | 4 | 9529 | 23.66 | 0.051909 | 12.25 | 6.08 | 0 |
| | 5 | 18470 | 45.86 | 0.010648 | 2.51 | 6.49 | 0 |

Lastly, the flood susceptibility index was calculated by summing the PR of each factor and the RF of each class using equation (6).

$$FVI = \sum_{j=1}^n FR \quad (6)$$

where $N_{pix}(SX)$ is the number of flood points in class I of variable X . $N_{pix}(X)$ is the integral of pixels in variable X , m is the total classes in the variable X , total factors of the study region are the n [35].

Model Validation

It is important to categorize areas that could be affected by potential flooding while conducting a flood susceptibility study. To validate the susceptibility maps is very important concerning known potential floods, despite the validation method used [42]. The region beneath the curve is a common, all-encompassing technique of assessing accurateness that can be used to assess forecast and success rates [43]. The justification or validation method was carried out by comparing defined flood data with the likelihood map of acquired flooding, using AUC [44]. This gave a strong classification with $AUC = 1$ and a random classification with $AUC = 0.5$. AUC has been used in a variety of experiments to assess the efficacy of susceptibility mapping [45]. The techniques include splitting the

probability map into equal-area categories, with the performance and prediction curves determining each probability category. On the x-axis, percentages of flood-prone areas are plotted from maximum to minimum, and percentages of % of flood actions are plotted on the y-axis. A steeper curve suggests that a larger proportion of flood actions or events fall into more susceptible categories.

Results and Discussion

Several independent variables, referred to as factors for ideal conditions, play a precise role in flood susceptibility and vulnerability mapping [43]. All ten conditioning variables, including elevation, NDVI, NDSI, slope, aspect, curvature, distance from the path, Distance from the river, LULC, and rainfall, each have their spatial distribution and statistical database. The elevation is a significant factor in flood incidence as water often flows from higher locations to lower land areas [46]. Previous research has found a low likelihood of flooding in higher elevation areas and a high likelihood of flooding in the lowland areas [47]. Generally, the Frequency Ratio value will decline as the height of the area increases [48]. Table 2 shows the 2 lower elevated classes in the study region (183 m and 183 to 442 m) have high-Frequency Ratio values of

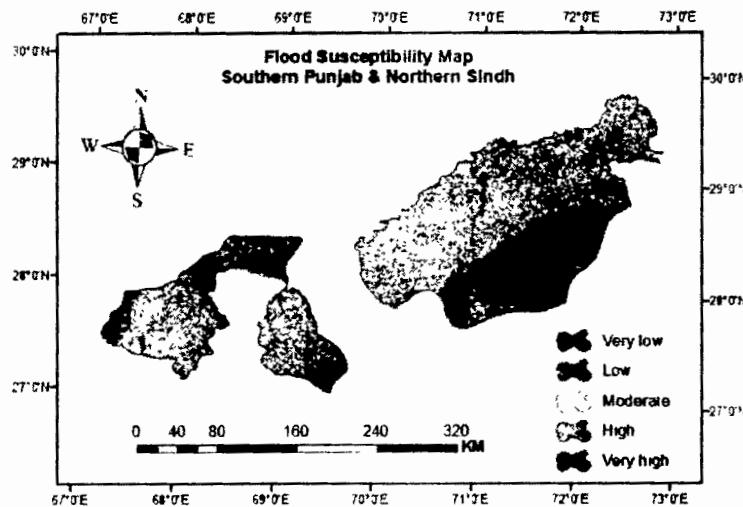


Fig. 5 Flood susceptibility map using FR model.

2.5 & 8.5, respectively, indicating a high likelihood of flooding in low elevated areas. Flooding is less probable in areas with a low FR value and a high altitude [59].

