

# **Flash Flood Hazard Assessment using Hydrological and Machine Learning Models with Multi-Satellite-Based Precipitation and d4PDF Climate data sets in Saudi Arabia**

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### Dedication

My humble efforts are wholeheartedly dedicated

To my beloved Father and mother

To my wife and children (Jory, Abdulrahman, Sarah and Noor)



## Summary

Floods are among the most prevalent natural hazards globally, causing significant damage and loss of life. The primary tool for flood risk assessment and damage mitigation is hydrologic early warning systems, which predict flood events using rainfall observations from ground stations. However, challenges such as data scarcity, spatial disruption, network density issues, and measurement errors in ground stations have necessitated using satellite-based rainfall products to address these limitations. Satellite-based precipitation estimates (SbPEs) and reanalysis precipitation datasets (RPDs) have become increasingly accurate, offering improved spatial and temporal resolution beneficial for hydrological applications and rainfall-runoff modeling. The challenges posed by climate change, particularly the increasing frequency of extreme events like floods, further complicate flood risk assessments, especially in regions like Saudi Arabia.

The main challenge in assessing rainfall and runoff in Saudi Arabia is the limited availability and accuracy of observational data (1) rainfall station and monitoring that can be measured with reliable and less uncertain data with low maintenance cost. In addition, the extreme climatic variability under climate change impact with dam management and mitigation measures in KSA (2) the identification of suitable locations for new dams where they can effectively serve multiple purposes, including groundwater recharge, flood control, water storage, and protection.

Therefore, the main objectives of this research thesis are to (1) Examine both the hydrological model and Machine learning to develop the flash flood susceptibility maps, (2) Deep understand the Spatiotemporal climatic variability of extreme storms, (3) To evaluate SBP rainfall data and Re-analysis Rainfall data over KSA, and (4) To develop Flood Hazard Map based on SBP and hydrological modeling including distribution of dams locations and purposes.

This thesis consists of seven chapters that explain the flood risk assessment from different sources of rainfall data and culminate in the analysis of extreme rainfall in the present and future, using hydrological models and machine learning techniques to find the hazard mapping over Saudi Arabia. The introduction and the literature review about the rainfall-runoff processing under climate change in Saudi Arabia were presented [Ch.1, 2]. Afterward, a set of investigations was conducted through various analyses and modeling to find out the flash flood hazard and susceptibility

map [Ch.3, 4, 5, 6]. Finally, the recommendation and future prospects were proposed with research conclusions in [Ch.7]. The detailed structure of the thesis is described as follows:

**Chapter 1 Introduction:** This chapter includes a general background, the importance of the topic, and an overview of the methodology, in addition to the thesis research motivation and objectives. Finally, it reports the whole thesis structure. It also highlights the research gaps and insufficient studies to develop flood hazard mapping in Saudi Arabia.

**Chapter 2 Comprehensive state-of-the-art of the rainfall-runoff processing under climate change:** This chapter summarizes and reviews the literature on various aspects relevant to extreme rainfall analysis. It also highlights the research gaps and insufficient studies about flash flood challenges historically and in different climate scenarios. Finally, the climate shift impacts on extreme rainfall events and trends and how causes severe effects on infrastructures and properties due to extreme flash floods.

**Chapter 3 Spatiotemporal climatic shifting of Extreme storms under different climatic scenarios:** The study provides a deep understanding of the spatiotemporal climatic variability of extreme storms under different climatic scenarios using the d4PDF climate model. This subtopic focuses on identifying shifts in rainfall patterns from the present to the future, analyzing different thresholds for rainfall frequency and magnitudes, and conducting trend analysis using the Mann-Kendall statistic and S-slope model across Saudi Arabia. Significant variability is expected, with increases in precipitation frequency and magnitude during spring, autumn, and summer, and decreases in winter. The findings highlight critical shifts in extreme events, particularly during wet and dry seasons, and their implications for infrastructure and long-term development strategies, aligning with Saudi Vision 2030.

**Chapter 4 Comparison and Evaluation of Satellite-Based Precipitation on the Rainfall-Runoff process Over KSA:** This subtopic explores the evaluation of satellite-derived rainfall products against observational data to understand the spatial and temporal rainfall patterns in Saudi Arabia. The study compares seven high-resolution satellite-based precipitation estimates (TRMM, PERSIANN-CDR, PERSIANN-CCS, PERSIANN-PDIR, PERSIANN-PERS, CHIRPS V2.0, and GPM IMERG V6) and four reanalysis precipitation datasets (GPCC, JRA55, ERA5, and NCEP) with data from 233

conventional rain-gauges over the period 2000–2019. The performance of these datasets is assessed using continuous and categorical statistics, revealing significant variability depending on time series, location, and thresholds. The study finds that while certain satellites like TRMM, CDR, and IMERG perform well in representing flood depth and extent, others like PDIR tend to overestimate floods. Using SbPEs and RPDs for rainfall estimation presents uncertainties, but these satellite products significantly enhance hydrological predictions, supporting water resource management systems.

**Chapter 5 Stormwater management modeling and machine learning for flash flood susceptibility prediction in Wadi Qows:** This research aims to examine integrating hydrological models with machine learning techniques to develop flash flood susceptibility maps. The study utilizes machine learning models like Random Forest, LightGBM, and CatBoost alongside the Personal Computer Storm Water Management Model (PCSWMM) by assessing nine independent factors influencing flood risks. The effectiveness of these models is demonstrated through their application in Wadi Qows, Saudi Arabia, where approximately 300 flash flood sites were identified from post-flood surveys. The results, validated with a receiver operating curve (ROC) analysis, show high accuracy in predicting flood-prone areas, making these models valuable tools for proactive disaster management and improving mitigation measures in flood-vulnerable regions.

**Chapter 6 Flood Hazard Mapping Scenarios:** The research develops flood hazard maps over Saudi Arabia based on historical and projected future precipitation data from the d4PDF climate model. The study investigates spatial and temporal patterns of extreme rainfall events and their expected changes from 2000–2011 to 2031–2100. The analysis identifies regions, particularly in central, eastern, and western Saudi Arabia, where extreme rainfall events are likely to increase. The study also examines the distribution of dams and their correlation with flood risk, finding adequate protection in some regions but insufficient infrastructure in others. The hazard maps, created using the RRI model with maximum rainfall events, provide crucial insights for decision-makers to implement mitigation measures for flash flood risk reduction in vulnerable regions. The correlation between the distribution of dams and the extreme events frequency shows sufficient protection and mitigation measures in southwest regions such as (Baha, Asir, and Jazan), and limited dam infrastructure in (Jouf, Tabuk, and Najran), while lack of any dams in Eastern Region

except two small dams for protection. Decision-makers can use the outcomes of this study in Saudi Arabia to implement mitigation measures for flash flood risk reduction.

**Chapter 7 Conclusion and Outlook:** This chapter summarizes the study's conclusions and findings by offering several recommendations for flash flood mitigation. It also discusses this research limitations and suggests directions for future studies.

**Keywords:** Extreme events, Flash flood, Trend and frequency, Spatial and temporal variability, d4PDF data, Wadi QOWS, Saudi Arabia.

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# CHAPTER 1

## Introduction and research Outline

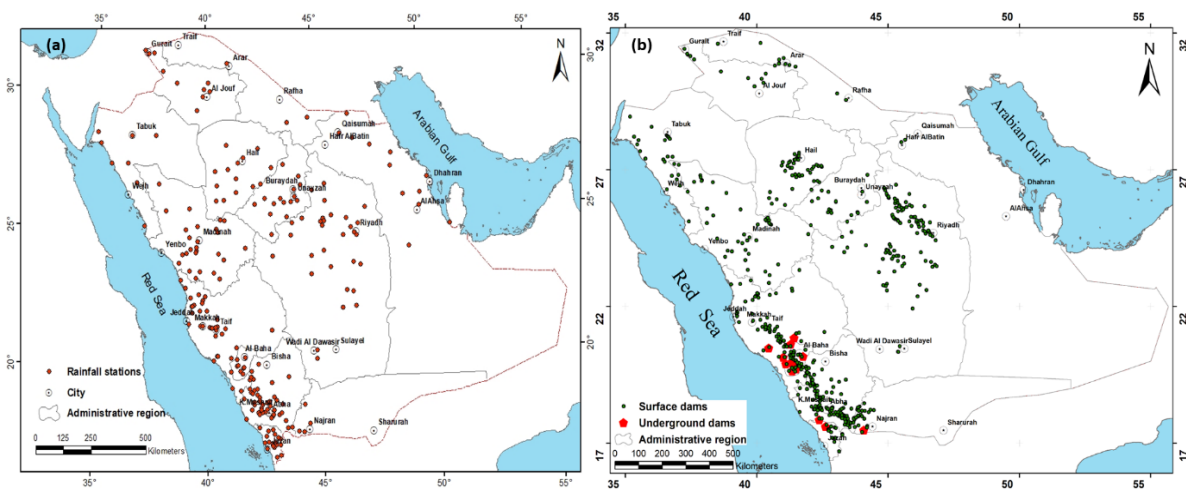
### 1.1. Study background

Extreme events in arid regions are characterized by significant variables in spatial and temporal domains. Due to climate change flash floods cause widespread disruption to the environment and human activities. Saudi Arabia has experienced numerous flash floods in major cities in the last two decades. A notable example is the 2009 Jeddah flood which claimed 113 victims, damaged more than 10,000 homes, and destroyed approximately 17,000 vehicles. In response, the government constructed eight new dams in Jeddah to mitigate future flooding. However, a flash flood struck Jeddah City again in 2022 as shown in (Figure 1.1).

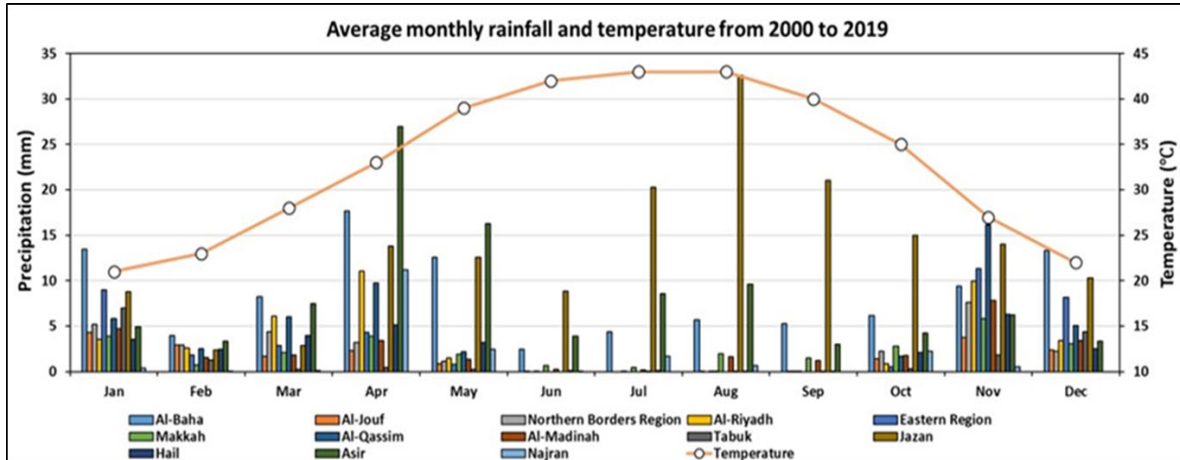


**Figure 1.1** The last flash flood happened in Jeddah city in 2022.

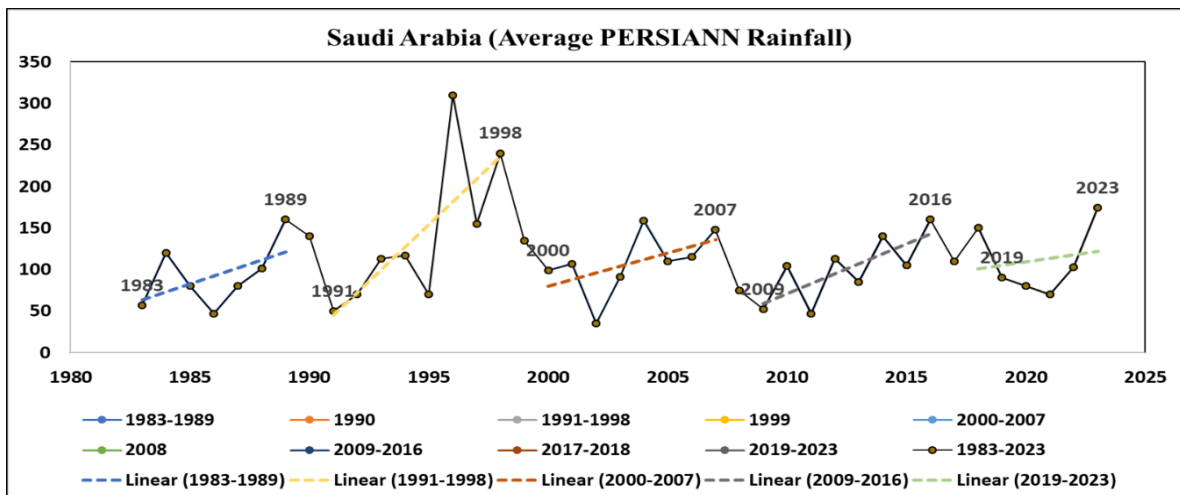
Saudi Arabia has 232 rainfall stations and 573 including surface and underground dams over 13 administrative regions (Figure 1.2). Due to increased extreme events, the government has planned to build 1000 dams for Vision 2030. However, the average rainfall is very low and high varying from region to region. The annual rainfall is about 100 mm per year except for the southwestern regions of Saudi Arabia, which are about 300 mm. The southwestern regions have heavy rainfall especially in the Jazan region during the dry season (Figure 1.3). The surface heating over Saudi Arabia induces convection leading to cumulonimbus clouds driven by orographic effects. This phenomenon facilitates the development of strong depressions over the central Red Sea, causing extreme rainfall. The wet season rainfall is dynamic in Saudi Arabia where much rain falls in the northeastern, central, and southwestern parts. The average annual temperature is 33 °C in Saudi Arabia. The warmest month of the year is July, with an average temperature of about 43 °C, while January is the coldest month in Saudi Arabia with an average temperature of 21 °C. Based on PERSIANN rainfall data, the average annual precipitation exhibits an increasing trend in seven-year cycles, each after a decreased rainfall period lasting for one or two years as illustrated in (Figure 1.4).



**Figure 1.2** (a) Distribution of 232 rainfall stations (b) Distribution of 573 surface and underground dams over Saudi Arabia.



**Figure 1.3** Observation of monthly average rainfall and temperature in 13 administrative regions



**Figure 1.4** Annual average rainfall of PERSIANN data from 1983 to 2023 over Saudi Arabia.

Saudi Arabia has recently faced unusual climatic conditions. The frequent natural disasters and extreme rainfall affecting various regions. Notably, the flash floods in Jeddah in 2009 and 2011 stand out as some of the most significant natural disasters in the country's history. Improvements are necessary in several aspects of hydrology, including implementing flood control measures to assess the practical impact of flash floods and monitoring for both rainfall and runoff stations to enhance the dissemination of real-time data and improve the

accuracy of hydrological model results. The analysis of satellite rainfall data and estimate of rainfall-runoff processes under climate change represents a critical aspect of hydrological research with profound implications for water resource management and climate adaptation strategies. Satellite-based precipitation estimation has emerged as a valuable tool for hydrologists and offers spatially and temporally continuous data over large areas where rainfall stations are limited and not in good distribution condition.

In the context of climate change, alterations in precipitation intensity, frequency, and distribution can significantly affect effective flash flood management and hazard mitigation. Recent studies indicate an increasing trend in extreme rainfall events, which can lead to more frequent and intense flooding (Almazroui, 2020; Almazroui, Raju, et al., 2017; Atif et al., 2020). Utilizing advanced hydrological models allows the effects of these changes to be simulated and predicted. By incorporating various climatic scenarios, valuable insights into future risks can be provided which can help develop adaptive strategies for water resource management and disaster preparedness and support the creation of hazard maps. Previously, the average economic damage value may have exceeded USD 19 million annually (Mashael Al, 2010). However, it has been observed that the average damage has increased alongside the increase in extreme rainfall events over the past two decades.

Advancements in computational power combined with satellite rainfall data, topographic data, and machine learning techniques have allowed simulation models to describe hydrological processes and develop the inundation map accurately. Flood modeling and machine learning techniques are increasingly employed to create flood hazard and susceptibility maps. Those approaches have been applied in Wadi Qows in Jeddah city, using rainfall data and depth points collected in 2009. The physical model has been calibrated and validated using this event and is subsequently applicable across all of Saudi Arabia. In this study, hydrological models have been used such as the Rainfall-Runoff-Inundation (RRI) model, and the Personal Computer Storm Water Management Model (PCSWMM) along with geographic information systems (GIS) to model the flood hazards map in Wadi Qows

and then over Saudi Arabia as well. In addition, machine learning algorithms have been employed to create flood susceptibility maps such as the random forest (RF), LightGBM, and CatBoost.

Climate change has resulted in spatial and temporal rainfall shifts across different parts of Saudi Arabia. The current study uses the observed daily station dataset to identify trends and frequencies of extreme rainfall in the present condition. Additionally, Database for Policy Decision making for Future climate change d4PDF data is employed to simulate future climate scenarios based on various emission scenarios. This comprehensive analysis aims to develop adequate and effective climate adaptation strategies for these sensitive regions likely to experience a pronounced climate shift. Climate shifting based on precipitation refers to alterations in the long-term precipitation patterns regionally and globally, which can significantly impact ecosystems, water resources, agriculture, and human societies (Cai et al., 2013; Cook et al., 2014; Krishnan et al., 2012). For instance, Australia, India, and the Southwestern United States have experienced prolonged periods of drought due to changes in precipitation patterns associated with El Nino/Southern Oscillation (ENSO) related precipitation decrease, affecting water resources and agriculture (Trenberth, 2005). There are noticeable changes in the snow environment in the Scandinavian highlands including fewer days with substantial snow depth and decreased precipitation falling as rain instead of snow reducing snow cover (Lind et al., 2023). Overall, many studies indicate that there is a high variability of climate over the world. This study's first work has been done based on our knowledge, which systematically addresses and highlights the spatiotemporal climate shifting of extreme rainfall events in hyper-arid environments such as Saudi Arabia. Changing precipitation patterns is a hallmark of spatial and temporal climate shifts in Saudi Arabia. It has been noted that rainfall is decreasing in some regions and increasing locally and intensely in other regions. However, the North Atlantic Oscillation (NAO) and the El Niño Southern Oscillation (ENSO) have contributed to alterations in atmospheric circulation patterns. These changes are linked to a shift in the path of rainfall. This has caused increased

drought in some areas and increased humidity in other areas. Consequently, these shifts affect regional and local fluctuations in the characteristics of rainfall (Hasanean & Almazroui, 2015).

This study compares and evaluates satellite-based precipitation estimates with observational rainfall data from the ground stations over Saudi Arabia (KSA). Satellite-based precipitation products offer extensive spatial coverage. However, these satellite estimates can vary in accuracy due to algorithm differences based on sensor types and atmospheric conditions. The research involves analyzing the performance and reliability of various satellite data by comparing them with observational rainfall data in different temporal scales (monthly, seasonal, and annual) such as TRMM, PERSIANN-CDR, PERSIANN-CCS, PERSIANN-PDIR, PERSIANN-PERS, CHIRPS V2.0, GPM IMERG V6, GPCC, JRA55, ERA5, and NCEP. Statistical Metrics have been utilized to assess the accuracy and reliability of the satellite estimates such as Pearson Correlation Coefficient (correlation), Bias Ratio (BIAS), root mean square error (RMSE), and Mean Error (MAE). In addition, Categorical Statistics have been used to evaluate the ability of satellites to discriminate between precipitation and no precipitation events days such as the Probability of Detection (POD), the False Alarm Ratio (FAR), and the Categorical Success Index (CSI). Moreover, different thresholds have been used to assess extreme rainfall events. Accurate precipitation data is crucial for effective water resource management, flood forecasting and climate studies. The findings of this study are expected to represent the accurate satellite precipitation products in KSA. The results will be valuable for improving precipitation monitoring and modeling, contributing to better water management, and disaster preparedness strategies.

## **1.2. Study motivation and objectives**

The overall objective is to propose a flash flood assessment using rainfall-runoff modeling and machine learning techniques considering climate variability in Saudi Arabia.

**Objective 1:** Examining the hydrological model and Machine learning to develop the flash flood susceptibility maps.

**Objective 2:** To deeply understand the Spatiotemporal climatic variability of extreme storms.

**Objective 3:** To evaluate SBP rainfall data and Re-analysis Rainfall data over KSA.

**Objective 4:** To develop a Flood Hazard Map based on SBP and hydrological modeling including distribution of dam locations and purposes

## **1.3. Overall methodology**

Due to the lack of continuous rainfall records in most of the rainfall stations, several based-satellite and reanalysis rainfall data were analyzed and compared with observation rainfall data on monthly, seasonal, and annual scales. In addition, climate shifts have been assessed using d4PDF climatic data in the Near Future (NF) from 2031 to 2050 and the Far Future (FF) from 2051 to 2100. Moreover, climate change has increased the number of extreme events dramatically. However, many studies have not analyzed climate shifts deeply in all seasons with different thresholds. Therefore, extreme rainfall trends have been analyzed historically and in the future. In addition, (RRI) model has been utilized to create hazard maps over Saudi Arabia using different rainfall thresholds and extreme rainfall events in various climatic scenarios. Recently, machine learning has been more utilized in various sciences. Therefore, machine learning was applied in Wadi Qows using extreme rainfall data in 2009, and all algorithms were calibrated with flood depth points during this event. Moreover, Machine learning techniques have been compared with (PCSWMM) model in terms of flood extent.

The research methodology is shown in Figure 1.5, presenting a comprehensive approach to data collection and analysis. This methodology combines multiple sources of information, including observational data, satellite-based data, and future climate scenarios, to achieve the research objectives.

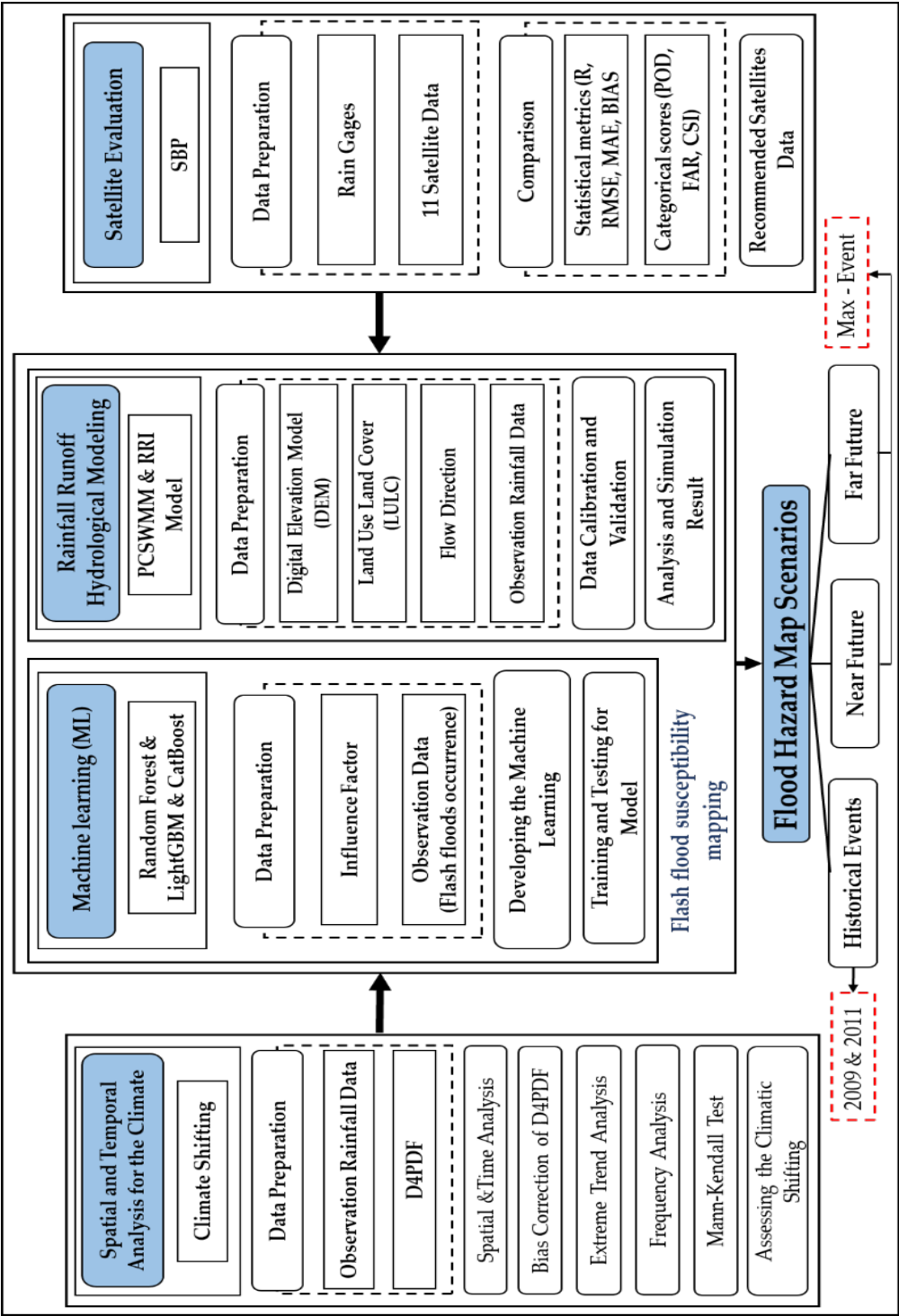
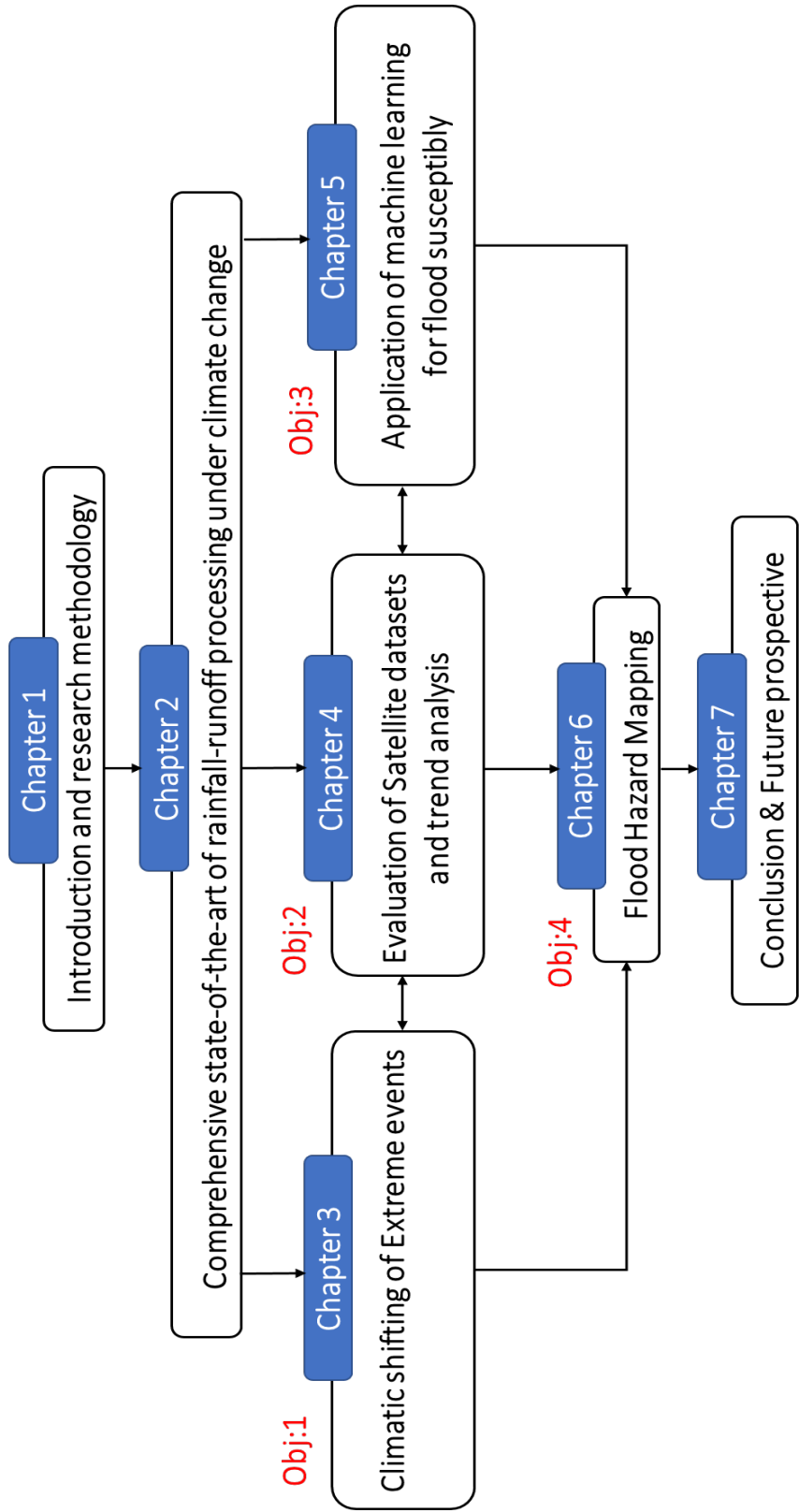


Figure 1.5 Research methodology

#### **1.4. Structure of the thesis**

This thesis covers all the objectives of flash flood assessment and analysis of extreme rainfall historically and in the future to predict flood hazard and susceptibility maps. This dissertation consists of seven chapters as shown in Figure 1.6.

- **Chapter 1** Includes the general background information and research problems, motivations and objectives, research outline, and thesis structure.
- **Chapter 2** Presents an overview of flash floods in arid regions, including extreme rainfall analysis spatially and temporally, previous conventional methods, challenges, and gaps.
- **Chapter 3** This chapter examines spatial and temporal rainfall shifts from the present to the future. Various rainfall frequency and magnitude thresholds were analyzed across Saudi Arabia, employing the Mann-Kendall statistic and S-slope model. These findings aid in understanding climate change impacts and integrating climate considerations into Saudi Vision 2030 development strategies.
- **Chapter 4** Comparison and Evaluation of Satellite-Based Precipitation on the Rainfall-Runoff process Over KSA for monthly and seasonal records with different rainfall intensity thresholds. Such studies significantly enhance hydrological predictions' accuracy, which supports water resource management systems.
- **Chapter 5** Evaluates machine learning algorithms and the physical hydrological model to predict flash flood susceptibility maps (FFSMs) in Wadi Qows, Saudi Arabia. ML-derived FFSMs aligned well with the PCSWMM flood map. These findings can help planners improve flood mitigation in Saudi Arabia.
- **Chapter 6** Developing hazard maps for Saudi Arabia under scenarios of extreme events, historical maximum floods, and future maximum floods. These findings can guide decision-makers in implementing flood risk mitigation measures.
- **Chapter 7** This chapter summarizes the conclusions and results of this study, providing several recommendations for flash flood assessment and mitigation.



**Figure 1.6** Thesis flowchart structure



## CHAPTER 2

# Comprehensive state-of-the-art of rainfall-runoff processing under climate change

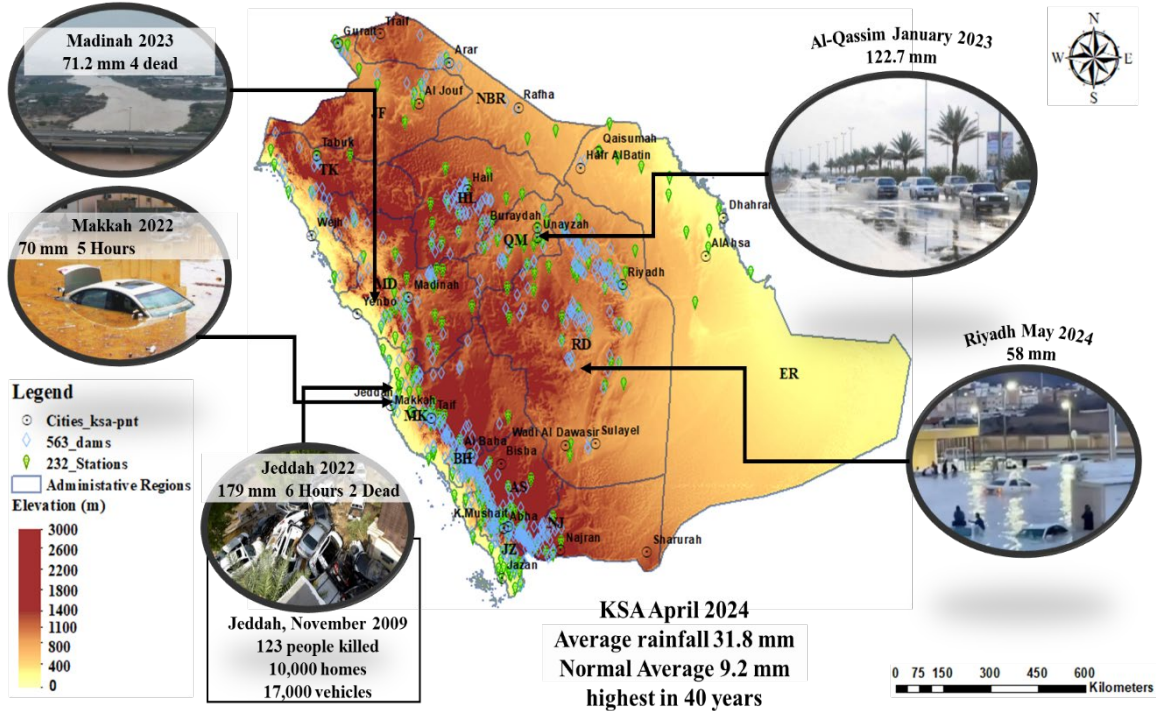
### **2.1. Flash floods under climate change challenges and gaps**

Flash floods are rapid and extreme flow events that occur within a short period following intense rainfall or dam failure, are particularly common in arid and semi-arid regions (Hou et al., 2020; Q. Yang et al., 2020). These regions often have steep slopes, impervious layers, and sparse vegetation, which reduce water absorption and increase runoff, exacerbating the severity of the flood (Asefaw, 2020). The primary challenge associated with flash floods is inherent unpredictability and the limited time available for early warning issues, which

are particularly hazardous to human life and infrastructure (Saber & Habib, 2016). The scarcity of reliable data, particularly in arid regions like the Arabian Peninsula, complicates water resource management and flash flood forecasting (Alarifi et al., 2022). Climate change has a significant influence on the frequency and intensity of flash floods. As global temperatures rise, precipitation patterns are altered, leading to more extreme and unpredictable rainfall events (Hussain Shah et al., 2023). In arid regions, where the ground is often dry and unable to absorb large amounts of water quickly, this results in a higher likelihood of flash floods. Additionally, climate change can exacerbate the factors contributing to flash floods, such as increased evapotranspiration, changes in soil moisture, and more frequent extreme weather events.

Rainfall-runoff processes is a critical factor in hydrology and water resource management, especially in arid regions such KSA due to limited water availability. Flash floods in KSA pose unique challenges and reveal specific gaps in the last two decades due to the country's geographical, climatic, and social characteristics (AlQahtany & Abubakar, 2020; Mani & Goniewicz, 2023). In addition, flash floods and climate change are closely linked. This relationship poses significant challenges to hydrological processes in Saudi Arabia. The country is vulnerable to variations in rainfall patterns and intensities, directly influencing runoff processes. Despite the rarity of rainfall, KSA has been witnessing an increasing frequency of flash floods, but they pose significant challenges. The extremes of rainfall are often unpredictable and pose severe risks to human life and infrastructure. In addition, accurate prediction and management of flash floods require robust meteorological data. However, Saudi Arabia suffers from limited data availability and insufficient monitoring distributions (Hassan et al., 2021; Masoud et al., 2024). Moreover, rapid urbanization and land use changes can exacerbate flash floods' impacts. On the other hand, impervious surfaces in urban areas reduce natural infiltration and increase runoff. In addition, upgrading and expand urban drainage systems need to be developed and expanded to handle intense rainfall events. The existing infrastructure is one of these challenges and was

not designed to withstand extreme conditions. Climate change has become a major factor affecting rainfall intensity and frequency in the last two decades. KSA experienced severe storms within the last two years as shown in (Figure 2.1), and is still suffering from flash floods under the current existing dams. Moreover, according to the Ministry of Environment, Water and Agriculture (March-April, 2024) flash floods have occurred in many wadis including the western and southwestern regions, as well as in the capital city of Riyadh. The volume of water storage in dam lakes increased to (829 million m<sup>3</sup>), which is the highest volume of water storage in dam lakes since 2010 and dam lakes harvested 243 million cubic meters. Climate change is contributing to the intensification of extreme rainfall in various parts of the world and heightening the potential to affect the frequency and intensity of extreme weather events (Luong et al., 2020; Meehl et al., 2000). The Arabic and Gulf Cooperation Council countries are no exception from these climate effects (Almazroui et al., 2012). Over the last two decades, extreme flash floods have become more prevalent across the Middle East and North Africa (MENA) region.



**Figure 2.1** Resent flash flood over Saudi Arabia under climate change impact in clouding rainfall stations and dams location

Extreme flooding has lately occurred in several Arab nations, including Saudi Arabia, Jordan, Oman, Egypt, Yemen, and Sudan (Abdel-Fattah et al., 2018; Abdelmoneim et al., 2023; Esmail et al., 2022; Youssef et al., 2016). Climate models are deemed the most powerful tools by providing comprehensive data to assess the potential effects of climate variability. Either global circulation models (GCM) or regional climate models (RCM) are two types of climate models that are widely used to examine historical and projected patterns of the climate at the local, regional, and global scales (Me et al., 2022; Vautard et al., 2021), and climate models have the advantage of being able to produce large amounts of climate data. Therefore, Database for Policy Decision-Making for Future Climate Change (d4PDF) climatic data has been used in this study due to customized for extreme weather analysis through having data over thousands of years for the past and future climates in the RCP8.5

development scenario (Davour, 2019). Moreover, future simulations are constructed using multi-ensemble members with different initial conditions based on the observed sea surface temperature values, global mean of greenhouse gas concentration, sea-ice thickness, three-dimensional zone, and aerosols distribution (Mizuta et al., 2017).

