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Impact of Climate Change on Flood Frequency Analysis, A Case Study of Kalam Basin

by

Bilal Bashir

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This work is dedicated to the most precious blessings of my life - ***my Beloved Family.*** *You are my strength and my greatest source of love. Thank you for always standing by my side, supporting me through every challenge, and encouraging me to move forward. Your love and presence have always been a beacon of happiness and inspiration for me.*

CERTIFICATE OF APPROVAL

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Bilal Bashir

Abstract

The Kalam Basin, located in the mountainous region of northern Pakistan, is highly vulnerable to the increasing impacts of climate change, particularly extreme hydrological events. By combining historical data (1989-2014) with future projections from the Coupled Model Intercomparison Project Phase 6 (CMIP-6) under SSP2-4.5 and SSP5-8.5 scenarios, the research employs advanced methodologies. Bias correction is applied using the delta method, hydrological simulations are conducted with HEC-HMS, and flood frequency analysis is performed using the Gumbel Extreme Value Distribution. The results highlight a significant increase in precipitation under the SSP2-4.5 scenario, with projected increases ranging from 34% to 56% for the years 2026 to 2050, 36% to 53% for 2051 to 2075, and 37% to 53% for 2076 to 2100.Similarly, for the SSP5-8.5 scenario, projected increases in precipitation range from 40% to 62% for the years 2026 to 2050, 40% to 55% for 2051 to 2075, and 41% to 57% for 2076 to 2100. Mean temperatures are projected to rise by 0.59°C to 2.63°C under SSP2-4.5, while for SSP5-8.5, the rise is expected to be between 1.52°C and 3.83°C, indicating substantial warming trends. These changes will accelerate snowmelt, alter runoff timing, and intensify monsoon rainfall, contributing to higher flood risks. Flood discharge simulations reveal significant increases in peak flows under future climate scenarios. For instance, the 100-year return period flood discharge rises from 75,993.7 cusecs historically to 92,094.8 cusecs under SSP2-4.5 and 98,156.7 cusecs under SSP5-8.5. As compared to Historic flood the result shows increase of 21.19% under SSP 2-4.5 and 29.16% under SSP 5-8.5. These results indicate that extreme floods previously expected once every 100 years may occur as frequently as every 50 years, particularly under SSP5-8.5, signaling a drastic reduction in recurrence intervals. The study emphasizes the urgent need for adaptive flood risk management strategies to mitigate these impacts. Recommendations include the development of climate-resilient infrastructure, sustainable land-use planning, restoration of natural flood buffers like wetlands, and improvements to early warning systems for better community preparedness. Furthermore, the research highlights the importance of regional climate modeling and the integration of high-resolution datasets to accurately capture the unique hydrological dynamics of mountainous regions. By providing a thorough analysis of historical trends and future scenarios, this study offers valuable insights for policymakers and practitioners to design effective water resource management and climate adaptation strategies for vulnerable regions such as the Kalam Basin.

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Abbreviations and Symbols

ANN	Artificial Neural Network
ARC SWAT	ArcGIS-integrated Soil and Water Assessment Tool
CDO	Climate Data Operators
CMIP-6	Coupled Model Intercomparison Project Phase 6
FFA	Flood Frequency Analysis
FWS	Flood Warning System
GAMLSS	Generalized Additive Models for Location, Scale, and Shape
GCM	General Circulation Model
GIS	Geographic Information System
HEC-HMS	Hydrologic Engineering Center - Hydrologic Modeling System
HKH	Hindu Kush-Himalayan
IPCC	Intergovernmental Panel on Climate Change
PMD	Pakistan Meteorological Department
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SSP	Shared Socioeconomic Pathway
SVM	Support Vector Machine
WCRP	World Climate Research Program

Chapter 1

Introduction

1.1 General

Flooding is one of the most destructive natural disasters, affecting millions of people worldwide every year. It accounts for approximately 40% of all natural disasters and has both immediate and long-term impacts on lives, infrastructure, and ecosystems. With the accelerating impacts of climate change, flood risks have become more pronounced, altering the frequency, intensity, and spatial distribution of these events. Changing climatic patterns, such as increased rainfall intensity, rising temperatures, and accelerated glacier melting, have contributed to more frequent and severe flooding globally [1].

Pakistan, with its diverse landscape and highly variable climate, is particularly susceptible to flooding. The country experiences various types of floods, including riverine floods, flash floods, urban floods, and glacial lake outburst floods. Riverine floods caused by the overflow of major rivers, such as the Indus and its tributaries, are the most common. Flash floods, triggered by intense rainfall in hilly areas, often cause significant damage due to their sudden onset and destructive force. Urban floods, primarily a result of inadequate drainage systems and poor urban planning, have increasingly impacted large cities, including Karachi, Lahore, and Peshawar, in recent years [2-3].

The Kalam Basin, located in the upper catchment of the Swat River in Khyber Pakhtunkhwa, is a prime example of a region vulnerable to multiple flood types.

Its unique geographycharacterized by steep slopes, snow-fed rivers, and monsoon-driven rainfallcreates a high risk of both riverine and flash floods. Climate change has intensified these risks by increasing monsoon rainfall variability and accelerating glacier melting. As a result, the basin has experienced several extreme flood events in recent decades, including the catastrophic floods of 2010 and 2022, which caused widespread devastation across Swat, Peshawar, and Nowshera valleys [4-5].

The 2010 floods, often referred to as one of the worst natural disasters in Pakistans history, submerged one-fifth of the countrys total land area, impacting 20 million people and causing USD 10 billion in damages. The Swat region was particularly hard-hit, with severe destruction to infrastructure, livelihoods, and agricultural lands. Similarly, the 2022 floods were exacerbated by changing climatic conditions, displacing over 33 million people and resulting in massive economic and social losses. These events highlight the urgency of understanding flood dynamics and their relationship to changing climatic factors [3], [6].

Globally, climate change has disrupted hydrological systems by intensifying the water cycle, resulting in extreme precipitation events and increasing the frequency of high-magnitude floods. Studies suggest that heavy precipitation events in South Asia have become more frequent and intense over the past few decades, with projections indicating further increases under future climate scenarios. For the Kalam Basin, these climatic shifts are expected to cause more frequent and severe flooding, threatening the livelihoods of local communities and the regions fragile ecosystem [7-8].

Flood frequency analysis is an essential tool for assessing these risks. It establishes a relationship between the magnitude of flood events and their probability of occurrence, helping identify the return periods of extreme floods. By combining historical observations with future climate projections, flood frequency analysis provides a robust framework for understanding the potential impacts of climate change on flood risks. When integrated with hydrological modeling, this approach can offer valuable insights into the spatial and temporal variations of floods, enabling more effective planning and risk mitigation [9-10].

The Kalam Basin, being a critical part of the upper Indus River system, plays a significant role in the countrys water resources. The regions hydrology is influenced by a combination of snowmelt, glacier-fed flows, and monsoon rainfall. These factors interact in complex ways, with climate change acting as an additional stressor. Rising temperatures in the Hindu Kush and Himalayan ranges have accelerated glacier retreat, while erratic monsoon patterns have led to both droughts and floods in the basin. This makes the basin an ideal case study for analyzing the impacts of climate change on flood frequency and developing adaptive strategies to mitigate future risks [11-12].

1.2 Research Motivation and Problem Statement

The Kalam Basin in northern Khyber Pakhtunkhwa faces serious risks from flash floods and riverine floods, which threaten lives, infrastructure, and livelihoods. Major floods, such as those in 2010 and 2022, caused widespread destruction, emphasizing the need to understand flood magnitudes and how often they occur under changing climate conditions. These floods are caused by intense rainfall, rapid snowmelt, and unpredictable monsoon patterns, which have become worse due to climate change. To address these challenges, it is important to develop accurate flood projections and create strong management strategies for the Kalam Basin.

Although previous studies have used historical data and older climate models like CMIP-5, no research has applied the latest CMIP-6 data in the Kalam Basin. To the best of my knowledge and based on the available literature, no study has yet been conducted using the state-of-the-art CMIP-6 data for this region. Therefore, this research represents the first attempt to analyze the impacts of climate change on flood frequency in the Kalam Basin using CMIP-6 data. CMIP-6 provides better accuracy and higher resolution, allowing more precise assessments of future flood risks. This study aims to fill this gap by analyzing both historical and future flood patterns, calculating flood magnitudes for different return periods, and developing models to predict floods under changing climate scenarios.

The results of this study will help in designing effective flood management strategies, including improved early warning systems and climate-resilient infrastructure.

By understanding the link between climate change and flood risks, this research will help policymakers and communities in the Kalam Basin prepare for future floods, reduce damage, and improve resilience.

1.3 Primary Goal of the Research Program and Specific Objectives of this study

The following goals are pursued:

- To evaluate historical flood data for the Kalam basin and use statistical techniques for flood frequency analysis such as Gumble extreme value theory, are used to characterize the probability distributions of flood events under current climatic conditions.
- To study the varied rainfall and temperature patterns that influence flood occurrences in the Kalam basin.
- To develop a flood frequency model for the Kalam Basin using HEC-HMS, integrating climate change scenarios to evaluate future flood risks.

1.4 Scope of Work and Study Limitations

The scope of work includes:

- Collecting and analyzing observed historical climate data for the Kalam Basin.
- Selecting suitable Global Climate Models (GCMs) and climate change scenarios based on the IPCC AR6 report.
- Bias correction and analysis of simulated future climate data under SSP2-4.5 and SSP5-8.5 scenarios.
- Developing a flood frequency model using HEC-HMS to simulate flood risks under both current and future conditions.

- Comparing historical and projected data to assess the impacts of climate change on flood frequency and magnitude.

Study limitations include:

- Limited availability of historical data, which is only available up to 2017 for precipitation and up to 2011 for temperature from the Kalam Climate Station. Therefore, the study used data up to 2017 for precipitation and up to 2011 for temperature.
- Potential inaccuracies in future projections due to the reliance on SSP scenarios, which are subject to assumptions and uncertainties.
- Dependence on a single climate station for observed data, which may not represent spatial variations within the basin.

1.5 Structure of the Thesis

The thesis is structured into six chapters, which include:

Chapter 1: The section is titled "Introduction" and provides an overview of the background on climate change and its associated impacts. It outlines the motivations driving the research, the objectives of the study, and the methodology used. Additionally, this section describes the structure and organization of the thesis.

Chapter 2: This section provides a comprehensive literature review on various aspects of climate change and its effects on hydrological systems. It includes discussions on the impacts of climate change, global warming, and associated damages, as well as flood frequency analysis methods and approaches. The review also explores the role of climate models in flood analysis, with a focus on historical and projected flood trends in the Kalam Basin. Further, it delves into flood risk management and adaptation strategies, alongside the application of the delta method for bias correction and the use of Gumbel distribution in flood analysis. Finally, the chapter highlights the application of HEC-HMS in flood risk assessment and management.

Chapter 3: This section is titled "Study Area, Data, and Methodology" and provides an overview of the background information. It includes a description of the study area and the dataset used. Additionally, it outlines the methodology employed in the research, covering the selection of GCMs, the application of the delta method, and rainfall frequency analysis. It also discusses the watershed characteristics, curve number estimation, and the methodology used for HEC-HMS modeling.

Chapter 4: This chapter presents the results and analysis of the study, including the bias correction of precipitation and temperature data. It examines rainfall patterns and trends, temperature variations, and future temperature projections. Additionally, it includes the analysis of flood hydrographs based on the findings.

Chapter 5: : It consists of conclusion, future recommendations and final thoughts.

Chapter 2

Literature Review

2.1 Climate Change and Its Impacts on Hydrological Systems

Climate change, mostly caused by human-made greenhouse gas emissions, is significantly changing water systems worldwide. This shift has big effects on how often and how severe floods occur in delicate areas such as the Kalam Basin in northern Pakistan. As the planet gets warmer, the water cycle becomes stronger. This means the air can hold more water, resulting in heavier rainfall and more intense precipitation [13]. [14] stated that when the temperature goes up by one degree Celsius, the amount of moisture in the air rises by about 7%. This leads to heavier and more regular rainfall. South Asia has especially seen this impact on the monsoon season, making it more unpredictable and intense [15]. With the increasing intensity of rainfall, places like Kalam, nestled in mountainous regions with steep land and poor drainage, face higher chances of flooding. This is because heavy rainwater flows quickly over the surface due to the landscape, raising the risk of floods [16]. Besides heavier rainfall, the increasing temperatures affecting snowmelt and glacier retreat play a crucial role in altering water systems in high-altitude basins. The Hindu Kush-Himalayan (HKH) region, known as the Third Pole, has seen substantial glacier retreat, with glacier mass loss speeding up in recent years [16], [17]. As these glaciers retreat, they not only store less water in the long run, but also change when and how much water flows into rivers. [18]

noticed that as glaciers melt due to warming, it causes rivers to peak earlier and more intensely, raising the chances of floods in spring. Similarly, [19] noted that more snow melting and glacial runoff can lead to higher chances of floods in the HKH area before and during the monsoon season, like in the Kalam Basin. Additionally, severe water-related incidents in this region can get worse due to feedback loops like deforestation, urban growth, and changes in land use. [4] found that changes in land use in northern Pakistan, such as cutting down trees and expanding farms, have made the soil less able to absorb water and increased the amount of water flowing over the ground, which raises the chances of flooding. Sediment transport from glacial erosion also contributes to riverbed elevation, further exacerbating flood hazards [20]. Recent research shows that heavy rainfall, snow melting, and changes in glaciers are causing more frequent and severe floods in northern Pakistan. This has resulted in devastating floods in the Swat River Basin [21]. Despite these worrying patterns, theres still a lot we dont know about how climate change will affect water systems. Predicting future floods mostly depends on climate models, but its tough to accurately translate global climate predictions to local areas due to uncertainties. [22]. Moreover, the changing weather patterns due to climate change make it harder to analyze floods using conventional methods. This means you may need to explore more sophisticated methods like Bayesian approaches and machine learning models to tackle these challenges effectively [23]. Facing these challenges shows why its crucial to have flood risk plans that are tailored to each region and include projections for climate change and factors related to the community.

In conclusion, climate change is profoundly reshaping water systems, especially in sensitive regions like the Kalam Basin of northern Pakistan. Rising temperatures, intensified precipitation, accelerated glacier retreat, and increased snowmelt have all contributed to the growing frequency and severity of floods in these mountainous areas. Human-induced factors such as deforestation, land use changes, and sediment buildup further worsen the situation by reducing natural water absorption and raising river levels. While recent studies highlight these alarming trends, significant uncertainties remain in predicting future flood risks at the local scale due to complex climate dynamics. Therefore, developing region-specific flood risk management strategies that incorporate advanced modeling techniques and community-based considerations is essential to minimize the impacts of climate-induced floods in the future.

2.2 Flood Frequency Analysis: Methods and Approaches

The role of flood frequency analysis in hydrological modeling and water resource management is critical and has provided an insight into how extreme flood events might occur in a given return period. Classic methods of flood frequency analysis were typically based on statistical approaches where the stationarity of past hydrological pattern was assumed to hold into the future. An example is the widely used Log-Pearson Type III distribution, adopted by institutions such as the United States Geological Survey (USGS) for flood frequency estimations. [24], [25]. But nowadays, the idea that thing stay the same is being questioned because of climate change. This is because climate change is causing changes in how much rain falls, the temperatures, and how the land is used, making the conditions not stay constant. [26]. New methods known as nonstationary FFA have come up to adapt to changing conditions. These methods consider factors like time and climate changes to improve how they analyze hydrological patterns as they evolve[27]. Experts are using advanced statistical techniques like Generalized Additive Models for Location, Scale, and Shape (GAMLSS) to tackle nonstationarity. These methods enable the parameters of probability distributions to change over time or in response to climatic factors. [28] Likewise, Bayesian methods are gaining popularity in FFA because they can integrate existing information and measure uncertainties accurately [29]. These models are proving effective in places like the Kalam Basin, where changes in weather patterns greatly affect flood patterns. Moreover, techniques based on copulas are becoming popular for analyzing the relationship between various hydrological factors like rainfall and river flow, giving a comprehensive view of FFA from different angles. [30]. Recently, there have been advancements in combining hydrological modeling with FFA. Hydrological models like HEC-HMS are commonly paired with statistical techniques to mimic river flows and evaluate flood threats in various situations[31]. When it comes to climate change, scientists are combining climate projections from General Circulation Models (GCMs) and Regional Climate Models (RCMs) with various models. They use downscaling methods like statistical and dynamical downscaling to connect the big-picture GCM results with specific local water-related uses[32]. In the Kalam Basin, the terrain is tricky and the weather changes a lot. This requires specific evaluations for the area. New technology like Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) are changing the way we look at flood forecasting and analysis. These methods are good at finding patterns and relationships in water data. They help predict floods, especially when the conditions are uncertain[33]. Recent research has shown that machine learning models are helpful in enhancing flood prediction accuracy, especially in areas where data records are limited or irregular [34]. Moreover, by using remote sensing data like satellite-based rainfall and land cover information, the Flood Forecasting Authority now has a more detailed view of flood risks in areas with limited data, such as northern Pakistan. This improved data allows for better understanding of when and where floods might occur [35]. Even with progress, there are still challenges in choosing the right ways to manage Free Flowing Rivers in different weather conditions. The uncertainties in climate forecasts and water system modeling show the importance of having strong methods that can handle various situations[36]. Moreover, how well FFA methods work really comes down to how good and accessible the hydrological data is. This can be a real challenge in less developed areas[37]. To overcome these challenges in places such as the Kalam Basin, you need to blend conventional methods with new ideas that match the specific water features of the area.

Flood frequency analysis (FFA) plays a vital role in hydrological modeling and water resource management, especially in climate-sensitive regions like the Kalam Basin. While traditional stationary approaches provided valuable insights, climate change and evolving land-use patterns have challenged their reliability. As a result, non-stationary models, advanced statistical techniques like GAMLSS, Bayesian approaches, and copula-based methods are now enhancing flood prediction under changing conditions. Integration of hydrological models with machine learning, remote sensing, and climate projections further improves forecasting accuracy, particularly in data-scarce regions. However, the success of these methods depends heavily on data quality and availability. Therefore, a combination of traditional and modern approaches, tailored to the local context, is crucial for effective flood risk assessment and management in the face of growing uncertainties.

2.3 Climate Change Impacts on Flood Frequency

The way our climate is changing has a big impact on how floods happen around the world. Studies show that as the Earth gets warmer, we see more intense rainfalls leading to changes in how floods occur (IPCC, 2014). This is especially noticeable in places like Kalam, with its mountains, where things like snow melting, heavy rains, and shifts in seasons are all influenced by these changing weather patterns. Many research studies show that the changing patterns of rainfall, including how often it occurs and how heavy it is, play a major role in causing severe water-related events[37], [38]. Changes like these can make it tricky to analyze flood frequencies. Traditional methods rely on the assumption of consistency, but climate change disrupts this by bringing in changing patterns [32].

Studies at the regional level have shown that there are notable changes in how floods behave due to climate conditions. For instance, [39] looked at water flow data from northern Pakistan and saw that there were more instances of high-water flow, which matched up with stronger monsoons. Similarly, [40] have noticed changes in river flow patterns in the Swat and Kabul Rivers. They attribute these changes to more melting glaciers and changing rainfall patterns. This connection highlights how rising temperatures and glacier retreat are making floods more likely in areas like the Kalam Basin. Predictions show that these changes will continue, with heavy rainstorms becoming more common and intense, especially in the monsoon season. [41]. Furthermore, scientists have used global climate models (GCMs) and regional climate models (RCMs) to predict how climate change will affect the likelihood of floods. Research that utilizes these models, like the studies conducted by [42] have showed that South Asia, including Pakistan, is among the regions most exposed to climate-induced flooding. Predictions show that flood risks are expected to increase because of heavier rainfall and faster snowmelt caused by unusual temperatures. Adapting to these shifting patterns requires combining climate information with hydrological models to forecast flood dangers accurately in the future[43]. Moreover, human activities like building cities, cutting down forests, and expanding farmlands have made the effects of climate change on flooding worse. These actions have changed how water moves through the land, making it harder for the ground to absorb water and causing more water to run off[44]. Changes in the Kalam Basin make heavy rainfall more impactful because the modified terrain doesnt slow down surface runoff. Non-stationary methods consider climate factors like temperature and precipitation patterns to enhance flood frequency forecasts in evolving weather conditions[27]. Moreover, its crucial to take steps to adapt, such as improving how we manage watersheds and setting better rules for floodplains. These actions play a key role in lessening risks in areas such as the Kalam Basin, where the effects of climate change are especially severe[45]. However, there are still some gaps in our understanding of how local climate changes affect water systems. This means more research is needed, focusing on specific regions.

Climate change is significantly altering flood patterns, especially in vulnerable regions like the Kalam Basin. Rising temperatures, intense rainfall, glacier retreat, and seasonal shifts are increasing the frequency and severity of floods. Traditional analysis methods struggle with these changing conditions, making non-stationary approaches and advanced modeling techniques essential for accurate flood prediction. Additionally, human activities like deforestation and urbanization worsen flood risks by increasing surface runoff. To effectively reduce these risks, integrating climate data with hydrological models and adopting adaptive measures such as watershed management and strict floodplain regulations is crucial. Still, further region-specific research is needed to fully understand and address local climate impacts on water systems.