Slope controls the occurrence of flooding, so low-level land areas in rainy spells have a close link to the flood situation. Flooding and flood events are more likely to occur when the slope gradient is lower [50]. The infiltration method is often influenced by the gradient of the slope. An increasing gradient reduces penetration but surface runoff increases; so the result, in areas with abrupt descent gradient, a large amount of water becomes inactive, resulting in flooding [51]. The findings show that the two lower slope gradient grades, $<2.39^\circ$ and $2.39^\circ-5.31^\circ$, respectively, have the maximum FR values of 9.7 and 5.7. The slope gradient above 24.7° , the other side shows the lowest FR value of 3.04. 2) Table. Approximately 59.3% of strong floods occurred in study areas with a slope of less than 12.1%. Since the aspect is linked to physiographic trends and soil moisture patterns, it can be useful in hydrologic situations [52]. Aspect has a significant impact on hydrologic processes such as evapotranspiration and frontal precipitation direction, as well as weathering and vegetation growth, particularly in drier climates [53]. In this study area, the results showed that ranges between 65 and 283 to 359 had high FR values of 8.9 and 7.1. Curvature is also a significant element that reflects the topography's morphology [54]. There are three different types of curvature maps. A convex surface has a positive curvature value, a flat and plane surface has a zero-curve value, and a concave surface has a negative curvature value [47]. The results show that the flat surface had the highest RF of 0.61, while the concave surface had the lowest RF of 0.15. (Table 2). It was revealed that approximately 83 percent of previous floods occurred on slopes with a flat or convex form. The NDVI is another significant flooding

conditioning element. The index's range values are from -1 to +1 [49]. According to Khosravi, an indication of water is shown by negative values and positive (+ve) values indicate vegetation, thus NDVI has a negative (-ve) association with flooding. Higher NDVI values suggest a lower or lesser flood risk, while lower NDVI values indicate a higher flood risk [55]. The NDVI values in this sample range from -0.353 to 0.018 and were quantile divided into five groups. The FR was highest at 0.13 (Table 2) for the class -0.353 to 0.018, indicating that flooding is likely in the study areas.

Normalized difference soil index (NDSI) was used to identify signature variations in the immixing coastal swamp from satellite imagery. Deng created the normalized difference soil index (NDSI) by reversing the adjusted normalized difference water index (MNDWI), which is dependent on the high reflectance of bare soil in the shortwave infrared wavelength. Despite this, the NDSI can detect large, dry bare soil parcels whereas tiny, scattered parcels are often overlooked. The thermal infrared wavelength (TIR) has been used to detect bare land [56]. The findings showed that class levels of 0.135 to 0.225 and 0.225 to 0.511 had high FR values of 0.88 and 0.183 in this

Table 3 Flood Susceptibility zone of study area under different subzones

| Zone | Class | Area (km ²) | Area % |
|-----------|-------|-------------------------|--------|
| Very low | 31-44 | 10495 | 19.73 |
| Low | 44-48 | 10831 | 20.37 |
| Moderate | 48-53 | 10835 | 20.37 |
| High | 53-59 | 10572 | 19.88 |
| Very high | 59-72 | 10434 | 19.62 |

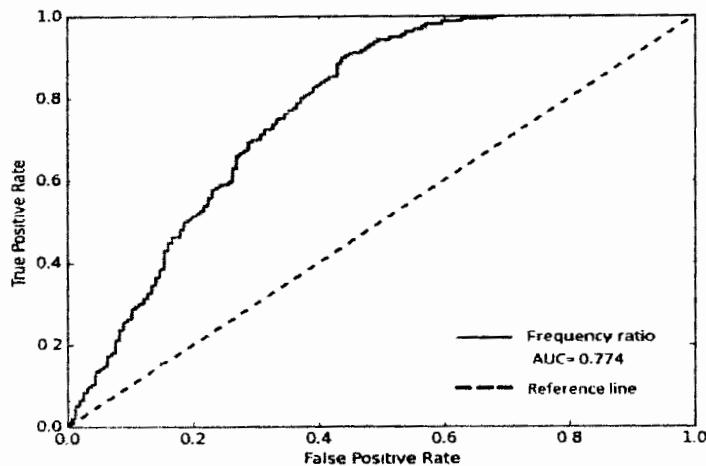


Fig 6. AUC for model performance and validation.

