Doctoral Dissertation

Sustainable Agricultural Water Resources Management in Afghanistan Using the Hydrological Modelling

（水文学的モデリングアプローチによるアフガニスタンにおける持続可能な農業水資源管理）

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...Dedicated to my cherished family, whose boundless love and support sustained me, and to my esteemed professors, without whom this achievement would have been impossible…

Declaration

I hereby declare that I have completed the present work entitled "Sustainable Agricultural Water Resources Management in Afghanistan Using the Hydrological Modelling" solely and without illegal aid from outside sources. There are no further sources or aids besides those listed, which have indicated sections borrowed verbatim or thematically from the utilized references.

Hiroshima, August 19, 2024

Wahidullah Hussainzada

Certificate of Course Work

This is to certify that **Wahidullah Hussainzada** was admitted to the candidacy of a Ph.D. degree after successfully completing all the courses required for Ph.D. program. The details of the course works done are given below.

No	Course code	Course name	Credits
1	WSQA0165	Special Study of Advanced Science and Engineering Transdisciplinary Science and Engineering	12
2	8E050101	SDGs Ideas Mining Seminar for Specialists	1
3	8E550502	Skills and Arts of Leadership	1
4	WRA60201	Technology Strategy and R&D Management	1
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Abstract

Life on earth depends on water resources since every creature needs water for survival. Considering the very small fraction of freshwater globally, providing sufficient healthy water is a matter of death or life for people and ecosystems. Water resources are at risk of degradation, pollution, and scarcity due to rapid increases in consumption. Interdisciplinary solutions to water scarcity and environmental challenges require tools from science and engineering integrated with management tools. The present study presents a series of studies to evaluate water resource availability in data-scarce regions of the world with complex hydrological situations and vulnerability to water scarcity.

The current study evaluated the hydrological dynamics of four watersheds in Afghanistan. The targeted study regions were located in two major river basins in Afghanistan, namely, the Northern Rive Basin (NRB) and the Amu Darya River Basin (ARB), out of five major basins. The NRB is the smallest watershed in the Afghanistan in terms of surface water availability, and the ARB is the largest watershed in Afghanistan. The Balkhab River Basin (BRB) is representative of the NRB, and the three sub-catchments of Kokcha, Khanabad, and Kunduz are representative of the ARB. The four sub-catchments cover 22367.7, 11993.5, 28023, and 28835.2 km^2 in Kokcha, Khanabad, Kunduz, and the BRB, respectively. All the targeted sub-catchments were sourced from high terrain and flow toward flat lands downstream. The flow regime is complicated in the region. Precipitation accumulates in the high mountains during the winter seasons and dominates the discharge flow in the melting season during the early spring with increasing temperatures. The precipitation in the spring season accelerates the melting rate and increases the discharge in the stream, significantly causing flooding. Water infiltrated from snowmelt and rainfall in high terrains will show as lateral flow or springs along the river after a significant amount of time, contributing to the river flow during the summer and autumn seasons.

This study utilized two computer-based hydrological models to simulate long-term streamflow in watersheds. The models were calibrated and validated against historical discharge records collected by the Ministry of Energy and Water (MEW). The Soil and Water Assessment Tool (SWAT) and hydrological enhancement of Weather Research and Forecast (WRF-Hydro) are two computer-based hydrological models most commonly used by scholars in the field. The BRB hydrological model was developed using SWAT, and the WRF-Hydro model was adopted to model the Kokcha, Khanabad, and Kunduz sub-catchments in the ARB. Statistical indices

were used to evaluate the model performance during the calibration and validation periods. Historical data could provide a basic understanding of the water availability in watersheds, but the spatial coverage is low. The main purpose of the hydrological models in this study was to reveal the hydrological dynamics of the watersheds and generate spatial data for further analysis.

A proper understanding of consumption sources is the key to successful water resource management. The agricultural sector of Afghanistan consumes 98% of the country's water resources, and the remaining 2% is consumed for municipal water supply and industrial usage. Considering that large portions of water resources go to the agricultural sector, irrigation water consumption was estimated using the Penman–Monteith method to estimate the crop water requirement (CWR) for the ARB. Irrigation water usage is a factor of the land area and crop type. Unfortunately, Afghanistan does not have a database for crop type maps. To address data scarcity, remote sensing approaches were adopted to generate spatial and temporal crop type maps for the entire study period. The normalized difference vegetation index (NDVI) products from Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua and Terra were used to generate the crop type map. The NDVI products were classified into major crop types in Afghanistan using an ensemble of three machine learning algorithms: random forest (RF), support vector machine (SVM), and gradient boosting model (GBM). This study used a voting classifier for the model ensemble and balance weighting to account for the uneven distribution of the different classes in the training and testing accuracy. RF shows the highest accuracy rate among the others, and the ensemble of the three improves the performance accuracy. The models were trained for 2020 based on the availability of observation data and were temporally transferred for 2014 to 2019 over the same spatial coverage. The crop water requirements, crop types and irrigation areas for the BRB were adopted from a previous study and statistical yearbook of Afghanistan.

Finally, the outputs from the hydrological modelling step and estimation of water consumption were integrated into water resource management approaches to assess current management practices in watersheds. The assessment of the BRB revealed severe water shortages downstream and the inequitable allocation of water among users. To address these shortcomings, this study proposed the construction of a reservoir dam in the midstream region of the BRB to store water during late autumn and winter, when surplus water exists in the river and consumption is almost zero in agricultural lands. The location of the dam was determined using the analytic hierarchy process, a multicriteria decision analysis, based on expert opinions.

The dam structure can regulate the water by storing it during the surplus flow and releasing the water during the peak irrigation season. The ARB analysis revealed a high availability of water from May to September. The total consumption and available water in the river reach a balance between April and October. As a result of the assessment of irrigation systems in Afghanistan, the irrigation efficiency of the system is extremely low, with almost 50% losses in irrigation canals and agricultural fields. The purpose of this study was to increase irrigation system efficiency by lining irrigation canals and improving the amount of irrigation water applied in the field to the sprinkler to reduce large losses. In the ARB case, lining canals will improve the system efficiency by 9% and can save 14.25% more by changing the irrigation scheme from surface irrigation to a more efficient sprinkler irrigation system. The current study did not use any hard approaches, such as dam construction, in the ARB since all the rivers are transboundary water and Afghanistan does not have a treaty with other shareholders.

The output of these series of studies is a road map for sustainable irrigation water management in Afghanistan. The findings suggest that based on the goals of the Water Affair Management Law (WAML) passed in 2020, a road map for the sustainable management of irrigation water can follow these steps. First, watershed capacity and weakness can be identified using computer-based hydrological models. Water consumption should be estimated according to the current situation as well as the risks associated with climate change. Water allocation among users should be reformed to ensure the equal distribution of water among users upstream-to-downstream. In particular, attention should be given to the rehabilitation of existing infrastructure as well as the development of new infrastructures based on water availability to improve food security and residents' livelihoods by improving system efficiency. The government should increase its interference in water management by replacing the informal traditional system with more centralized modern irrigation systems and enhancing the policy for engaging the private sector in agricultural-related activities. The findings of this study can provide deeper insight into water resource management in Afghanistan for water planners and decision-makers.

Keywords: Hydrological Modelling, Water Resources Management, Irrigation Water, Crop Water Requirements, WRF-Hydro, SWAT, Crop Type Mapping

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Chapter 1

Introduction

1.1 General background

Water resource management has been linked directly to human activity and economic development historically. Rapid growth of the planet population during the past century increased the consumption of natural resources. In the current century, water consumption has increased two times faster than population growth (United Nation, 2020). Seckler et al. (1999) study from 1990 to 2025 in 118 countries, indicates that a quarter of the global population and one third of the developing countries' population will endure from extreme water shortage in the coming century. Regions characterized by arid and semiarid climates with limited rainfall are more susceptible to water scarcity. Recent research indicates a rise in drought severity in Afghanistan, Central Asia, and Iran, areas predominantly defined by these dry climatic conditions (Qutbudin et al., 2019; Ta et al., 2018; Zoljoodi & Didevarasl, 2013). The increase in the earth population increases the need for more food and water consumption. On the other hand, climate change affects water resources and increases drought severity.

Water resources in arid and semiarid regions of the world are under pressure due to limited resources, rapid increases in population, over abstraction of groundwater, increasing per capita water demand and agricultural use (H. S. Wheater, 2008). Floods are infrequent but extremely damaging to infrastructure and threaten livestock and residents. Ecosystems degrade due to the over abstraction of groundwater and the management of surface waters. Climate change is impacting water resource availability and regimes worldwide. Clearly, proper management of water resources is essential, and appropriate decision support systems based on scientific approaches and reliable data sources are needed. Continuous monitoring of water quality and quantity is essential for better understanding the hydrological dynamics in watersheds (Dechmi et al., 2012). However, long-term large-scale data collection that can be generalized to watersheds is expensive and time consuming (Santhi et al., 2006). In this context, hydrological modelling tools and remote sensing data can be used as alternatives to ground observations.

Computer-based hydrological models are simplified version of real-world systems comprising of a series of modern equations and a logical sequence of operations (H. Wheater et al., 2007). Modelling is a common tool in many fields of scientific studies, especially in water science. Hydrological models have wide-range of applications, including modelling of existing watersheds with derivable input and output data (water resources management, operation flood prediction, or extension of data array to assess water resources for flood design), coupled hydrology and meteorology (Global Climate Models), coupled hydrology and geochemistry (acid rain and nutrients), and estimation runoff in the ungaged basin , predicting the impact of changes (land use and land cover) (H. Wheater et al., 2007). The best model can exhibit a results close to observations with fewer input variables and complexity (A. Singh, 2018). Overall, hydrological models can be classified into (1) empirical models or metric models, (2) conceptual models, and (3) physically based models based on process descriptions (A. Singh, 2018). Physically based models excel over other models due to their incorporation of the physical processes into model parameters, addressing many shortcomings found in other kinds of models (A. Singh, 2018; V. P. Singh, 2018).

Integrated water resources management (IWRM) involves different water management scenarios and tools, but a single solution cannot be applied to every situation (Grigg, 2016). However, every approach should involve three concerns: how water is handled by the use of infrastructure, how to manage those infrastructures, and how water-related services are delivered. Traditional irrigation scheme is still applied for water management in the developing countries and highly acceptable by the local farmers. The central and local government are avoiding interfering with the water allocation and management to prevent water conflicts between users. Under current condition, considering rapid population growth and increase in water consumption, adoption of the traditional water management practices need to be replaced by more scientific based approaches.

1.2 Integrated water resources management (IWRM)

Life on earth depends on the availability of water since every organism needs it to survive. Considering that a tiny fraction of the global water is in the form of freshwater, providing sufficient healthy water is a death-or-life issue for people and ecosystems. Global water resources are at risk of pollution, degradation, and scarcity due to rapid increases in earth populations and environmental issues. Interdisciplinary solutions to water scarcity and environmental challenges require tools from science and engineering integrated with management tools.

WRM for human use, a subset of management of natural water cycle, targets for optimal use of water resources through planning, development, and distribution (Maurya & Singh, 2021).According to Grigg (2016), water management levels in watersheds are (a) the *water resources engineering level*, which focuses on the use of infrastructures to manage the water in the watershed; (b) the *water resource management level,* which involves decision making about water allocation using infrastructures; and (c) *the integrated water resource management level*, which involves broad set activities linking water decisions to actions in water-dependent sectors such as the environment, health, and food.

Humans created permanent settlements approximately 10,000 years ago by adopting the agrarian way of life, with habitats largely dependent on water (Vuorinen et al., 2007). Ancient civilizations, e.g., Indus Valley, Egyptia, Mesopotamian, and Chines, were pioneers in restraining water resources to meet irrigation and water consumption needs (de Feo et al., 2014). During the 20th century, water consumption increased 16-fold, while in the 1900s, just over 200 million people (14% of the global population) lived in areas with water scarcity issues; until the 1980s, this number significantly increased to two billion people (42%), and in the 2000s, 3.8 billion people (58%) faced water shortages (Kummu et al., 2016). The rapid increase in water consumption and limited fresh water worldwide necessitates efforts to improve conservation and proper management strategies.

Proper decisions by the government have a vital influence on water resources. Historically, many successful and unsuccessful examples of management schemes have caused major environmental challenges, economic losses, and ecosystem degradation. The Soviet Union initiated a large irrigation project using the Amu Darya and Syr Darya Rivers to irrigate the arid landscape and turn it into productive cropland. Intense irrigation in the watershed caused 92% of the volume of the Aral Sea to decrease by the 1960s (Micklin, 2010). Among the successful water-related projects, we can refer to the Morvarid canal initiated by Dr. Tetsu Nakamura (R.I.P.). After stretching over 27 km, this canal converted wastelands into productive agricultural lands, revitalizing local economies and livelihoods (Hatsumi, 2022). The sustainability of water resource management projects has emerged as a critical determinant of their success, underscoring the importance of adopting environmentally and socially responsible practices.

1.3 Previous studies on water resources management

Numerous studies focused on the management of water resources have been undertaken during the past few decades. These studies adopted different approaches to overcome real-life problems related to water quality. To date, water-related studies have addressed the issues of irrigation water management (Dwijendra et al., 2022; Matyakubov et al., 2021; Muzammil et al., 2020), drought-related studies (Bhaga et al., 2020; Nielsen-Gammon et al., 2020), hydrological studies and water availability identification (Mashaly & Fernald, 2020), water governance and policy (Mishra et al., 2021; C. Y. Zhang & Oki, 2023), and climate change impacts on water resources (Mishra et al., 2021; Schilling et al., 2020).

Numerous studies have adopted hydrological models as the basis for water resource management studies. Lee et al. (2022) utilized the WRF-Hydro model for demonstration of the characteristic of recent drought events occurred between 2008 and 2015 in the South Korea using standardized soil moisture index (SMI) and standardized streamflow index (SSI) was estimated using WRF-Hydro model to assess the hydrological and agricultural droughts in the study region. Numerous scholars utilized SWAT model for sediment and runoff modelling (Dhami et al., 2018), sediment management and chemical yield (Himanshu et al., 2019), impact assessment of the substitute management in the agriculture sector (Ullrich & Volk, 2009), assessing drought based on the evapotranspiration at the basin scale (Dash et al., 2021), the effect of implementing technological advancement and innovation to enhance water productivity and efficiency (Huang & Li, 2010), estimating crop water productivity (Faramarzi et al., 2010), evaluating different management practices and determining the optimal solutions (Panagopoulos et al., 2014).

Despite recent advancements in water-related studies, hydrological modelling in mountainous watersheds in arid and semiarid regions of the world is still challenging. Almost all the modelling tools were primarily developed for humid region applications (H. S. Wheater, 2008). Currently, arid and semiarid mountainous watersheds hydrological studies become an hot topic for the researchers (Noor et al., 2014). Generally, the simulation of the snowmelt effect in the large watersheds are challenging due to difficulties in determination of the specific model parameters and absence of a unified specific theory explaining the mechanism of the snowmelt-runoff (Kang & Lee, 2014). To manage water resources properly, appropriate decision support systems, including modelling tools, are needed.

Afghanistan is a landlocked country with arid and semiarid climates. The sparse precipitation and limited water resources make the livelihood environment harsh for the residents of the country. As reported by the World Food Program (WFP) between November 2023 and March 2024, an estimated $15.8x10^6$ people are prone to experience a extreme level of acute food insecurity (WFP, 2023). Considering Afghans' high levels of food insecurity and poverty, immediate countermeasures are necessary to enhance people's food security and economic conditions. Afghanistan's economy is highly depending on the agriculture sector. This sector accounts for 18.6% of the gross domestic product (GDP), and 80% of the total population's livelihood in rural areas is directly or indirectly linked to this sector (Mahmoodi, 2008; NSIA, 2019). Irrigation water in Afghanistan are managed by a traditional distribution method headed by *mirab* is appointed by the water users (Viala, 2003). *Mirab* roots comes from combination of Arabic and Persian words, refers to watermaster, and this term is widely used in Central Asia and Iran. To overcome these challenges, an enhanced water governance system is required to interfere with water management strategies and decisions.

1.4 Purpose of this study

Considering global water issues, managing water resources to the integrated level is required for the equal distribution of water resources among users while considering system sustainability and vital ecosystems. This study aimed to improve water resource management in developing countries with limited sources of reliable data and resources to enhance the livelihood of residents and maintain the environment.

The objectives of this study are as follows:

i. To investigate the water availability in complicated watersheds originating in arid and semiarid mountainous regions of the world using two famous hydrological modelling tools.
ii. To estimate the water consumption in different sectors, e.g., the water supply sector and agriculture sector, in countries with limited observations and reliable sources of data using machine learning algorithms and remote sensing.
iii. To integrate the outputs from hydrological models with multicriteria decision analysis techniques and other scientific approaches for decision making on water allocations and engineering solutions.
iv. The best scientific engineering solutions among the different scenarios for overcoming water shortage issues and ensuring an equal distribution of water

resources among water users without compromising the environment and ecosystem should be identified.

v. The roadmap for sustainable water resource management in Afghanistan is constructed considering the equal water distribution among water users and the role of stockholders in achieving this goal.

The outcomes of the current study will provide valuable insights into the contributions of hydrological models to water resource management practices. This study addresses real-world problems in arid and semiarid regions of the world with complicated hydrological phenomena and water dynamics.

1.5 Significance of the current studies

Current documents present a series of studies aiming to utilize scientific approaches to manage water resources at the national level. These studies start by determining water availability by utilizing hydrological modelling tools followed by estimating water consumption in different sectors and continuing to apply management strategies to enhance water resource management. The following could be summarized as the contribution of the current series of studies to improving water resource management in mountainous watersheds originating in arid and semiarid parts of the world.

i. This study provides insight into hydrological processes in data-scarce regions of the world, where less attention has been given by scholars and less information on these watersheds is available to the public and scientific community.

ii. This study investigated the impact of the Noah multi-parameterization land surface model (Noah-MP LSM) of WRF-Hydro in a mountainous basin and enhanced the performance of the WRF-Hydro model in simulating the snow melting process.

iii. In this study, the hydrological model outputs were coupled with multiple criteria decision analysis (MCDA) approaches to mitigate water resource management practices in watersheds. The approaches in this study introduce a more scientific decision-making process for water management practices and water governance at the watershed level.

iv. This study adopted multiple machine learning algorithms and their ensemble based on a voting classifier to generate a crop type map using remote sensing approaches where field observations of the spatial extent of agricultural lands are scarce and limited.

1.6 Thesis outline

The structure of the dissertation is arranged to present the steps toward the sustainable water resources management framework to address the water challenges in a country step-by-step as follows:

Chapter 1 provides the general context of the global water issue and, more specifically, the challenges in mountainous watersheds originating in arid and semiarid parts of the world and describes the study objectives and contributions.

Chapter 2 reviews the literature, in which the theoretical background, past studies, and description of models have been incorporated.

Chapter 3 provides a description of the study areas and general information about the Afghanistan climatology.

Chapter 4 describes the methodologies and tools used to achieve the goals of the current study.

Chapter 5 presents detailed studies of hydrological modelling utilization over two watersheds in Afghanistan. This is one of the smallest and largest watersheds in terms of water availability in the country.

Chapter 6 explains the water consumption estimation for the different sectors of water supply and agriculture.

Chapter 7 describes the management strategies and pathways for the sustainable management of water resources in both watersheds.

Chapter 8 presents a summary of the studies and presents recommendations for developing a pathway for integrated water resource management for Afghanistan.

Chapter 2

Water resources management in Afghanistan

2.1 Water governance and policy

After 2001, efforts toward the modernization of irrigation systems in Afghanistan started. The New Water Law (NWL) passed in 2009, and the US Government Inter-Agency Water Strategy for Afghanistan (WSA) enhanced the role of the central government, especially the Ministry of Agriculture, Livestock and Irrigation (MAIL) and the Ministry of Energy and Water (MEW), as the main stakeholders in agricultural water policy (Reeling et al., 2012). The river basin councils were established as the primary result of implementing the NWL and WSA to take an integrated approach for irrigation by involving stakeholders in irrigation water management. The MEW conveys water from the source to irrigation canals. This association will maintain the mirab system for water allocation between water users. The Water Affair Management Law (WAML) passed in 2020 replaced the 2009 NWL. The law clarifies sectoral responsibilities, affirms the authority of the Supreme Council of Water, Land and Environment (SCoWLE) and reforms the key structures to resolve water conflicts and harmonize water sector policy and implementation (USAID, 2020a). **Table 2.1** represents the stakeholders and their responsibilities for integrated water resources management based on the 2020 WAML. WAML is available online on the website of the MEW in the national languages of Persian and Pashto (https://mew.gov.af/dr/).

The objectives of the WAML 2020 are as follows:

1. Regulation of the existing water and optimization of water justice, the efficient use of resources, and economic usage.
2. Sustainable and integrated development of water resources.
3. The quality and quantity of services in the water sector should be improved.
4. The enhancement of the water supply, irrigation system, and wastewater management obtaining proper technological approaches.
5. Improving water governance through regulation of water resources.
6. Conservation of water resources for current and future generations.

Table 2.1 Water resources management entitles. Source: (USAID, 2020a).

Mandate	Institution	Roles and Responsibilities
National	National Water Affairs Regulatory Authority (NWARA)	Formed in 2020 through presidential decree, the National Water Resources Authority (NWARA) replaced the Ministry of Energy and Water (MEW). It serves as the principal ministry responsible for water resources management, overseeing data from regional meteorological, snow survey, and hydrometric stations. NWARA develops and enacts water policies, offering technical assistance and resources to national and sub-national entities. Under the Water Affairs Management Law, NWARA has the authority to allocate water every three years for drinking, irrigation, industry and commerce, environmental needs, energy, and tourism.
	Supreme Council of Water, Land and Environment (SCoWLE)	The organization oversees the development and planning of land, environment, and water resources, coordinates sectoral policies, and approves sectoral budgets. It is chaired by the President of Afghanistan and includes representatives from various line ministries.
	National Environmental Protection Agency (NEPA)	In-charge of monitoring surface water quality along with MEW and River Basin Agencies.
	Ministry of Mines and Petroleum	In-charge of managing and monitoring subsurface water quality, subsurface water availability and balance studies, and allowing for deep wells.
	Ministry of Public Health	In-charge for determining water quality standards based on consumption, including for drinking, irrigation, commercial use, and domestic use.
Sub-natioanl	River Basin Agencies (RBAs), Sub-basin Agencies (SBAs)	Created under NWARA's auspices, these institutions are not uniformly established across all basins. RBAs and SBAs formulate basin management and water usage plans aligned with national water policy, in collaboration with River Basin Councils (RBCs). They are tasked with monitoring surface water quality.
	River Basin Councils (RBCs), Sub-Basin Councils (SBCs)	River Basin Councils (RBCs) and Sub-Basin Councils (SBCs) comprise stakeholders from water user groups and government officials from relevant ministries. They offer guidance on water management strategies, resolve water disputes, and collaborate on water allocation plans. These councils also oversee the allocation of water and ensure the protection of water rights.
	Water Users Associations (WUAs), Irrigation Associations (IAs)	Water User Associations (WUAs) are tasked with managing water use, distributing water, and maintaining main canals; they are registered under NWARA. Irrigation Associations (IAs) have similar responsibilities but are registered with the Ministry of Agriculture, Irrigation, and Livestock (MAIL). These organizations may not be uniformly established across all river basins.

2.2 Water resources in Afghanistan

Afghanistan has a significant amount of water resources, ultimately springing from snowmelt accumulated in the high mountains in the winter, with more than 80% of the water resources coming from the Hindu-Kush Mountains (Ahmad & Wasiq, 2004). The river in Afghanistan starts from a high mountain range in the northeastern and central Afghanistan. The water flows from the high mountain terrain toward flat lands at the national boundary of the country. Afghanistan is officially divided into five major basins: the Kabul, Helmand, Hari-rod Murghab, Northern, and Amu Darya River Basins. **Figure 2.1** shows the major Afghanistan's basin divisions.

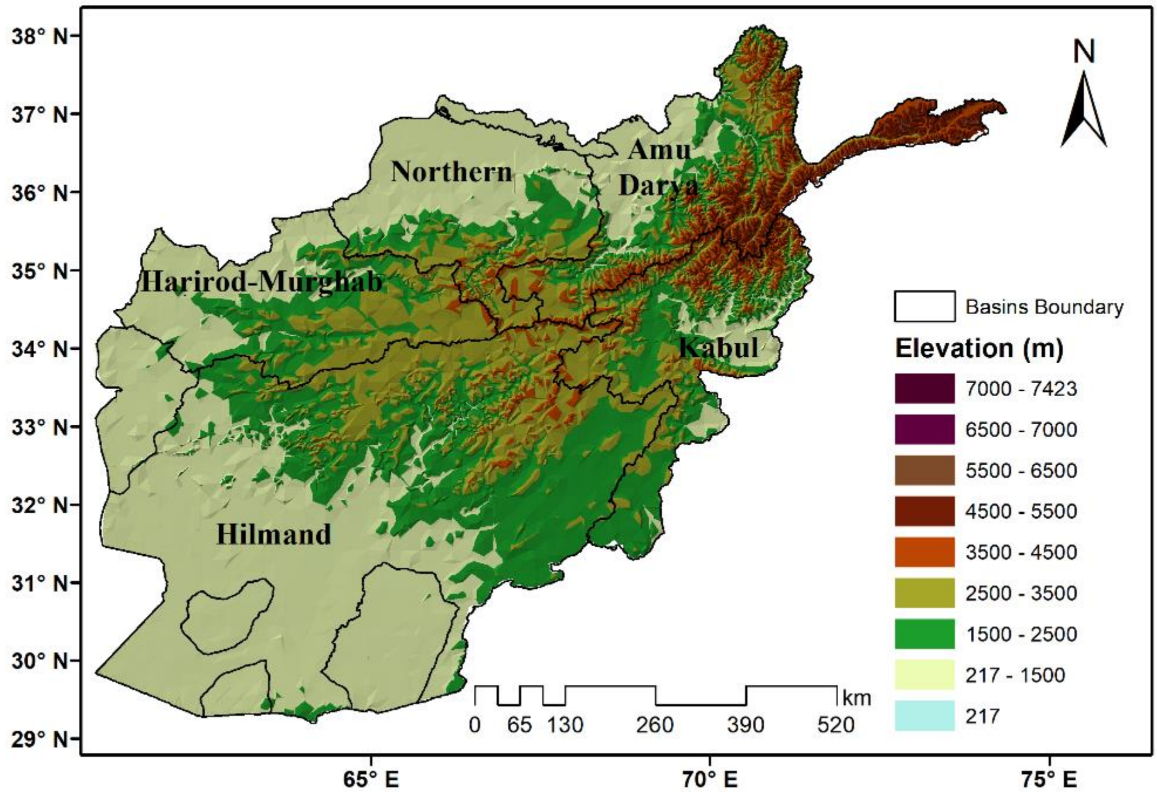

Figure 2.1 Afghanistan major basin division and topography.

Kabul River basin: The ~700 km long Kabul River basin starts from the high mountains in central Afghanistan and flows through the mountainous topography toward Pakistan in southeastern Afghanistan (Shroder & Ahmadzai, 2016). The watershed area is 79360 km^2, and the average annual flow is 24 bcm (Ahmad & Wasiq, 2004). According to Ahmad & Wasiq, (2004), this river can irrigate a limited area of agricultural land in Afghanistan because of the suitable land for agricultural activity. The Kabul River passes through eleven provinces and 7 million people and irrigates 300000 ha of intensively irrigated land (Shroder & Ahmadzai, 2016).

Helmand River basin: This is the longest (~1150 km) river in Afghanistan, rising from the central part of the country and ending in the Sistan depression and Iranian border (Shroder & Ahmadzai, 2016). Three major dams have been constructed on this river: the Kajaki dam (1950s), Dahla dam (1950s), and Kamal Khan Dam (2015). The mean annual flow in the Helmand River is 7 km^3/year, with a mean discharge of 90-4000 m^3/s (Shroder & Ahmadzai, 2016).

Hari-rod Murghab: This 1100 km long river is dominated by heavily irrigated regions around the Herat (Shroder & Ahmadzai, 2016). Hari-rod Murghab is a transboundary river flowing to Iran. The average annual discharge of this river is 55 m^3/s (Shroder & Ahmadzai, 2016)s. The Salma dam was recently constructed on this river in 2016. The main purpose of this dam is to control water resources and hydroelectric power generation.

Northern: This watershed is the smallest in the country with no transboundary water. All the water is consumed within the watershed. The Northern River basin owns the smallest annual flow, only 2% of annual total flow. This watershed covers 12.26% of the total Afghanistan area, and 9.51% of the country's population residing in the basin (Alim, 2006; MAIL. Atlas, 2004).