## **2.2. Machine Learning ML Approaches.**

Machine learning (ML) techniques have been utilized in numerous research areas in various scientific disciplines over the past few years and are widely used in the hydrological field. Many algorithms are providing powerful tools for data analysis and predictive modeling. In the context of flash flood susceptibility modeling, ML offers various models to simulate flood prone area. ML can enhance predictive capabilities, identify vulnerable areas and support decision-making for flood management. Machine learning with data-driven hydrological models predicts discharge time-series without requiring knowledge of physical parameters related to the watershed (Tripathy & Mishra, 2023). Machine learning models are a black-box and the hydrological cycle variables (influence factors) are directly related to the runoff depth point represented as (an inventory map), and are good enough for runoff modeling (B. Mohammadi & Mehdizadeh, 2020; Okkan et al., 2021). According to (G. Singh & Pandey, 2021), sixteen influence factors need to be considered in flash flood susceptibility (FFS) modeling: slope, aspect, convergence index, distance from the river, geology, lithology, hydrological soil group, land use land cover, L-S factor, rainfall, normalized difference vegetation index, plan curvature, profile curvature, stream power index, topographic position index and topographic wetness index. ML algorithms have been applied globally to rainfall and runoff prediction. Moreover, Machine learning algorithms have proven to be highly efficient with limited data available and easy to implement (En-Nagreg et al., 2024). Another benefit of ML methods in hydrological modeling is their low processing cost. For example, while a neural network might require several hours for the

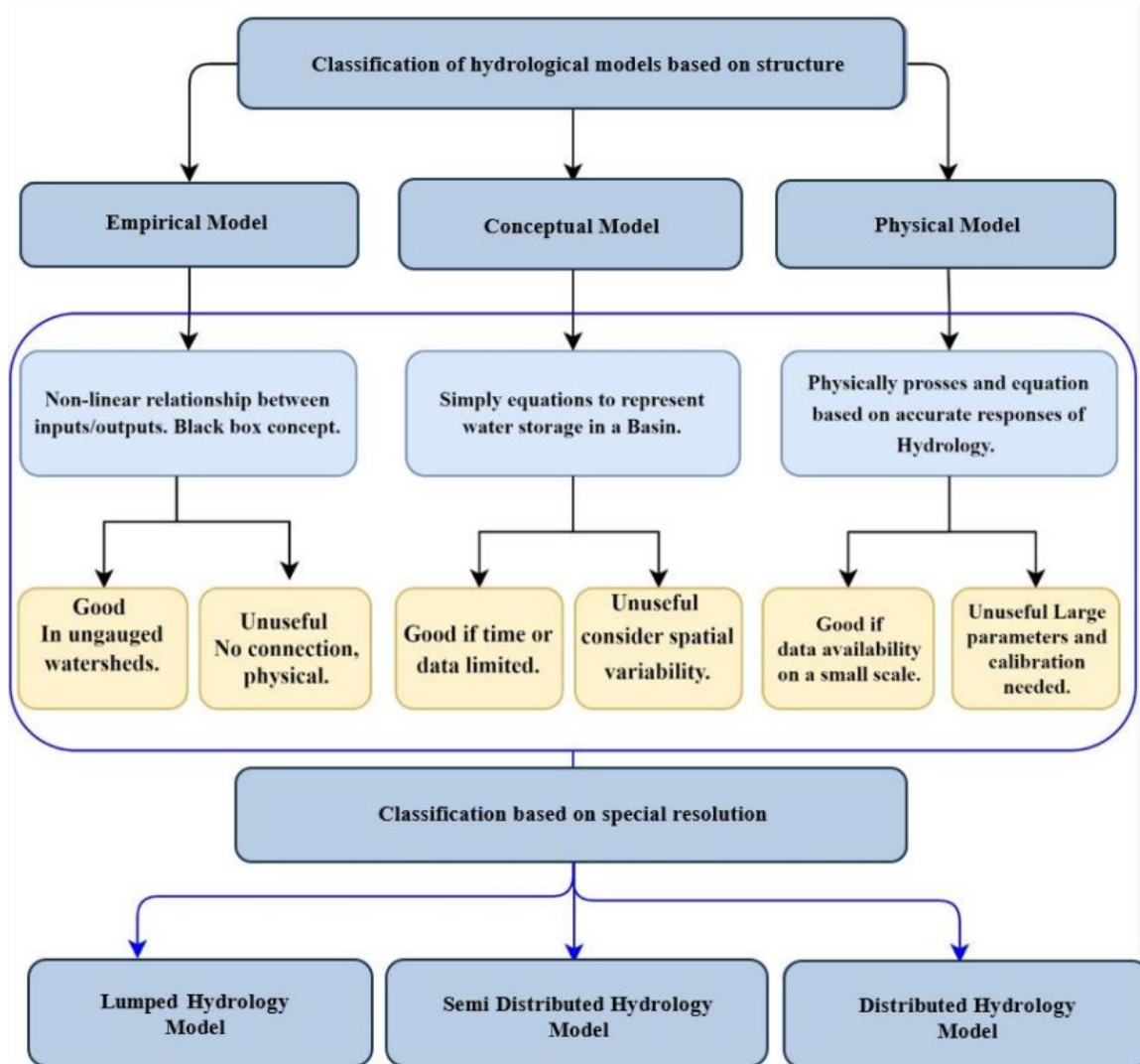
training and validation process, the trained model can then operate quickly enough, often within minutes or even seconds (Santos et al., 2024). However, multiple studies have highlighted that ML models should be used cautiously because their non-linear nature can result in overfitting issues (El Baida et al., 2024; Museru et al., 2024). There are several methods widely used to conduct flood susceptibility mapping (FSM) such as artificial neural networks (ANN), and logistic regression (LR) (Kaya & Derin, 2023; Shahabi et al., 2021), support vector machines (SVM) (Karim et al., 2023; Kaya & Derin, 2023), and decision trees (DT) (Karim et al., 2023; Tehrany et al., 2013). Moreover, these algorithms have been used to produce a groundwater potential mapping in KSA and results indicated that individual models (ANN, SVM, and LR) were combined with an ensemble learning method (RF) within a stacking framework, the predictive accuracy of the hybrid model improved (Mallick et al., 2022). Previous research has demonstrated that using ensemble modeling techniques can enhance model performance (Fadhillah et al., 2021; Feizizadeh et al., 2023). In addition, researchers utilize these algorithms by training them on a subset of flash flood event locations, and then testing or validating them on a separate set of locations, and finally comparing the results to evaluate the effectiveness of the chosen approach. Over the past two decades, the rise of soft computing techniques has further enhanced prediction and forecasting capabilities. The (ANN) approaches have been widely used due to their ability to model non-linear relationships (Shahabi et al., 2021), and have a high comparability for water level prediction with a physical based MIKE 11 model (Panda et al., 2010). Random Forest, CatBoost, and LightGBM have emerged as prominent algorithms due to their robustness and efficiency (Saber et al., 2023). ML models can enhance the accuracy and reliability of these maps by analyzing complex patterns and relationships in large datasets. Machine learning algorithms may aim to replace physical models and there are also attempts to use them with physical models, which have been applied in Egypt and the US (Fleming et al., 2021; Saber et al., 2021). Random Forest excels in robustness and handling noisy data, CatBoost is utilized to handle categorical feature data and provides balanced

performance, and LightGBM is used in speed and efficiency for large-scale datasets (Kumar et al., 2023). CatBoost, and LightGBM are increasingly popular for their accuracy and efficiency in handling complex datasets and short computational time (Saber et al., 2021). Despite the challenges that have attempts made to apply ML approaches to overcome the limitations of a lack of data available for model calibration and validation, the application of ML algorithms remains limited in arid regions (El-Haddad et al., 2021). According to the Koppen–Geiger climate classification, Saudi Arabia is considered as semi-arid region (Peel et al., 2007). In recent years in KSA, ML models have been integrated with GIS and remote sensing techniques to predict flood susceptibility maps. However, very limited studies still conduct flood spatial variability using artificial intelligence models. Examples of these models include: a bagging ensemble (BE), logistic tree (LT), kernel support vector machine (k-SVM), and k-nearest neighbor (KNN), and the best accuracy values about 97% for the BE, LT methods (A. Al-Areeq et al., 2022). In addition, another ML algorithms have been used such as Gradient Boosting Classifier (GBC), Extreme Gradient Boosting Classifier (XGBC), Ada Boosting Classifier (ABC), Random Forest Classifier (RFC), and the Light Gradient Boosting Machine Classifier (LGBMC), where the ratio of the number of true positives to the total number of actual positive cases ranged from 89% to 91%, with RFC and LGBMC exhibiting the best performances (Ghanim et al., 2023). Combining ML models with physical hydrological models can provide better insights to predict flash floods (Alamoudi et al., 2023; Saber et al., 2023). Flash flood risks are constantly increasing due to climate change. Therefore, conducting flood susceptibility mapping is essential for identifying areas at risk of flash floods and potential damage. This modeling is also crucial for helping engineers, planners, policymakers, and authorities develop effective strategies to reduce potential flood damage.

### **2.3. Physical Based Models.**

Rainfall-runoff modeling has evolved significantly since the 19th century, beginning with empirical formulas and rational methods (Vargas-Castañeda et al., 2015). The development of the unit hydrograph concept was a major milestone, followed by the emergence of conceptual models in the 1950s (Yevjevich, 1991). A hydrologic model aims to analyze the nonlinear and intricate relationship between rainfall and runoff using empirical equations and various parameters (Moradkhani & Sorooshian, 2008). The advent of computer technology enabled the creation of more sophisticated models like the Stanford Watershed Model (SWM) and Hydrologic Modeling System HEC-1, which allowed for the analysis of both small and large watershed areas with extensive spatial and hydrological data (Borah et al., 2019). Hydrologic Modeling System (HEC-HMS) is the upgraded version of HEC-1. However, the watershed modeling system (WMS) and its integration with GIS and RS can improve the more explicit estimation of water management at small and catchment sizes (Elewa et al., 2020). Remote Sensing (RS) data enhancement extraction of flood inundation areas can be used to simulate flooding through integration with hydrology models (Nguyen et al., 2022). Rainfall-runoff models are mathematical representations of the complex interactions between inputs, variables, and parameters in watershed hydrology. Physically based models one of models where use physical equations to describe hydrological processes, requiring detailed data on watershed characteristics such as size, shape, topography, and land use, which play a crucial role in determining the most suitable model for a given area (S. Yang et al., 2020). Therefore, several factors for the hydrological and topographical watershed characteristics such as the resolution of the digital elevation model and (quality, length) of the rainfall data series, can significantly impact the modeling process.

Physical models for rainfall and runoff can be broadly categorized into three types: lumped, distributed, and semi-distributed models as shown in (Figure 2.2).

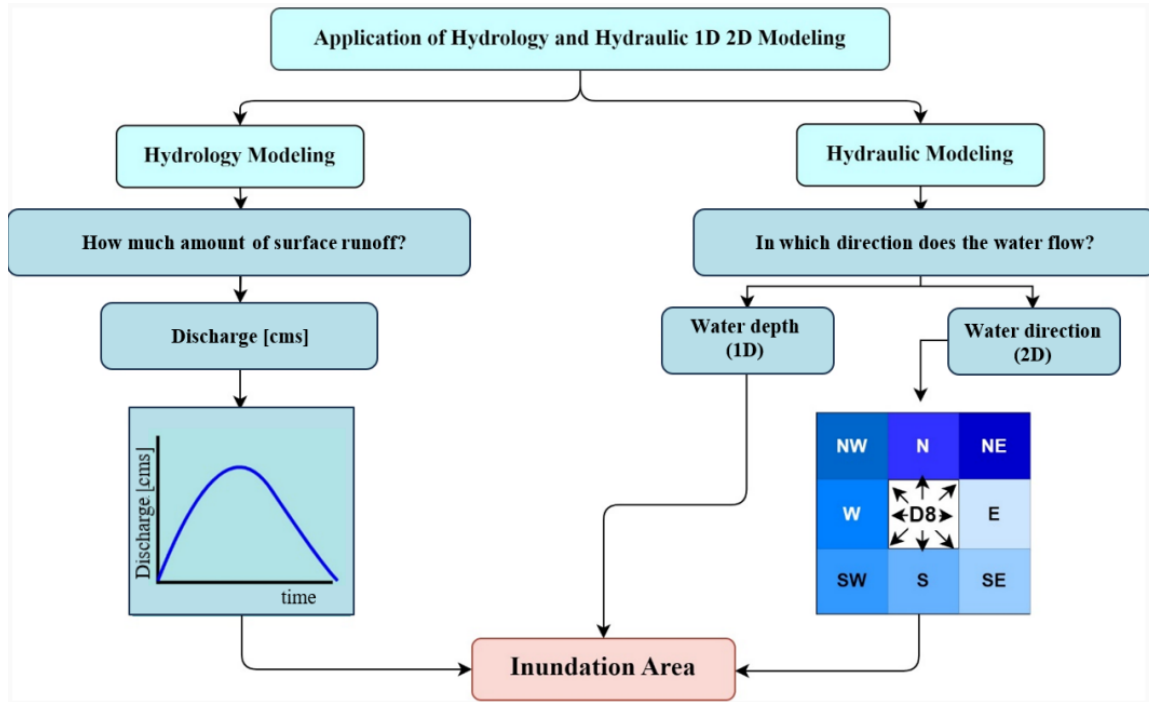


**Figure 2.2** Application of hydrological models (Alshammari et al., 2024)

Lumped Models treat the watershed as a single unit with spatially averaged parameters such as hydrologic Fortran (HSPF) simulation program. However, lumped models are simpler to implement, and their lack of spatial resolution limits their accuracy in heterogeneous watersheds (Yuan et al., 2020). In contrast, distributed models divide the watershed into smaller units, allowing for detailed spatial representation of hydrological processes such as soil and water assessment tool (SWAT) and MIKE SHE considering

variations in land use, soil type, and topography. Moreover, it is more computationally intensive but provide greater accuracy, especially in large and diverse watersheds (Devia et al., 2015). Physical models like SWAT have been applied to simulate the impact of land use changes on water availability in the Middle East and North Africa (MENA) where the parameters related to soil properties and land use are the most sensitive (Hachemaoui et al., 2022). In addition, semi-distributed models such as the hydrological modeling system (HEC-HMS) offer a compromise between lumped and distributed models. They group similar sub-watersheds together, capturing some spatial variability while maintaining computational efficiency (A. M. Al-Areeq et al., 2021). Physical models often require extensive calibration to local conditions, which can introduce uncertainty. Techniques like Monte Carlo simulations and sensitivity analysis are commonly used to quantify this uncertainty.

Hydrological models are crucial in estimating water movement and distribution at local and catchment scales. They are commonly used to simulate the relationship between rainfall and runoff. Many studies in hydrological modeling focus on a) Loss Methods, b) Direct Runoff, and c) 2D modeling (Amaddii, 2023; David et al., 2023). This review concluded that the most widely used hydrological models across various environments are the Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) and the Soil Water Assessment Tool (SWAT). Additionally, the Hydrologic Engineering Center-River Analysis System (HEC-RAS) is highly regarded for its effectiveness in assessing floodplains using 1D and 2D hydraulic water depth models as shown in (Figure 2.3).



**Figure 2.3** Application for 1D and 2D for flood depth and extend (Alshammari et al., 2024)

Recently, advancements in climate modeling and hydrological simulation have enabled more accurate predictions of future climatic impacts on hydrological systems. These tools are essential for assessing potential changes in rainfall trends and frequency. Among these models, the Personal Computer Storm Water Management Model (PCSWMM) and the Rainfall-Runoff-Inundation (RRI) model are widely recognized for their applications in various hydrological analyses. PCSWMM has proven to be effective in handling complex urban hydrological networks and providing high-resolution simulations and has reliability and efficiency in many studies (Bibi et al., 2023; Panos et al., 2021; Z. Peng et al., 2019; Sidek et al., 2021). However, the Rainfall-Runoff-Inundation (RRI) model is designed to simulate rainfall-runoff processes and subsequent flooding accounting for both surface and subsurface flows (Herath et al., 2024; Try et al., 2022).

Moreover, the results demonstrated the model's capability to predict flood extents and depths with reasonable accuracy and is better for large-scale watershed and floodplain studies. In this framework, PCSWMM and RRI models were applied to simulate 2009 historical urban flood events in Jeddah, Wadi Qows. Moreover, the RRI model was used to cover all of Saudi Arabia. Furthermore, the assessments for extreme rainfall are critical for developing adaptive strategies to mitigate the adverse effects of climate change on water resources and infrastructure.

#### **2.4. Hydrological and Climatic Datasets.**

Water is a critical resource, and its significance is expected to grow in the coming years. The 21st century has witnessed rapid technological advancements alongside significant environmental impacts including climate change and global warming. These changes have led to an increase in flash floods due to altered rainfall patterns, more frequent extreme events such as extreme floods in Asia and Europe, and the increasing intensity and frequency of such events in KSA over the last two decades. On the other hand, the global water crisis exemplified by events such as Cape Town's drought from 2017 to 2018 highlights the urgent need for reliable and accurate rainfall data.

Building a comprehensive database for observing, predicting, and managing flash floods in Saudi Arabia requires integrating various types of precipitation data. The accuracy of observation data and the rain gauge networks are essential for measuring rainfall intensity and distribution. Most of the hydrology data is absent in developing countries, especially those related to observation (Paul et al., 2021). Hydrological models and machine algorithms outcomes are affected by the accuracy of rain gauge data in terms of model calibration and validation. Most of the Middle East and North Africa (MENA) countries suffer from the limitation of observational data and uncertainty including KSA (Alamoudi et al.,

2023; Hussain Shah et al., 2023; Saber et al., 2020; Saber & Habib, 2016). Two hundred thirty-three rainfall gauge data have been utilized in this study. These data were provided by the Ministry of Environment, Water & Agriculture. Several previous studies highlighted that extreme precipitation events have become more frequent and intense in Saudi Arabia (Almazroui, 2020; Almazroui, Raju, et al., 2017; Atif et al., 2020). Thus, there will likely be a higher frequency and intensity of extreme rainfall in the future, leading to an increased risk of urban flash floods. In both 2009 and 2011, devastating flood events occurred in Jeddah, causing widespread flooding. The total estimated damage was approximately 3 billion USD due to heavy rainfall's extreme intensity and frequency (Hamza & Saegh, 2023; Youssef et al., 2016). Therefore, continuous climate monitoring and modeling are essential to comprehensively understand the impact of climate change on extreme rainfall in Saudi Arabia.

Climate change is a significant global issue in Arab regions and is widely regarded as a critical problem and challenge in contemporary times (Saber et al., 2020). In the Middle East, including Saudi Arabia, extreme climate events profoundly negatively impact human life, society, and the environment (Atif et al., 2020; Saber et al., 2020). The wet season rainfall on the Arabian Peninsula is primarily influenced by Mediterranean storms that contribute to Saudi Arabia's winter rainfall (Hasanean & Almazroui, 2015). Saudi Arabia has recently witnessed several extreme events, prompting questions about the extent to which these occurrences can be linked to regional climate change. It is important to note that the Active Red Sea Trough is associated with heavy rainfall events (Almazroui, 2020; Hasanean & Almazroui, 2015). Several studies have utilized RClimDex software in terms of percentile-based calculations (Almazroui et al., 2022; Almazroui, Nazrul Islam, et al., 2017). According (Almazroui, 2020) defines an extreme event in KSA of daily maximum rainfall using the 90th, 95th, and 99th percentiles. Recently, numerous studies have been conducted on climate extremes in Saudi Arabia, with some analyses focusing on calculating climate extreme indices based on specific thresholds (Almazroui, 2019).

The d4PDF is a suitable model for predicting extreme events and has a mega-ensemble climate projection dataset (Maneechot et al., 2023). The previous study (Nayak & Takemi, 2022) validated d4PDF datasets with one of the well-reputed observed datasets named APHRODITE and has been found in good agreement with spatial correlation coefficients of 0.99 and 0.76 in temperature and precipitation, respectively. Many research studies have recently used the d4PDF dataset such as (Bharambe et al., 2023) to study climate change and drought impact assessment over the Godavari River Basin in India; (Melnikova & Sasai, 2020) used to study the effects of anthropogenic activities on global terrestrial gross primary production (GPP); (Hori & Yoshimori, 2023) used it to understand the “role of atmospheric temperature advection in the lower troposphere and its relation to the local change in the mean state of the atmosphere”. d4PDF provides data on a wide range of climate variables and extremes, generated by running the climate model multiple times. This allows for exploring uncertainty in climate projections, which are also performed on the global and regional scales, along with interdisciplinary climate impact assessment studies (Ishii & Mori, 2020). These variables are essential for assessing how climate change might affect various sectors, such as agriculture, water resources, and infrastructure. It aims to provide data that can inform adaptation and mitigation strategies decisions. The d4PDF climate projection data has been utilized in this thesis to analyze extreme rainfall under different climatic scenarios over KSA. The analysis reveals that significant spatiotemporal variability is expected in the future, indicating increased in precipitation frequency and magnitudes during spring, autumn, and summer. Conversely, there is a significant decrease in precipitation in winter across most regions. In general, the expected monthly change ranges from 45% to 61% in the near and far future.

## **2.5. Flash Flood Risk Management**

Flooding is a natural phenomenon that has affected human history for millennia, manifesting in various forms, such as coastal floods. In Asian coastal megacities, the risk and

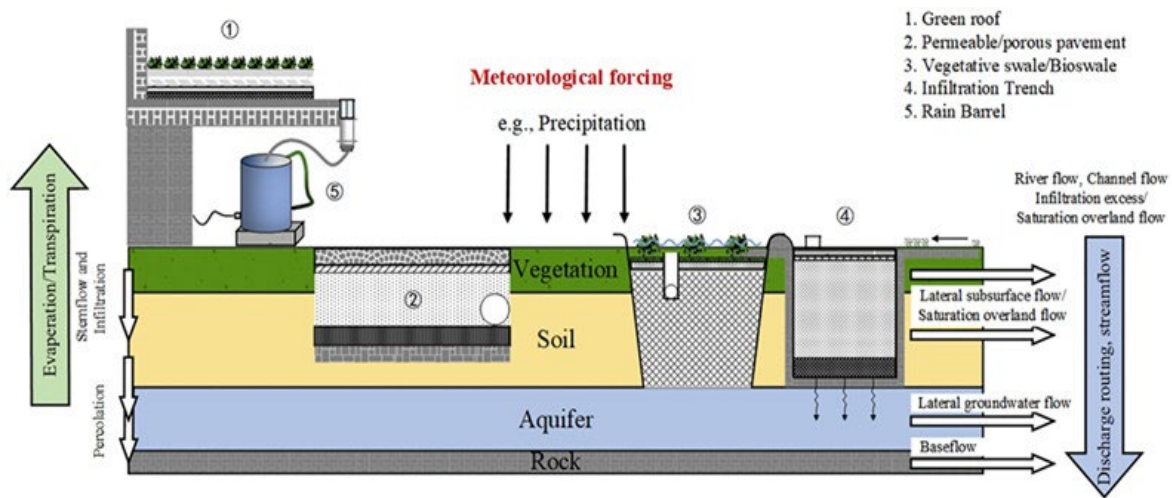
impact of floods are intensifying due to climate change and rapid urbanization. As sea surface temperatures rise, the frequency and intensity of precipitation events increase, exacerbating flood hazards. Simultaneously, rapid economic expansion and land-use changes heighten the exposure of people and assets to these hazards (Chan et al., 2021, 2022). While extreme measures, such as relocating populations, are sometimes considered, they are often impractical due to the dense populations and economic importance of cities like Jakarta, Bangkok, and Shanghai. Asian cities have historically relied on hard-engineering solutions for flood protection. For instance the Indonesian government is gradually moving the capital away from Jakarta (Sugihartati et al., 2020). However, this approach is increasingly viewed as unsustainable and financially unviable. Consequently, flood risk management (FRM) has evolved to incorporate a more holistic approach, combining structural defenses with non-structural measures, land-use planning, and emergency preparedness.

Flash floods are among the most devastating environmental hazards in arid regions with minimal rainfall. They occur when extreme rainfall events cause accumulation in downstream areas (Abdelkareem & Al-Arifi, 2021). Effective management of water resources in these areas requires a deep understanding of the Wadi system's hydrological processes, including topographical conditions, urbanization, basin scales, and soil permeability (Saber & Habib, 2016). Historical flash floods have had significant social, economic, and environmental impacts, emphasizing the need for improved forecasting and mitigation strategies. Current hydrological models and methods for predicting flash floods have limitations, and there is a pressing need for more advanced tools and methodologies. The development of arid-zone hydrology is significantly hindered by the lack of high-quality observational data, a limitation that has been widely recognized (McMahon, 1979; Pilgrim et al., 1988). Flash flood events are complex and are influenced by various geological, morphological, and hydrological factors, including rock types, elevation, slope, sediment transport, floodplain area, rainfall, runoff, evaporation, and water storage (Farquharson et

al., 1992; Flerchinger & Cooley, 2000; Nouh, 2006; Şen, 2004). To manage flash floods effectively, scientists and engineers should employ hydrological models coupled with climate models to predict future changes in rainfall and runoff within Wadi systems. However, a significant challenge in calibrating and simulating flash floods in arid regions is the deficiency of observed data. This issue is exacerbated by factors such as the inaccessibility of large areas, inadequate monitoring networks, non-arable land, poor data quality, and a lack of skilled personnel for database management (Janizadeh et al., 2021; Llasat Botija, 2021; Saber & Habib, 2016; Viglione et al., 2010). Additionally, the vulnerability to flash floods is expected to increase due to land use changes and extreme events driven by climate change (Change, 2001; Rosso & Rulli, 2002). There is a need to develop high-quality datasets implement suitable structural measures, and devise mitigation measures, emphasizing effective early warning systems to mitigate damage and minimize the flood, especially in arid regions where extreme events can be devastating. The scarcity of rainfall, poor soil absorption, and insufficient infrastructure contribute to the severity of flash floods in these regions. Moreover, observational difficulties at Wadi systems and the lack of a comprehensive flash flood event archive hinder the development of a coherent framework for analyzing flash flood risk, hazards, and vulnerabilities. Advancing hydrological models through multidisciplinary research collaborations and integrating GIS, remote sensing, and advanced modeling techniques is crucial for improving Wadi systems' flash flood forecasting and water management. The goal of modern flood risk management and modeling is to control flood disasters by accurately predicting the extent, depth, location, duration, and timing of flash floods using complex mathematical models. This requires integrating the hydrological and climatic models to enable early warnings and scenario analyses of flash floods under future climatic conditions, allowing for qualitative estimates of flash flood risks (Viglione et al., 2010).

The development of arid-zone hydrology is significantly hindered by the lack of high-quality observational data, a limitation that has been widely recognized (Hu et al., 2021). Flash

flood events are complex and are influenced by various geological, morphological, and hydrological factors, including rock types, elevation, slope, sediment transport, floodplain area, rainfall, evaporation, and water storage (M. H. Ali et al., 2022; Hussain Shah et al., 2023; Khan et al., 2022). In addition, flooding commonly occurs in urban areas due to creation of impervious surfaces. Recently pluvial flooding has occurred more frequently in urban area. To mitigate the risks of pluvial flooding in a more environmentally friendly manner. There has been growing attention to nature-based solutions such a green roof and infiltration trench as shown in (Figure 2.4). However, nature-based solutions are less effective in addressing pluvial flooding caused by extreme rainfall events (Basu et al., 2021; Huang et al., 2020).



**Figure 2.4** nature-based solutions infrastructures which can affect the hydrological processes (Huang et al., 2020)

Effective Risk management for flash flooding has to be treated as a long-term task includes mitigation and preparing for flooding disasters, analyzing risk, and providing a risk analysis system to mitigate the negative impacts caused by flooding.



## CHAPTER 3

# Observing climatic shifting of extreme storms under different future scenarios over Saudi Arabia

### 3.1. Introduction

Climate shifting, particularly in terms of precipitation patterns, refers to long-term alterations observed regionally or globally, impacting ecosystems, water resources, agriculture, and human societies (Cai et al., 2013; Cook et al., 2014; Krishnan et al., 2012). The Earth has already experienced a 1°C rise in temperature and is projected to approach a 1.5°C increase in the coming decades (IPCC Sixth Assessment Report 2023). The Middle East, including KSA, and North Africa are significantly affected by these climate shifts (Almazroui et al., 2012). Over the past two decades, extreme flash floods have become more prevalent across the MENA region, including KSA, due to intensified extreme precipitation events (Abdel-Fattah et al., 2018; Kantoush et al., 2022; Saber et al., 2020). Studies have documented a notable increase in extreme precipitation events in KSA from 1960 to 2013

(Almazroui et al., 2012; de Vries et al., 2016). Recent analyses indicate around a 40% increase in rainfall intensity based on different climate models (Al Zawad & Aksakal, 2010; Almazroui, Nazrul Islam, et al., 2017). This trend is expected to continue, raising concerns about urban flash floods and associated risks (Almazroui, Raju, et al., 2017; Atif et al., 2020). Particularly, devastating flood events in Jeddah in 2009 and 2011 resulted in significant damage and casualties, highlighting the vulnerability to extreme rainfall events (Bashir, 2023; Youssef et al., 2016). Continuous monitoring and modeling of climate shifts are crucial for understanding and mitigating these impacts in KSA and neighboring regions.

Climate change impacts have been pronounced globally, affecting many regions with prolonged droughts and increased extreme rainfall events. Recent studies utilizing global precipitation datasets highlight an annual maximum daily precipitation increase in many regions worldwide, excluding equatorial areas (Sarkar & Maity, 2021). KSA, predominantly arid, has also experienced shifts in precipitation patterns linked to global climate change. These changes are evident as spatial and temporal variations in rainfall across the country. Influenced by phenomena like the North Atlantic Oscillation (NAO) and El Niño Southern Oscillation (ENSO), altered atmospheric circulation patterns have led to regional differences in rainfall distribution. Some areas experience increased aridity while others see intensified local rainfall, affecting regional water resources and agricultural practices (Hasanean & Almazroui, 2015). Observations over periods like 1979–1993 showed an increase in rainfall followed by a significant decrease from 1994–2009, with increased frequency in northern and southern regions contributing to heightened flash flood risks (Almazroui et al., 2012, 2022). These dynamics pose challenges for KSA's water resource management, agriculture, and infrastructure development.

Monitoring and understanding precipitation pattern changes, known as climate shifting, is crucial for climate scientists, policymakers, and communities. Despite numerous climate

change studies, few have focused specifically on climate-shifting dynamics. Recent research highlights the dynamic nature of precipitation patterns and stresses the importance of regional-level analyses (Bindhu et al., 2021; Lawrence et al., 2023). For example, shifts in extreme daily precipitation from mid-summer to fall and early summer have been observed in regional and global climate models (Brönnimann et al., 2018). In Gansu Province, China, a warmer and more extreme climate post-shift is indicated by increased frequency and magnitude of extreme temperatures compared to pre-shift periods (An et al., 2020). Similarly, declines in mean winter precipitation in southwest Western Australia have been linked to shifts in weather patterns and fewer exceptionally wet years (Tolhurst et al., 2023).

The Middle East and North Africa (MENA) and Gulf regions have recently witnessed a rise in the frequency and intensity of extreme flood events. Especially, devastating floods struck Derna, Libya, in the past year. Similarly, the United Arab Emirates, Oman, and KSA experienced severe storms within the last months (March-April, 2024). These events highlight a shift in the climatic patterns of these traditionally arid regions. This study investigates historical and projected changes in rainfall patterns in KSA under various climate scenarios. It represents a pioneering effort in systematically investigating and highlighting the spatiotemporal climate shifts associated with extreme rainfall events in hyper-arid environments. This can contribute valuable insights to understanding the phenomena of climatic shifting.

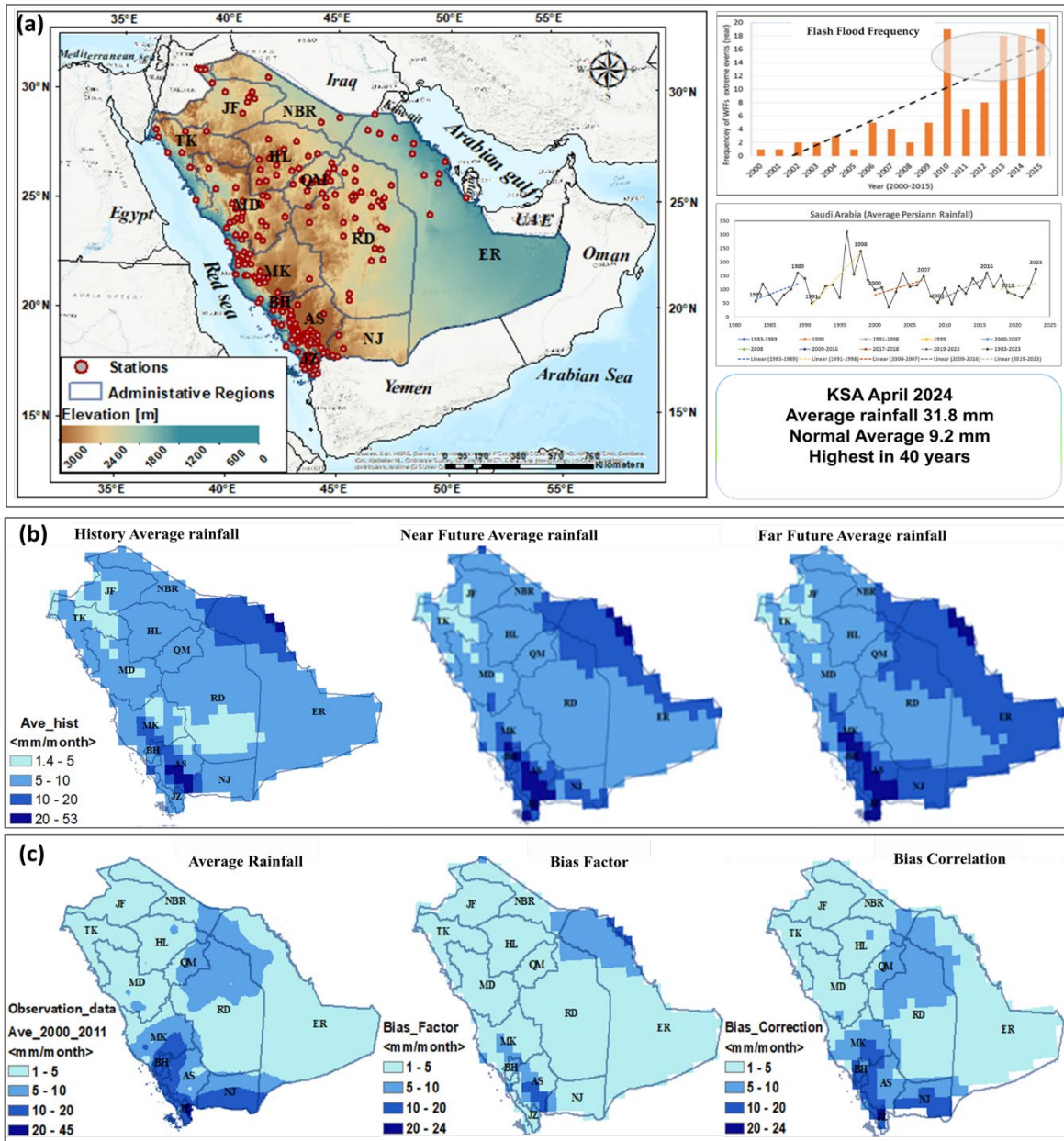
## **3.2. Results**

### **3.2.1. Spatial Average of Rainfall and Bias Correction**

#### **3.2.1.1. Bias Correction of d4PDF (Historical and future)**

Recently, extreme floods have increased in MENA and gulf countries such as KSA. Over the last two decades, extreme flood events have dramatically increased 5,6. Additionally, for instance, KSA received the highest rainfall average in April 2024 about 31.8 mm, which is

higher than 9.2 mm, which is the normal average (Figure 3.1a). This can give proof that there is an increase in the rainfall events in this region which the climatic change impacts might cause. The spatial average of the monthly observational rainfall data from 223 Rain gauge stations (Figure 3.1a) and the d4PDF historical monthly rainfall data over the period 2000–2011 were collected and visualized (Figure 3.1b). The d4PDF shows overestimation in comparisons with the historical rainfall. However, it could show the same spatial patterns as the real data. It is noticed that the overestimation percentage value in the climatic data comes with low rainfall values of more than 100 % such as NBR, JF, HL, and TK regions. On the other hand, the high rainfall value in the d4PDF data is an underestimation in BH, JZ, MK, and NJ regions, which range from -1.2 % to -43.3 %. As a result, the high amount of rainfall underestimates the climatic data (d4PDF) and vice versa. Generally, the total average d4PDF data is overestimated by around 48 % over the whole KSA. The total average rainfall in the observation data is 102.2 mm/month, while the total average rainfall in the d4PDF data is 87.01 mm/month. For the following sections, the bias correction factors were estimated and applied for the d4PDF datasets to be used in the extreme analysis (Figure 3.1C).



**Figure 3.1** (a) Historically, extreme floods have increased over MENA, including KSA, and recent extreme floods show temporal climate variability every seven years. (b) The spatial distribution of the average rainfall (mm/month) from rain gauges; and future average rainfall (d4PDF); both show that, the climate of KSA is highly variable, (c) biased factor and biased correction maps of historical d4PDF rainfall data based on the observational rain gauge data.

### 3.2.1.2. Spatial Average of Rainfall (Historical and Future)

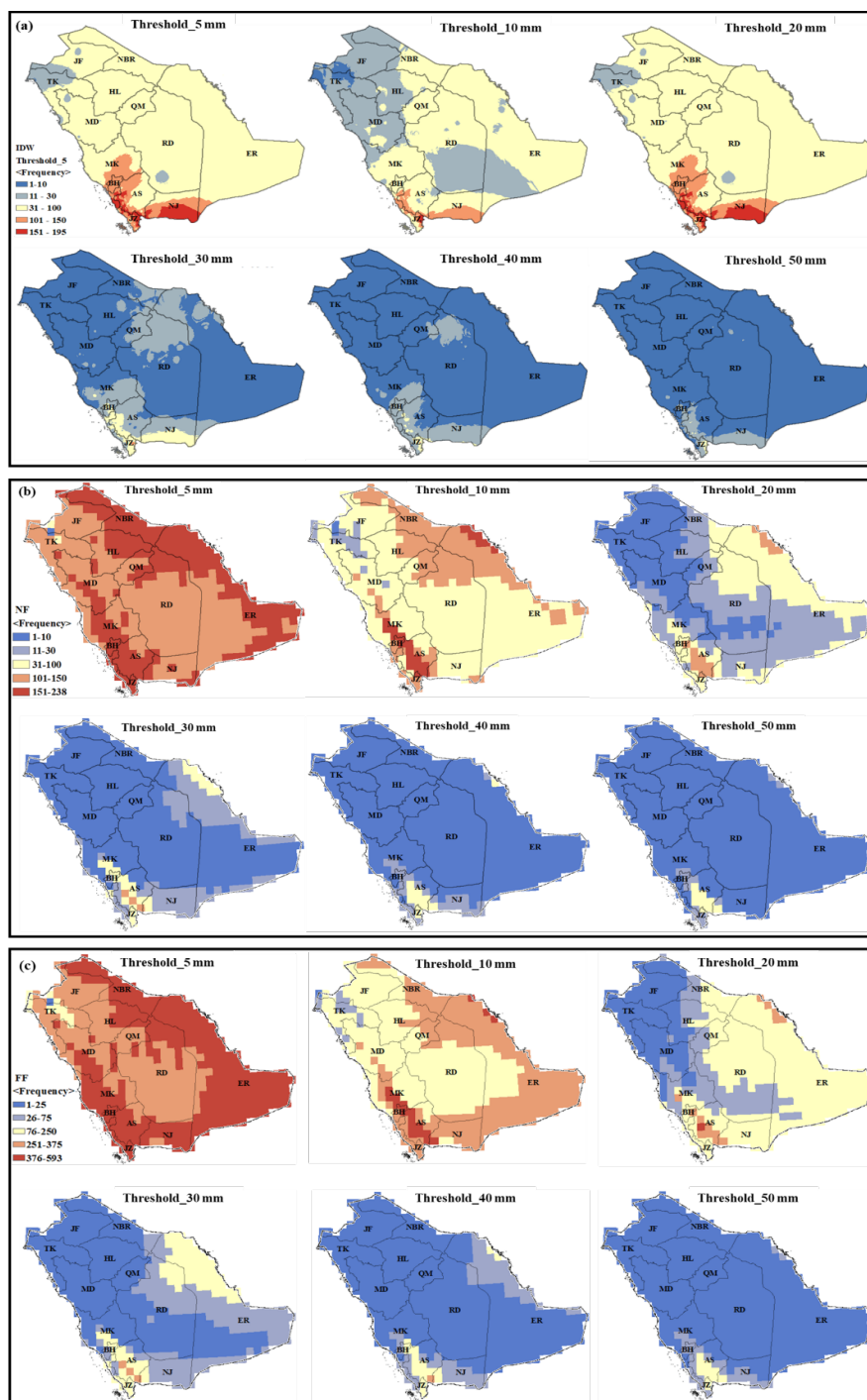
Considering all seasons, the total average rainfall across the country shows an increasing trend from historical to future scenarios (Figure A1). Spatial maps indicate an increase in monthly rainfall, particularly in the west, southern, and eastern regions, ranging from 10 to 56 mm per month, which aligns with (Bahrawi et al., 2021). Abha and Khamis Mushait in AS province, and Taif in MK province, have the highest annual mean rainfall. In winter, the northern regions (MD, TK, JF, and NBR) will experience a decrease in average rainfall, from 1 to 10 mm per month (Figure A1(b)). Spring will increase rainfall in almost all regions, especially along the Red Sea coast, from TK to JZ, and central and eastern regions, ranging from 10 to 40 mm per month (Figure A1(c)). During summer, the southwest regions (NJ, JZ, AS, BH, and MK) will see an increase from 20 to 80 mm per month (Figure A1(d)). In autumn, the southwest region will experience an increase from 10 to 30 mm per month (Figure A1(b)). Generally, rainfall patterns show high temporal and low spatial variation, consistent with findings by (Almazroui et al., 2022; Subyani, 2019). Rainfall is expected to increase between 23% to 81.3% in Near Future (NF) scenario and between 16.6% to 111.6% in Far Future (FF) scenario compared to historical data. The AS region will experience the highest increase, 81.3% (NF) and 111.6% (FF), while the TK region will experience the lowest increase, 26% (NF) and 16.6% (FF). When comparing NF and FF scenarios, some regions will experience decreases, such as JF and TK, with changes of -6.8% and -6.4% respectively. The overall change in average rainfall is estimated at 45% for NF and 61% for FF scenarios as shown in (Table 3.1).