study area. The distance from the road is a big factor in flood susceptibility and vulnerability mapping. Flood levels are influenced significantly by impervious roads and adjacent urban surfaces. They reduce the terrain's penetration potential and double as a runoff outlet [57]. According to the results, distances from the path of less than 0.11 m and 0.11 to 0.18 m have high FR values of 8.1 and 7.2, respectively. The distance from the river is an additional factor to include when determining flood vulnerability since the places closest to the river bank are the ones that are most threatened by high water after a flood. In most cases, depth is estimated above the stream's mouth or higher than the convergence. Every land region located far away from the stream's mouth or confluence is classified as low risk, while an area located close to the stream's convergence is classified as high risk [58]. The maximum FR values in this study area are 8.18 and 1.27, respectively, with class levels between 0.45 and 0.68 and 0.68 and 1.04. The rainfall is merely a source of water in the study area, apart from glaciers. In semi-arid areas, sudden rainfall can trigger flash floods [59]. A significant number of earlier studies have found a connection between flooding and rainfall [60]. In every region, the quantity of rainfall is the main significant cause of flooding. No one expects the rain to cause flooding [46]. In this study area, it is noted that the FR value (6.4) is high in areas with lots of rain (130.1 to 177.1 mm).

Land use patterns are shown as humans and natural cycles [49]. Runoff is increased in urban areas because of the extensive impervious soil, and it is increased in fallow agriculture because near is little vegetation to regulate and avoid the rapid release of water into the soil surface. Those areas are the most susceptible and vulnerable to floods and they are in danger of flooding and also soil erosion. Because of their economic wealth, housing, and high population, built-up areas along rivers are the most prone to floods [61]. In the study

area, the high FR values observed in water bodies and agricultural land are 0.18 and 0.095, respectively, indicating that unprotected areas are highly susceptible and vulnerable to flooding. (Fig. 5)

(Table 3) The ratings for each subclass of all conditioning parameters are dependent on the Frequency Ratio values presented in Table 2. The vulnerable groups range from extremely high to extremely high, and they are mainly concentrated in the study area's middle (Fig. 5). Higher runoff potentiality, poor to very poorly drained soil, lower slope gradient, lower elevation, alluvial deposits, braided flood plain, and closer proximity to the main river define these high to very high flood susceptibility areas, which are significant conditioning factors for flood vulnerability and susceptibility mapping using the Frequency Ratio (FR) model. Several models are suggested and proposed by various researchers, but it is critical to assess the model's accuracy and success rate to validate it for flood susceptibility and vulnerability analysis. In terms of success rate and prediction and forecast accuracy, the FR model's performance is validated [42]. The maximum accuracy of 1.0, indicating that the model was capable of accurately predicting natural hazards without bias [62]. The accuracy prediction was calculated using the remaining 69 flood points that were not used during the model building and the success rate was calculated using 161 training flood points. Susceptibility classes ranging from 'moderate' to 'very high' are considered as possible floods that could happen in the future.

Validation through the Area under the Curve (AUC)

The flood forecast rate is determined by the prediction or forecasting curve. As a consequence, it must be evaluated as a necessary result and output

of a model to determine flood vulnerability and susceptibility mapping performance [2]. (Fig. 5) The AUC parameter was used to validate the model in this analysis, which plots factual positive rate on the y-axis against fake positive rate on the x-axis and was calculated using equation (7).

$$AUC = \frac{\Sigma TP + \Sigma TN}{P+N} \quad (7)$$

Where P represents the entire integer of floods while N represents the total integer of non-floods, and TP and TN indicate the number of pixels properly classified [63]. In the validation process, 30% of the total number of flood points were used. After review, the AUC for the model was 0.774 indicating a success rate of 0.77 percent. Despite the input data limitations and precision, this percentage was deemed satisfactory. It also describes how well the frequency ratio model and factors worked in the study area or predicted floods.