Amu Darya: This watershed starts at an altitude of 4900 m on the Wakhan glacier in country and travels 2540 km to the Aral Sea (Ahmad & Wasiq, 2004). The Wakhan River confluences with the Pamir River, which flows from Zor-Kul Lake, the Panj River; after the confluence with the Vakhsh River, the right tributary, it is called the Amu Darya River. The estimates of the mean annual flow vary from 13.3-19 km3 depending on the weather and the sub-basins included in the estimations (Ahmad & Wasiq, 2004). This 2540 km long river is the border between Afghanistan, Tajikistan, Uzbekistan, and Turkmenistan.

2.3 Irrigation water in Afghanistan

Afghanistan is located in Central Asia and is one of the least developed countries in the world. The United Nation Development Program's Human Development Index for Afghanistan 2021 is 0.48, which ranks the country 189 out of 203 worldwide (UNDP, 2021). The country's is highly economy dependent on agricultural activities, with 80% of the population living in rural areas (NSIA, 2023). There is a limited area in the country suitable for rain-fed agriculture, and the majority of the country relies on irrigation for agricultural activities. The yearly mean precipitation in Afghanistan varies from 75 mm in the southwest to 1170 mm in the northeastern region (Reeling et al., 2012). The sparse precipitation makes irrigation crucial for agricultural activities. The irrigation system used for surface water in Afghanistan. The agricultural irrigation system in Afghanistan relies on surface water, where 85% of cropland is irrigated from this source and 75% of irrigation water is conveyed through canal networks (ICARDA, 2002).

Irrigation infrastructure has been highly degraded in Afghanistan due to a few decades of war and conflict. The irrigation water distribution systems in the country can be divided into two possible categories: (1) informal or traditional irrigation systems and (2) formal or modern irrigation systems. The traditional informal system is highly localized and managed by communities. The community chooses a person as the water master (*Mirab*) to manage the water in the secondary and tertiary irrigation canals. *Mirab* is responsible for the distribution and allocation of irrigation water among users as well as resolving water conflicts between farmers (Pain, 2004). Generally, in informal irrigation systems, there is very little involvement of the local or central government in water allocation and distribution. According to Hussainzada & Lee, (2022), the water allocation to the main canal of the Balkhab River basin is decided by the local government based on the annual tax payment of the farmers, and the local government avoids interfering with water allocation at the field level. This traditional system is acceptable to the local community; however, reforms in irrigation systems could increase productivity and enhance residents' livelihoods. Formal modern irrigation systems are those with permanent intake structures that operate and are maintained by the irrigation department in each province. The last two decades paved the way for an increase in centralized water resource management systems in Afghanistan (Reeling et al., 2012).

2.4 Hydrological models

2.5.1 Soil and Water Assessment Tools (SWAT)

SWAT is a semi-distributed physical base hydrological model developed to simulate the impact of water management, agricultural chemical yield, and sediment in a large watershed at various time steps (Arnold et al., 1998; Y. Duan et al., 2018; Grusson et al., 2015). SWAT can simulate the hydrological phenomena in a watershed on a daily, monthly, or annually time basis. The required inputs are daily air temperature, rainfall data, solar radiation, wind speed, and humidity.

SWAT adopts two different methods to estimate surface runoff: 1) the Soil Conservation Service (SCS) Runoff Curve Number and 2) the Green-Ampt infiltration method (Y. Duan et al., 2018). In the current study, the SCS curve number method was adopted to simulate the watershed hydrological dynamics. Further sub-catchments are divided into smaller units called hydrological response units (HRUs). Each HRUs are composed of the homogenous land use, soil type, and slope within subbasins. Firstly, SWAT estimates the surface runoff in HRUs level, and then the results are aggregated for the subbasins. Finally, the total discharge for the entire watershed is obtained by the hydrological model (Arnold et al., 1998; Rostamian et al., 2008). The model predicts the surface runoff based on the following governing equation (**Eq. 2.1**):

$$SW_t = SW + \sum_{t=1}^{t} (R_i - Q_i - ET_i - P_i - QR_i) \tag{2.1}$$

where SW_t and SW are the final and initial soil water contents at time t, respectively; R, Q, ET, P, and QR are the daily amounts of precipitation, runoff, evapotranspiration, percolation, and return flow, respectively; and all the units are mm H2O.

The model calculates potential evapotranspiration (PET) based on three operations Priestley-Taylor, Penman–Monteith, and Hargreaves. PET estimations are a function of air temperature and extraterrestrial radiation in the Hargreaves method (Arnold et al., 1998). In the current work, the Hargreaves method was adopted to estimate PET. In case of missing data, the most common method for estimation of PET is Hargreaves temperature-based method (Zhansheng Li et al., 2018). Arnold et al., (1998) modified the Hargreaves method for SWAT by substituting the extraterrestrial radiation with the maximum possible solar radiation at the Earth's surface (RAMX), and the temperature exponents ranged from 0.5 to 0.6 (**Eq. 2.2**).

$$\mathrm{E}_o = 0.0032 \left(\frac{RAMX}{HV}\right) (T + 17.8)(T_{mx} - T_{mn})^{0.6} \tag{2.2}$$

where T_{mx}, T_{mn}, and T are the daily maximum, minimum and average air temperature in $°C$, respectively, and HV is the lateral heat of vaporization (J g-1).

Snow present in the catchment will melt as the temperature of the 2nd layer is higher than $0°C,$ and the volume of snowmelt will be the same as that of the daily rainfall to estimate the runoff and percolation (Arnold et al., 1998). Degree-day method adopts by the model for snowmelt calculation using a linear function of temperature by fixing a threshold temperature for snowmelt (Y. Duan et al., 2018).

2.5.2 WRF-Hydro

The WRF-Hydro model has been developed to facilitate the coupling of hydrological models with atmospheric models via the depiction of terrestrial hydrological processes associated with the spatial redistribution of subsurface, surface, and channel waters all over the land surface (Gochis et al., 2020). The WRF-Hydro modules incorporate terrestrial hydrological processes, which are either developed internally or adapted from existing distributed hydrological models (Gochis et al., 2020). **Figure 2.2** represent a schematic diagram of the conceptual architecture of WRF-Hydro.

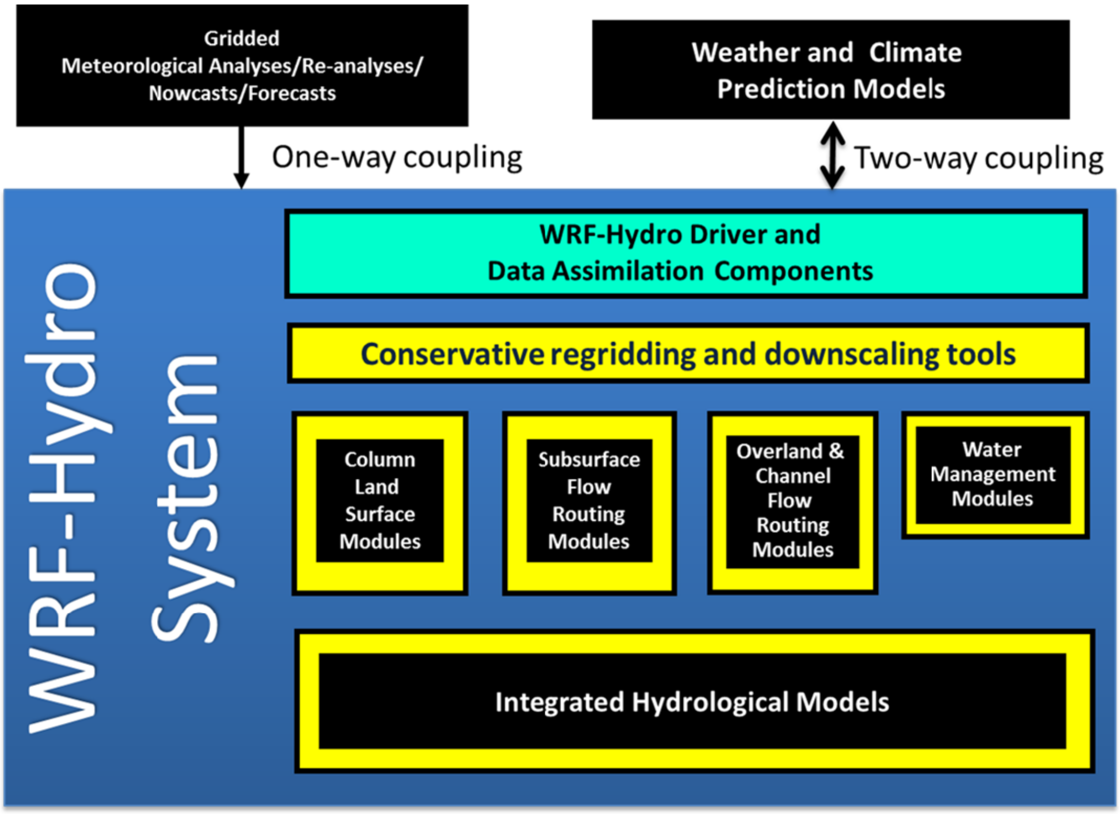

Figure 2.2 General representation of the conceptual schematic of WRF-Hydro model architecture showing different categories of model component.

The WRF-Hydro model structure enables the option of running stand-alone versions of the model or being fully coupled with an atmospheric model. In both situations, the models require static input and time-evolving dataset for its operation. WRF-Hydro is developed to simulate the land surface hydrology and energy fluxes and states at a high spatial resolution of 1 km or less (Gochis et al., 2020). The WRF-Hydro model enables the opportunity to choose multiple model components and physics. The following model components and physics are integrated into the WRF-Hydro model.

- 1-dimensional land surface parameterization

- Surface overland flow
- Reservoir routing
- Conceptual baseflow
- Saturated subsurface flow
- Channel routing

First, the 1-D column land surface model (LSM) estimates the vertical fluxes of energy (e.g., net radiation and sensible and latent heat), soil moisture and the thermal state, and moisture (infiltration excess, deep percolation, and canopy interception) (Gochis et al., 2020). Next, the depth of ponded water, infiltration excess, and soil moisture are extracted from the 1D land surface model to a finer resolution, usually ranging from 30 to 100 meters, in the routing grid. These data are then transferred to the overland and subsurface flow terrain-routing modules. Typically, static inputs such as land cover and soil maps are generated using the WRF Preprocessing System (WPS). The USGS 24-type land cover or MODIS-modified IGBP 20-category land cover and STATSGO soil classification database are the inputs for the 1D LSMs. The subsurface lateral flow is estimated prior to the routing overland flow to allow the exfiltration from fully saturated grid cells to be added to infiltration excess estimated from the LSM. Next, WRF-Hydro determines the water table depth based on the depth of the top of the saturated soil layers that are nearest to the surface. The depth of the soil column is typically 2 m, and there are four layers of soil in WRF-Hydro. In the next step, the overland flow is defined with three options of fully unsteady, spatially explicit, or diffusive wave formulation to determine when the depth of water in the grid cell exceeds the retention depth. Additional modules for representation of the stream channel process, reservoirs and lakes, and stream baseflow are incorporated into the model for a better representation of the hydrological process. A detailed description of the model physics selection and modules is available at Gochis et al., (2020). **Figure 2.3** shows a conceptual representation of the physical components and outputs of the WRF-Hydro model.

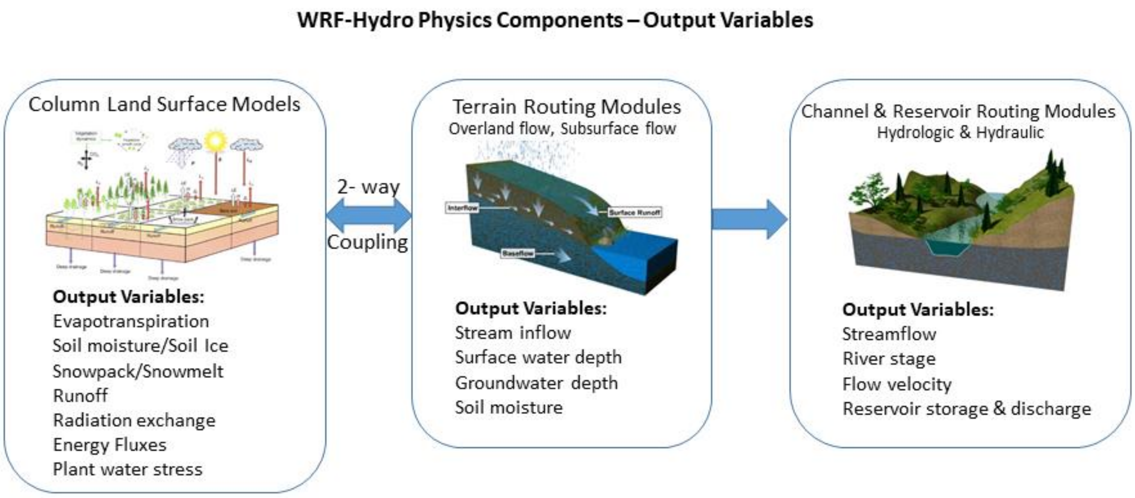

Figure 2.3 Illustrative diagram depicting WRF-Hydro physical components and corresponding outputs (Gochis et al., 2020).

Chapter 3

Study Area

3.1 Watershed in Afghanistan

Afghanistan is officially divided into five major basins. The basins are the Northern, Amu Darya, Harirod Murghab, Helmand, and Kabul (Indus) River Basins. Each of those watersheds was subdivided into sub-catchment (**Figure 3.1 (a)**). The major basins are officially subdivided into sub-catchments (**Figure 3.1 (b)**). The head water of all the rivers in Afghanistan starts from the high mountains in northeastern and central Afghanistan and flows towards the borders of the country. Among the five major basins except the Northern River Basin (NRB), all others are transboundary rivers. **Table 3.1** represents the contribution of each major basin to the national water generation annually. The Amu Darya River Basin (ARB) is the largest watershed in terms of flow generation, contributing 57% of the total annual surface water, and the NRB is the smallest watershed, contributing only 2% of the total annual surface water. In this study, to understand the hydrological dynamics of Afghanistan, we conducted two separate case studies by selecting representatives from the smallest watershed and largest watersheds. **Figure 3.1 (c)** shows that the Balkhab River Basin (BRB), one of the sub-catchments of the NRB, is representative of small watersheds. **Figure 3.1 (d)** shows three sub-catchments of the ARB as representative of the large watersheds in Afghanistan.

Historical field measurements are highly important for hydrological and water-related studies. The hydrometeorological data collection history in Afghanistan has a short period. The data collection started in the 1950s as an urge for irrigation in the Helmand River Basin (HRB), but later, due to decades of war and conflict, the data collection stopped for almost three decades. The data collection infrastructure was later restored after the 2000s with the aid of USAID. **Figure 3.2** shows the locations of the hydrometeorological stations and automated weather stations (AWSs) throughout the country. The hydrometeorological stations are located near the rivers and collect discharge, temperature, and precipitation data. **Table 3.2** provides further details on the variables at the hydrometeorological stations. Details of the variables collected at the AWS stations are presented in **Table 3.3**.

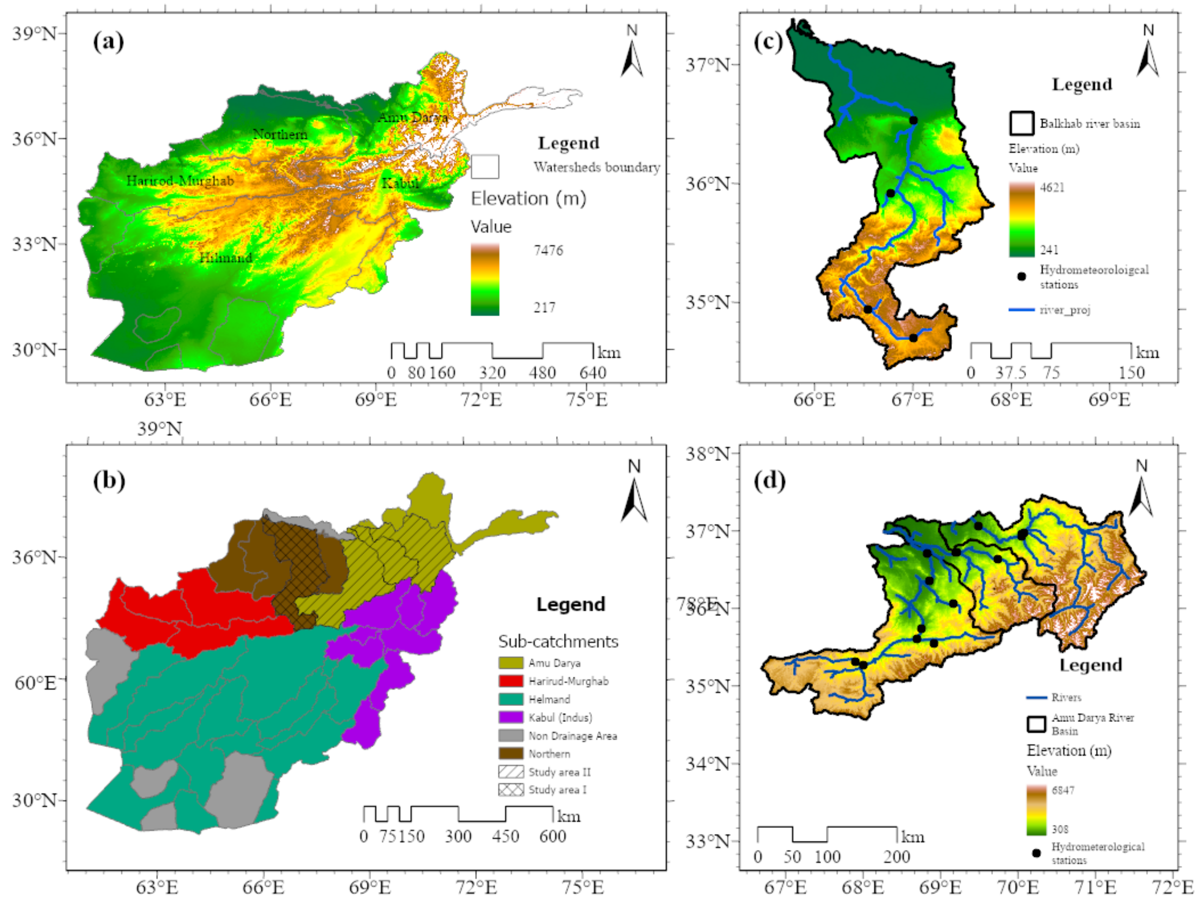

Figure 3.1 Map of the study area depicting the watershed boundary and locations: (a) major watershed boundary and elevation map of Afghanistan, (b) Sub-catchment division of five major basins, (c) Balkhab River Basin (BRB) elevation and hydrometeorological station location, and (d) Amu River Basin (ARB) elevation and hydrometeorological station location.

Table 3.1 Mean annual surface water flow in Afghanistan (Favre & Kamal, 2004).

River basin	Mean annual water flow (km^3)	Surface area (%)	Total annual flow (%)
Amu Darya	48	14	57
Harirod Murghab	3	18	4
Helmand	9.3	43	11
Northern	1.8	13	2
Kabul	22	12	26

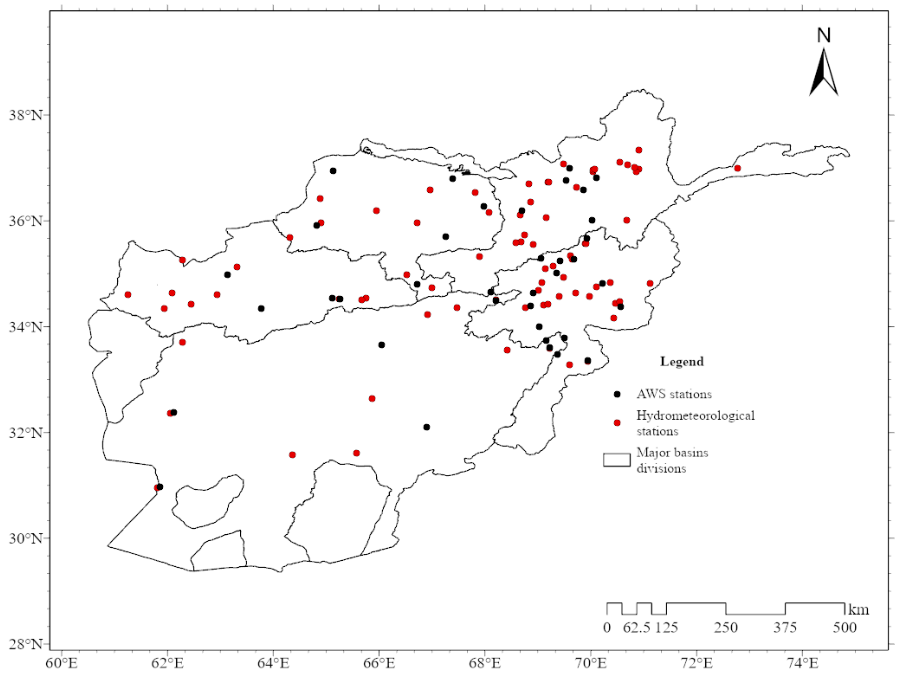

Figure 3.2 Details of the hydrometeorological stations variables collection.

Table 3.2 Details of the hydrometeorological station variables.

No	Variables	Temporal resolution
1	Minimum air Temperature	15 min
2	Maximum air temperature	15 min
3	Relative humidity	15 min
4	River discharge	Daily

Table 3.3 Details of the automated weather station (AWS) variables.

No	Variables	Temporal resolution
1	Minimum air Temperature	1 hourly
2	Maximum air temperature	1 hourly
3	Relative humidity	1 hourly
4	Wind speed	1 hourly
5	Wind direction	1 hourly
6	Sunshine hours	1 hourly
7	River discharge	Daily

3.2 Balkhab River Basin

As mentioned in section 3.1 of this document, two representative study regions were selected to understand the hydrological dynamics and water resource management in Afghanistan. BRB is representative of a watershed with low flow. The BRB originated in the NRB in northern Afghanistan. The BRB head water starts from a series of six lakes in the southern part of the study region and flows northwards to the flat lands. The data provided by the NRB management authority BRB include 190 springs contributing to the water resources in the sub-catchment. The majority of water in the river is allocated for irrigating of 296,774 ha of land, facilitated by three small regulator dams and 101 engineering and traditional irrigation canals along the river. Afghanistan receives mean annual precipitation of 270 mm, varying from 1270 mm in the high mountains to 75 mm in the southwestern region (Habib, 2014). The BRB is dominated by semi-arid climate, with an mean annual precipitation of 247 mm. Notably, no precipitation occurs during summer seasons. Throughout the rest of the year, water primarily comes from snowmelt collected in highland areas during winter and groundwater flow. Snowmelt and subsurface water significantly contribute to the stream flow in the late spring, early autumn, and summer, when watershed has no precipitation almost. Five hydrometeorological stations (**Figure 3.3 (c)**) are situated in the BRB. They record the minimum and maximum temperatures, precipitation, relative humidity, and stream discharge on a daily bases. In the present study, daily input data were used for monthly surface runoff simulations. The annual mean temperature varies from 7.56 °C in the highlands of the south to 18.93 °C in the north according to the data recorded from 2010 to 2018 provided by the Ministry of Energy and Water, Islamic Republic of Afghanistan. The BRB dominated land cover type are range land and grasses, encompassing 62.25% of the total area.

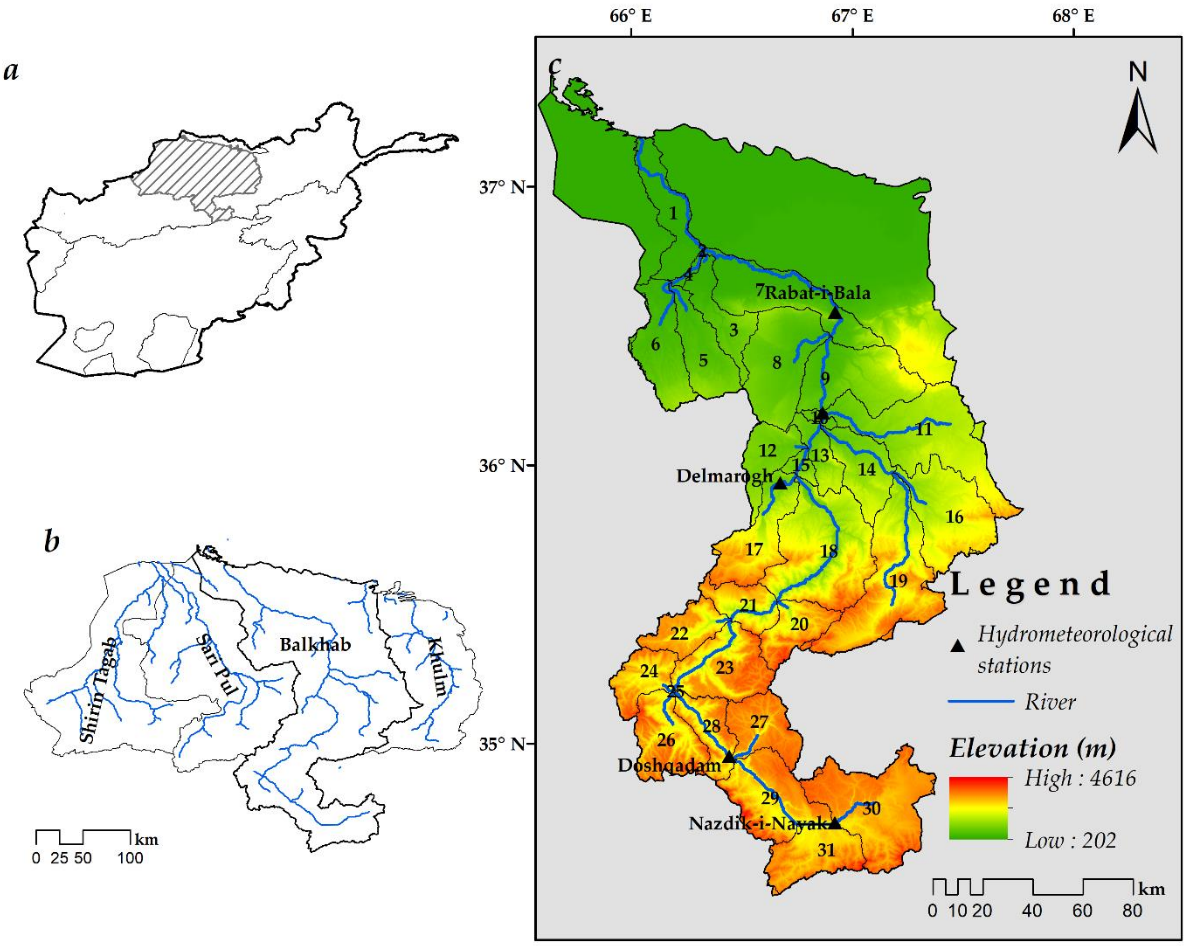

Figure 3.3 Study area map showing the location of the northern river basin, Afghanistan: (a) Afghanistan map and five major watersheds; (b) Northern River basin with four sub-catchments: Khulm, Balkhab, Sari Pul, and Shirin Tagab; (c) Balkhab River basin, elevations, and subbasin divisions (Hussainzada & Lee, 2021).

3.3 Amu Darya River Basin

The ARB is the largest watershed in terms of generating surface water, with a contribution of 57% of the total volume (**Table 3.1**). The agricultural sector contributes 33.7% to the GDP, while industry and services contribute 16.1% and 45.0%, respectively. The study area is located in the ARB, situated in the northeastern region of the country. The ARB is divided into five subbasins: Kunduz, Kokcha, Pang, Khanabad, and Ab-i-Rustaq. Current study focused on the three sub-catchments: Kokcha, Khanabad, and Kunduz watersheds (**Figure 3.4**). The locations of 14 active hydrometeorological stations within the ARB are shown in **Figure 3.4** with black and red circles; after data quality control, five stations (assigned as red circles in **Figure 3.4**) were identified as reliable sources for further analysis and investigations, and nine of them were not considered reliable sources of data. The study area situated in a complex topography with significant variation in elevation from 6,847 to 308 m.a.s.l.