**Table 3.1** rate of change in future rainfall under different climatic scenarios over KSA

| Region             | Obs (mm) | NF (mm) | FF (mm) | Num-Stations | %Bias | % NF | % FF  |
|--------------------|----------|---------|---------|--------------|-------|------|-------|
| (AS)               | 9.56     | 21.3    | 24.2    | 37           | 41.6  | 81.3 | 111.6 |
| (BH)               | 11.57    | 17.5    | 19.5    | 7            | -14.1 | 65.4 | 82.7  |
| (NJ)               | 4.05     | 9.7     | 9.8     | 4            | 106.5 | 32.8 | 35.9  |
| (JF)               | 2.59     | 6.3     | 6.1     | 8            | 109.2 | 34.2 | 27.4  |
| (MD)               | 3.23     | 7.2     | 7.7     | 24           | 80.7  | 41.8 | 57.7  |
| (QM)               | 5.64     | 9.1     | 9.9     | 18           | 37.4  | 23.3 | 38.6  |
| (RD)               | 4.62     | 8.5     | 9.9     | 31           | 27.9  | 55.4 | 86.4  |
| (ER)               | 4.35     | 10.4    | 12.6    | 13           | 85.5  | 63.5 | 103.2 |
| (HL)               | 3.81     | 8.4     | 8.7     | 14           | 104.3 | 16.0 | 23.1  |
| (JZ)               | 16.69    | 20.5    | 24.3    | 26           | -43.3 | 66.1 | 89.0  |
| (MK)               | 6.82     | 9.9     | 11.0    | 37           | -1.2  | 47.4 | 62.5  |
| (NJ)               | 11.01    | 11.4    | 13.9    | 6            | -33.2 | 36.5 | 59.9  |
| (TK)               | 2.32     | 5.7     | 5.5     | 8            | 120.8 | 23.0 | 16.6  |
| Average Total Area |          |         |         |              |       | 45   | 61    |

### 3.3. Historical and Future Frequency Analysis

We estimated the frequency of extreme rainfall events based on thresholds of  $\geq 5$ ,  $\geq 10$ ,  $\geq 20$ ,  $\geq 30$ ,  $\geq 40$ , and  $\geq 50$  mm (Figure 3.2). This classification helps understand the frequency of extreme events in the study area. The d4PDF future datasets were used to estimate these frequencies for near and far future scenarios. In future climates, extreme events increase in all thresholds compared to the historical period (Figure 3.2). Historically (Figure 3.2a), extreme event frequencies range from 11 to 195 for lower thresholds (5, 10, and 20 mm), while higher thresholds (30, 40, and 50 mm) show frequencies from 1 to 11, except in the southwestern regions (AS, BH, JZ, NJ), where frequencies range from 11 to 150. These regions, with high extreme frequencies, also show decreasing average rainfall, indicating a drought risk and increased extreme floods. In the near future (Figure 3.2b), frequencies range from 11 to 238 for 5 mm and 10 mm thresholds, decreasing at 20 mm. For thresholds of 30 mm, 40 mm, and 50 mm, frequencies from 1 to 30 dominate the country, except for the northeastern and southwestern regions, which show higher frequencies from 30 to 238. In the far future (Figure 3.2c), similar spatial variability is observed but with higher frequencies. For instance, frequencies from 76 to 375 are noted in the northeastern and southwestern regions for higher thresholds (30 mm, 40 mm, and 50 mm). This suggests these regions will experience increased extreme rainfall events and potential droughts, aligning with (Almazroui, 2020) findings of increased extreme precipitation intensity in the southern Arabian Peninsula (Zittis et al., 2022).

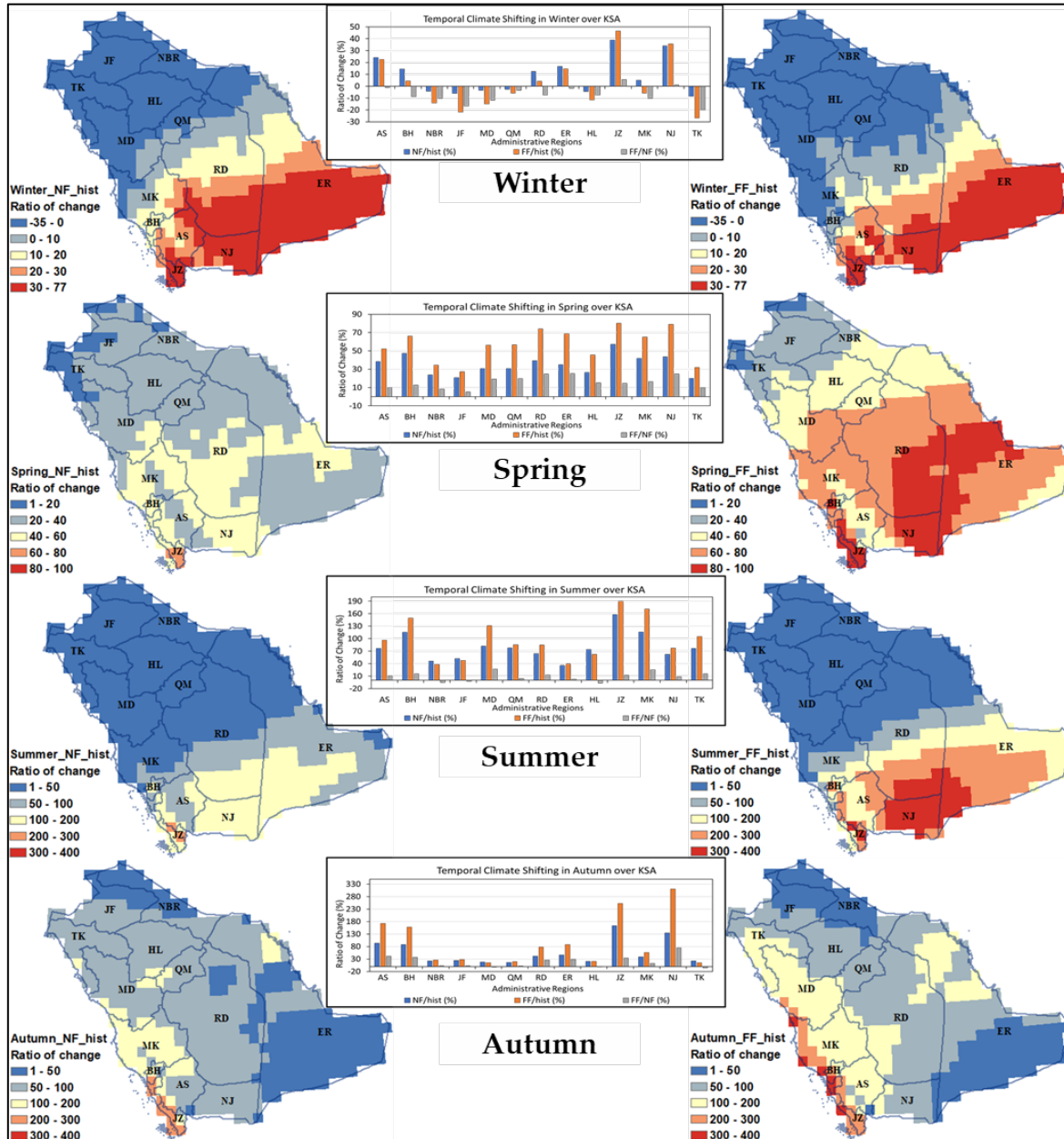


**Figure 3.2** Monthly frequency of extreme rainfall for thresholds: 5,10, 20, 30, 40, and 50 mm in KSA: (a) history rainfall during 2000-2019, (b) Near Future scenario from d4PDF data during 2031-2050, (c) Far Future scenario from d4PDF data during 2051-2100.

### 3.4. Observing Temporal and Spatial Climate Shifting

#### 3.4.1. Temporal and Spatial Seasonal Climatic Analysis

The rate of change in future rainfall was assessed for all seasons under two scenarios ((Tables 3.2-3.5): NF\_hist (near-future vs. historical), and FF\_hist (far-future vs. historical). In KSA, summer is usually dry. However, in NF and FF scenarios, most regions are projected to see a rainfall increase (**Figure 3.3**). Most areas will experience more than a 60% increase, except for NBR, JF, and ER regions, which will see increases ranging from 35.8% to 52% (Table 3.2). Notably, BH, JZ, and MK will significantly increase, from 115.3% to 189.5%. Conversely, in winter season the NBR, JF, and HL regions will decrease from -4.4% to -6.1% in the NF-hist scenario (Table 3.3). As shown in Figure 3.3, temporal average rainfall is expected to rise in both NF\_hist and FF\_hist scenarios. <sup>16</sup> found that regional climate models align well with the d4PDF scenarios in this work. Summer precipitation will increase, particularly in southern and southwestern regions, though some areas will see reduced rainfall between future scenarios. Spring is part of the wet season in KSA. In all scenarios, most regions are projected to experience an increase in average rainfall, as shown in Figure 3.3. The temporal average rainfall is expected to increase in both NF\_hist and FF\_hist future climate scenarios, however a decrease is noted between the FF and NF scenarios. The increase in average rainfall in the FF scenario is higher compared to the NF scenario. The NF scenario shows a high change ratio from 38.4% to 57.3% in regions like AS, BH, RD, ER, JZ, MK, and NJ, while these regions show a change from 52.2% to 80.1% in the FF scenario. MD and QM regions see moderate increases of about 30.8% (NF) and 56.2% (FF). The lowest increases are in NBR, JF, HL, and TK regions, ranging from 20.7% to 34.4% (Table 3.3). Autumn is generally dry except for November. An increase in rainfall during autumn is more pronounced in the FF scenario compared to NF. Regions AS, BH, JZ, and NJ are projected to see the most significant increases, ranging from 172.5% to 310%. Other regions show moderate to weak increases, with the lowest in MD and QM (15.4% to 19.2%) (Table 3.4).



**Figure 3.3** Spatial and temporal distribution of climate shifting in over 13 administrative regions for all seasons (Winter Spring, Summer, Autumn) showing the ratio of change in rainfall from historical data to near-future climate (Left panel), and from historical data to far-future climate (right panel), and all seasons show an increase in the future precipitations except for the winter shows a decreasing in the future which indicate climate shifting (middle panel).

**Table 3.2** rate of change in future rainfall during the summer season

| RegionsI_summer | hist_Ave | NF_Ave | FF_Ave | NF/hist (%) | FF/hist (%) |
|-----------------|----------|--------|--------|-------------|-------------|
| AS              | 22.3     | 39.4   | 43.8   | 76.8        | 96.2        |
| BH              | 10.4     | 22.4   | 25.9   | 115.3       | 149.4       |
| NBR             | 0.9      | 1.3    | 1.2    | 46.0        | 38.2        |
| JF              | 0.6      | 1.0    | 0.9    | 52.0        | 48.0        |
| MD              | 1.0      | 1.8    | 2.2    | 82.2        | 131.2       |
| QM              | 0.9      | 1.5    | 1.6    | 77.7        | 85.6        |
| RD              | 2.9      | 4.8    | 5.5    | 64.1        | 85.1        |
| ER              | 5.7      | 7.7    | 7.9    | 35.8        | 39.7        |
| HL              | 0.9      | 1.5    | 1.4    | 74.1        | 62.5        |
| JZ              | 15.5     | 40.0   | 45.0   | 157.8       | 189.5       |
| MK              | 3.5      | 7.6    | 9.6    | 115.9       | 171.1       |
| NJ              | 14.9     | 24.3   | 26.5   | 62.6        | 77.1        |
| TK              | 0.5      | 0.9    | 1.0    | 76.9        | 105.3       |

**Table 3.3** rate of change in future rainfall during the winter season

| Regions_winter | hist_Ave | NF_Ave | FF_Ave | NF/hist (%) | FF/hist (%) |
|----------------|----------|--------|--------|-------------|-------------|
| AS             | 6.0      | 7.4    | 7.3    | 24.2        | 22.6        |
| BH             | 14.8     | 16.9   | 15.4   | 14.5        | 4.4         |
| NBR            | 11.5     | 11.0   | 9.9    | -4.4        | -14.2       |
| JF             | 7.9      | 7.4    | 6.2    | -6.1        | -21.8       |
| MD             | 9.9      | 9.6    | 8.5    | -3.4        | -15.0       |
| QM             | 9.2      | 9.0    | 8.7    | -2.6        | -5.9        |
| RD             | 5.5      | 6.2    | 5.7    | 12.5        | 4.1         |
| ER             | 7.9      | 9.2    | 9.0    | 16.7        | 14.7        |
| HL             | 8.6      | 8.2    | 7.6    | -4.4        | -11.6       |
| JZ             | 5.9      | 8.2    | 8.6    | 38.8        | 46.6        |
| MK             | 10.5     | 11.0   | 9.8    | 4.9         | -5.9        |
| NJ             | 2.0      | 2.7    | 2.7    | 34.0        | 35.6        |
| TK             | 7.9      | 7.2    | 5.8    | -8.5        | -26.8       |

**Table 3.4** rate of change in future rainfall during the spring season

| Regions_spring | hist_Ave | NF_Ave | FF_Ave | NF/hist (%) | FF/hist (%) |
|----------------|----------|--------|--------|-------------|-------------|
| AS             | 18.6     | 25.7   | 28.3   | 38.4        | 52.2        |
| BH             | 11.7     | 17.3   | 19.5   | 47.4        | 66.0        |
| NBR            | 13.6     | 16.9   | 18.3   | 23.9        | 34.4        |
| JF             | 9.2      | 11.1   | 11.7   | 20.7        | 27.2        |
| MD             | 8.3      | 10.9   | 13.0   | 30.8        | 56.2        |
| QM             | 13.1     | 17.1   | 20.5   | 30.8        | 56.7        |
| RD             | 12.4     | 17.3   | 21.6   | 39.5        | 74.1        |
| ER             | 14.3     | 19.3   | 24.2   | 34.9        | 68.8        |
| HL             | 11.7     | 14.8   | 17.0   | 26.4        | 45.6        |
| JZ             | 6.0      | 9.5    | 10.8   | 57.3        | 80.1        |
| MK             | 9.1      | 13.0   | 15.1   | 41.8        | 65.1        |
| NJ             | 8.4      | 12.1   | 15.1   | 43.5        | 78.9        |
| TK             | 8.0      | 9.6    | 10.6   | 20.1        | 32.0        |

**Table 3.5** rate of change in future rainfall during the autumn season

| Regions_Autumn | hist_Ave | NF_Ave | FF_Ave | NF/hist (%) | FF/hist (%) |
|----------------|----------|--------|--------|-------------|-------------|
| AS             | 6.3      | 12.2   | 17.2   | 93.2        | 172.5       |
| BH             | 6.7      | 12.6   | 17.2   | 88.0        | 157.8       |
| NBR            | 7.7      | 9.4    | 9.7    | 22.1        | 26.1        |
| JF             | 4.4      | 5.5    | 5.7    | 24.1        | 27.8        |
| MD             | 5.7      | 6.7    | 6.6    | 18.1        | 15.4        |
| QM             | 7.5      | 8.8    | 9.0    | 16.4        | 19.2        |
| RD             | 4.0      | 5.6    | 7.1    | 41.4        | 78.2        |
| ER             | 4.9      | 7.1    | 9.2    | 45.7        | 87.8        |
| HL             | 7.2      | 8.7    | 8.7    | 20.4        | 20.4        |
| JZ             | 9.3      | 24.4   | 32.8   | 163.3       | 252.9       |
| MK             | 6.0      | 8.4    | 9.4    | 38.7        | 56.0        |
| NJ             | 2.8      | 6.6    | 11.6   | 134.1       | 310.5       |
| TK             | 4.1      | 5.0    | 4.7    | 22.4        | 14.9        |

This data indicates a remarkable spatial climate change during autumn. The FF-NF scenario (Figure 3.3) shows a decline in some regions like TK, MD, HL, and parts of ER. Winter is typically wet, but most regions experience a decrease in average rainfall in all future scenarios, except for AS, JZ, and NJ regions. Negative changes range from -2.6% to -26% in regions like NBR, JF, MD, QM, HL, and TK. MK shows a 5.9% decrease in the FF scenario. Some regions, like JZ and NJ, show increases in both NF and FF scenarios, ranging from 34% to 46.6%. AS and ER increase from 14.7% to 22.6%, while BH and RD see very low changes, about 4.1% in the FF scenario. The FF-NF scenario indicates up to a 20% decrease in most regions, with exceptions in JZ and NJ.

The results indicate a noticeable climate shift in KSA. During the dry seasons (summer and autumn), average rainfall will increase significantly, reaching 157.8% and 163.3% in NF and 189.5% and 310% in FF. During the wet seasons (winter and spring), average rainfall is expected to increase by 38% and 57.3% in NF and 46.6% and 80.1% in FF. Conversely, significant decreases in rainfall are observed in the winter season, from -4.4% to -26.8% in most regions. This indicates a climate shift, with dry seasons becoming wetter and wet seasons becoming drier, suggesting a temporal shift in climatic patterns seasonally in KSA.

#### 3.4.2. Temporal and Spatial Climate Shifting in Different Thresholds

In this section, historical rainfall data (2000-2019) and future climatic datasets (NF: 2031-2050, FF: 2051-2100) were analyzed (Figure 3.4). The frequency of rainfall events was estimated using thresholds (5mm, 10mm, 20mm, 30mm, 40mm, 50mm) to understand extreme events' spatial and temporal variability compared to historical data. The rate of change is calculated as follows:

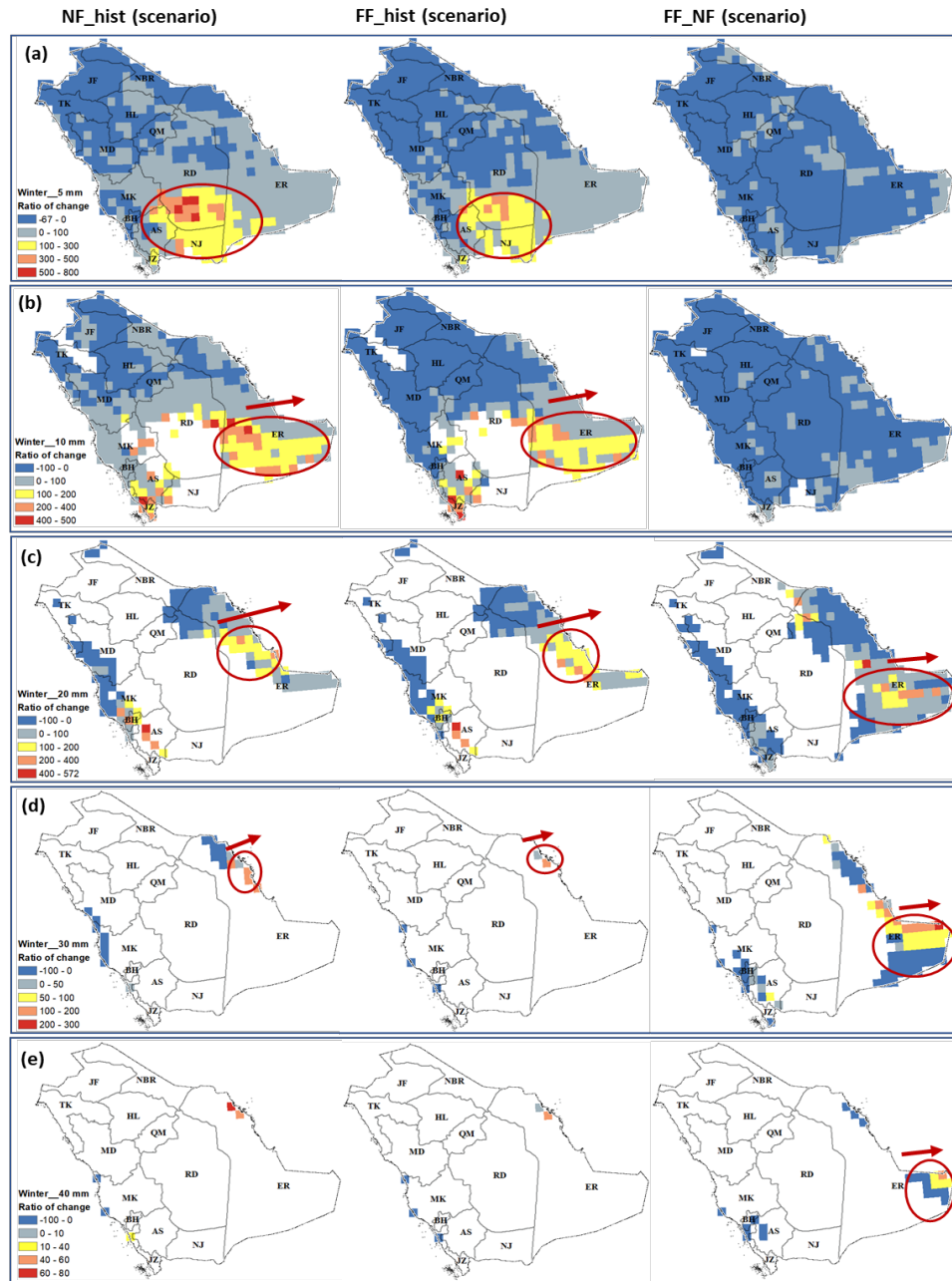
$$Rate\ of\ change(\%) = \frac{future - hist}{hist} * 100$$

These estimates have been done for three scenarios (1. NF from Historical, 2. FF from Historical, and 3. FF from NF) with different thresholds.

In the winter season, the 5 mm threshold shows increasing rainfall event frequency in central and southern KSA, notably in RD, AS, and NJ regions for both NF\_hist and FF\_hist scenarios (Figure 3.4a). A climate shift appears at the 10 mm threshold, moving precipitation eastward to the ER region (Figure 3.4b), continuing at 20 mm and 30 mm thresholds (Figures 3.4c and 3.4d). This phenomenon diminishes at 40 mm and 50 mm thresholds (Figure 3.4e). In the FF\_NF scenario, this shift is evident in the ER region at 20 mm, 30 mm, and 40 mm thresholds (Figures 3.4c, 3.4d, 3.4e).

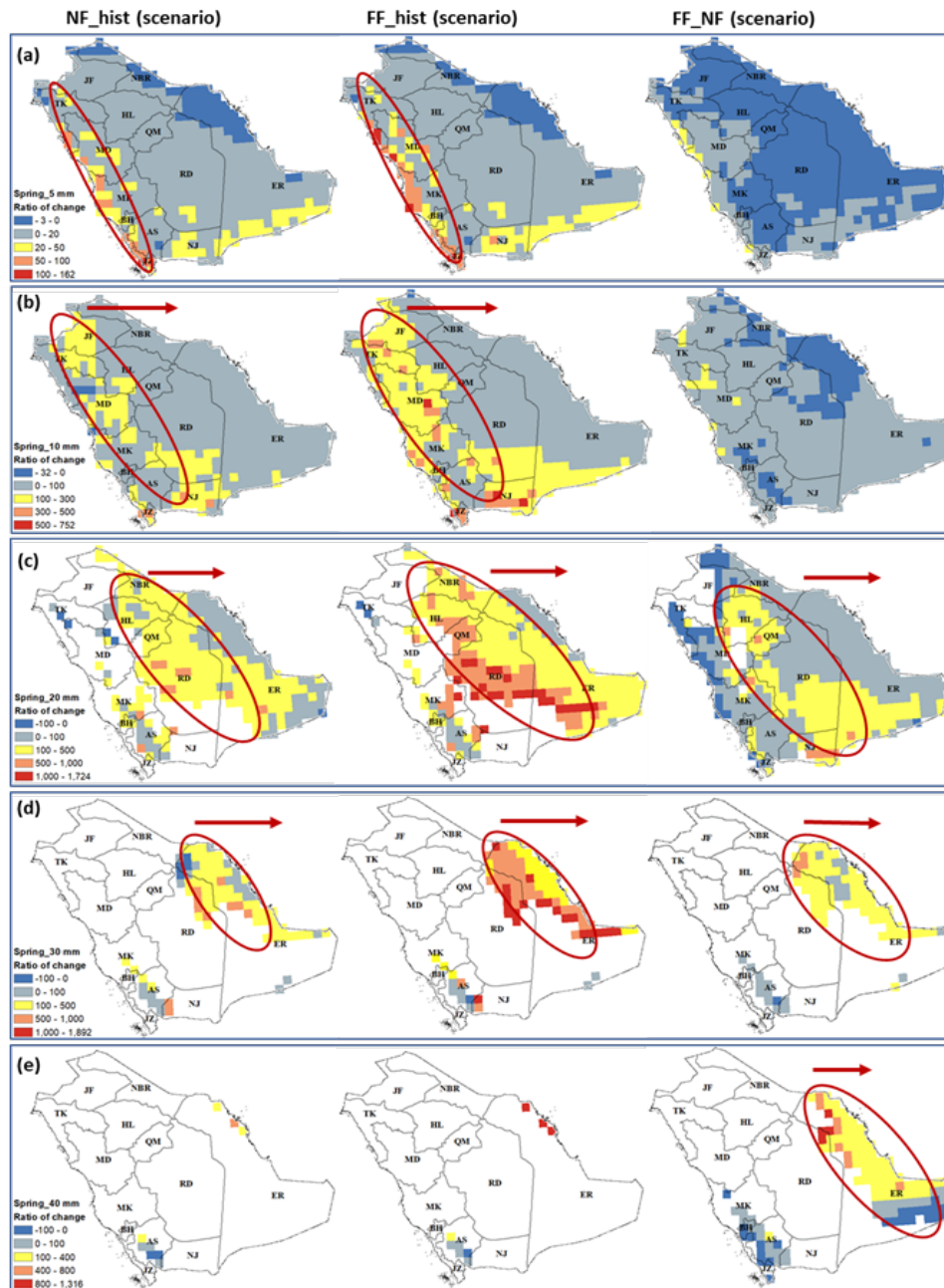
The El Niño Southern Oscillation (ENSO) significantly impacts KSA's winter and spring precipitation variability by altering moisture availability and westerly jet patterns, leading to extreme rainfall. ENSO-related changes in the Pacific Ocean influence distant weather patterns, including those in the Middle East. El Niño events cause periodic warming, reducing wet season rainfall, while La Niña events increase rainfall during the wet season<sup>12</sup>. ENSO effects are far-reaching and affect KSA's weather patterns. Additionally, the westerly jet stream's position and strength are crucial in determining precipitation patterns, influencing weather systems and moisture transport (Kamil et al., 2017).

The results indicate a winter shift in extreme frequency and magnitude towards southeastern KSA, near the Arabian Gulf, which frequently experiences cyclones from the Indian Ocean. This shift may be due to the southward movement of global pressure belts in winter (northern hemisphere), with Atlantic cyclones moving eastward across the Mediterranean Sea, often dissipating under stronger low-pressure centers to the north or high-pressure cells to the east (Barth & Steinkohl, 2004). This could explain the observed climatic shift in rainfall patterns from west to east across KSA (Figure 3.4).



**Figure 3.4** Spatial and temporal distribution of climate shifts in the winter season over 13 administrative regions with three different scenarios: history rainfall during 2000-2019, Near Future scenario from d4PDF data during 2031-2050, Far Future scenario from d4PDF data during 2051-2100, where the ratio of change with different thresholds: 5, 10, 20, 30, and 40 mm in panel (a), (b), (c), (d), (e).

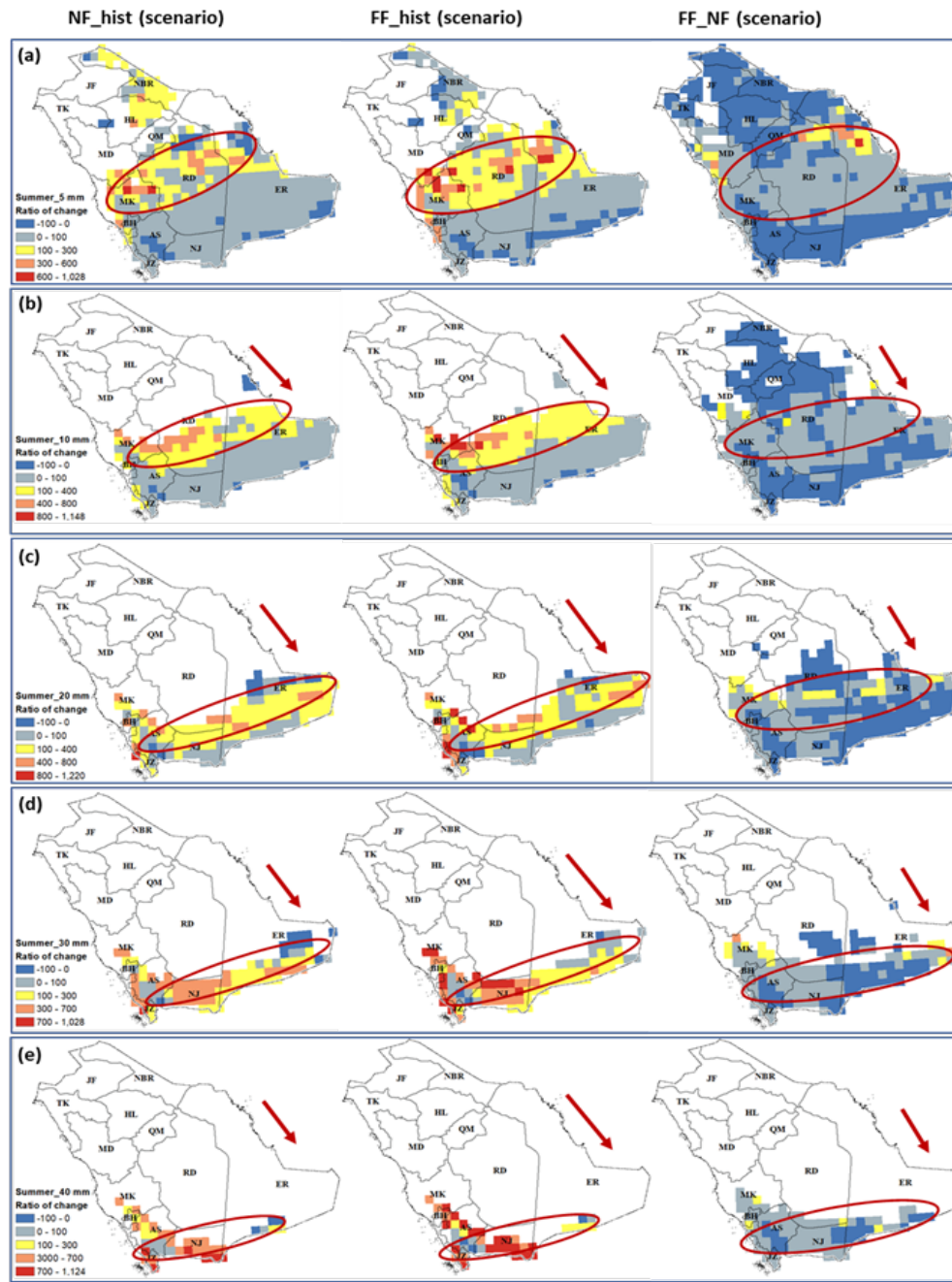
During the spring season, increasing rainfall is mainly observed along the Red Sea coast and southern parts of KSA, especially for rainfall within 5 mm (Figure 3.5a). For higher rainfall rates (10 mm, 20 mm, and 30 mm), a climate shift towards the east is evident in both NF\_hist and FF\_hist scenarios, diminishing at 40 mm threshold (Figures 3.5b-e). In the FF\_NF scenario, this shift begins at 20 mm and continues up to 40 mm thresholds, indicating the climatic shift is expected to persist into the far future. Especially, extreme rainfall over 40 mm increases in the ER region during spring (Figures 3.5c-e). The Arabian anticyclone is a key atmospheric circulation system in Southwest Asia, influencing daily weather conditions, particularly humidity and temperature distribution. Research by (Karimi et al., 2019; Lashkari et al., 2016; Lashkari & Mohamadi, 2015; Z. Mohammadi & Lashkari, 2018) highlights the anticyclone's role in shaping precipitation patterns. During spring, the anticyclone is typically farther southeast, over the Arabian Sea, allowing low-level moist air masses to spread precipitation across KSA. This explains the widespread rainfall in KSA during spring, likely influenced by the Arabian anticyclone. High-pressure systems like anticyclones have higher atmospheric pressure at the surface compared to their surroundings. Positioned over the Arabian Sea, the anticyclone allows moist air masses to create clouds and precipitation, affecting the Arabian Peninsula in October, November, and December, which aligns with the spring season (Athar et al., 2013).



**Figure 3.5** Spatial and temporal distribution of climate shifts in the spring season over 13 administrative regions with three different scenarios: history rainfall during 2000-2019, Near Future scenario from d4PDF data during 2031-2050, Far Future scenario from d4PDF data during 2051-2100, where the ratio of change with different thresholds: 5, 10, 20, 30, and 40 mm in panel (a), (b), (c), (d), (e).

In the summer season, rainfall patterns are expected to increase significantly, particularly in central parts extending from East to West of KSA. Although summer is typically a dry season in KSA, the future projections indicate a higher rate of change in rainfall, suggesting a shift towards wetter conditions with higher rainfall frequency (Figure 3.6). This shift may be linked to the El Niño Southern Oscillation (ENSO), which influences summer rainfall variability by strengthening the Indian monsoon and increasing moisture transport and deep convection over the southwestern highlands of KSA. During the warm ENSO phase, the subtropical jet shifts southward, increasing mid-latitude storms and rainfall, whereas the cold phase has the opposite effect (Kamil et al., 2017).

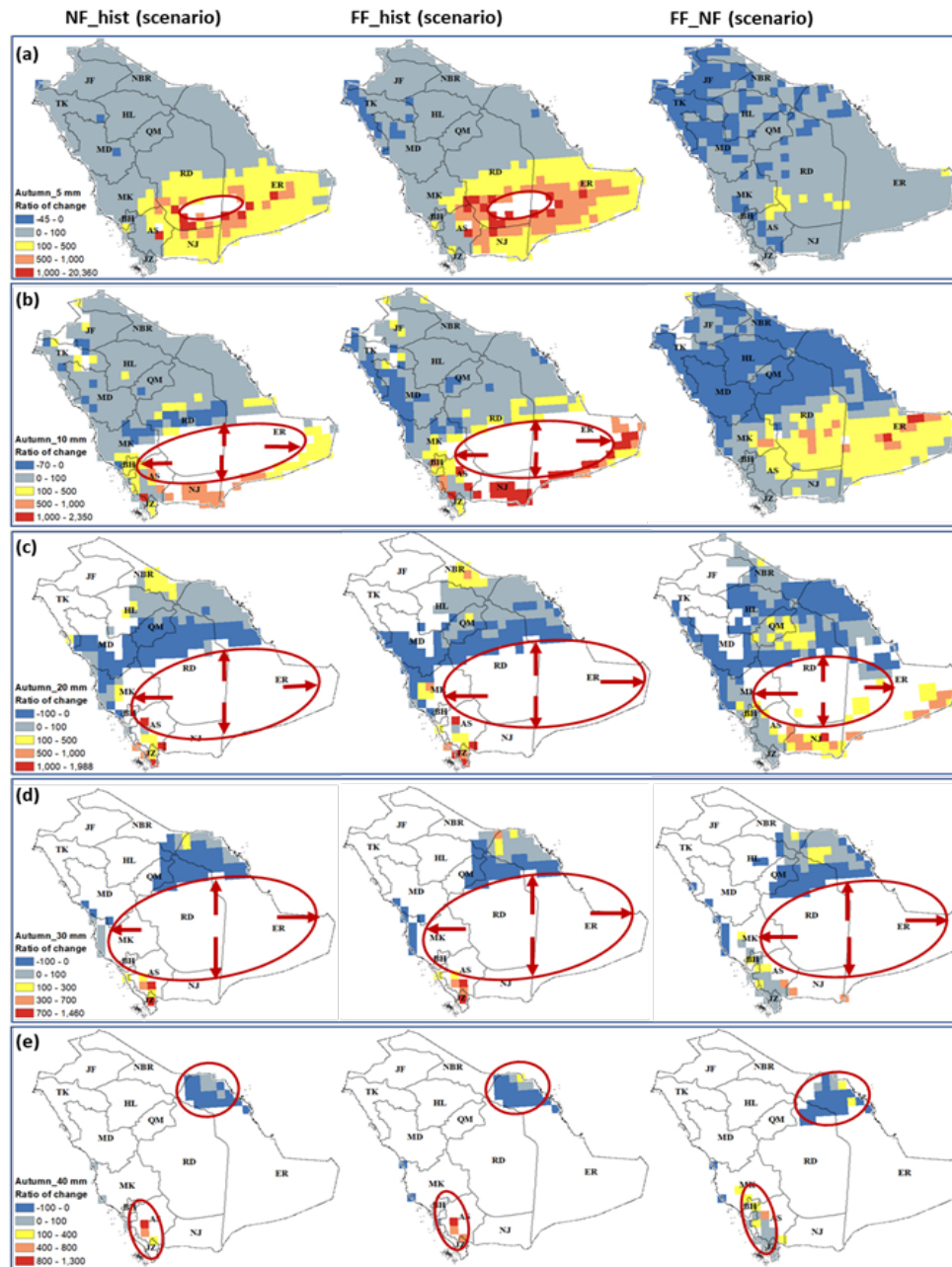
Additionally, strong surface heating with the Red Sea Trough (RST), which refers to depressions over the central Red Sea leading to cloud development and precipitation, starts affecting central KSA regions such as MK, RD, and ER at the 5 mm threshold (Figure 3.6). The rainfall pattern shifts southward at the 10 mm threshold, reaching southern and southwestern parts of KSA, evident across all thresholds (Figure 3.6) from 20 mm to 40 mm in all three climatic scenarios (NF\_hist, FF\_hist, FF-NF) (Almazroui, 2020).



**Figure 3.6** Spatial and temporal distribution of climate shifts in the summer season over 13 administrative regions with three different scenarios: history rainfall during 2000-2019, Near Future scenario from d4PDF data during 2031-2050, Far Future scenario from d4PDF data during 2051-2100, where the ratio of change with different thresholds: 5, 10, 20, 30, and 40 mm in panel (a), (b), (c), (d), (e).

In the autumn season, future rainfall patterns resemble those of winter but with broader expansion, particularly in the southern part of KSA, especially for rainfall rates within 5 mm (Figure 3.7a). However, there is a core of drought in the central region of the rainfall pattern, expected to intensify in future scenarios (NF\_hist and FF\_hist). This drought expands from the 10 mm to the 30 mm threshold, particularly pronounced in regions like MK, RD, ER, NJ, and AS (Figure 3.7b-d). In the FF\_NF scenario, drought begins to appear at 20 mm and 30 mm thresholds in regions such as AS and JZ (Figure 3.7c, d). Conversely, some parts of AS and JZ show increasing extreme rainfall, while parts of ER exhibit negative values compared to historical rainfall at thresholds of 40 mm (Figure 3.7e).

Governorates in MK, BH, AS, and JZ are expected to experience significant rainfall variability during autumn, in alignment with findings by (de Vries et al., 2016) that climatological precipitation in autumn is mainly confined to the Jeddah region and stretches northeastward in KSA. The spatial maps across the three scenarios illustrate these climatic impacts, showing how moist tropical air masses move westward across the Arabian Sea, curve northward over the Red Sea region, and return eastward across central KSA following the easterly low-level circulation (de Vries et al., 2016). Additionally, predictions from the integrating Particle Swarm Optimization (PSO) ensemble machine learning algorithm and an artificial neural network (ANN) model suggested that the Asir region will face moderate to extreme drought events in the coming years (2018–2025) (Alsubih et al., 2021), which aligns with observed drought patterns in the autumn season.



**Figure 3.7** Spatial and temporal distribution of climate shifts in the autumn season over 13 administrative regions with three different scenarios: history rainfall during 2000-2019, Near Future scenario from d4PDF data during 2031-2050, Far Future scenario from d4PDF data during 2051-2100, where the ratio of change with different thresholds: 5, 10, 20, 30, and 40 mm in panel (a), (b), (c), (d), (e).

### **3.5. Discussions**

In this study, we examined the spatial and temporal variability of rainfall patterns across KSA (KSA) using historical data (2000-2019) and future climate scenarios (2031-2050, 2051-2100). Our analysis focused on understanding why rainfall patterns vary significantly between seasons and why the direction of this variability differs across seasons and regions over KSA.