Conclusion

Flood vulnerability mapping analysis is critical for reducing destructive floods through the implementation of authentic solutions. Flood susceptibility data is a valuable tool for planners when it comes to implementing proper land use in flood-prone areas. The aim and intentions of this study are to be aware of the interconnection of flood frequency and flood factor variables in Southern Punjab and Northern Sindh, Pakistan, using a BSA-based FR model. Ten conditioning factors were taken, including slope, aspect, profile curvature, elevation, NDVI, NDSI, distance from the road, distance from the river, LULC, and rainfall, and individual layers were created with 30 m² resolution based on the flood inventory map. For the creation of the layers, a random sampling technique was used to pick (161) 70% of the overall flood point and (69) 30% for validation. The accuracy with which factor layers are prepared is crucial to the validation of flood-prone mapping. The final flood vulnerability map was divided into five zones: very low (19.73%), low (20.37%), in moderate (20.37%), high (19.88%), and very high (19.62%) respectively. As compared to other districts such as Larkana, Rahimyar Khan, Sukkur, and Bahawalpur, Jacobabad has a high susceptible district for floods. This region is highly sensitive, and the adaptive capacity is very low. The high to the very high zone is mainly seen in the study area's middle. Higher runoff potentiality, alluvial deposits, poor to very poorly drained soil, braided flood plain, lower elevation, lower slope, and proximity to the central river define these moderate to very high flood susceptibility areas, which are significant conditioning factors for flood susceptibility. Susceptibility, which varies from "high" to "very high" is recognized

as a possible future flood. The ROC curve was used to assess and measure the significance of the current Frequency Ratio model for vulnerability mapping. The product reveals that the approach used in this study provides consistent and correct results, with a performance rate of 77.4%. As a result, it can be accomplished that precision of the conditioning variables has a significant effect on flood susceptibility mapping since as the normal level of parameters improves, the accuracy of the model improves as well. Low slope (-2.15°-2.39°), low elevation (-68-183 m), and high NDVI (-0.353-0.018) are the most significant parameters and classes for flood-prone areas of southern Punjab and northern Sindh. There is a dire need to realize the trends of climatic extreme events especially floods and pursue the recommended adaptation strategies to manage such extremes in the future. By identifying flood-prone zones, this representation of the model will assist the government officers, planners, decision-makers, and legislatures in implementing appropriate administrative plans in the research area and limiting the development process.

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Conflict of Interest

The authors declare that they have no conflict of interest.

References

- YOUSSEF A.M, PRADHAN B, HASSAN A.M Flash flood risk estimation along the St Katherine road, southern Sinai, Egypt using GIS based morphometry and satellite imagery. *Environmental Earth Sciences*. **62** (3), 611, 2011.
- TEHRANY M.S, PRADHAN B, JEBUR M.N Flood susceptibility analysis and its verification using a novel ensemble support vector machine and frequency ratio method. *Stochastic Environmental Research and Risk Assessment*. **29** (4), 1149, 2015.
- PRADHAN B Flood susceptible mapping and risk area delineation using logistic regression, GIS and remote sensing. *J Spatial Hydrol*, **9**, 1, 2010.
- LI X, ZHANG Q, SHAO M, LI Y. A comparison of parameter estimation for distributed hydrological modelling using automatic and manual methods. *Advanced Materials Research*, 356-360, 2372-2375, 2012.
- WANG Y, HONG H, CHEN W, LI S, PAMUČAR D, GIGOVIC L, DROBNJAK S, BUT D.T, DUAN H A hybrid GIS multi-criteria decision-making method for flood susceptibility mapping at Shangyou, China. *Remote Sensing*. **11** (1), 2019

6. CLOKE HL, PAPPENBERGER F Ensemble flood forecasting: A review. *Journal of Hydrology*, **375** (3-4), 613, 2009.

7. BRONSTERT A Floods and climate change: Interactions and impacts. *Risk Analysis*, **23** (3), 545, 2003.

8. WIHO Disaster data-key trends and statistics in world disasters report. WIHO, Geneva, Switzerland, 2003.

9. OPOLOT E Application of remote sensing and geographical information systems in flood management: a review. *Research journal of applied sciences engineering and technology*, **6** (10), 1884, 2013.

10. GUHA-SAPIR D, SANTOS I, GUHA-SAPIR D, HOYOIS P. The Frequency and Impact of Natural Disasters Oxford Scholarship Online The Frequency and Impact of Natural Disasters May 2016, 1, 2013.