2.4 Role of Climate Models in Flood Analysis

Advanced tools like climate models make it possible for us to deepen knowledge and understanding of how flood dynamics develop over time under varied climatic scenarios. Such a model simulates various climate systems integrated with atmospheric, hydrological, and land surface procedures. Identification of possible flood prone areas could be made alongside the evaluation of future flood situations by using these kinds of models. [46] General Circulation Models (GCMs) and Regional Climate Models (RCMs) have been important in climate change projection where their outputs are used widely in flood frequency analysis and disaster risk management[47]. GCMs project global-scale changes in temperature and precipitation, whereas RCMs allow for more localized and higher-resolution views of climate change impacts in a region that can be essential for localized flood analysis in a basin such as Kalam. A research emphasis on the downscaling method that helps to fill the gap between the coarse resolution of GCMs and finer spatial detail necessary for hydrological applications. The statistical and dynamical downscaling techniques have been applied to adapt climate projections to specific hydrological features of river basins. For example, [43] established the efficacy of high-resolution RCMs in predicting extreme precipitation events in South Asia, improving the accuracy of flood risk valuations. Similarly, [48] This includes using statistically downscaled GCM outputs to predict the variation in river discharge under different monsoon regimes, with notable increases in extreme flood events projected under high-emission scenarios. For Pakistan, studies have utilized climate models to assess the impact of altering precipitation patterns and glacial thawing on river flow dynamics. [49] employed RCM simulations to assess future flood risks in the Upper Indus Basin, which found a noticeable increase in the frequency of high-flow events driven by strengthened monsoon activity and glacial retreat. This is consistent with the findings of [50], who reported that increased glacier melt resulting from warming temperatures contributes to higher peak flows in Himalayan River systems. These findings highlight the utility of climate models in identifying and quantifying climate-driven flood risks, especially in complex topographies such as the Kalam Basin. However, qualms remain a major challenge in using climate models for flood analysis. These uncertainties rise due to differences in model structure, emission scenarios, and parameterization schemes, leading to different projections of floods[51]. Ensemble modeling has come out as a robust technique to address these uncertainties by combining outputs from multiple GCMs and RCMs. For instance, [42] Ensemble techniques have been shown to enhance the confidence of flood risk projections by averaging model biases and increasing the dependability of future flood scenarios.

Moreover, the addition of climate model outputs with hydrological models has greatly advanced flood analysis. Hybrid approaches that combine climate and hydrological modeling provide more accurate predictions of flood events by accounting for both climatic and watershed-specific factors. Studies like those by [52] highlights the potential of integrating outputs from RCMs with distributed hydrological models in flood event forecasting over data-scarce basins. The approaches would be particularly pertinent to regions like the Kalam Basin, for which limited observational data force dependence on model-based predictions. Indeed, climate models have remained essential in the flood analysis up to now. The current trend is to upgrade the resolution of the models and improve their parameterization and integrate these with remote sensing and machine learning algorithms[53].

Climate models like GCMs and RCMs play a vital role in understanding and predicting flood risks under changing climatic scenarios. Their integration with downscaling techniques helps bridge the gap between global projections and local hydrological needs, especially in complex regions like the Kalam Basin. Despite uncertainties due to model structure and emission scenarios, ensemble modeling improves confidence in flood predictions. Combining climate models with hydrological simulations enhances accuracy, making these hybrid approaches essential for data-scarce regions. Future advancements aim to improve model resolution and integrate remote sensing and machine learning for better flood risk assessment.

2.5 Historical and Projected Flood Trends in the Kalam Basin

The Kalam Basin, nestled in the northern highlands of Pakistan, has experienced substantial changes in flood patterns due to both natural variability and anthropogenic influences. Historical flood trends in the basin have often been linked to intense monsoon activity, snowmelt, and glacial outburst floods, making the region highly vulnerable to extreme hydrological events [54]. The catastrophic floods of 2010, which caused significant damage to the Swat River and its tributaries, highlight the basin's vulnerability to climate-driven hazards. These floods, attributed to unprecedented monsoon rainfall and mismanaged infrastructure, highlight the need for robust flood management strategies and reliable flood trend analyses [55]. Studies on historical trends have emphasized the increasing frequency and magnitude of extreme precipitation events in the region. For instance, [5] analyzed historical rainfall data in the Upper Indus Basin, including the Kalam region, and reported significant upward trends in extreme precipitation indices, especially during the monsoon season. Similarly, [56] observed a shift in seasonal runoff patterns due to accelerated snowmelt and glacial retreat, which exacerbate flood risks during early summer. Projected flood trends for the Kalam Basin indicate heightened risks under future climate change scenarios. Climate models consistently predict an increase in the intensity and variability of precipitation, which, coupled with rising temperatures, will likely intensify flood occurrences in the region [14]. Regional climate projections indicate that peak river flows are expected to rise due to enhanced glacier melt and monsoon rainfall, potentially leading to more frequent and severe flooding[57]. Using ensemble modeling approaches, [58] forecasted a significant increase in 100-year flood events for the Swat River under RCP 4.5 and RCP 8.5 scenarios, emphasizing the urgent need for adaptive flood risk management. Historical flood analyses also reveal the compounding effects of deforestation and land-use changes in aggravating flood risks in the basin. The removal of forest cover for agriculture and urban development has increased surface runoff and reduced natural flood attenuation capacities [59]. These anthropogenic factors interact with climatic drivers, creating a complex web of flood determinants that require integrated management approaches. The future flood dynamics of the Kalam Basin are further complicated by uncertainties in climate projections and their translation to hydrological impacts. Regional Climate Models (RCMs) and downscaled Global Climate Models (GCMs) have been employed to address these uncertainties and provide localized projections[60]. For instance, [61] demonstrated the utility of high-resolution RCMs in capturing the orographic effects that drive precipitation variability in the basin. Their findings suggest a clear intensification of extreme rainfall events over the coming decades, which could exacerbate flood hazards. Mitigating the impacts of projected flood trends requires adaptive strategies informed by a thorough understanding of both historical patterns and future scenarios. Studies recommend an integrated approach combining improved early warning systems, sustainable land management, and climate-resilient infrastructure to reduce vulnerabilities[62]. As climate change continues to alter hydrological regimes, historical and projected flood trends provide a critical foundation for informed policy-making and disaster preparedness in this sensitive region.

In conclusion, the Kalam Basin faces growing flood risks driven by intensified monsoon rains, accelerated snowmelt, glacial retreat, and human-induced land-use changes. Historical trends and future projections both indicate a rise in extreme flood events, compounded by deforestation and poor infrastructure. Climate models highlight increased precipitation and peak flows, stressing the need for integrated flood management strategies. Strengthening early warning systems, promoting sustainable land use, and developing climate-resilient infrastructure are vital to reduce vulnerabilities and safeguard the region against worsening flood hazards.

2.6 Flood Risk Management and Adaptation Strategies

Flood risk management (FRM) in regions like the Kalam Basin is a complex and evolving challenge due to the interplay of natural hydrological processes and the impacts of climate change. Effective management strategies are essential to mitigate the risks of flooding, which is exacerbated by altered precipitation patterns, snow and glacial melt, and land-use changes. Adaptation strategies aimed at reducing vulnerability and enhancing resilience are critical in minimizing the socioeconomic impacts of flooding while ensuring sustainable development in the basin. The first step in flood risk management involves understanding the flood hazard and vulnerability of affected areas. Research by [63] emphasizes the importance of detailed flood risk assessments that incorporate historical flood data, current hydrological conditions, and future climate projections. Such assessments allow for the identification of high-risk areas and the implementation of targeted mitigation measures. In the Kalam Basin, flood-prone areas are often associated with high runoff due to snowmelt and rainfall, as well as poorly regulated infrastructure in urban centers [64]. These assessments should use high-resolution flood modeling tools that simulate various flood scenarios based on climate projections and topographical data. One of the key adaptation strategies for flood risk management in mountainous regions is the improvement of flood forecasting and early warning systems (FWS). Early warning systems provide timely information to vulnerable communities, enabling them to take preventive actions. In the Kalam Basin, such systems can be enhanced by incorporating satellite-based remote sensing technologies and advanced hydrological models ([65], [66]. For example, the use of Geographic Information Systems (GIS) and remote sensing data allows for the real-time monitoring of snowmelt, glacier melt, and precipitation events that can trigger flooding, providing crucial lead time for communities to prepare. Another crucial adaptation strategy is the development of flood control infrastructure, including flood barriers, dams, and diversion channels. However, these infrastructural measures must be designed with the increasing frequency and intensity of floods in mind due to climate change[67]. [68] advocate for the integration of climate change projections into flood infrastructure planning, recommending that infrastructure be designed to withstand future extremes. Additionally, nature-based solutions such as the restoration of wetlands and forest cover can be integrated into flood management plans, as these systems naturally mitigate flood risks by absorbing excess water and reducing runoff[69]. Land-use planning and sustainable development are also key components of flood risk adaptation.[54] suggest that land-use regulations must prioritize flood resilience, particularly in flood-prone areas of the Kalam Basin. Proper zoning and the restriction of construction in floodplains can prevent the exacerbation of flood impacts. Furthermore, sustainable agricultural practices, such as the conservation of soil and water, can help reduce surface runoff and enhance flood resilience [49]. Community-based adaptation (CBA) is another important strategy for flood risk management. According to [70], CBA emphasizes local knowledge and participation in flood risk management. In the Kalam Basin, this could involve the establishment of local flood management committees, training residents on flood preparedness, and promoting sustainable livelihoods that reduce dependence on flood-prone areas[71]. Finally, international cooperation and policy frameworks are crucial for flood risk management in transboundary river basins such as the Kalam Basin. Regional collaboration between Pakistan and neighboring countries, along with international institutions, can help in the development of shared flood management strategies, data exchange, and funding for flood mitigation projects [72].

In summary, effective flood risk management in the Kalam Basin requires a multi-faceted approach combining advanced forecasting systems, resilient infrastructure, nature-based solutions, and sustainable land-use planning. Integrating community-based adaptation and regional cooperation further strengthens flood resilience. By incorporating climate projections and local vulnerabilities, these strategies can reduce flood impacts, safeguard livelihoods, and promote sustainable development in this climate-sensitive region.

2.7 Delta Method for Bias Correction

The delta method is a widely used statistical approach for downscaling and bias correction in climate studies[73]. It adjusts outputs from climate models by applying observed changes in historical data to future projections. This method is particularly favored for its simplicity, transparency, and computational efficiency, making it suitable for hydrological studies, including flood frequency analysis under climate change scenarios. [74] highlighted the effectiveness of the delta method in transferring climate change signals from General Circulation Models (GCMs) to localized hydrological models, which is crucial for assessing climate impacts on flood regimes. Similarly, [75] found that the delta method performs well in preserving mean changes in precipitation and temperature, critical factors influencing flood modeling. Applications of the delta method have been demonstrated in various studies. For example, [76] used it to downscale GCM data to analyze changes in extreme rainfall and flood events in Australian river basins. Their findings confirmed the method's reliability in capturing changes in mean climate variables that influence flood frequencies. [77] also demonstrated the delta method's robustness in preserving statistical characteristics of historical data, making it a reliable tool for evaluating flood risks in Europe. In the context of flood frequency analysis, [78] applied the delta method to bias-correct precipitation data from multiple climate models in Korean river basins, concluding that it effectively evaluates flood magnitude changes under RCP scenarios. [79] employed the delta method for downscaling precipitation and temperature data in the Upper Indus

Basin, demonstrating its reliability in assessing future flood risks in mountainous regions like the Kalam Basin. These studies collectively underline the delta methods applicability in diverse climatic and geographical contexts, providing credible projections for hydrological extremes and aiding in climate-resilient planning and flood risk mitigation.

Overall, the delta method proves to be a reliable and efficient tool for downscaling and bias correction in climate impact studies. Its ability to preserve mean changes and statistical characteristics makes it valuable for flood frequency analysis, especially in regions like the Kalam Basin. By providing credible future projections, the method supports climate-resilient planning and effective flood risk management.

2.8 Gumble Distribution

The Gumbel distribution, also known as the Extreme Value Type-I distribution, remains a prevalent tool in flood frequency analysis (FFA) due to its capacity to model extreme hydrological events. Recent studies have scrutinized its applicability and limitations. For instance, a comprehensive review highlighted the Gumbel distribution's simplicity in parameter estimation but cautioned against its use in flood frequency analysis without reservations, especially when statistical indicators of the analyzed data deviate from the distribution's inherent characteristics[80]. Similarly, an analysis of the Nera River's flood frequency using the Gumbel distribution underscored its utility in modeling annual maximum flows, while also emphasizing the necessity for careful application to ensure accurate predictions[81]. Furthermore, research on the lower Burhi Dehing River in Assam applied Gumbel's extreme value distribution to predict future flood frequencies, demonstrating its effectiveness in hydrological modeling[82]. However, these studies collectively suggest that while the Gumbel distribution offers a straightforward approach for FFA, its application should be accompanied by thorough data analysis and consideration of alternative models to account for potential deviations in statistical characteristics.

The Gumbel distribution remains a widely used and practical tool for flood frequency analysis due to its simplicity. However, careful evaluation of data suitability and comparison with alternative models are essential to ensure accurate flood predictions, especially in regions with complex hydrological patterns like the Kalam Basin.

2.9 Application of HEC-HMS in Flood Risk Assessment and Management

In the field of hydrological modeling for flood risk assessment and management, various software tools are available, each with distinct features and capabilities. HEC-HMS is particularly noted for its user-friendly interface and the ability to process standard inputs like precipitation, soil characteristics, and land use information, making it highly suitable for simulating watershed hydrology. Other software such as MIKE SHE offers a more comprehensive approach, handling detailed interactions between surface and groundwater but requiring more intricate data inputs. SWAT is renowned for its capability to assess the impact of land management over large areas, relying on extensive climatic and land use data. Additionally, RiverFlow2D specializes in high-resolution, two-dimensional hydraulic modeling of floodplains, demanding precise topographic and hydrodynamic data.

Given the range of software available and the specific nature of the input data they require, HEC-HMS was selected for its balance of advanced features and user accessibility. It supports effective modeling with commonly available data and is extensively used within the hydrological community, facilitating reliable comparisons and validations with other studies.

HEC-HMS (Hydrologic Engineering Center - Hydrologic Modeling System) has emerged as a crucial tool for flood risk assessment and management, especially in areas like the Kalam Basin, where flood events are influenced by complex hydrological processes such as snowmelt, glacial melt, and rainfall. The application of HEC-HMS in the Kalam Basin allows for a detailed simulation of rainfall-runoff relationships, river routing, and flood prediction, making it a central tool in the evaluation of flood hazards under varying climatic conditions. The model is particularly effective in mountainous regions like Kalam, where the interaction between snowmelt and rainfall significantly contributes to flood events [83]. The model has been widely used to simulate hydrological processes in the Upper Indus Basin, which shares similar climatic and geographical characteristics with the Kalam Basin. Previous studies have shown that HEC-HMS is well-suited for modeling complex snowmelt runoff processes, a critical factor in flood dynamics in mountainous basins [84]. The ability to simulate these processes accurately enables the assessment of the impacts of climate change on flood regimes, particularly with respect to changes in snowmelt timing and volume [19]. For example, HEC-HMS was successfully used to model snowmelt runoff in the Upper Indus Basin, demonstrating its utility in flood forecasting [85]. These models have become increasingly relevant due to the projected changes in the hydrological cycle, including shifts in snowmelt patterns and rainfall intensity [86]. In the Kalam Basin, HEC-HMS is utilized to predict runoff from both rainfall and snowmelt, combining meteorological data (such as temperature and precipitation) with snowmelt simulations. Studies have highlighted the importance of incorporating snowpack dynamics into hydrological models, especially in regions where snowmelt is a significant contributor to streamflow and flooding. Additionally, researchers have found that the model is highly effective in capturing seasonal flow variations, providing insights into the potential changes in flood patterns due to altered snowmelt and precipitation dynamics. The integration of HEC-HMS with other tools, such as Geographic Information Systems (GIS) and remote sensing data, enhances the model's accuracy by incorporating real-time satellite data on land use, snow cover, and topography[52]. This integration allows for high-resolution flood modeling, providing more reliable predictions of flood risks[83].For example, the combination of HEC-HMS with remote sensing data has been used to improve flood forecasting in regions of Pakistan, providing decision-makers with more precise flood predictions. HEC-HMS also plays a critical role in flood risk management by simulating the effectiveness of flood control measures such as dams, levees, and diversion channels. In addition to flood control infrastructure, HEC-HMS is instrumental in flood forecasting and early warning systems. Studies have shown that early warning systems based on HEC-HMS can significantly reduce the risks associated with flooding, as they provide communities with critical lead time for evacuation and preparedness [87]. The model has also been integrated with real-time weather data, providing more accurate and timely flood alerts, which is essential for reducing flood damage in flood-prone regions. Furthermore, the model has been used in combination with climate projections to assess the potential impacts of climate change on future flood risks. By incorporating climate change scenarios, researchers have been able to simulate future flood conditions under different greenhouse gas emission pathways [86], [88] This allows for the identification of areas that are likely to experience increased flood risks and the formulation of appropriate adaptation strategies. HEC-HMS has also been applied in the context of floodplain mapping, providing valuable information for land-use planning and disaster risk reduction. According to [87]accurate floodplain maps generated using HEC-HMS can be used to guide land-use decisions and prevent the construction of critical infrastructure in flood-prone areas. This is particularly important in the Kalam Basin, where growing urbanization and agriculture in flood-prone areas increase the vulnerability of local communities to flood hazards[83], [84].

In conclusion, HEC-HMS is a powerful tool for simulating, forecasting, and managing flood risks in the Kalam Basin. Its ability to model complex hydrological processes, integrate climate projections, and evaluate flood mitigation strategies makes it an invaluable tool in the context of flood risk management. As climate change continues to alter hydrological patterns, HEC-HMS will remain a central tool in assessing and adapting to the evolving flood risks in the Kalam Basin.

Chapter 3

Research Methodology

3.1 General

Climate change is a global phenomenon that has profound impacts on the environment, economy, and society. Kalam Basin, located in Pakistan's Khyber Pakhtunkhwa province, is particularly vulnerable to the adverse effects of climate change due to its unique geographical features and socioeconomic conditions. Future climate scenarios for the region have been projected using Global Climate Models (GCMs), which help assess potential changes in temperature, precipitation, and flood patterns. However, the results from different GCMs can vary significantly, requiring robust statistical techniques for evaluation. The methodology for this study, titled "Impact of Climate Change on Flood Frequency Analysis: A Case Study of Kalam Basin," adopts a systematic approach to analyze GCM outputs and evaluate the potential impacts of climate change on flood risks in the research area.

3.2 Study Area

The Kalam Basin, located in the northern region of Pakistan, is part of the upper Swat Valley in the Khyber Pakhtunkhwa province. The basin is characterized by rugged mountainous terrain, dense forest cover, and a network of rivers and streams, with the Swat River being the primary watercourse. The geographic coordinates of the basin lie approximately between 3530' to 360' N latitude and 7230' to 730' E longitude. Figure 3.1 shows the study area of kalam basin. The area has significant hydrological importance due to its contributions to the overall Swat River system, which plays a crucial role in irrigation, hydroelectric power generation, and local livelihoods downstream.

Kalam is situated at an elevation of approximately 2,000 meters above sea level, with surrounding peaks reaching heights above 5,000 meters. The basin experiences a temperate highland climate, with cold winters and mild summers. Snowfall is common during the winter months, and melting snowpack contributes substantially to river flow during the spring and summer seasons. The region receives substantial precipitation, primarily from both the monsoon system and western disturbances, which influence the hydrology and flood dynamics.

The Kalam Basin is vulnerable to extreme weather events, including heavy rainfall and glacial melt, making it susceptible to flooding. In recent decades, climate change has intensified these hydrological processes, leading to more frequent and severe flood events. The 2010 floods in the Swat Valley, including Kalam, caused widespread devastation, highlighting the region's vulnerability to climate-induced hydrological extremes. Changes in precipitation patterns, temperature increases, and glacial retreat have significantly altered the flood regime and water availability in the basin.

The basins hydrological and meteorological characteristics make it a pertinent area for studying the impacts of climate change on flood frequency. A combination of physical factors, such as steep slopes, high precipitation rates, and snow/glacial melt dynamics, influence flood behavior. Inhabitants of the basin rely heavily on agriculture, forestry, and tourism, all of which are directly affected by flood occurrences and water resource availability.

Flood frequency analysis in this context aims to understand how climate variability and long-term climate change are modifying flood patterns, peak flow magnitudes, and recurrence intervals. This analysis provides critical insights for flood risk management, infrastructure planning, and sustainable water resource management in the region. By examining historical data and future projections, this research will contribute to the development of climate-resilient strategies to mitigate flood impacts in the Kalam Basin and similar mountainous river basins.