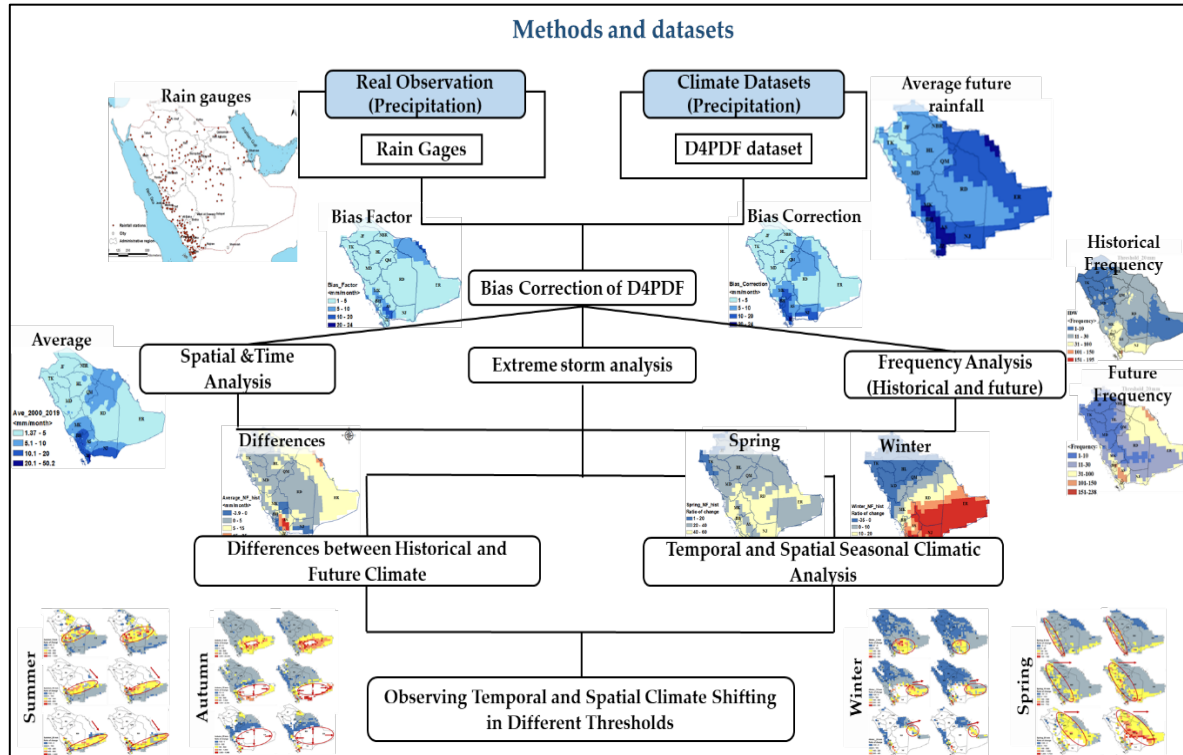
During the winter season, we observed rainfall variability primarily in the southern parts of KSA, such as AS, NJ, and the southern RD region, particularly evident at the 5 mm threshold. This pattern shifts eastward towards the ER region. The shift towards the east in winter can be attributed to cyclones originating from the Indian Ocean, influenced by the southward movement of global pressure belts. In spring, rainfall variability was prominent along the Red Sea coast and the southern part of KSA, gradually shifting eastward with increasing rainfall thresholds, covering most regions of KSA. This eastward shift during spring is likely influenced by the movement of moist tropical air masses across the Arabian Sea, guided by the climatological easterly low-level circulation. Summer, traditionally a dry season in KSA, showed significant rainfall increases centered in the central regions like RD, MK, and ER at the 5 mm threshold, with a southward direction observed afterward. This shift in summer precipitation patterns is associated with the Red Sea Trough (RST), a meteorological phenomenon generating strong depressions over the central Red Sea, leading to cloud development and subsequent precipitation. During autumn, a broad belt of rainfall variability was observed in the southern part of KSA, encompassing regions such as RD, MK, BH, AS, NJ, JZ, and ER. This season exhibited a core of drought amidst the rainfall pattern, expanding with increasing thresholds in NF\_hist and FF\_hist scenarios, with some regions showing increasing extreme rainfall and others experiencing drought conditions.

These findings underscore the high spatial and temporal variability of precipitation changes across KSA, influenced by global climate drivers such as ENSO and the jet stream. ENSO, for instance, affects moisture availability and westerly jet patterns, leading to fluctuations in

wet-season precipitation. The direction and intensity of these shifts vary seasonally, impacting how rainfall patterns evolve from west to east, or north to south, depending on the dominant climatic conditions. This study contributes to understanding how climate shifts are evident across different seasons and regions within KSA, providing insights into future climate scenarios and their implications for water resources, agriculture, and resilience strategies. By detailing these climate shifts, our findings can inform sustainable development practices and adaptive measures to mitigate the impacts of climate change locally in KSA and globally.

### **3.6. Data and Methods**

In order to assess climatic shifts in KSA from 2000 to 2019, daily rainfall data from 233 stations across 13 administrative regions were analyzed. The d4PDF mega-ensemble climate projection dataset was employed and was noted for its reliability in predicting future climate changes with minimal uncertainty. Validation and its application in various studies were emphasized. The analysis categorized rainfall variability by different thresholds, examining historical and future scenarios spatially and temporally. The methodology included spatial division into 13 regions, showcasing examples of average rainfall data. A flow chart outlining the methodology and data analysis is depicted in Fig. 3.8.



**Figure 3.8** Methods and datasets used for analyzing climatic shifting of precipitation patterns in KSA. The figure outlines the workflow, starting from real observation data (rain gauges) and climate datasets (d4PDF), progressing through bias correction and spatial & time analysis, to evaluate historical and future climate differences. It includes steps for extreme storm analysis, frequency analysis, and seasonal climatic analysis across different seasons (summer, autumn, winter, and spring), ultimately observing temporal and spatial climate shifts at different thresholds.

### 3.6.1. Study area and rain gauges

To comprehensively assess climatic shifts temporally and spatially, we collected daily historical rainfall data from 2000 to 2019 and utilized the d4PDF mega-ensemble climate projection dataset to project future climatic patterns in KSA. The analysis covered 233

stations across 13 administrative regions, sourced from the Saudi Arabian Ministry of Environment, Water & Agriculture. Spatially, rain gauges were denser in coastal and central regions compared to sparser areas like NBR and JF. Monthly time series datasets derived from daily records ensured consistency with climatic analyses. The Arabian Peninsula, spanning 32° to 55° East longitude and 15.5° to 32.5° North latitude, experiences a wet season from November to April and a dry season from May to October, characterized by varying rainfall dynamics.

### **3.6.2. Climatic Data (d4PDF)**

The d4PDF mega-ensemble climate projection dataset is instrumental in predicting future climate changes with minimal uncertainty. It integrates outputs from multiple global warming simulations conducted by a global atmospheric general circulation model (AGCM) with a 60 km horizontal grid spacing. This dataset incorporates various factors such as sea surface temperature (SST), greenhouse gas concentrations (GHG), sea-ice thickness, three-dimensional ozone distribution, and aerosols to simulate future climate scenarios (Mizuta et al., 2017). Utilizing multiple ensemble members with different initial conditions enhances its ability to detect regional climate patterns and spatiotemporal changes accurately (Ishizaki et al., 2023). The d4PDF dataset employs the highest level of greenhouse gas emission scenarios, specifically, the IPCC's RCP8.5 scenario, recommended for studying extreme local climate events and planning adaptations to global warming (Ishii & Mori, 2020; Mizuta et al., 2017). Validation studies like (Nayak & Takemi, 2022) have demonstrated reliability, showing good agreement with observed datasets such as APHRODITE, with high spatial correlation coefficients for temperature and precipitation. Recent studies across various disciplines have employed the d4PDF dataset. For example, (Bharambe et al., 2023) used it to assess climate change and drought impacts over the

Godavari River Basin in India, while (Melnikova & Sasai, 2020) explored the effects of anthropogenic activities on global terrestrial gross primary production (GPP).

### **3.6.3. Extreme Analysis and Climatic Shifting**

To analyze rainfall variability in KSA spatially and temporally, the country was divided into 13 administrative regions. Monthly, seasonal, and annual time series data were evaluated and categorized into different thresholds ( $\geq 0$ ,  $\geq 5$ ,  $\geq 10$ ,  $\geq 20$ ,  $\geq 30$ ,  $\geq 40$ , and  $\geq 50$  mm) to understand historical and future climatic shifts. This study covers periods from 2000-2019 historically and projections for 2031-2100, divided into Historical (2000-2011), Near Future (2031-2050), and Far Future (2051-2100). Spatial and temporal analyses assessed how rainfall patterns and intensities vary across these periods and thresholds. Figures depict average monthly rainfall for each period: (a) Historical (2000-2011), (b) Near Future (2031-2050), and (c) Far Future (2051-2100) based on d4PDF data.



## CHAPTER 4

# Comparison and Evaluation of Satellite-Based Precipitation on the Rainfall-Runoff process Over KSA

### 4.1. Introduction

Rainfall is vital to society as it affects agriculture and the environment and is useful in developing sustainable water management strategies, monitoring water quality, and forecasting flash floods, according to (Alazzy et al., 2017; Brunetti et al., 2018; Munksgaard et al., 2019; Pendergrass et al., 2017; Sirisena et al., 2018; Solakian et al., 2019). As a consequence, rainfall data has been crucial over the years since water is a major factor in all the daily operations of humanity, from food production to energy generation. However, meteorological observations from Asia, Africa, and South America often comprise erroneous rainfall records and suffer significant reporting time delays (Koutsouris et al., 2016; Thiemig et al., 2012). In Europe, satellite products generally perform well in the summer but relatively poorly in the winter, owing to the difficulties in retrieving low-intensity precipitation during the winter (Kidd et al., 2012). Satellite-based products,

orography, and seasonal variability affect the accuracy of the satellite rainfall retrieval techniques (Stampoulis & Anagnostou, 2012). Therefore, understanding changes in rainfall variability is essential to grasping the hydrologic cycles of the ecosystem, especially now as global climate temperature has also increased variability in the hydrologic cycle. The studies of (M. Abu Abdullah et al., 2019, 2019; Masood et al., 2019) confirm there is a dearth of data in terms of long-term intensity and frequency of rainfalls which have caused tremendous flooding in many regions of the Kingdom of Saudi Arabia. This therefore suggests that since the country is mainly defined by arid and semi-arid climactic conditions the recent rainfall patterns are affected by global change. Water scarcity is predominant in arid regions such as the Kingdom of Saudi Arabia where the rate of evaporation is greater than precipitation (Masood et al., 2019; Subyani, 2019). Although arid ecosystems have high ambient daytime temperatures, the occurrence of sporadic precipitations has largely defined the physiological, anatomical, and behavioral processes of the living organisms in these regions (Heffelfinger et al., 2018).

The objective of this article is to validate all different SbPEs statistically by comparing against ground-measured rainfall records at monthly, seasonal, and annual time scales over KSA. Since there is high variability in rainfall in space and time over KSA, it is recommended to provide reliable estimates of rainfall with a high degree of confidence. This study is also timely as the changing rainfall variability for long terms with 233 rainfall gages as observation data in the region has not been fully studied and thus information is lacking specifically on how to utilize rainfall trends for productivity purposes and to accordingly prepare for adverse effects of heavy rainfall occurrences. Hydrologists used satellite data as the inputs for the hydrological models (Kidd & Levizzani, 2011), while others used the data to fill up the paucity in the data with different statistical methods (Dile & Srinivasan, 2014). Reliable information on precipitation at sufficiently detailed spatial and temporal scales is essential for early warning systems. However, KSA has an extremely low density of reliable weather stations in some states that provide accurate rainfall measurements over long time

periods. Therefore, the two sources of information of rainfall data from satellites and ground stations will be combined to get a reliable map of the rainfall distribution over the country.

Three types of rainfall products are considered: the gauge-only, the satellite-based and the reanalysis ones. There are many types of recording rain gauges. However, only three types, namely, the tipping bucket, the universal weighing type gauge, and the float-type gauge, are commonly used by hydrometeorological agencies to measure precipitation. All three types of gauges have numerous measurement problems that can be summarized as follows: (1) the underestimation of heavy precipitation due to splashing; (2) instrumental problems; (3) external factors such as wind and evaporation of precipitation; and (4) observer errors (Tapiador et al., 2012). Also, the intermittency of precipitation coupled with sampling in time and space is the major challenge for precipitation observation (Hegerl et al., 2015; Trenberth et al., 2017). At the temporal scale, gauge-based precipitation products are restricted to monthly sampling. The data latency and lack of fine temporal resolution make it difficult to use these products in real-time research or for tracking changes in short-term extremes. In addition, gauge measurements represent point values and not aerial measurements, and thus, they cannot describe spatial variations in precipitation. The satellite-based products directly drive hydrological models to study and discuss the influence of precipitation data quality on the accuracy of hydrological simulations (Nhi et al., 2018; Zhu et al., 2016) while, reanalysis precipitation data products that are not performing well in hydrological modeling terms. The improvement of satellite and reanalysis of precipitation data by different correction methods was studied and discussed (F. Peng et al., 2020; Wang et al., 2020). Satellite-based precipitation products have advantages over ground-based observations to achieve a worldwide comprehensive observation of rainfall due to its wide spatial coverage and temporal continuous measurements (As-syakur et al., 2016; Prakash et al., 2016). One of the important instruments that contributed to determining precipitation measurements and data is the

Tropical Rainfall Measuring Mission (TRMM) since it's launched from 1997 to 2015 and the NASA-JAXA Global Precipitation Measurement Mission (GPM) which has been collecting data since 2014 (Ma et al., 2021). It helps provide important rainfall data in tropical and sub-tropical ecosystems all over the world (NASA, 2023). In fact since its entire operation from 1997 to 2015, NASA shares that this research satellite was able to provide critical information in weather forecasting such as occurrences of tropical cyclones, weather predictions, and flooding interventions. Through the measurements provided by the Tropical Rainfall Measuring Mission, Tekeli in 2017 different flood indexes obtained from the TRMM were compared to forecast flood events in Jeddah, Saudi Arabia as rainfall rate measurements obtained were accurate. The satellite-based precipitation products of TRMM validated that TRMM products are performing well and are essential tools to estimate and observe rainfall (Abd Elhamid et al., 2020; Almazroui, 2011a; T. P. Singh et al., 2019; Tarek et al., 2017). (Almazroui, 2011a) in his study in Saudi Arabia, reported a high correlation value ( $r = 0.9$ ) between the TRMM rainfall data and the values observed from the rain gauge stations and it relied on 29 ground stations, for the 1998 to 2009 period, while this study depends on 233 ground stations. In addition, the estimation of precipitation has been verified by various widely used satellite products, which are Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) family of products (Hong et al., 2007; Miao et al., 2015), Integrated Multi Satellite Retrievals for Global Precipitation Measurements (IMERG) (Huffman et al., 2015; Shi et al., 2020), Global Satellite Mapping of Precipitation (GSMaP) (Ushio et al., 2009), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015). IMERG has been evaluated over KSA for the period from October 2015 to April 2016 and compared with 189 ground stations. The final run product was revealed over most parts of the country (Mahmoud et al., 2018). The PERSIANN system uses neural network function classification/approximation procedures to compute an estimate of rainfall rate at each  $0.25^\circ \times 0.25^\circ$  pixel of the infrared (IR) brightness temperature ( $T_b$ ) image provided by

geostationary satellites and the temporal resolution is daily, spatial resolution and updating time once in three months (Miao et al., 2015; Sorooshian et al., 2000). An adaptive training feature facilitates updating of the network parameters whenever independent estimates of rainfall are available. Also, GPCC is consistent in exhibiting the drying trend in the East African long rains (W. Yang et al., 2015).

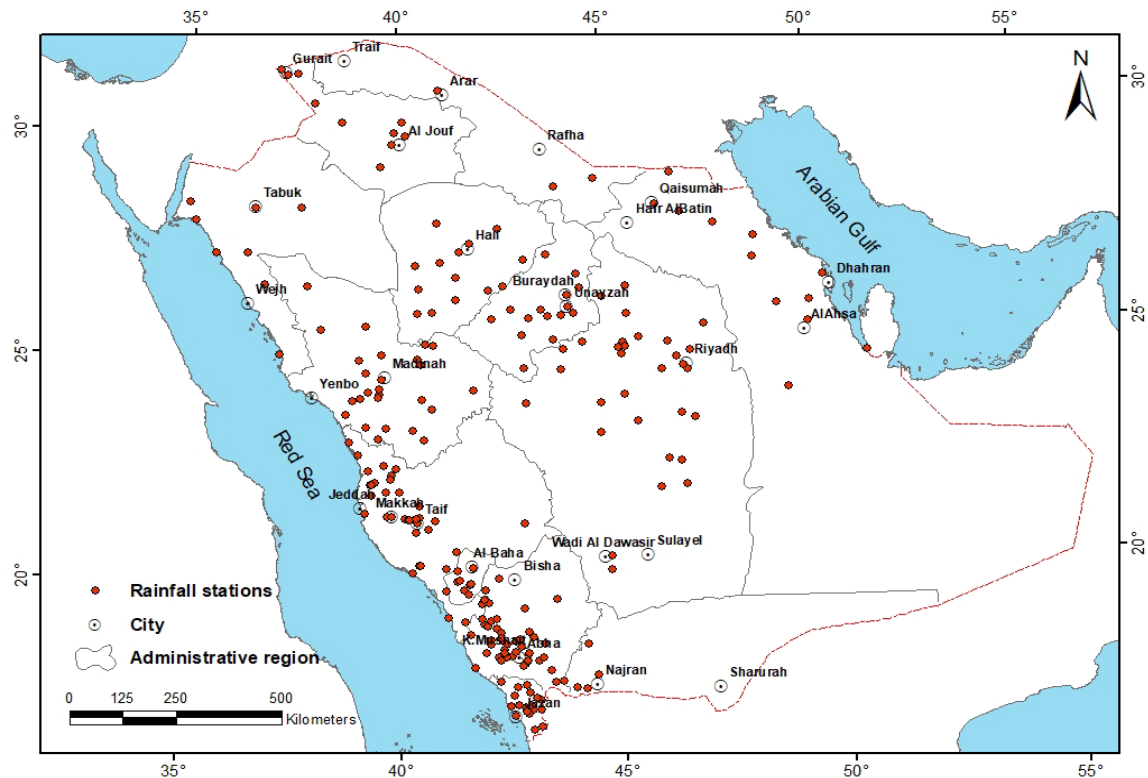
Products (TRMM, IMERG, SHIRPS, PERS, PDIR, CDR, CCS) and four types of reanalysis precipitation products (GPCC, ERA5, JRA55 and NCEP) were statistically and hydrologically verified. The results of this study have implications for improving water supply, flood forecasting, and ecosystem protection for all 13 administrative regions over KSA. many previous studies have indicated that satellite-based products generally have difficulty representing precipitation in areas with complex topography in which precipitation is controlled by the orography and characterized by high spatiotemporal variability (Derin & Yilmaz, 2014). In addition, the surface runoff process was simulated using the open-source rainfall-runoff-inundation (RRI) model to predict streamflow and flood inundation based on observed runoff depth points from field surveys, along with rainfall distribution which is a common hydrological analysis with the scarcity of data available (Bitew & Gebremichael, 2011; Saber et al., 2022). Furthermore, various satellite products and reanalysis precipitation data were utilized in this study to identify the most accurate satellite representation of the flood depth and flood extent.

In this paper, efforts have been made to utilize satellite-based data and reanalysis data to calibrate them concerning the observed data to estimate the rainfall over Saudi Arabia. In addition, the study measures the accuracy of the satellite data based on a calibrated hazard map from observation of rainfall and flood depth point data recorded in Wadi Qwos 2009 as a spatial case study to analyze the impact on the hydrological response at the basin scale such as flood extent predictions. Therefore, being able to assess how the spatial-temporal factors affect the distribution and the intensity of rain patterns is an important contribution

to the economic development decision makers of Saudi Arabia (Al-Ahmadi & Al-Ahmadi, 2013; Almazroui, 2011b) specifically in the achievement of the Saudi Arabia Vision 2030 goals. Therefore, an in-depth analysis of historical rainfall data and extreme records is necessary for developing policies linked with future planning for the water sector.

#### **4.2. Study Area**

This study encompasses the entirety of Saudi Arabia, situated on the Arabian Peninsula in Southwest Asia, covering an area of approximately 2.15 million km<sup>2</sup>. Bordered by the Red Sea and the Arabian Gulf, Saudi Arabia is predominantly characterized by an arid climate, featuring vast desert regions. This aridity poses challenges to water availability, given that rainfall is generally low and irregular (Hasanean & Almazroui, 2015). The annual rainfall across Saudi Arabia averages around 100 mm, except for the southwestern region. The annual rainfall over KSA is approximately about 100 mm except for the southwestern region. The annual rainfall region, which is mostly a mountainous area, is estimated about 300 mm which represents 60% of the total annual rainfall in Saudi Arabia (Hag-elsafi & El-Tayib, 2016). Consequently, it receives the highest precipitation in the country, with significant decreases observed in other regions. The spatial distribution of ground stations utilized in this study covers 13 administrative regions, as depicted in Figure 4.1: Al-Baha (BH), Al-Jouf (JF), the Northern Borders Region (NBR), Al-Riyadh (RD), the Eastern Region (ER), Makkah (MK), Al-Qassim (QM), Al-Madinah (MD), Tabuk (TK), Jazan (JZ), Hail (HL), Asir (AS), and Najran (NJ). Each region contains rainfall stations with varying spatial distribution densities.

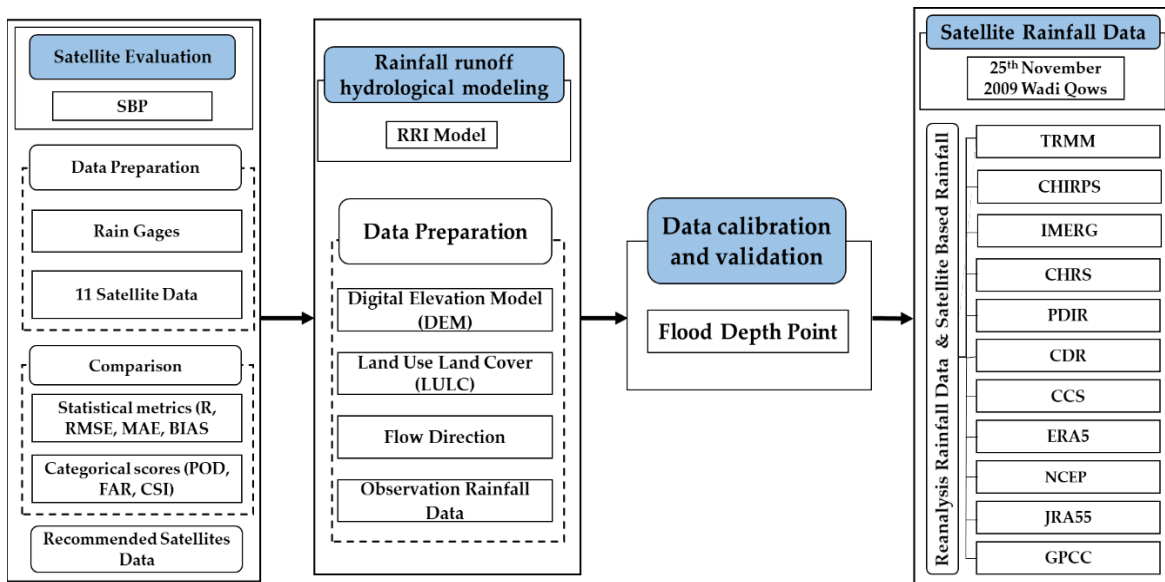


**Figure 4.1** Locations of the rainfall stations used over KSA are shown with red dots into 13 administrative regions.

### 4.3. Datasets and methodology

In this study, we have collected three kinds of data sets including Rain gauge precipitation data, reanalysis gridded precipitation data, and Satellite-based precipitation data, as shown in Table 4.1. The study collected and analyzed data from 233 stations located across Saudi Arabia available from 1970 to 2019. These data were provided by the Saudi Arabian Ministry of Environment, Water & Agriculture until (2019), which is responsible for rainfall information. Also, the grid data obtained from products of satellite-based data (TRMM, IMERG, SHIRPS, PERS, PDIR, CDR, CCS) and four types of reanalysis precipitation products (GPCC, ERA5, JRA55, and NCEP). All satellite and reanalysis products are

accumulated to the monthly scale to be consistent with gauge observations to understand the spatial and temporal variability of the climatic conditions based on the observation rain gauge data in comparison with available satellite data set over KSA. In addition to understanding the climatic variability based on (trend analysis, frequency, and magnitude). Moreover, understanding the extreme events such as flash floods within twenty years in the time period. For these reasons, we extracted satellite estimates for the satellite products for the point-based station locations to compare with available rain gauge data instead of interpolating the gauge measurements into a gridded product to come up with some conclusion about which satellite data is much more accurate over KSA. Several widely used statistical indices were selected to quantitatively evaluate the accuracy and error, including Root-mean-square error (RMSE), Mean error (MAE), Pearson correlation coefficient ( $r$ ), Relative error of bias (BIAS), and Percent bias (PBIAS). ( in Figure 4.2)



**Figure 4.2** Flowchart of this study's methodology

#### **4.3.1. Rain gauges**

There are 233 stations distributed across KSA that were used from 2000 until 2019 (denoted by red circles in Figure 4.1). These data were provided by the Saudi Arabia Ministry of Environment, Water & Agriculture until (2019). However, 118 stations were used among them for the evaluation, excluding the stations that had unreliable values (reflecting the bias and correlation results). The maximum and minimum amount of bias considered for the evaluation process was 150/-150. Also, the correlation values of more and less than 0.1 and -0.1 in all stations have been excluded from this study to show a more accurate trend.

#### **4.3.2. Satellite Rainfall data and reanalysis datasets**

##### **4.3.2.1. Satellite-Based Rainfall Datasets**

The gridded precipitation data was obtained from the Tropical Rainfall Measuring Mission (TRMM) for the period 2000–2019, and the second generation the joint NASA-JAXA Global Precipitation Measurement Mission (GPM) Zhao et al., (2015), which has been collecting data since 2014 which provides daily rainfall estimates at (0.25°) resolution. (<https://gpm.nasa.gov/missions/GPM>) NASA (2021). Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) data is an IR-based quasi-global rainfall dataset for drought monitoring and warning, which has been applied since 1981 until recently. The grid data was obtained from (CHIRPS) for the period of (2000–2019), which provides daily rainfall estimates at (0.05°) resolution (Funk et al., 2015). Integrated Multi-satellite Retrievals for Global Precipitation Measurements (IMERG) is another satellite product developed by NASA. This product has a spatial resolution of 0.10° × 0.10° and spatial coverage of 50°N-50°S. (Huffman G.J., 2020). The satellite-based data was obtained from Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN). Four types were used:

- a. Center for Hydrometeorology and Remote Sensing (CHRS), which provides daily rainfall estimates at (0.25°) resolution with coverage of 60°S - 60°N since March 2000 until recently.

- b. PERSIANN-Cloud Classification System (PERSIANN-CCS), which provides daily rainfall estimates at high resolution (0.04°) with coverage of 60°S - 60°N since January 2003 until now (Hong et al., 2007; Hsu et al., 2010).
- c. PERSIANN-Climate Data Record (PERSIANN-CDR), for the period (2000 –2020), which provides daily rainfall estimates at (0.25°) resolution with coverage of 60°S - 60°N from 1983 until now (Miao et al., 2015; Mondal et al., 2018).
- d. PERSIANN-Dynamic Infrared Rain Rate near real-time (PDIR-Now), which provides daily rainfall estimates at high resolution (0.04°) with coverage of 60°S - 60°N since March 2000 until now.

#### **4.3.2.2. Reanalysis Rainfall data**

The gridded reanalysis data was acquired from the Global Precipitation Climatology Centre (GPCC) for the period (2000–2019), which provides daily rainfall estimates at (1.0°) resolution. Version 2020 of daily global land-surface precipitation totals based on precipitation data provided by national meteorological and hydrological services, and regional and global data collections.

ERA5 is the latest fifth-generation reanalysis of the European Centre for Medium-Range Weather Forecasts (ECMWF). The ERA5 dataset includes a range of products with different spatial and temporal resolutions, from global analyses with a horizontal resolution of approximately 31 km and a temporal resolution of 1 hour, to high-resolution forecasts with a horizontal resolution of as fine as 9 km and a temporal resolution of 15 minutes. In this study, daily ERA5 precipitation data was downloaded for the period (2000-2019) from [https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=era5\\_prcp\\_daily](https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=era5_prcp_daily).

JRA-55 (Japanese 55-year Reanalysis) is a long-term global atmospheric reanalysis dataset produced by the Japan Meteorological Agency (JMA) in 2010. The JRA-55 dataset, which is available from 1958, includes a range of products with different spatial and temporal resolutions, from global analyses with a horizontal resolution of 0.56 degrees (approx. 56

km) and a temporal resolution of 6 hours to high-resolution forecasts with a horizontal resolution of as fine as 1.125 km and a temporal resolution of 1 hour. 6 hourly JRA55 were used in the current study, which can be downloaded online <https://rda.ucar.edu/datasets/ds628.0/> for the analysis period.

NCEP, or the National Centers for Environmental Prediction, is a division of the National Weather Service (NWS) in the United States that produces global weather forecasting and climate prediction products, including reanalysis datasets. NCEP/NCAR is a global reanalysis dataset of atmosphere fields established by the National Centers for Environmental Prediction and the National Center for Atmospheric Research. (Wang, G., et al. 2019). NCEP/NCAR precipitation has been globally available from 1948 until now with 1.88° spatial resolution. Daily data from NCEP/NCAR were freely downloaded in this work, [https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=nprate\\_daily](https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=nprate_daily).

**Table 4.1** General characteristics of the precipitation products

| Product      | Grid Size     | Time<br>Resolution | Time<br>Period | Type                         | Source                                                                |
|--------------|---------------|--------------------|----------------|------------------------------|-----------------------------------------------------------------------|
| Observations | Point Based   | Daily              | 2000-2019      | Gauge                        | Saudi Arabia<br>Ministry of<br>Environment,<br>Water &<br>Agriculture |
| IMERG        | 0.10° × 0.10° | Daily              | 2000-2019      | satellite based              | NASA's IMERG                                                          |
| CHIRPS       | 0.05° × 0.05° | Daily              | 2000-2019      | Gauge and<br>satellite based | University of<br>California                                           |
| TRMM         | 0.25° × 0.25° | Daily              | 2000-2019      | satellite based              | NASA-JAXA                                                             |

|       |              |               |              |                 |                                                            |
|-------|--------------|---------------|--------------|-----------------|------------------------------------------------------------|
| CHRS  | 0.25°× 0.25° | Daily         | 2000Mar-2019 | satellite based | University of California, Irvine                           |
| PDIR  | 0.04°× 0.04° | Daily         | 2000Mar-2019 | satellite based | University of California, Irvine                           |
| CDR   | 0.25°× 0.25° | Daily         | 2000-2019    | satellite based | University of California, Irvine                           |
| CCS   | 0.04°× 0.04° | Daily         | 2003-2019    | satellite based | University of California, Irvine                           |
| NCEP  | 1.88°× 1.88° | Daily         | 2000-2019    | Reanalysis      | National Centers for Environmental Prediction, USA         |
| JRA55 | 1.25°× 1.25° | Daily-6 hours | 2000-2019    | Reanalysis      | Japan Meteorological Agency (JMA)                          |
| ERA5  | 0.25°× 0.25° | Daily         | 2000-2019    | Reanalysis      | European Centre for Medium-Range Weather Forecasts (ECMWF) |
| GPCC  | 1.0°× 1.0°   | Daily         | 2000-2019    | Reanalysis      | Global Precipitation Climatology Centre                    |

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#### 4.3.2.3. Evaluation criteria

Several previous studies have selected rain gauge measurements as the precipitation validation data for evaluating the applicability of satellite precipitation datasets in different regions (Hordofa et al., 2021; Liu, 2016; F. Peng et al., 2020). In this study, five widely used statistical indices were applied, including root mean square error

(RMSE), Pearson correlation coefficient ( $r$ ), and PBIAS. RMSE measures the average magnitude of the error. Pearson correlation coefficient is the covariance of the two variables divided by the product of their standard deviations which describes the agreement between the different products of satellite and ground observations. Percent bias (PBIAS) which is the best value is 0; negative (positive) values indicate an underestimation (overestimation) of the rainfall observation amounts. The higher the goodness of fit for the observations, the greater the coefficient.

$$RMSE = \sqrt{\frac{\sum (R_g - R_s)^2}{n}}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n (R_g - R_s)$$

$$r = \frac{\sum (R_g - \overline{R_g})(R_s - \overline{R_s})}{\sqrt{\sum (R_g - \overline{R_g})^2} \sqrt{\sum (R_s - \overline{R_s})^2}}$$

$$PBIAS = \frac{\sum_{i=1}^n (R_s^i - R_g^i)}{\sum_{i=1}^n R_g^i} \times 100$$

$R_g$  is gauge rainfall observation.

$R_s$  is a satellite rainfall estimate.

$n$  is the number of data pairs.

$\overline{R_g}$  is average gauge rainfall observation.

$\overline{R_s}$  is average satellite rainfall estimates.

Furthermore, categorical statistical analysis was used to evaluate the ability of satellites to distinguish between precipitation and non-precipitation days. Three categorical indices were employed in the current study, including Probability of Detection (POD), False Alarm Ratio (FAR), and categorical success index (CSI). The POD indicates what fraction of the

observed events were correctly estimated, the False Alarm Ratio (FAR) indicates what fraction of the predicted events did not occur, and the categorical success index (CSI) indicates the fraction of precipitation correctly detected by satellites.

$$POD = H/(H+M)$$

$$FAR = F/(H+F)$$

$$CSI = H/(H+F+M)$$

Where,

H number of hits (satellite estimated precipitation and precipitation was observed in the rain gauge)

M number of misses (satellite did not estimate precipitation but the rain gauge estimated precipitation)

F number of false alarms (satellite estimated precipitation but precipitation was not observed in the rain gauge)

#### **4.3.2.4. Rainfall-Runoff Inundation (RRI) modeling**

The two-dimensional Rainfall-Runoff Inundation (RRI) model is applied in this study to assess the ability of satellite and reanalysis data in predication streamflow. One of its features is its ability to simultaneously simulate the runoff and flood inundation. On the other hand, The Kingdom has recently witnessed many flash flood events, particularly in the last two decades, without real forecasting to reduce the impact of the flash floods. The second purpose of the application of the RRI model is the prerequisite required for the application of highly advanced hydrologic models in some areas such as our study area Wadi Qows. In order to assess the flood risk and flash flood inundation mapping to mitigate and reduce the impact of the flash flood events. The RRI model has been successfully used to simulate surface runoff and flood inundation in many basins in various regions all over the world. (Alshammari et al., 2024; Herath et al., 2024; Phyo & Uchida, 2024). Additionally, it

reveals an outstanding performance in the Wadi system despite its application is usually for humid regions (Hamlat et al., 2021; Mohammed, 2017).

The model deals with slopes and river channels separately (Abdel-Fattah et al., 2018). In other words, the model assumes that the river channel and the slope at the stream network cell are both in the same grid. The stream is discretized as a single line along its centerline of the overlying slope grid cell (Abdelmoneim et al., 2023). The channel flow is calculated using the 1D diffusive wave model, whereas the flow on the slope grid cells is generated using the 2D diffusive wave model.

There have been many flash floods within the last two decades without real forecasting to reduce the impact of the flash floods. Therefore, highly advanced hydrologic models will used to be validated and calibrated in some areas such as our study area Wadi Qows. In order to assess the flood risk and flash flood inundation mapping. In the study area, there have been some previous studies on flood susceptibility mapping that use HEC-HMS model and HEC-RAS model (Abd El Shafy & Mostafa, 2021; Alsubeai & Burckhard, 2021; Al-Zahrani et al., 2016). Therefore, testing different methods and models are highly recommended, particularly in regions where data are limited and hydrological models are challenging. For these reasons, the Rainfall-Runoff-Inundation (RRI) model will be used. Which is a two-dimensional model capable of simulating rainfall-runoff and flood inundation simultaneously.

Three statistical indices widely used to evaluate the performance of each product in the hydrological application. The Nash Sutcliffe efficiency (NSE) was first used to assess the statistical goodness of fit of simulated flows. The NSHE scale runs from  $-\infty$  to 1, with higher numbers suggesting greater agreement (Legates & McCabe Jr., 1999). If NSE is less than zero, the model has no ability in predicting the measured (Lakew et al., 2017). The coefficient of determination ( $R^2$ ) and percent bias (BIAS) are also used to determine the

agreement of simulation outputs versus the measured. Its equations are displayed as follows, respectively.

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{obs} - Q_{sim})^2}{\sum_{i=1}^n (Q_{obs} - Q'_{sim})^2} \quad (4.10)$$

$$BIAS = \frac{\sum_{i=1}^n (Q_{sim} - Q_{obs})}{\sum_{i=1}^n Q_{obs}} \times 100\% \quad (4.11)$$

$$R^2 = \frac{[\sum_{i=1}^n (Q_{obs} - Q'_{obs}) (Q_{sim} - Q'_{sim})]^2}{\sum_{i=1}^n (Q_{obs} - Q'_{obs})^2 \sum_{i=1}^n (Q_{sim} - Q'_{sim})^2} \quad (4.12)$$

Where  $Q_{sim}$  and  $Q'_{sim}$  are the simulated discharge and its averaged, respectively, and  $Q_{obs}$  and  $Q'_{obs}$  are the in-situ discharge measurements streamflow and its average. With  $NSE = 1$ ,  $BIAS = 0\%$  and,  $R^2 = 1$ , the best performance was achieved.

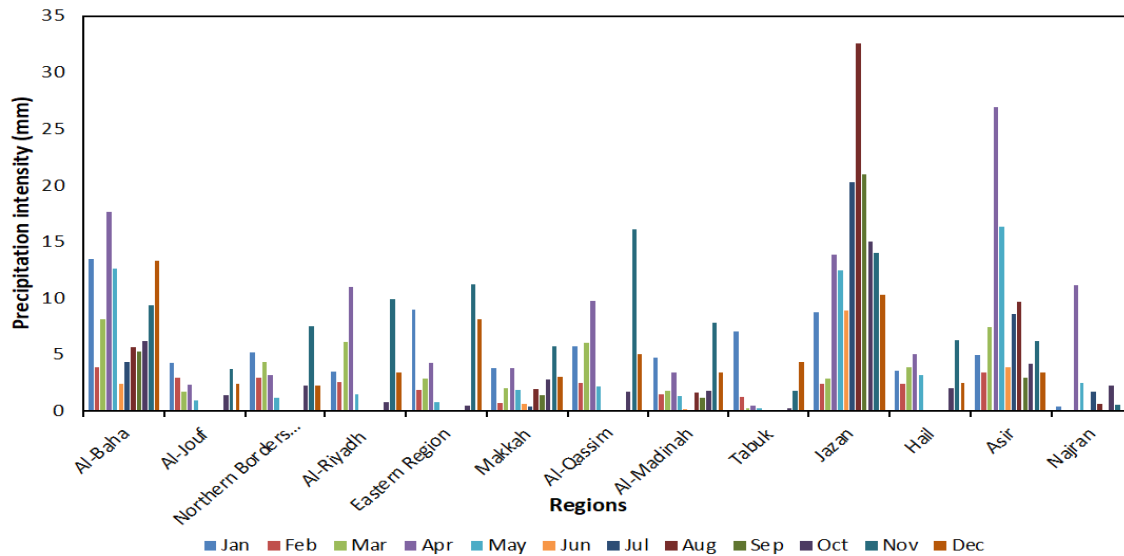
#### 4.4. Results and discussions

##### 4.4.1. Comparison between Observation, Satellite, and Reanalysis data

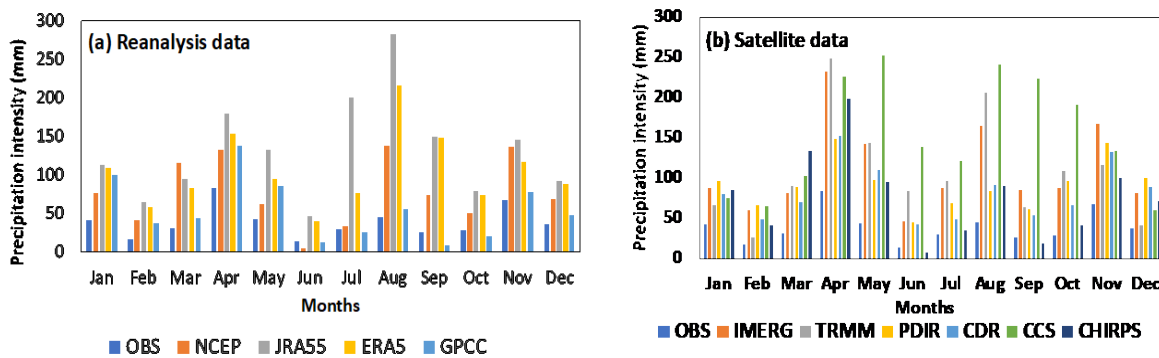
##### 4.4.1.1. Monthly Scale

An analysis of the observational data for the 20 years 2000–2019 has been carried out to understand rainfall patterns over KSA. Monthly rainfall records were examined across thirteen administrative regions of KSA as shown in Figure 4.3. The observational dataset indicates that the highest rainfall amounts occur during the wet season from October to May and the lowest amounts are recorded during the dry season from June to September. Notably, April exhibits extreme rainfall levels, with a secondary peak observed in November within the rainy season as depicted in Figure 4.3. It is worth mentioning that this pattern is consistent across most regions except for Jazan and Asir which are located in southwestern

Saudi Arabia. Data availability is predominantly challenging for hydrologists either due to limited availability and accuracy or not being measured. Nowadays, remote sensing data (e.g., satellite and reanalysis data) have become an alternative and vital tool in estimating precipitation and overcoming these challenges. However, the understanding of their accuracy, which differs from one region to another, and their uncertainty are typically hindering researchers in applying them. Thus, evaluating the performance is crucial to better grasp their ability to estimate the precipitation, particularly in the KSA which is distinguished by its diversity of topography. Figure 4.4 illustrates a comparison of the average monthly rainfall between the satellite and reanalysis data with the observed. All satellite and reanalysis data reveal a significant overestimation in all months except in June NCEP and in September and in October GPCC was underestimated (see, Figure 4.4 a). JRA55 demonstrates a dramatic overestimation, particularly in July, August, and September. On the other hand, GPCC data outperforms all products followed by CDR which appears a reasonable performance with a slight overestimation. Overall, GPCC reanalysis data exhibits the best representation of observed data. Conversely, JRA55 and CCS demonstrate the worst performance characterized by substantial overestimation across all months as illustrated in Figure 4.4.