11. HARAGUCHI M, LALL U. Flood risks and impacts: a case study of Thailand's floods in 2011 and research questions for supply chain decision making. *Int J Disaster Risk Reduct*, **14**, 256, 2015.

12. DHAR O.N, NANDARGI S. Hydrometeorological Aspects of Floods in India 1994, 1, 2003.

13. DE GROEVE I, KUGLER Z, BRAKENRIDGE G.R. Near real time flood alerting for the global disaster alert and coordination system Intelligent Human Computer Systems for Crisis Response and Management. *ISCRAM 2007 Academic Proceedings Papers*, 33-39, 2007.

14. AHMAD D, AFZAL M. Flood hazards and factors influencing household flood perception and mitigation strategies in Pakistan. *Environmental Science Pollution*, **27**, 1, 2020.

15. NDMA. Annual Report, **148**, 148, 2017.

16. ALFXANDFR M, PRIEST S, MEES H. A framework for evaluating flood risk governance. *Environmental Science and Policy*, **64**, 38, 2016.

17. KHAN A, KHAN B, QASIM S, KHAN S. Causes, Effects and Remedies A Case Study of Rural Flooding in District Charsadda, Pakistan. *Journal of Managerial, January*, 2013.

18. SORIANO I.R.S., PROT J.C., MALLAS D.M. Expression of tolerance for *Meloidogyne graminicola* in rice cultivars as affected by soil type and flooding. *Journal of Nematology*, **32** (3), 309, 2000.

19. HIAQ M, AKHTAR M, MUHAMMAD S, PARAS S, RAHMATULLAH J. Techniques of Remote Sensing and GIS for flood monitoring and damage assessment: A case study of Sindh province, Pakistan. *Egyptian Journal of Remote Sensing and Space Science*, **15** (2), 135, 2012.

20. ESTEVES L.S. Consequences to flood management of using different probability distributions to estimate extreme rainfall. *Journal of Environmental Management*, **115**, 98, 2013.

21. SINDH POPULATION POLICY. Population Welfare Department Government of Sindh, 2016.

22. WAQAS H, LU L, TARIQ A, LI Q, BAQA M F, XING J, SAJJAD A. Flash flood susceptibility assessment and zonation using an integrating analytic hierarchy process and frequency ratio model for the chitral district, khyber pakhtunkhwa, pakistan. *Water* (Switzerland), **13** (12), 2021.

23. OUMA Y.O, TATEISHI R. Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: Methodological overview and case study assessment. *Water* (Switzerland), **6** (6), 1515, 2014.

24. LIAO X, CARIN L. Migratory logistic regression for learning concept drift between two data sets with application to UXO sensing. *IEEE Transactions on Geoscience and Remote Sensing*, **47** (5), 1454, 2009.

25. DEWAN TH. Societal impacts and vulnerability to floods in Bangladesh and Nepal. *Weather and Climate Extremes*, **7**, 36, 2015.

26. PAPAIOANNOU G, VASILIADES L, LOUKAS A. Multi-criteria analysis framework for potential flood prone areas mapping. *Water ResourManag*, **29** (2), 399, 2015.

27. RAHMATI O, ZEINIVAND H, BESHARAF M. Flood hazard zoning in Yasooj region, Iran, using GIS and multi-criteria decision analysis. *Geomatics, Natural Hazards and Risk*, **7** (3), 1000, 2016, 2016.

28. POUSSIN J.K., BOTZEN W.J.W., AERTS J.C.J.H. Factors of influence on flood damage mitigation behavior by households. *Environ Sci Policy*, **40**, 69, 2014.

29. KONADU D.D, FOSU C. Digital Elevation Models and GIS for watershed modelling and flood prediction – A case study of Accra Ghana. *Appropriate Technologies for Environmental Protection in the Developing World – Selected Papers from ERTEP 2007*, 325, 2009.