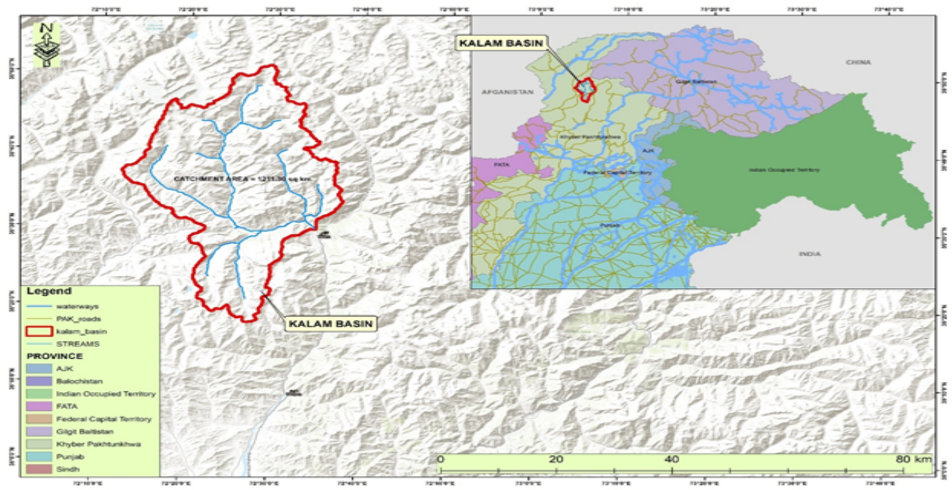

FIGURE 3.1: Study area of Kalam basin

3.3 Brief Methodology

The methodology adopted in this study aims to analyze the impact of climate change on flood frequency in the Kalam Basin using historical climate data and future projections using from multiple Global Climate Models (GCMs). First, data collection was performed by obtaining temperature, precipitation, and hydrological data from the Kalam Climate Station for the period 1989 to 2014.

Furthermore, future climate data were download from the World Climate Research Programme (WCRP), which provided a set of GCMs representing various climate change scenarios. For this research, two climate scenarios, SSP2-4.5 and SSP5-8.5, were selected based on the IPCCs Sixth Assessment Report. From the 31 available GCMs, five were selected for this research based on different climate conditions: AWI-CM-1-1-MR (Germany), BCC-CSM2-MR (China), MPI-ESM1-2-HR (Germany), MPI-ESM1-2-LR (Germany), and NorESM2-MM (Norway). These models represent hot, cold, dry, wet, and average climate scenarios.

After selecting the GCMs, frequency analysis using the Gumbel Extreme Value distribution was applied to precipitation data for different return periods at the Kalam Climate Station (1989-2014) and for the selected GCMs over the same period. The delta method was used for bias correction by comparing results from the Kalam station with the GCMs under two climate scenarios: SSP2-4.5 and SSP5-8.5 during the base period (1989-2014). The bias-corrected delta values were then applied to future GCM projections for three time periods: 2025-2050, 2051-2075, and 2076-2100. Using the corrected future data, Gumbel distribution analysis was performed for return periods of 5, 10, 25, 50, 100, 200, 500, and 1,000 years. This data was subsequently used for hydrological modeling with HEC-HMS to simulate flood discharges under both current and projected climate scenarios.

In addition to precipitation data, temperature data from the Kalam Climate Station (1984-2017) and corresponding GCM data for the same period were analyzed under two climate scenarios: SSP2-4.5 and SSP5-8.5. The daily temperature data were converted to mean monthly averages. The delta method was then applied by calculating the difference between historical observations and GCM outputs. This delta was added to future temperature projections from both climate scenarios. Variations in temperature were analyzed to illustrate potential changes over time, showing how climate change could influence temperature patterns in the study area.

Hydrological modeling using HEC-HMS software was conducted to simulate discharge for various return periods under both historical and projected climate conditions. The model estimated discharge values for return periods of 5, 10, 25, 50, 100, 200, 500, and 1,000 years. Finally, the results from the frequency analysis and hydrological modeling were evaluated to assess changes in flood magnitude and frequency, highlighting the potential impacts of climate change. The findings contribute to understanding flood behavior in the basin and provide valuable insights for water resource management and flood risk mitigation strategies.

3.4 Data Collection

3.4.1 Introduction

A data set is a collection of information used for supporting analysis, conclusions, and research findings. The data set might contain any kind of information relevant to the research issue, such as responses to surveys, experimental findings, and

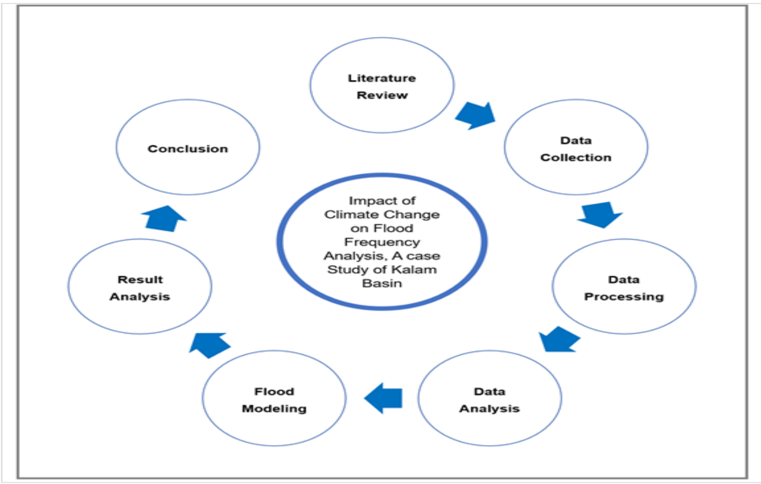

FIGURE 3.2: Study work flow

historical records. Selecting and using a suitable data collection is crucial to the successful completion of an MSc thesis project since it forms the basis for the investigation and conclusions. Additionally, transparent and repeatable research outcomes are guaranteed by a well-defined data collection process. Historical daily data for temperature (33 years, from 1984 to 2017) and precipitation (54 years, from 1963 to 2017) were collected from the Pakistan Meteorological Department.

3.4.2 Data Collection from Meteorological Department

3.4.2.1 Temperature Data

The temperature data for the Kalam region were collected from the Pakistan Meteorological Department (PMD) for the period from 1984 to 2011. The Kalam region experiences large changes in temperature throughout the year, typical of a mountainous climate. The mean monthly maximum temperature ranges from 8.23C in January to 26.51C in June, showing a steady rise from winter to summer. Similarly, the mean monthly minimum temperature varies from as low as -6.88C in January to a high of 14.64C in July. These temperature differences highlight the contrast between cold winters and warm summers. Winters are especially cold, with temperatures often dropping below freezing, while summers are mild to warm. These temperature patterns play an important role in affecting snowmelt, river flow, and water availability in the Kalam Basin. Understanding this temperature behavior is important for studying floods, water management, and the impact of future climate change on weather extremes in the region. For detailed information, please refer to Tables 3.1 and 3.2.

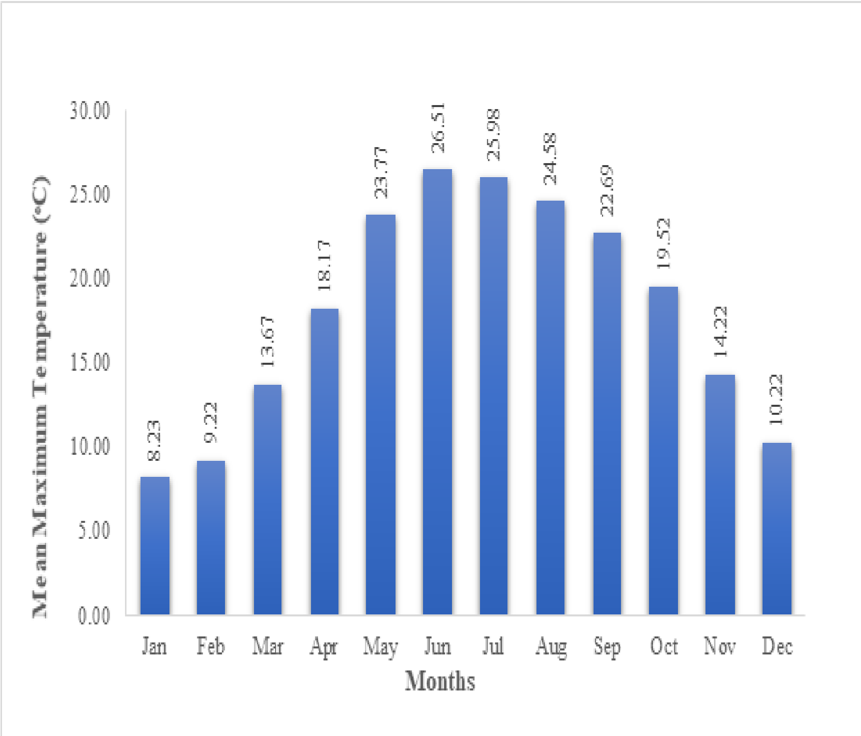

FIGURE 3.3: Mean Monthly Maximum Temperature of Kalam Station (°C)

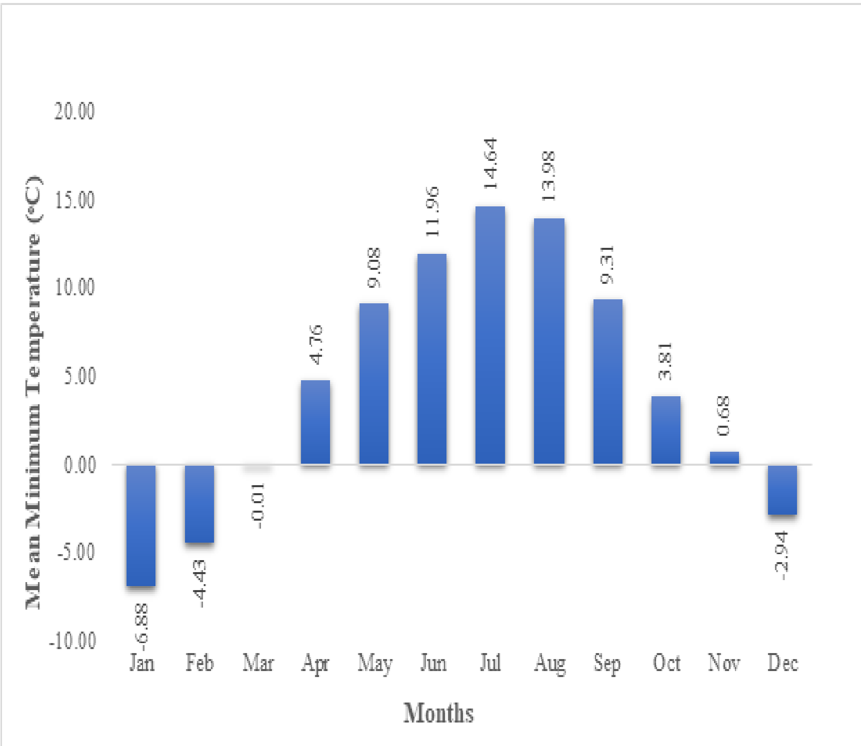

FIGURE 3.4: Mean Monthly Minimum Temperature of Kalam Station (°C)

Table 3.1: Mean Monthly Maximum Temperature of Kalam Station (°C)

Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
1984	8.33	8.39	25	16.11	22.78	29.44	22.78	25	21.67	19.44	12.22	8.33
1985	7.22	13.33	13.89	16.11	22.22	26.11	25	25	23.33	18.33	13.33	7.78
1986	9.44	9.44	11.11	16.11	21.11	26.11	25.56	23.89	22.78	20	13.33	9.44
1987	11.11	9.44	11.67	18.33	27.22	25.56	26.67		25	15.56	17.22	13.33
1989	11.67	9.44	12.78	17.22	20.56	25	25	23.33	22.78	19.44	13.89	10.56
1993	7.22	8.33	9.44	20	23.89	26.11	24.44	24.44	23.33	18.89	16.11	11.67
1994	5	5.56	12.22	14.44	22.78	26.67	25.56	25	21.11	20	14.44	7.22
1995	7.78	7.22	10.56	14.44	22.78	27.22	26.67	21.11	21.67	18.89	17.22	6.67
1998	7.78	7.78	13.89	19.44	21.67	23.33	27.22	26.11	22.78	22.78	20	17.78
1999	7.78	7.78	12.22	20	24.44	27.78	26.67	25	23.33	21.11	12.22	15
2000	9.7	10.11	12.35	20.15	26.86	26.19	25.93	25.34	22.85	22.8	13.98	11.7
2001	13.24	12	14.16	18.96	26.34	26.72	26.63	25.5	23.48	20.77	16.91	10.07
2002	11.51	7.46	13.37	18.09	26.34	27.06	26.7	26.25	22.41	20.18	12.3	
2003	9.8	7.58	12.46	17.76	20.68	26.04	25.86	25.13	22.41	20.18	12.3	10.02
2004	7.38	13.21	17.89	19.52	24.64	24.87	26.38	26.13	24.65	17.89	14.81	9.84
2005	4.71	6.25	11.67	16.74	19.98	29.26	27.81	26.27	24.76	19.68	8.94	10.99
2006	6.57	11.67	12.89	18.11	25.84	25.24	26.59	24.98	23.76	22.64	12.96	7.19
2007	10.25	10.62	11.54	24.52	23.46	26.13	26.43	25.79	22.02	20.18	14.09	7.69
2008	3.3	11.42	16.02	18.26	25.91	26.87	25.23	25.23	22.02	17.17	13.43	9.89
2009	6.11	8.41	12.49	16.22	23.15	27.26	26.36	25.59	22.04	19.77	13.89	7.56
2010	7.99	7.5	18.89	19.02	23.76	27.93		15.89	17.57	11.11		
2011	7.19	9.96	14.3	20.28	26.58	26.22	26.04	25.29	23.37	22.65	15.13	11.61
Mean	**8.23**	**9.22**	**13.67**	**18.17**	**23.77**	**26.51**	**25.98**	**24.58**	**22.69**	**19.52**	**14.22**	**10.22**

Table 3.2: Mean Monthly Minimum Temperature of Kalam Station (°C)

Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
1984	-7.78	-7.22	1.11	3.89	9.44	13.89	14.44	17.22	9.44	4.44	-0.56	-5
1985	-5.56	-4.44	2.22	5.56	8.33	10.56	16.67	16	9.44	4.44	0	-3.89
1986	-6.67	-7.78	-1.67	3.89	7.22	11.11	15	14.44	9.44	4.44	0	-4.44
1987	-5	-2.22	0.56	4.44	8.89	10	11.67		10	3.89	8.89	13.33
1989	-8.89	-7.22	-1.11	2.22	6.67	10	12.78	12.22	8.33	2.78	-1.11	-2.22
1993	-6.11	0	0	4.44	8.89	11.67	13.33	12.22	11.11	3.33	1.11	-0.56
1994	-5.56	-6.11	-0.56	2.22	8.33	11.67	16.67	16.67	8.89	2.78	0	-4.44
1995	-8.89	-3.89	-1.67	3.33	7.78	10.56	13.33	15	7.78	3.33	8.33	-6.67
1998	-7.78	-5	-3.33	6.11	8.89	10	14.44	14.44	10	5.56	0.56	-1.67
1999	-5.56	-3.33	-0.56	6.11	9.44	12.78	14.44	15	12.22	5	-0.56	-3.33
2000	-5.78	-6.9	-0.52	5.61	10.91	12.5	13.91	14.7	10.76	6.42	-0.7	-4.44
2001	-5.82	-4.52	0.36	6.26	10.57	13.28	16.04	14.8	9.65	6.33	1.67	-2.31
2002	-6.16	-5.79	-2.85	5.39	10.5	12.06	13.87	15.5				
2003	-4.32	-2.96	-1.51	4.72	7.35	11.26	14.48	12.54	10.44	3.45	-0.95	-3.3
2004	-5.61	-3.6	2.99	6.81	9.41	11.93	13.21	13.92	9.89	2.58	0.57	-1.92
2005	-8.46	-5.1	0.54	3.43	5.22	10.63	16.15	13.12	10.52	3.53	-4.56	-4.44
2006	-7.3	-1.92	-0.011	4.67	11.31	11.74	16.24	15.39	9.83	5.95	0.96	-5.61
2007	-7.82	-1.92	-0.02	7.31	9.5	13.5	14.82	14.1	8.87	2.94	0.41	-5.07
2008	-10.29	-5.67	1.38	4.48	10.07	15.04	14.48	13.53	7.96	4.06	0.43	-3.98
2009	-3.53	-2.18	1.15	2.07	9.89	11.67	16.83	16.76	9.22	2.51	-1.04	-5.13
2010	-9.23	-4.9	3.08	6.81	10.27	14.7		1.33	0.31	-4.32		
2011	-9.19	-4.88	0.18	5.04	10.81	12.5		14.62	11.35	6.47	0.13	-3.62
Mean	**-6.88**	**-4.43**	**-0.01**	**4.76**	**9.08**	**11.96**	**14.64**	**13.98**	**9.31**	**3.81**	**0.68**	**-2.94**

3.4.2.2 Precipitation Data

As per meteorological department data of the monthly total precipitation for Kalam over the 54-year period from 1963 to 2017, the summer months were usually June, July, and August, with total precipitation around 913.9 mm. The highest average monthly precipitation occurs during the peak rainfall months, with 190.36 mm recorded, indicating a pronounced wet season. Other months, such as those with values around 26.17 mm and 33.29 mm, experience much lower rainfall, reflecting a drier period. For detailed information, please refer to Tables 3.3.

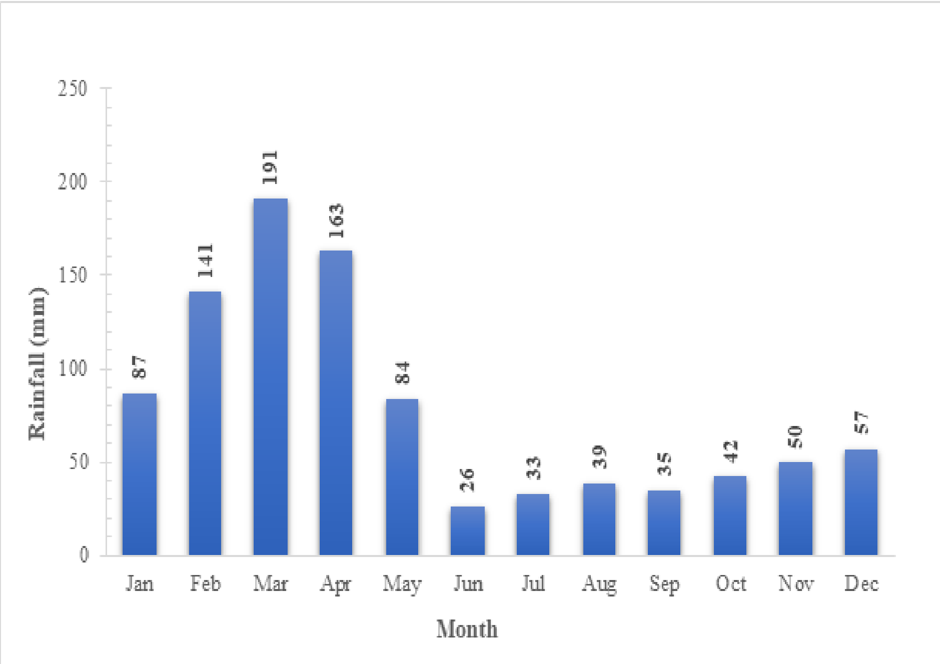

FIGURE 3.5: Shows mean monthy rainfall data of Kalam Climate Station for period (1963-2017)

3.5 Data Analysis

This master's thesis provides a comprehensive analysis of Kalam's temperature and precipitation data, covering 54 years of precipitation data (1963-2017), excluding the year 1988, and 33 years of temperature data (1984-2017), in order to identify long-term climate trends and examine any potential effects of climate change. A large dataset collected from meteorological records is used in the study, together with advanced statistical methods and data visualization tools for thorough analysis. By examining patterns, variations, and potential changes in temperature

TABLE 3.3: Mean Monthly Precipitaion of Kalam Climate Station

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average Annual
1963	0	70.2	308	204.9	169.9	5.2	38.2	31.3	20.7	18.7	60.5	48.7	976.3
1964	159.6	136.1	110.8	253.7	67.2	12.5	61.9	28.8	15.8	27.4	28.8	157.8	1060.4
1965	156.8	232.6	223.6	314.8	117.9	0.8	38.7	20.7	23.3	25.1	37.4	39.6	1231.3
1966	152.7	214.7	294.6	27.4	2.6	32	20.4	74.6	71.3	0	25.4	0	915.7
1967	50.8	192.6	125.2	210.7	122.7	16.5	11.9	22.4	40.6	64	5.3	104.9	967.6
1968	40.5	62.2	135.4	249.5	132.3	7.6	2.8	65.3	6.4	43.2	35.8	14.5	795.5
1969	80.2	175.6	210.8	213.1	80.1	27.7	16.1	31.5	43.4	89.7	21.4	7.9	997.5
1971	7.4	169.5	69.1	216.2	12.5	27	49.3	9	30	14.8	6.9	24.4	636.1
1972	131.6	150.8	105.9	231	144.2	31.1	22.1	76	82.3	44	32.5	121.6	1173.1
1973	125.5	179.6	191.5	157	57.5	1	35.2	38.4	57	33.3	8.1	21.8	905.9
1974	77.7	169	74.3	135.9	94.5	33.3	33.9	26.1	76.5	11.7	0	106.2	839.1
1975	56.9	154.6	217.1	253.9	195.1	1.5	48.5	113.3	28.5	49.8	35.8	60	1215
1976	86.3	205.2	191.4	136.9	61.7	27	29.3	67.8	43.1	30.5	24.1	31.1	934.4