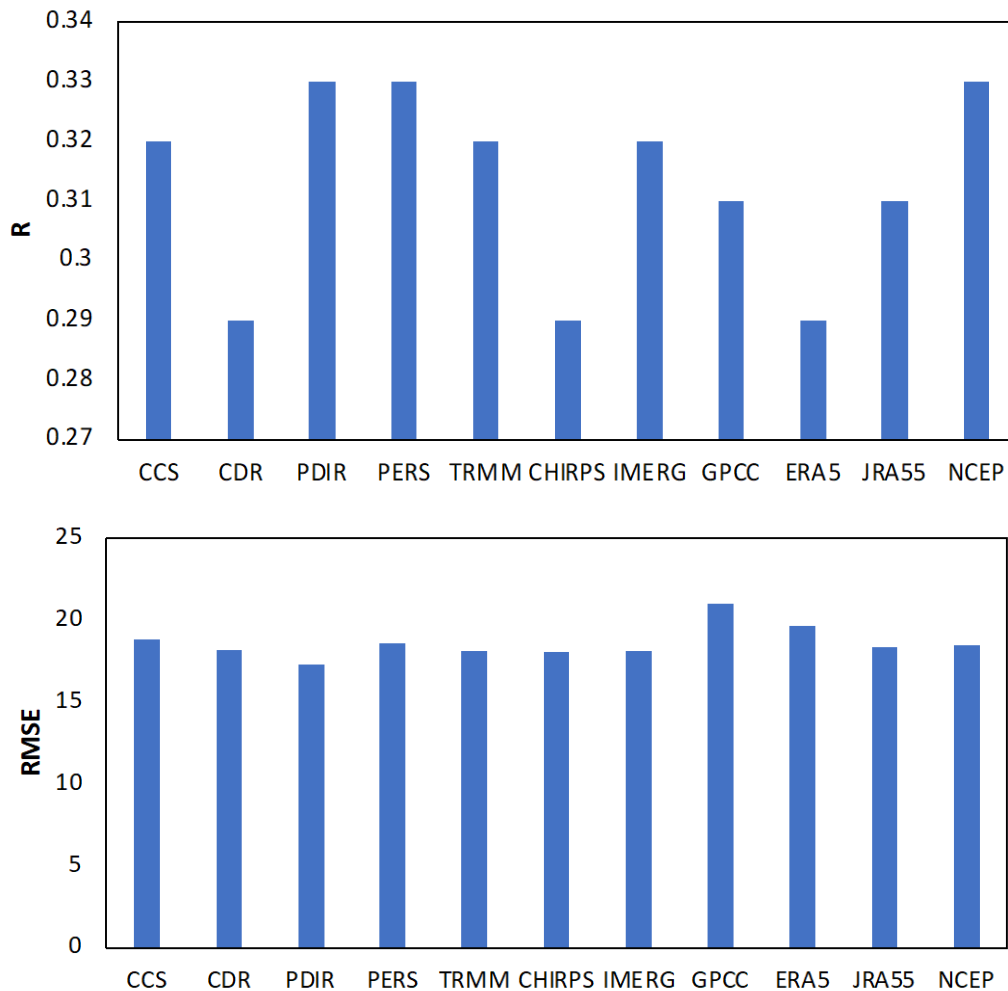
**Figure 4.3** Monthly average rainfall data for all administrative regions in KSA from 2000 to 2019

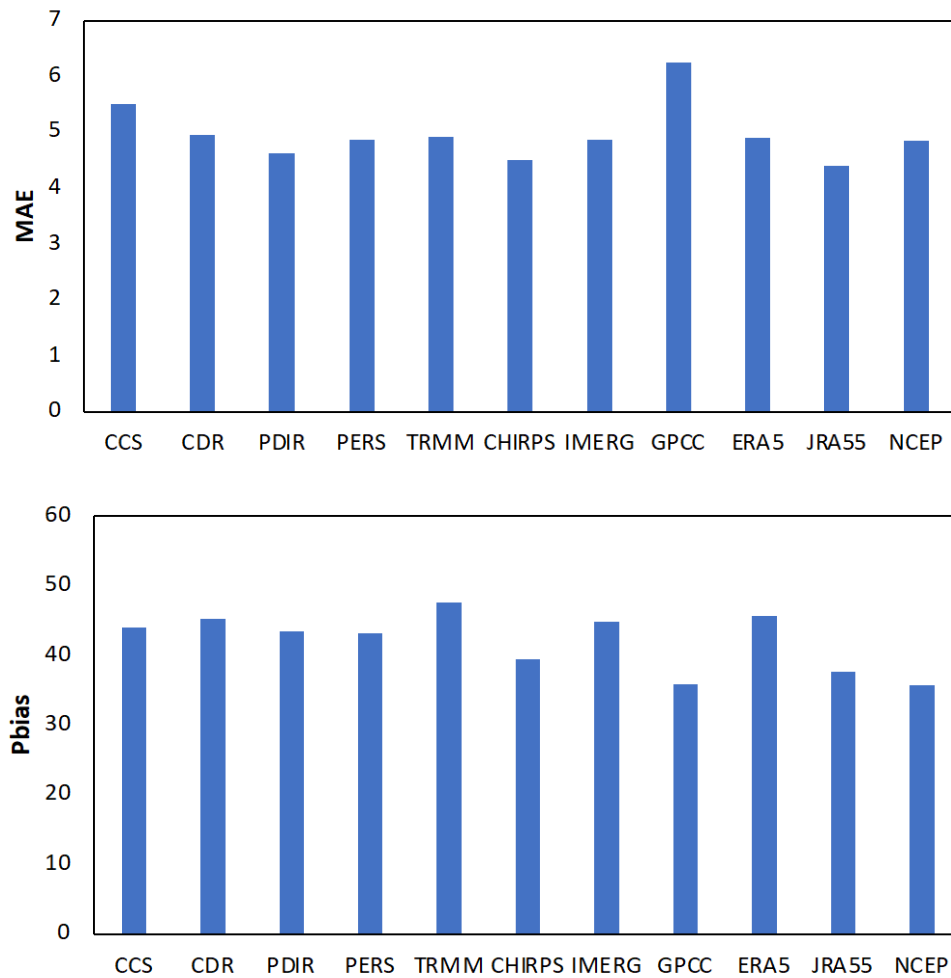


**Figure 4.4** The total monthly rainfall is averaged on each month from 2000–2019 from all analyzed stations (a) observed data and reanalysis data (NCEP, JRA55, ERA5, and GPCC) (b) Comparison of rainfall (mm/month) obtained from the observed data and satellite data (IMERG, CHIRPS, TRMM, PERS, PDIR, CDR, and CCS).

Continuous statistical metrics for the monthly scale are summarized for rainfall intensity thresholds ( $\geq 0$  mm) in Figure 4.5 In general, all products show poor performance against the observed data on a monthly scale, indicating correlation values that are less than 0.5

and significant overestimation in Pbias. For more illustration of their performance in from low to high rainfall events, continuous statistical indices were analyzed for 118 rainfall stations across various rainfall intensity thresholds ( $\geq 5$ ,  $\geq 10$ ,  $\geq 30$ , and  $\geq 50$  mm) per month, as shown in Figure 4.6 It is noteworthy that no and low rainfall intensities ( $< 5$  mm) were excluded not only to overcome the uncertainty of remote data which is the misprediction of small rainfall but also to focus on their performance in significant rainfall intensities that probably lead to flash floods.

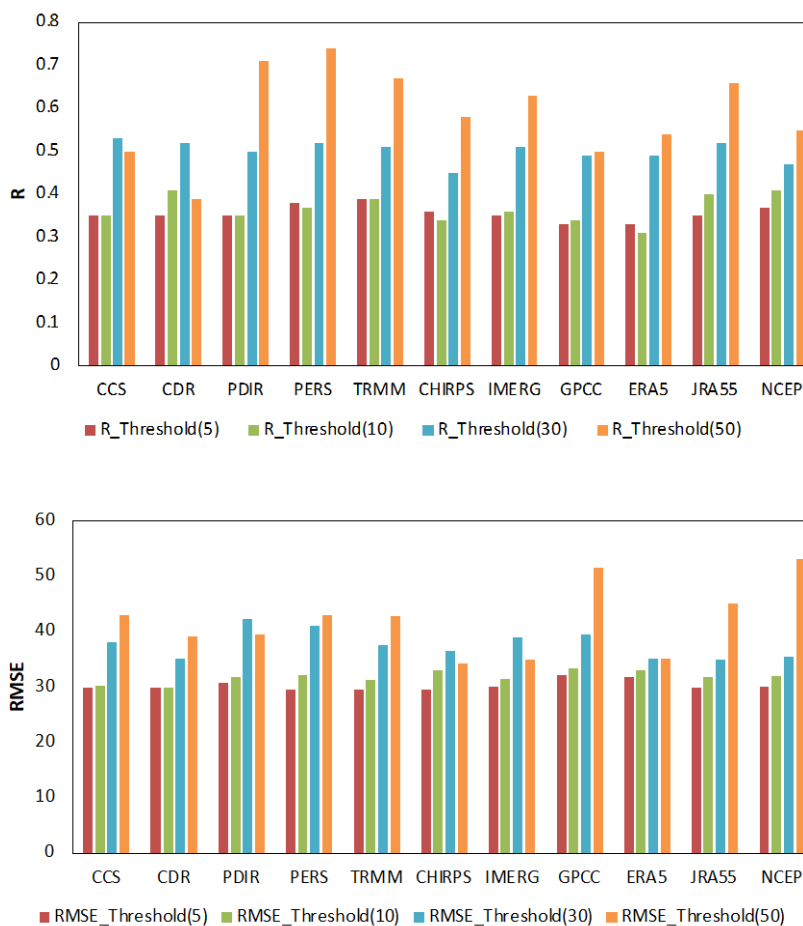


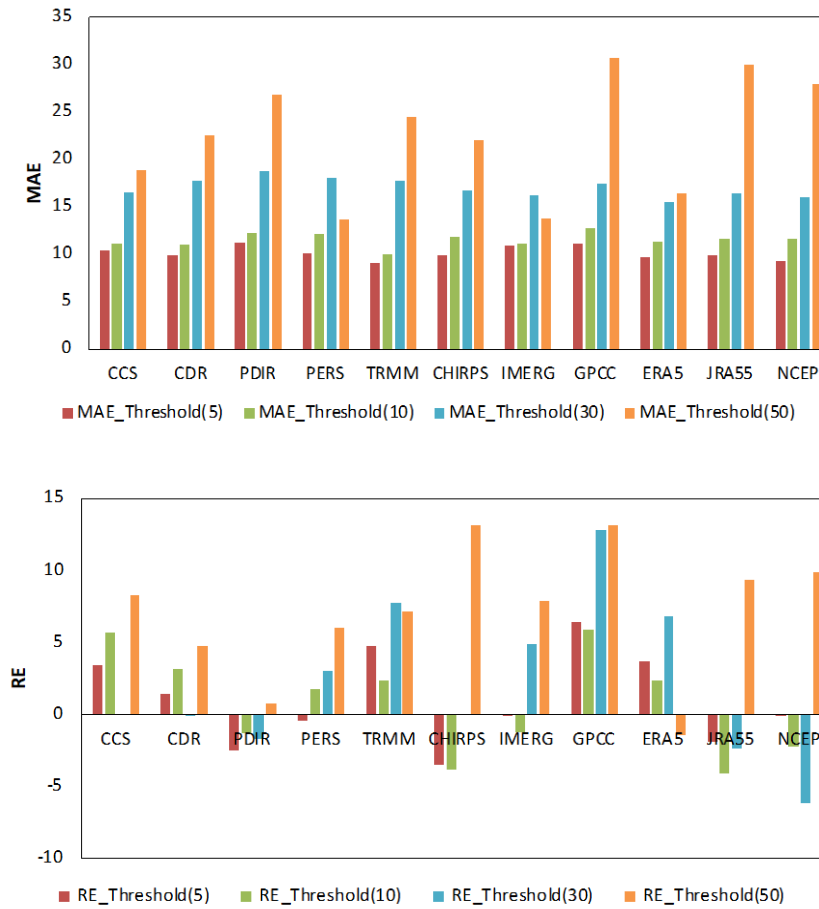


**Figure 4.5** Statistical measurement between total observation rainfall with satellite data and reanalysis data (a) R, (b) RMSE, (c) MAE, and (d) Pbias.

Figure (4.6) illustrates that PDIR and CHIRPS satellite data exhibit higher accuracy in terms of bias across different thresholds, with a Pbias value not exceeding 5%. Conversely, GPCC reanalysis data demonstrates higher accuracy for all rainfall data recorded at threshold (5), with a Pbias value of approximately 35%. The correlation coefficients for all products range from 0.3 to 0.5 for thresholds ranging from 0 to 30 mm and from 0.4 to 0.7 for thresholds ranging from 40 to 50 mm. Root Mean Square Error (RMSE) values remain consistent across all products and different thresholds, ranging from 20 to 50. Mean Absolute Error (MAE)

follows a similar pattern, with values ranging from 5 to 30 across all different thresholds and products, except for PERS, IMERG, and ERA5. All products have closer values of RMSE and MAE for all thresholds, except ( $\geq 50$  mm) thresholds. NCEP illustrates a relatively reasonable agreement among other products with a R value of 0.37 and an insignificant underestimation (Pbias = -0.02%) in ( $\geq 5$  mm) thresholds, followed by IMERG and PERS. On the other hand, PDIR shows a good correspondence with the observed data (R=0.71 and Pbias=0.8) for the ( $\geq 50$  mm) thresholds, contrarily, CHIRPS appears the poorest performance. Overall, PDIR might be the best product by indicating good performance in most thresholds with less Pbias value and reasonable R values compared with other products.





**Figure 4.6** Statistical measurement between total observation rainfall with satellite data and reanalysis data in different thresholds ( $\geq 5$ ,  $\geq 10$ ,  $\geq 30$ , and  $\geq 50$  mm). Correlation (a), RMSE (b), RE (c), and MAE (d).

Categorical statistical indices (based on POD, FAR, and CSI) are commonly used to assess the ability of remote sensing data to predict rainfall correctly. The accuracy of satellite and reanalysis data for these indices typically corresponds with rain threshold events; this means that remote sensing data are less successful in approaching the identical magnitude of an extreme rain event. Hence, these indices were applied for two thresholds (5 mm and 30 mm) owing to our main target which is the investigation of the performance of selected products in extreme rainfall events. Figure 4.7 illustrates the rain events prediction based

on categorical statistical indices (POD, FAR, and CSI) at different rainfall thresholds of 5mm/month and 30mm/month. All products were detected well in the low rainfall event with a threshold of 5 mm, as denoted in Figure 4.7. The POD ranges from 0.831 to 0.833, FAR from 0.296 to 0.2968, and CSI from 0.618 to 0.620. However, the performance deteriorates with a threshold of 30 mm, with the POD ranging from 0.30 to 0.31, FAR from 0.76 to 0.77, and CSI from 0.140 to 0.141. In general, CCS outperforms all products by showing the highest POD (0.833) and CSI (0.620) values and the lowest FAR (0.2968) for (5mm) thresholds. Also, PDIR and PERS have reasonable performance for both thresholds, as displayed in Figure 4.7. In contrast, CDR shows weak performance in both thresholds.

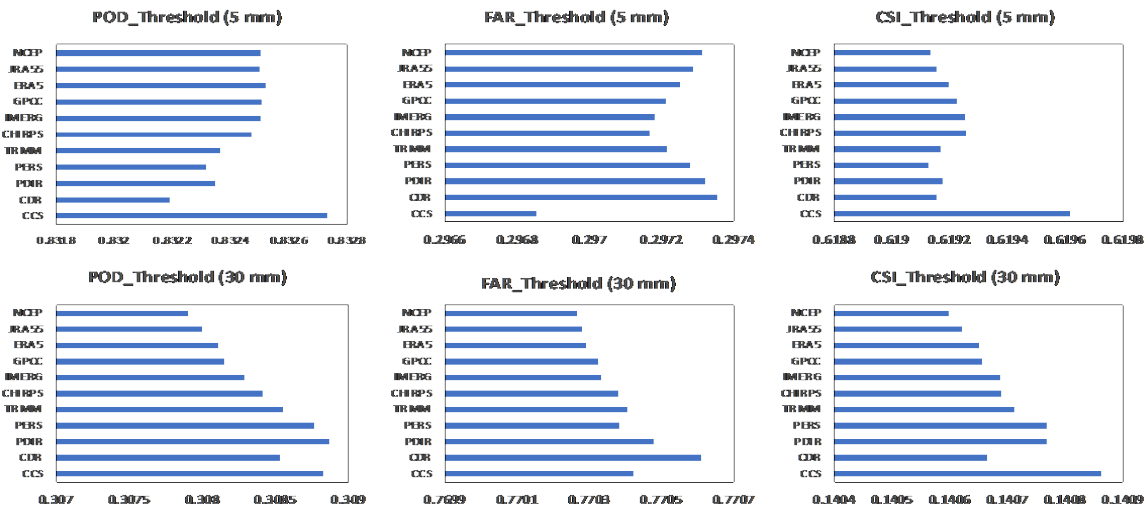
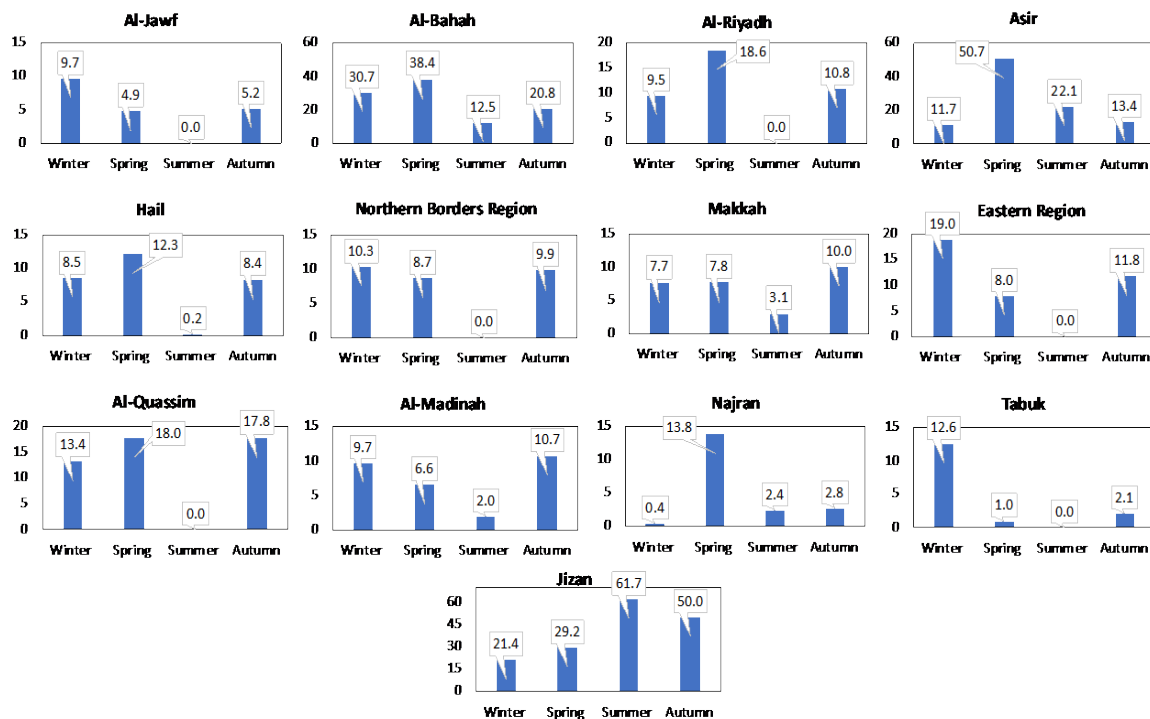


Figure 4.7 Categorical scores between total observation rainfall with satellite data and reanalysis data in two thresholds ( $\geq 5$  and  $\geq 30$  mm). POD, FAR, and CSI.

#### 4.4.1.2. Seasonal Scale

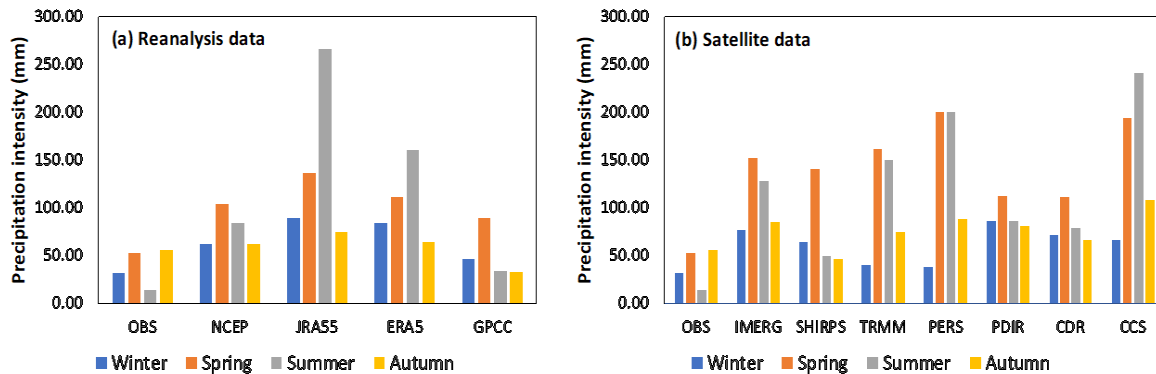
Saudi Arabia is one of the driest countries in the world where extreme rainfall occurs a few days a year in some regions of the country. The country's seasons are divided as follows: winter (December to February), spring (March to May), summer (June to August), and autumn (September to November). These seasons are characterized by distinct synoptic

conditions (Almazroui, 2011b). The wet season spans from October to May, encompassing the winter and spring seasons, while the dry season occurs from June to September which covers the summer and autumn seasons. However, heating over KSA during the dry season convection generates cumulonimbus cloud due to orographic effects, allowing for the development of strong depressions over the central Red Sea, which consequently causes heavy rainfall to occur in the southwestern regions which is more pronounced in Jazan region and aligned with (Barth & Steinkohl, 2004) as shown in Figure 4.6 and 4.7. The wet season rainfall is dynamic in Saudi Arabia (de Vries et al., 2016). Therefore, a lot of rain falls in the northeastern, central, and southwestern parts of Saudi Arabia. On the other hand, rainfall predominates in the southwestern regions during the dry season which corresponds with (Almazroui et al., 2022).



**Figure 4.8** Seasonality average rainfall data for all administrative regions in KSA from 2000 to 2019

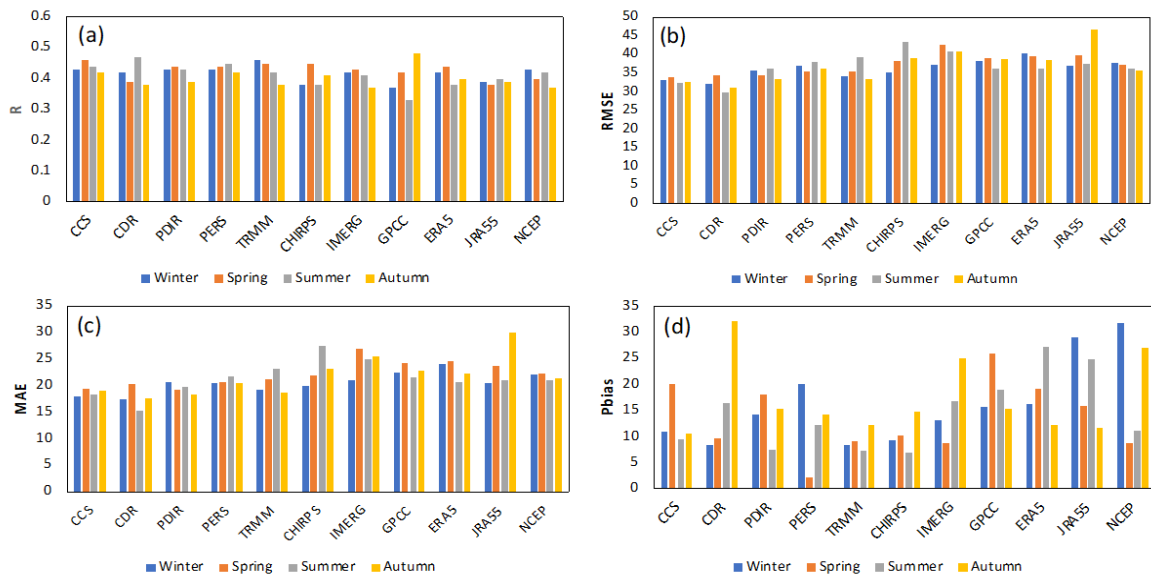
The seasonal rainfall records have been analyzed based on observational data in thirteen administrative regions of Saudi Arabia (see, Figure 4.8). The dataset reveals that the highest amounts of rainfall are typically observed during the winter and spring seasons across all regions, except for the Jizan region where the highest amounts of rainfall occur during the summer season. Figure 4.9 illustrates the comparison of seasonal average rainfall for each satellite and reanalysis data against the observed data. JRA55, PERS, and CCS reveal a large overestimation in the summer and in the Spring. However, PERS and TRMM are well corresponded with the observed data in the Winter season. Additionally, GPCC shows a reasonable performance compared to the observation in most seasons, except in the Spring. Both GPCC and CHIRPS demonstrate a slight underestimation in the Autumn season. Generally, JRA55 and CCS have the worst agreement in all seasons, contrary, PDIR shows a reasonable performance in all seasons with a slight overestimation.



**Figure 4.9** Comparison seasonality average rainfall data with reanalysis data (a) and seasonality average rainfall data with satellite data (b) in KSA from 2000 to 2019

As for the seasonal scale, continuous statistical measurements have also been analyzed for 118 rainfall stations with different seasons, as demonstrated in Figure 4.10. Most statistical measurements such as Correlation, RMSE, and MAE almost have the same values for all products in different thresholds: the range of values (0.33 to 0.49), (30 to 46), and (15 to 30) respectively. CDR, TRMM, and CHIRPS satellite data have more accuracy in terms of bias

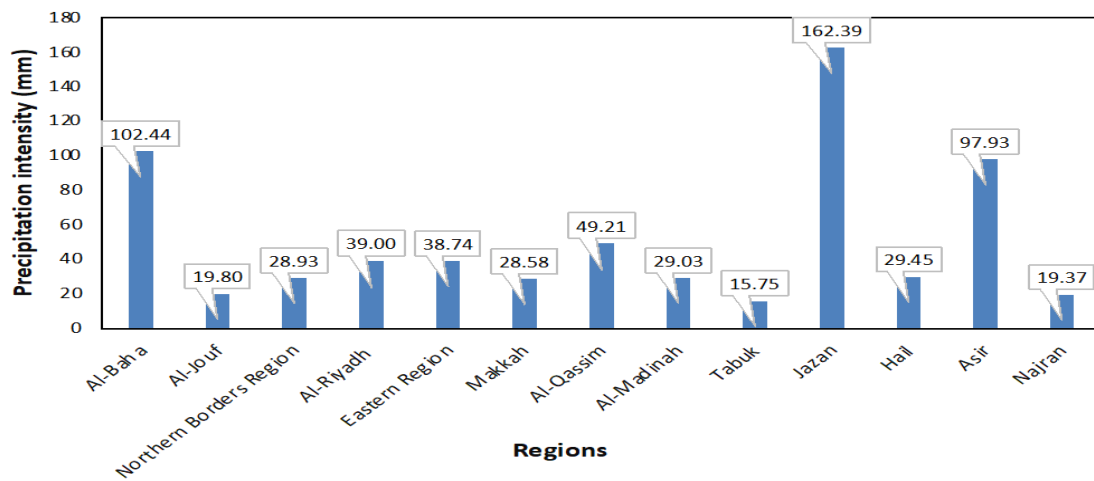
during the seasonality period especially in the rainy season with (Pbias) values almost not exceeding 10%. It also is worth mentioning that NCEP has a poor performance in the rainy seasons (Winter and Autumn) with a large overestimation, reflected in Pbias value of 31.9% and 27 %, respectively; however, its performance is significantly improved in the dry seasons (Spring and Summer), indicating in the decrease of Pbias values to 8.7% and 11%. Additionally, PDIR shows relatively good performance despite its overestimation.



**Figure 4.10** Continuous statistical measurement between total observation rainfall with satellite data and reanalysis data with all seasons. (a) R, (b) RMSE, (c) MAE, and (d) Pbias.

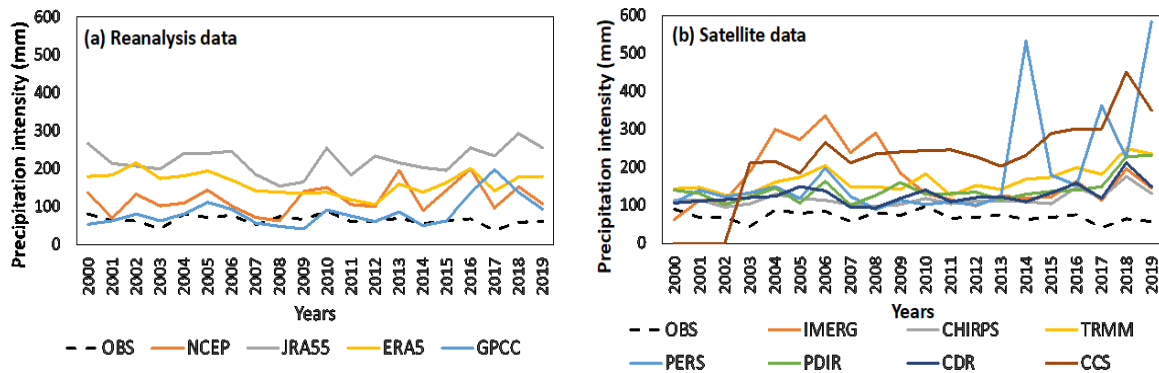
#### 4.4.1.3. Annual Scale

Figure 4.11 represents the annual average rainfall of each province in KSA for the analysis period from 2000 to 2019. The figure illustrates that the southwestern parts, which include Jizazn, Asir, and AL-Baha, receive a large amount of rainfall up to 162.39 mm/year compared with the remaining administrative regions.



**Figure 4.11** Annually average rainfall data for all administrative regions in KSA from 2000 to 2019

Figure 4.12 illustrates the average annual rainfall of each product compared with the average annual rainfall from 2000 to 2019. The figure identifies seven drought years, namely 2003, 2007, 2008, 2009, 2011, 2012, and 2017. An extreme drought year, notably in 2007, corresponds with the findings of (Syed et al., 2022). GPCC reanalysis data outperforms the satellite data with a slight difference compared with observation data expected for the recent years from 2015 to 2019, similar to the finding of (El Kenawy & McCabe, 2016) as shown in Figure 4.12(a). On the other hand, CHIRPS, TRMM, PDIR, and CDR were relatively good against observation data despite the overestimation, as displayed in Figure 4.12(b). Similarly, IMERG data shows the same performance for the whole period except from 2003 to 2009. In general, rainfall in the region is characterized by high spatial and temporal variability, the annual average rainfall over Saudi Arabia is approximately 100 mm/year.

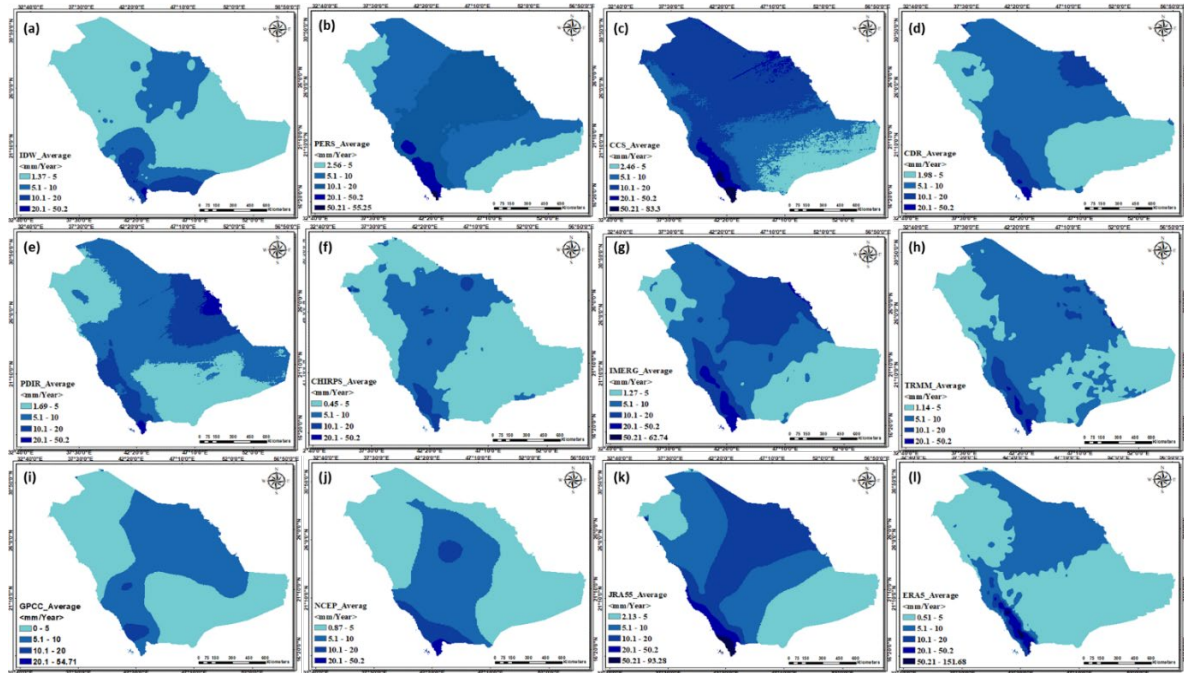


**Figure 4.12** Comparison of average annual rainfall (mm/y) for the analysis period (2000-2019) (a) observed data and satellite data (IMERG, CHIRPS, TRMM, PERS, PDIR, CDR, and CCS). (b) observed data and reanalysis data (NCEP, JRA55, ERA5, and GPCC).

#### 4.4.2. Rainfall Spatial Distribution

Saudi Arabia is prone to flash floods, particularly in regions experiencing extreme rainfall events. Despite the overall low average rainfall in the country, certain areas remain vulnerable to flash floods even with low thresholds events such as 20 mm. even without heavy rainfall. The hydrological and energy cycles respond not only to the amount of precipitation but also to other factors such as the spatial pattern, intensity, and duration of rainfall (Heistermann & Kneis, 2011; Sorooshian et al., 2011). Therefore, high-resolution precipitation estimates are essential for various applications. As shown in Figure (4.13), heavy mean monthly rainfall (<50.2 mm) occurred periodically over the southwestern region for CCS, JRA55, PERS, IMERG, ERA5, and GPCC which indicated an overestimation of rainfall data. Conversely, CDR, PDIR, NCEP, TRMM, and CHIRPS showed an underestimation of rainfall data. Both the CHIRPS and GPCC monthly rainfall datasets exhibit homogeneous spatial rainfall patterns, achieved through interpolation using the Inverse Distance Weighting (IDW) and Thiessen methods for average observational rainfall data. Similarly, TRMM and NCEP datasets demonstrate a relatively uniform spatial distribution of rainfall,

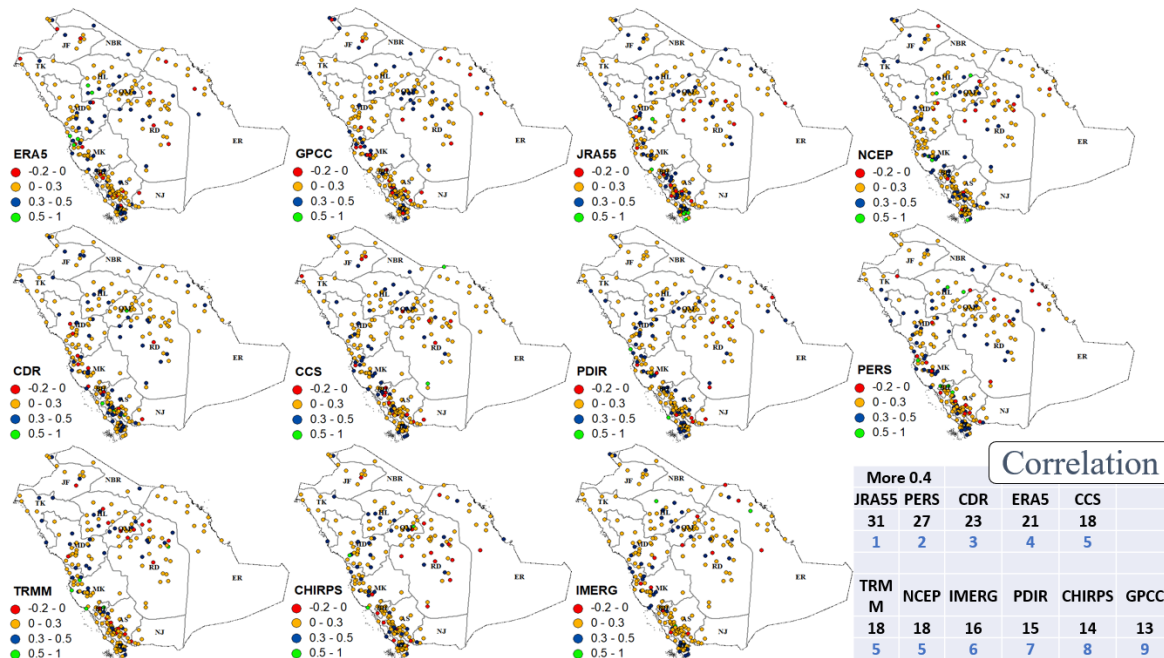
with minor quantitative variations. However, ERA5 exhibits homogeneous spatial rainfall patterns with significant quantitative differences. This suggests that heavy mean annual rainfall (>150 mm) occurred periodically over the southwestern area.



**Figure 4.13** The spatial distribution of the average monthly rainfall (mm) obtained from observation as IDW methods (a), observation as Thiessen methods (b), CCS (c), CDR (d), PDIR (e), NCEP (f), JRA55(g), TRMM (h), PERS (i), CHIRPS (j), IMERG (k), ERA5 (l) and GPCC (m) in Saudi Arabia during the period 2000–2019.

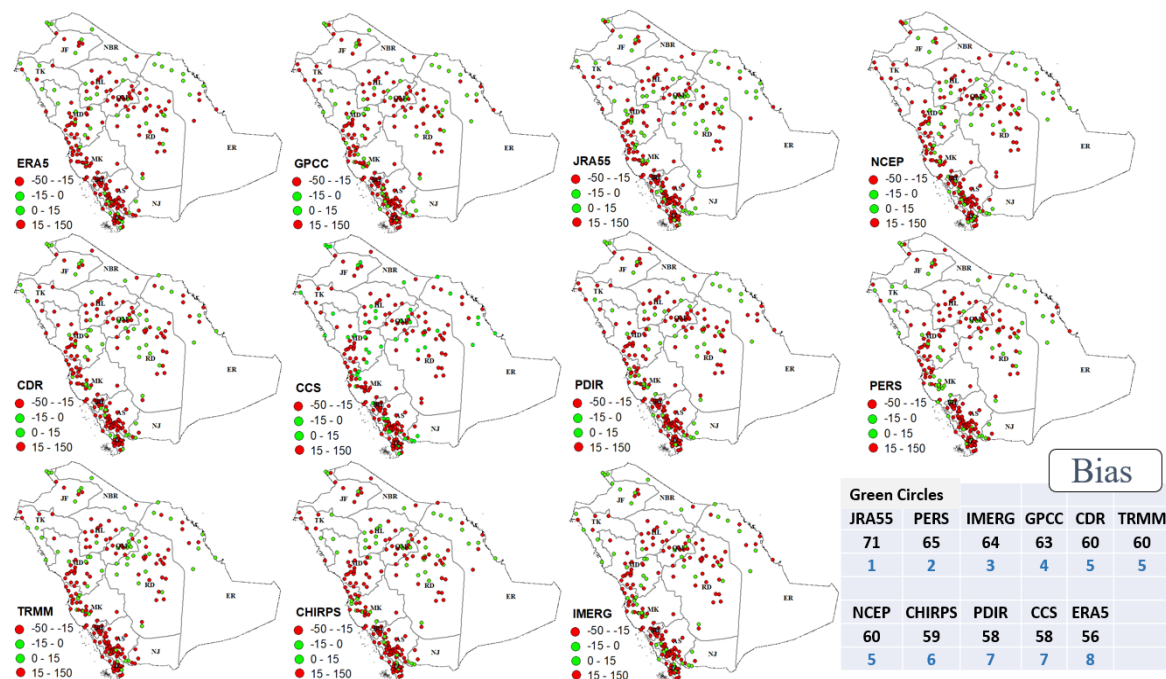
Figure 4.14 illustrates the correlation between rainfall measurements obtained from various satellite sources and those recorded by ground-based rainfall stations. Each point on the spatial map represents a specific range of correlations. A strong positive correlation between the satellite data and ground truth rainfall measurements would result in the range (0.5 - 1) represented by green circles. The moderate correlation range (0.3 - 0.5) is depicted by blue circles. Conversely, a weaker correlation would be reflected in stations

with correlation ranges (0 - 0.3) represented by red and yellow circles. In terms of correlation on an annual scale, JRA55 and Pers are the best compared to other products.