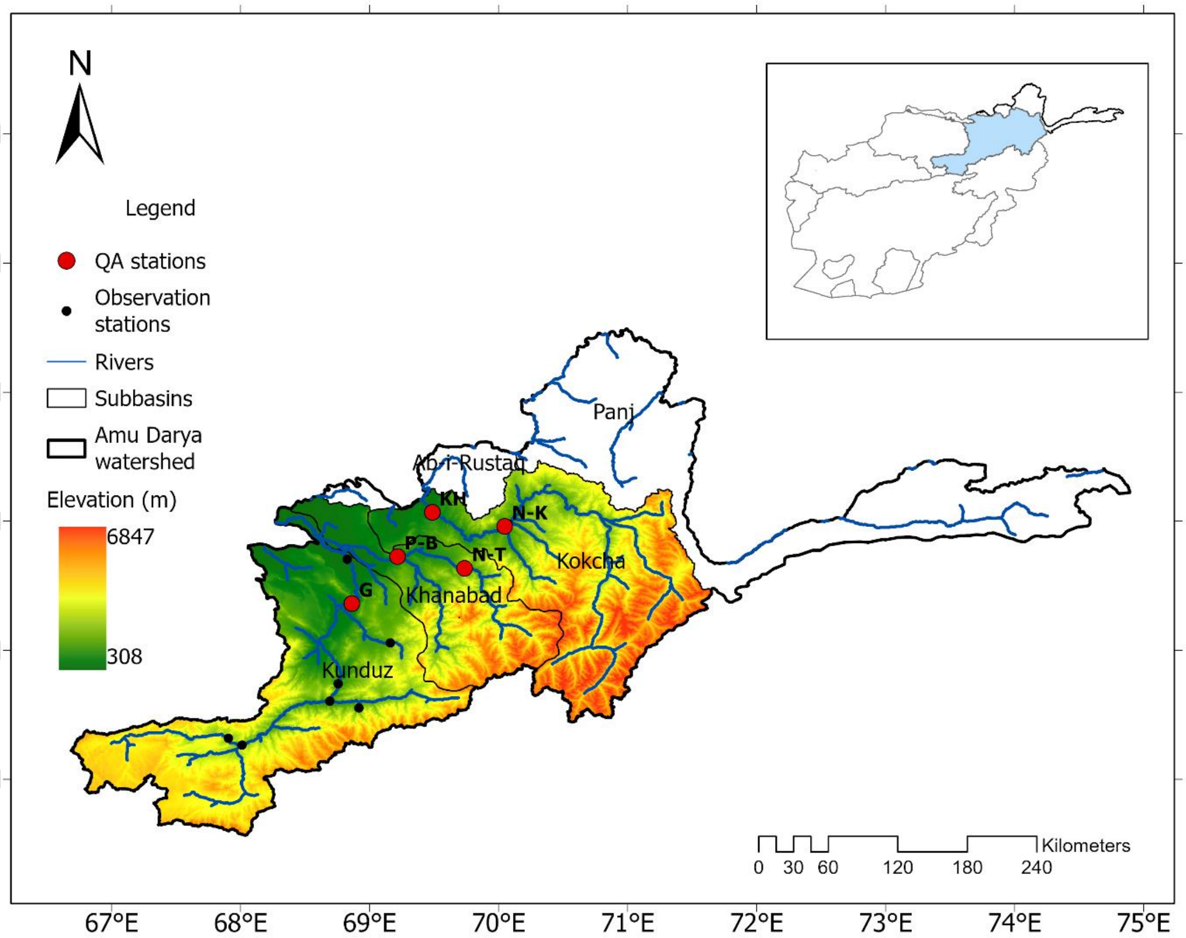

Figure 3.4 The study area map showing the ARB and its five sub-catchments Panj, Kokcha, Khanabad, Kunduz, and Ab-i-Rustaq and the geographical locations of the observation stations and five reliable stations (red circles) after data quality control; Khawjaghar (KH), Gerdab (G), Pul-i-Bangi (P-B), Nazdik-i-Taluqan (N-T), and Nazadik-i-Keshem (N-K).

Chapter 4

Materials and methods

The current document is representative of two case studies over the Afghanistan watershed. While both studies focused on the utilization of hydrological models and their integration into water resource management practices, different tools were adopted in each case study. Hereafter, we refer to each of the case studies as the BRB case and ARB case.

4.1 General research approach

The overall aim of this study is to determine pathways for sustainable water resource management of surface water in Afghanistan. The major sectors consuming water in the country are the agricultural sector, with more than 98%, domestic water consumption, and the industrial sector. The spatial distribution and length of field measurements in Afghanistan are limited. To overcome the data limitations, the goal of the current study was to determine the hydrological dynamics of the study region utilizing an advanced computer-based hydrological model to determine the water availability in the watersheds. The second step is to determine the water consumption in each sector using available secondary data and remote sensing techniques to generate the data in the sectors where observations do not exist or are limited. The final step is to determine the water balance between the available water resources and consumption to determine the weakness and strength of the watersheds and apply suitable management practices considering the equal water distribution among the water users and maintaining the environment. **Figure 4.1** shows the overall methodology used in this document for both case studies to determine the road map of sustainable water resource management in Afghanistan.

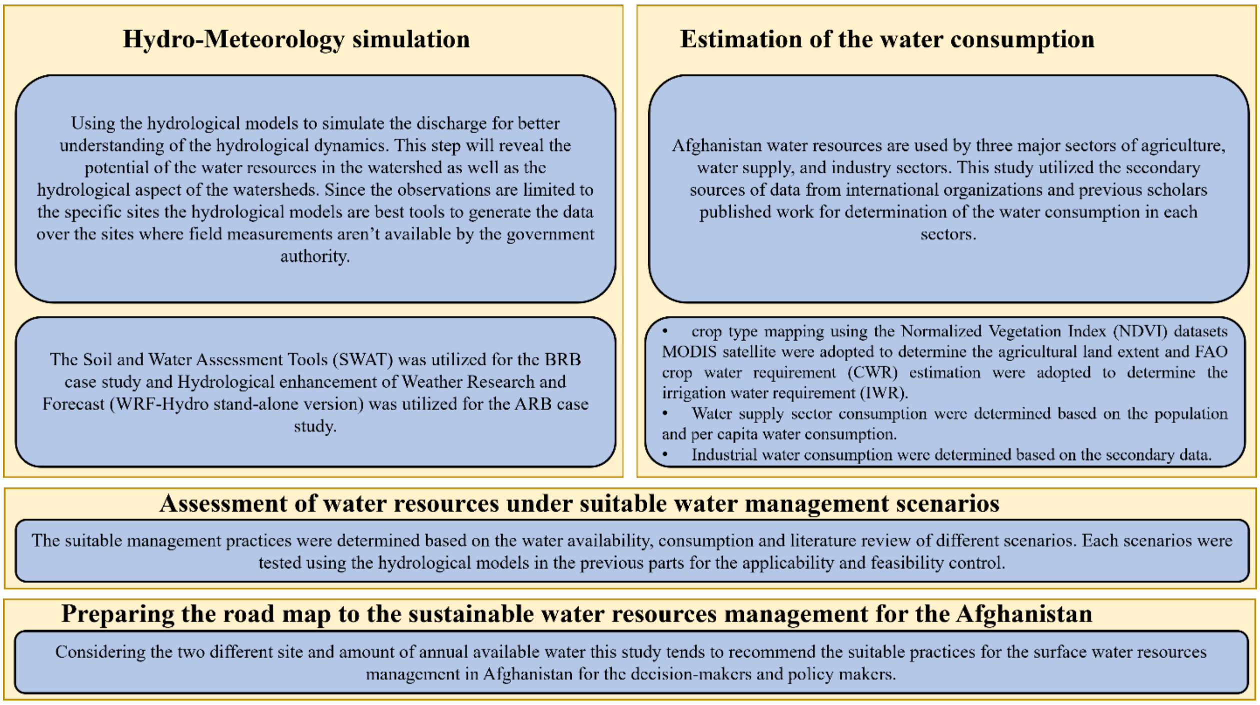

Figure 4.1 Overall framework of the study of sustainable water resource management.

4.2 Hydrological modelling

4.2.1 Soil and Water Assessment Tools (SWAT) model setup

In this study, a previous SWAT model for the BRB was adopted from a previous work (Hussainzada & Lee, 2021). ArcSWAT 2012 with the ArcGIS interface was used for BRB watershed model development. In the first step of the modelling, the watershed was selected using the ALOS PALSAR DEM with a 12.5 m spatial resolution. BRB divided into 31 subbasins based on the flow accumulation and elevations of the watershed in the watershed delineation step (**Figure 3.3 (c)**). Secondly, each subbasins were divided into HRUs based on the homogenous land cover, soil type, and slope. The study area were sub-divided into 1532 HRUs further for all 31 subbasins. Then, the metrological inputs from the five hydrometeorological stations from 2010 to 2018 was added into the model as the forcing data. The study period divided into three different period, spin-up from 2010-2012, calibration period from 2013 to 2015, and validation period from 2016 to September 2018 on monthly basis. The major model process for the SWAT model setup, calibration, and validation is summarized in the workflow diagram (**Figure 4.2**).

The BRB originates from six lakes upstream that provide continuous flow through their reservoirs, while 190 springs along the river also contribute to its baseflow, crucial during the rainless dry season. Additionally, irrigation canals along the river withdraw a significant amount of water throughout the year. These various water inputs and withdrawals were incorporated into the model as point sources to create a robust hydrological model for the BRB.

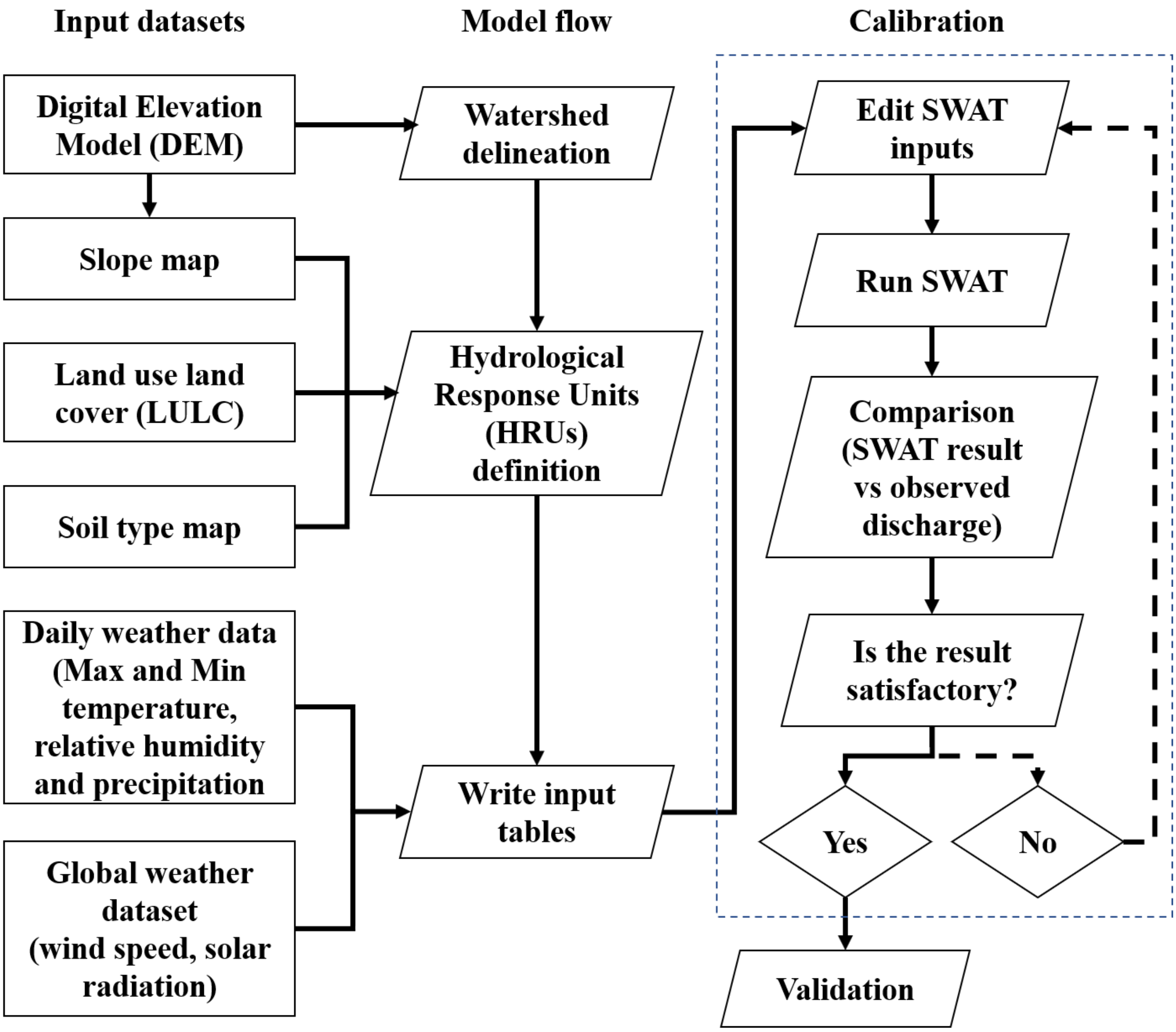

Figure 4.2 Flowchart for SWAT hydrological modelling of this study.

4.2.2 SWAT model input dataset

The SWAT inputs include temperature, relative humidity, precipitation, windspeed, digital elevation model (DEM), solar radiation, soil type map, land cover map, slope map, and water inflow and outflow from the river.

Daily maximum and minimum temperatures, relative humidity, and precipitation data collected from five hydrometeorological stations between 2010 and 2018 were utilized as inputs for the SWAT model (**Figure 4.3**). The solar radiation and wind speed data were retrieved from the NASA Prediction of Worldwide Energy Resources (POWER) (https://power.larc.nasa.gov/) at the same geographical location of the observation stations. Daily recorded discharge data are available for all five stations. In this study, the average monthly discharge from four stations located on the main river was used as the control point for the calibration and validation of the SWAT model.

1- Digital Elevation Model (DEM): The ALOS PALSAR Radiometric terrain corrected (RT1) images (**Figure 3.3 (c)**) were utilized from the Alaska Satellite Facility Distributed Archive Data Center (ASF DAAC) website with a 12.5 m spatial resolution and used as an input. RT1 products are generated using high-resolution and mid-resolution DEMs (Logan et al., 2014). The DEM was used to generate slope map in the SWAT model (**Figure 4.4 (c)**).
2- Land use/land cover: In 2010, the Land Cover Atlas of the Islamic Republic of Afghanistan was created through collaboration between the FAO and the Ministry of Agriculture, Irrigation, and Livestock (MAIL), Afghanistan. This initiative, part of the "Strengthening Agricultural Economic, Market Information and Statistics Services," utilized medium-resolution satellite imagery from SPOT-4 and Global Land Survey (GLS) Landsat Thematic Mapper, alongside high-resolution satellite imagery, air photographs, and supplementary data sources (FAO, 2016). The land cover map for the BRB is depicted in Figure **4.4 (a)**.
3- Soil type map: In many regions worldwide, reliable soil type maps are lacking, prompting the adoption of two widely used global soil type maps: the FAO/UNESCO Soil Map of the World and the Harmonized World Soil Database (HWSD_v121) (K. C. Abbaspour et al., 2019). The FAO/UNESCO soil map of the world (**Figure 4.4 (b)**) was used as the soil type map in the SWAT model. The FAO/UNESCO soil map of the world was created using a topographic map series from the American Geographical Society of New York, scaled at 1:5,000,000, focusing on a topsoil layer of 30 cm and a subsoil layer of 70 cm (K. C. Abbaspour et al., 2019).

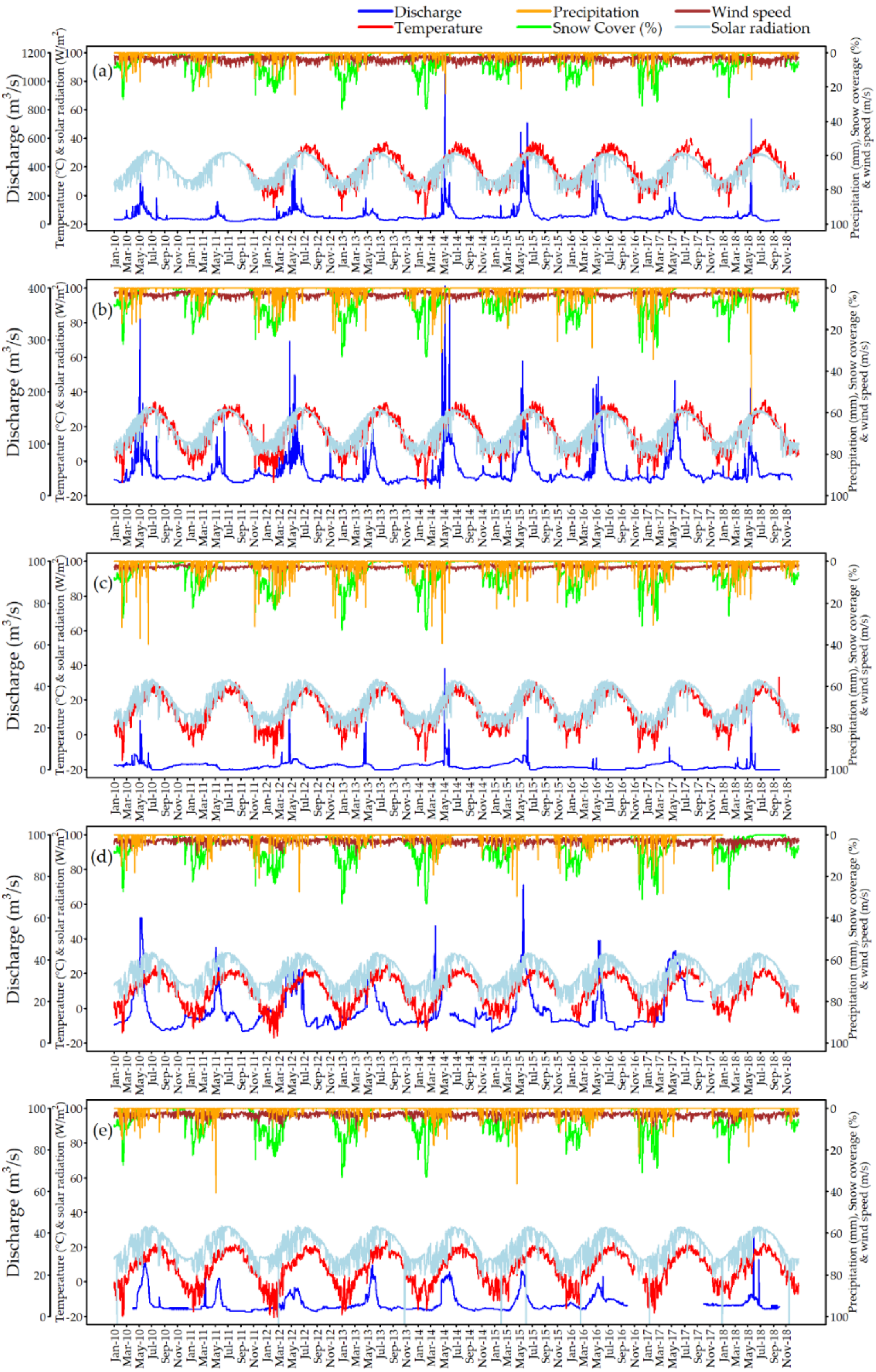

Figure 4.3 Temporal data series including temperature, precipitation, and discharge from monitoring stations; percentage of snow cover derived from MODIS data; and NASA-PWER data on solar radiation and wind speed. Shown for stations: (a) Rabat-i-Bala, (b) Pul-i-Baraq, (c) Delmarog, (d) Doshqadam, and (e) Nazdik-i-Nayak. (Hussainzada & Lee, 2021).

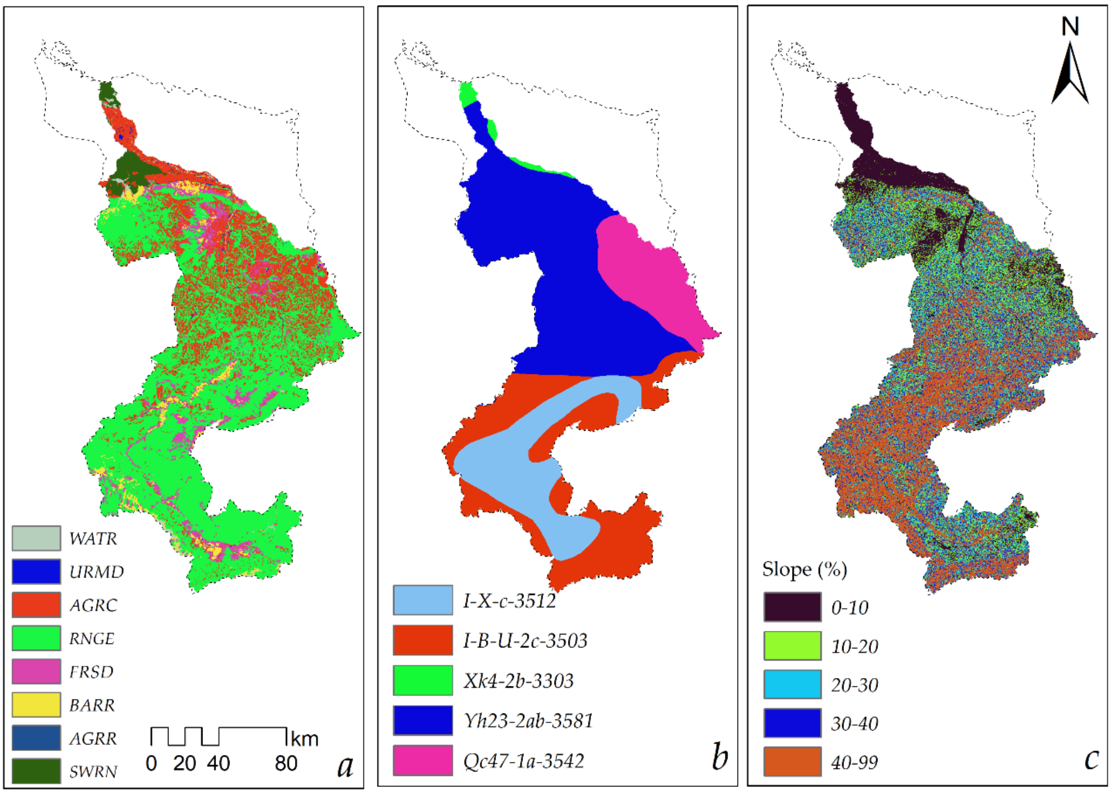

Figure 4.4 Input data used to define Hydrologic Response Units (HRUs). Shown are: (a) BRB land cover map, (b) FAO/UNESCO global soil type map, and (c) BRB slope map derived from the DEM (Hussainzada & Lee, 2021).

4- Point source data: The BRB is situated in a mountainous area with 190 springs along the river, no geographical location or volume of water yield are recorded. Historical streamflow during the dry season was used to overcome the issue of subsurface data scarcity. It has been assumed that the contributions of snowmelt and to the river discharge during the July, August, and September are negligible. The monthly mean precipitation of the five BRB stations are shown in Figure 4.5, the precipitation is almost zero during July, August, and September. In the same bar plot, the snow coverage area was plotted by its percentage as per Hussainzada, (2020). In this research, monthly snow cover percentages for the BRB were obtained by combining daily snow cover data from MODIS Aqua and Terra satellites. Figure 4.5 illustrates the monthly average discharge recorded at four stations in subbasins 7, 10, 28, and 30: Rabat-i-Bala, Pul-i-Baraq, Doshqadam, and Nazdik-i-Nayak, respectively, during these three dry months. The dotted lines in Figure 4.5 show the mean discharge 2010-2018. Subbasin 30 originates from six lakes, providing a consistent discharge of 4.22 m^3/s. In subbasins 7, 10, and 28, groundwater contribution is determined by the discharge difference between upper and lower stations during non-rainy months. **Table 4.1** details groundwater contributions across these subbasins.

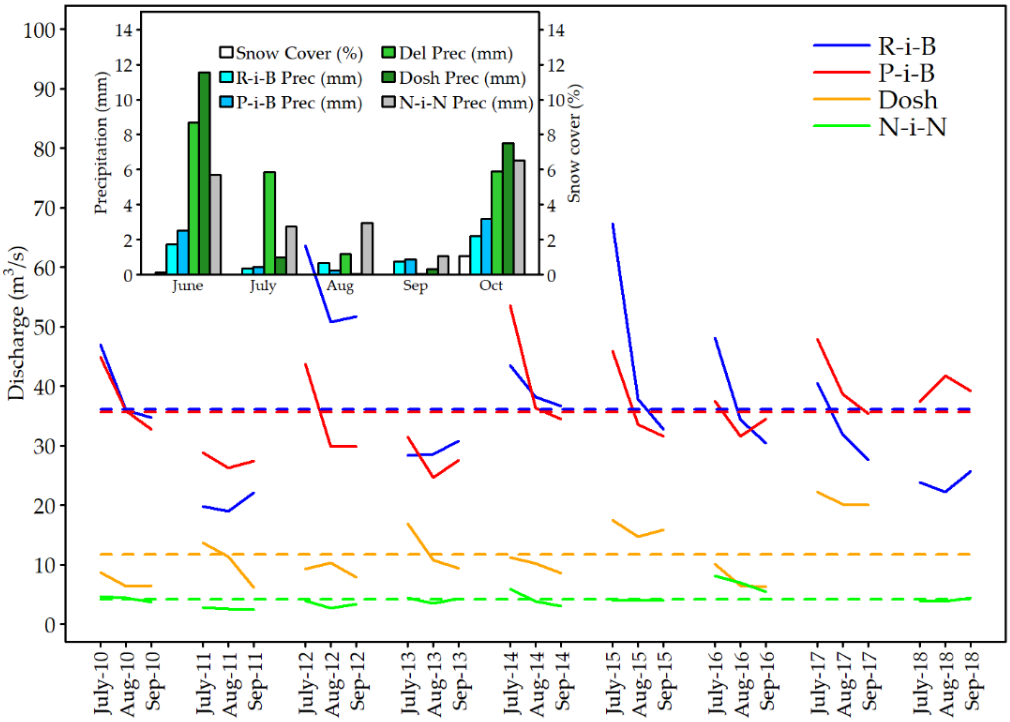

Figure 4.5 Historical observation of monthly streamflow and rainfall in the BRB for subbasins 7, 10, 17, 28, and 30 and monthly average snow cover area over the BRB retrieved from MODIS snow cover product collection 6.

Table 4.1 The observed mean discharge at the recording stations during the nonrainy months and calculation of the subsurface water contribution using the difference between records in the non-rainy seasons.

Sub-basins	mean monthly river discharge (m^3/s)	Groundwater contribution (m^3/s)
7	36.05	0.39
10	35.66	25.38
28	11.72	7.50
30	4.22	4.22

5- Irrigation canals: Data on irrigation canals are incorporated into seasonal practices for crop cultivation in watershed modeling. In the BRB's agricultural sector, water is accessed via 101 irrigation canals and three regulator dams downstream of the river. **Figure 4.6** shows the irrigation canal intakes geographical locations along the Balkhab

River. Thirty-four canals feed from the main Balkhab River and irrigate 258,305.5 ha of agricultural land, and other canals are small canals that feed from springs or small temporary streams mostly located upstream in the southern part of the study area. The sources of water for the other sixty-seven canals are springs or temporary small rivers. In this study, these canals and their effects on river discharge were neglected.

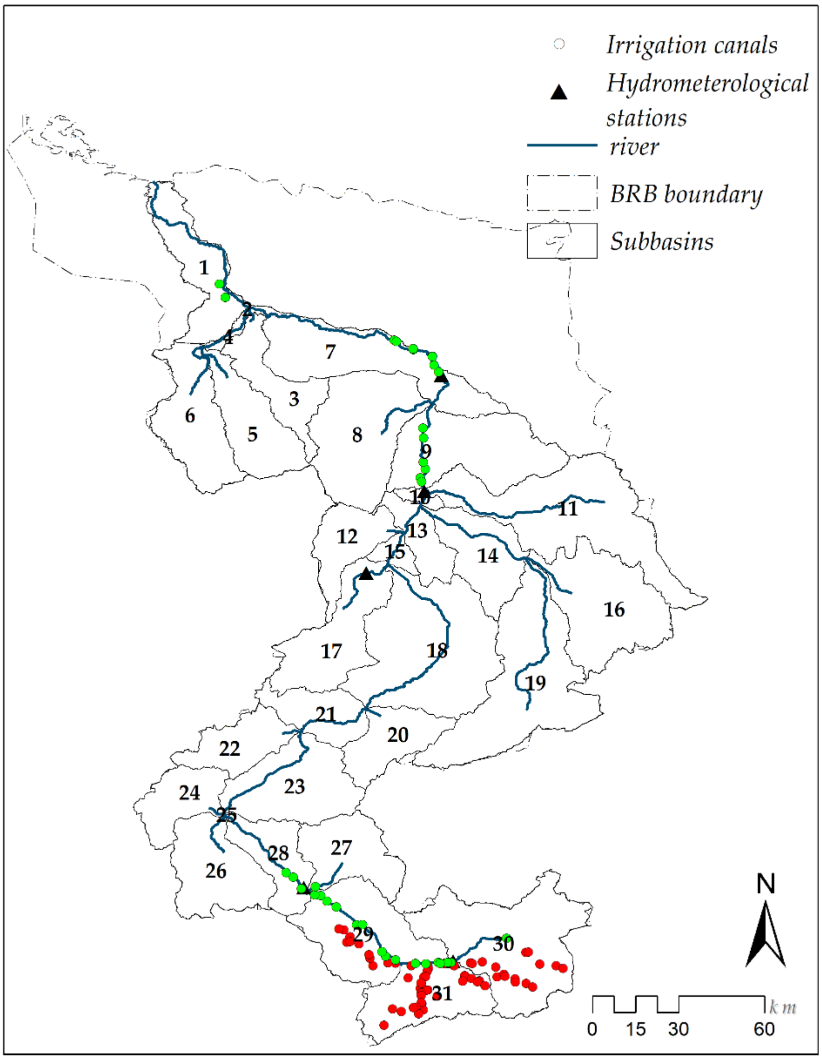

Figure 4.6 The geographical location of the irrigation canals along the BRB. The source of the data was provided by the NRBA, Islamic Republic of Afghanistan.