Continued on next page

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average Annual
1977	123.6	29.2	99.8	138.9	42.7	4.9	16.1	32.6	13.4	29.5	48.9	35.5	615.1
1978	73.2	45.9	148.7	123.3	62.3	20.9	129.7	19.1	34.4	12.6	112.2	10.1	792.4
1979	42.4	92.3	176.3	200.4	139.7	13.2	11.7	75.1	14.6	1.3	44.2	22.3	833.5
1980	114.8	36.3	4.9	104.7	89.3	31.5	43.7	25.4	32.1	87.9	84.1	26.7	681.4
1981	78.4	216.7	221.3	213.8	69.5	19.9	28.6	57.9	31.4	22.6	31.7	0	991.8
1982	56.7	185.2	167.5	63.5	49	11.7	27.8	12	25.6	32.2	123.3	0	754.5
1983	49.2	32.3	278.5	62.6	59.3	11	15.3	44.4	16.3	9.9	0	0	578.8
1984	37.1	159.9	176.9	145.6	90	10.7	23.6	22.5	45.8	6.6	83.2	76.7	878.6
1985	78.5	26.1	52.9	137.5	85.4	6.9	37.2	53.9	10.8	72.5	27.9	145	734.6
1986	27.2	147.3	363.2	178.1	52.7	19.7	27.4	97.1	12.4	9.7	182.9	39	1156.7
1987	0	82.2	323.7	234.9	101.8	79.9	26.9	3.3	18.5	206.6	0	63.5	1141.3
1988	58.5	96.1	193.5	91.3	52.2	50	38.6	40.9	7.9	3	0.5	133.2	765.7
1989				79	185.4	7.9	48.2	31.4	26.1	35.8	92.2	0.5	506.5
1990				53.7	14	27.5	15	23.3	9.9				143.4

Continued on next page

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average Annual
1991	166.4	263.2	336.5	201.9	172.2	25.7	30.5	10.9	84.3	3.1	6.3	70.9	1371.9
1992	232.7	171.1	336.9	228.9	167.3	38.6	6.6	47.6	121.1	71.6	16	71.9	1510.3
1993				9.9	76.8	56.9	85.1	37.9	9.6	60.9	58.8	33.8	429.7
1994	164.4	149.3	181.5	248	73.5	25.1	23.1	24.8	61.5	78.2	30.8	105	1165.2
1995	9.2	101.2	226.9	231.2	93.8	104	53.7	12.3	29.5	29.5	27.9	59.5	978.7
1996	66.8	148.4	323.3	207.5	128.3	46	28.8	28.3	8.7	75.7	19.8	21.6	1103.2
1997	25.4	31.5	284.8	168.7	84.2	16.5	6.6	47.3	26.5	15.5	18	8.2	733.2
1998	144.8	220.4	152.6	203.5	135.1	47.9	20	27.2	19	7.7			978.2
1999	116	197.5	336.4	191.4	59	27.9	45.9	37.2	49.7	5.9	139.3	0	1206.2
2000	87	47.5	218.2	31.5	15	30.7	30.8	14	39.5	64.1	69.4	86.4	734.1
2001	4.8	137.9	77.2	69	24.7	18.3	66.9	34.8	67.1	3.8	70.4	0	574.9
2002	53.1	176.5	228.1	187.6	26.4	57.2	18	57.3	23.1	0	33.3	121.1	981.7
2003	23.3	202.3	218.6	282.2	107.8	4.3	5.5	36.2	64.3	27.4	111.8	110.6	1194.3
2004	67	117.3	81.2	170.2	47.3	19.4	28.7	25.8	29.3	211.3	45.7	117.9	961.1

Continued on next page

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average Annual
2005	75.8	347.1	245.4	230.2	124.3	16.3	20.8	35.8	9.2	92.6	82.3	5.1	1284.9
2006	180.2	218.9	81.5	109.2	35.6	21	35	53.4	23	2.3	168	169.4	1097.5
2007	9	54.7	257.5	77	84	36.8	18.3	31.7	19.1	5.6	1.3	25.5	620.5
2008	237.2	45.7	45.8	101.6									
0.0”	6.4	30.5	16.5	40.6	19.1	29.2	100.5	673.1					
2009	156.2	115.6	188.1	234.4	87.9	50.9	78.8	58.4	63.5	84.2	92.7	109.3	1320
2011	58.4	213.3	113	64.7	44.6	20.4	30.6	59.9	29.2	30.5	59.8	24.2	748.6
2012	113	124	152	68	112	24.1	14	41	97	48	39	89	921.1
2013	39	234	177	137	45	46	12	96	17	28	31	17	879
2014	24	148	260	119	93	7.1	31	36	6.1	80.3	66	7	877.5
2015	55	224	179.5	184	71.8	26.1	47.4	60.4	74.6	102.5	90	50	1165.3
2016	76	23	234	264.3	89.5	47.5	34.5	52	20	9	14.8	25	889.6
2017	176	168	117	120.2	48	26.8	63	29.8	2.7	21	5	37	814.5
Average	**84.5**	**142.9**	**190.4**	**161.8**	**84.6**	**26.2**	**33.3**	**40.7**	**35.3**	**41.5**	**48.6**	**54.1**	**913.9**

and precipitation, the study offers crucial information on the dynamics of the local climate.

3.5.1 General-Circulation-Models (GCMs)

3.5.1.1 Climate Change Assessment

A comprehensive methodology was applied for selecting climate change models and performing bias correction, as illustrated in Figure 3-5 and detailed in the following sub-sections.

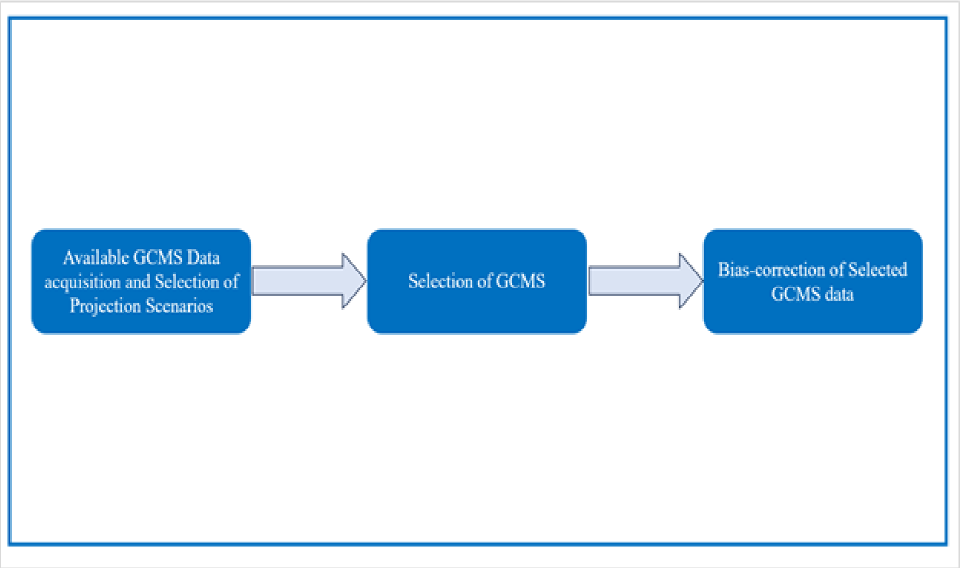

FIGURE 3.6: Schematic Diagram for climate change models selection and bias-correction

3.5.1.2 Available GCMS Data

To assess the range of potential future climate change in Kalam, the data of several global climate models (GCMs) from the latest set of the Coupled Model Intercomparison Project Phase 6 (CMIP-6) of World Climate Research Programme (WCRP) were analyzed. Contrary to CMIP-5 where selection of any RCP and SSP is possible, latest CMIP6 data is available mainly for specific SSP and RCP combinations such as SSP 1-2.6, SSP2-4.5, SSP3-7.0 and SSP5- 8.5 Scenarios. It is worth mentioning here that CMIP-6 represents a substantial expansion over CMIP5, in terms of the number of modelling groups participating, the number of future scenarios examined, and the number of different experiments conducted.

However, compared to CMIP-5 data limited CMIP-6 data is available at daily scale. In addition, the climate data were quality controlled, and selection of simulations were refined by selecting a subset of the climate models of the available scenarios middle of the road SSP2-4.5 and business as usual (extreme) scenario suggested for climate change inclusive hydrological impact assessment study.

Therefore, all CMIP-6 based GCMs daily data, where SSP2-4.5 and SSP 5-8.5 scenarios data is available, were acquired/downloaded. There are about 31 GCMs, which provide daily climate data for the study area (see Table 3.4). These GCMs were evaluated and used.

Table 3.4: List of available GCMs used for the study area

No.	CMIP6 Global Climate Model	Country	Resolution (long X, lat Y) in degrees
1	ACCESS-CM2	Australia	1.3 x 1.9
2	ACCESS-ESM1-5	Australia	1.3 x 1.9
3	CanESM5	Canada	2.8 x 2.8
4	CNRM-CM6-1	France	1.4 x 1.4
5	CNRM-ESM2-1	France	1.4 x 1.4
6	EC-Earth3	Europe	0.7 x 0.7
7	EC-Earth3-Veg	Europe	0.7 x 0.7
8	GFDL-ESM4	USA	1.3 x 1.0
9	INM-CM4-8	Russia	1.5 x 2.0
10	INM-CM5-0	Russia	1.5 x 2.0
11	IPSL-CM6A-LR	France	1.3 x 2.5
12	MIROC6	Japan	1.4 x 1.4
13	MPI-ESM1-2-HR	Germany	0.9 x 0.9
14	MPI-ESM1-2-LR	Germany	1.9 x 1.9
15	NorESM2-LM	Norway	1.9 x 2.5
16	MRI-ESM2-0	Japan	1.1 x 1.1
17	BCC-CSM2-MR	China	1.1 x 1.1
18	CESM2	USA	0.9 x 1.3
19	CESM2-WACCM	USA	0.9 x 1.3
20	UKESM1-0-LL	UK	1.3 x 1.9
21	CNRM-CM6-1-HR	France	0.5 x 0.5
22	FGOALS-g3	China	2.3 x 2.0
23	FIO-ESM-2-0	China	1.3 x 0.9
24	KACE-1-0-G	South Korea	1.3 x 1.9
25	MIROC-ES2L	Japan	2.8 x 2.8
26	NESM3	China	1.88 x 1.88
27	NorESM2-MM	Norway	0.9 x 1.3
28	CAMS-CSM1-0	China	1.1 x 1.1
29	CIESM	China	0.9 x 1.3
30	FGOALS-f3-L	China	1.0 x 1.3
31	AWI-CM-1-1-MR	Germany	0.9 x 0.9

3.5.1.3 Selection of Climate Scenarios

For this study on the Kalam Basin, two climate scenarios, SSP2-4.5 and SSP5-8.5, were selected based on the IPCC's Sixth Assessment Report. SSP2-4.5 is a "middle-of-the-road" scenario where greenhouse gas emissions remain high but start to slowly decrease around the middle of the century. In this scenario, the global temperature is expected to rise by about 2.7°C by 2100. On the other hand, SSP5-8.5 represents a more extreme future with rapid economic growth powered by fossil fuels, leading to a temperature increase of around 4.4°C by the end of the century. These scenarios were chosen to explore both moderate and severe impacts of climate change on flood frequency, helping to better understand future flood risks and plan for effective management.

3.5.1.4 Selection of GCMS Data

The approach for selection of GCMs is based on dry, wet, hot, cold and average projections. The future climate data projections for hydrological modelling and impact studies, at least five GCMs were selected and used for this research study. The selection of five GCMs out of a pool of more than 20 GCMs were based on dry, wet, hot, cold and average projections of models data using 1989-2014 as base data and 2021-2100 as future projected data under SSP2-4.5 and SSP 5 -8.5 scenario. The final Selected GCMs are listed in Table 3-5.

It is noteworthy to mention that before bias correction of selected five GCMs, these were compared for the climate sensitivity with all GCMs presented. Figure 3.6 presents the scatter plot between annual mean temperature climate change (T) and annual mean precipitation change (P) for the period 2020-2050 as compared to the base period of 1989-2014. The selected five GCMs are marked with diamond-shaped symbols. AWI-CM-1-MR represents the (Hot, Wet) model, while BCC-CSM2-MR represents the (Hot, Dry) model. Similarly, MPI-ESM1-LR is categorized as the (Cold, Dry) model. Regarding temperature change, the high-resolution MPI-ESM1-HR represents the (Cold, Wet) model, whereas NorESM2-MM is considered the average model, representing the other extreme within the group. Therefore, these selected models encompass the entire range of future temperature and precipitation variations, making them well-suited for impact assessment.

TABLE 3.5: List of final selected GCMs

S. No	GCMs	Country	Horizontal grid spacing (in degrees)
1	AWI-CM-1-1-MR	Germany	0.90.9
2	BCC-CSM2-MR	China	1.11.1
3	MPI-ESM1-2-HR	Germany	0.90.9
4	MPI-ESM1-2-LR	Germany	1.91.9
5	NorESM2-MM	Norway	0.91.3

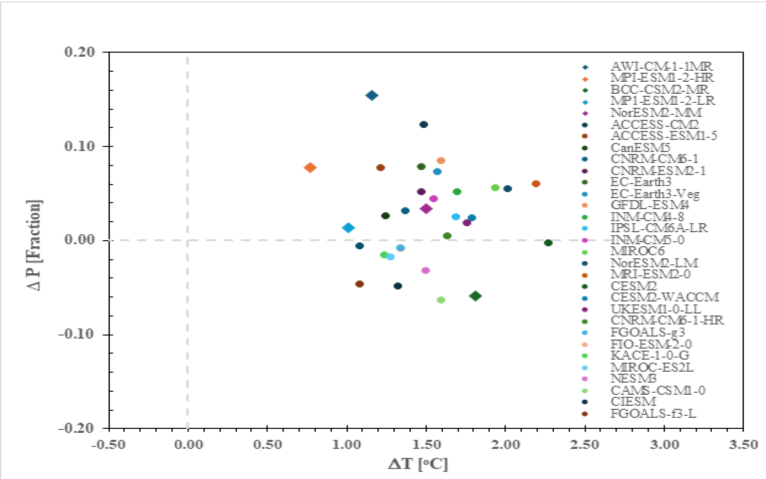

FIGURE 3.7: Mean annual precipitation change

Figure 3.6 Scatter plot between mean annual precipitation change (mm/d) and annual mean temperature change (C) for the period 2020-2050 as compared to the base period of 1989-2014. The five models used in this study are highlighted with diamond-shaped markers.

3.5.1.5 Statistical Downscaling of Selected GCMs Data

The statistical downscaling of selected General Circulation Models (GCMs) data was conducted using Climate Data Operators (CDO). The nearest neighbor method was applied to refine the GCM data to a 5x5 km grid resolution, ensuring localized focus for the Kalam Basin. A custom grid file defined the target resolution, and the CDO remapnn operator was used for interpolation. This method efficiently assigned the value of the nearest GCM grid point to the target grid, preserving the original data characteristics.

The processed data, covering SSP2-4.5 and SSP5-8.5 scenarios, were downscaled and stored in NetCDF format for further analysis. The nearest neighbor method was particularly effective for this study as it maintained data integrity while enabling high-resolution datasets essential for flood risk assessments in the Kalam Basin.

3.5.1.6 Bias Correction of Selected GCMS Data

The five selected GCMs under both the SSP2-4.5 and SSP5-8.5 scenarios were bias-corrected using data from the Kalam climate station. The delta method was applied for bias correction of both precipitation and temperature data. These bias-corrected datasets were then utilized for flood estimation in the Kalam Basin.

3.5.1.7 Bias-Correction Methods

The delta method is widely used for bias correction in Global Climate Models (GCMs) and Regional Climate Models (RCMs) to adjust their output to match observed climate statistics. It is a simple, yet effective, method for correcting systematic biases in simulated data for future climate projections.

There are different methods available for bias correction of GCMs however for this master thesis delta method is used.

3.5.1.8 Concept of the Delta Method

The delta method assumes that climate models capture relative changes or anomalies in climate variables (temperature, precipitation, etc.) reasonably well, even if they do not reproduce the current climate accurately. Instead of using raw model outputs, adjustments are applied to observed historical data to obtain future projections.

3.5.1.9 Methodology for Bias Correction using the Delta Method

I. Temperature Analysis

To assess future climate projections, a stepwise approach has been adopted for temperature analysis. First, the **temperature change factor (△T)** is calculated using **Equation 3.1**, as proposed by [89]:

$$\Delta T = T_{\text{model future}} - T_{\text{model historical}} \tag{3.1}$$

- $T_{\text{model future:}}$ Future simulated temperature from GCM
- $T_{\text{model historical:}}$ Historical simulated temperature from GCM

Equation 3.1 quantifies the difference between future and historical simulated temperatures, offering insights into expected climate variations.

To enhance the accuracy of future temperature projections, bias correction is applied. The **bias-corrected future temperature** is computed using **Equation 3.2**, following the **Delta Method approach** [90-91]:

$$T_{\text{corrected future}} = T_{\text{observed historical}} + \Delta T \tag{3.2}$$

- $T_{\text{observed historical:}}$ Observed historical temperature

By applying Equation 3.2, the future temperature is adjusted based on historical observations, ensuring that the projected values better reflect real-world conditions.

II. Precipitation Analysis

To assess future precipitation projections, a stepwise approach has been adopted for precipitation analysis. First, the **precipitation change factor (△P)** is calculated using Equation 3.3, as proposed by [89]:

$$\Delta P = \frac{P_{\text{model future}}}{P_{\text{model historical}}} \tag{3.3}$$

- $T_{\text{model future:}}$ Future simulated precipitation
- $T_{\text{model historical:}}$ Historical precipitation

Equation 3.3 quantifies the ratio of future to historical precipitation, providing insight into expected changes in rainfall patterns.

To improve the accuracy of future precipitation projections, bias correction is applied. The **bias-corrected future precipitation** is calculated using Equation 3.4, following the **Delta Method approach** [91]:

$$P_{\text{corrected future}} = P_{\text{observed historical}} \times \Delta P \tag{3.4}$$

- $T_{\text{observed historical:}}$ Observed historical precipitation

By applying Equation 3.4, future precipitation projections are adjusted based on observed historical data, ensuring that the estimated values more accurately reflect real-world climate conditions.

3.5.2 Watershed Characteristics

The catchment area of Kalam Basin has been demarcated using Shuttle Radar Topography Mission (SRTM) 30m Digital Elevation Model (DEM). The total catchment area of Kalam Basin is about 1211.30 Sq-kms (467.68 Sq-miles) as shown in Figure 3.7. The length of longest stream is about 66,000 m while the slope of longest stream is 0.0049 m/m. The watershed characteristics are as follows.

TABLE 3.6: Characteristics of catchment

Name	Catchment Area (Sq Km)	Length of Longest Stream (m)	Height Difference "H" (m)	Slope (m/m)
Kalam Basin	1211.3	66000	3293	0.0049

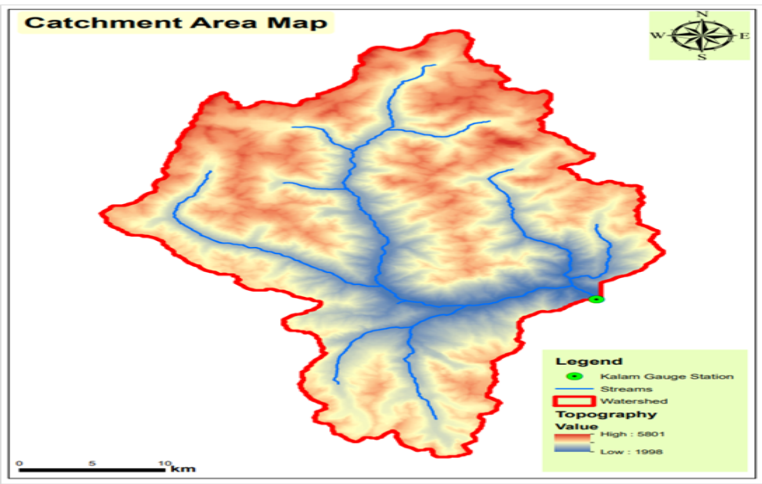

FIGURE 3.8: Catchment area map

3.5.3 Rainfall Frequencies

This thesis employs the Gumbel Extreme Value distribution for frequency analysis of the Kalam Basin, focusing on both historical data and future projections derived from General Circulation Models (GCMs). Although several methods exist for frequency analysis, the Gumbel Extreme Value distribution is chosen due to its effectiveness in modeling extreme events, such as floods, by estimating the return periods of rare occurrences. This approach is particularly suitable for the Kalam Basin, where understanding the behavior of extreme events is essential for water resource management and infrastructure planning.

The analysis uses daily maximum precipitation data from the Kalam Basin, covering the period from 1981 to 2014 (excluding 1988). Additionally, frequency analysis is conducted on data from five GCMs for the historical period (1981-2014) and future periods (2025-2050, 2050-2075, and 2075-2100), each considered in 25-year intervals for both climate scenarios of SSP2-4.5 and SSP5-8.5. This methodology enables a comprehensive understanding of extreme events both in the past and under future climate scenarios, providing valuable insights into the risks and challenges posed by climate variability.

3.5.3.1 Gumbel's Method

Gumbel (1941) introduced the extreme value distribution, commonly referred to as Gumbel's distribution. It is extensively used in hydrological and meteorological research for predicting flood peaks, maximum rainfall, and similar events.