**Figure 4.14** Correlation between total observation rainfall with satellite data and reanalysis data

Figure 4.15 illustrates the bias ratio between rainfall measurements obtained from various satellite sources and those recorded by ground-based rainfall stations. Each point on the spatial map represents a specific range of bias. A good bias ratio within the range of (-15 to 15), represented by green circles. Conversely, a high bias ratio range is depicted by red circles. In terms of bias ratio on an annual scale, JRA55 and Pers are still the best compared to other products. This identification of systematic biases or discrepancies between the datasets provides valuable insights into the reliability and accuracy of satellite rainfall products for various applications, such as flood forecasting or drought monitoring.



**Figure 4.15** Bias between total observation rainfall with satellite data and reanalysis data

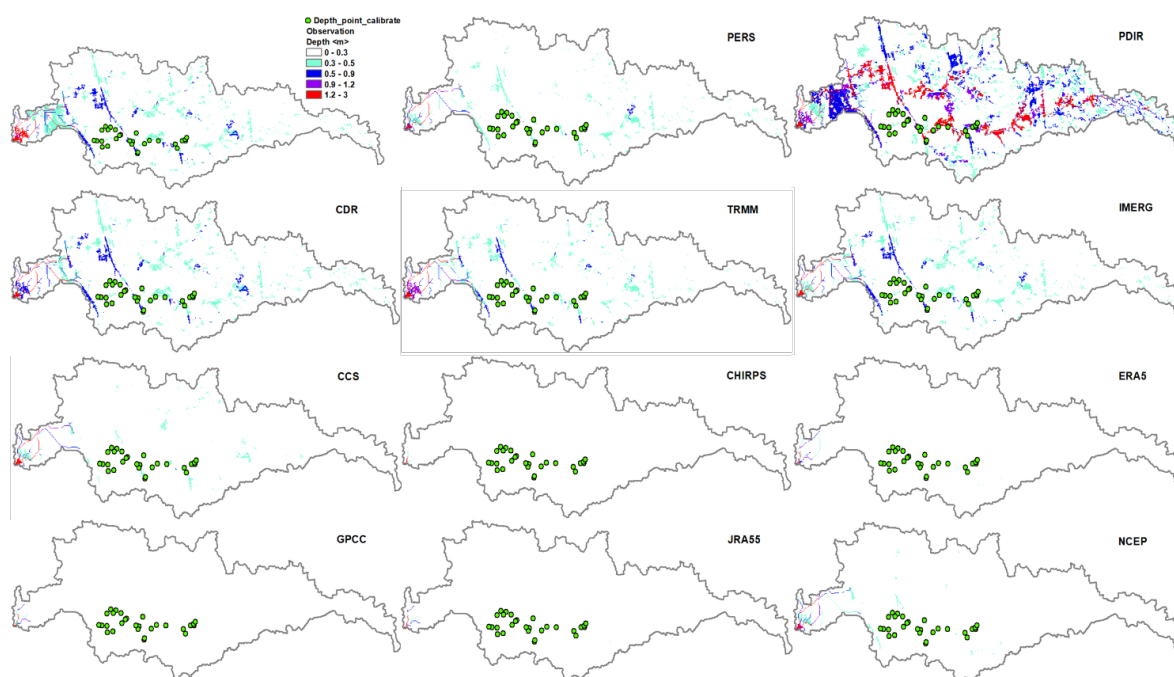
#### 4.4.3. RRI Model

The study area of Wadi Qows does not have any monitoring for flash floods, except the flood points were collected after the extreme flash floods of 2009 in Jeddah City. Therefore, the model was calibrated based on the 28 flood depth points recorded in this event as shown in table (4.2), where  $R^2 = 0.85$ ,  $NCE = 0.72$ , and bias = -20%. The results are acceptable in such kind of physical hydrological models. In addition, all SBP data have been used in the RRI model to determine the accuracy of the flood extent predictions compared with the calibrated model from observation rainfall data as shown in Figure (4.16). The results indicate the Flood Hazard Map represented by TRMM, IMERG, and CDR rainfall data have a good accuracy in both flood events, as noticed in Table 4.2. Furthermore, the 2011 rainfall event was utilized to confirm the data accuracy of all satellite products in the RRI model. The data from CDR and TRMM exhibit greater accuracy in terms of flood depth and extent as displayed in Figure (4.17) and Table 4.2. It is worth noting that while PDIR rainfall

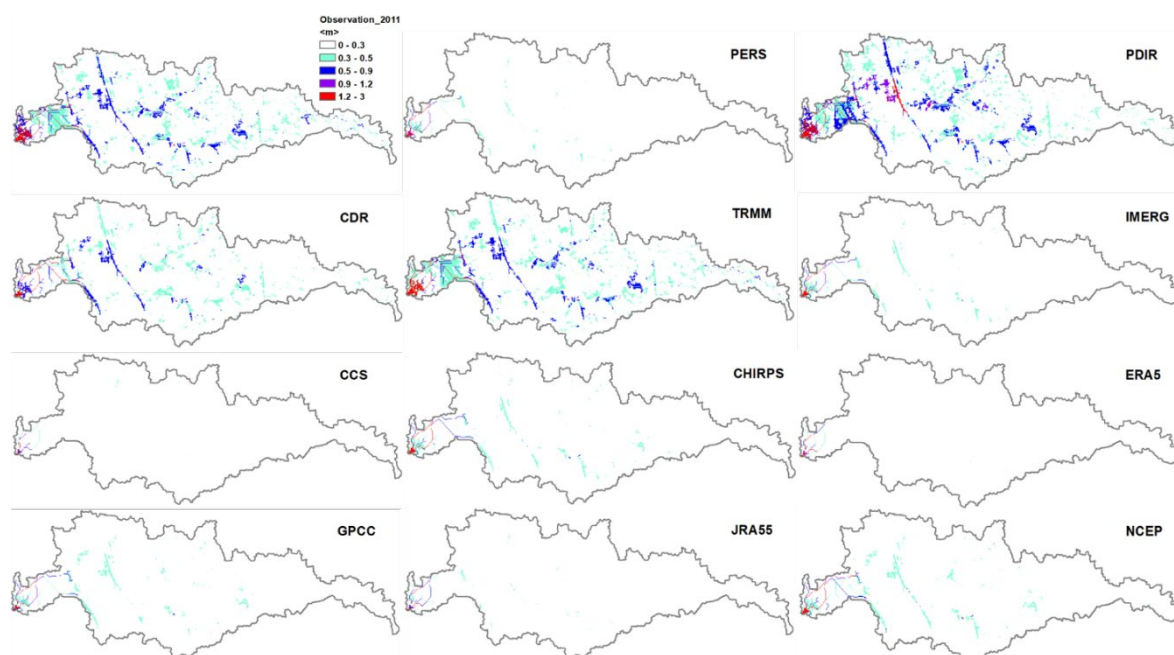
data provides a good representation of floods but tends to overestimate in both the 2009 and 2011 events.

**Table 4.2** Statistical indices for the evaluation of different products in Wadi Qwos 2009

|                     | 2009 event     |       |      | 2011 event     |        |      |
|---------------------|----------------|-------|------|----------------|--------|------|
| Statistical indices | R <sup>2</sup> | NSE   | Bias | R <sup>2</sup> | NSE    | Bias |
| <b>Calibration</b>  | 0.85           | 0.72  | -20% |                |        |      |
| <b>TRMM</b>         | 0.99           | 0.95  | -19% | 0.9998         | 0.9991 | -3%  |
| <b>PERS</b>         | 0.98           | 0.8   | 39%  | 0.9533         | 0.5465 | -59% |
| <b>PDIR</b>         | 0.91           | -0.58 | 80%  | 0.9624         | 0.96   | -5%  |
| <b>NCEP</b>         | 0.96           | 0.64  | -53% | 0.9811         | 0.7434 | -46% |
| <b>JRA55</b>        | 0.93           | 0.36  | -74% | 0.9187         | 0.4693 | -65% |
| <b>IMERG</b>        | 1              | 0.99  | -6%  | 0.9676         | 0.6004 | -55% |
| <b>GPCC</b>         | 0.9            | 0.33  | -75% | 0.9654         | 0.6074 | -56% |
| <b>ERA5</b>         | 0.8            | 0.37  | -73% | 0.9076         | 0.3578 | -73% |
| <b>CHIRPS</b>       | 0.85           | 0.21  | -85% | 0.9563         | 0.6763 | -50% |
| <b>CCS</b>          | 0.95           | 0.69  | -50% | 0.7738         | 0.2538 | -80% |
| <b>CDR</b>          | 1              | 1     | -5%  | 0.9986         | 0.9633 | -16% |



**Figure 4.16** RRI model for rainfall and runoff response for satellite and reanalysis data in 2009



**Figure 4.17** RRI model for rainfall and runoff response for satellite and reanalysis data in 2011

#### **4.5. Conclusions**

The quantity of rainfall received in Saudi Arabia is important to understand and assess the availability of water for improving and maintaining Saudi Arabia's vision of supporting national projects related to the optimal utilization of water resources. While ground station observations are typically accurate, they are limited in spatial coverage and may suffer from gaps or inconsistencies due to factors such as station density and maintenance. On the other hand, satellite data offer broader spatial coverage and can fill in gaps in observational data. However, satellite data rely on algorithms and models to estimate weather parameters, which may introduce uncertainties and errors, especially in complex terrains or during extreme weather events. In this study, we analyzed the statistical metrics, categorical scores, and the trend of rainfall in historical data versus satellite data over 13 administrative regions in KSA using the observed rainfall data for 2000–2019 along with the RRI model to simulate the runoff. Statistical measurements have been conducted on the monthly, seasonal, and annual periods of rainfall characteristics and variability associated with ground station observations in Saudi Arabia for the period 2000-2019, along with satellite data and reanalysis data. The JRA55 and PERS are a good satellite in Annual scale in terms of correlation and Bias. While in the seasonal scale the TRMM and CHIRPS satellite have the accurate rainfall data compare to other satellite based on Bias. However, in monthly scale the CDR, PDIR, PERS, TRMM, and ERA5 are the accurate satellite in terms of Bias. It is worth mentioning, the performance of satellites in low rainfall intensity are detecting well. However, their performance tends to decrease as rainfall intensity increases. Based on the findings from RRI model, the TRMM and CDR are the best satellite represent the flood depth and extent. Overall, the combination of observational and satellite-derived data allows for a more comprehensive understanding of rainfall patterns and variability over the KSA. This integrated approach enables better-informed decision-making in various sectors such as agriculture, water resource management, and disaster preparedness. It

facilitates the identification of trends, assessment of risks, and development of strategies to optimize water resources and mitigate the impact of extreme weather events.



## CHAPTER 5

# Stormwater management modeling and machine learning for flash flood susceptibility prediction in Wadi Qows, Saudi Arabia

### 5.1. Introduction

In the last two decades, there has been an extensive evaluation of machine learning strategies worldwide for forecasting flood risk. As a result, flood modeling has advanced greatly due to recent innovations in machine learning techniques. Information may be captured without establishing assumptions, and complicated datasets can be processed quickly and accurately using these approaches (Arabameri et al., 2020). Machine learning techniques are widely applicable in water-related applications (e.g. Random forest, LightGBM and CatBoost), and can accurately predict flash flood susceptibility in arid regions with high performance (Saber et al., 2021). Due to extremely short lag durations, flash floods are more disastrous than any other form of floods (Vinet, 2008), particularly in dry

regions (Abdel-Fattah et al., 2018; Abdrabo et al., 2020; Saber et al., 2020). Flash floods have been recorded and verified to have severe impacts in developing and developed nations (Bisht et al., 2018; Esmail et al., 2022); nevertheless, flood occurrences are more severe in developing nations, such as those in the Middle East and North Africa (MENA). Flash floods are becoming more common as a result of changes in violent storm patterns and global climate change (Hirabayashi et al., 2013; Pachauri et al., 2015). Flash flood susceptibility mapping is one of the most critical metrics according to researchers and governments throughout the globe (S. A. Ali et al., 2020). In Saudi Arabia, climate change has a substantial impact on flash flood variability, and flash floods have increased over the last two decades. For instance, flash floods occurred in Jeddah city in 2009 and 2011. The number of “Jeddah drowning” victims reached 113 in 2009 (Youssef et al., 2016). The flood susceptibility map can provide a better understanding of which areas are most at risk for future flooding (Band et al., 2020; Chowdhuri et al., 2020; Malik et al., 2021; Saha et al., 2021), and such flood susceptibility mapping can be a good guide for the decision maker for future effective flash flood management strategies.

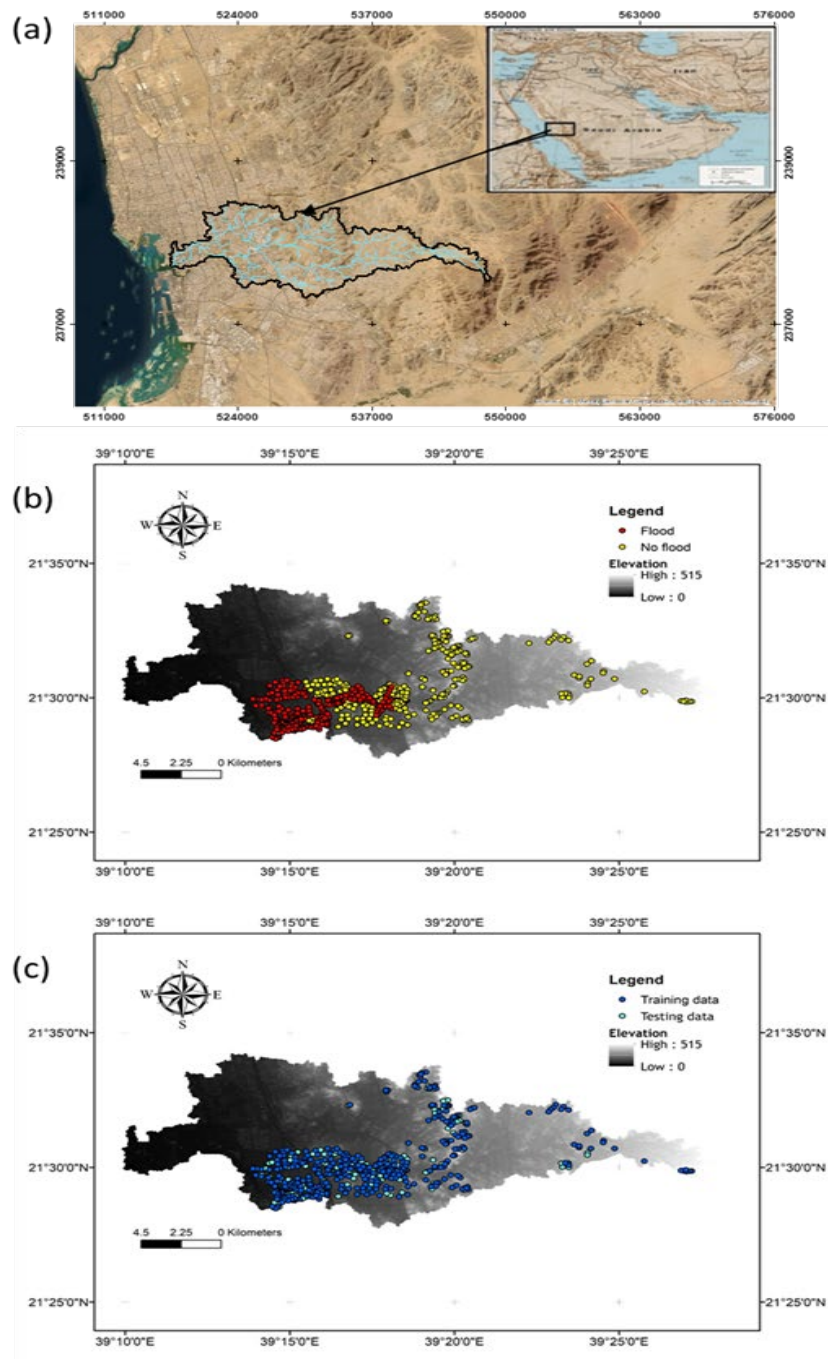
In Saudi Arabia, there are limited previous studies focused on ML approaches for flood susceptibility (A. Al-Areeq et al., 2022; Youssef, Mahdi, Al-Katheri, et al., 2022; Youssef, Mahdi, & Pourghasemi, 2022), and to our knowledge, there is no study comparing physically based approaches and ML algorithms. Therefore, the aim of this study is to develop flash flood susceptibility maps (FFSMs) by adopting machine learning (ML) models (random forest, LightGBM, and CatBoost) and hydrological modeling analyses (Personal Computer Storm Water Management Model; PCSWMM). Wadi Qows in Saudi Arabia was selected as a case study (Figure 5.1a). The main framework of this paper consists of an introduction, study area, methodology (datasets and features, ML algorithms, and model accuracy), results, and finally a conclusion.

## **5.2. Study Area**

Saudi Arabia (Figure 5.1a) is located in southwestern Asia between 32° and 55° east longitude and between 15.5° and 32.5° north latitude; the country is divided into 13 administrative regions. Saudi Arabia has a desert climate with very low average annual rainfall, except in the southwestern region, which receives an average of approximately 300 mm of precipitation annually. This region receives the highest precipitation amount in the country, while precipitation decreases significantly in the rest of the regions. Wadi Qows is situated in eastern Jeddah city between 39.1° E and 39.6° E and between 21.2° N and 21.8° N.

## **5.3. DATA AND METHODS**

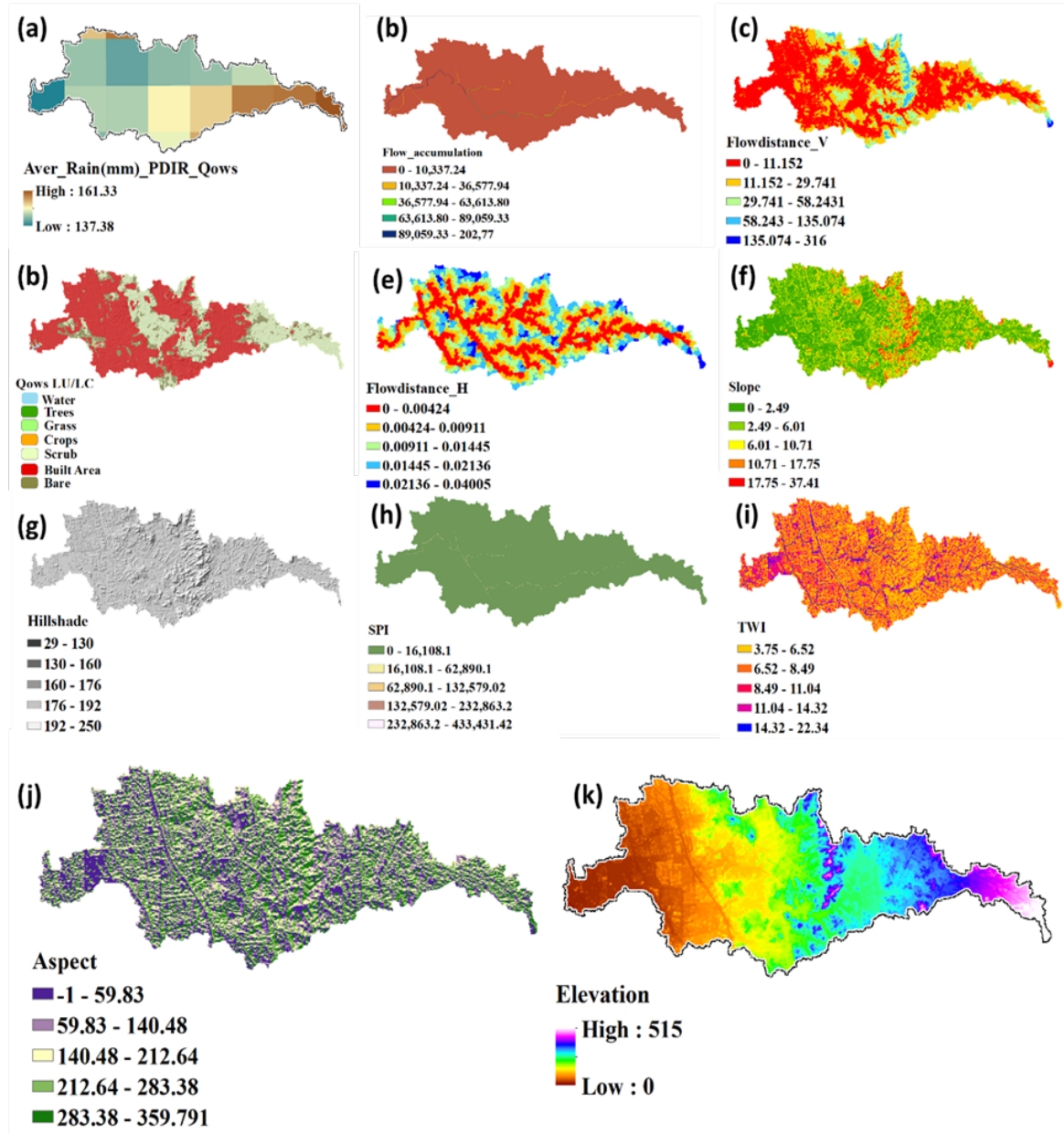
The FFSMs in both approaches of ML and the physical model have been estimated. First, in preparing the flood and non-flood inventory map, about 300 points were selected based on the post-flood survey of the most extreme event of 2009 that hit the region with very destructive impacts. Secondly, the effective influencing factors were prepared and developed. To select the effective contributors for flood susceptibility, the selection features methods were applied. To develop the flood susceptibility mapping, ML algorithms, namely, the random forest (RF), LightGBM, and CatBoost algorithms (Saber et al., 2021), were employed. Also, the accuracy of their performance was assessed based on several statistical measures, in addition to comparing with the physical-based model in terms of flood extent.



**Figure 5.1** (a) The Wadi Qows study area in Jeddah Governorate, Saudi Arabia, (b) flooded and non-flooded locations, and (c) the flood inventory map used to construct the training and testing datasets

### **5.3.1. Datasets and influencing factors**

First, a flood inventory map (Figures 5.1b and 5.1c) is generated based on 300 inundated sites. These places were determined based mostly on post-flood studies undertaken after the flash floods on November 25, 2009 that hit Jeddah, Saudi Arabia. Non-flooded locations (300) across the watershed were randomly picked using GIS tools from the topographic information such as DEM based on our experience. In this research, in order to use machine learning for flood susceptibility mapping, observational flooded and non-flooded points were collected from the post flood survey of the flood event of 2009, with datasets divided into 70% for training and 30% for testing. Then, after model training and validation, we applied the model over the whole basin to predict the flooded and non-flood regions and finally we could create a spatial map for the whole region for the flood susceptibility. Eleven flood-controlling factors such as elevation, aspect, slope, hillshade, flow accumulation, horizontal flow distance, vertical flow distance, stream power index (SPI), rainfall, land use/land cover, and topographic wetness index (TWI) were developed by using ArcGIS spatial tools with the same resolutions of 10m (Figure 5.2). These factors were selected based on the previous studies as the most dominant and effective influencing factors for flooding occurrences. Additionally, we performed feature selection to identify the factors that contribute most significantly to flood susceptibility in the study area.



**Figure 5.2** Flood-influencing factors: (a) rainfall, (b) flow accumulation, (c) flow distance, (d) land use/land cover, (e) flow distance, (f) slope, (g) hillshading, (h) SPI, (i) TWI, (j) aspect, and (k) elevation

### **5.3.2. Machine learning**

ML algorithms, namely, the RF, LightGBM, and CatBoost algorithms, were employed. The accuracy of the final results of the ML models was assessed by considering different statistical measures, including the most dominant factor, the area under the curve (AUC). The final flood susceptibility maps developed by the ML models were compared with the flood inundation maps obtained from the physical hydrological model. In this study, we used three ML Algorithms: 1) CatBoost: An algorithm proposed by (Dorogush et al., 2018), which uses gradient boosting for regression trees and builds a model in a gradient manner through increasingly precise approximations. 2) LightGBM: A variant of the gradient boosting decision tree (GBDT) algorithm developed by Microsoft (Ke et al., 2017). The structure of this algorithm is based on weak learners being combined to form a strong learner. 3) RF: A ML algorithm that belongs to the category of ensemble learning methods. The algorithm of RF was introduced by (Breiman, 2001) based on binary decision trees as a combination of the random subspace method and bagging ensemble learning. More details can be found in (Saber et al., 2021).

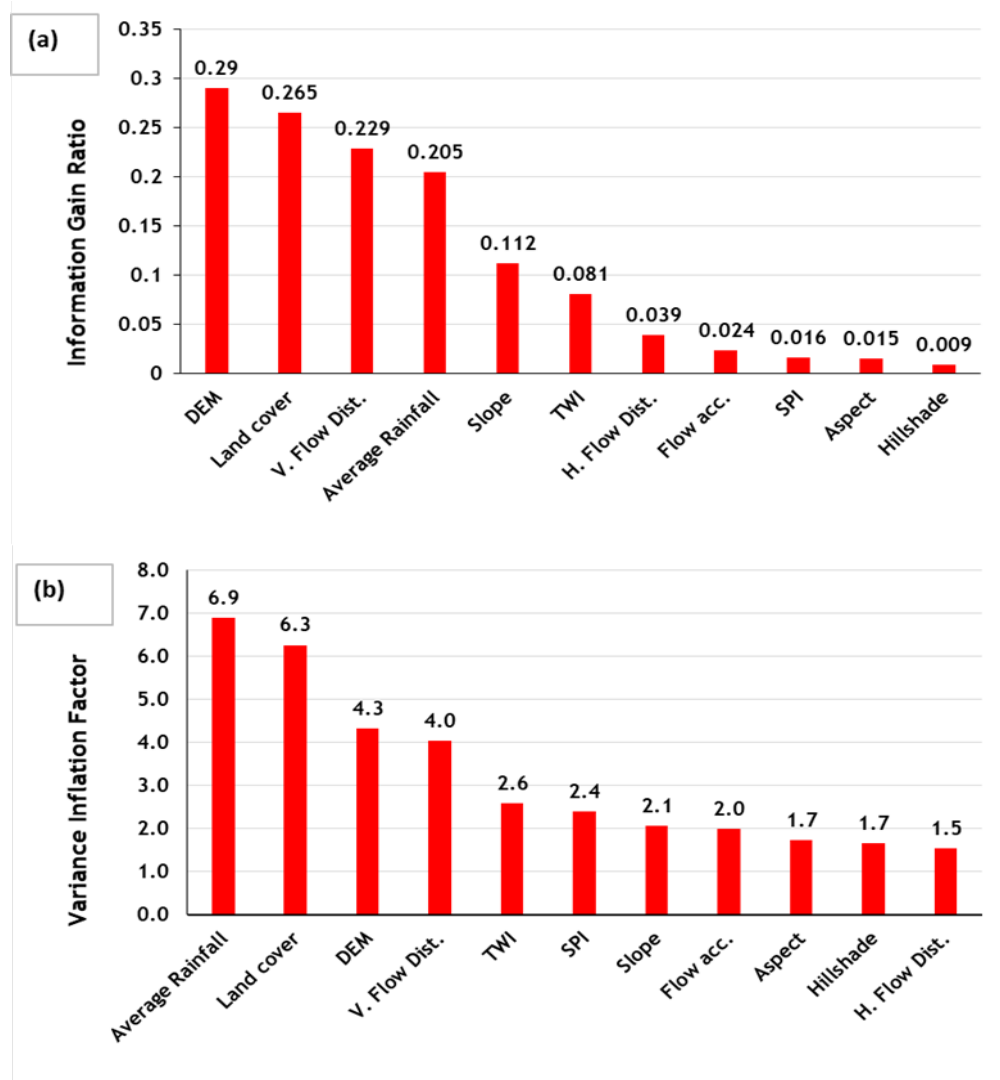
### **5.3.3. Multicollinearity assessment and feature selection**

Spearman's coefficient correlations between two features were calculated, and multicollinearity was tested among all influencing factors studied here. This research used the variance inflation factor (VIF) methods to conduct a multicollinearity analysis, which measures the behavior of variance against the correlation with other independent variables and provides a measure of how much a variable is contributing to the standard error in the regression. The purpose of which was to identify pre-existing relationships between variables. Research of a community's susceptibility to flooding frequently includes this factor (Bui et al., 2019), and a threshold  $> 5$  denotes multicollinearity. However, in other research, the relevant predictors are deemed collinear if the VIF value is more than ten and are therefore advised to be left out of the models (Dou et al., 2019). This value was adopted

in this study to detect the existence of correlations between the flood-influencing factors identified as being mutually correlated (Table 5.1). The influencing features show information gain ratio (IGR) scores greater than zero, which indicates their relative importance in flood prediction. The IGR was computed and is illustrated in (Figure 5.3a). The influencing features show IGR scores greater than zero, which indicates their relative importance in flood prediction. Also, the VIF values for the average rainfall (= 6.90) and LCLU (= 6.26) factors were greater than the threshold value ( $> 5$ ), indicating a multicollinearity problem (Figure 5.3b). Based on these feature selections, from among 11 factors, only nine features were selected as shown in Table 5.1.

**Table 5.1** Spearman's correlation coefficients for FFS mapping: Topographic wetness index (TWI), standardized precipitation index (SPI), slope, land cover, hillshade, vertical distance to rivers (V flow dist), horizontal distance to rivers (H flow dist), flow accumulation (Flow acc.), digital elevation model (DEM), average rainfall, aspect

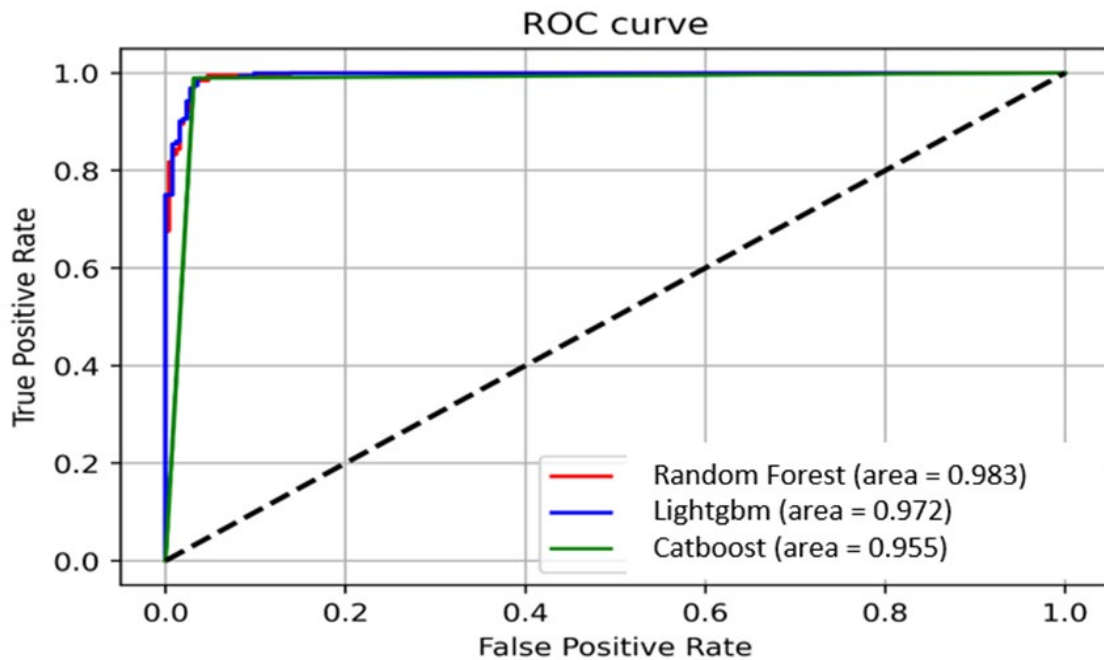
|            | TWI   | SPI   | Slope | Landcover | Hillshade | Vflowdist | Hflowdist | Flowacc | DEM  | AverageRai | Aspect |
|------------|-------|-------|-------|-----------|-----------|-----------|-----------|---------|------|------------|--------|
| TWI        | 1.00  |       |       |           |           |           |           |         |      |            |        |
| SPI        | 0.32  | 1.00  |       |           |           |           |           |         |      |            |        |
| Slope      | -0.59 | -0.05 | 1.00  |           |           |           |           |         |      |            |        |
| Landcover  | 0.32  | 0.07  | -0.50 | 1.00      |           |           |           |         |      |            |        |
| Hillshade  | 0.10  | 0.00  | 0.14  | -0.12     | 1.00      |           |           |         |      |            |        |
| Vflowdist  | -0.48 | -0.10 | 0.57  | -0.55     | 0.11      | 1.00      |           |         |      |            |        |
| Hflowdist  | -0.26 | -0.11 | 0.20  | -0.20     | 0.01      | 0.53      | 1.00      |         |      |            |        |
| Flowacc    | 0.33  | 0.64  | -0.07 | 0.01      | 0.05      | -0.07     | -0.09     | 1.00    |      |            |        |
| DEM        | -0.46 | -0.08 | 0.57  | -0.67     | 0.15      | 0.82      | 0.39      | -0.04   | 1.00 |            |        |
| AverageRai | -0.13 | -0.06 | 0.18  | -0.34     | 0.18      | 0.14      | 0.00      | -0.01   | 0.45 | 1.00       |        |
| Aspect     | -0.35 | -0.03 | 0.32  | -0.17     | 0.39      | 0.23      | 0.14      | -0.09   | 0.18 | 0.08       | 1.00   |



**Figure 5.3** Analyses of influencing factors: (a) information gain ratio (IGR) and (b) variance inflation factor (VIF) flood susceptibility results: Digital elevation model (DEM), land cover, vertical distance to rivers (V. Flow Dist.), average rainfall, slope, topographic wetness index (TWI), horizontal distance to rivers (H. Flow Dist.), flow accumulation (Flow acc.), standardized precipitation index (SPI), aspect, hillshade

### 5.3.4. Evaluation of the models

The receiver operating characteristic (ROC) curve measure is a commonly used and validated strategy for assessing the reliability of a model in geospatial research. Therefore, the AUC-ROC parameter and other quantitative metrics (accuracy, recall, precision, and the F1-score) were employed to check the model performance and compare its classification ability with the abilities of other models. Table 5.2 shows the details of statistical measures of model performance. All category techniques resulted in roughly the same outcomes in terms of statistical indicators. According to the AUC-ROC results, the random forest algorithm outperformed the other models (Figure 5.4). Still, the other two models (CatBoost and LightGBM) showed higher accuracy and precision values than the RF (Table 5.2).



**Figure 5.4** Performance of the Random Forest, CatBoost, and LightGBM models based on the areas under the receiver operating characteristic (ROC) curves

**Table 5.2** Statistical measures used for the model performance evaluation: Accuracy (ratio of accurately classified observations to the total number of observations), precision (ratio of accurately classified positive observations to the total number of classified positive observations), recall (ratio of accurately classified positive observations to the total number of observations), the F1-Score (precision and recall with a weighted average) and AUC (prediction accuracy of the examined models)

| Criteria  | Random Forest | LightGBM | CatBoost |
|-----------|---------------|----------|----------|
| Accuracy  | 0.932         | 0.938    | 0.955    |
| Precision | 0.894         | 0.903    | 0.933    |
| Recall    | 0.977         | 0.977    | 0.977    |
| F1_score  | 0.933         | 0.939    | 0.955    |
| AUC       | 0.983         | 0.972    | 0.955    |

### 5.3.5. Personal Computer Storm Water Management Model (PCSWMM)

PCSWMM is a software tool for the simulation and analysis of urban stormwater systems, and it was developed by Computational Hydraulics International (CHI) (*Computational Hydraulics International (CHI)*, n.d.). The model requires input datasets as follows: 1) The DEM was acquired from the Shuttle Radar Topography Mission (SRTM) satellite data at a resolution of 30m. 2) Rainfall data was generated from the PERSIANN rainfall satellite data (Center for Hydrometeorology and Remote Sensing, 2017). 3) The land use was divided into two types namely Urban and Desert based on Google Earth data. The catchment model was run to estimate the event that occurred on November 25, 2009 in Jeddah city, a devastating flood event with a total daily rainfall rate exceeding 85 mm within four hours. The 2D cells were generated based on the attributes of the bounding polygon. The model was calibrated based on the flood depth data collected from the post-flood survey of the storm event of 2009.

## **5.4. RESULTS**

### **5.4.1. Machine learning**

The assessment system of measurement of the newly assessed algorithms (CatBoost, LightGBM, and RF) validated their high overall performances when predicting flooding in an arid environment. Accordingly, those techniques were employed to estimate flood susceptibility maps for Wadi Qows. Several statistical indices (Accuracy, Precision, Recall, F1\_score, and AUC) were used to evaluate the ML algorithms. From the results, the highest AUC was obtained by the RF model (98.3%). AUC was 97.2% and 95.5% for LightGBM and CatBoost, respectively. However, CatBoost displayed the best accuracy and precise classification performance, with an accuracy = 95.5% and precision = 93.3%, followed by the LightGBM model, with an accuracy = 93.8% and precision = 90.3%, and finally the RF model with an accuracy = 93.2% and precision = 89.4%. In comparison with previous studies (Saber *et al.*, 2021), the AUC for RF indicated higher accuracy, however, LightGBM and Catboost had lower accuracy.

### **5.4.2. PCSWMM**

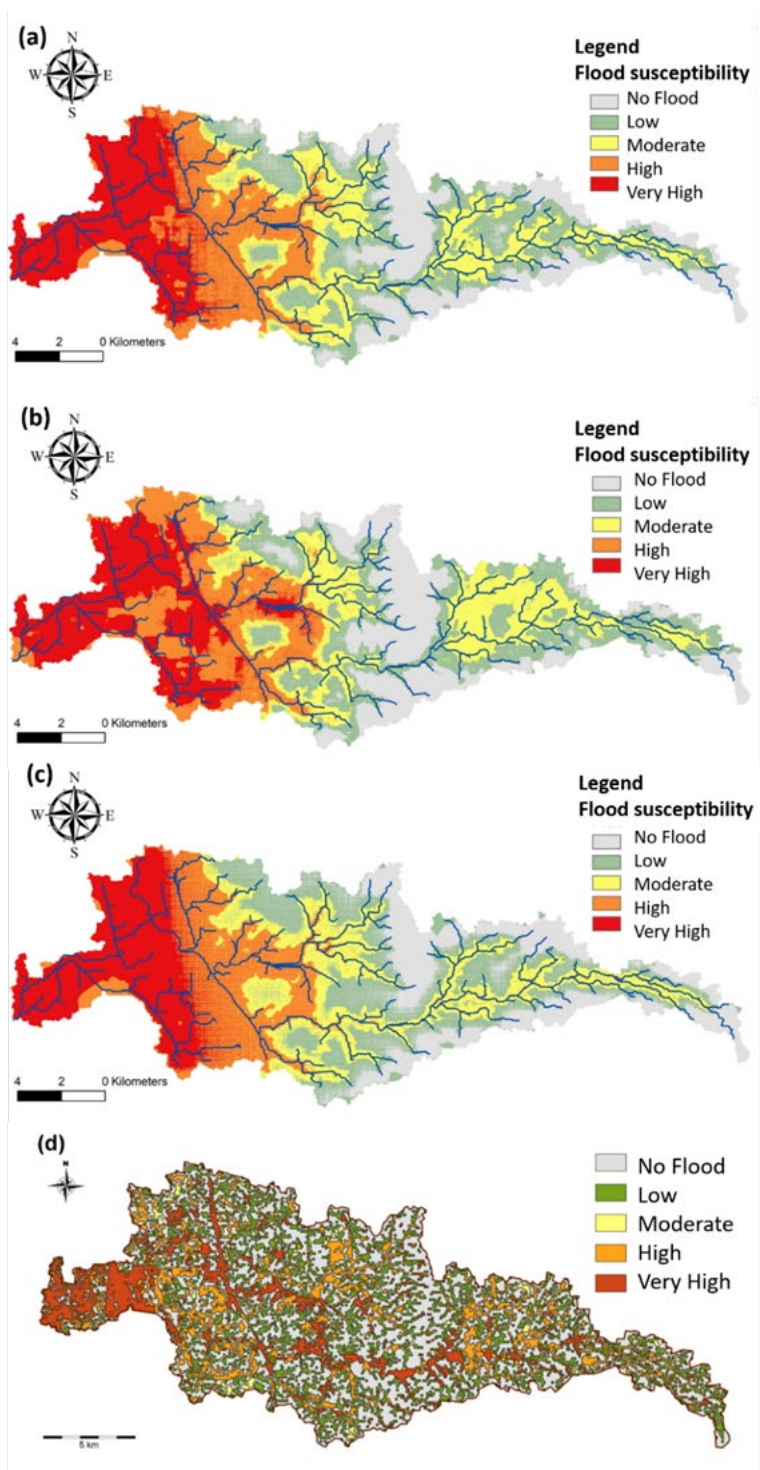
The model has been calibrated based on the observed data obtained from the field survey in the 2009 event. The model accuracy based on the comparison with the flood depth was about 80%. The most influential parameters were Manning's roughness coefficients with a range from 0.015-0.04, and soil porosity with a range from 0.05-0.6. The PCSWMM model analysis revealed that the areas with high impervious surface coverage were more prone to flooding and runoff issues, highlighting the importance of implementing effective stormwater management strategies in urbanized areas to mitigate the negative impacts of urbanization on the hydrological cycle.