4.2.3 SWAT model calibration and validation

Model calibration and parameter sensitivity analysis are the keys to successful hydrological model setup (Karim C Abbaspour, 2007; Mengistu et al., 2019). In this study, the SWAT calibration and uncertainty procedure (SWAT-CUP) v5.2.1 (Karim C Abbaspour, 2007) sequential uncertainty fitting algorithm (SUFI2) was adopted for the calibration and uncertainty analyses. The details of the SUFI2 algorithm are presented in Homan, et al., (2011) and Karim C Abbaspour, (2007).

The model calibrated for period of January 2013 to December 2015 using monthly streamflow records in the four stations, Rabat-i-Bala, Pul-i-Baraq, Doshqadam, and Nazdik-i-Nayak, which are located in subbasins 7, 10, 28, and 30, respectively. To ensure the model robustness for the BRB, the model validation was performed between January 2016 to September 2018.

The parameter optimization was conducted using SWAT-CUP (SUFI2) at multiple sites for the parameters listed in **Table 4.2**. The monthly mean streamflow at four stations in sub-catchments 7, 10, 28, and 30 were used for calibration of SWAT model. The parameters for calibration were chosen carefully based on the visual inspection of the first SWAT output and extensive literature of the previous studies. The snow parameters and rainfall parameters used as drivers (SFTMP, SMTMP, SMFMX, SMFMN, and TIMP), which introduce water into the system, should be calibrated separately from other parameters (Karim C. Abbaspour et al., 2017).

The SWAT model can generate more than one solution for the model due to non-uniqueness. This means that the model can generate the same signal with two different sets of parameters (Karim C. Abbaspour et al., 2017). The issue of non-uniqueness can be reduced by calibrating the model at multiple sites and introducing more variables for simulation. An increase in the number of controlling points for model performance can increase the reliability of the model output after calibration. However, using more variables (i.e., discharge, ET, sediments, or crop yield) in the calibration process can ensure a better model representation from the original site conditions. In this study, we could not access datasets other than the discharge dataset, which must be included in future studies.

The variability in precipitation and temperature with respect to elevation in mountainous watersheds is an important phenomenon that affects model performance. To assess the variations in temperature and precipitation with elevation, five elevation bands were introduced into the model. Then, the precipitation and temperature lapse rate were calibrated separately in the model. The contribution of snowmelt to surface runoff is one of the most important processes that should be considered in the model. The snow parameters were calibrated and replaced in the model before the other parameters were adjusted. Then, the seven most sensitive parameters were tuned using SWAT-CUP with 1000 iterations to find the most suitable set of parameter values.

After careful calibration of lapse rate and snow parameters in the model, the rest of the model parameters were subjected into sensitivity analysis to define the most sensitive parameters. The set of parameters controlling the groundwater, soil, and land use related process were shortlisted and presented in **Table 4.2**. The groundwater parameters are highly affecting the baseflow during the low flow seasons with controlling the threshold depth of water in shallow aquifer for return flow (GWQMN), movement of water from shallow aquifer back to the saturated zone and soil moisture and evapotranspiration (GW_REVAP), and lag time between percolation to aquifer and its return to the baseflow (GW_DELAY). The soil and land use parameters are other important aspects of the SWAT model control runoff amount. The soil and parameters control the amount of water soil can store (SOL_AWC), adjusts the soil evaporation process (ESCO), infiltration and percolation rate (SOL_K), and control the runoff potential based on soil type, land use, and hydrologic conditions (CN2).

Knowledge of hydrology parallel to correct understanding of the site and its hydrological conditions is needed for choosing appropriate parameters during the calibration process. The chosen parameters were subjected to a sensitivity test using the SWAT-CUP platform to determine their sensitivity and changes on the hydrograph. The seven additional parameters in **Table 4.2** were used for the final model calibration with 1000 simulations.

4.3 WRF-Hydro modelling

WRF-Hydro is an accessible hydrometeorological modeling system initially designed to integrate Weather Research and Forecast (WRF) atmospheric models. It simulates surface and subsurface water movement along with processes in shallow aquifers (Gochis et al., 2018). WRF-Hydro model also could be utilized in uncoupled mode with external forcing data in offline mode or called as standalone version. Current study utilized WRF-Hydro standalone model to simulate the hydrological dynamics of the ARB. In its present setup, the Noah-MP land surface model (LSM) simulates vertical energy flux and water dynamics, encompassing processes such as surface runoff, snowmelt, evapotranspiration, aquifer recharge, and soil water storage and drainage (Niu et al., 2011). **Figure 4.7** illustrate the overall procedures for the model configuration, calibration, and validation.

Table 4.2 Parameter ranges and fitted values for the model calibration in the SWAT-CUP model.

No	Parameter	Description	Range		Fitted values	Method
			Min	Max		
Temperature and precipitation lapse rate						
1	TLAPS	Temperature lapse rate	-8	-4	-5.26	v[1]
2	PLAPS	Precipitation lapse rate	0	100	1.5	v[1]
Snow parameters						
3	SFTMP	Snowfall temperature	-5	5	4.65	v[1]
4	SMTMP	Snow melts base temperature	-5	5	-3.55	v[1]
5	SMFMX	Maximum melt rate for snow during year (occurs on summer solstice)	0	5	0.325	v[1]
6	SMFMN	Minimum melt rate for snow during the year (occurs on winter solstice)	0	5	0.475	v[1]
7	TIMP	Snowpack temperature lag factor	0	1	0.645	v[1]
8	SNOCOVMX	Minimum snow water content that corresponds to 100% snow cover	0	450	20.25	v[1]
9	SNO50COV	Snow water equivalent that corresponds to 50% snow cover	0	0.85	0.59925	v[1]
Groundwater parameters						
10	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	2500	1523.75	v[1]
11	GW_REVAP	Groundwater "revap" coefficient	0	0.1	0.00355	v[1]
12	GW_DELAY	Groundwater delay (days)	0	500	27.75	v[1]
Soil and land use parameters						
13	SOL_AWC()	Available water capacity of the soil layer	-0.3	0	-0.12915	r[2]
14	CN2	SCS runoff curve number f	-0.4	0	0.3334	r[2]
15	ESCO	Soil evaporation compensation factor	0	0.5	0.14375	v[1]
16	SOL_K()	Saturated hydraulic conductivity	0	0.3	0.14625	r[2]

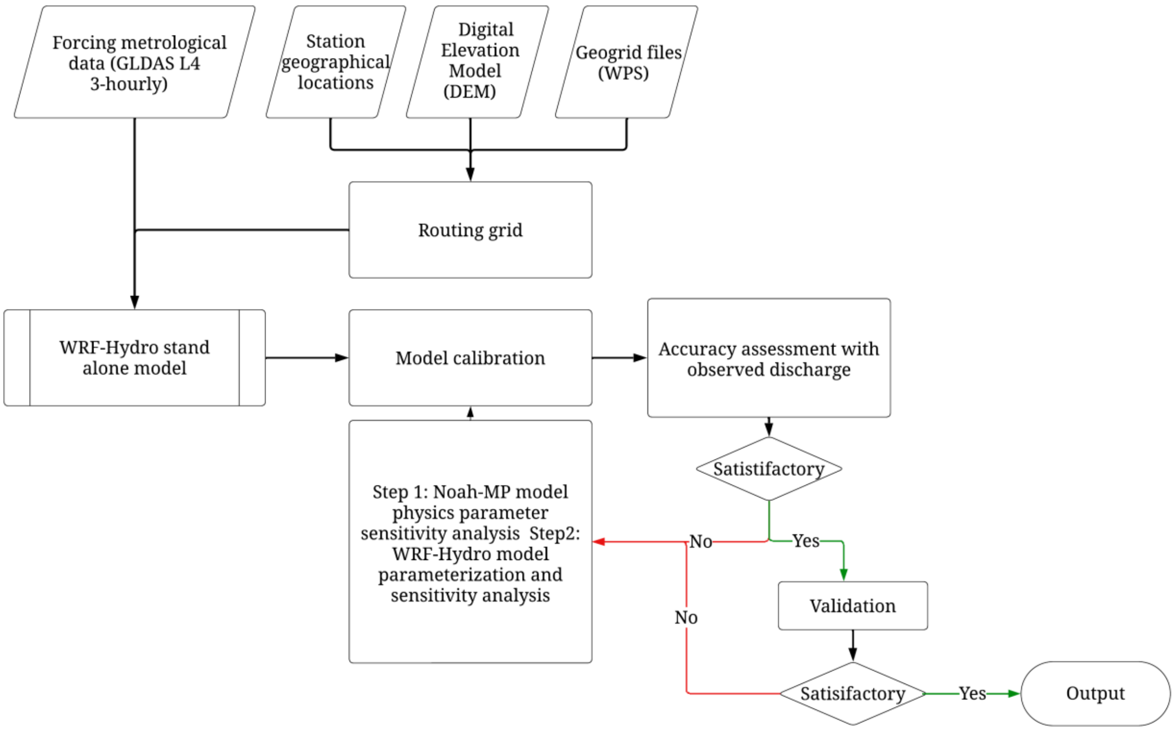

Figure 4.7 Overall flow diagram of the WRF-Hydro model configuration.

4.3.1 WRF-Hydro model calibration and validation

Noah-MP is the default LSM in the WRF-Hydro mode since the version 5 was released, which is an enhanced version of Noah-LSM offering various parameterization choices (Niu et al., 2011). The Noah-MP model offers an various range of user-control process, unlike Noah model (Yu et al., 2023). The physics scheme of the Noah-MP model underwent sensitivity analysis by initially configuring all schemes with recommended settings and subsequently adjusting each scheme individually to determine the optimal configuration. The recommended configuration for Noah-MP and the customized setup for the current study model are detailed in **Table 4.3**.

The mode parameters were calibrated manually by changing the values within the acceptable range. The parameters set were chosen based on the literature review and subjected to the sensitivity analysis (Liu et al., 2021; Mascaro et al., 2023; Shafqat Mehboob et al., 2022; Yu et al., 2023). Following sensitivity analysis, three of the parameters were set to the new optimal values and the remaining were kept as default values, as summarized in **Table 4.4**.

Table 4.3 Noah-MP name list for the physics option used for WRF-Hydro modelling.

Parameterization description	Selected after sensitivity test	Model recommended option
Dynamic vegetation	4- Table LAI	4- Table LAI
Canopy stomatal resistance	1-Ball-Berry	1-Ball-Berry
Soil moisture factor for stomatal resistance	1-Noah	1-Noah
Runoff and groundwater	3-Original surface and subsurface runoff	3-Original surface and subsurface runoff
Surface layer drag Coeff.	2-Original Noah (Chen97)	1-M-O
Supercooled liquid water	1-No iteration	1-No iteration
Frozen soil permeability	1-Linear effects, more permeable	1-Linear effects, more permeable
Radiation transfer	3-Two-stream applied to vegetated fraction	3-two-stream applied to vegetated fraction
Ground snow surface albedo	2-CLASS	2-CLASS
Partitioning precipitation into rainfall & snowfall	2 -BATS	1 - Jordan (1991)
Lower boundary condition of soil temperature	1-Zero heat flux from bottom	2 -TBOT at ZBOT (8 m) read from a file (original Noah)
Snow/soil temperature time scheme	2-Full implicit	1-Semi-implicit
Surface resistance to evaporation/sublimation	1 -Sakaguchi and Zeng, 2009	1 -Sakaguchi and Zeng, 2009
Glacier treatment	2-Ice treatment more like original Noah	1-Include phase change of ice

4.3.2 Datasets for WRF-Hydro modelling

WRF-Hydro models requires the minimum input data includes the air temperature, precipitation, surface wind speed, specific humidity, shortwave radiation, longwave radiation, and surface pressure. In this study, Global Land Data Assimilation System (GLDAS) gridded data with 3-hourly temporal resolution served as boundary conditions for the model. After rigorous data quality checks, observed discharge data from five gauging stations were selected for evaluating model accuracy. **Table 4.5** represent the data used for the WRF-Hydro model setup, calibration and validation.

Table 4.4 Summary of model parameters calibration. R means value has been multiplied by the factor, and A means the parameter's value has been replaced by a selected value.

No	Parameter	Abbreviation	Range	Selected value	Hydrological response controlling
		Soil parameters			
1	Soil pore size distribution index	BEXP	0.01-10	0.6^R	Infiltration
2	Saturated hydraulics conductivity	dksat	0.0001-0.00001	Default	Infiltration
		Snow parameter			
3	Melt factor for snow depletion curve	MFSNO	0.1-8.5	1^A	Snow ablation
		Groundwater parameters			
4	Maximum bucket depth	Zmax	5-250	250^A	Baseflow
5	Exponent of bucket model	Expon		Default	Baseflow
		Runoff parameters			
6	Surface runoff parameterization	REFKDT	0.1-5	Default	Partition of total runoff into surface and subsurface runoff
7	Linear scaling of "openness" of bottom drainage boundary	Slope	0.1-1	Default	Aquifer recharge

Table 4.5 Summary of the input data used in the WRF-Hydro model.

No	Description	Sources	Spatial resolution	Temporal resolution	Source
1	Forcing data (wind speed u and v component, temperature at 2 m, precipitation, specific humidity, incoming shortwave radiation, incoming long wave radiation, surface pressure)	Global Land Data Assimilation System (GLDAS)	0.25×0.25 deg	3 h	https://ldas.gsfc.nasa.gov/gldas/gldas-get-data
2	Digital elevation model (DEM)	SRTM	1 arcsec	-	https://earthexplorer.usgs.gov/
3	Observation discharge for calibration and validation	MEW	Point data	Daily	Ministry of Energy and Water, Islamic Republic of Afghanistan

4.3.3 Observed discharge data quality control

ARB authority utilized velocity-area method to measure the river discharge. They employ a current meter to measure velocity and use wading or cableways to measure water depth. Errors in the observed data are inevitable and typically categorized as observational errors or inherent uncertainties (Onogi, 1998). The observational errors are classified into random and systematic errors. Random errors are associated with misreading caused by human error, while systematic error is the refers to the discrepancy between the mean of all observations from the true values (Onogi, 1998). Also, rough errors may rises from problematic observations, human errors during the record, or data corruption during transmission. Quality control of data is essential to reduce the error in the records. To clear the data from the errors, after careful inspection of the discharge records, two measures were adopted for error removal.

1. Daily observations showing identical values persisting for more than 10 consecutive days were identified as suspect data points (Gudmundsson et al., 2018).
2. To detect outliers, the Z-score was adopted (Díaz Muñiz et al., 2012). The Z-score was calculated as per **Eq. (4.1)**, Z-score larger than 3 and smaller than -3 were counted as outliers.

$$Z = \frac{x_i - \bar{x}}{\sigma} \tag{4.1}$$

where x_i is the observation, $\bar{x}$ is the mean value of the observations, and σ is the standard deviation. Then, records with less than 10% error in the total of observation period were counted as reliable record. **Table 4.6** summarized quality control stations result. Five stations discharge records were flagged as reliable and were used for further analysis.

4.4 Model performance assessment

Statistical analysis were used to evaluate the hydrological model performance, namely, the correlation coefficient (R) (**Eq 4.2**), coefficient of determination (R2) (**Eq. 4.3**), Nash-Sutcliffe efficiency (NSE) (**Eq 4.4**), Kling-Gupta efficiency (KGE) (Kling et al., 2012) (**Eq 4.5**), and percent bias (PBIAS) (Gupta et al., 1999) (**Eq 4.8**).

$$r = \frac{\sum_{i=1}^{n}(Q_i - \bar{Q}) \times (P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2 \times \sum_{i=1}^{n}(P_i - \bar{P})^2}} \tag{4.2}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(Q_i - \bar{Q}) \times (P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2} \times \sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}\right)^2 \tag{4.3}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_i - P_i)^2}{\sum_{i=1}^{n}(Q_i - \bar{Q})^2} \quad (4.4)$$

$$KGE = 1 - \sqrt{(1-r)^2 + (\beta - 1)^2 + (\gamma - 1)^2} \quad (4.5)$$

$$\beta = \frac{\bar{P}}{\bar{Q}} \quad (4.6)$$

$$\gamma = \frac{\sigma_s/\bar{P}}{\sigma_o/\bar{Q}} \quad (4.7)$$

$$PBIAS = \frac{\sum_{i=1}^{n}(Q_i - P_i)(100)}{\sum_{i=1}^{n} Q_i} \quad (4.8)$$

where Q_i is the measured discharge (m^3/s), P_i is the simulated discharge (m^3/s), $\bar{Q}$ is the average observed discharge (m^3/s), $\bar{P}$ is the average simulated discharge (m^3/s), β is the bias ratio (dimensionless), γ is the variability ratio (dimensionless), $\sigma_{s,o}$ is the standard deviation of the simulated and observed discharge, and n is the number of days.

Table 4.6 List of discharge measurement stations in the ARB and the results of quality control.

No	Station	River	Number of suspects	Total number of readings	Percentage of suspect's data (%)	Remark
1	Balay-i-Kelgai	Kunduz	666	3652	18.2	Unreliable
2	Doshi	Kunduz	896	3652	24.5	Unreliable
3	Gerdab	Kunduz	343	3652	9.3	Reliable
4	Tangi-Nahrin	Kunduz	1864	3652	51.0	Unreliable
5	Dasht-i-Safid	Kunduz	675	3652	18.4	Unreliable
6	Pul-i-Chogha	Khanabad	427	2557	16.6	Unreliable
7	Khawjaghar	Kokcha	231	3652	6.3	Reliable
8	Nazdik-i-Taluqan	Khanabad	211	3652	5.7	Reliable
9	Pul-i-Bangi	Khanabad	218	3652	5.9	Reliable
10	Keshem	Kokcha	519	3652	14.2	Unreliable
11	Nazdik-i-Keshem	Kokcha	63	2399	2.6	Reliable
12	Pul-i-Teshkan	Kokcha	884	3652	24.2	Unreliable
13	Khenjan	Kunduz	867	3652	23.7	Unreliable
14	Doab	Kunduz	545	3652	14.9	Unreliable

4.5 Estimation of the agricultural water consumption

The agricultural sector consumes more than 90% of the water in Afghanistan (Akbari & Torabi Haghighi, 2022). To determine the agricultural water consumption over both study regions, we determined the agricultural land area and crop type. The crop water requirement (CWR) and irrigation water requirement (IWR) were estimated for each site and included in the estimations. The details on estimating the crop type map, CWR, and IWR are defined in the upcoming sections.

4.5.1 Crop type map

Mapping crop types at the field level is crucial for various applications in agricultural monitoring and ensuring food security. In countries with limited site observations, remote sensing data are an alternative. The FAO 2020 crop type map for Afghanistan with a spatial resolution of 10 m was used as the field label for the 6 different crop types instead of field observations (FAO, 2020a). **Figure 4.8** shows the crop type map provided by UNFAO. The FAO crop type map for Afghanistan was resampled to a MODIS spatial resolution of 250 m, after which the labels for each pixel were retrieved.

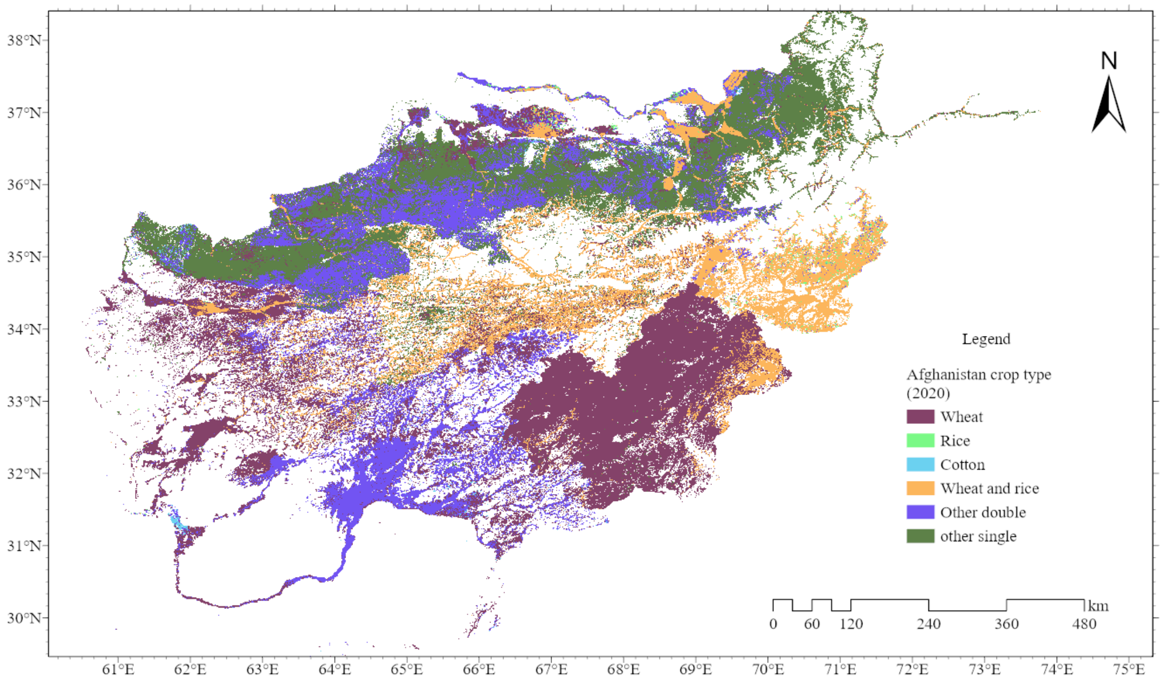

Figure 4.8 Afghanistan crop type map 2020 (FAO, 2020a).

In literature machine learning classification has become a major focus in remote sensing (Belgiu & Drăgu, 2016; Mountrakis et al., 2011; M. Pal, 2005; Wang et al., 2019). Machine learning is generally able to model complex class signatures, accept a variety of input predictor data, and do not make assumptions about data distribution (Maxwell et al., 2018). While conventional methods have been widely used, they may struggle to capture complex relationships or variations in spectral signatures especially in mixed pixel scenarios and heterogenous landscapes. In the other hand machine learning approaches benefits from the atomization of the process and requires less processing time with respect to the traditional methods.

The NDVI data for each pixel were retrieved from the MODIS Aqua NDVI product (MYD13Q1) and the MODIS Terra NDVI product (MOD13Q1) from 29th August of the previous year to 6th September of the following year to cover the full cycle of crop cultivation to the harvesting stage. The labels from the 2020 Afghanistan crop type map were matched with 8 days of NDVI data for each pixel. Three land classification supervised methods, random forest (RF), support vector machine (SVM), and gradient boosting model (GBM), were used to predict crop type maps for 2020 from the MODIS satellite normalized difference vegetation index (NDVI) input. The data were divided into 80% for training and 20% for testing. The three models hyperparameters were tuned to see the sensitivity of the model performance with respect to them. **Table 4.7** summarized the set of the hyperparameters used for each model during training. Finally, the voting classifier method with a majority voting setup was used to determine the crop type label for each pixel.

NDVI can represent the cyclic and seasonal growth of the crops through its temporal variation in the NDVI's values. However, there are few limitations on usage of the NDVI as indicators for the crop types mapping such as similarity of the phenological stages, environmental variability, temporal resolution, human errors, etc. Different crops can exhibit similar phenological stages, making it difficult to distinguish between them. Environmental variability also can vary the phenological stages, parameters such as temperature, precipitation, soil type should also be encountered during crop type classification. Phenological observations require frequent monitoring over time to accurately capture the various growth stages of crops. This high temporal resolution can be resource-intensive and challenging to maintain consistently across large areas. In the other hand the quality of the observation data could extremely improve or decline the quality of the crop type maps produced through remote sensing approaches.

The ARB is located in a mountainous region with large differences in elevation. Temperature variation is a function of elevation, and crop growth also strongly impacts the accumulated heat experienced by crops. The ARB was divided into eight elevation zones with 500 m differences in elevation to determine the temperature variation with elevation. Areas with slopes greater than 20% are relatively steep and not suitable for agricultural activities (Qamer et al., 2021). Non-irrigated areas were masked from the MODIS NDVI dataset to reduce the estimation time for the models. After testing the models for 2020, the same model was used to construct a crop type map for the ARB from 2014 to 2019. Figure 4.9 represents the overall workflow for the prediction of the crop type map in the ARB. The hyperparameters used for each machine learning model are summarized in **Table 4.7**.

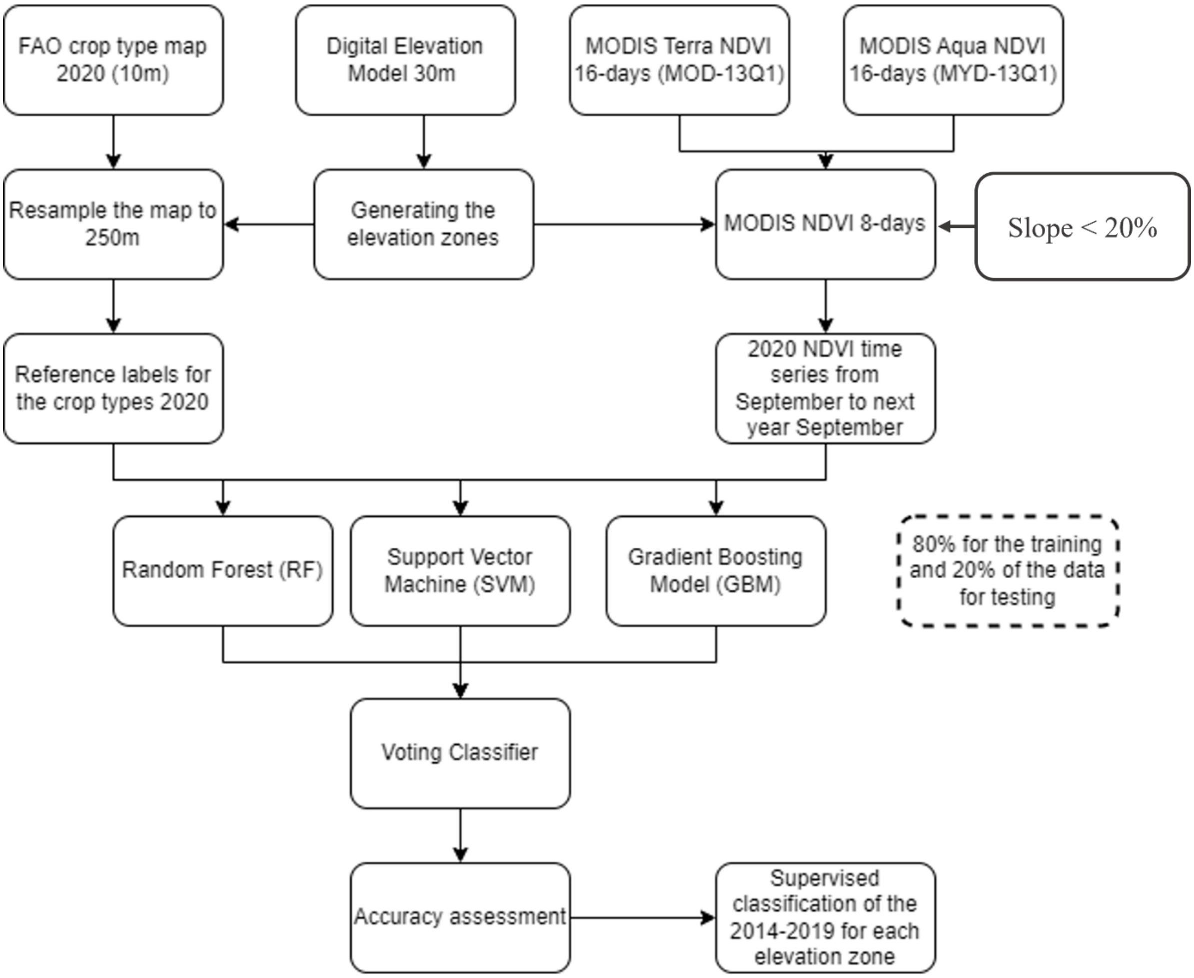

Figure 4.9 Overall flowchart for the prediction of the crop type map for ARB.