I. Probability Density Function (PDF):

The Probability Density Function (PDF) presented in Equation 3.5 is commonly used in the Gumbel Extreme Value Distribution, which is widely applied for modeling extreme events such as maximum rainfall or flood peaks.

$$f(x) = \frac{1}{\alpha} \exp\left(-\frac{x-\mu}{\alpha}\right) \exp\left[-\exp\left(-\frac{x-\mu}{\alpha}\right)\right] \tag{3.5}$$

where,

- x = flow (or extreme event)

- μ = location parameter (can be calculated as $\bar{x} - 0.5772\alpha$)
- α = scale parameter (can be calculated as $\frac{\sqrt{6}s_x}{\pi}$)
- s_x = Standard deviation of the data
- $\bar{x}$ = mean of the data

II. Cumulative distribution function (CDF)

The Cumulative Distribution Function (CDF) for the Gumbel Extreme Value distribution is expressed as:

$$F(x) = \exp\left[-\exp\left(\frac{-(x-\mu)}{\alpha}\right)\right] \tag{3.6}$$

This equation (Eq. 3.6) represents the probability that a variable x is less than or equal to a given value. Here, μ is the location parameter that shifts the distribution, and α is the scale parameter that determines the spread of the data.

III. Reduced Variable y

The reduced variable equation, (Eq. 3.7), standardizes by normalizing it with the mean and scale parameter , aiding in comparative analysis and simplifying extreme value assessments.

$$y = \frac{x-\mu}{\alpha} \tag{3.7}$$

IV. Quantile function (to find x_t,flow for a given return period T)

The quantile function estimates flow x_t for a given return period (T) in flood frequency analysis. The reduced variate is calculated using Equation (3.8):

$$y_t = -\ln\left[-\ln\left(1 - \frac{1}{T}\right)\right] \tag{3.8}$$

The flow is then determined using Equation (3.9):

$$x_t = \mu + \alpha y_t \tag{3.9}$$

Here, μ is the mean, and α is the scale parameter. These equations are essential for calculating flood magnitudes using the Gumbel distribution.

3.5.4 Hydrological Modelling

SCS Unit Hydrograph method has been used for the estimation of flood peak, time to peak etc. using the information derived in the preceding sections. Hydrologic Modelling System (HEC-HMS) software prepared by US Army Corps of Engineers has been used for the simulation of rainfall-runoff / inflow-outflow flood hydrographs. The methodology adopted for modeling of HEC-HMS software as shown in below figure 3.8.

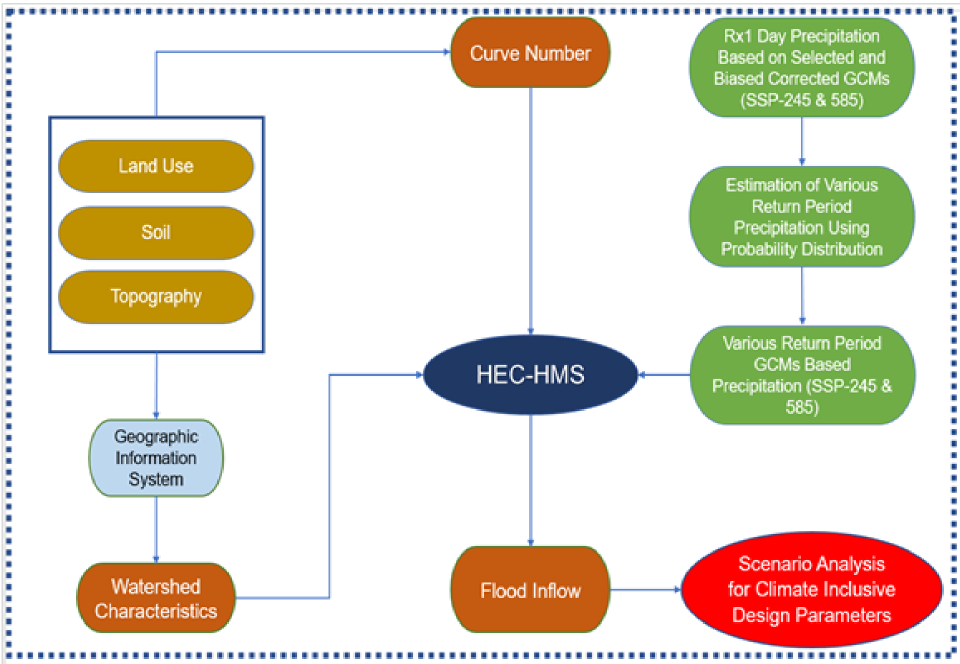

FIGURE 3.9: Methodology adopted for Hydrological modeling

3.5.4.1 Estimation of Curve Number (CN)

The runoff curve number is an empirical parameter used in hydrology to predict direct runoff or infiltration from rainfall excess. To estimate the curve number, land use and soil data are utilized. For the land use data, the latest Sentinel 2 (2021) dataset with a grid size of 10 m has been downloaded for the computation of the curve number. The land use of the project area is predominantly covered by Rangeland, Baren land, built-up areas, Snow/ice and trees. Regarding soil data, the area is classified as loam, which corresponds to Category C of the soil group. Category C soil is highly permeable, making it suitable for the analysis. Average curve number of 83 has been adopted for the estimation of peak discharges.

TABLE 3.7: Curve Number for Hydrologic Soil Group Type C

Land use	**Area, Sq.Km**	**%**	**CN**	**Product**
Trees	98.49	8.21	77	6.32
Crops	0.09	0.01	88	0.01
Urban and Built-Up	2.6	0.22	90	0.19
Baren Land	329.01	27.43	86	23.59
Snow/Ice	162.56	13.55	90	12.2
Rangeland	606.55	50.58	79	39.95
Total	**1199.3**	**100**		**83**

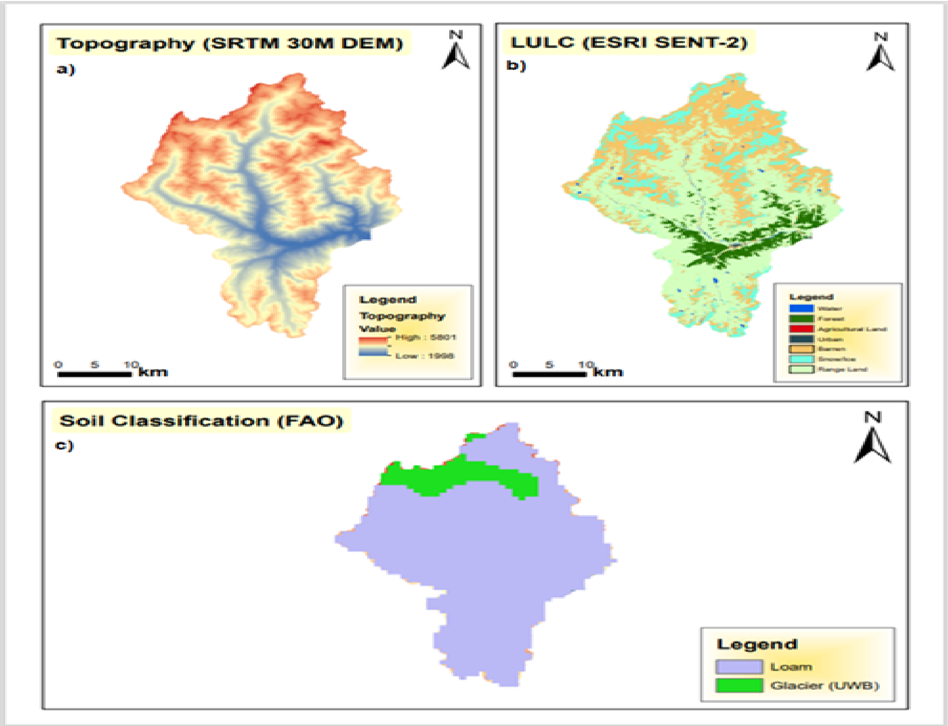

FIGURE 3.10: a) SRTM Digital Elevation Model (30m x 30m), b)ESRI LULC and c)FAO Soil

3.5.4.2 Time of Concentration

For this research, a 30-meter resolution Digital Elevation Model (DEM) was utilized to delineate the catchment area and extract stream patterns within the Kalam Basin. The DEM, sourced from the USGS Earth Explorer using SRTM 1 arc-second data, provided detailed topographical information. This data, processed through ArcGIS with the ArcHydro extension, enabled accurate identification of watershed boundaries and drainage networks. The use of ArcGIS and ArcHydro ensures precise catchment characterization and offers a reliable and efficient alternative to manual mapping techniques.

To estimate the time it takes for water to flow from the most distant point of the catchment to the outlet, the time of concentration (Tc) was determined. This critical parameter was calculated using Kirpichs empirical formula, which is widely applied in flood hydrology due to its simplicity and applicability in small to medium-sized basins. The formula considers catchment length and slope, making it suitable for analyzing rainfall-runoff behavior in the mountainous terrain of the Kalam Basin. Accurate computation of Tc ensures better flood prediction and enhances the reliability of hydrological models.

$$T_c = \left(\frac{11.9L^3}{H} \right)^{0.385} \tag{3.9}$$

(Applied Hydrology by Chow, Maidment and W.Mays Mcgrawhill international edition pp 500)

where,

L=Length of the longest stream in km/ miles and

H = Difference in altitude of the stream at start and point of interest in feet.

In combination with other catchment parameters, the derived values were used to simulate flood events for different return periods. These simulations help assess the impact of current and future climate scenarios on flood behavior, providing valuable insights for flood risk management and planning in the region.

3.5.4.3 Time Distribution of Excess Rainfall

The United States Soil Conservation Service (SCS), now known as the Natural Resources Conservation Service (NRCS), developed hypothetical temporal storm distributions classified as Type I, Type IA, Type II, and Type III. Since the Kalam Basin is subject to heavy monsoon rainfall and intense storms, the Type III rainfall distribution is the most appropriate for simulating rainfall-runoff events and estimating design floods under AMC II conditions. The Type III distribution is well-suited for areas experiencing short-duration, high-intensity rainfall, like the Kalam Basin. It is frequently used in flood design calculations because it best represents the rainfall patterns most likely to cause significant flooding in such regions. The chosen distribution is shown in the figure below:

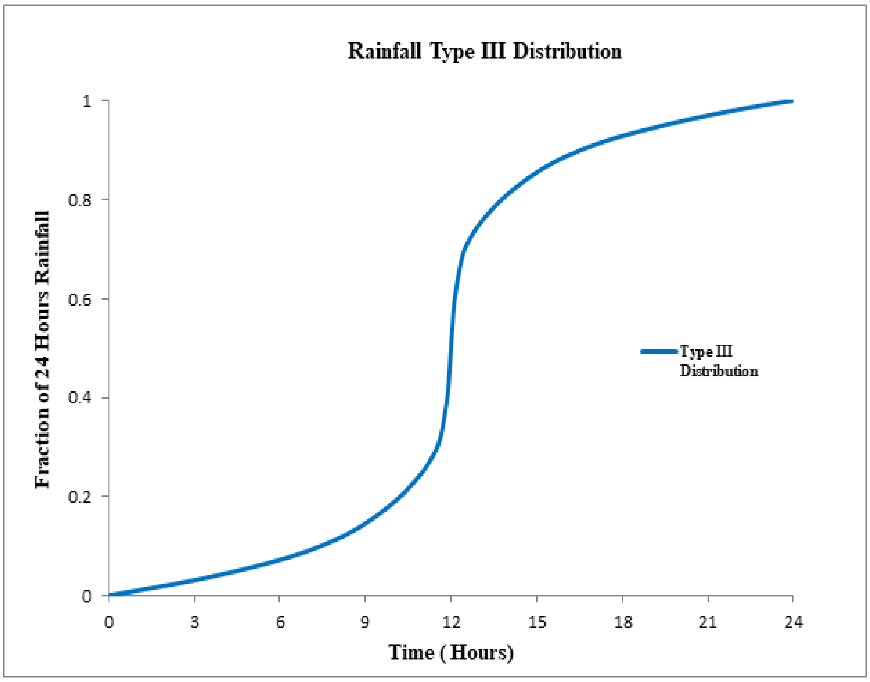

FIGURE 3.11: Adopted Distribution of rainfall for computation of design flood

Chapter 4

Results and Analysis

4.1 General

This study presents a detailed analysis of the impact of climate change on flood frequency in the Kalam Basin, focusing on future flood risks under different climate scenarios. The results reveal significant trends in climate variables, with substantial increases in temperature and notable shifts in precipitation patterns projected for the future. The application of the Gumbel Extreme Value Distribution and the use of bias-corrected climate data from Global Climate Models (GCMs) provided a robust framework for understanding the potential changes in flood behavior. The analysis showed that future flood discharges, calculated for various return periods, are likely to increase, indicating an escalating flood risk for the region. These findings highlight the urgency of integrating climate change considerations into flood risk management strategies and hydraulic infrastructure design. The study underscores the importance of adaptive measures, such as incorporating climate resilience, to mitigate the increasing risk of flooding.

4.2 Bias Correction of Precipitation

For precipitation bias correction, data from the Kalam station for the period 1989 to 2014 was first analyzed using the Gumbel Extreme Value distribution to model extreme precipitation events. The same distribution was then applied to data from

Table 4.1: Results of Bias Correction on Climate Scenario of SSP2-4.5

Return Period (Year)	1989–2014 (Kalam) Climate Station Historical	GCM Ens 1989–2014	Delta Factor △	SSP2-4.5					
				Unbiased Corrected			Biased Corrected		
				GCM 2026–2050	GCM 2051–2075	GCM 2076–2100	GCM 2026–2050	GCM 2051–2075	GCM 2076–2100
5	3.41	2.37	1.44	2.5	2.58	2.63	3.59	3.71	3.78
10	3.96	2.55	1.55	2.72	2.76	2.81	4.23	4.28	4.36
25	4.66	2.78	1.67	3.01	2.98	3.04	5.04	4.99	5.09
50	5.17	2.95	1.75	3.22	3.15	3.21	5.65	5.52	5.63
100	5.69	3.12	1.82	3.44	3.32	3.38	6.26	6.05	6.16
200	6.20	3.29	1.88	3.65	3.48	3.54	6.87	6.57	6.68
500	6.87	3.51	1.96	3.92	3.70	3.77	7.68	7.25	7.37
1000	7.38	3.68	2.01	4.13	3.87	3.93	8.30	7.76	7.89

TABLE 4.2: Results of Bias Correction on Climate Scenario of SSP5-8.5

Return Period (Year)	**1989–2014 (Kalam) Climate Station Historical**	**GCM Ens 1989–2014**	**Delta Factor △**	**SSP5-8.5**					
				Unbiased Corrected			**Biased Corrected**		
				GCM 2026–2050	**GCM 2051–2075**	**GCM 2076–2100**	**GCM 2026–2050**	**GCM 2051–2075**	**GCM 2076–2100**
5	3.41	2.37	1.44	2.73	2.76	2.81	3.93	3.96	4.04
10	3.96	2.55	1.55	3.02	2.94	3.01	4.69	4.57	4.66
25	4.66	2.78	1.67	3.38	3.18	3.25	5.66	5.32	5.45
50	5.17	2.95	1.75	3.65	3.35	3.44	6.40	5.87	6.03
100	5.69	3.12	1.82	3.92	3.52	3.62	7.15	6.42	6.60
200	6.20	3.29	1.88	4.19	3.69	3.80	7.89	6.96	7.17
500	6.87	3.51	1.96	4.54	3.92	4.04	8.89	7.67	7.92
1000	7.38	3.68	2.01	4.80	4.09	4.23	9.64	8.21	8.48

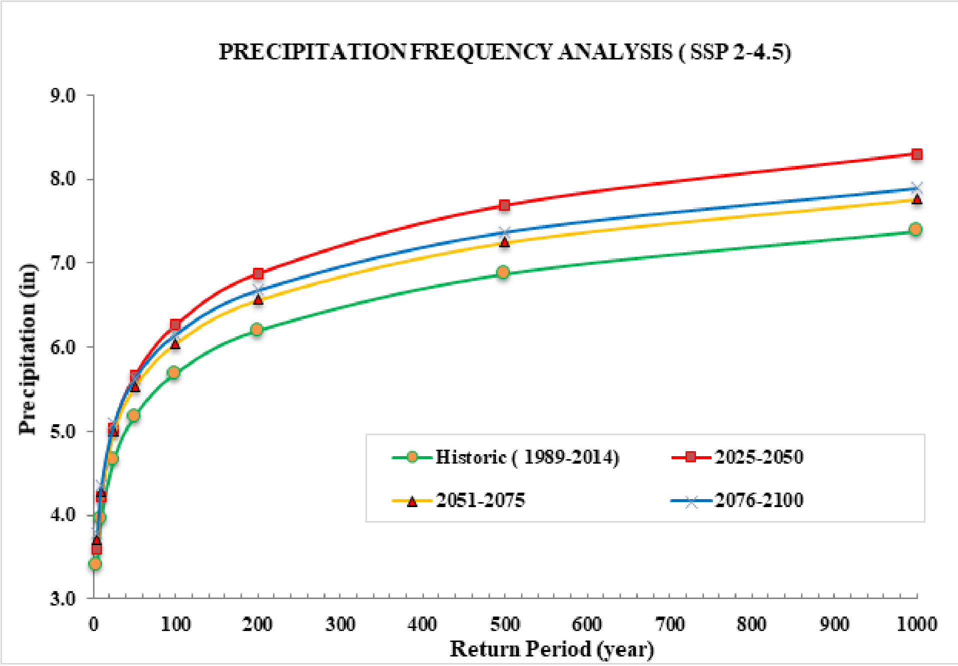

Figure 4.1: Comparison of Frequency analysis between Historical and Climatic Scenarios for SSP2-4.5

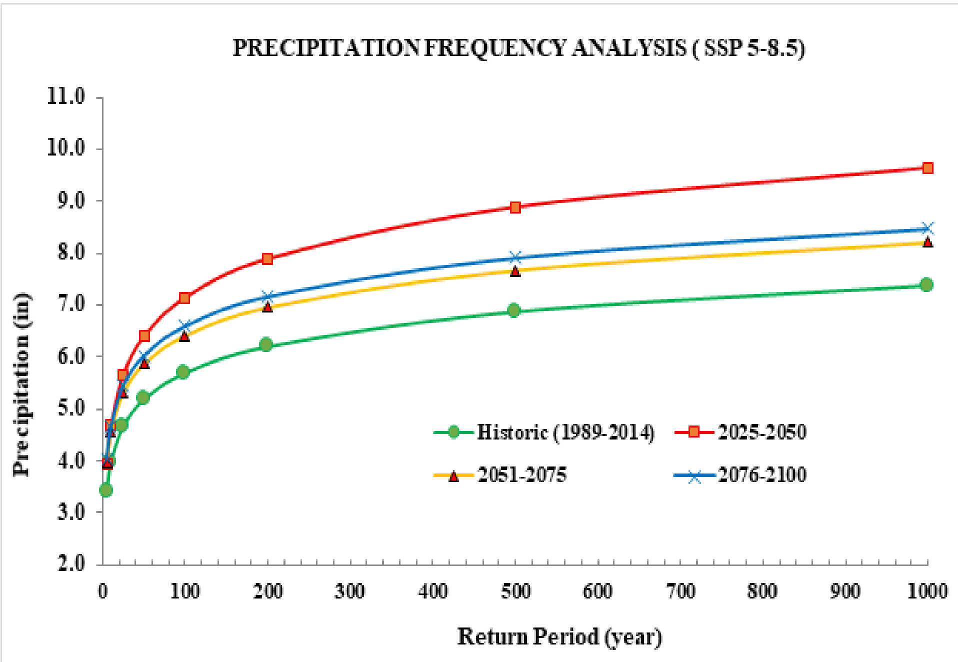

Figure 4.2: Comparison of Frequency analysis between Historical and Climatic Scenarios for SSP5-8.5

five General Circulation Models (GCMs) for the same period. Using these analyses, the delta method was applied to calculate the delta factor, as described in the methodology, by comparing the Gumbel distribution results for both the Kalam station data and the GCMs. These delta factors were subsequently applied to future GCM projections by multiplying them with future GCM outputs for three time periods: 2026-2050, 2051-2075, and 2076-2100, under two climate scenarios SSP2-4.5 and SSP5-8.5. The results, showing projected future precipitation patterns and variability in the Kalam Basin, are presented in the tables below. Additionally, frequency plots are included alongside the tables to visually compare precipitation extremes for the historical and future periods.

4.3 Bias Correction of Temperature

The temperature bias correction analysis using observed data from the Kalam climate station (1984-2017) and projections from five General Circulation Models (GCMs) highlights significant future warming trends under the SSP2-4.5 and SSP5-8.5 scenarios for the period 2025-2100. In this analysis, the delta method was applied to calculate the difference between observed and modeled temperatures, and these delta factors were used to adjust future GCM outputs, ensuring more accurate projections. A comparison of the mean monthly temperatures for historic and future periods reveals substantial seasonal variations.

Under the SSP2-4.5 scenario, both winter and summer temperatures show noticeable increases. In January, the historical mean temperature of 0.7C is projected to rise to 3.0C, indicating a warming of approximately 2.3C. February and March follow similar trends, with temperatures increasing from 2.4°C to 4.9°C and from 6.8°C to 8.9°C, respectively. The summer months exhibit more significant changes. June's temperature, historically recorded at 19.2°C, is projected to reach 21.6°C, while July's mean increases from 20.3°C to 22.3°C. These temperature rises will likely influence snowmelt patterns, runoff timing, and evapotranspiration, all of which are critical for flood modeling and water resource management.