30. MERZ B, THIEKLN A H, GOCHT M. Flood risk mapping at the local scale: concepts and challenges. In: Begum S, Steve MJF, Hall JW (eds) Flood risk management in Europe. *Advances in Natural and Technological Hazards Research*, **25**, 231, 2007.

31. PRADHAN B. Flood susceptible mapping and risk area delineation using logistic regression, GIS and remote sensing. *J Spatial Hydrol*, **9**, 1, 2010.

32. OHLMACHER G C, DAVIS J C. Using multiple logistic regression and GIS technology to predict landslide hazard in northeast Kansas, USA. *EngGeol* **69**, 331, 2003.

33. KIA M B, PIRASTEH S, PRADHAN B, MAHMUD A R, SULAIMAN WNA, MORADI A. An artificial neural network model for flood simulation using GIS: Johor River Basin, Malaysia. *Environmental Earth Sciences*, **67** (1), 251, 2012.

34. BATES P.D., MARKS K.J., HORRITT M.S. Optimal use of high-resolution topographic data in flood inundation models. *Hydrological Processes*, **17** (3), 537, 2003.

35. PARDHAN B, SHAFEE M, PIRASTEH M. Maximum flood prone area mapping using RADARSET images and GIS: Kelantan River Basin. *International Journal Geoinformation* **5** (2), 49, 2009.

36. REGMI A D, DEVKOTA K.C., YOSHIDA K, PRADHAN B, POURGHASEMI H R, KUMAMOTO T, AKGUN A. Application of frequency ratio, statistical index, and weights-of-evidence models and their comparison in landslide susceptibility mapping in Central Nepal Himalaya. *Arab J Geoscience*, **7** (2), 725, 2013.

37. YALCIN A. GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Adasen (Turkey): Comparisons of results and confirmations. *Catena*, **72** (1), 1, 2008.

38. LEE M, KANG J, JEON S. Application of frequency ratio model and validation for predictive Korea Adaptation Center for Climate Change . Korea Environment Institute, 613-2 Bulgwang-Dong. *Geoscience and Remote Sensing Symposium (IGARSS), IEEE International IFFF*, 1, 895, 2012.

39. JFBUR M N, PRADHAN B, TEHRANY M S. Optimization of landslide conditioning factors using very high-resolution airborne laser scanning (LiDAR) data at catchment scale. *Remote Sens Environ*, **152**, 150, 2014.

40. AKGUN A., DAG S., BULUT F. Landslide susceptibility mapping for a landslide-prone area (Fındıklı, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models. *Environmental Geology*, **54** (6), 1127, 2008

41. PHAM B.T., AVAND M., JANIZADEH S., PHONG T.V., AL-ANSARI N., HIO L.S., DAS S., LE H.V., AMINI A., BOZCHALOEI S.K., JAFARI F. GIS based hybrid computational approaches for flash flood susceptibility assessment. *Water*, **12** (3), 683, 2020.

42. CHUNG C.J.F., FABBRI A.G. Validation of spatial prediction models for landslide hazard mapping. *Natural Hazards*, **30** (3), 451, 2003.

43. POURGHASEMI H.R., PRADHAN B., GOKCEOGLU C. Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Natural Hazards*, **63** (2), 965, 2012.

44. TIEN BUI D., PRADHAN B., LOFMAN O., REVIIAUG, I. Landslide susceptibility assessment in vietnam using support vector machines, decision tree, and nave bayes models. *Mathematical Problems in Engineering*, **2012a**

45. TIEN BUI,D., PRADHAN B., LOFMAN O., REVIIAUG I., DICK O.B. Spatial prediction of landslide hazards in Hoa Binh province (Vietnam) A comparative assessment of the efficacy of evidential belief functions and fuzzy logic models. *Catena*, **96**, 28, 2012b

46. SAHANA M., PATEL P.P. A comparison of frequency ratio and fuzzy logic models for flood susceptibility assessment of the lower Kosi River Basin in India. *Environmental Earth Sciences*, **78** (10), 1, 2019.