Table 4.7 Hyperparameters used for each machine learning model for crop type prediction.

Method	Hyperparameter	value
Random Forest	criterion	“gini”
	n_estimators	100
	max_depth	None
	bootstrap	True
	class_weight	‘balanced’
Support Vector Machie	kernel	‘rbf’
	C	1.0
	gamma	‘scale’
	class_weight	‘balanced’
Gradient Boosting Model	n_estimators	100
	criterion	'friedman_mse'
	class_weight	‘balanced’

In the BRB, the crop types were identified according to the national agricultural profile between 2016-2018, and the agricultural land area was determined based on an official NRB reports. According to the NSIA (2019), the primary cultivated crops and their respective cultivation areas include wheat (60.0%), rice (3.3%), barley (3.3%), maize (3.6%), pulses (2.3%), vegetables (4.3%), potato (1%), onion (0.3%), fruits (9.3%), almond (0.6%), oilseeds (2.6%), and others (9.4%). The new irrigation scenarios proposed in the current study involve allocating wheat (65%), rice (5%), maize (5%), pulses (4%), spring vegetables (5%), summer vegetables (4%), and orchards (12%) across the entire downstream BRB. The crop land areas were calculated based on the irrigation area served by the canals in the BRB. **Table 4.8** shows the 11 major canals in the downstream of the BRB and percentages of water allocation to each canal individually according to the NRB.

Table 4.8 The area of irrigated land and water allocations for the 11 downstream irrigation canals (NRBA, 2019).

No	Canal name	Irrigation land area (ha)	Water allocation (%)
1	Imam Sahib	7741.9	3.80
2	Nahar-i-Shahi	14005.2	10.66
3	Sia Gird	7702.0	2.85
4	Balkh	8086.6	1.33
5	Moshtaq	9207.1	3.98
6	Chemtal	8003.4	3.12
7	Abdullah	22866.3	13.32
8	Dawlat Abad	38728.2	14.27
9	Char Bolak	36078.3	14.27
10	Fayaz Abad	17180.5	11.42
11	Aqcha	88706.0	20.94
Total		258305.5	100*

4.5.2 Crop Water Requirement (CWR) and Irrigation Water Requirement (IWR) estimation

Field water management is one of the most important factors affecting crop yield in agricultural areas. Water shortages in the field cause crop water stress and reduce crop yield. The FAO (RG, 1998) defines field evapotranspiration (ET) from disease-free, fertilized crops grown in a large field under proper soil moisture conditions and full yield conditions as *crop evapotranspiration under standard conditions* (ET_c).

$$ET_c = CWR = K_c \times ET_0 \tag{4.9}$$

where ET_c is crop evapotranspiration (mm/day), K_c is the crop coefficient, and ET_0 is the reference crop evapotranspiration (mm/day).

In the case of the ARB, ET_0 was calculated from metrological data input. Several empirical and semi-imperial methods have been developed over the past five decades (Savva & Frenken, 2002). In the present study, the Penman–Monteith method was adopted for estimation of the reference evapotranspiration. In this method, a reference surface is defined with an assumed crop height of 0.12 m, an albedo of 0.23, and a fixed surface resistance of 70 s/m (RG, 1998). The Penman–Monteith equation is shown in the below equation (RG, 1998):

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (4.10)$$

where ET_o is the reference evapotranspiration (mm/day), R_n is the net radiation at the crop surface (MJ m-2 day-1), G is the soil heat flux density (MJ m-2 day-1), T is the mean daily air temperature (°C), u_2 is the wind speed at 2 m height (m/s), e_s is the saturation vapour pressure (kPa), e_a is the actual vapour pressure (kPa), $(e_s - e_a)$ is the saturation vapour pressure deficit (kPa), Δ is the slope vapour pressure curve (kPa °C), and γ is the psychrometric constant (kPa °C).

For the detailed step-by-step procedures for the calculation of ET_o, please refer to (Savva & Frenken, 2002) section 2.3.3. In the case of the BRB, the CWR was adopted from a recent published study conducted in southern Afghanistan (Wali et al., 2019). Wali et al. (2019) utilized remote sensing image processing procedure and generate crop type maps for 2017. Then calculate crop water requirements for different crop type. The climatic conditions in Khost Province, with a average annual temperature of 10.4 °C and a average annual precipitation of 188 mm, are similar to the climatical conditions of the BRB. CWR for different types of the crop from Wali et al. (2019) are summarized in **Table 4.9** for entire year.

The irrigation water requirement (IWR) is the amount of water required for crops to fully satisfy the CWR. According to (RG, 1998), the IWR can be estimated via the following equation:

$$IWR = ET_c - P_e \quad (4.11)$$

where IWR is the irrigation water requirement, ET_c is the CWR, and P_e is the effective precipitation. The effective precipitation is the amount of rainfall that is retained in the root zones and can be used by the planet. The amount of precipitation water that forms runoff, evaporates, and percolates deep into the ground must be excluded to estimate the effective rainfall. As suggested by (RG, 1998), effective precipitation was estimated as follows using the empirical formulas developed for the arid and sub-humid climates.

$$P_e = 0.8 \times P - 25 \; if \; P > 75 \; mm/month \quad (4.12)$$

$$P_e = 0.6 \times P - 10 \; if \; P < 75 \; mm/month \quad (4.13)$$

where P indicates the monthly precipitation (mm).

Table 4. The estimation of the monthly irrigation water consumption for 1 ha of agricultural land downstream of the BRB was adopted from Hussainzada & Lee (2022).

Crop type	Area (%)	Monthly crop water requirement (m^3/ha/mon)											
		Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Wheat	65	213.9	339	514.2	828.75	610.4						59	111.2
Orchards	12			57	130.8	163.6	166	167.3	147.1	57.5			
Spring vegetables	5		8.4	25.05	58.2	46.8							
Maize	5					11	42.4	74.95	60.15	18.8			
Summer vegetables	4					35.08	49	53.8	42.04	2.32			
Rice	5					27.85	76.95	85.5	77.4	61.9	31.3		
Pulses	4					6.44	39.52	59.28	26.72	0			
Total	100	213.9	348	569.2	1017.8	901.1	373.8	440.8	353.4	140	31.3	59	111.2

It should be noted that the IWR of rice paddy fields is an exception, and the following water should be included in the estimation. The amount of water needed for land preparation before sowing (200 mm), the average percolation and seepage losses (1.7 mm/day), and the amount of water needed to establish a water layer during sowing and maintenance during the growing period (100 mm/month) were measured. Rice was cultivated in the nursery from 22nd May and transferred to the land between 1st June and 20th June after harvesting the wheat. It should be considered that the area for the nursery is 5% of the land after the transformation of the rice to the field. In Afghanistan, seed bags are first put into water for approximately 2-3 days, after which pregerminated seeds are sown in nursery beds for 30-40 days (Kakar et al., 2019).

4.5.3 Input dataset for the estimation of ET_0

The metrological dataset from observation stations located in the ARB was used for the estimation of ET_0. **Table 4.10** shows a summary of the dataset and their sources for the estimation of ET_0. Missing data are a challenge for the estimation of ET_0. In the current study, the missing data were determined via field analysis via the sample arithmetic mean method by averaging the available records for the same days from 2014 to 2019 and adding them to the missing cells. Since all the variables are not located in the same geographical location, the sunshine hours from the closest stations were moved to the records where sunshine hours were not available. It is difficult for precipitation and wind speed data to shift from one station to another station due to the effect of topographical conditions between two sites. To overcome this problem, wind speed data were adopted from the NASA Prediction of Worldwide Energy Resources (POWER), and precipitation data were adopted from Modern-Era Retrospective Analysis for Research and Application (MERRA-2). The wind speed data were compared with the observed wind speed data and proved to be reliable. **Table 4.11** summarizes the results of the statistical analysis of the wind speed. It should be noted that the three stations with the lowest statistics are located between the city center and are covered by trees, which means that wind movement and air circulation are affected by these stations. The precipitation dataset from MERRA-2 was shown to be reliable at the daily time scale, as in a previous study over Afghanistan (Samim, 2024).

Table 4.9 Summary of the input data for the estimation of the reference evapotranspiration and irrigation water requirement (IWR).

No	Variable	Resolution	Source
1	Maximum air temperature	Daily	Ministry of Energy and Water (MEW), Islamic Republic of Afghanistan
2	Minimum air temperature	Daily	MEW
3	Maximum relative humidity	Daily	MEW
4	Minimum relative humidity	Daily	MEW
5	Wind speed	Daily	NASA Prediction of Worldwide Energy Resources (https://power.larc.nasa.gov/data-access-viewer/).
6	Sunshine hours	Daily	MEW
7	Precipitation	Daily	Modern-Era Retrospective analysis for Research and Application (MERRA-2)

ET_0 was estimated over the 10 metrological stations all over the ARB. The locations of the observation stations are shown in **Figure 4.11**. The red circles show the locations of the stations used for the estimation of $ET_{0,}$ and the blue circle shows the locations of the stations with wind speed and sunshine hours records.

Table 4.10 Summary of the statistical analysis for the accuracy assessment of the POWER wind speed.

No	Station	R	MBE	SD_Obs	SD_MERRA2
1	Farkhar	0.002	-1.6	0.23	0.47
2	Keshem	0.041	-1.90	0.19	0.59
3	Khawjaghar	0.45	-0.10	0.91	0.71
4	Rustaq	0.248	-1.50	0.34	0.59
5	Taluqan	0.599	-0.23	0.67	0.71
6	Worsaj	0.427	-0.25	0.80	0.62
7	Yakawlang	0.389	2.16	2.93	1.20
8	Tapa-i-Farhat	0.337	-0.97	0.68	0.76

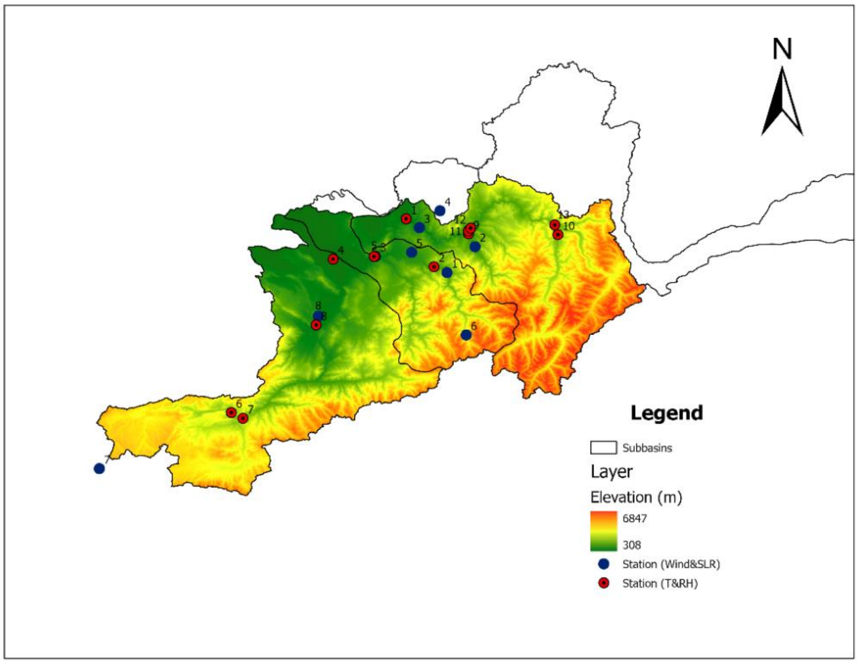

Figure 4.10 Locations of the observation stations used for the estimation of ET_0 are shown with red circles, and the locations of the wind speed and sunshine hour observation stations are shown with blue circles.

4.5.4 Crop coefficient and crop calendar

The crop calendar is important for determining the different plant growth phases. The crop calendar data were collected from the MAIL. The crop calendar exhibits four different phases for crop growth, namely, sowing, development, mid-season, and harvesting. The sowing period includes seeding to 10% growth of the plant, the development stage is the time required for the plant to reach full growth, the midseason is the plant flowering stage until it reaches maturity, and harvesting is the time required for the farmer to harvest agricultural products. **Figure 4.11** represents the crop calendar in the ARB for the major crops, including all four stages of growth. The crop coefficient represents the crop water requirement ratio to the standard condition defined by the FAO for healthy grassland with a height of 0.12 m. The crop coefficient data were adopted from Table 12 of the FAO guidelines (RG, 1998). Figure 4.12 shows a graphical representation of the crop coefficient for the five major crops for the ARB: wheat, rice, cotton, barley, and maize.

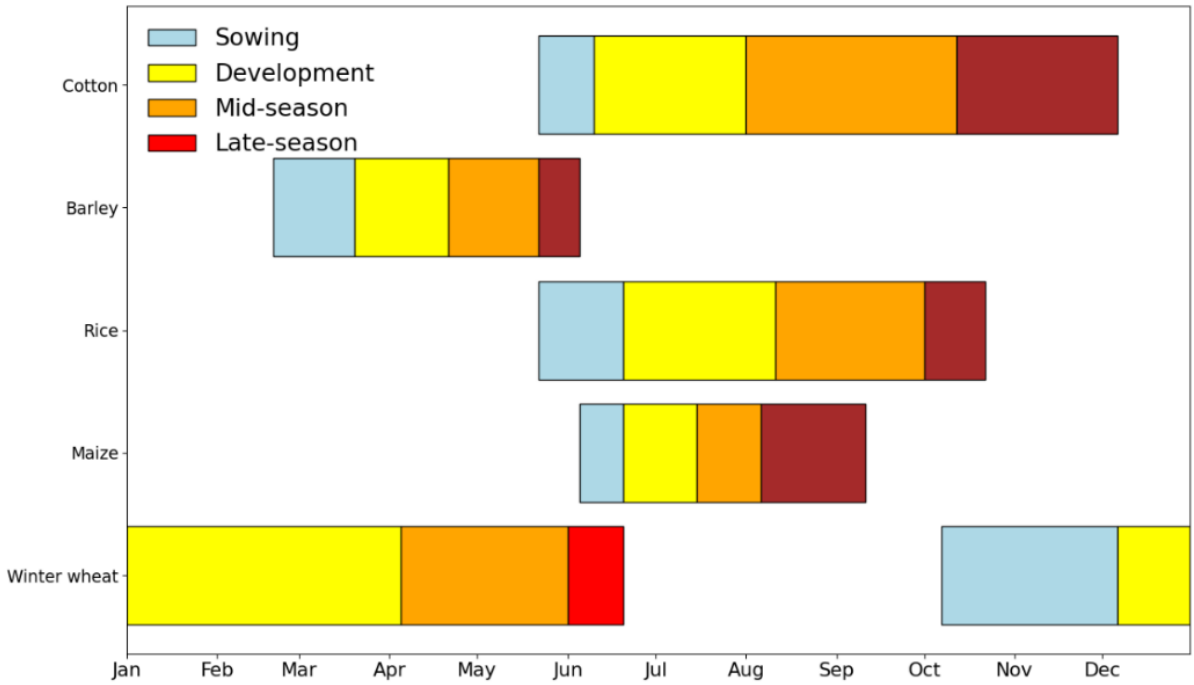

Figure 4.11 Crop calendar for the major crops in the ARB.

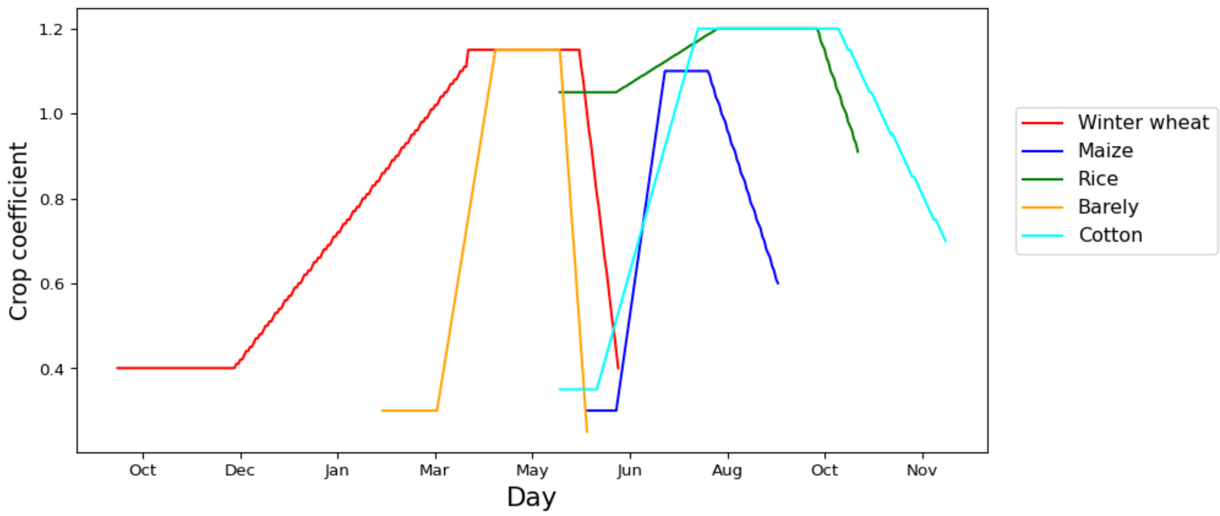

Figure 4.12 Crop coefficients for the major crops in ARB based on Table 12 of the FAO guideline for CWR.

4.6 Domestic water supply consumption

Domestic water consumption by local residents is highly important for the management of water resources. The municipal water supply systems in Afghanistan mostly rely on groundwater sources, with individual wells and storage systems supplying water to limited households. In places where a systematic water supply system is unavailable, locals dig their individual wells for the water supply where groundwater sources are available. As reported by the United States Agency International Development (USAID), only 42% of Afghans have access to safe drinking water (USAID, 2020b).

In this study, we include domestic water consumption in the surface water budget from rivers passing through residential settlements. The Afghanistan Ministry of Urban Development and Land (MoUD) determined the per capita demand for water supply to be 140 l/day/person. The settlement population was adopted from the National Information and Statistics Authority. The effective life span for water supply projects was considered to be 50 years from the present until the 2070s. The population growth was estimated based on the following equation and a population growth rate of 2.1% (NISA, 2020):

$$P_t = P_0(1 + r)^n \qquad (4.14)$$

where P_t is the projected population at time t, P_0 is the initial population, r is the population growth rate, and n is the number of years for the projection.

Table 4.11 Domestic water supply consumption for the ARB and BRB regions projected for the 2070s.

No	Province	Population [2020]	Projected population [2070]	Drinking water consumption (m3/day) [2070]
		ARB region		
1	Badakhshan	1,091,758	3,016,667	422,333
2	Takhar	1,133,568	3,132,193	438,507
3	Kunduz	1,184,024	3,271,610	458,025
	Total	4,975,740	13,748,605	1,924,805
		BRB region		
4	Mazar-i-Sharif	584,886	1,686,024	236,043

4.7 Dam suitability assessment using analytical hierarchy process (AHP)

Selection of suitable site for dams are primary water resource management strategy (Karakuş & Yıldız, 2022). Selecting a dam site quantitatively involves evaluating several criteria, including soil type (S), drainage (D), slope (Sl), elevation (E), and land use/land cover (LULC). Additionally, this study utilized GIS and Analytic Hierarchy Process (AHP) through multicriteria decisions analysis (MCDA) to identify suitable dam site areas. Each criterion's level of importance was identified using the expert opinions.

The level of importance of each criterion was identified using expert opinions. The questionnaire was sent via email to 13 experts in the field, including university professors, NGO and international organization staff, and researchers specializing in water-related subjects in Afghanistan. Responses from 10 of these experts were used to rank the criteria, while the remaining three were found to be inconsistent. Following list outlines the criteria and their description. The natural break method was used to classify the criteria to very low, low, medium, high, and very high suitability for dam site areas. The results are shown in **Table 4.12**.

- Soil: Soil classification are crucial in finding to determine the infiltration characteristics and water holding capacity or different areas (Cabrera & Lee, 2018).

- Discharge: The volume of water flow in the river per unit of time (m^3/s). Precipitation, snowmelt, and subsurface water contribute to the river discharge (Hussainzada & Lee, 2021).
- Slope: As the slope increases, the flow velocity also rises. A steeper gradient reduces infiltration and increases surface runoff. Conversely, in areas with a lower gradient, a large volume of water can become stagnant, leading to flooding (Lei et al., 2020).
- Elevation: The direction of over land flow and the depth of the water level are regulated by the elevation (Al-Ruzouq et al., 2019).
- Land Use and Land Cover: The barren land are more desirable than the agricultural land and built-up due to lower cost of land accessions.

Table 4.12 AHP's criteria classification according to their importance.

Criteria	**Classification [Level of suitability]**				
	Very Low [1]	**Low [2]**	**Moderate [3]**	**High [4]**	**Very High [5]**
LULC	Built-up	Agriculture	Forest	Water Bodies	Barren Land
Discharge (m3/s)	0.03-0.61	0.62-2.59	2.60-5.11	5.12-19.89	19.90-50.18
Elevation (m)	3054-4621	2255-3054	1439-2255	706-1439	241-706
Slope (deg)	39.30- 83	26.64-39.30	16.24-26.63	7.4-16.24	0.1-7.5
Soil	-	Rock outcrops (RK)	Coarse and rocky soil (LP)	Sandy clay loam (AR)	Silt loam (CL)

The first step in AHP is the pairwise comparison matrix, where each criterion compared to other criterions in a scale of one to nine from Saaty (1980). However, in the current assessment with adjust the scale from one to five based on the number of criteria defined. Secondly, all the values are normalized, where each individual value in the comparison matrix (C_{ij}) was divided by the sum of the columns in the pairwise comparison matrix to estimates the normalized value (X_{ij}) (**Eq 4.15**).

$$X_{ij} = C_{ij} / \sum_{i=1}^{n} C_{ij} \quad (4.15)$$

As a next step the weights were generate for each criterion (W_{ij}) by dividing the normalized value (X_{ij}) based on the number of criteria (n) (**Eq 4.16**).

$$W_{ij} = \sum_{i=1}^{n} X_{ij}/n \quad (4.16)$$

Lastly, the consistency ratio was assessed with three subcomponents. The first component determines the consistency measure (CM). The CM can be derived by multiplying the pairwise matrix by the weight (W_{ij}), and then dividing the result by the weighted sum vector with the criterion weight. The Consistency index (CI) is subsequently calculated using **Equation 4.17**, where λ_{max} represent the average of the CM, and n is the total number of criteria. Finally, the Consistency Ratio (CR) is determined using **Equation 4.18**, with the Relative Index (RI) value defined in the relative index table by Prof. Saaty (1980).

$$CI = (\lambda max - n) / (n - 1) \quad (4.17)$$

$$CR = CI/RI \quad (4.18)$$

Chapter 5

Hydrological modelling

5.1 Introduction

Historically, human activity and economic development are crucially linked with water resources and their management. The water scarcity issue has significantly exacerbated over the past century and demands urgent attention and sustainable solutions. A surge in population is the key driver of water scarcity, as an increase in population corresponds to a greater demand for water (FAO, 2020b). According to FAO (2020b), the annual per capita freshwater availability has declined by more than 20% in the past two decades, and the issue is more serious in western Asia and northern Africa. In these regions, the per capita freshwater barely reaches the annual average of 1000 m3, which is conventionally considered the threshold of severe water scarcity (FAO, 2020b). Countries with arid and semi-arid climates face heightened vulnerability to the challenges of drought and water scarcity. Past studies have reported noticeable increases in drought severity in Afghanistan, Central Asian countries, and Iran (Qutbudin et al., 2019; Ta et al., 2018; Zoljoodi & Didevarasl, 2013). Given the water crisis and challenges in these regions, a comprehensive approach considering extensive scientific studies of water resources is essential to address these issues.

Modelling is a common tool in many fields of scientific studies, especially in water science. Hydrological models have various applications, e.g., modelling existing watershed with existing input and output datasets (operational flood prediction, water resources management, or extension of data array for flood design of water resources assessment), coupled hydrology and meteorology (global climate models), coupled hydrology and geochemistry (nutrients and acid rain), ungaged basin runoff estimation, and prediction of the impact of changes (land use and land cover) (H. Wheater et al., 2007). Commonly, hydrological models can be classified as (1) empirical models or metric models, (2) conceptual models, and (3) physically based models based on process descriptions (A. Singh, 2018). According to Singh (2018), physically based models are suitable to overcome many shortcoming of the two other types of models due to the physical interpretation of the procedures incorporated into the model parameters.

In this study, the two most commonly used hydrological models were adopted for assessing water resource availability. The SWAT model was adopted from a previous study conducted in the BRB (Hussainzada & Lee, 2021). A hydrological model was developed for the ARB using WRF-Hydro hydrological models. Both models provide valuable long-term data about the hydrological dynamics of watersheds and water availability. The outputs from the hydrological models were used for water resource management and for testing the mitigation scenarios.

5.2 Literature review

The WRF-Hydro model has a various applications in studies evolves water-related issues. (Lee et al., 2022) utilized the WRF-Hydro model to demonstrate the characteristics of the most recent droughts occurring in the South Korea during 2008-2015, and the SSMI and SSI were calculated using WRF-Hydro simulations to evaluate agricultural and hydrological droughts. Next study assessed the capacity of the WRF-Hydro model in coupled mode to be used as a flood early warning system at the Ouémé River basin in Benin, which situated in West Africa, during 2008 to 2010 (Quenum et al., 2022). WRF-Hydro is one of the potential hydrological models that can be used in water resource planning. A scholar adopts WRF-Hydro fully coupled to simulate the streamflow of the Tono dam in West Africa during 1999 to 2003 with spatial resolution of 5 km and used the output of the WRF-Hydro model as input to a water balance model to simulate dam water levels (Naabil et al., 2017). The literature proves that WRF-Hydro model is capable of simulating hydrological processes in large to small watersheds.

The SWAT is another famous physical-based model widely used for predicting sediment and water circulation, chemical yield and agricultural productivity, studies associated with impact of climate change on the water resources, and policy testing. The following are a few examples of SWAT applications worldwide. In Guiamel & Lee, (2020a), SWAT was utilized to estimate the theoretical potential of hydropower generation in the Mindanao River Basin, Philippines. Another study adopted SWAT models to simulate 7 days of low flow each year with a ten years return period (7Q10) and analyze drought impacts at the Muskingum watershed of eastern Ohio, USA Shrestha et al. (2017). In Maghsood et al. (2019), SWAT was utilized in the northern Iran to simulate flood frequency of Talar River basin, encountering the impact of climate change with Coupled Model Intercomparison Project phase 5 (CMIP5) general circulation models (GCMs) dataset as input. In Xie & Cui, (2011), SWAT was adopted to investigate paddy rice field irrigation and assess the crop yield management in Zhanghe, China (Xie & Cui, 2011).

Despite its significance, there have been limited studies focusing on watershed modelling in Afghanistan. To date, few scientific attempts have focused on hydrological modelling over Afghanistan's watersheds by utilizing the Soil and Water Assessment Tool (SWAT) to simulate hydrological processes on a monthly time scale (Aawar & Khare, 2020; Ayoubi & Dongshik, 2016; Hussainzada & Lee, 2021; Ougahi et al., 2022; Tani & Tayfur, 2023). Hydrological models with rough temporal and spatial resolutions are useful tools and can provide a overall insight of the seasonal variation in water resources availability, aiding in the formulation of strategies for sustainable water resource management. Based on the existing literature, all hydrological modelling attempts over Afghanistan are on a monthly time scale, which is useful for water resource management. However, finer temporal resolution, such as daily and sub-daily models are essential for various purposes, e.g., flood prediction, assessing the impacts and consequences of watershed management, water storage management, fresh-water ecology, and generating input for socio-economic modelling, and ecological modelling (John et al., 2021).

In the current study, attempts were made to evaluate the performance of the Noah-MP LSM to enhance the simulation of snow processes at the ARB in Afghanistan. To evaluate the impact of the parameterization scheme of the Noah-MP LSM sensitivity analyses were conduct to and physics in the LSM were explored by calibrating different schemes and comparing the result with observations. WRF-Hydro model parameters were subjected to the sensitivity analysis and calibrated for the ARB to reconstruct the streamflow over three sub-watersheds in the ARB at 3 km spatial and daily temporal resolutions after careful optimization of the Noah-MP physics schemes. This study can contribute to the understanding and provide clear insight on the importance of the LSM model physics scheme within WRF-Hydro model for simulation of snowmelt-runoff processes and its impact on the simulation of streamflow magnitude and timing. Dechmi et al. (2012) emphasized on the importance of the water resources monitoring in the intense cultivated watershed for better understanding of the hydrological dynamics in the watershed. Meanwhile, long-term monitoring of the water resources and data collection is costly and time consuming (Santhi et al., 2006). In the other hand, it would be challenging to generalize a site-specific result of experiments to the regional level in watersheds with mixed soil type and land use and watersheds with complex topography (Santhi et al., 2006). Hydrological models could be used as an alternative for water resource management and useful tools to simulate the hydrological dynamics of the watershed using the limited observations as model performance verification source.