The SSP5-8.5 scenario, representing higher emissions and a more extreme climate future, shows even more pronounced temperature increases. January's mean temperature rises from 0.7°C to 4.3°C, and February sees an increase from 2.4°C to 6.2°C. During the summer, July's temperature is projected to increase significantly, from 20.3°C to 23.8°C, marking a 3.5°C rise. August follows a similar trend, with a projected increase from 19.3°C to 22.3°C. The fall season also

Table 4.3: Results of Bias Correction for Climate Change Scenario of SSP2-4.5

Months	**Average Temperature (SSP2-4.5)** **Period (1984-2017)**	**Average Temperature of Kalam Station** **Period (1984-2017)**	**Delta △**	**Un Bias Corrected Future GCM** **Period (2025-2100)**	**Bias Corrected Future GM** **Period (2025-2100)**
Jan	-12.9	0.7	13.5	-10.6	3
Feb	-10.7	2.4	13.1	-8.2	4.9
Mar	-5.9	6.8	12.7	-3.8	8.9
Apr	-1.9	11.5	13.4	0.7	14.1
May	3.3	16.4	13.1	5.6	18.7
Jun	8.7	19.2	10.5	11.1	21.6
Jul	12.4	20.3	7.9	14.4	22.3
Aug	11.7	19.3	7.6	13.2	20.9
Sep	7.6	16	8.3	7.7	16.1
Oct	-0.9	11.7	12.6	-0.5	12.1
Nov	-7.9	7.5	15.3	-6.2	9.2
Dec	-11.3	3.6	14.9	-9.4	5.6

Table 4.4: Results of Bias Correction for Climate Change Scenario of SSP5-8.5

Months	**Average Temperature (SSP2-4.5)**	**Average Temperature of Kalam Station**	**Delta △**	**Un Bias Corrected Future GCM**	**Bias Corrected Future GM**
	Period (1984-2017)	**Period (1984-2017)**		**Period (2025-2100)**	**Period (2025-2100)**
Jan	-12.9	0.7	13.5	-9.3	4.3
Feb	-10.7	2.4	13.1	-6.9	6.2
Mar	-5.9	6.8	12.7	-2.5	10.2
Apr	-1.9	11.5	13.4	1.9	15.3
May	3.3	16.4	13.1	6.6	19.7
Jun	8.7	19.2	10.5	12.5	22.9
Jul	12.4	20.3	7.9	15.9	23.8
Aug	11.7	19.3	7.6	14.7	22.3
Sep	7.6	16	8.3	9.2	17.5
Oct	-0.9	11.7	12.6	0.8	13.4
Nov	-7.9	7.5	15.3	-4.8	10.5
Dec	-11.3	3.6	14.9	-8.3	6.6

experiences warming, with September's temperature rising from 16.0°C to 17.5°C. This scenario presents severe warming across all months, emphasizing the substantial impact of climate change on the regions hydrology and flood risks.

Overall, the bias-corrected temperature projections under both climate scenarios highlight a clear warming trend, with SSP5-8.5 showing the most severe impacts. This increase in temperatures will likely accelerate snowmelt, alter streamflow patterns, and heighten flood risks in the Kalam Basin. These findings underscore the urgent need for adaptive flood risk management strategies and sustainable water resource planning to mitigate the adverse effects of climate change.

4.4 Rainfall Variation

The analysis of rainfall patterns in the Kalam Basin reveals significant changes in both intensity and frequency of extreme rainfall events under different climate scenarios. Historical data from the Kalam station and the five General Circulation Models (GCMs) indicate a clear pattern of rainfall variation. However, when projecting future rainfall for the periods 2026-2050, 2051-2075, and 2076-2100 under the SSP2-4.5 and SSP5-8.5 scenarios, notable changes are observed.

Under the SSP2-4.5 scenario, precipitation increases progressively, with Table 4.6 showing a rise of 34% for the 5-year return period and 56% for the 1000-year return period by 2026-2050. This trend continues with increases ranging from 37% to 53% by the period 2076-2100, indicating a relatively moderate but consistent intensification of rainfall events.

In contrast, the SSP5-8.5 scenario projects more pronounced changes. As shown in Table 4.8, precipitation is expected to increase by 40% for the 5-year return period and up to 62% for the 1000-year return period by 2026-2050. Over the subsequent time periods, this scenario exhibits even greater intensification, with percentage increases reaching as high as 64% by 2076-2100. Comparatively, SSP5-8.5 consistently shows higher rainfall increases than SSP2-4.5 across all return periods and future timelines, with differences ranging from approximately 6% to 8% for short-term events and up to 11% for long-term return periods in later time slices.

Table 4.5: Results of Frequency Analysis under Climate Change Scenario of SSP2-4.5

	Precipitation (mm) SSP2-4.5							
Year	**5 Year**	**10 Year**	**25 Year**	**50 Year**	**100 Year**	**200 Year**	**500 Year**	**1000 Year**
1989-2014	2.37	2.55	2.78	2.95	3.12	3.29	3.51	3.68
2026-2050	3.59	4.23	5.04	5.65	6.26	6.87	7.68	8.3
2051-2075	3.71	4.28	4.99	5.52	6.05	6.57	7.25	7.76
2076-2100	3.78	4.36	5.09	5.63	6.16	6.68	7.37	7.89

Table 4.6: Percentage Change in Precipitation under SSP2-4.5

	Percentage Increase/Decrease							
Year	**5 Year**	**10 Year**	**25 Year**	**50 Year**	**100 Year**	**200 Year**	**500 Year**	**1000 Year**
2026-2050	34%	40%	45%	48%	50%	52%	54%	56%
2051-2075	36%	40%	44%	47%	48%	50%	52%	53%
2076-2100	37%	41%	45%	48%	49%	51%	52%	53%

Table 4.7: Results of Frequency Analysis under Climate Change Scenario of SSP5-8.5

	Precipitation (mm) SSP5-8.5							
Year	**5 Year**	**10 Year**	**25 Year**	**50 Year**	**100 Year**	**200 Year**	**500 Year**	**1000 Year**
1981-2014	2.37	2.55	2.78	2.95	3.12	3.29	3.51	3.68
2026-2050	3.93	4.69	5.66	6.4	7.15	7.89	8.89	9.64
2051-2075	3.96	4.57	5.32	5.87	6.42	6.96	7.67	8.21
2076-2100	4.04	4.66	5.45	6.03	6.6	7.17	7.92	8.48

Table 4.8: Percentage Change in Precipitation under SSP5-8.5

	Percentage Increase/Decrease							
Year	**5 Year**	**10 Year**	**25 Year**	**50 Year**	**100 Year**	**200 Year**	**500 Year**	**1000 Year**
2026-2050	40%	45%	51%	54%	56%	58%	61%	62%
2051-2075	40%	44%	48%	50%	51%	53%	54%	55%
2076-2100	41%	45%	49%	51%	53%	54%	56%	57%

The return periods for extreme rainfall events are expected to become shorter due to climate change. For example, a flood that previously occurred once every 100 years is now projected to happen within 50 years, particularly under the SSP5-8.5 scenario. Comparing SSP2-4.5 and SSP5-8.5 shows that climate change will significantly increase flood frequency. Under SSP5-8.5, floods with a 100-year return period in the past are likely to occur much more often, possibly every 50 years or even sooner. While SSP2-4.5 also predicts more frequent extreme events, the increases are smaller. This reduction in return periods highlights a growing flood risk, with the most severe effects expected under SSP5-8.5. This reduction in the return period of extreme events highlights the increasing frequency of extreme weather, which could have serious implications for water management, agriculture, and infrastructure planning in the region. The detailed results of these analyses, including comparisons of historical and future rainfall patterns for different return periods, are summarized in the tables below:

4.5 Temperature Variation and Future Projections

The analysis of temperature patterns for the Kalam Basin compares observed data (1984-2017) with future projections under different climate scenarios. The historical data shows seasonal temperature changes, with the highest temperatures occurring from June to August and the lowest from December to February. Future temperature projections were adjusted using bias correction for SSP2-4.5 and SSP5-8.5 scenarios to predict changes more accurately. Under the SSP2-4.5 scenario (Figure 4.3), temperatures are expected to increase moderately across all months with mean temperatures rising by 0.59°C to 2.63°C in Oct and April respectively. The summer months (June, July, and August) show significant warming, while winter months (January and February) are also projected to become warmer. This indicates a possible reduction in snowfall and changes in water availability patterns.

The SSP5-8.5 scenario (Figure 4.4) shows a much greater increase in temperature. For example, Aprils temperature rises from 11.47°C in the historical record to

15.29°C, while Septembers temperature increases from 16.00°C to 17.51°C. The temperature of SSP 5-8.5 indicate substantial warming trends, with mean temperatures rising by 1.52°C to 3.83°C in Sep and April respectively. These projections suggest a more intense warming trend, which could affect snowmelt, water resources, and local ecosystems.

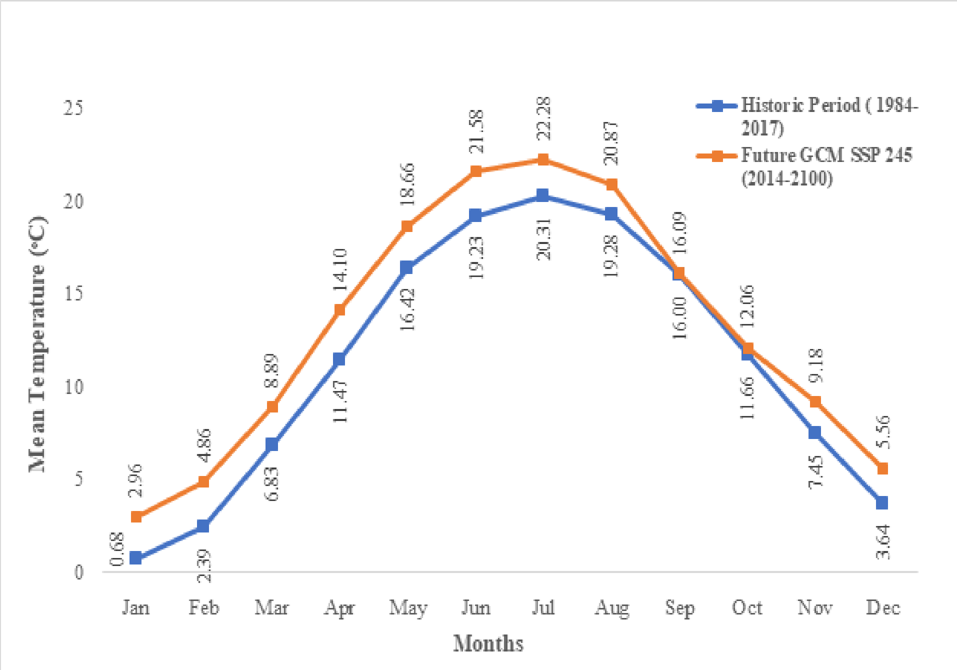

FIGURE 4.3: Results of temperature Variation between Historical and Climatic Scenarios for SSP2-4.5

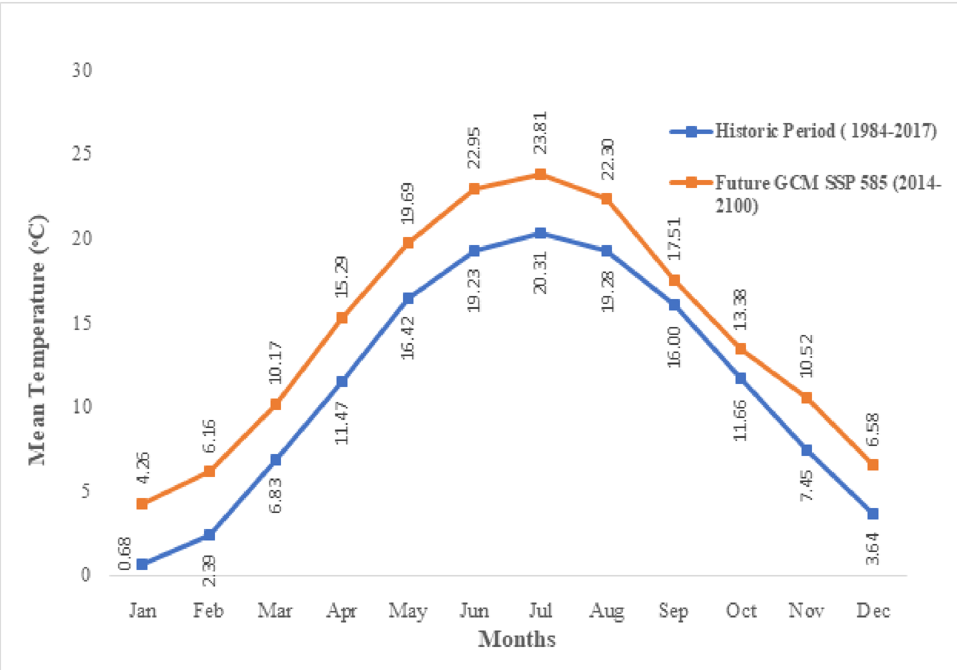

FIGURE 4.4: Results of temperature Variation between Historical and Climatic Scenarios for SSP5-8.5

The graphs highlight a clear increase in temperatures under both scenarios, with SSP5-8.5 showing more severe impacts. This rising trend in temperatures and increased heat extremes point to the need for improved water management strategies and climate adaptation measures to reduce the risks to agriculture, water supply, and local communities in the Kalam Basin.

4.6 Flood Hydrographs

For this study, the Gumbel Extreme Value distribution was used to analyze historical flood data from the Kalam climate station and bias-corrected GCM data for different return periods. The HEC-HMS hydrological model was used to improve the flood analysis. To develop the model, the SCS Curve Number method was applied to estimate runoff based on land use and soil type. Land use data from Sentinel-2 (2021) and soil data were used to calculate a weighted curve number of 82 for the study area. Catchment characteristics, including lag time, were determined using the Kirpich formula.

The HEC-HMS model was used to simulate flood discharges for different return periods under historical conditions and future climate change scenarios (SSP2-4.5 and SSP5-8.5). The results show that under historical conditions, the flood discharge for a 100-year return period was 75,993.7 cusecs, increasing to 115,809.2 cusecs for a 1000-year return period. In the SSP2-4.5 scenario, flood discharges increase, ranging from 36,593.4 cusecs (5-year flood) to 139,135.5 cusecs (1000-year flood). Under the SSP5-8.5 scenario, flood discharges become even higher, reaching 37,933.7 cusecs (5-year flood) and 149,547.6 cusecs (1000-year flood).

A major finding of this study is that floods are becoming more frequent and severe due to climate change. The 100-year flood under historical conditions (75,993.7 cusecs) is now expected to happen much more often. In SSP2-4.5, the 50-year flood discharge is 78,632.4 cusecs, which is slightly higher than the historical 100-year flood. This means that a flood that used to happen once every 100 years is now likely to happen every 50 years. Similarly, under SSP5-8.5, the 50-year flood discharge is 83,445.4 cusecs, which is even higher than the historical 100-year flood. This suggests that a flood of this size will now happen twice as often as before.

When comparing the historical 100-year flood (75,993.7 cusecs) with the future 100-year floods, it is clear that flood magnitudes are increasing while their recurrence intervals are decreasing. The SSP2-4.5 (100-year flood: 92094.8 cusecs) is 21.19% higher than the historical 100-year flood, while the SSP5-8.5 (100-year flood: 98156.7cusecs) is 21.16% higher. This means that extreme flood events will happen more often and with greater intensity in the future

The flood hydrographs show how peak discharge changes over time, highlighting an increase in extreme flood events. The comparison of historical and future flood projections shows that a 100-year flood in the past is now expected to occur every 50 years or even more often. This significant increase in flood risk highlights the urgent need for better flood management and adaptation.

This indicates a significant increase in flood risk due to climate change, emphasizing the need for better flood management strategies in the Kalam Basin.

Table 4.9: Result of Flood discharges (Cusecs) on Historic Kalam Climate Station

Return Period	**Flood Discharge (Cusecs)**
5	29494.2
10	39687.6
25	53695.6
50	64679
100	75993.7
200	87689.8
500	103550.1
1000	115809.2

Table 4.10: Result of Flood discharges (Cusecs) on Climate Change Scenario of SSP2-4.5

Return Period	**Flood Discharge (Cusecs)**
5	36593.4
10	48845.4
25	65580.9
50	78632.4
100	92094.8
200	105941.3
500	124679.7
1000	139135.5

TABLE 4.11: Result of Flood discharges (Cusecs) on Climate Change Scenario of SSP5-8.5

Return Period, Years	Flood Discharge (Cusecs)
5	37933.7
10	51140.7
25	69200.5
50	83445.4
100	98156.7
200	113249.5
500	133705.7
1000	149547.6

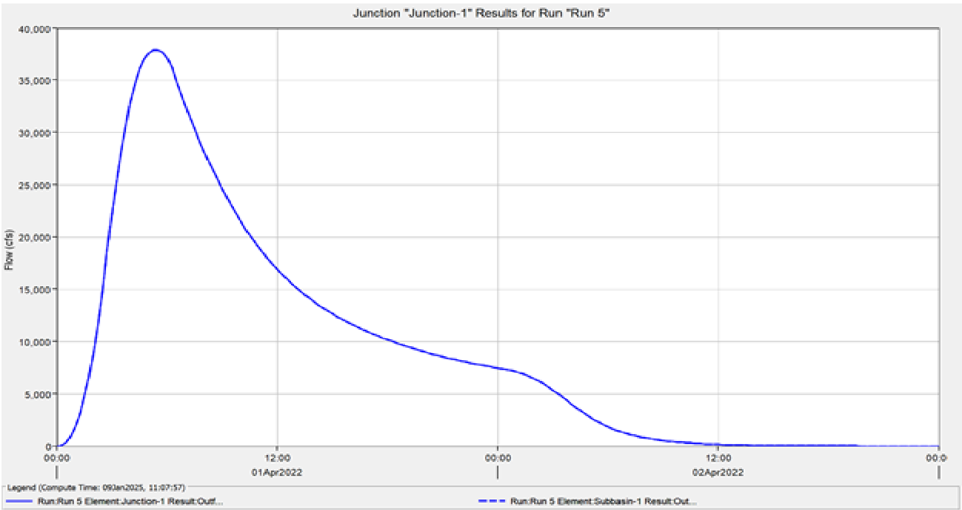

FIGURE 4.5: 5 Years return period flood (SSP5-8.5)

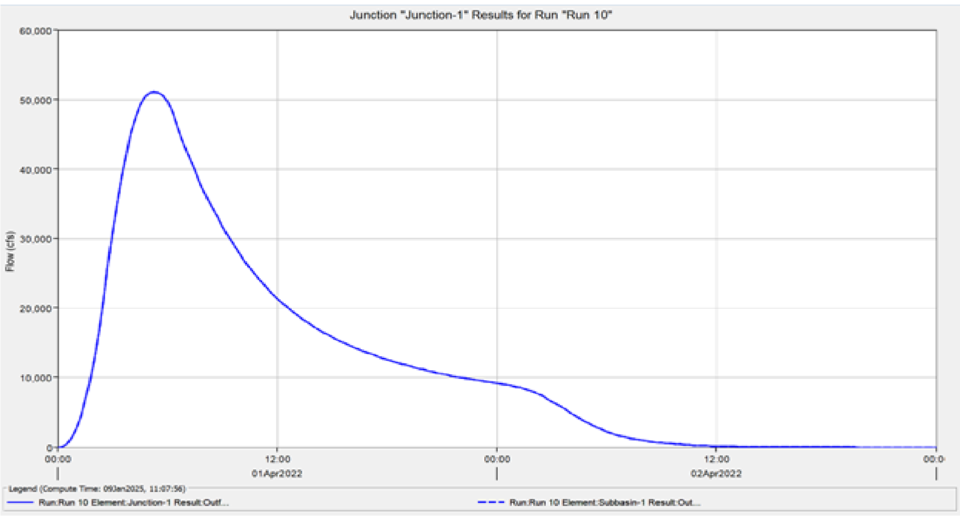

FIGURE 4.6: 10 Years return period flood (SSP5-8.5)

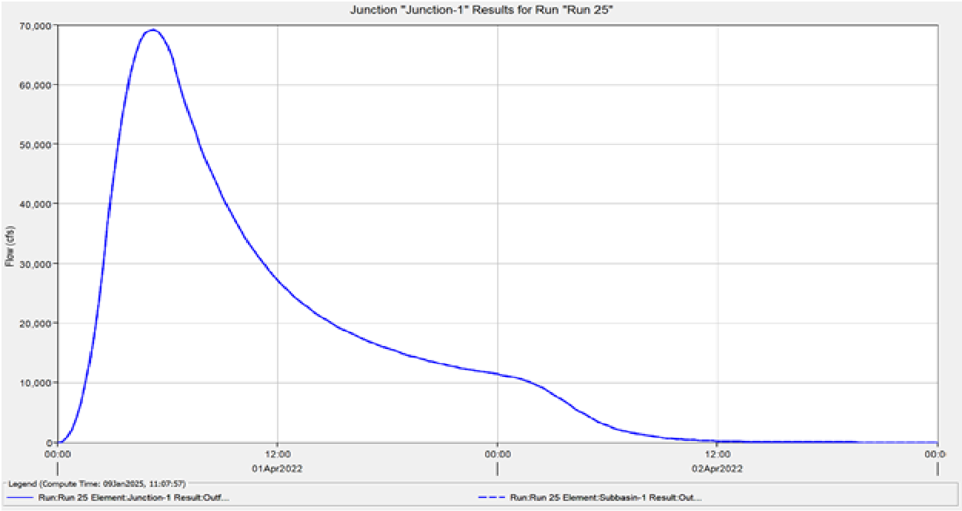

FIGURE 4.7: 25 Years return period flood (SSP5-8.5)