### **5.4.3. Flood susceptibility mapping**

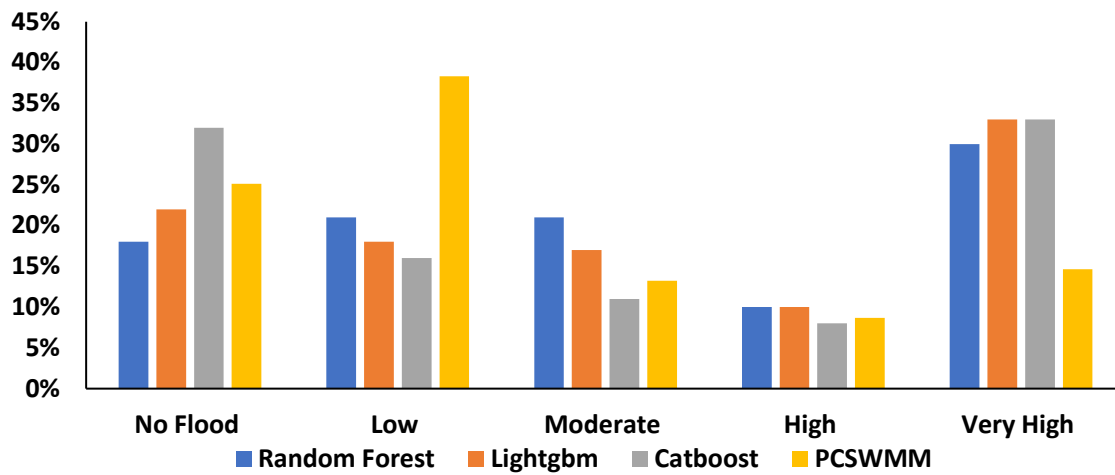
The three FFSMs developed using the ML models were compared with the flood

inundation map obtained with the PCSWMM, as shown in Figure 5.5. The FFSMs developed by the ML methods show reasonable spatial distributions. They agree somehow in the flood extent with the actual situation in the case of the flood of 2009 in Jeddah city, revealing that the adopted ML approaches are efficiently applicable for FFSMs in arid regions. The FFSMs were classified from low to very high levels of susceptibility. Most downstream areas dominated by high populations are affected mainly by high and very high flood levels, as shown in Figure 5.5. Figures 5.5 and 5.6 indicate that the FFSMs developed by these three models are comparable with the PCSWMM results in terms of flood extension. Nevertheless, other flood levels, such as the estimated areas of high and extremely high flood risk zones, comprise 40% (RF), 43% (CatBoost), and 41% (LightGBM) of the study area. Generally, the results show acceptable agreement between the two approaches in the spatial extent of the flooding area.

The hydrological model used in this study (PCSWMM) can simulate a flood inundation map (depth and extent). This depth and extent are based on the input storm which varies from one event to another. Also, ML can give the probability of flood occurrence as an extent (flood susceptibility). Due to the limited observational data, we attempt to develop a ML model to predict flood susceptibility in the region. Additionally, we implement a physical model to explain somehow the efficiency of the ML model by comparing the flood inundation extent with the flood susceptibility. Therefore, we compare the extent of the flood event of 2009 with the existing flood susceptibility map that shows that somehow ML is reliable in this application. However, the flood inundation map developed by physical model can be variable if we change the input storm. Therefore, currently, we are working on two issues; the first one, using ML to develop flood depth prediction which allows us to directly compare with the flood inundation map developed by the physical model, and the second one, to develop a hybrid model of both ML and physical models to accurately predict the flood depth and susceptibility in such data-scarce regions.



**Figure 5.5** Flood susceptibility maps produced by the LightGBM (a), Random Forest (b), CatBoost (c), and PCSWMM (d) analyses



**Figure 5.6** Affected flood susceptibility areas obtained with three ML methods and the flood inundation map of the PCSWMM model

## 5.5. CONCLUSION

This research demonstrates the feasibility of using ML algorithms (RF, LightGBM, and CatBoost) for evaluating FFSMs in dry environments. The FFSMs developed by the machine learning model show an acceptable consistency with the FFSM by PCSWMM from the aspect of their spatial distributions. The area under the ROC is greater than 97%, revealing that the applied approaches can reliably forecast flood zones. According to the FFSM, the densely populated coastal region is among the most vulnerable to floods, placing it in the highest risk category. However, one of the crucial limitations of this study is the lack of data which leads to uncertainty in both hydrological and machine learning models. The availability of high-quality data is often a challenge, especially in regions with limited monitoring stations or in areas with a lack of historical flood records such as Saudi Arabia. Therefore, addressing the data limitation issue is crucial to improve the accuracy and reliability of these models and to support effective decision-making in flood risk management. Such a limitation can be improved by developing a hybrid approach combining both physical-based models and machine learning algorithms to accurately

predict flood risk maps. A logical extension of this work is to develop such a hybrid model for flood depth prediction.



## CHAPTER 6

# Flood hazard assessment using RRI model over Saudi Arabia under different climatic scenarios of d4PDF

### 6.1. Introduction

Extreme rainfall events have been affected significantly by climate change in terms of frequency and intensity globally. In the Arab Gulf countries, UAE and Oman have experienced unusual and intense rainfall events and flooding in April 2024 leading to the destruction of infrastructure and loss of lives (*What Is Cloud Seeding and Did It Cause Dubai Flooding?*, 2024). The frequency of extreme flood events in the past few decades has increased in the Middle East region (Kantoush et al., 2022). Flash flood risk mitigation requires precise and accurate flood monitoring measures to support hazard management. This task is generally difficult and more challenging in the Middle East and North Africa (MENA) region than in other regions due to the lack of observational rainfall datasets, which can affect the accuracy of the results(Amouzay et al., 2023).

Saudi Arabia has experienced extreme rainfall events that can be linked to climate change, such as the major devastating Jeddah flood events in November 2009, December 2010, January 2011, November 2017, and November 2022(Almazroui, 2011b; Atif et al., 2020). Recently from 27 March to 5 April 2024, flash floods have occurred in many wadis in the western and southwestern regions, as well as in the capital city of Riyadh according to the report from the Ministry of Environment Water & Agriculture (2024). Moreover, the volume of water storage in dam lakes increased to the highest volume of water storage in dam lakes since 2010 reaching (829 million m<sup>3</sup>)(*The highest in (14) years*, n.d.). Although the region is predominantly known for its dry conditions, but recent years have seen unusual and severe rainfall incidents. Anomalous weather patterns, such as those influenced by the Indian Ocean Dipole or the El Niño-Southern Oscillation, can bring unexpected heavy rains to the Arabian Peninsula(Atif et al., 2020). Therefore, highlighting the increasing unpredictability of weather patterns has become even more alarming.

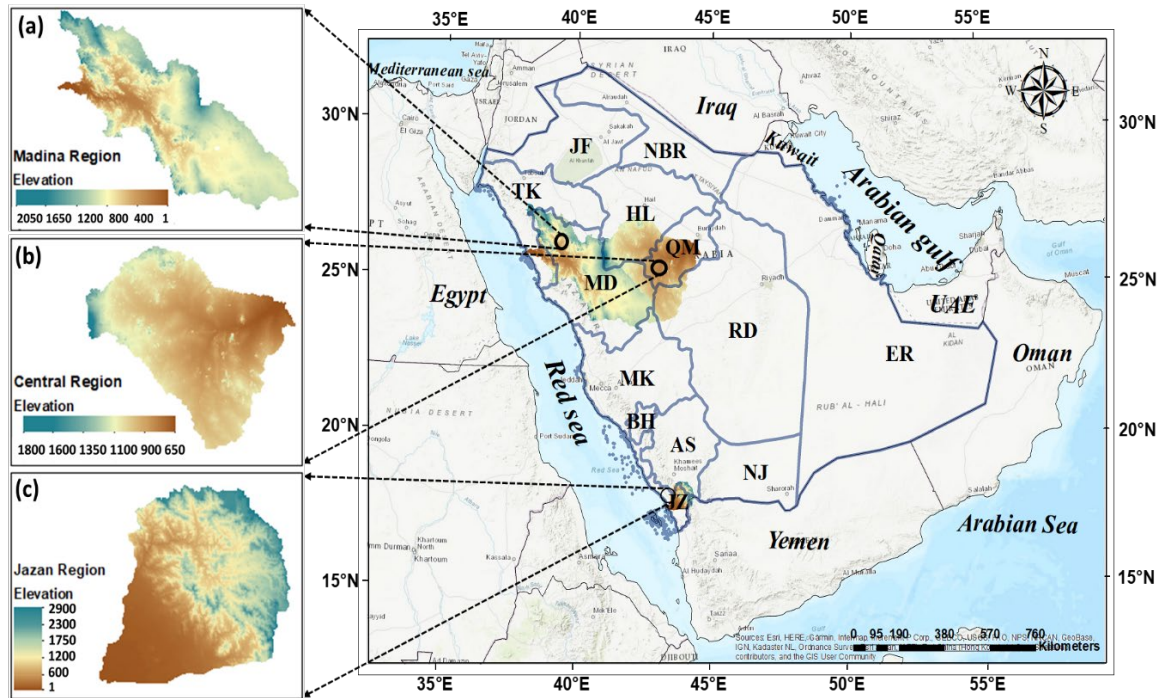
Numerous of studies have been applied in various regions over the world such as Oman, Sudan, and Vietnam, to develop flood hazard maps using RRI model(Abdel-Fattah et al., 2018; Abdelmoneim et al., 2023; Saber et al., 2023). However, there is no studies over KSA have considered the climate scenarios using the database for policy decision-making for future climate changes d4PDF. Despite, many researchers have assessed flood hazards in different regions of Saudi Arabia. For instance, Abdelkarim et al.(Abdelkarim et al., 2019) was applied remote sensing data, hydrologic modeling (water modeling system, WMS), and hydraulic modeling (Hydrologic Engineering Center River Analysis System, HEC-RAS) to determine the flood hazard that affects the sustainable urban development of Tabuk City based on their collected from 1998 to 2018.

The main objective of this study is assessing the flood hazard under different climate scenarios over several regions based on the 2D hydrologic Rainfall-Runoff-Inundation (RRI) model. The RRI model is widely used for real-time flood forecasting and issuing early warnings in different regions over the world (Abdelmoneim et al., 2023; Sayama et al.,

2012). The novelty of this research firstly is to develop flood hazard map for the whole Saudi Arabia. Secondly, is using d4PDF climatic data for the first time over MENA region. This approach not only enhances the understanding of flood risks but also contributes to the strategic planning for infrastructure resilience.

## **6.2. STUDY AREA**

Saudi Arabia is located in the southwest of Asia and is situated between 32° to 55° East in longitude and 15.5° to 32.5° North in latitude, and it is divided into 13 administrative regions: Al-Baha (BH), Al-Jouf (JF), the Northern Borders Region (NBR), Al-Riyadh (RD), the Eastern Region (ER), Makkah (MK), Al-Qassim (QM), Madinah (MD), Tabuk (TK), Jazan (JZ), Hail (HL), Asir (AS) and Najran (NJ). It has a desert climate with very low average annual rainfall. Excepting the southwestern region of Saudi Arabia, which receives an average of about 300 mm of precipitation annually. This region receives the highest amount of precipitation in the country and decreases significantly in the rest of the regions. Three regions have been selected as shown in Figure 6.1 to conduct historical and future flood data analysis due to the coastal areas are more urbanized and affected by flood historically.



**Figure 6.1** Locations of 13 administrative regions over Saudi Arabia, and three case study in, (a) Madinah, (b) central, and (C) Jazan regions.

### 6.3. DATA AND METHODOLOGY

#### (1) Rain gauges data

The gauged daily rainfall data for the period 2000–2019 were obtained for 233 stations located across Saudi Arabia from the Saudi Arabian Ministry of Environment, Water & Agriculture until (2019). The distribution of those rain gauges is more representative and reliable for extreme rainfall events in the spatial and temporal domain compared to most previous studies which used only 29 stations(Almazroui et al., 2022; Atif et al., 2020) to analyze data for the whole of Saudi Arabia. The monthly time series datasets were estimated from the daily timescale to be consisting with the other climatic datasets.

## **(2) d4PDF dataset**

The d4PDF dataset contributes to forecasting the future extreme rainfall trend(Ohba & Sugimoto, 2019). The d4PDF has been used in this study for present and future climate variables. It contains the results of 100 ensemble simulations for the past and future climates using a resolution global 60 km horizontal mesh(Mizuta et al., 2017). The d4PDF data (2K) from 2031 to 2050 and d4PDF data (4k) from 2051 to 2100 provide data on a wide range of climate variables and climate extremes, which involve running the climate model multiple times with slight variations.

## **(3) Extreme storm analysis**

In order to understand the extreme storm variability, the rainfall data have been divided to different thresholds ( $\geq 30$ ,  $\geq 40$ , and  $\geq 50$  mm/event). The changing of the average monthly rainfall data with different thresholds has been analyzed to determine the changes in the frequency and intensity of rainfall extremes in the spatial and temporal distribution. The analysis has been done for both historical (2000-2019) and future scenarios (2031-2100). Mann-Kendall test(Kendall, 1948; Mann, 1945) has been used in this study as non-parametric test for testing non-linear trend and turning point.

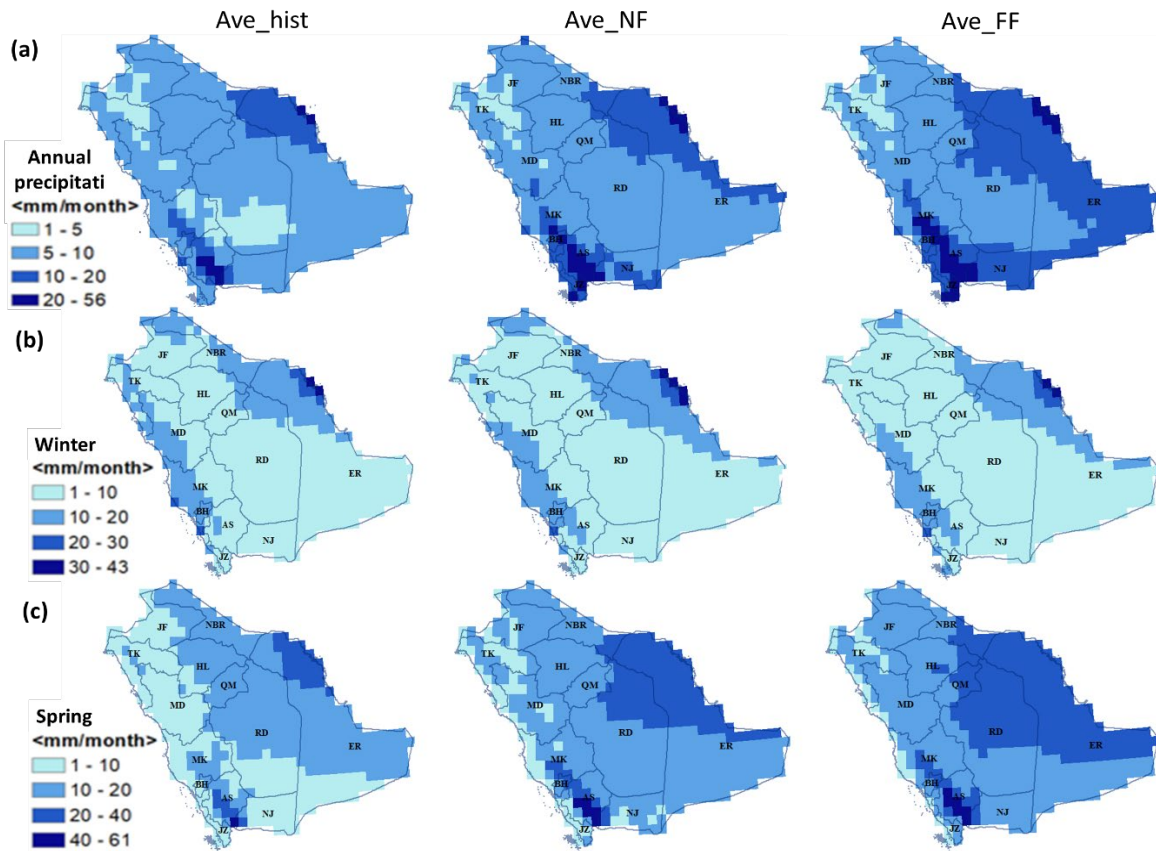
## **(4) Rainfall-Runoff modeling**

The Rainfall-Runoff-Inundation (RRI) model has been used to predict flash flood hazard maps over KSA using d4PDF climatic data. The RRI model is a 2D physical model capable of simulating rainfall-runoff and flood inundation. It is also useful for flood risk management and water resources planning(Sayama et al., 2012). The main inputs in RRI model are four layers. Three layers from MERIT 90m resolution: DEM, flow direction, and flow accumulation. Last layer is land use land cover used from USGS with 1 kilometer resolution. The RRI model was calibrated and validated at Wadi Qows basin in KSA using the flood inundation depth data of a flash flood event in 2009.

## **6.4. RESULTS AND DISCUSSION**

### **(1) The spatial distribution of long-term average rainfall**

In this section, the average rainfall was estimated over the whole country considering rainy season in both historical and future scenarios. The spatial maps show the average of monthly rainfall will increase spatially from historical rainfall data to the near future scenario as well as the obvious increase in the far future scenario. Moreover, the average of annual precipitation will increase in the southwest regions and eastern regions and ranges from 10 to 56 mm per month as shown in Figure 6.2 (a). The result is agreed with the finding of (Bahrawi et al., 2021) where Abha and Khamis Mushait cities located in AS province have the highest annual mean rainfall, and then Taif city. In the winter season, the average rainfall in the northern regions such as (MD, TK, JF, and NBR) will decrease in the future from 1 to 10 mm per month as shown in Figure 6.2 (b). In general, in Figure 6.2 (c), the aligns with findings by (Almazroui et al., 2022). Consequently, there is a notable high average rainfall dominates in coastal and interior regions during the spring season which variation in rainfall patterns spatially and temporally.



**Figure 6.2** Spatial distribution of the average rainfall d4PDF from 2000-2011 (hist), 2K-monthly average rainfall d4PDF from 2031-2050 near future (NF), and 4K-monthly average rainfall d4PDF from 2051-2100 far future (FF): (a) Annual precipitation, (b) Average rainfall in winter, (c) Average rainfall in spring.

In addition, the Mann-Kendal trends of annual rainfall with different thresholds have been analyzed in each station to detect trends in time series as shown in Figure 6.3 (a) for the period 2000–2011 for historical. It shows an increasing and decreasing trend which is more than 90% level of significance. There was increased rainfall trend in the region of AS in thresholds of 30, 40, and 50 mm/year. In contrast, there was decreasing rainfall trend in some part of ER region in thresholds 30 and 40 mm/year, and MK region in threshold 30 mm/year.

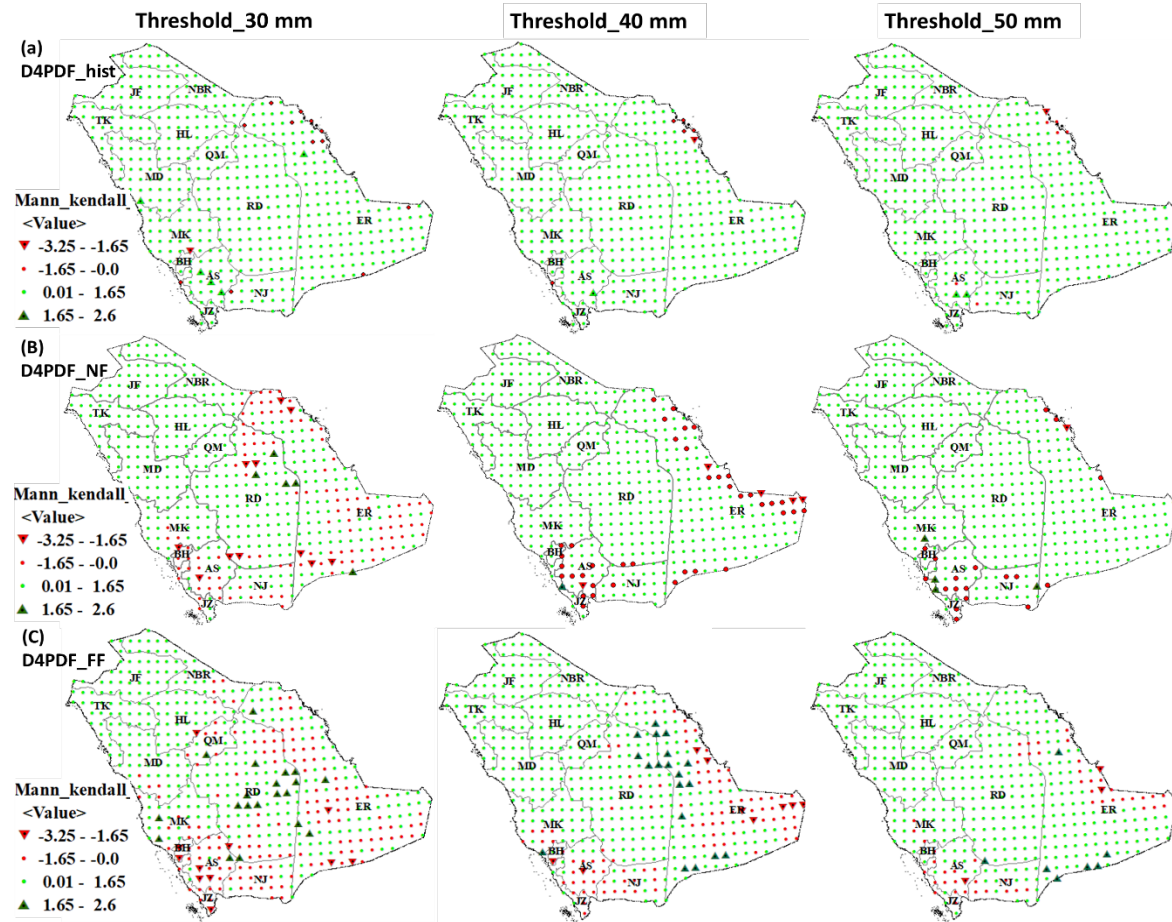


Fig.6.3 Mann-Kendall test (a) Historical d4PDF rainfall (hist) from 2000 to 2011. (b) Climatic data d4PDF near future (NF) from 2031 to 2050. (c) Climatic data d4PDF far future (FF) from 2051 to 2100. All panels are in different thresholds 30, 40, and 50 mm/year. The upward (green) and (red) triangles show increasing and decreasing significant trends.

The Mann-Kendall test for the extreme rainfall trend has been utilized as shown in Figure 6.3 (b) from 2031 to 2050 for a near future prediction scenario. The most extreme rainfall trend in high thresholds indicates to decreasing trend in the AS region, while some part of the RD region indicates to increasing trend. In addition, the Mann-Kendall test for the extreme rainfall trend from 2051 to 2100 has been applied as a far future prediction scenario. In Figure 6.3 (c) the trend has a decreasing in the AS region. However, the

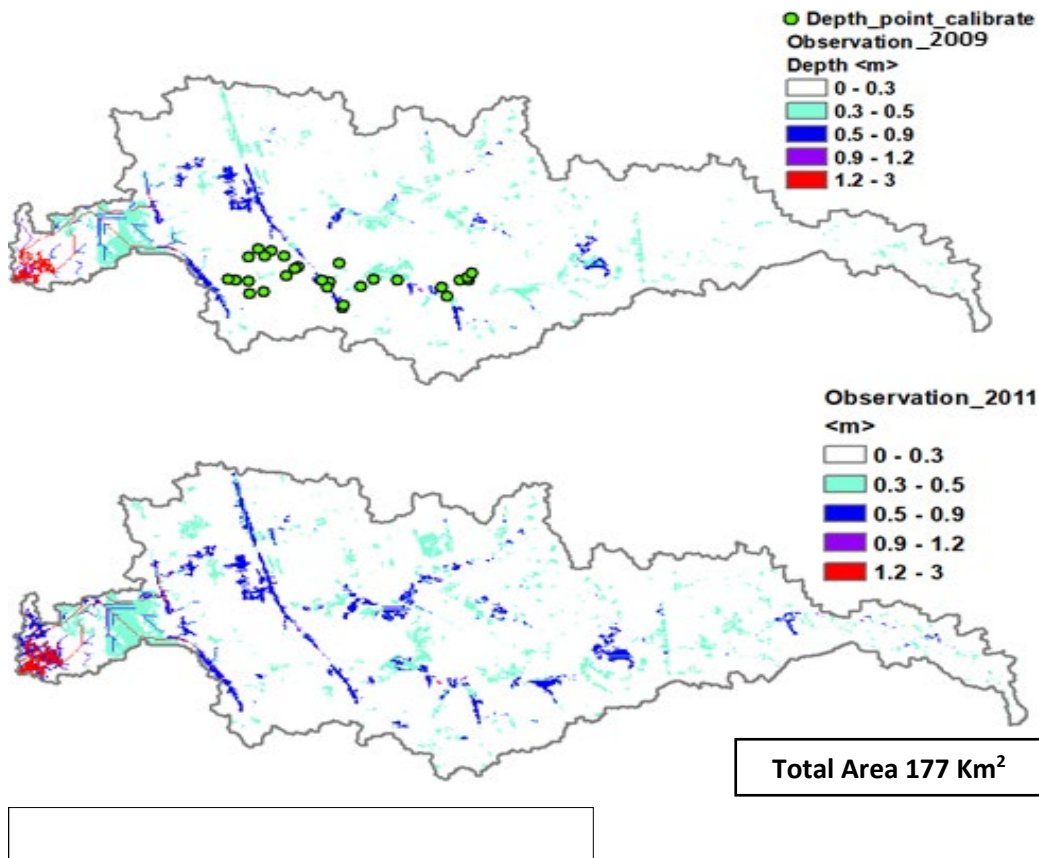
increasing trend will be more pronounced in the RD and ER regions. In general, the extreme events trend has been observed directly proportional to the rainfall intensity thresholds increasing in most of the regions over KSA except the AS region.

## (2) RRI Model Calibrations and Validation

In this section, the model has been calibrated and validated using two extreme floods of 2009 and 2011 respectively. The post flood survey of 28 flood depth points recorded in the 2009 event as shown in Table 6.1, has been used in this calibration and validation. Based on the post survey recorded in the 2009 event, the accuracy of the model show:  $R^2 = 0.85$ ,  $NSE = 0.72$ , and bias = -20%, which are acceptable to proceed with developing hazard maps. Furthermore, the 2011 rainfall event was used to confirm the accuracy of the calibration as shown in Figure 6.4.

**Table 6.1** simulated flood inundation depth and observed flood depth (Obs) based on the flood event in Wadi Qows 2009

|    | Simulate | Obs  |    | Simulate | Obs  |
|----|----------|------|----|----------|------|
| 1  | 0.83     | 0.70 | 15 | 1        | 1.00 |
| 2  | 0.62     | 0.40 | 16 | 0.69     | 1.00 |
| 3  | 0.17     | 0.10 | 17 | 0.63     | 0.50 |
| 4  | 0.08     | 0.10 | 18 | 0.6      | 0.78 |
| 5  | 0.17     | 0.20 | 19 | 0.59     | 0.78 |
| 6  | 0.21     | 0.20 | 20 | 0.15     | 0.10 |
| 7  | 0.17     | 0.10 | 21 | 0        | 0.00 |
| 8  | 1.1      | 2.00 | 22 | 0        | 0.00 |
| 9  | 0.67     | 1.30 | 23 | 0.09     | 0.00 |
| 10 | 0.75     | 1.00 | 24 | 0.41     | 0.50 |
| 11 | 0.7      | 1.00 | 25 | 0.28     | 0.30 |
| 12 | 0.84     | 1.30 | 26 | 1.33     | 2.00 |
| 13 | 0.61     | 0.56 | 27 | 0.3      | 0.20 |
| 14 | 0.52     | 1.00 | 28 | 0.31     | 0.20 |

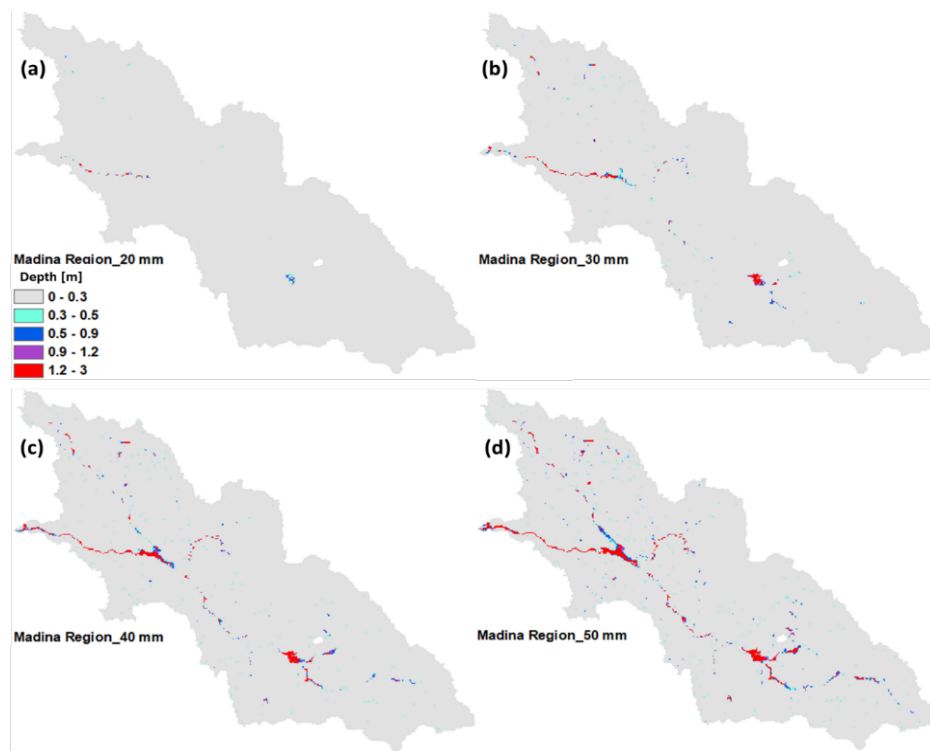


**Figure 6.4** Wadi Qows calibrated in the RRI model based on the flood depth data recorded in 2009 and 2011.

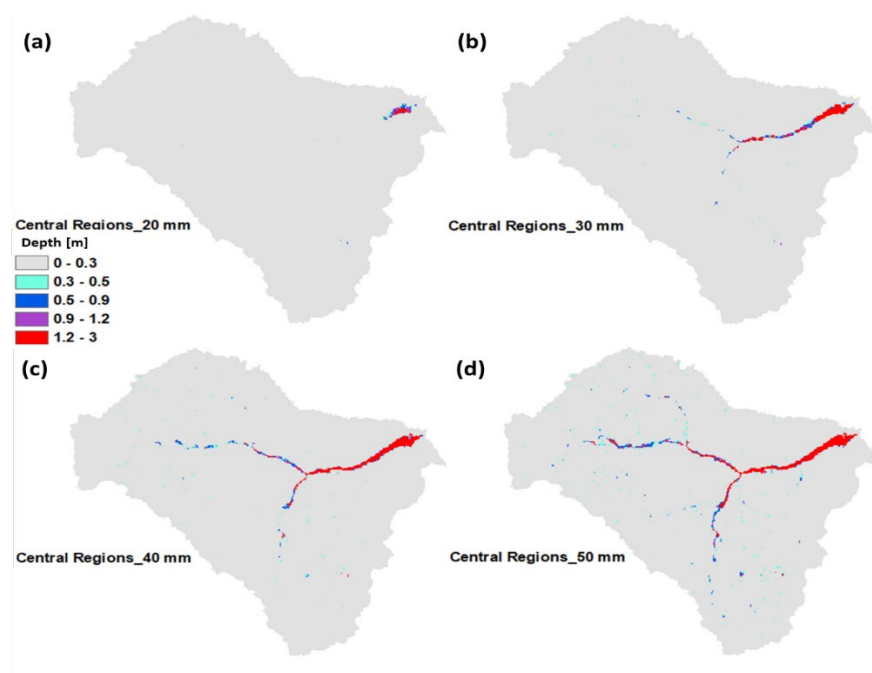
### (3) Hazard mapping over KSA

We have considered different scenarios including the extreme events represented by different thresholds ( $\geq 20$ ,  $\geq 30$ ,  $\geq 40$ , and  $\geq 50$  mm/event). Historical and future maximum events are applied to develop hazard mapping under different extreme conditions in three different regions of Saudi Arabia (Madinah, Central, and Jazan). The results of hazard maps at different basins show significant spatial variability from historical periods to future projections as shown in Figure 5, 6, and 7. For instance, both the Madinah and Central regions show not remarkable difference in the flood hazards in the future and historically. The maximum recorded rainfall in the Madinah and Central regions was 60 mm and 70 mm,

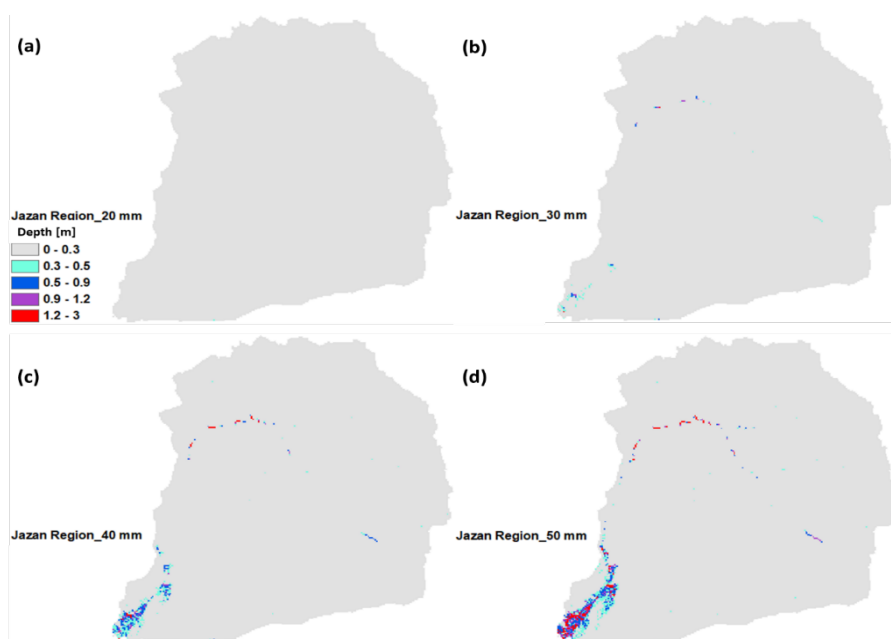
respectively, and based on the projected d4PDF future climate, the maximum was estimated about 50 mm and 55 mm, respectively. Figure 6.8 shows the historical hazard maps for (a) Madinah, (b) Central regions, and (c) Jazan. On the other hand, the Jazan region's maximum historical rainfall records was about 125 mm, while the maximum projected rainfall from d4PDF data is about 300 mm. Accordingly, the future hazard maps for this region shows an increasing the spatial hazard impacts, especially in the downstream areas as shown in Figure 6.8 (d). The developed hazard maps in KSA are highly variable based on the regions and these findings also agree or align with our rainfall pattern analysis in the previous sections. This study can be extended over the whole KSA with more detailed of spatial datasets to develop flood hazard maps for KSA historically and under future climatic scenarios.



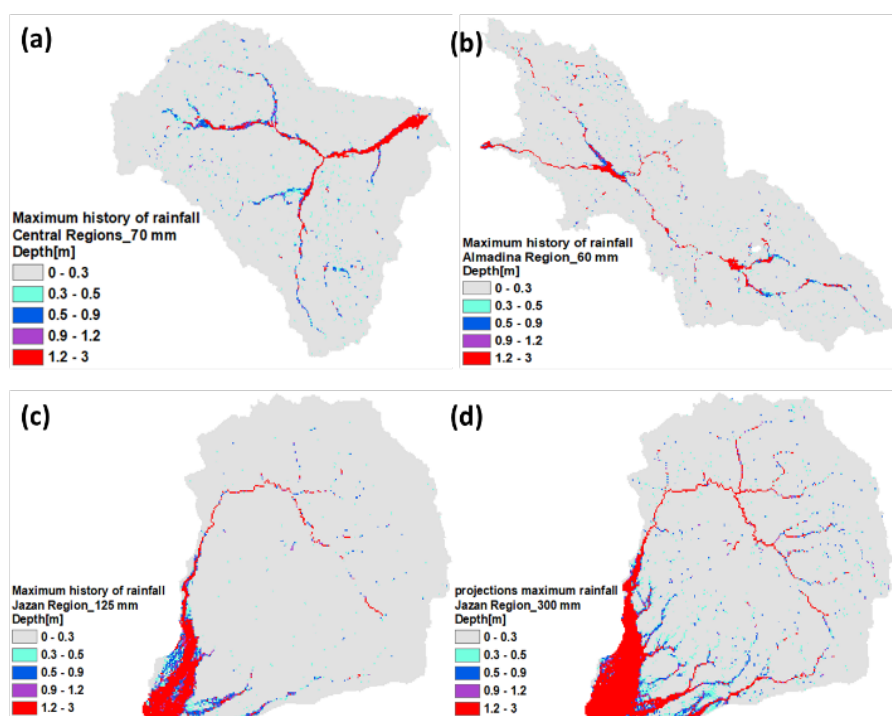
**Figure 6.5** Flood hazard map in Madinah region includes different thresholds 20, 30, 40, and 50 mm from a to d respectively.



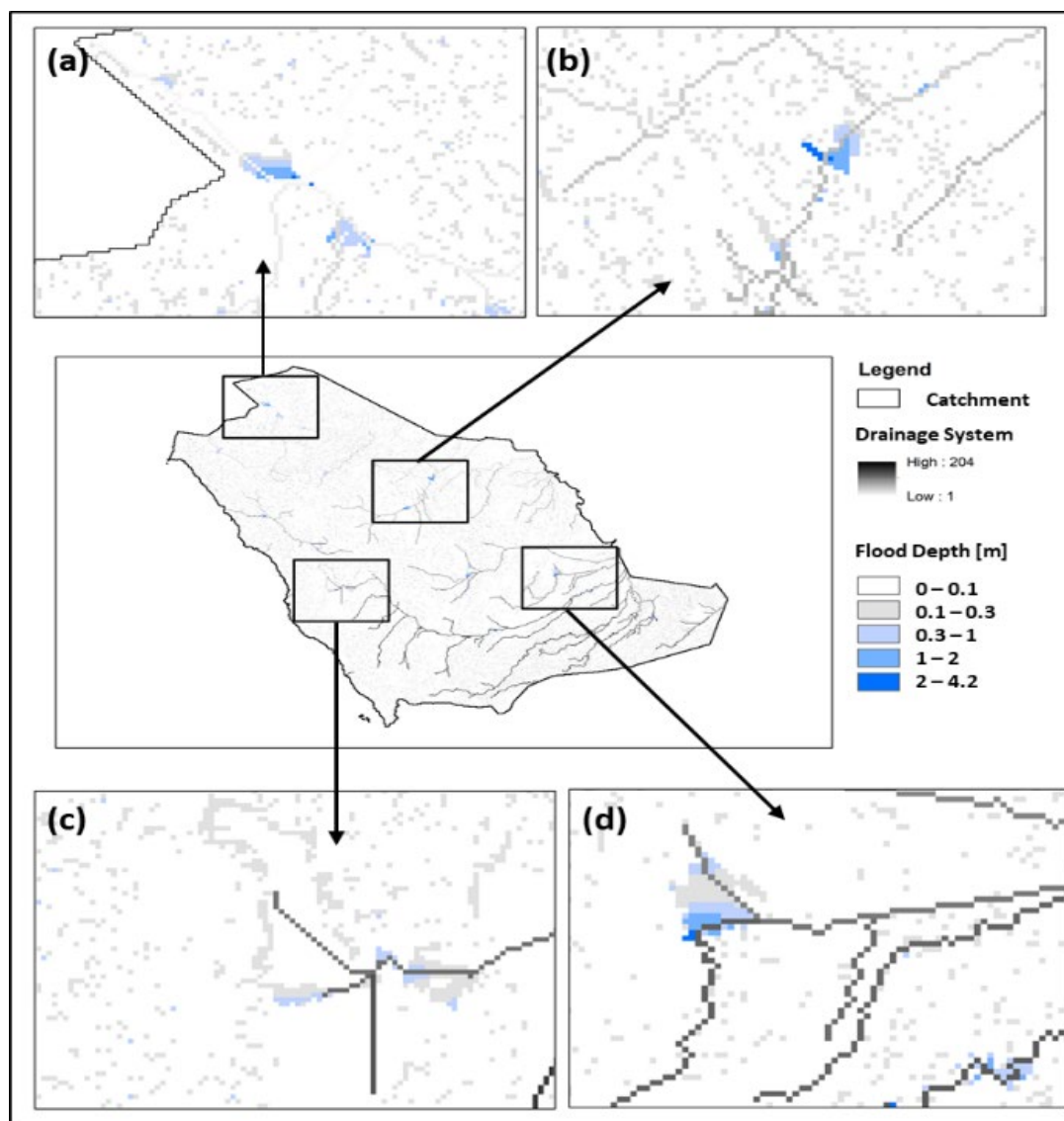
**Figure 6.6** Flood hazard map in central regions include different thresholds 20, 30, 40, and 50 mm from a to d respectively.