5.3 Hydrological model for the BRB

5.3.1 Baseflow

The relationship between the contribution of groundwater and streamflow is poorly understood in hydrology (Foster & Allen, 2015; Welch & Allen, 2012). In the low precipitation season, subsurface water discharge is a primary source of water in the downstream lowland (Evans et al., 2015; Foster & Allen, 2015; Welch & Allen, 2012). **Figure 5.1** dedicates the hydrographs of two simulations (1) with constant subsurface and (2) without subsurface input to the SWAT model. The hydrographs illustrate a uniform gap between the simulation results without subsurface water input with respect to the observations. Meanwhile, the simulation after subsurface contribution is considered in the model significantly improved the baseflow in the model results.

However, the model without subsurface water inclusion still simulates the temporal variation and pattern of the recorded discharge, but the mode is unrealistic due to large underestimation. In terms of the statistical indices for the model performance, the model performance is satisfactory to very good considering the R^2 values, while the NSE and PBAIS values were unsatisfactory in subbasins 7, 10, and 28. High underestimation declined the NSE range between -0.71 and -0.15 and the PBAIS range between 56.1% and 69.7%. In the subbasin 30, the model performance did not differ in both cases of with and without subsurface water input since the subbasins situated at the upstream of the river where six lakes feed perennial discharge to the river. The model statistical indicators summary without the subsurface water contribution case is replicated in **Table 5.1**.

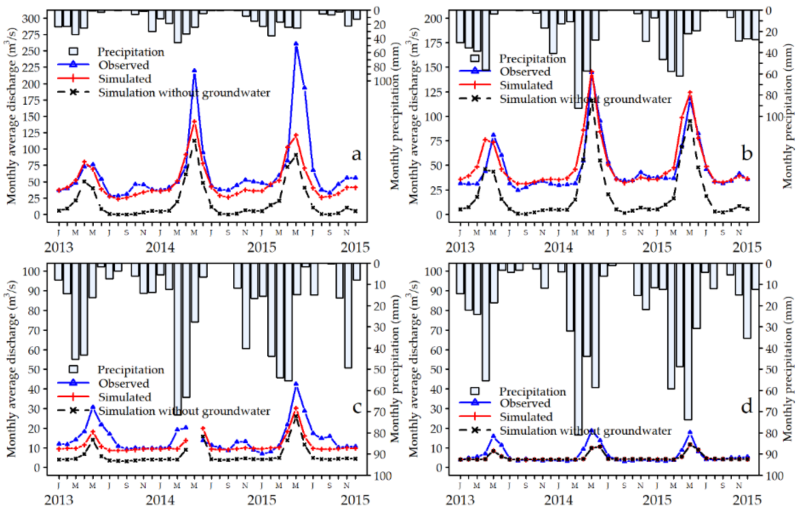

Figure 5.1 Comparative analysis of observed versus simulated monthly average discharges, both with and without groundwater contribution, alongside monthly precipitation data for the calibration period from 2013 to 2015. The subbasins analyzed are: (a) subbasin 7, (b) subbasin 10, (c) subbasin 28, and (d) subbasin 30.

Table 5.1 Summary of the model performance statistical indicators over the BRB.

Subbasin	Calibration W/O groundwater contribution			Calibration with groundwater contribution			Validation		
	R^2	NSE	PBIAS	R^2	NSE	PBIAS	R^2	NSE	PBIAS
7	0.70	-0.15	69.7	0.70	0.52	23.4	0.63	0.58	10.7
10	0.86	-0.17	56.5	0.86	0.83	-8.5	0.66	0.61	-4.6
28	0.69	-0.71	58.1	0.67	0.40	23.4	0.58	0.47	20.2
30	0.80	0.57	17.5	0.80	0.57	17.5	0.76	0.43	20.2

5.3.2 Calibration results of the SWAT model over the BRB

The simulation result from the model calibration were compared verses four gauging station situated in the subbasins 7, 10, 28, and 30. **Figure 5.2** dedicate the calibration results between the simulation and observed monthly discharges at the gauging stations in addition to the monthly precipitation records in each station. Hydrographs of the uncalibrated simulation show that the peak flows appeared earlier in March and April than the observations peak in May. The uncalibrated peak flows corresponded well with the peaks of observed precipitation. Thus, this lang in the peak flow can be caused by rapid snowmelt or misclassifying snow as rainfall in the model. Calibration of the temperature lapse rate, precipitation lapse rate, and snow parameters can enhance the resulting discharge hydrograph by encountering the snowmelt conditions in the model.

There is a good agreement between observation and simulated discharge after calibration of those selected parameters. The model accurately reflected streamflow variations across all subbasins during the steady-flow conditions of winter, summer, and autumn, consistently underestimating the observed discharges in subbasin 7. However, it struggled to accurately replicate the peak flows in subbasins 7, 28, and 30 during the spring of 2014 and 2015, resulting in underestimations of these peak flows.

The model uncertainty results demonstrated acceptable outputs, with p-factors of 0.89, 0.61, 0.71, and 0.56 for subbasins 7, 10, 28, and 30, respectively, and r-factors of 0.75, 1.27, 1.32, and 1.06, respectively. The P-factor represents the percentage of observations encompassed by the 95% PPU uncertainty range, while the r-factor indicates the relative width of the 95% probability band. (J. Yang et al., 2008). The model evaluation considering the statistical indices is summarized in **Table 5.1**. The model performance can be evaluated with the general criteria presented in **Table 5.2** (Aqnouy et al., 2019; Guiamel & Lee, 2020b). Considering the ranges described in **Table 5.2**, the model performed satisfactorily to very well with the respect to the R^2 values. With respect to the NSE indices the model performance can be classified as satisfactory to very good in three subbasin and unsatisfactory for subbasin 28. Meanwhile, the model performance is satisfactory to good for all the observation point with respect to the PBIAS values.

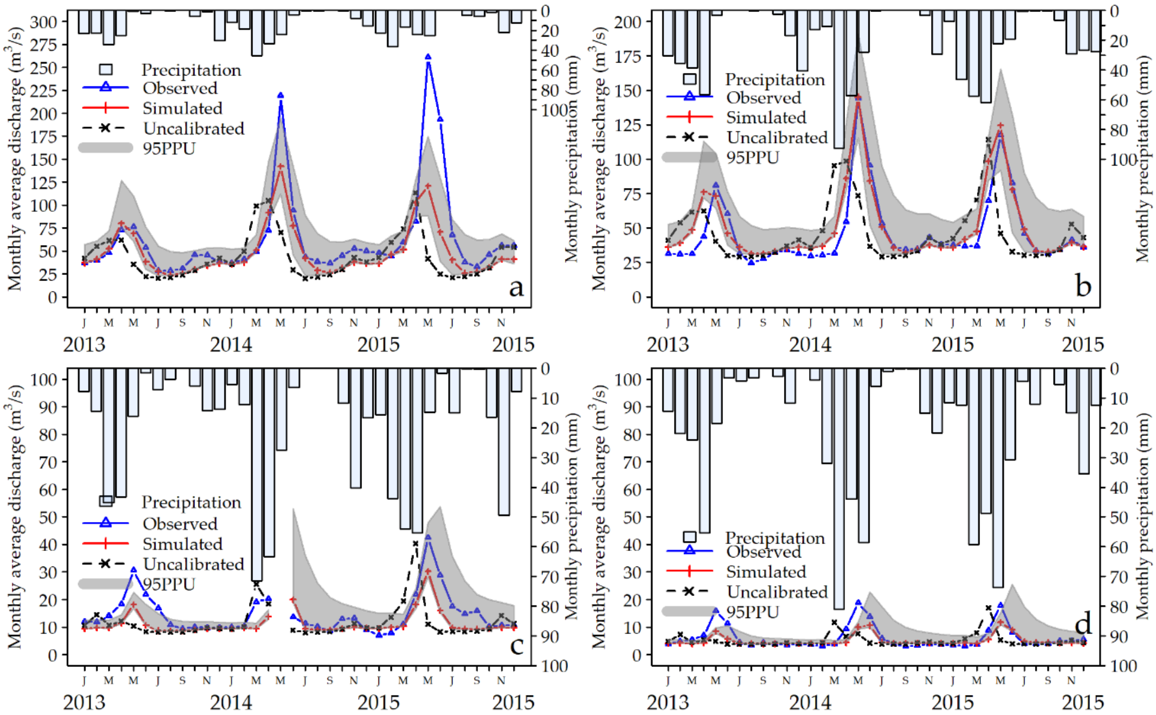

Figure 5.2 Comparative analysis of observed versus simulated monthly average discharges before and after calibration and the 95 PPU uncertainty ranges from the calibration and monthly rainfall from 2013 to 2015. a) subbasin 7, b) subbasin 10, c) subbasin28, and d) subbasin 30.

Table 5.2 General criteria for performance evaluation in a statistical test at the watershed scale.

Performance rating	R^2	NSE	PBIAS
Not Satisfactory	≤ 0.50	≤ 0.50	$\geq \pm 25\%$
Satisfactory	0.50-0.70	0.50-0.65	±15 - ±25
Good	0.70-0.80	0.65-0.75	±10 - ±15
Very good	≥ 0.80	≥ 0.75	$< \pm 10$

5.3.3 Validation of the SWAT model for the BRB

To ensure SWAT model robustness, the model was subjected to the validation for the period of January 2016 to September 2018 in subbasins 7, 10, 28 and 30. **Figure 5.3** is representing the validation results for all four subbasins. There is missing record in observation of discharge data in the subbasin 28 from October 2017 to September 2018 and in the subbasin 30 from

October 2016 to September 2017. The mode were set with optimal parameters values for the calibration period and single ran of the SWAT model were used for the validation purposes.

During the validation period, the model demonstrated acceptable performance, accurately resampling the flow pattern throughout the year and effectively attributing baseline discharge to groundwater input. However, the model validation showed underestimations in peak discharges for subbasins 7 and 10 in 2016.

The statistical indices for SWAT model performance are summarized in **Table 5.1**. The statistical indicator (R^2) for all four subbasins demonstrate satisfactory to good results. The PBIAS also dedicate satisfactory to very good results in all subbasins. The NSE results are satisfactory at the subbasins 7 and 10 and relatively lower values from satisfactory threshold for subbasins 28 and 30, with values of 0.47 and 0.43, respectively.

The comparison of statistical indicators between the calibration and validation periods revealed a slight decrease in performance during validation, except for subbasins 7 and 28, which showed slightly higher NSE values compared to their calibration period. These improvements were due to better simulation of peak flows and reduced underestimation during the validation period.

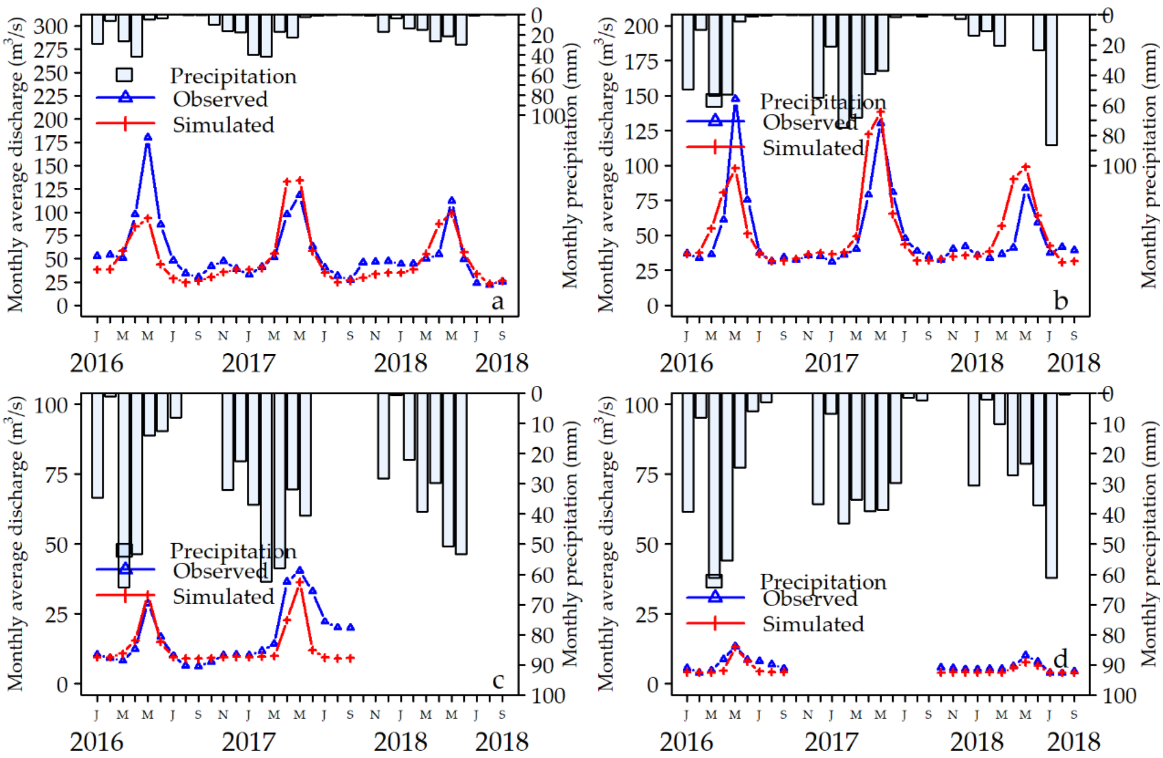

Figure 5.3 Comparative analysis of observed versus simulated monthly average discharges from the model validation, and the observed monthly total rainfall for the validation period from 2016 to September 2018. a) subbasin 7, b) subbasin 10, c) subbasin 28, and d) subbasin 30.

5.4 Hydrological model for ARB

5.4.1 WRF-Hydro's Noah-MP physics scheme calibration

In the simulation of the river discharge snow accumulation and snow melting process simulation is extremely important. As result of the sensitivity analysis for the Noah-MP physics option within WRF-Hydro model showed that LSM is particularly responsive to the snow/soil temperature time scheme (TEMP) and surface layer drag coefficient (SFC) physics option. **Figure 5.4(a)** to **Figure 5.4(e)** shows four possible combinations of two physics options. The hydrographs in **Figure 5.4** representing the significance physics options of the Noah-MP LSM model in the simulation of the snow-related process within the WRF-Hydro modelling system.

As you can see in **Figure 5.4**, the calibration of the SFC scheme between option 1 (M-O) and option 2 (the original Noah) marginally changed the snow accumulation and early melting season period. Meanwhile, the SFC scheme affected the snow ablation period. Default Noah-MP physics scheme simulate more rapid snow ablation. Noah-MP LSM shows a significant response to the TEMP physics option, 1 (semi-implicit) and option 2 (fully implicit), in-terms of snow-related process simulation. Semi-implicit physics option simulate the snow melting and end snow ablation earlier than the observation at all the observations points in the watershed. The fully implicit TEMP physics option enhanced the model simulation to capture the start and end of snow melting process on the daily basis significantly, as shown in the **Figure 5.4**. Basically, the thermal diffusion equation is being solved by the TEMP options with the Noah-MP model (You, Huang, Gu, et al., 2020; You, Huang, Yang, et al., 2020). TEMP significantly affects snow cover and melting within the model. After selecting the appropriate options for SFC and TEMP, the simulations of snow depth and the snow-water equilibrium process in the Noah-MP LSM, and consequently the discharge simulated by WRF-Hydro, showed substantial improvement. These options are crucial for accurately simulating snow depth and snow water equivalent in the modeling process. In areas with limited snow depth and snow water data, comparing recorded hydrographs can also help determine the discharge that reflects the snow melting process.

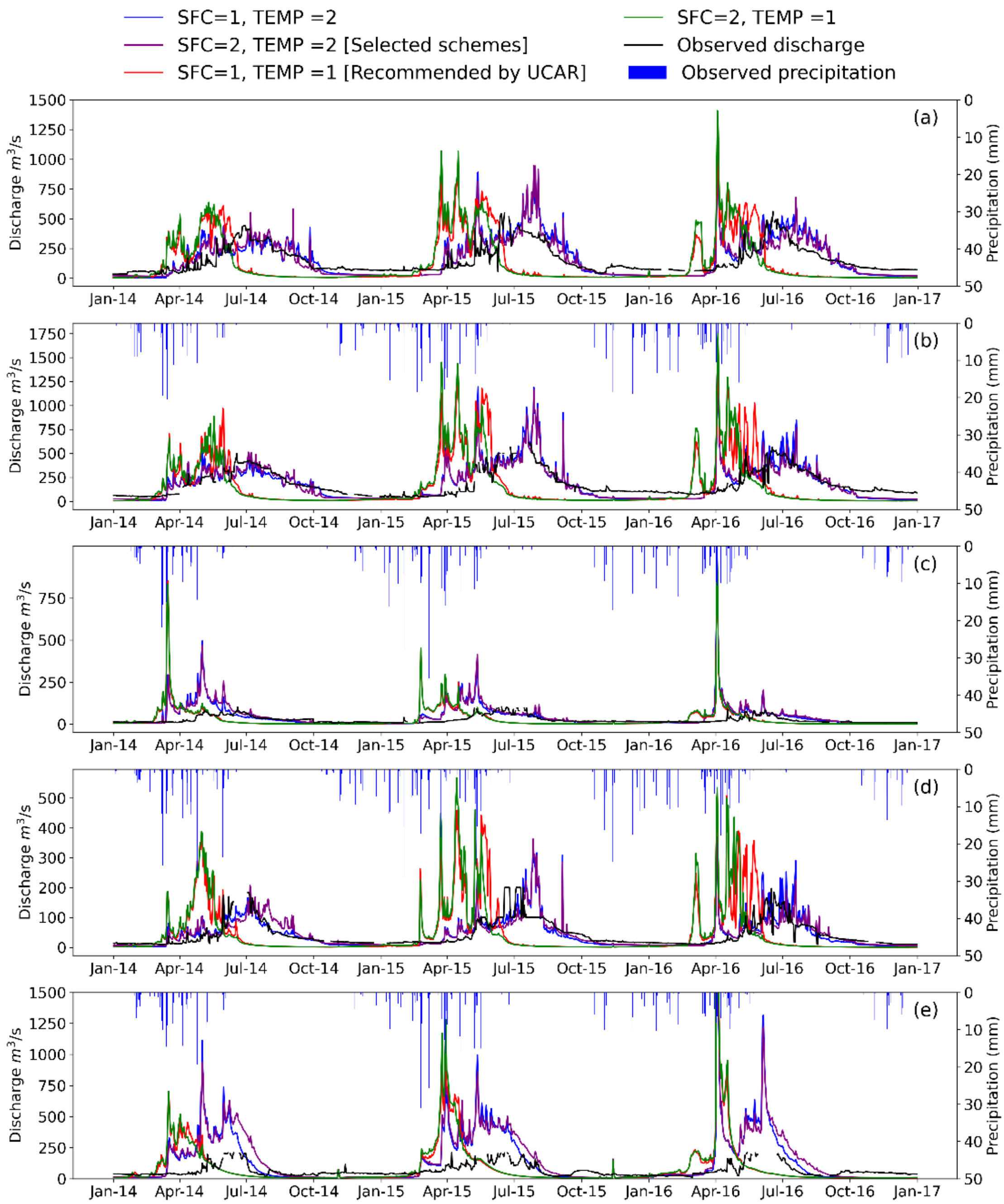

Figure 5.4 Daily discharge hydrograph of the four different experiments for the sensitivity of Noah-MP LSM physics to the snow dynamics in the WRF-Hydro model. (a) Nazdik-i-Keshem, (b) Khawjaghar, (c) Pul-i-Bangi, (d) Nazdik-i-Taluqan, and (e) Gerdab stations.

5.4.2 WRF-Hydro model calibration

Accuracy assessment of the model calibration results was performed using the statistical indices against the ground truth discharge data from five station situated on the three rivers of Kokcha, Kunduz, and Khanabad. **Figure 5.5** illustrate the hydrographs of simulated discharges after model calibration and the observed streamflow at the five stations (please refer to **Figure 3.4** for the locations of the observation stations). The Nazdik-i-Keshem station is situated in the Kokcha river midstream, and the Khawjaghar station observed the discharge in the downstream of the Kokcha River (**Figure 5.5(a)** and **Figure 5.5(b)**). **Table 5.3** summarized the model performance accuracy assessment result. The statistical indicators show good agreement between the observations and simulated discharge at the Nazdik-i-Keshem and Khawjaghar stations, with correlations of 0.80 and 0.85, NSE values of 0.33 and 0.52, R^2 values of 0.64 and 0.73, and KGEs of 0.70 and 0.74, respectively. According to Moriasi et al., (2015), this NSE value for Nazdik-i-Keshem station is unsatisfactory, but all the other statistical indices shows acceptable values. The hydrographs for simulated discharge and observed discharge over the Khanabad River at the Nazdik-i-Taluqan (right tributary of the Khanabad River) and Pul-i-Bangi (left tributary of the Khanabad River) stations are illustrated in **Figure 5.5(c)** and **Figure 5.5(d)**, respectively. The statistical indices representing a good agreement between the simulations and observations at the Nazdik-i-Taluqan station (R=0.65) and Pul-i-Bangi station (R=0.78). The R^2 and NSE values for the Nazdik-i-Taluqan station are 0.42 and 0.23, respectively. These values are not satisfying the model performance, while the KGE (0.64) is representing a good simulation for this station. At the Pul-i-Bangi station, the NSE and KGE values are -1.95 and 0.14, respectively, which do not satisfy the model performance accuracy. However, the R^2 (0.61) is showing the model performance is satisfactory. The model performance for the Gerdab station situated in the downstream of the Kunduz River (**Figure 5.5(d)**) during the calibration did not significantly change, but the correlation coefficient (R) was 0.59, which dedicates an agreement between the observations and simulated discharge.

There are various efficiency criteria for evaluating hydrological models, each with its own limitations. The main drawback of the NSE is that it calculates the differences between simulated and observed values as squared values. This approach causes larger values in the time series to be overemphasized while smaller values are disregarded (Legates & McCabe, 1999). As shown in Legates and Davis (1997), Correlation-based measures are more sensitive to outliers than values near the mean. Each efficiency criterion provides different insights into the model's performance. Moreover, the study regions encompass a large watershed with significant spatial and temporal variability, meaning a single set of model parameters cannot accurately capture all hydrological processes. Inadequate model efficiency criterion values could be attributed to the quality of the observation dataset and the presence of missing data. Hydrologists must make both subjective and objective assessments of how closely the model's simulated behavior matches the observed data (Krause et al., 2005). In this context, the subjective assessment of the model behavior and performance should be formulated by the hydrologists (e.g., under- and overestimation, falling limb, rise limb, and baseflow) alongside with the objective evaluations using mathematical formulations (Krause et al., 2005).

Overall, the model accurately captured the baseflow and seasonal fluctuations at all stations except for the Gerdab station (**Figure 5.5(e)**). During model calibration, the model effectively resampled the seasonal fluctuation in discharge by accurately reconstructing the streamflow at the beginning and end of the melting season. The most sensitive parameter was the soil pore size distribution index (BEXP), which regulates infiltration into the soil column and influences both baseflow and peak flow. BEXP determines the actual hydraulic conductivity of the soil column based on its saturated hydraulic conductivity (Yu et al., 2023). A higher BEXP value during the simulation allowed more water to infiltrate the soil column, thereby reducing surface runoff, and vice versa. The melt factor for the snow depletion curve (MFSNO) controls snowmelt characteristics, enabling adjustments to delay or accelerate melting in the model. The maximum bucket depth (Z_{max}) and the exponent of the bucket model (EXPON) are parameters of the groundwater bucket model that control baseflow. Additionally, the linear scaling of the "openness" of the bottom (slope) manages the interaction between the water that infiltrates the soil column and the aquifer at the bottom of the soil column.

Table 5.3 Summary of statistical indicators for the WRF-Hydro model performance over ARB.

No	Station	Calibration [daily]				Validation [daily]			
		R	NSE	R^2	KGE	R	NSE	R^2	KGE
1	Nazdik-i-Keshem	0.800	0.330	0.640	0.700	0.770	0.460	0.590	0.590
2	Khawjaghar	0.850	0.520	0.730	0.740	0.830	0.580	0.700	0.630
3	Nazdik-i-Taluqan	0.650	0.230	0.420	0.640	0.670	0.310	0.450	0.530
4	Pul-i-Bangi	0.780	−1.950	0.610	0.140	0.420	−5.760	0.170	−0.780
5	Gerdab	0.590	−9.210	0.350	-0.560	0.710	−8.640	0.500	−0.460

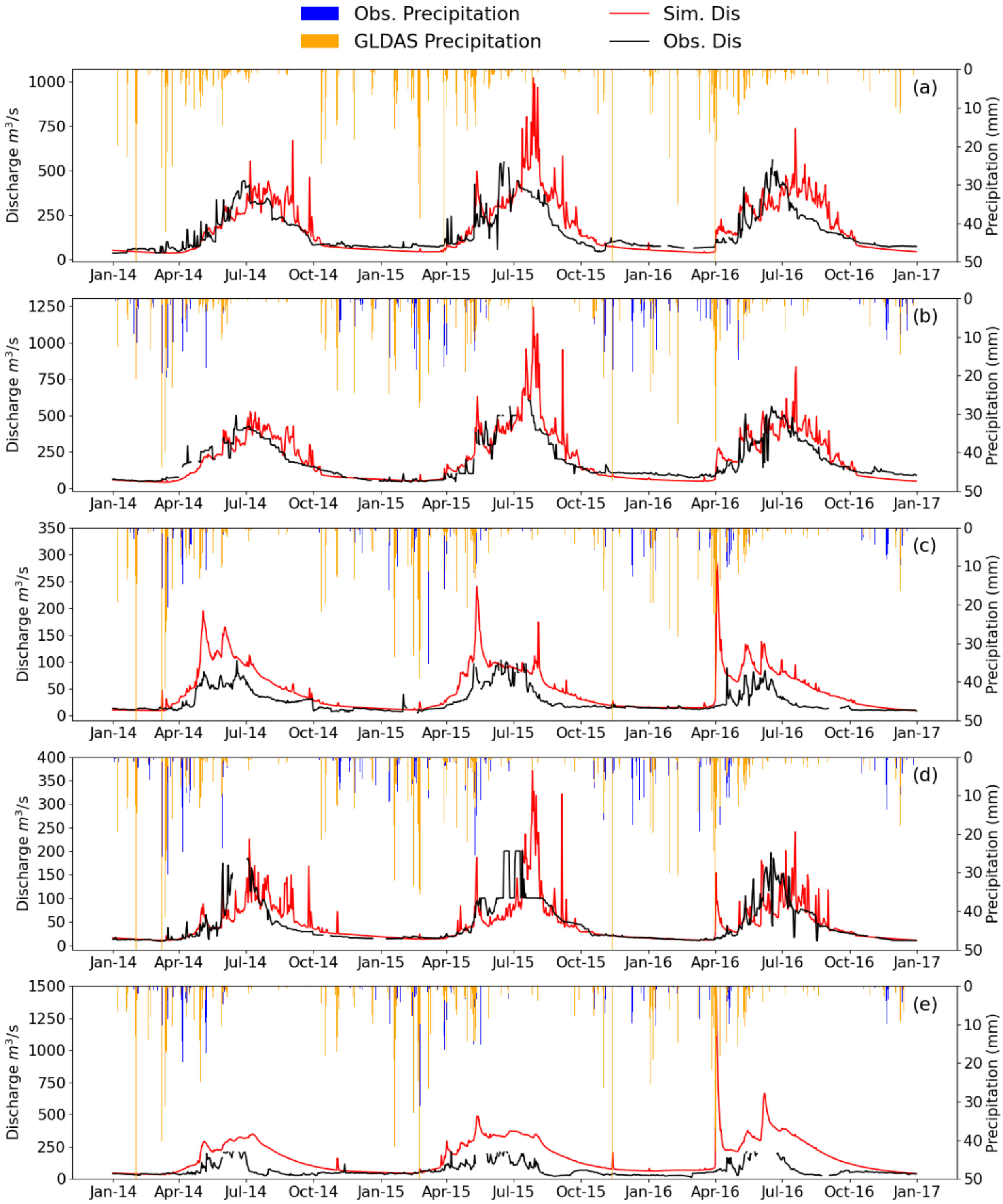

Figure 5.5 Simulated discharge verses observed discharge, recorded rainfall and GLDAS rainfall at five measuring stations in the ARB for the calibration period; (a) Nazdik-i-Keshem, (b) Khawjaghar, (c) Pul-i-Bangi, (d) Nazdik-i-Taluqan, and (e) Gerdab stations.