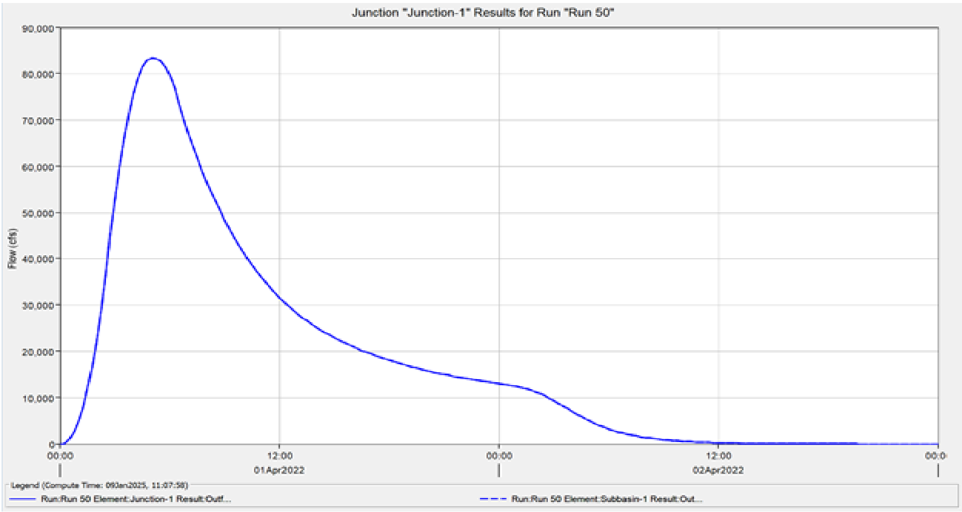

FIGURE 4.8: 50 Years return period flood (SSP5-8.5)

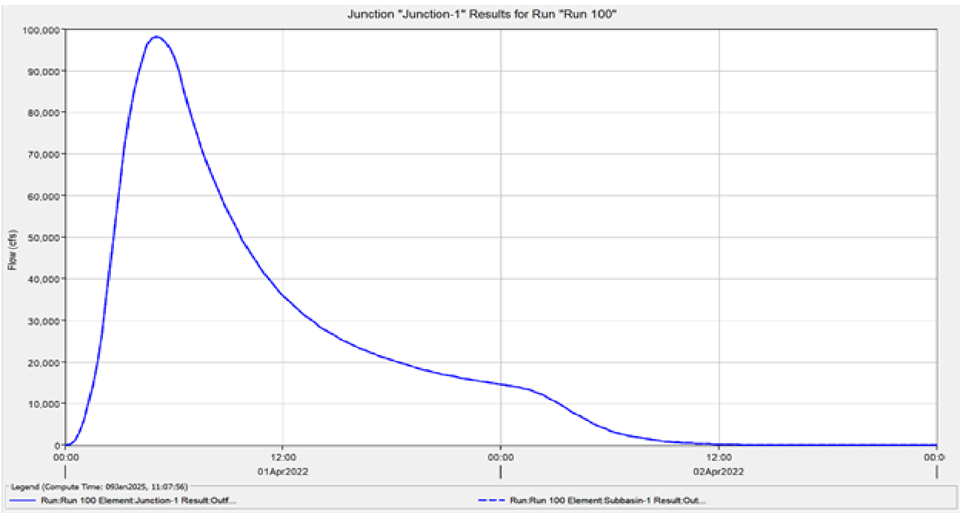

FIGURE 4.9: 100 Years return period flood (SSP5-8.5)

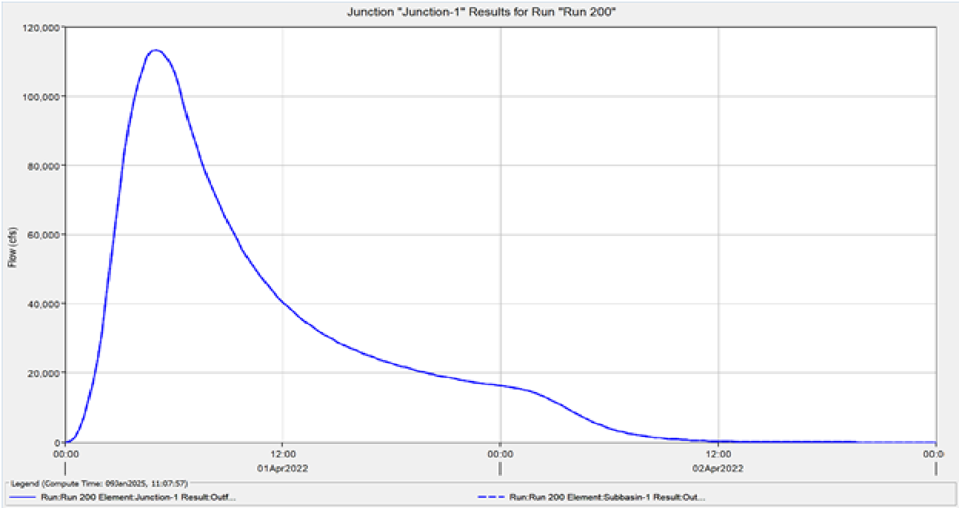

FIGURE 4.10: 200 Years return period flood (SSP5-8.5)

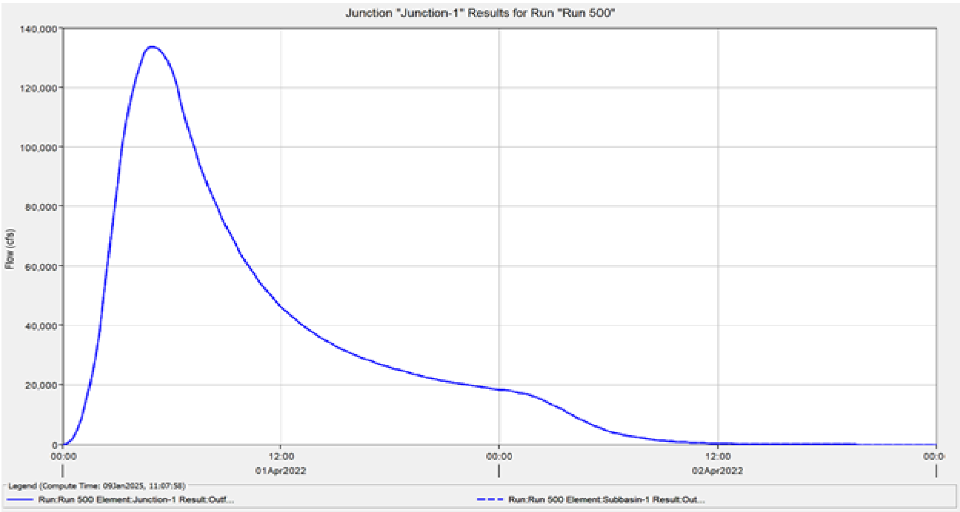

FIGURE 4.11: 500 Years return period flood (SSP5-8.5)

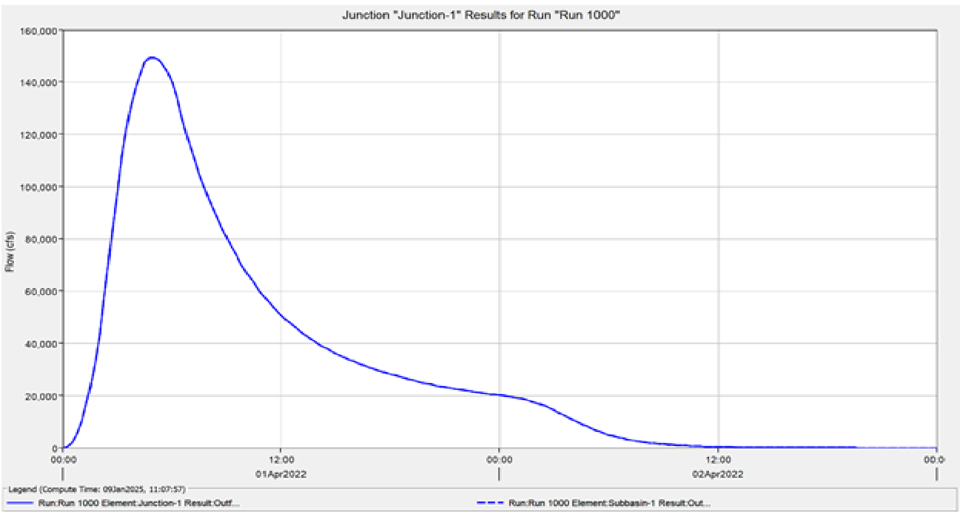

FIGURE 4.12: 1000 Years return period flood (SSP5-8.5)

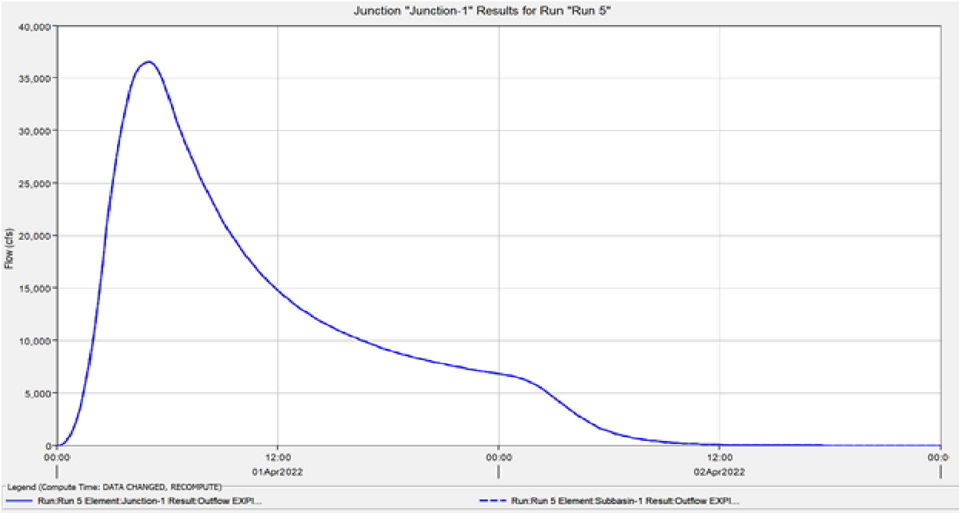

FIGURE 4.13: 5 Years return period flood (SSP2-4.5)

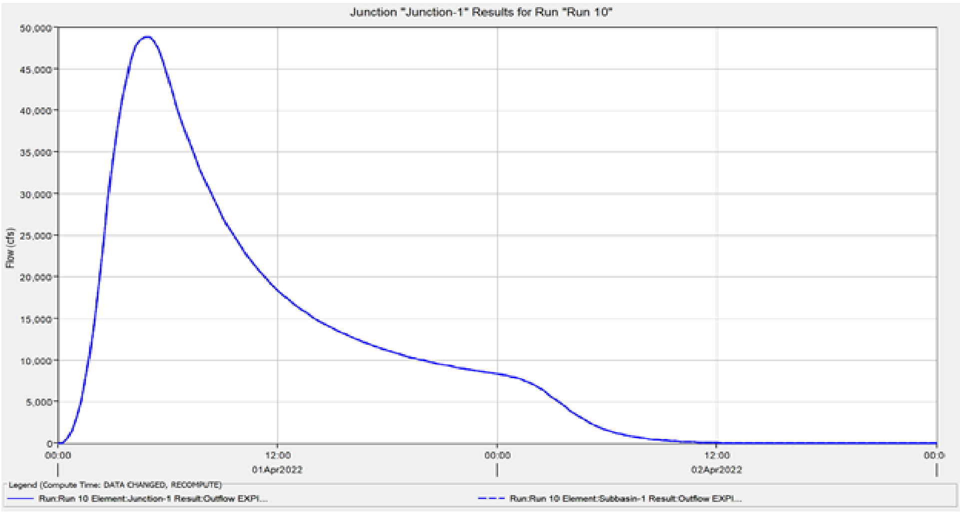

FIGURE 4.14: 10 Years return period flood (SSP2-4.5)

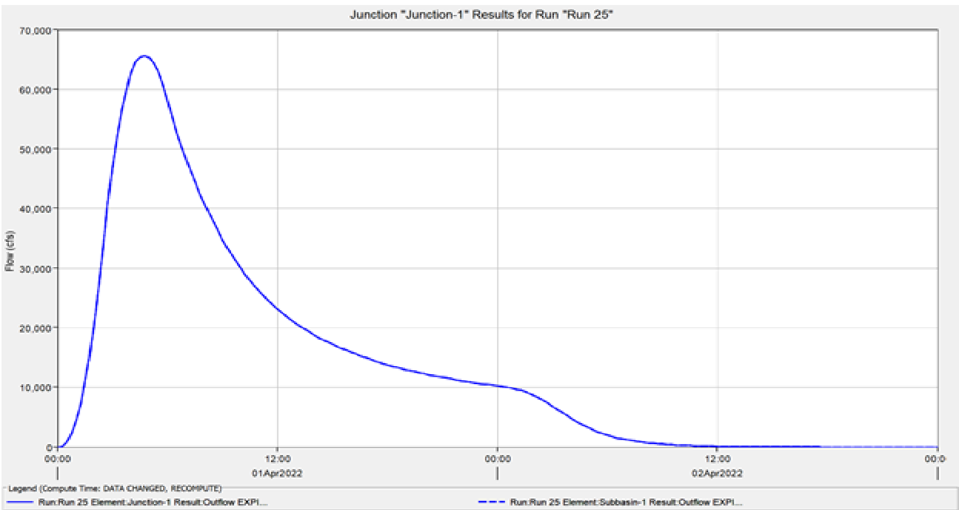

FIGURE 4.15: 25 Years return period flood (SSP2-4.5)

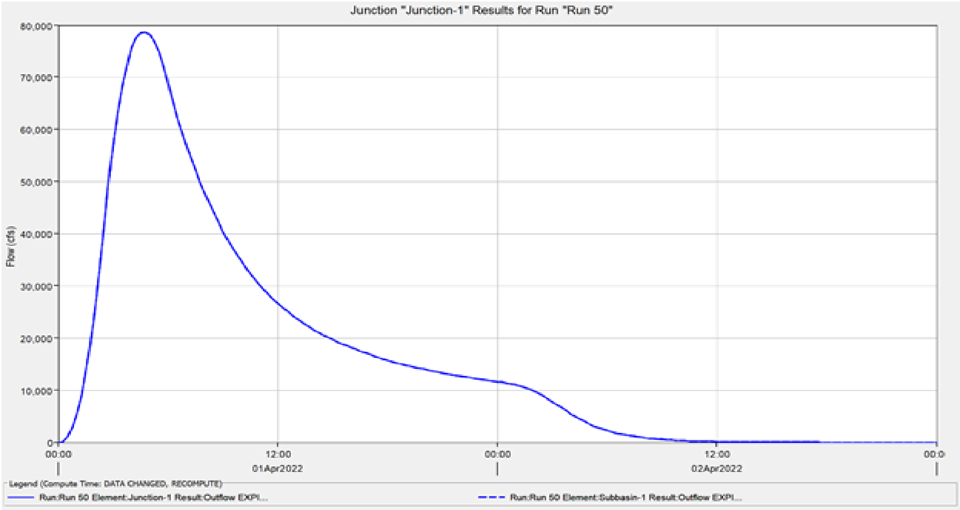

FIGURE 4.16: 50 Years return period flood (SSP2-4.5)

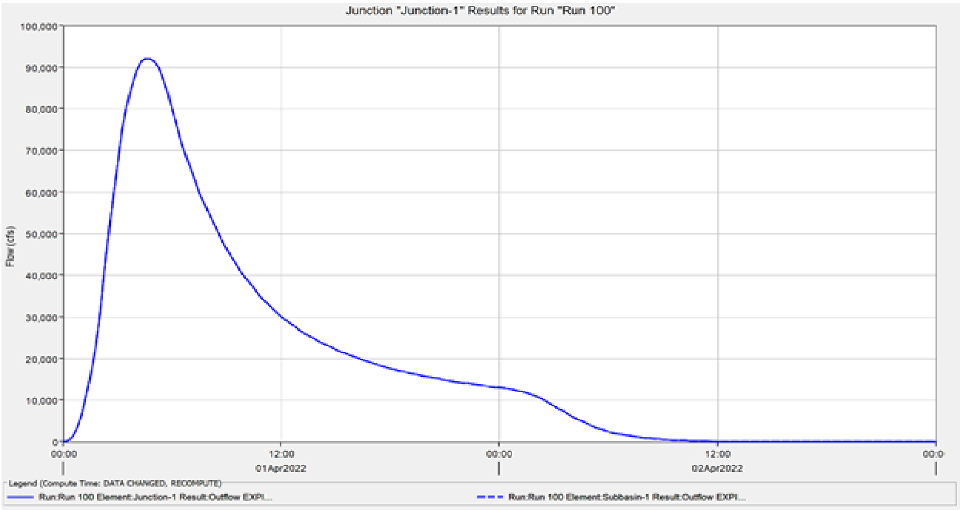

FIGURE 4.17: 100 Years return period flood (SSP2-4.5)

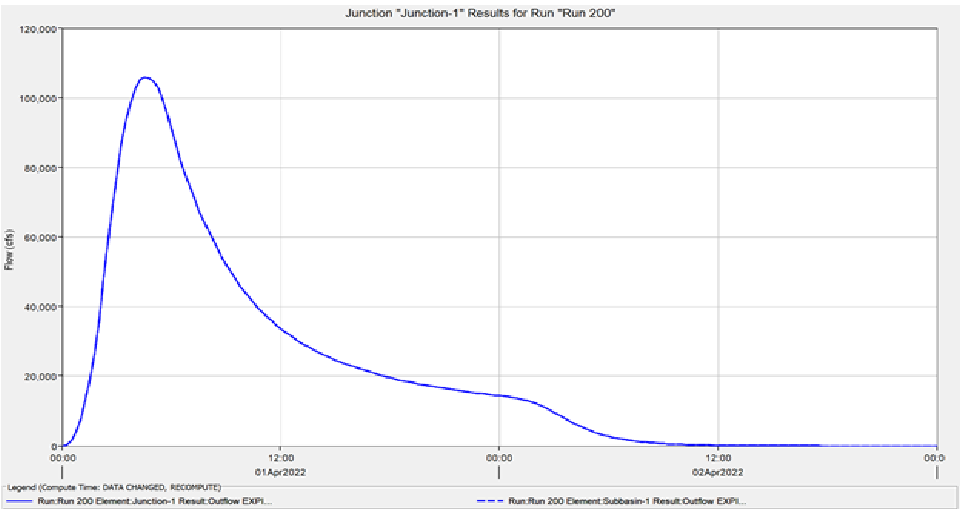

FIGURE 4.18: 200 Years return period flood (SSP2-4.5)

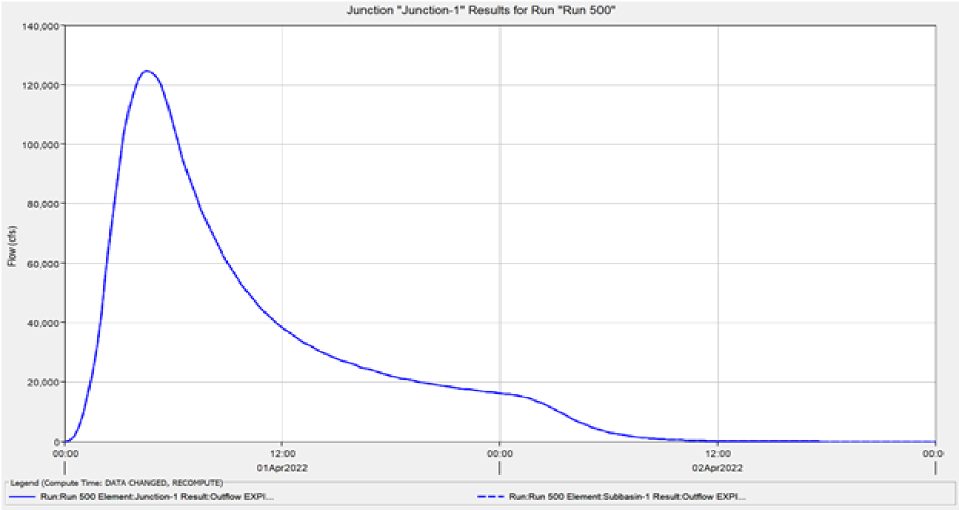

FIGURE 4.19: 500 Years return period flood (SSP2-4.5)

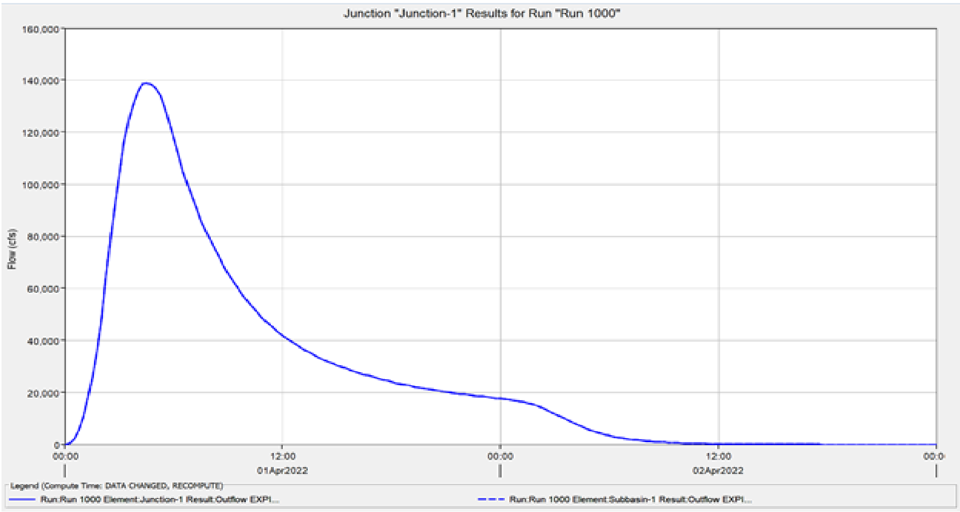

FIGURE 4.20: 1000 Years return period flood (SSP2-4.5)