47. DAS S. Geospatial mapping of flood susceptibility and hydro-geomorphic response to the floods in Uhas basin, India. *Remote Sensing Applications. Society and Environment*, **14** (February), 60, 2019

48. KHOSRAVI K., MELLSSE A.M., SHAHABI H., SHIRZADI A., CHAPI K., HONG H. Flood susceptibility mapping at Ningdu catchment, China using bivariate and data mining techniques. *Extrem Hydrol Clim Var*, **419**, 2019.

49. KHOSRAVI K., NOHANI E., MAROUFINIA E., POURGHASEMI H.R. A GIS-based flood susceptibility assessment and its mapping in Iran: a comparison between frequency ratio and weights-of-evidence bivariate statistical models with multi-criteria decision-making technique. *Natural Hazards*, **83** (2), 947, 2016

50. RADMFHR A., ARAGHINEJAD S. Flood Vulnerability Analysis by Fuzzy Spatial Multi Criteria Decision Making. *Water Resources Management*, **29** (12), 4427, 2015.

51. SHIAFIZADEH-MOGHADAM H., VALAVI R., SHIAHABI H., CHAPI K., SHIRZADI A. Novel forecasting approaches using combination of machine learning and statistical models for flood susceptibility mapping. *Journal of Environmental Management*, **217** 1, 2018

52. ERCANOGLU M., GOKCEOGLU C. Assessment of landslide susceptibility for a landslide prone area (north of Yenice, NW Turkey) by fuzzy approach. *Environ Geol*, **41**, 20, 2002.

53. SIDLL R.C., OCIIIAI H. Landslides: processes, prediction, and landuse. *American Geophysical Union, Washington, D.C. Water Res Mouograph*, **18**, 312, 2006.

54. RAZANDI Y., POURGHASEMI H.R., NEISANI N.S., RAHMATI O. Application of analytical hierarchy process, frequency ratio, and certainty factor models for groundwater potential mapping using GIS. *Earth Science Informatics*, **8** (4), 867, 2015

55. PAUL G.C., SAJIA S., HEMBRAM T.K. Application of the GIS-Based Probabilistic Models for Mapping the Flood Susceptibility in Bansloi Sub-basin of Ganga-Bhagirathi River and Their Comparison. *Remote Sensing in Earth Systems Sciences*, **2** (2-3), 120, 2019

56. AGHDAM I.N., VARZANDEH M.J.M., PRADHAN B. Landslide susceptibility mapping using an ensemble statistical index (Wi) and adaptive neuro-fuzzy inference system (ANFIS) model at Alborz Mountains (Iran). *Environ Earth Sci*, **75**, 1, 2016

57. SHUSTER W.D., BONTA J., THURSTON H., WARNEMEYNDL E., SMITH D.R. Impacts of impervious surface on watershed hydrology: A review. *Urban Water Journal*, **2** (4), 263, 2005.

58. CHAPI K., SINGH V.P., SHIRZADI A., SHAHABI H., BUI D.T., PHAM B.T., KHOSRAVI K. A novel hybrid artificial intelligence approach for flood susceptibility assessment. *Environmental Modelling and Software*, **95**, 229, 2017

59. DAS S. Geographic information system and AHP-based flood hazard zonation of Vaitarna basin, Maharashtra, India. *Arabian Journal of Geosciences*, **11** (19), 2018.

60. HONG H., PANAHY M., SHIRZADI A., MA T., LIU J., ZHOU A.X., CHEN W., KOUGIAS I., KAZAKIS N. Flood susceptibility assessment in Hengfeng area coupling adaptive neuro-fuzzy inference system with genetic algorithm and differential evolution. *Science of the Total Environment*, **621**, 1124, 2018

61. NANDI A., MANDAL A., WILSON M., SMITH D. Flood hazard mapping in Jamaica using principal component analysis and logistic regression. *Environmental Earth Sciences*, **75** (6), 1, 2016

62. PRADHAN B., BUCHROITHNER M.F. Comparison and validation of landslide susceptibility maps using an artificial neural network model for three test areas in Malaysia. *Environ Eng Geosci*, **16**, 107, 2010

63. TIEN BUI D. New hybrids of anfis with several optimization algorithms for flood susceptibility modeling. *Water*, **10** (9), 1210, 2018