5.4.3 WRF-Hydro model validation over ARB

The validation results are depicted in **Figure 5.6** for all five stations in the ARB, with a summary of the statistical analysis presented in **Table 5.3**. A comparison of statistical data between the calibration and validation periods showed slight improvements in NSE and R^2 values. There were minor differences observed in the statistical indicators for the Nazdik-i-Keshem, Khawjaghar, and Nazdik-i-Taluqan stations between these two periods. R and R^2 values slightly decreased during validation, except for an increase of +0.03 in R^2 for the Nazdik-i-Talquan station. NSE values showed slight improvements for Nazdik-i-Keshem (+0.13), Khawjaghar (+0.06), and Nazdik-i-Taluqan (+0.08). Hydrographs for Nazdik-i-Keshem, Khawjaghar, and Nazdik-i-Taluqan stations are shown in **Figures 5.6(a)**, **5.6(b)**, and **5.6(c)**, respectively. KGE values decreased compared to those during calibration. Conversely, the statistical performance of the Pul-i-Bangi station decreased during validation compared to calibration. For the Gerdab station, an R^2 of 0.50 is acceptable, but KGE and NSE values did not meet satisfactory ranges. Overall, the model effectively captured seasonal variability, except for a delayed start of the melting season in 2018 observed at Nazdik-i-Keshem and Khawjaghar stations.

5.5 Discussion

5.5.1 Effects of groundwater contribution to the SWAT model result

Correct definition of the hydrological process within the catchment and quality of the input datasets are the key to creation of a reliable model that can present the watershed actual condition. A thorough comprehension of the hydrological processes and water management activities at a study site can enhance the accuracy and reliability of hydrological modeling, yielding more dependable results. In mountainous basins characterized by steep terrain, snowmelt from high-elevation regions and water infiltration are primary water sources, contributing to streamflow downstream through lateral flow or springs. In developing countries with limited observational and ground truth data, acquiring precise and robust records of hydrological processes can be challenging and occasionally unattainable.

SWAT structures divides underground water storages into deep and shallow aquifers, while the water infiltrating to the deep aquifer are excluded from the water budget estimation and is considered as lost water from the system (Luo et al., 2012). BRB owns approximately 190 springs along the river contributing to the baseflow. As described in Luo et al., (2012), the inclusion of the deep aquifer contribution to the baseflow can improve the model output.

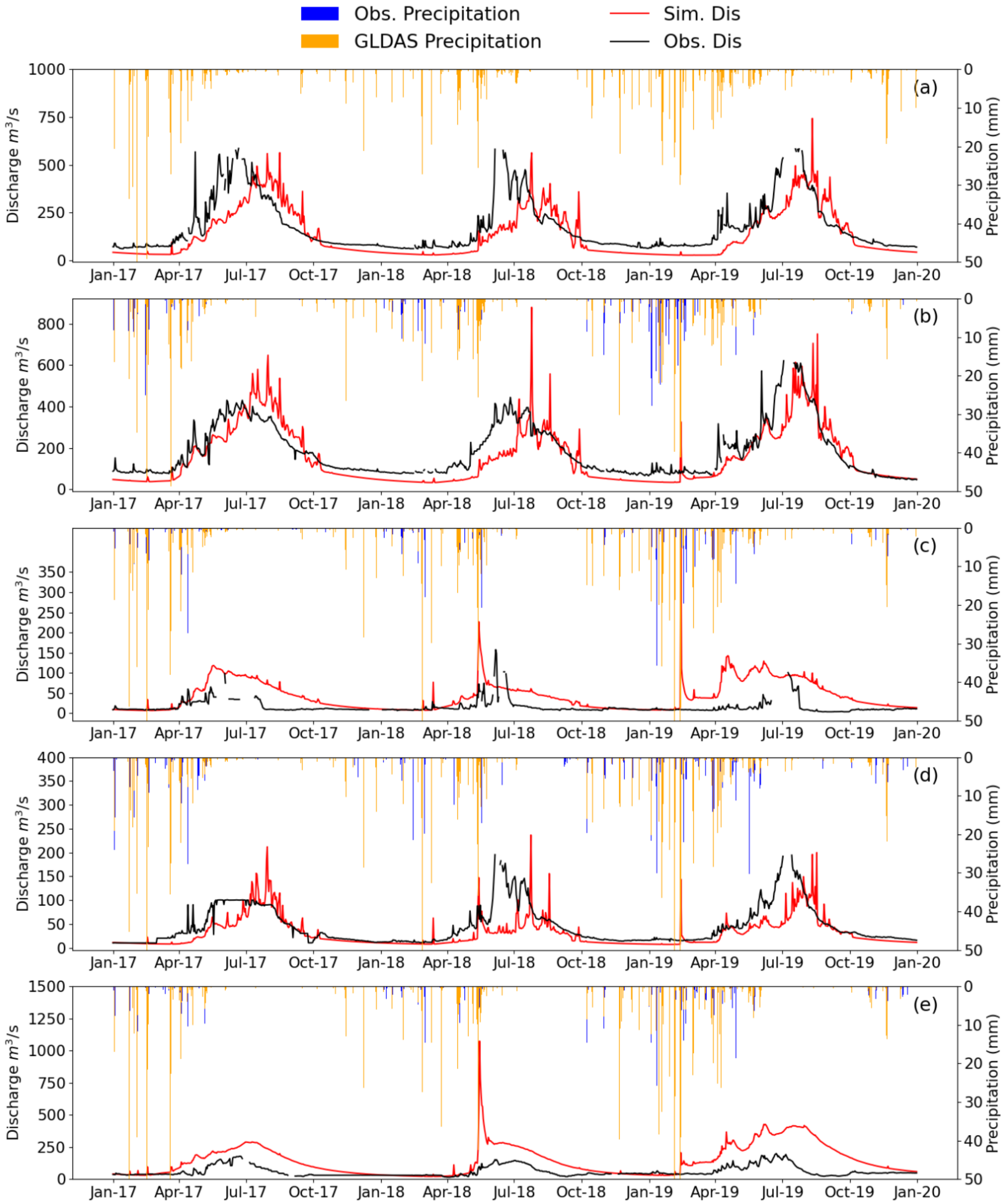

Figure 5.6 Model validation comparison between the model outputs and observed discharge at five stations in the ARB: (a) Nazdik-i-Keshem, (b) Khawjaghar, (c) Nazdik-i-Taluqan, (d) Pul-i-Bangi, and (e) Gerdab.

Summer seasons in the BRB are relatively dry with almost zero precipitation records. However, the spring and winter seasons are wet condition with considerable amount of the total precipitation happening during these periods. The hydrograph in **Figure 4.5** depicates the discharge during the months of July, August, and September, when the amount of rainfall is relatively low and the snow cover area in the mountains of the BRB almost melted and disappeared. In such environmental condition the contribution of the groundwater from deep aquifer are significantly important for the watershed hydrological dynamics.

Current calculations using the observed average baseflow during the dry season, when the contributions of precipitation, shallow aquifer, and snowmelt reach a minimum, can enhanced the modelling output by reduction of the underestimation in the baseflow simulation. Systematic underestimation of the baseflow in the **Figure 5.1** is noticeably visible for subbasins 7, 10, and 28, this constant underestimation of the baseflow can come from a constant source of water, which is the deep aquifer water reaching downstream as springs.

5.5.2 Baseflow simulation in WRF-Hydro model

In the arid and semi-arid regions correct simulation groundwater contribution from aquifer to streamflow is essential for successful hydrological modelling where the precipitation is limited and sparse. A simple conceptual base flow bucket model has been incorporated into the WRF-Hydro model that connects the overlaying channel and baseflow in one directions (Gochis et al., 2020). This simplified bucket model serves as a highly conceptual and abstract representation of groundwater processes, where the parameters and depth of the bucket lack physical significance. Numerous studies have indicated that the baseflow bucket model inadequately represents the groundwater's contribution to streamflow. Therefore, due to insufficient information, the baseflow bucket model was omitted from the model structure (Liu et al., 2021; Naabil et al., 2017). However, simulations of streamflow for long-term where the low-flow and baseflow processes extremely contributing to the river discharge, adoption of this model is essential (Gochis et al., 2020). Effective utilization of the bucket model in simulations necessitates precise and thorough calibration of its parameters.

Groundwater parameters should be calibrated not only for the calibration period but also during the spin-up period. The model begins with an initial water depth in the groundwater bucket (Z_{inti}), which increases during the spin-up phase. This period must be long enough to allow the water depth in the ground bucket to stabilize. The slow bucket discharge depends on the ratio of the water depth in the soil column to the maximum soil column water depth (Z/Z_{max}) and the model parameters. If the water depth exceeds the maximum depth of the soil column, it overflows and acts as a spring, resulting in a high discharge value. It is crucial to calibrate groundwater parameters before other model parameters, and since it takes several years for the bucket model to stabilize, parameter tuning should also be conducted during the spin-up period.

5.5.3 Peaks in the hydrograph SWAT model

The model accurately predicted baseflow variations, but it struggled to simulate peak flows as effectively. The underestimation of peaks was particularly noticeable in the upstream subbasins 28 and 30. During spring, increased rainfall and snowmelt lead to significant rises in streamflow. Higher air temperatures and rainfall accelerate the snowmelt process, causing rapid melting on rainy days. This rapid melting, combined with rainfall and steep slopes in upstream mountainous areas, can lead to flooding in early spring. Additionally, flash floods in mountainous regions are another cause of peak flows during periods of intense, short-duration rainfall at high altitudes.

The SWAT model's snowmelt algorithms are based on the degree-day factor, which estimates snowmelt based on temperature increases above a certain threshold. This method does not account for the contribution of rainfall to rapid snowmelt, leading to an underestimation of peak flows during early spring when most floods were recorded at the BRB stations. Furthermore, SWAT failed to account for the minor temporary river branches upstream, which can contribute to peak flows during the spring snowmelt season.

5.5.4 WRF-Hydro model Noah-MP model physic schemes for the snowmelt season

Snow plays a vital role in the hydrological cycle, significantly affecting soil moisture and surface runoff, particularly in mountainous areas. Snow accumulates during winter and contributes to streamflow as temperatures rise above the melting point. Meltwater can contribute to surface flow either through direct runoff or by infiltrating the soil and recharging groundwater. The accuracy of simulations for snow accumulation and melt is strongly influenced by two physical schemes: (1) the surface layer drag coefficient and (2) the snow/soil temperature time. TEMP has a major impact on snow accumulation and melting processes. Changing TEMP options in the Noah-MP physics settings markedly alters the hydrograph, as illustrated in **Figure 5.4**. For instance, TEMP option 1 simulates the snow melting season approximately one month earlier than the observed data. Additionally, SFC options significantly influence the hydrograph during the snow ablation period, resulting in either more rapid or slower ablation.

5.6 Conclusion

In this study, the WRF-Hydro model effectively matched the timing of streamflow signals over the ARB. The findings improved the performance of the WRF-Hydro model in simulating the snowmelt process, enhancing the timing and magnitude of the simulated discharge. This study suggests the careful selection of LSM model physics schemes for watersheds with high altitudes and significant snowmelt contributions to surface runoff. Successful model calibration relies heavily on the baseflow bucket model parameters. It is recommended that users calibrate groundwater parameters during the spin-up period, while other parameters can be calibrated during the calibration period. Simulating the contribution of groundwater to streamflow in mountainous regions is challenging due to high topographic relief, hydrological heterogeneity, and limited data availability (Z. Chen et al., 2023). The timing of water infiltration into the ground significantly affects streamflow, making its simulation complex. Despite the simplification of the process for long-term simulation, the performance of the groundwater bucket flow model in the WRF-Hydro model is reasonably good. Among the WRF-Hydro model parameters, the soil pore size distribution index (BEXP) was the most sensitive. BEXP improved the simulation of baseflow and peak flows by controlling the amount of infiltration into the soil column.

Chapter 6

Water consumption

6.1 Introduction

The rapid increase in the global population has caused considerable growth in food demand worldwide and necessitates the monitoring of agricultural activities, especially in areas with severe food insecurity issues. Afghanistan is currently facing food issues, and more than 15 million people (36% of the total population) are food insecure (FAO, 2024). Major steps to overcome food insecurity issues and achieve sustainable food security are accurate forecasting of crop yield, understanding farm management, establishing the relationship between nutrition and crop choice in the field, assessing the impacts of changes in policy and aid, and predicting climate change impacts on the agricultural sector (Wang et al., 2019). Understanding the type of field crop farmers cultivate on farms is the first step toward sustainable food security management. Traditionally, crop type information is obtained from field surveys and censuses. However, this method is costly and time consuming and difficult to update frequently. Currently, with advancements in the field of remote sensing and access to higher resolution satellite images, remote sensing approaches could fill the gap of data scarcity for the generation of crop type maps.

Timely inventory of the crop type and their spatial distribution are essential for agricultural management and decision making. In most of the areas in the world this information is available at an average and rough estimation at an administrative level. Spatial distribution of the agricultural lands and types of crops cultivated by the farmer is crucial for estimation of the irrigation water demand. In this context, crop type maps are referred to as spatial distribution of the different crops cultivated in a region in the different years. Field surveys and censuses could provide a general overview of the region's agriculture information but collection of entire watersheds information on yearly basis is extremely expensive and required enormous amount of time and resources.

Recent successes in machine learning techniques such as support vector machines (SVMs), random forests (RFs), and neural networks have allowed the automated analysis of large-scale satellite imagery (Wang et al., 2019). There have been several efforts to construct crop type maps for the country-wide or regional level across the world but not for every region of the world, e.g., the US Department of Agriculture (USDA) Crop Land Data Layer (CDL) for the United States (USDA, n.d.), Agri maps for Europe and some parts of Africa (Inglada et al., 2015), the Agriculture and Agri-food Canada's annual inventory (Fisette et al., 2013), the subset map of crops in China by year and provinces in China (Dong et al., 2016).

In this chapter, the objective is to generate a crop type map for the study region using the MODIS satellite NDVI products and machine learning methods. These crop type maps will be used as the primary input for the estimation of irrigation water consumption for the respective years to determine the demand and assess the agricultural sector and crop yield in different years. The supervised classification method was used for the generation of the map with the labels for the crop type obtained from the map already developed for the Afghanistan crop type during 2020 with six major crops. Three different supervised machine learning algorithms were ensembled with a majority voting classifier to train the algorithms for classification of the crop type.

6.2 Literature review

Compared to traditional statistical or census methods, remotely sensed data can provide spatial and temporal information on crop types at local or broader scales. Publicly available satellite images and remote sensing techniques provide the opportunity to map land use and land cover changes inexpensively and quickly. Currently, a wide range of satellite imagery, such as Landsat (Wang et al., 2019), Sentinel-2 (Wali et al., 2019), SPOT-5 (C. Yang et al., 2011), and MODIS (Y. Chen et al., 2018), can be used for mapping crop types. The use of machine learning in remote sensing-related studies is common, especially for identifying land cover and land use. Both supervised and unsupervised methods can be used for land type classification. Supervised classification requires historical data, while unsupervised methods cluster the input based on similarities in the structure of the data and pattern.

Supervised classifications are the most preferable method. Unsupervised methods are vulnerable to outliers, noisy features, and high dimensionality and require the user to specify the number of cultures that the user does not know about the data (Hastie et al., 2009). RF and SVM are methods widely utilized for crop type mapping (Wang et al., 2019). RF derived from an ensemble of decision trees has been proven to yield reliable classifications over the past two decades (Hastie et al., 2009). SVMs were developed in the 1970s and became popular in remote sensing applications (Zheng et al., 2015). The SVM classifier is a nonparametric supervised classification method derived from statistical learning theory developed over the last two decades(Zheng et al., 2015). The gradient boosting model (GBM) is a tree boosting method widely used for the classification of crop type maps (T. Chen & Guestrin, 2016; H. Zhang et al., 2019).

Numerous efforts to utilize remote sensing data and machine learning methods have been made globally. Wang et al., (2019) used Landsat 8 images for the generation of crop type maps for nine US states using both supervised and unsupervised classifications with field label data from the USDA CDL dataset as a reference. They used RF for supervised classification and the K-means and Gaussian mixture model (GMM) method for unsupervised clustering classification of maize and soybean in nine states. In their study, they tested the transferability of the supervised model geographically and spatially. To examine the geographical transfer ability of the trained model, the model was trained for one state, and the same model was used for the other eight states. The same approach was utilized for the temporal transformation of the training model, and the model trained for 2016 was tested for six additional years from 2010 to 2015. The findings show more than 70% accuracy for temporal transformation except in North Dakota State.

Another study over India used the Airborne Visible Infrared Imaging Spectrometer-Next Generation (AVIRIS-NG) with 4 m resolution and 115 random point samples for validation purposes (Salas et al., 2020). In this study, five models, namely, RF, generalized linear model (GLM), boosted regression tree (BGT), multivariate adaptive regression (MAR), and maximum entropy (Maxent), were fitted individually for each crop presence probability in pixels with a range of 0-1 using six predictors. Zero means no probability, and 1 means the highest probability of occurrence. Finally, all the maps were overlapped to a single raster, and the pixel with the highest probability for a crop from all five products was assigned to that crop.

NDVI is the most commonly measure of the photosynthetic activity of vegetated land cover used to drive phenological parameters (Pan et al., 2015). However, several vegetation indices are proposed for reduction of canopy background influence and the atmosphere e.g., Soil Adjusted Vegetation Index (SAVI) or Enhanced Vegetation Index (EVI). EVI proved to be more sensitive over high biomass area such as forests where NDVI tends to be saturated Soil

Adjusted Vegetation Index (SAVI) or Enhanced Vegetation Index (EVI) (Foerster et al., 2012). While SAVI is more suitable for vegetation canopy structures, NDVI is good measure to represent photosynthetic capacity of vegetation cover (Foerster et al., 2012). NDVI time series curve can identify different types of crops based on its phenology.

Several studies have been conducted in Afghanistan to map crop types. Shahriar Pervez et al., (2014) used Moderate Resolution Imaging Radiometer (MODIS) normalized difference vegetation index (NDVI) products to map irrigated areas in Afghanistan using a decision tree and set an NDVI threshold for croplands. In this study, the permanent pastures and non-irrigated areas were masked, and the final products from 2000-2013 were compared to the lower resolution satellite imagery from Landsat-5. Another study, as part of a larger project for monitoring opium and cereal crops in Afghanistan, also used the MODIS NDVI product and field data to map crop types in Afghanistan (Simms et al., 2014). Another study in the Kabul River basin used the unsupervised classification method, crop calendar, and phenology to map crop types using Moderate Resolution Imaging Radiometer (MODIS) normalized difference vegetation index (NDVI) products from 2003 to 2013 (Akhtar et al., 2017). Wali et al., (2019) used Sentinel-2 10 m imagery and 1840 ground-truth data to map crop types and estimate crop water requirements in a large-irrigated area in Khost Province, Afghanistan.

This chapter presents the generation of spatial and temporal crop type maps for intensely irrigated watersheds in Afghanistan using Moderate Resolution Imaging Radiometer (MODIS) normalized difference vegetation index (NDVI) products and machine learning techniques. Crop type mapping ensemble three supervised classification using majority voting for pixels with field label data adopted from a 10 m crop type for Afghanistan during 2020. The weighting method was applied to the model considering the number of classes in the accuracy assessment. The model was temporally transformed from 2020 to 2014-2019. The outputs were used to evaluate the agricultural sector and variation in cropland during the study period and to estimate irrigation sector water consumption. This study can provide insight into water resource planning, irrigation management, and agricultural management.

6.3 Irrigation water consumption

6.3.1 Crop type mapping for ARB

As explained in the earlier section, ARB does not have the observed field data for the crop type spatial extent except for the FAO crop type map for 2020. To determine the crop type and spatial extent in the ARB, three machine learning algorithms and their ensembles were used to construct a model for 2020 and extend it to crop type mapping from 2014 to 2019. The model was trained using 80% of the NDVI signals and tested using the remainder of the input. **Figure 6.1** shows the accuracy of the individual models and their ensemble. The study area was split into eight elevation zones with 500 m differences in elevation to determine the effects of the temperature lapse rate on plant growth. Among the three models, RF continuously predicts crop types more accurately than do the SVM and GBM models. Similarly, the GBM and SVM models predict the crop type on each pixel with slight differences. Overall, the voting classifier, which selects the majority votes of the three individual models, has the highest accuracy rate among all the models in all the elevation zones. Previous studies have shown that machine learning algorithms can be temporarily transferred by testing models for specific years and that models can be used for the prediction of crop types in other years (Wang et al., 2019).

The final trained model for each elevation zone was adopted to predict the crop type and spatial extent from 2014 to 2019. **Figure 6.2** replicates the model prediction result for the crop type map of the ARB with a spatial resolution of 250 m. The output shows consistent results for the heavy irrigation area downstream of the ARB. Downstream of the ARB is flat land suitable for agricultural activities, with the majority of farmland located there. However, at higher elevations where steep slopes and mountain ranges limit suitable land for agriculture, the spatial distribution of croplands varies annually. These variations in the cropland area can be caused by multiple factors, such as drought periods, climatic conditions and the possibility of farmer migration, due to a lack of sufficient agricultural land for survival.

The accuracy assessment result shows RF outperformed two other models in all the elevation zones. Accuracy of RF model ranges between 70.7% to 99.9% with lowest in the elevation zone-6. SVM model performance ranges between 56.3% to 96.6% with lowest accuracy in the zone-3. GBM model performance ranges between 56.3% to 99%. The ensemble model shows an accuracy range of 75.9% to 99.9% overall and highest in all elevation zones with respect to all three individual models. The lower elevation zones represent the flat land with larger area of the agricultural land where the model captured the intense agricultural zones reasonably good. As the elevation increases the topography changes to mountainous regions where agricultural land is sparse and smaller in area. The smaller and sparse agricultural land decreases the model accuracy and causes lower accuracy in the model performance.

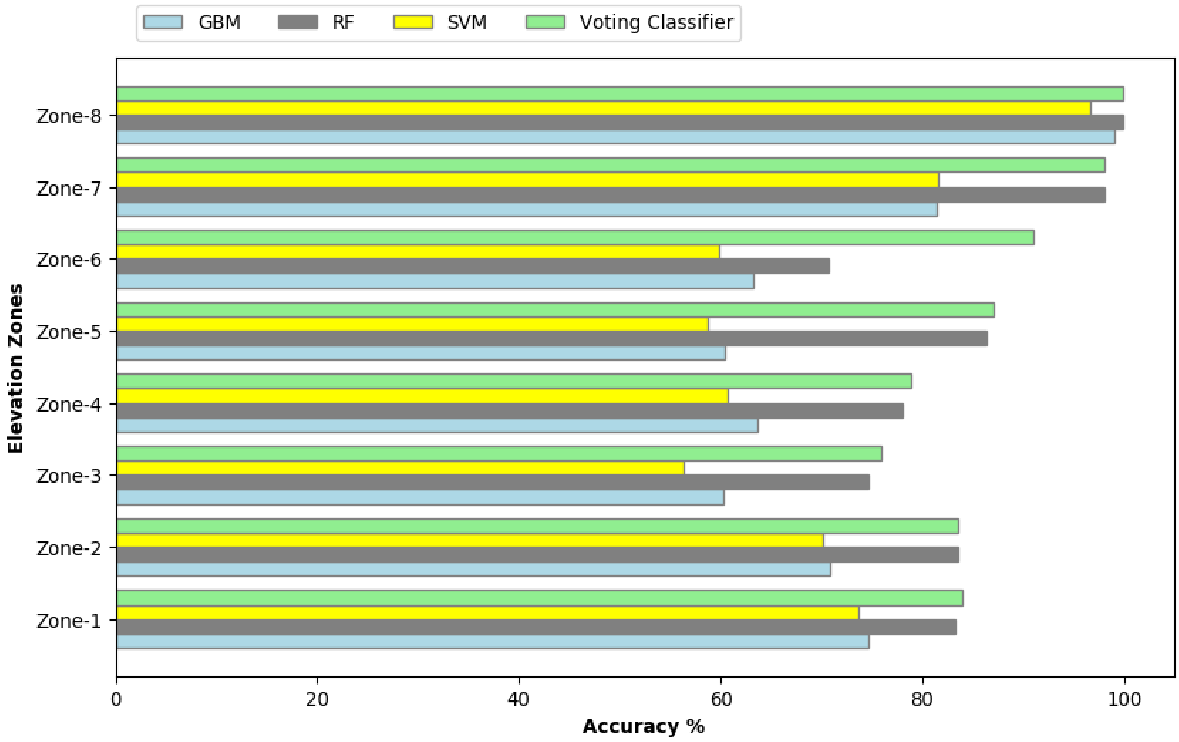

Figure 6.1 Assessment of the machine learning algorithms for detecting crop types during 2020.

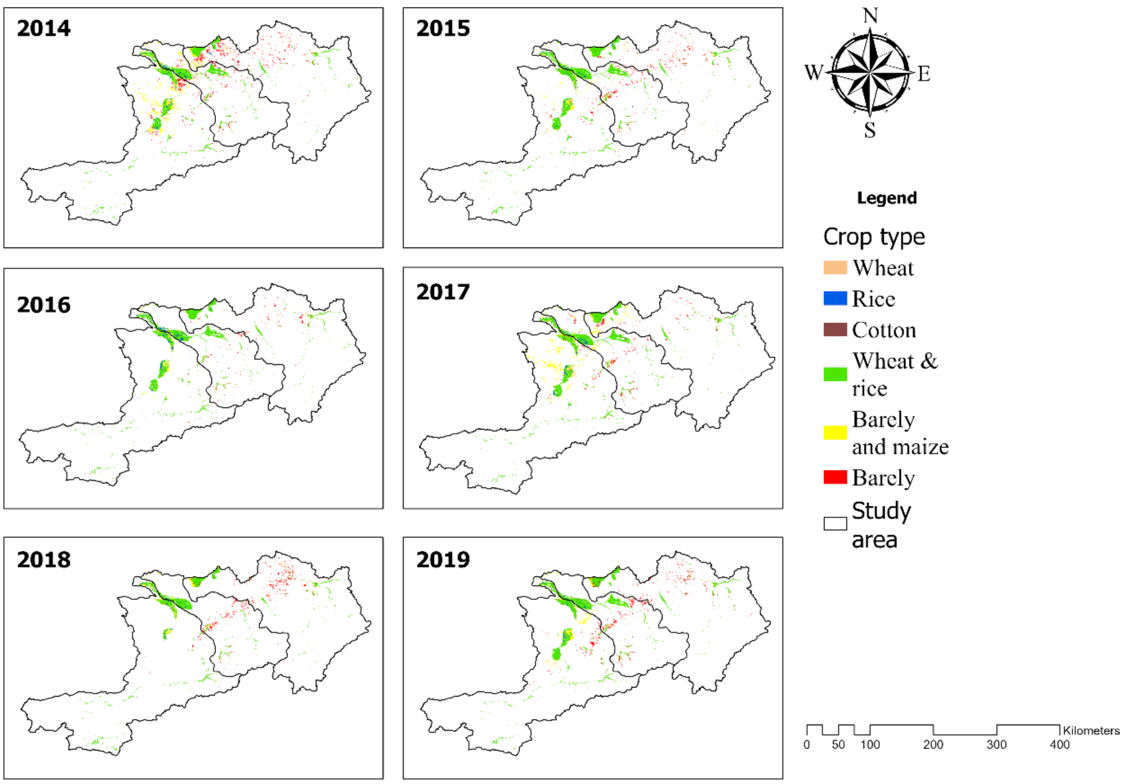

Figure 6.2 Crop type map for ARB from 2014 to 2019.

6.3.2 Crop water requirement (CWR) for ARB

The reference evapotranspiration for the ARB was estimated based on historic metrological datasets from the ARB. The reference evapotranspiration dataset was estimated over 13 metrological stations as per FAO guidelines (RG, 1998). The daily reference evapotranspiration time series is shown in Figure **6.3**. The reference evapotranspiration time series dataset in **Figure 6.3** and crop coefficient dataset in **Figure 4.12** were used to estimate the CWR during the cropping seasons. CWR values for five major crops in the ARB were converted to monthly mean values for further analysis and are presented in **Figure 6.4**.