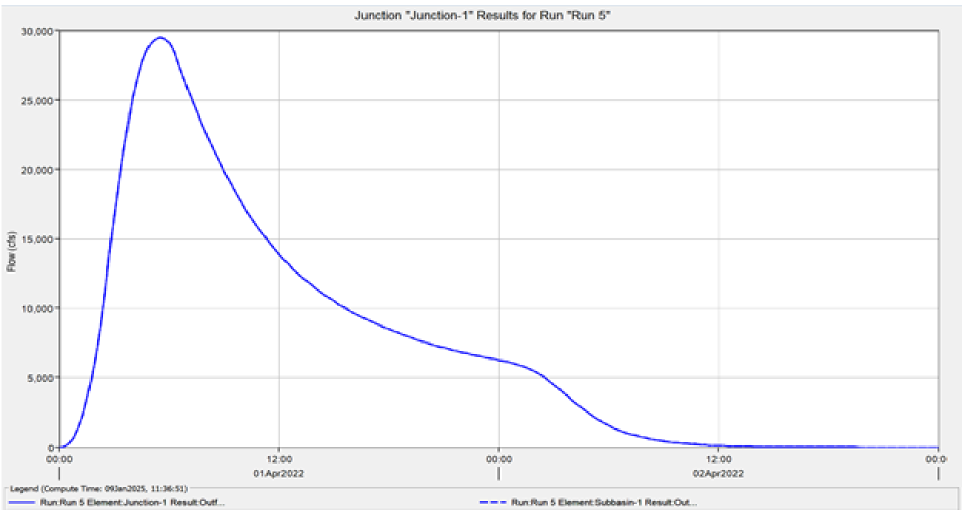

FIGURE 4.21: 5 Years return period Flood (Historic)

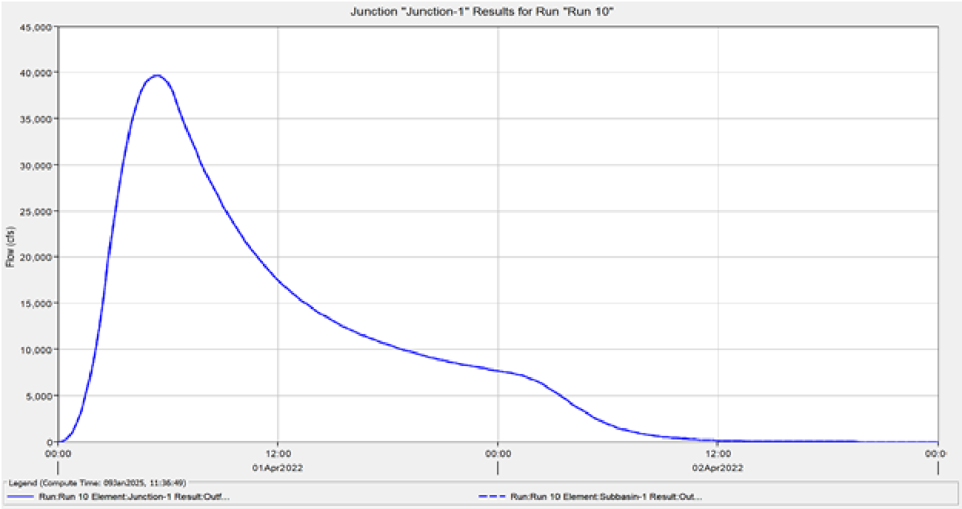

FIGURE 4.22: 10 Years return period Flood (Historic)

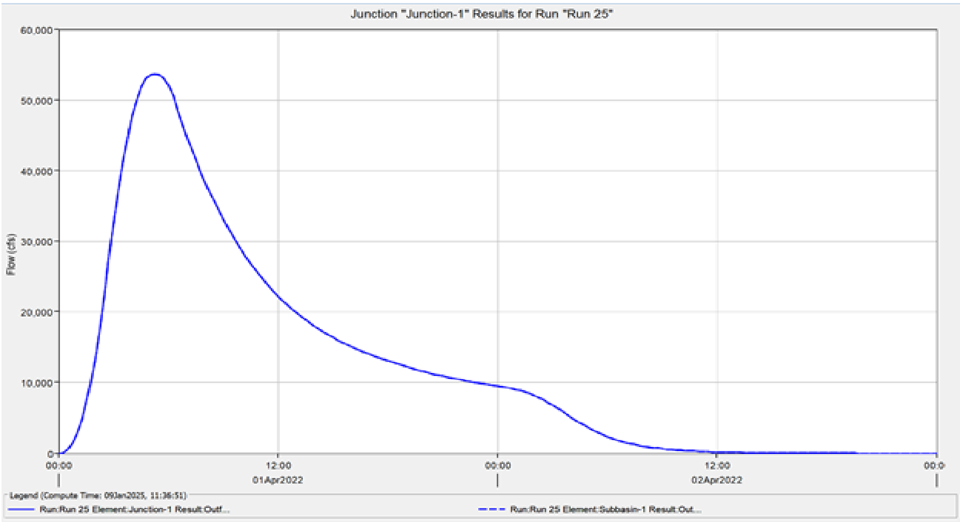

FIGURE 4.23: 25 Years return period Flood (Historic)

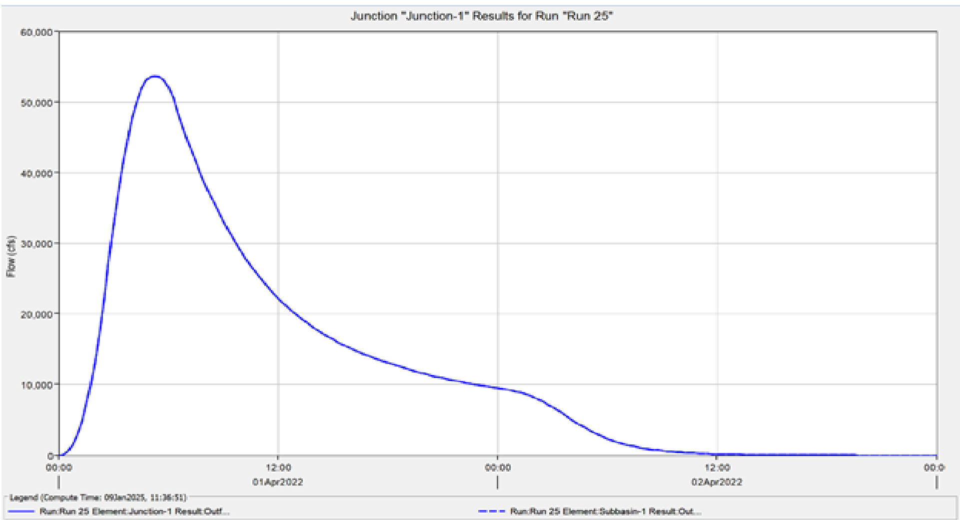

FIGURE 4.24: 50 Years return period Flood (Historic)

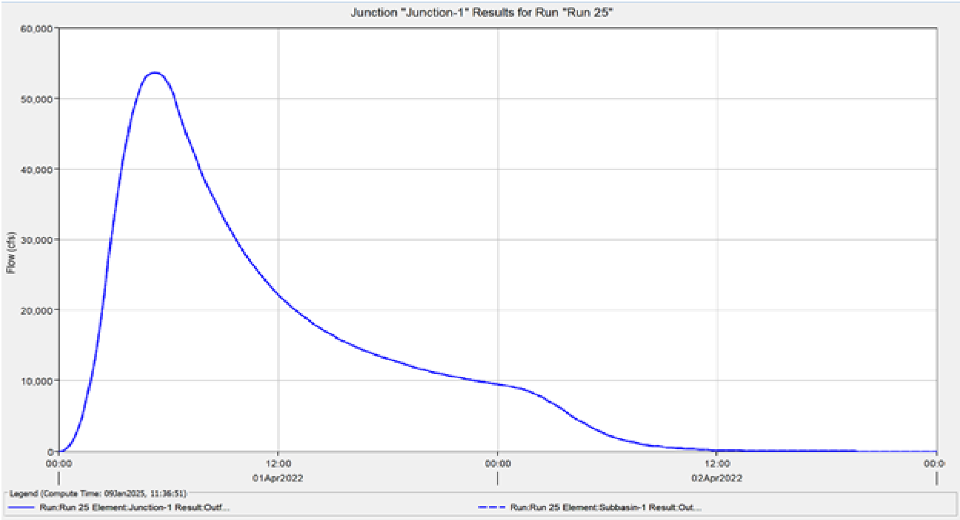

FIGURE 4.25: 100 Years return period Flood (Historic)

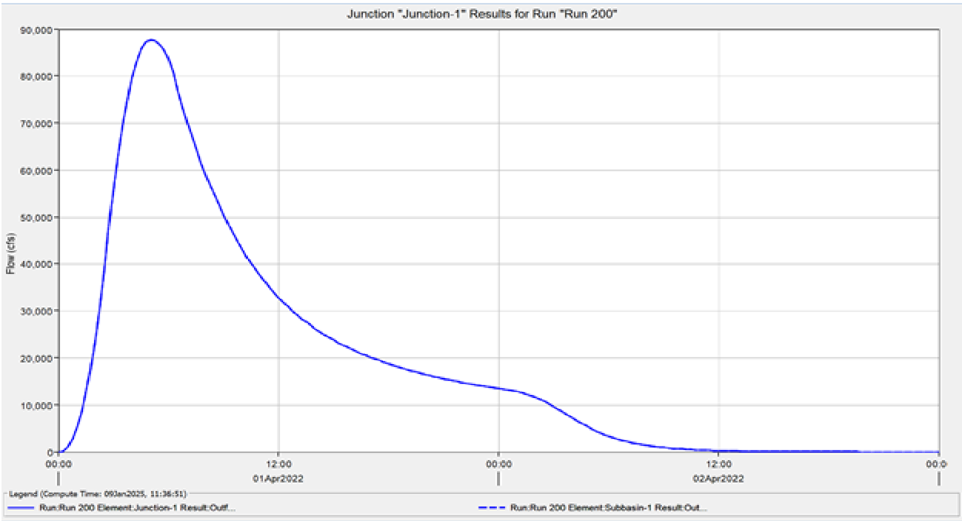

FIGURE 4.26: 200 Years return period Flood (Historic)

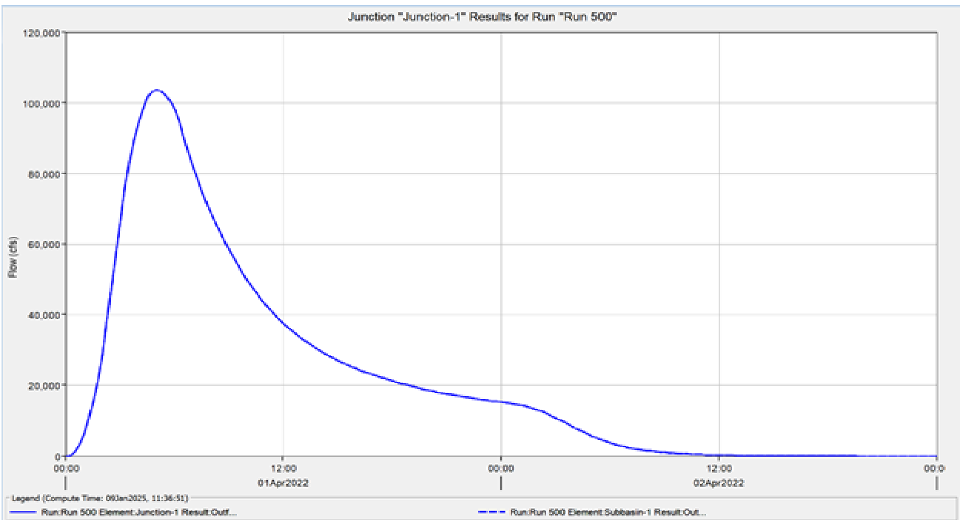

FIGURE 4.27: 500 Years return period Flood (Historic)

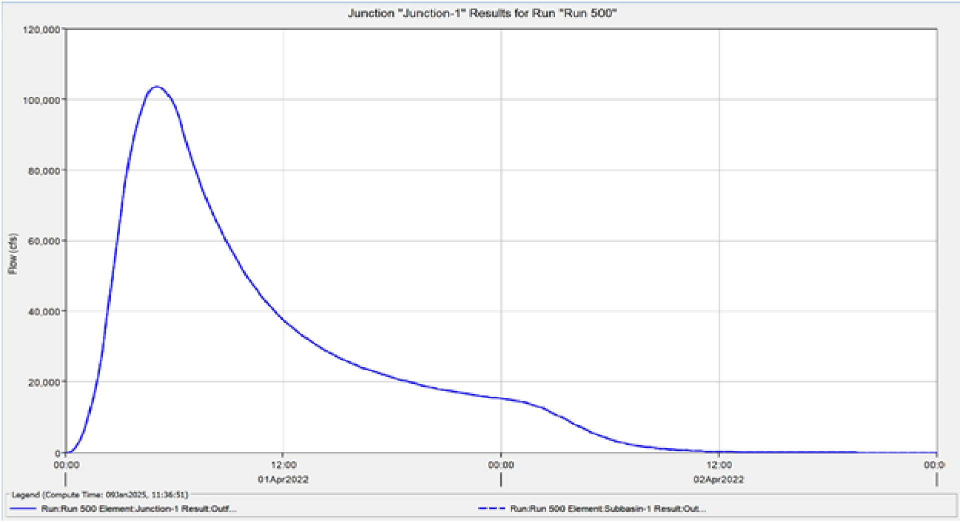

FIGURE 4.28: 1000 Years return period Flood (Historic)

Chapter 5

Conclusions and Recommendations

5.1 General

In conclusion, this study provides a comprehensive assessment of future flood risks and climate variability for the Kalam Basin using climate change scenarios and advanced modeling techniques. A robust methodology was employed, starting with the selection of 31 Global Climate Models (GCMs), from which five representative models were chosen based on hot, wet, cold, dry, and average projections. Historical precipitation data (1989 to 2014) from the Kalam Climate Station was used alongside GCM data for two climate scenarios: SSP2-4.5 (a middle-of-the-road pathway with a 2.7°C temperature increase by 2100) and SSP5-8.5 (a high-emission pathway with a 4.4°C temperature increase by 2100). Gumbel Extreme Value Distribution was applied to analyze the precipitation data, followed by bias correction using the delta method to project future precipitation for three time periods: 2025-2050, 2051-2075, and 2076-2100.

Similarly, temperature data from 1984 to 2017 was utilized, and future projections were bias-corrected for both scenarios. Trends and patterns in future precipitation and temperature were thoroughly analyzed and presented through tables and plots, revealing significant increases in temperature and shifts in precipitation patterns under future climate conditions. These findings highlight the potential impacts of climate change on hydrological behavior in the Kalam Basin.

Lastly, flood discharges for various return periods were calculated for historical and future scenarios using the HEC-HMS model with the SCS Curve Number method. This modeling approach incorporated basin characteristics, lag time calculated using Kirpich's formula, and weighted curve numbers derived from land use and soil data. The study underscores the importance of integrating climate resilience into hydraulic infrastructure design to mitigate flood risks effectively. This framework provides valuable insights for future research and policy-making related to flood risk management and climate adaptation in the region.

5.2 Global Climate Models (GCMs)

The selection of five Global Climate Models (GCMs) for future climate projections was carried out using a systematic approach to ensure a comprehensive representation of possible climatic variations. While GCM selection can be based on various criteria such as spatial resolution, model performance, and climate sensitivity, this study focused on selecting models that capture the full range of precipitation and temperature variability. The chosen models were selected based on the dry, wet, hot, cold, and average projection criteria, ensuring a balanced and robust assessment of future climate conditions in the Kalam Basin. The final selected GCMs are listed in the table below:

TABLE 5.1: List of final selected GCMs.

S. No	**Model Name**	**Characteristics**
1	AWI-CM-1-1-MR	Hot, Wet model (high precipitation)
2	BCC-CSM2-MR	Dry, Hot model (low precipitation)
3	MPI-ESM1-2-HR	Cold, Wet model (low temperature)
4	MPI-ESM1-2-LR	Cold, Dry Model (Moderate temperature change, minimal precipitation change)
5	NorESM2-MM	Warmest model (high temperature)

5.3 Flood Frequency Analysis

The flood frequency analysis for the Kalam Basin demonstrates a clear increase in precipitation across different return periods under future climate scenarios, highlighting the growing risk of extreme flood events. Historical data from 1989-2014 provides a baseline, with the 100-year return period precipitation recorded at 5.7 inches and the 1000-year return period at 7.4 inches. However, projections under SSP2-4.5 and SSP5-8.5 indicate significant increases in precipitation intensity, leading to heightened flood risks in the coming decades.

Under SSP2-4.5, precipitation is projected to increase gradually, with the 100-year return period precipitation rising from 5.7 inches (historical) to 6.26 inches (2025-2050), 6.05 inches (2051-2075), and 6.16 inches (2076-2100). Similarly, the 1000-year return period precipitation is expected to increase from 7.4 inches (historical) to 8.30 inches (2025-2050), 7.76 inches (2051-2075), and 7.89 inches (2076-2100). These projections suggest a moderate but consistent rise in flood risks over time.

Similarly, SSP5-8.5 projects a substantial rise in extreme precipitation, significantly increasing flood risks in vulnerable areas. The 100-year return period precipitation grows from 5.7 inches (historical) to 7.15 inches (2025-2050), 6.42 inches (2051-2075), and 6.60 inches (2076-2100). Likewise, the 1000-year return period precipitation rises from 7.4 inches (historical) to 9.64 inches (2025-2050), 8.21 inches (2051-2075), and 8.48 inches (2076-2100), highlighting the intensification of flood hazards over time.

These findings emphasize the urgent need to integrate climate-resilient designs in hydraulic infrastructure and adopt adaptive flood management strategies to mitigate the amplified flood risk posed by future climate conditions.

5.3.1 Precipitation and Temperature Patterns

In conclusion, the analysis of rainfall and temperature patterns in the Kalam Basin indicates significant changes due to climate change. Rainfall intensity is projected to increase under both the SSP2-4.5 and SSP5-8.5 scenarios, with a more pronounced increase observed under the higher-emission SSP5-8.5 scenario. This trend points to more frequent and intense extreme rainfall events, which could lead to reduced return periods for such events, highlighting the increasing frequency of floods. This change in rainfall patterns poses potential risks for water management, agriculture, and infrastructure planning in the region.

Similarly, temperature projections indicate a clear warming trend, with more significant increases under the SSP5-8.5 scenario. In the SSP2-4.5 scenario, a moderate rise in temperatures is expected throughout the year, with mean increases ranging from 0.59°C in October to 2.63°C in April. The summer months (June, July, and August) are expected to experience considerable warming, and the winter months (January and February) will likely see higher temperatures as well.

Under the SSP5-8.5 scenario, the temperature rise is even more significant. For instance, April's temperature is projected to increase from 11.47°C historically to 15.29°C, and September's from 16.00°C to 17.51°C. This scenario indicates a strong warming trend, with average temperature increases ranging from 1.52°C in September to 3.83°C in April.

This intensified warming could exacerbate challenges related to snow melt and water resources, increasing stress on agriculture, water supply, and local ecosystems. These findings highlight the urgent need for effective climate adaptation strategies to mitigate future risks in the Kalam Basin.

5.3.2 Future Flood Discharges

In conclusion, the findings of this study clearly show that climate change is leading to more frequent and intense flood events in the Kalam Basin. By applying the Gumbel Extreme Value distribution and simulating discharges through the HEC-HMS hydrological model, it was observed that future flood magnitudes are significantly higher than historical records. Under both SSP2-4.5 and SSP5-8.5 climate scenarios, extreme floods that once occurred every 100 years are now expected to occur every 50 years or even more frequently.

For instance, the historical 100-year flood discharge of 75,993.7 cusecs is projected to increase by over 21% under future conditionsrising to 92,094.8 cusecs in SSP2-4.5 and 98,156.7 cusecs in SSP5-8.5. Moreover, the 50-year flood discharges in both scenarios already exceed the historical 100-year level, indicating a clear reduction in flood return periods and an overall rise in flood risk.

These results highlight the urgent need for climate-resilient flood management strategies in the region. Without timely adaptation and planning, the increasing intensity and frequency of floods could lead to greater damage to infrastructure, livelihoods, and ecosystems. Therefore, this study provides critical insights for guiding future flood mitigation, water resource planning, and climate adaptation efforts in the Kalam Basin

5.4 Recommendations

- Future climate inclusive floods are expected to be higher than historic floods, and warrants effective flood management in Kalam Basin
- Flood management may require improved early warning systems, design of climate resilient infrastructure, and climate-adaptive policies to minimize future flood damages
- Results of the current study can be used to raise awareness about increasing flood risks due to climate change; implement community-based flood monitoring, training programs, and local early warning systems to reduce vulnerabilities and enhance preparedness against extreme climate events.
- The current study focuses on Kalam basin. Future research should focus on the entire Swat and Indus Basin.

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