**Figure 6.7** Flood hazard map in Jazan region includes different thresholds 20, 30, 40, and 50 mm from a to d respectively.



**Figure 6.8** (a, b, and c) Flood hazard map using maximum historical daily rainfall in three regions: Central, Madinah, and Jazan respectively. (d) Predicting future hazard maps using d4PDF climatic data in Jazan region.



**Figure 6. 9** Flood hazard map over KSA using 30 mm threshold.

Additionally, the RRI Model was applied over the whole KSA to develop an flood hazard map of 3km spatial resolutions with threshold of 30 mm as shown in Figure 6.9. This can be used as guidance for flood hazard for the decision makers to implement their mitigation measures. The logical extent of this work is to consider more precise spatial resolutions and examine different future scenarios. In the future, we will consider more extreme scenarios and future projections.

### 6.5. Dam reservoir and water management

Saudi Arabia has made significant efforts to implement and establish mitigation measures and water management strategies to sustain water resources for population and residents. These efforts aim to protect important cities with high population densities from extreme floods, as illustrated in Figure 6.10. Currently, there are 563 dams in KSA serving various purposes where 283 are for groundwater recharge, 234 are control dams (detention dam), 45 are storage dams for drinking water, and 1 is protection dam. On the other hand, the types of dams include 279 earthen dams, 13 underground dams, 3 stone dams, 218 concrete dams, and 50 aggregate or cumulus dams, as shown in Table 6.2.

**Table 6.2** Number of dams for purposes and types across Saudi Arabia

| Types of dams | Earthen     | Concrete | Aggregate | Underground | Stone | Dams |
|---------------|-------------|----------|-----------|-------------|-------|------|
|               | 279         | 218      | 50        | 13          | 3     | 563  |
| Purposes      | Groundwater | Control  | Storage   | Protection  |       |      |
|               | 283         | 1        | 45        | 234         |       | 563  |

The distribution of dams is a highly variable based on the current conditions, for instant most of the dams protection are widely spread throughout KSA and concentration in coastal and central areas. However, one of important area doesn't have dams such as north part of Eastern regions as shown in figure 6.11. Storage dams are designed to capture and store surface water from seasonal rainfall throughout the year for various purposes including domestic consumption, agriculture, and industrial. The majority of storage dams are located in the southwestern part of the country. These areas benefit from natural topography and seasonal rainfall, which is become a suitable for the construction of storage dams. However, new storage dams are needed in light of projected climate change and increasing urban expansion and particularly in the eastern and southern regions of the country. Groundwater

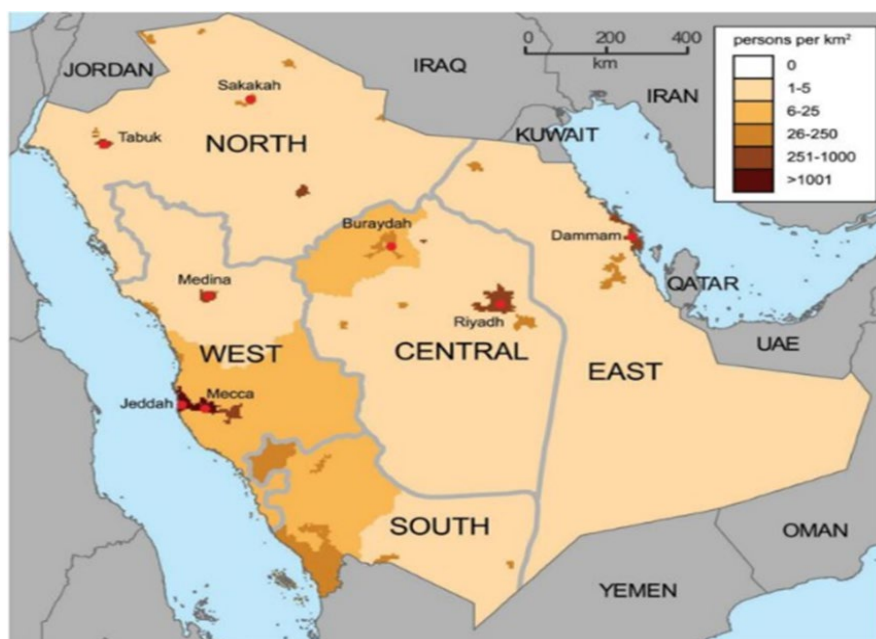
recharge dams are strategically located in regions with relatively higher rainfall to enhance aquifer recharge and help sustain groundwater levels. On the other hand, the concept of protection dams in Saudi Arabia focuses on mitigating the risks associated with flash floods and protecting communities, infrastructure, and agriculture from the impacts of extreme rainfall events. Due to infrequent flooding, the groundwater recharge becomes a crucial issue with very limited water resources and there are no surface water. This makes groundwater recharge the primary source of high-quality water and an essential method for water harvesting. The locations for protection dams are selected based on the current conditions such as historical flood data, topographical analysis, and hydrological modeling in urban areas. However, they are also crucial in rural areas where flash floods can devastate crops, livestock, and communities. Moreover, protection dams have recently begun to be implemented but are very limited. As shown in Table 6.2, there is currently only one Protection dam.

#### **6.5.1. Water management and flood protection Dams with extreme events in different thresholds**

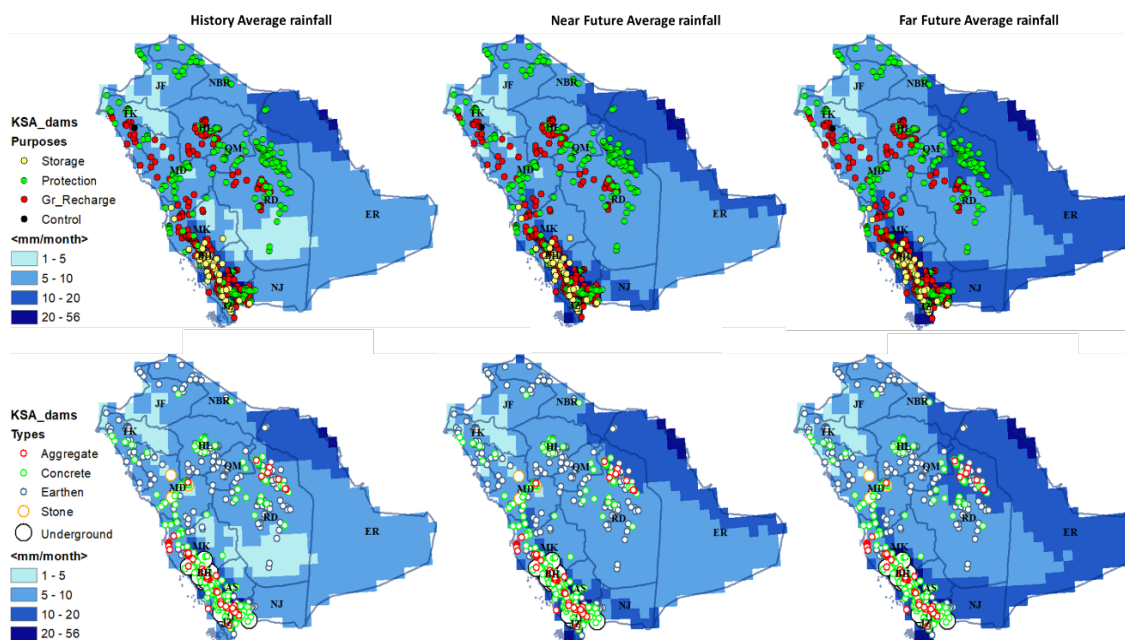
Water management and flood protection are critical issues in KSA due to limited water resources and susceptibility to flash floods. Dams play a crucial role in conserving water for controlling floods and ensuring stable water supplies for various sectors such as, agricultural, recharge groundwater, and drinking. In addition, it is essential to enhance resilience and adapt to the increasing variability in rainfall patterns due to climate change. The purposes of dams in KSA include groundwater recharge, flood control, water storage, and protection. Furthermore, there are various types of dams, such as earthen dams, underground dams, stone dams, concrete dams, and aggregate or cumulus dams. Based on the climatic rainfall analysis the average rainfall is expected to increase in the eastern and southwestern regions of Saudi Arabia as shown in Figure 6.11. However, some regions will increase the average rainfall but the rate of change is very low. Therefore, most of the dams are concentrated in

the southwest for various purposes such as groundwater recharge, flood protection, and drinking water storage but continues facing sedimentation issues as well. On the other hand, the eastern and southern regions have no sufficient dams to cover it. Primarily because these areas are largely desert. Therefore, we recommend proposing new dams in these regions for groundwater recharge and storage purposes. These areas are expected to become urban centers in the future and hold potential for agricultural activities. This presents a significant opportunity to transform them into water-rich and residential zones and making them ideal for groundwater storage. While the existing dam types are generally effective, there is a need to evaluate the earthen dam types in certain regions, particularly in Riyadh and Makkah under the climate change impact.

The distribution of dams based on purposes (storage, protection, groundwater recharge, and controlling) are very highly variable and classified. For instance, the central region such as Riyadh region there are protection dams more than groundwater recharge. Groundwater recharge is more available around the Red Sea coastal area and some of the dams located in the high intensity of population which is acceptable. However, RD and TK regions have both protection and groundwater recharge dams as well. On the other hand, regions such as the northern part of the ER and most of the NJ regions have almost no existing dams, despite the high population density in the northern part of the Eastern Region. Moreover, the expected rainfall projection will receive a huge rainfall amount in those regions. Therefore, the recommendation is to implement more storage, protection, and groundwater recharge dams. In addition, in the JF region there are only protection dams and have to be considered more groundwater recharge dams in the future. In terms of storage dams are concentrated and localized in the southwestern regions due to the majority of the total average rainfall occurring in this area. The storage and groundwater recharge dams are mainly for the water resource management.

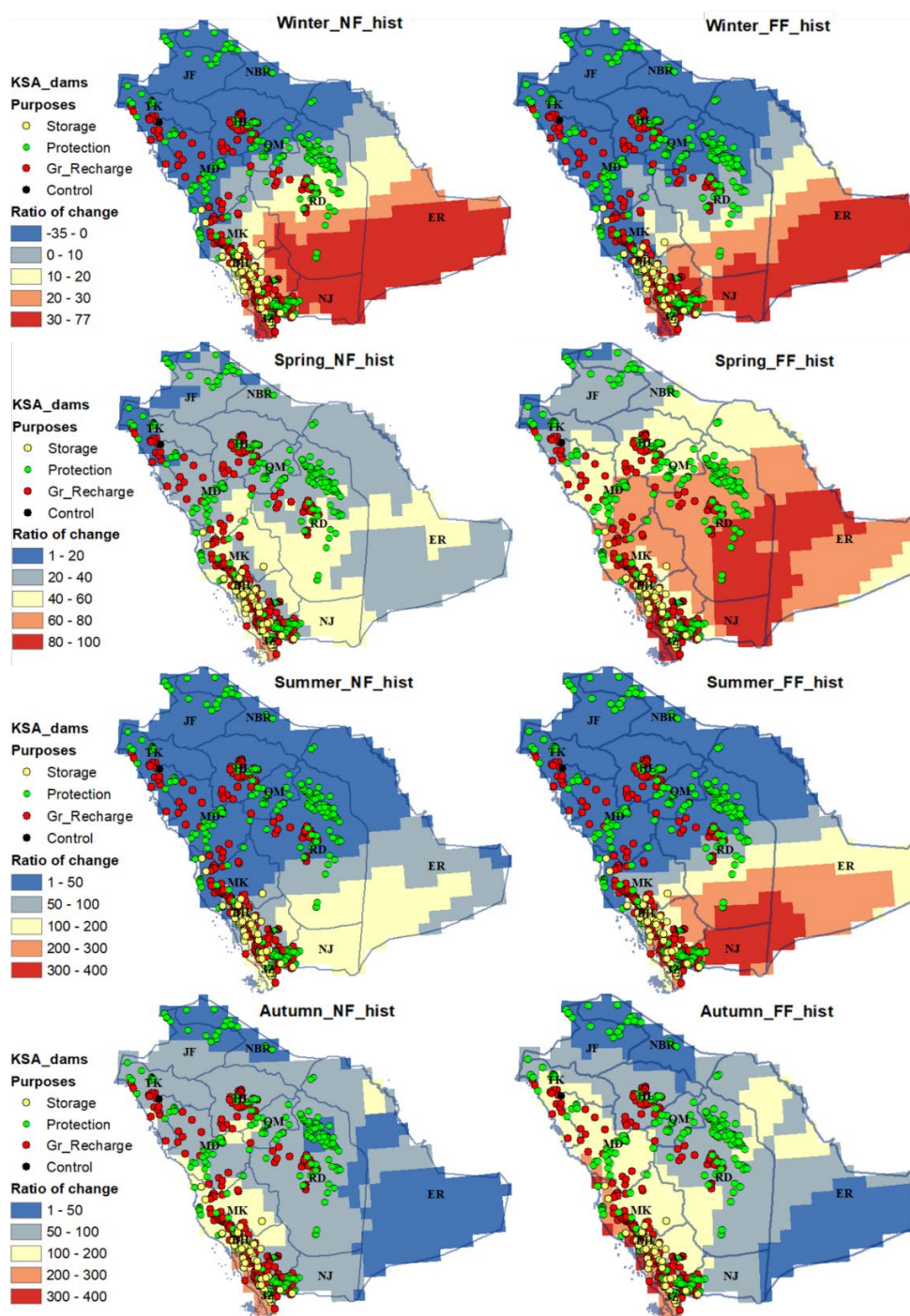


**Figure 6.10** Population density over Saudi Arabia and locations of some major cities (Messaoudi et al., 2021). Population density is indicated by shading as shown in the key, top right.



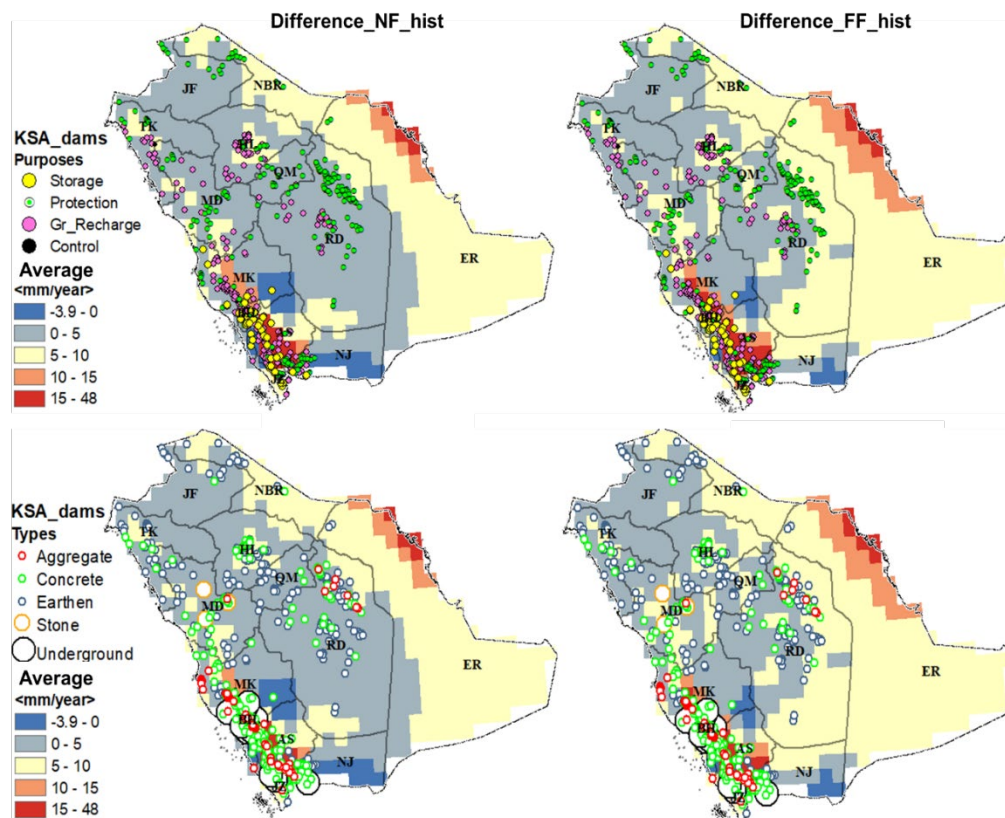
**Figure 6.11** The spatial distribution of the average rainfall (mm/month) from history and future average rainfall from (d4PDF) data, as well as the distribution of dam's types and purposes.

Accordingly, we recommend to increase the protection, groundwater recharge, and storage dams in the northern and eastern parts and NJ region for the water recourses and protection. While the southwest part in KSA has enough dams for both types of dams (water recourses and protection) based on figure 6.11. In terms of correlate the existing dams with the rate of change in the future conditions across Saudi Arabia throw different season. The effectiveness of existing dams will vary seasonally in both intensity and frequency under climate change impact. The rate of change from historical extreme rainfall to future projections has been assessed on a seasonal scale as shown in Figure 6.12. The results indicate a noticeable climate shift during the dry season which includes summer and autumn. The average rainfall will increase in most regions of KSA in autumn and south part in summer. In contrast, during the wet season which includes winter and spring the average rainfall is expected to slight increase. However, in the winter season rate of change in the future will decrease in north parts and start to increase gradually from center parts to southern parts. So, it would be better to consider more dams in central regions for the groundwater recharge and storage purposes as recommendation. While, in the spring season all regions are increasing with different rate but the highest rate of increasing based on far future projection are almost desert area and center part will increase as well. On the other hand, the remarkable increase will be in NJ region in the summer season with very height rate of change reach to 400 % although have very limited dams. Interestingly, NJ region will dramatically increase in the rate of change and due to height change the protection, groundwater recharge, and storage dams have to be consider in this area. While in the autumn season generally rainfall will increase over whole KSA, but the height increase in the rate of change will be notable in the coastal area such as MD, MK, BH, AS and ER regions. Therefore, better to increase more upstream dams of protection and groundwater recharge based on the future projection rainfall data. This can reveal that the climatic shifting of dry seasons towards wets seasons and wet seasons towards dry seasons is well observed. Therefore all dams over KSA have to reevaluate under climate change impact.



**Figure 6.12** Spatial and temporal distribution of climate shifting in over 13 administrative regions for all seasons (Winter Spring, Summer, Autumn) showing the ratio of change in rainfall from historical data to near-future climate (Left panel), and from historical data to far-future climate (right panel), as well as the distribution of dams purposes.

The analysis of the future climate impact in the water resources can give us as a good implication and indication that the existing dams distribution are not enough in some area is acceptable but other area is not enough in terms of water recharging. For instant, the groundwater recharge are morally concentrated in southwest part but other are expected to receive more rainfall in the future such as north area in ER region as shown in Figure 6.13. Therefore, this area have to be consider in the future, especially it will increase population in the future as shown in the map of density Figure 6.10. We recommend to extend the style of implementation of dams such as storage and underground dams in southwest part to other area such as north ER region which has a possibility to increasing rainfall and expectation for increasing of the population in the future.

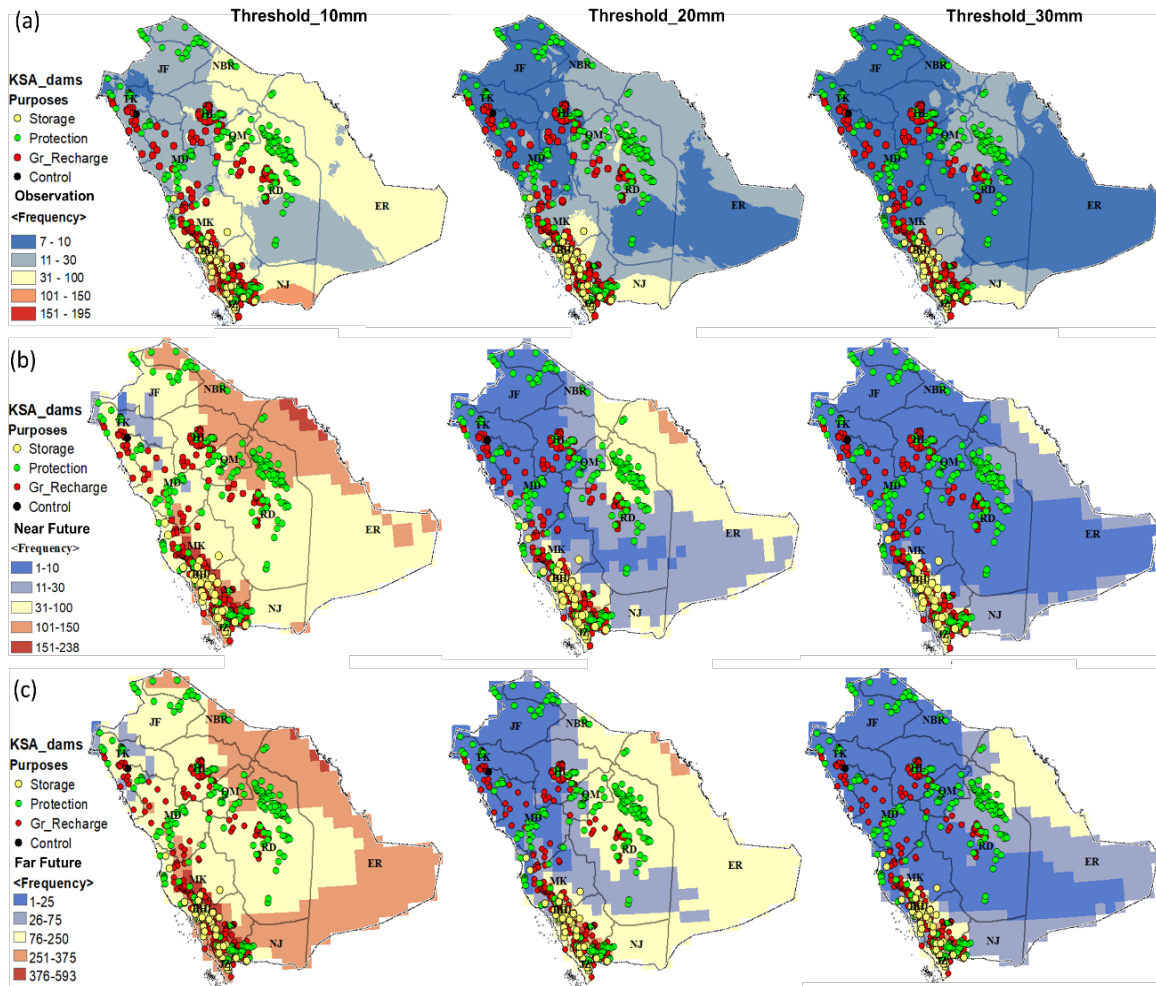


**Figure 6.13** The spatial distribution differences in average rainfall between Near Future (NF) and Far Future (FF) scenarios compared with historical rainfall averages, as well as the distribution of dams types and purposes.

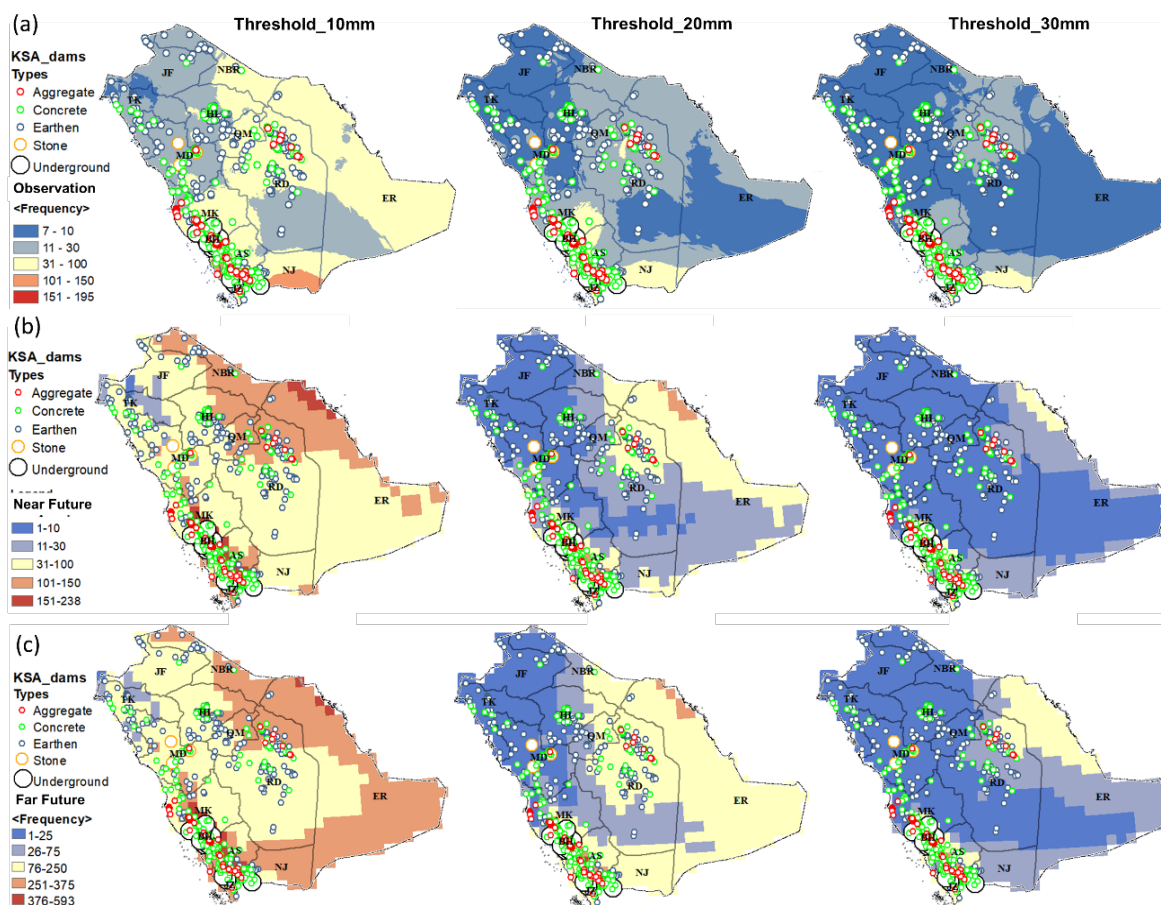
### **6.5.2. Disaster risk management**

Flood disaster risk management in KSA become critical with challenges related to urbanization, climate change, and extreme events. Despite the arid environment of KSA but is prone to flash floods, especially in urban area. Effective flood disaster risk management involves a comprehensive approach such as, early warning systems, infrastructure development, and community preparedness. The existing disaster risk management maps involves dams purposes and types which have been correlate with extreme event frequency maps in different thresholds and hazard maps as well as shown in Figures 6.14 to 6.16.

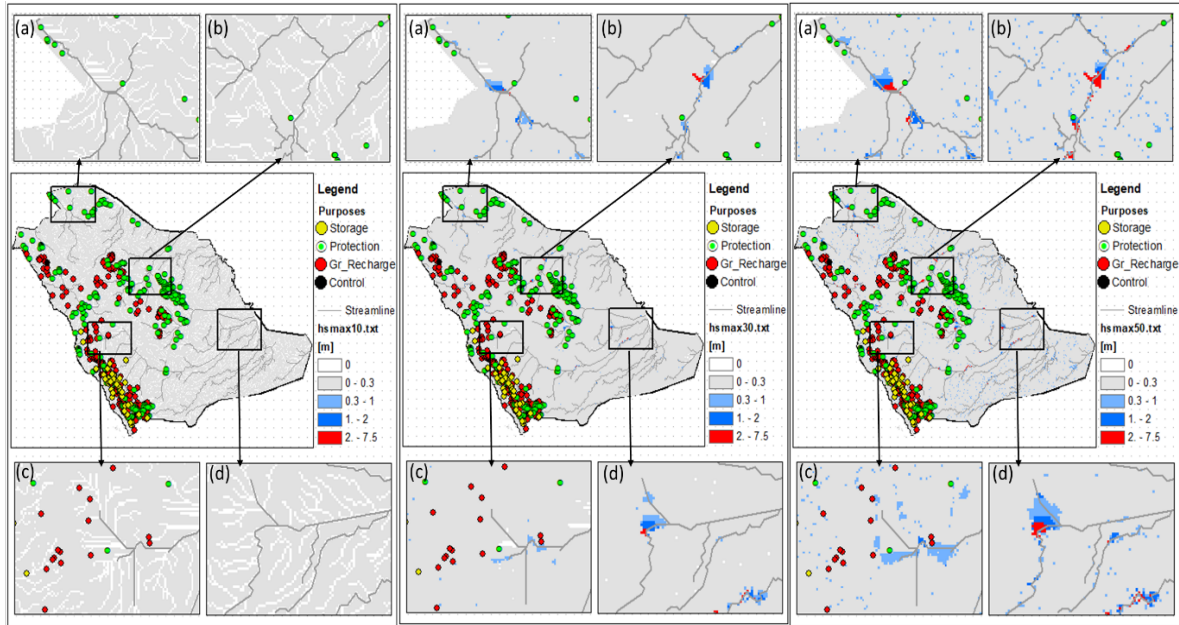
Protection dams are mainly located in the central and coastal Red Sea. Most of Saudi Arabia lacks sufficient protection dams which is a significant weakness, especially in regions such as JF and NBR, while other areas, such as north ER and most of NJ regions have no dams. Furthermore, in the NJ region, the thresholds of 10, 20, and 30 mm indicate an expected increase in flood frequency from 30 to 150 times under current and future conditions which is highlighting another vulnerability due to very limited protection dams. A similar situation exists in the northern part of the ER region, which has recently experienced a high population density without any protection dams. Additionally, the area between the MK and RD regions lacks any dams, despite an expected increase in rainfall frequency, as shown in Figure 6.15.



**Figure 6.14** Frequency distribution of extreme rainfall for thresholds: 10, 20, 30 mm over KSA in monthly scale from observation data during 2000-2019 and from d4PDF data near future during 2031-2051, and far future during 2051-2100, as well as the distribution of dams purposes.



**Figure 6.15** Frequency distribution of extreme rainfall for thresholds: 10, 20, 30 mm over KSA in monthly scale from observation data during 2000-2019 and from d4PDF data near future during 2031-2051, and far future during 2051-2100, as well as the distribution of dams types.



**Figure 6.16** Flood hazard map over KSA using thresholds: 10, 20, 30 mm, as well as the distribution of dams purposes.

Based on the hazard map in Figure 6.16 (a, b, and c), there are sufficient protection dams in areas due to height population density. Conversely, Figure 6.16 (d) indicates that this area lacks any protection dams, despite having a high possibility for flood risk. Therefore, the government must consider the impact of floods and conduct flood assessments, incorporating additional protection dams for any future urban development or oil and gas projects in this area.

## 6.6. Conclusion

In this study, flood hazard maps considering different scenarios of historical extreme events and climate change projections were devolved for several regions over KSA. In addition to spatial and temporal rainfall pattern analysis over the whole country. The results indicated that the hazard map of KSA are spatially highly variable and these findings align with the rainfall pattern analysis. This study offers a significant contribution to the field of

hydrological disaster risk assessment and management in Saudi Arabia. It proves the capability of the RRI Model to be applicable regionally. The correlation between the distribution of dams and the findings of this thesis along with future projections of changes in water averages and the frequency of extreme events, provides valuable insights for decision-makers. Interestingly, we found some areas have sufficient protection and mitigation measures such as southwestern regions and others have limited protection without adequate water management strategies particularly in the northern regions such as JF and TK. The southwestern areas, such as BH, AS, and JZ, have a sufficient number of dams. On the other hand, NJ area has a very limited dams infrastructure except small urban area. While the northern part of the ER region has lack of any dams infrastructure for storage, protection, or groundwater recharge. The northern ER region having a high population density of up to 1,000 people per square kilometer. The developed flood hazard map for the whole KSA is expected to be valuable and helpful for the decision-makers to implement and propose sustainable mitigation measures to cope with the impacts of extreme events which are expected to be more severe in the future. Therefore, we recommend that the government and decision-makers prioritize future planning for mitigation and dam construction. Our comprehensive analysis highlights the need for enhanced water management and flood protection measures in these vulnerable regions.



## CHAPTER 7

# Conclusion and Outlook

### 7.1. General conclusion

This chapter presents an overview of my thesis conclusion for the main findings and achievements with recommendations for future work prospective. The hydrological regime in arid regions is characterized by high variability of temporal and spatial rainfall distributions such as flash floods and high rates of change in rainfall from historical record to future projection. Efficient and sustainable water resources management should consider the extreme climate change adaptation and flood protection dams. However, the availability of high-quality data is often challenging due to limited reliable rainfall stations and lack of historical flood records in KSA.

Accordingly, the general conclusion of this study was to emphasize the importance of providing high-quality rainfall data and the impact of climate change in extreme events. This was achieved by evaluating the accuracy of satellite rainfall data as an alternative source based on available observational data. In addition, focusing on extreme rainfall analysis for both historical and future periods under climate change impact at different thresholds. Moreover, this approach highlights the importance of conducting a flood risk map to

enhance water resources management over KSA and implementing mitigation measures. These efforts are essential to support the achievement of KSA's Vision 2030.

## 7.2 In terms of objectives and findings

Precipitation estimation is very important in arid regions due to the lack of rainfall data and extremes events. In addition, it is essential to investigate the trend and frequency of extreme rainfall in historical data and future climate scenarios. Thereby, satellite-based data offer broader spatial coverage and fill the gaps in observational data to detect spatial and temporal changes in precipitation. Moreover, climatic data have been utilized to detect shifts in extreme events under future climatic scenarios.

Our achievements and findings in this section are the following:

- This study was undertaken to evaluate the performance of all satellite products and results show that JRA55 and PERS have a good correlation and bias at the annual scale, while TRMM & CHIRPS perform well at the seasonal scale. CDR, PDIR, PERS TRMM, and ERA5 demonstrate a good performance at the monthly scale in terms of bias.
- The investigation of annual rainfall trend has shown a decreasing trend such as MK region, while the frequency of extreme rainfall events has increased. Additionally, there is significant spatial variability in the trend over whole KSA, which explains the locality for flash flood extremes.
- I highlighted that climate shift direction has been found in the seasonal scale with extreme rainfall in the different thresholds, and result show the rainfall pattern shift from west to east in the southern regions in the winter, while movement from the

north to the south regions starting from the center part in summer. Climate shift indicates an easterly direction from the coastal Red Sea in the spring, while the drought area will be increase in the south part of country in autumn.

- The investigation of the frequency of extreme rainfall events has shown an increased in the future climate scenarios over most regions in KSA at 45% in the near future scenario and 61% in the far future scenario.
- The investigation of the average rainfall in all future climate scenarios in the wet season has shown a decrease in most regions in winter, while increased with a range of 20% to 100% especially in the far future scenario in spring.
- The investigation of the average rainfall in future climate scenarios in the dry season has shown an increasing average rainfall up to 300 percent in far future scenario and more pronounced in (Asir, Baha, Jazan, and Najran) regions in summer, while (Makkah, Baha, and Jazan) regions increasing from 100% to 150% in the near future scenario and (Tabuk, Madinah, Makkah, Baha, and Jazan) from 100% to 200% in far future in autumn.

Duo to the limitations in data, we develop flash flood susceptibility mapping in term of flood extension for Wadi Qows in KSA by using physical model and machine learning (ML) techniques. The PCSWMM physical model has been applied to demonstrate the efficiency of the ML by comparing them to the floodplain. The PCSWMM model was calibrated and validated by using hydrological components in the catchment area and flood depth points obtained from the field survey. While, eleven flood-controlling factors along with flood depth points were used in the ML algorithms and 70% of the data was allocated for training and 30% for testing the model's performance.

Our achievements and findings in this section are the following:

- This study was undertaken in the ML algorithm were predicted by the interrelations among eleven factors and 300 inundated sites in WADI Qows, and resulting from ML algorithms (RF, LightGBM, and CatBoost) could potentially be used to assess FFSMs in arid regions where the accuracy about 95%.
- This study's investigation has shown that in terms of the flood extent, both PCSWMM model and ML algorithms, are showing acceptable consistency in KSA.
- I highlighted that the FFSM results indicate that the highly populated coastal area is more prone to flooding than other areas and is classified under the high and very high susceptibility levels in our case study Jeddah city.
- I highlighted that flood susceptibility map provides a better understanding of which areas are most at risk for future flooding based on their inherent vulnerability.

Finally, the compatibility between dam locations along with spatial distribution of extreme rainfall frequency under climate change impact is important for decision-makers. Certain regions have adequate protection dams and mitigation measures, whereas others have limited protection dams that adversely impact water management strategies.

Our achievements and findings in this section are the following:

- The investigation into the rate of change from historical extreme rainfall to future projections during the wet season indicates a necessity for additional dams in central regions to enhance groundwater recharge and storage. The extreme rainfall is gradual increases from the central to the southern regions during winter. While

extreme rainfall is projected to increase in most regions of KSA and a significant increase is expected in the central and eastern regions.

- The investigation into the spatial distribution of dam locations have shown very limited dams in Najran region, with significant rate of change reaching 400 % in summer. While in the autumn season, a significant increase in extreme rainfall is expected in coastal areas such as Madinah, Makkah, Baha, Asir, and the Eastern Region. Constructing more upstream dams for protection and groundwater recharge is advisable based on future projected rainfall data.
- I highlighted that the northern part of the Eastern Region lacks any form of dam infrastructure for storage, protection, and groundwater recharge, despite having a high population density of 1,000 people per square kilometer.

### **7.3. Recommendation**

This study contains several issues that need to be addressed and require further investigation. It would be beneficial to assess water resources across KSA and identify reliable sources for rainfall data, where it's the only source of groundwater. Despite Saudi Arabia is classified as an arid region with low rainfall but still needs to identify potential areas for groundwater recharge and rainwater harvesting to enhance sustainable water resource management in the future under the impacts of climate change. Moreover, it is essential to identify potential areas at risk of flooding due to extreme events in both current and future climates and link with existing and projected dams.

It is recommended to utilize TRMM and CDR, which are the best satellites for representing flood depth and extent, as well as providing accurate satellite rainfall data based on bias corrections.

In addition, more advanced machine learning algorithms should be utilized to provide a comprehensive understanding of which areas are at risk for future flooding, based on flood susceptibility maps, and to generate more localized maps for different regions across KSA.

It's recommended that more dams be considered in the northern part of the Eastern Region due to the high population density of 1,000 people per square kilometer and the lack of any form of dam infrastructure.

Upgrade urban drainage systems to effectively manage increased runoff and develop implement early warning systems utilizing real-time rainfall data and risk maps. Additionally, educate communities about flood risks and preparedness measures.

#### **7.4. Future prospective**

- We have developed hazard map over whole KSA and the spatial resolution is cores about 3 Km. Therefore, our future plan have to consider updating flood risk map based on more calibration and more precise output spatial resolution such as 100 m or less.
- Develop more advanced machine learning methods to predict the flood depth which can be compatible with physical model and enhance the flood risk assessment.
- We still need to link climate shifts with global drivers and assess the relationship between large-scale atmospheric teleconnections and extreme flood events across the entire KSA.
- Address sediment management and dam reservoir issues in the context of climate change.
- Propose mitigation measures for the impacts of climatic change, especially in the case of climate shifting.

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