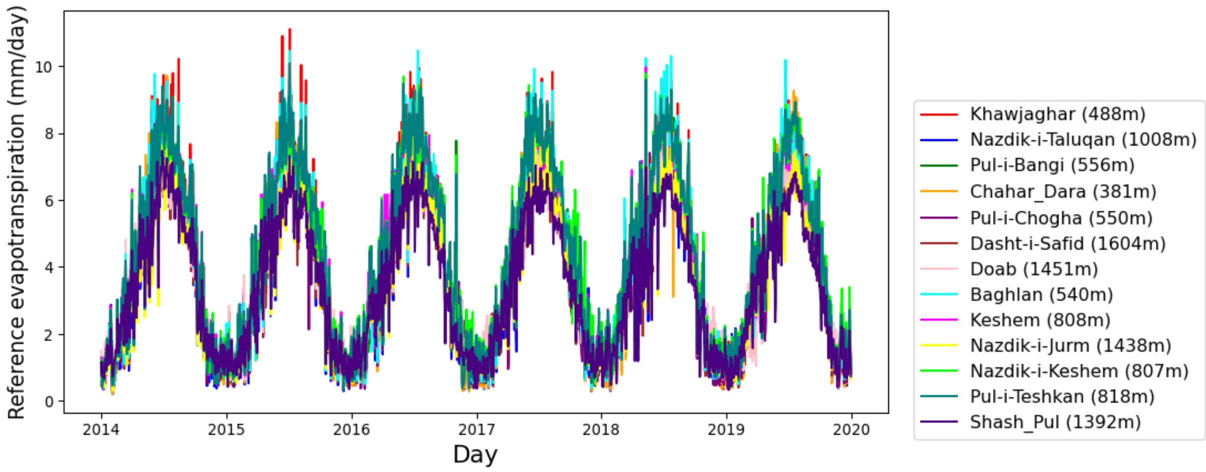

Figure 6.3 Daily time series of the CWR over ARB from 2014 to 2020.

6.3.3 Irrigation water requirement (IWR) for ARB

The IWR is the amount of water required to add to the soil for healthy plant growth. Prior to IWR estimation, it is necessary to estimate the effective precipitation. The effective precipitation is the amount of precipitation infiltrating the root zone of the crop, and it should be deducted from the reference evapotranspiration for the months. **Figure 6.5** represents the monthly effective precipitation amount for all stations from 2014 to 2019. The reference evapotranspiration values and effective precipitation were used to estimate the amount of irrigation required for each station from 2014 to 2019, and the results are summarized in **Figure 6.6**.

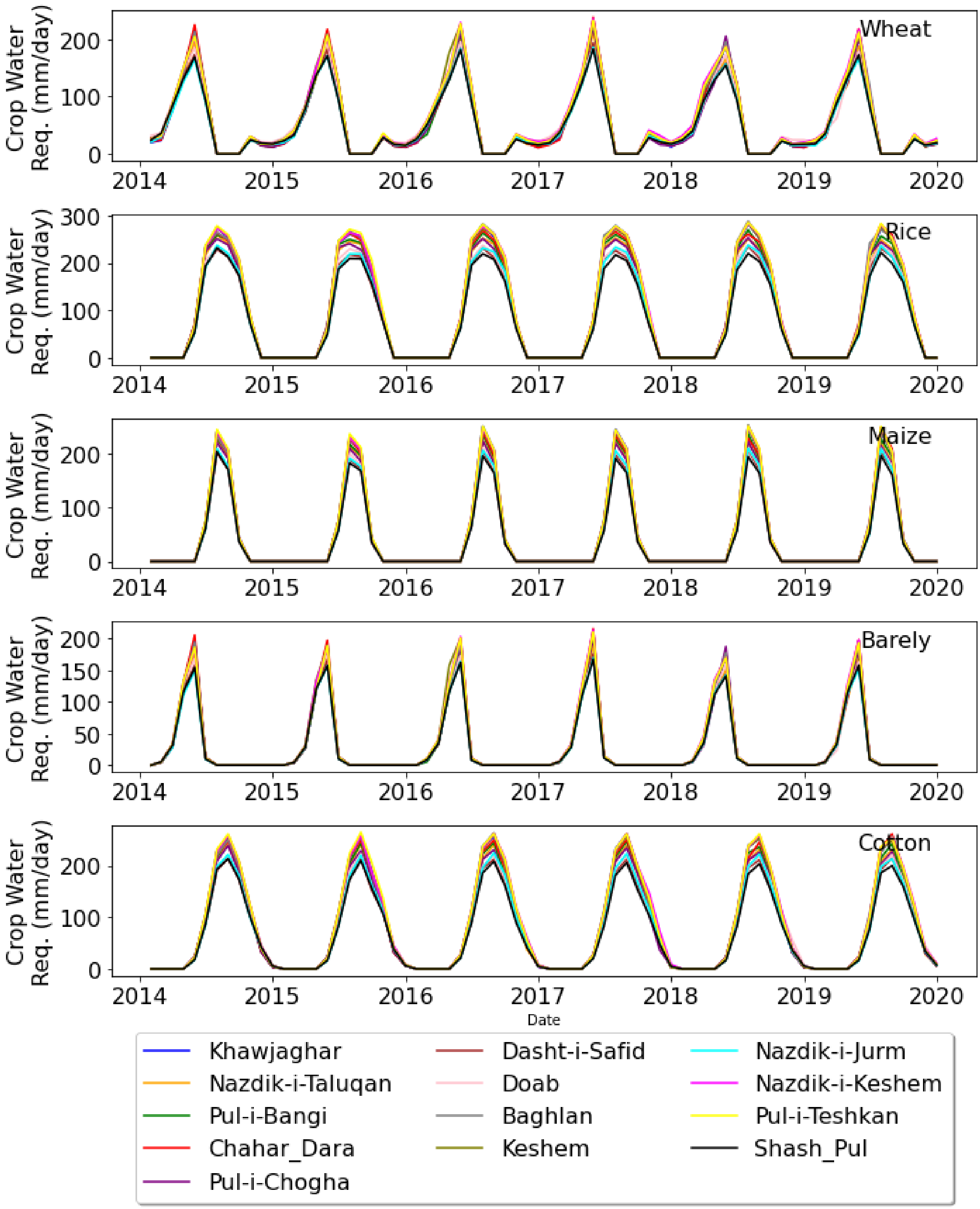

Figure 6.4 CWR for major crops in the ARB from 2014 to 2019.

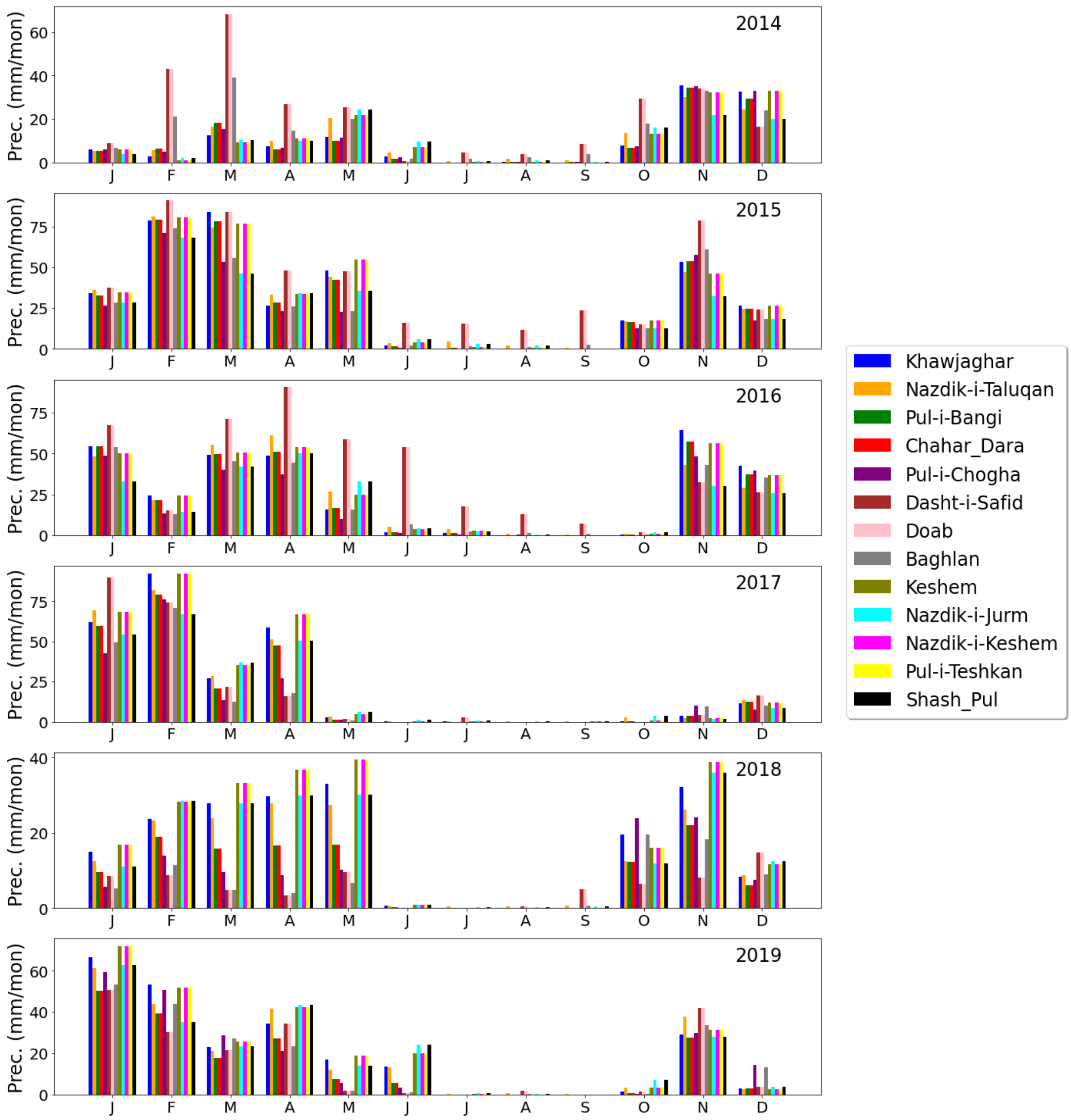

Figure 6.5 Monthly effective precipitation for the ARB from 2014 to 2019 in mm/month.

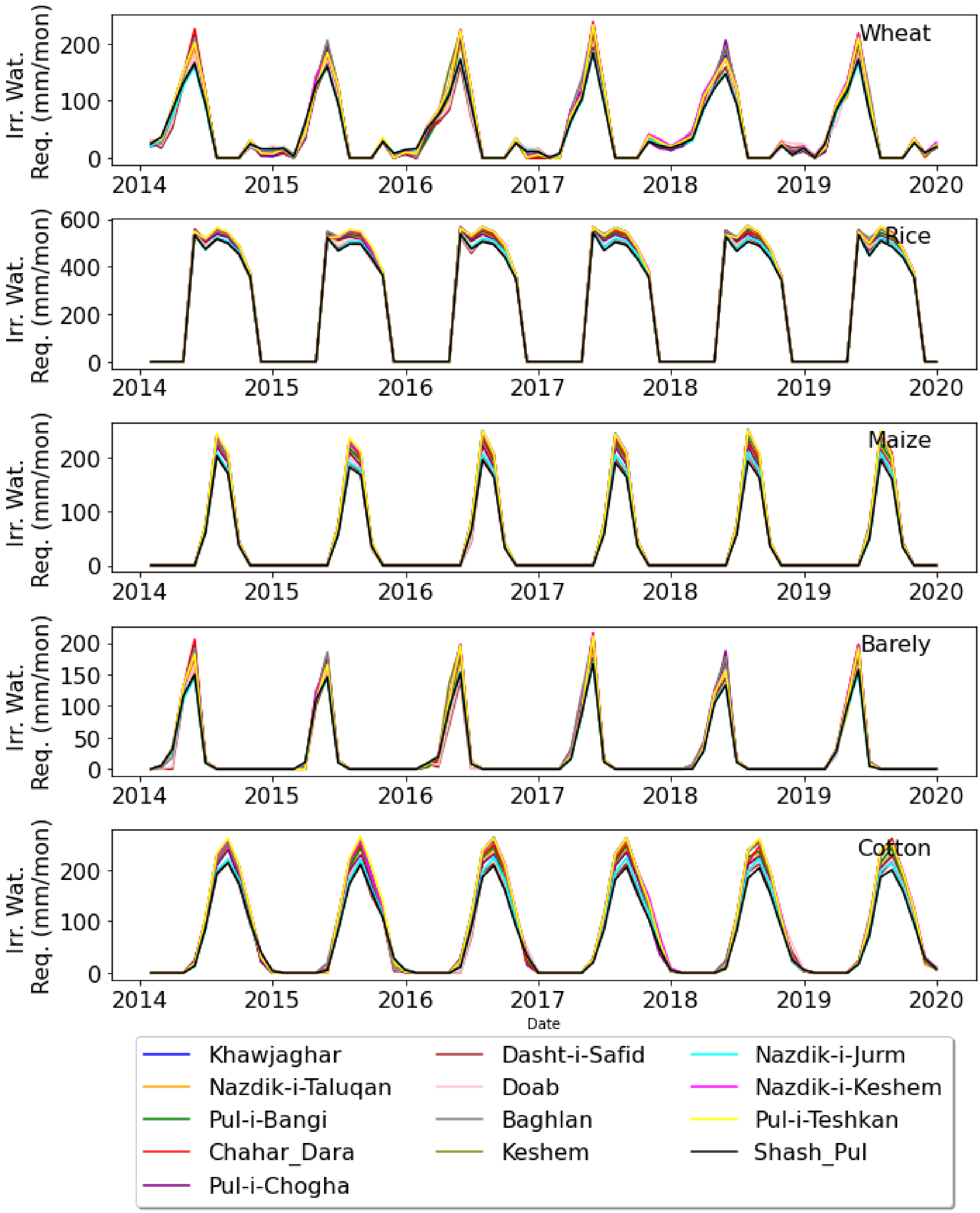

Figure 6.6 Irrigation water requirements (IWRs) for the ARB from 2014 to 2019.

6.3.4 Irrigation water requirements for BRB

The irrigation scheme in the BRB was determined based on the available secondary data. The crop type was determined based on the national agricultural profile from 2016 to 2018, and the agricultural land area was considered based on official NRB reports. According to the NSIA (2019), the main cultivated crops (and associated cultivation areas) are wheat (60.0%), rice (3.3%), barley (3.3%), maize (3.6%), pulses (2.3%), vegetables (4.3%), potato (1%), onion (0.3%), fruits (9.3%), almond (0.6%), oil seed (2.6%), and others (9.4%). The new irrigation scenarios proposed in the current study include wheat (65%), rice (5%), maize (5%), pluses (4%), spring vegetables (5%), summer vegetables (4%), and orchards (12%) for the entire downstream BRB. In addition, based on the crop water requirements for different crop types and the specified irrigation area for each crop (**Table 4.9**), the monthly water requirement for 1 ha of agricultural land is estimated, as shown in **Table 6.1**.

Table 6.1 The estimation of the monthly irrigation water consumption for 1 ha of agricultural land in the downstream region of the BRB was adopted from (Hussainzada et al., 2023).

Crop type	Area (%)	Monthly crop water requirement (m^3/ha/mon)											
		Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Wheat	65	213.9	339	514.2	828.75	610.4						59	111.2
Rice	5					27.85	76.95	85.5	77.4	61.9	31.3		
Maize	5					11	42.4	74.95	60.15	18.8			
Pulses	4					6.44	39.52	59.28	26.72	0			
Summer vegetables	4					35.08	49	53.8	42.04	2.32			
Spring vegetables	5		8.4	25.05	58.2	46.8							
Orchards	12			57	130.8	163.6	166	167.3	147.1	57.5			
Total	100	213.9	348	569.2	1017.8	901.1	373.8	440.8	353.4	140	31.3	59	111.2

6.4 Domestic water consumption

Domestic water consumption for both the ARB and BRB was estimated for the span of 50 years from now as the effective life of the water supply project. Currently, the domestic water supply in both study regions relies on the groundwater supplied by wells dug by the community or individuals or spring water where it is available in rural areas. Current water supply systems are not centralized water distribution systems. The assumption of this study is to replace the source of water supplied from groundwater with a centralized water distribution system that feeds available surface water. The use of groundwater sources is not reliable due to the long time needed for recharging the aquifer, and the risk of pollution is high since the groundwater is not treated prior to pumping into the water supply system.

6.5 Discussion

Proper estimation of water demand is essential for the management of water resources. The main sectors consuming water in Afghanistan are the agricultural sector and domestic water consumption. The main aim of this chapter is to determine the water demand in both study regions. Accurate estimates of the water resource availability in the study region are needed. In developing countries, there is a lack of ground observations. This chapter focuses on filling the critical gap of data scarcity using alternative datasets. Currently, advancements in space programs provide a wide range of datasets using remote sensing techniques. This study adopts the NDVI approach to detect greenery, and by integrating the NDVI datasets with machine learning algorithms, crop type maps are constructed for the study region considering spatial and temporal variations.

During crop type mapping, users should consider the effects of temperature on plant development stages. The ARB is a mountainous watershed that experiences large elevation differences from upstream to downstream. Temperature is a crucial factor affecting plant growth. Each species has a temperature range, and relatively high temperatures within that range generally promote shoot growth, including leaf expansion and stem elongation and thickness (Ohtaka et al., 2020). Generally, the temperature is lower at higher elevations during the day. Considering the impact of temperature on the growth of plants of the same species, reflection may vary depending on elevation and heat experience during the year. To determine the effect of temperature variation, the study region was split into elevation zones. Considering the elevation zones improved the ability of the model to determine crop types.

The model performance was enhanced using an ensemble of three machine learning approaches. Previous studies have shown that the RF model yields greater accuracy than other methods, e.g., the maximum likelihood classifier (ML), SVM, and other methods for crop type mapping (Citations). The findings of this study also support the literature and show that RF yields higher accuracy than do all other models. However, the RF model ensemble with SVM and GBM enhanced the crop typing performance and improved the accuracy of the model during the testing period. In this study, we also assigned weights to the classes based on the number of pixels from each class in the training sample. In arid and semiarid mountainous regions, agricultural lands are limited due to the topographical conditions and slope of the area.

6.6 Conclusion

This chapter focuses on water consumption in different sectors in regions with limited field observations. In these regions, secondary datasets and remote sensing data could be alternatives to actual observations. This chapter presents the estimation of water consumption in the agricultural sector using the NDVI remote sensing dataset from the MODIS satellite and machine learning algorithms using field-level labels. Domestic water consumption is also estimated using the secondary population dataset and per capita demand for the country. Encountering water consumption in these sectors could be useful for water managers and enhancing residents' livelihoods in terms of food security, agricultural planning, development strategies, and farmer decisions.

One of the key highlights of the chapter is the utilization of machine learning algorithms to map crop types and their spatial extents. Given the lack of observed field data, this approach fills a critical gap in understanding agricultural patterns, especially in regions such as the ARB. The ensemble modelling technique, which integrates RF, SVM, and GBM, demonstrates promising accuracy in predicting crop types across different elevation zones. This method not only enhances our understanding of current agricultural dynamics but also enables projections for future years, offering valuable input for policy planning and resource allocation.

Moreover, this chapter provides a comprehensive analysis of CWR and IWR for various crops in both the ARB and the BRB. By leveraging historical meteorological data and established methodologies such as the FAO guidelines, reference evapotranspiration and effective precipitation, which are essential parameters for determining irrigation needs, can be accurately estimated. The detailed breakdown of CWR and IWR for major crops over multiple years offers valuable insights into seasonal water demands, enabling stakeholders to optimize irrigation practices and mitigate water scarcity risks.

Furthermore, this chapter addresses the unique challenges and considerations associated with water management in both study regions. In the ARB, where downstream areas are heavily reliant on irrigation for agricultural productivity, the spatial distribution of croplands is influenced by factors such as elevation, climate variability, and land suitability. Understanding these dynamics is crucial for devising targeted interventions to optimize water usage and ensure sustainable agricultural development. Similarly, in the BRB, the proposed irrigation scheme aims to reallocate water resources based on crop water requirements and land suitability, thereby enhancing agricultural productivity while minimizing water waste.

In addition to irrigation water consumption, this chapter also sheds light on domestic water consumption patterns in both study regions. Forecasting future water demands and proposing measures to transition from groundwater to surface water sources underscore the importance of sustainable water supply infrastructure to meet the evolving needs of growing populations. Overall, this chapter provides a comprehensive analysis of water consumption dynamics in agricultural regions, leveraging advanced methodologies and empirical data to inform evidence-based decision-making. By addressing key challenges and offering actionable insights, it serves as a valuable resource for policymakers, water managers, and stakeholders involved in sustainable water management and agricultural development initiatives.

Chapter 7

Water resources management

7.1 Introduction

The agricultural infrastructure in Afghanistan has experienced degradation and collapse during recent decades of conflict and war. The inequitable water allocation among water users is another management issue in the country with upstream and midstream over-extraction of water downstream users facing water shortages and experiencing loss of their products. In particular, during low-flow years, downstream users face more difficulties due to the high consumption of upstream users (Salman et al., 2017). We can categorize the current irrigation challenges in Afghanistan into (1) lack of proper infrastructure to convey and manage water and (2) lack of proper management practices and policies for water resources. To overcome these challenges, both soft and hard approaches are needed for Afghanistan. Hard approaches refer to the construction of a new irrigation infrastructure and the rehabilitation of existing irrigation systems to improve its efficiency. Soft approaches refer to developing proper management practices and policies for water allocation, irrigation management, and agriculture management that consider sustainable practices and the equitable distribution of water among users for economic and social status development.

According to the FAO, the number of chronically undernourished people worldwide increased from 777 million in 2015 to 815 million in 2016 (RESILIENCE, 2017). As stated by Dinar et al. (2019), the food security situation has worsened in southeastern Asia, sub-Saharan Africa, and western Asia, especially in places that have experienced war and armed conflict or where natural disasters have occurred. Natural resource and water scarcity issues have become major global concerns with rapid increases in food demand. Considering the high uncertainty and risks, long-term water resource management needs to assess different mitigation scenarios under current and future conditions.

Afghanistan is highly dependent on the agricultural sector. Afghanistan National Statistics and Information Authority report from 2019 declared the contribution of the agriculture sector to the gross domestic product (GDP) as 18.6% of the total country GDP (NSIA, 2019).

Moreover, approximately 80% of the population lives in rural areas, and their livelihood is directly or indirectly tied to agricultural activities (Mahmoodi, 2008). The primary sources of irrigation water are surface water and groundwater, with surface water dominated the supply of 86% of the total water (Rout, 2008). The informal traditional water management system is dominant in Afghanistan, as described in Chapter 2 of this document. The mirabs are chosen by local farmers, and payments are made by locals with a specific amount of wheat for their services. They typically spend a significant amount of time walking through the canal system, checking and monitoring the water allocation regime, and supervising the local labor force for system maintenance. The mirabs manage the main, secondary, and tertiary canals, but they lack support and authority from higher institutions such as village and provincial councils or the national government for allocating water to canals from surface water bodies (Ward et al., 2013). The investigation in this study shows that the current system is not efficient and that the interaction between local communities and government agencies is not sufficient. The local government should impose more interference in water management and irrigation water allocation to modernize the existing system.

In intensely irrigated watersheds, continuous monitoring of water quality and quantity is required for a better understanding of hydrological dynamics (Dechmi et al., 2012). In this context, remote sensing data and watershed modeling tools are invaluable for testing management practices at the watershed level, reducing both costs and time. Traditional water management practices are still used for irrigation in developing countries and are generally accepted by local farmers. The government maintains minimal interference, avoiding changes to the management scheme to prevent water conflicts among users. However, given the increasing need for water and food, traditional practices should be replaced with scientific approaches. Therefore, the objective of this chapter is to utilize hydrological computer models to test best management practices (BMPs) in large, data-scarce watersheds. In undeveloped watersheds, hydrological models can identify the strengths and weaknesses of water resources before detailed studies, thus reducing the costs of further investigations and planning. These approaches can also support policy development and decision-making processes by considering hydrological conditions with lower costs and time requirements.

To distinguish between long-term planning and short-term management, it is important to clarify that my research encompasses both aspects, though they serve distinct purposes within the study. The long-term planning aspect is addressed through the cost-benefit analysis (CBA) under various scenarios, which provide a strategic foundation for the sustainable management of water resources over time. This element helps in understanding how conditions, including the construction of the proposed dam, will impact water availability, and the overall viability of the irrigation system considering water consumption. On the other hand, the short-term management component is reflected in the adjustments made to water allocation within the irrigation system, based on immediate crop water needs and current hydrological conditions. This dual focus ensures that the proposed solutions are not only viable in the long run but also responsive to present-day challenges and opportunities, thereby bridging the gap between strategic foresight and operational flexibility.

Water resources management and planning requires both short-term and long-term decisions. In the short term a correct understanding of the available resources and consumption is essential. While developing the watershed requires long-term planning to ensure match the future demands. As part of the current study, the construction of dam was proposed for the BRB water resources management to store the water during the low or non-irrigation seasons and using the stored water during the high irrigation season. Making long-term decisions due to high levels of uncertainty and impact of climate change is challenging. In this study the CBA analysis shows that the construction of dam will be financially feasible. However, this study could not consider the impact of climate change due to limitation in time and resources. For further details about the limitations on the considerations of the climate change impact please refer to section 8.1.4 of this document.

7.2 Literature review

The use of hydrological computer-based models in water resource management has recently become popular among scholars. Numerous studies have been conducted globally using hydrological modelling approaches to test management scenarios and policies for water resource management. The monitoring of water resources is site specific, and it is difficult to generalize the data due to the high spatial and temporal variability of water resources. In this context, hydrological computer-based models play a crucial role in water-related studies. Water-related issues are specific to climate, geographical location, socioeconomic status, and multiple other factors. There is no single framework applicable to all conditions, but proper management practices should account for the interactions between infrastructure and how it handles water resources and how services are delivered to end users.

The SWAT model among hydrological models is one of the most popular hydrological models adopted by scholars for water resource management studies. SWAT is a powerful model for performing irrigation and chemical yield evaluation studies at the watershed level. For instance, SWAT was utilized to simulate the impact of alternative agricultural management practices on water quantity and quality in the State of Saxony, central Germany (Ullrich & Volk, 2009). Ullrich & Volk, (2009) performed a parameter sensitivity analysis to enhance the modelling scale, and the model was subsequently used to evaluate the impacts of several management practices (e.g., conservation tillage, conventional tillage, and no tillage) on different plant types. In the next study, the SWAT model and genetic algorithm (GA) were utilized to optimize reservoir operation in two reservoirs in India along the Gang River (Anand et al., 2018). In this study, multiple scenarios were considered to optimize dam operation for satisfying irrigation water use in addition to hydroelectric power generation. Panagopoulos et al. (2014) used the SWAT model to evaluate the cost-effectiveness (CE) of various irrigation water management practices in the water-stressed catchments of Pinios, Greece, based on six BMPs. The study examined the CEs of deficit irrigation, wastewater reuse, precision agriculture, conveyance efficiency improvements, and combinations of these factors to assess the BMPs within the context of water scarcity in the study area (Panagopoulos et al., 2014).

7.3 BRB water management

As stated in the earlier chapter, the BRB water availability was determined using SWAT hydrological models. The main purpose of this chapter is to allocate water to the water sector and users while considering the available resources and encountering environmental and ecosystem vulnerabilities. The assessment of the current irrigation scheme revealed water shortages and stress in the agricultural sectors during the peak irrigation period. The annual total water in the BRB is more than sufficient for irrigation of the existing agricultural land, and surplus water could be allocated for further development of the basin.

7.3.1 Dam site identification using AHP

In this section the result of the AHP based on the experts' opinion for identifying the suitable dam site location has been presented. **Table 7.1** shows the pairwise comparison matrix for the aggregate results from the consistent responses. The normalized information, and relative importance weight of each criterion with the column (Weight) is presented in the **Table 7.2**. The λ_{max} and RI values in this study are 5.15 and 1.12, respectively. The CR value is 0.033, indicating a level of coherence in comparing each criterion. Finally, the suitability index (SI) using GIS and remote sensing technology was calculated via **Equation 7.1** below. This equation is derived from the AHP weights, as shown in **Table 7.2**.

$$SI = D \times 0.33 + S \times 0.23 + SL \times 0.20 + E \times 0.14 + LULC \times 0.10 \quad (7.1)$$

Table 7.1 Pairwise comparison matrix for dam suitable assessment based on the expert's opinion.

CRITERIA	D	S	SL	E	LULC
Discharge (D)	1.000	2.000	2.000	2.000	2.000
Soil (S)	0.490	1.000	2.000	2.000	2.000
Slope (SL)	0.530	0.640	1.000	2.000	2.000
Elevation(E)	0.400	0.550	0.500	1.000	2.000
LULC	0.480	0.450	0.440	0.470	1.000
Sum	2.900	4.690	5.400	7.780	9.720

Table 7.2 Matrix normalization with the weights and consistency measure (CM).

CRITERIA	D	S	SL	E	LULC	CM	Weight
Discharge (D)	0.350	0.440	0.350	0.320	0.220	5.200	0.330
Soil (S)	0.170	0.210	0.290	0.240	0.230	5.200	0.230
Slope (SL)	0.180	0.140	0.190	0.250	0.230	5.170	0.200
Elevation(E)	0.140	0.120	0.090	0.130	0.220	5.120	0.140
LULC	0.160	0.100	0.080	0.060	0.100	5.100	0.100
Sum	1.000	1.000	1.000	1.000	1.000	-	1.000

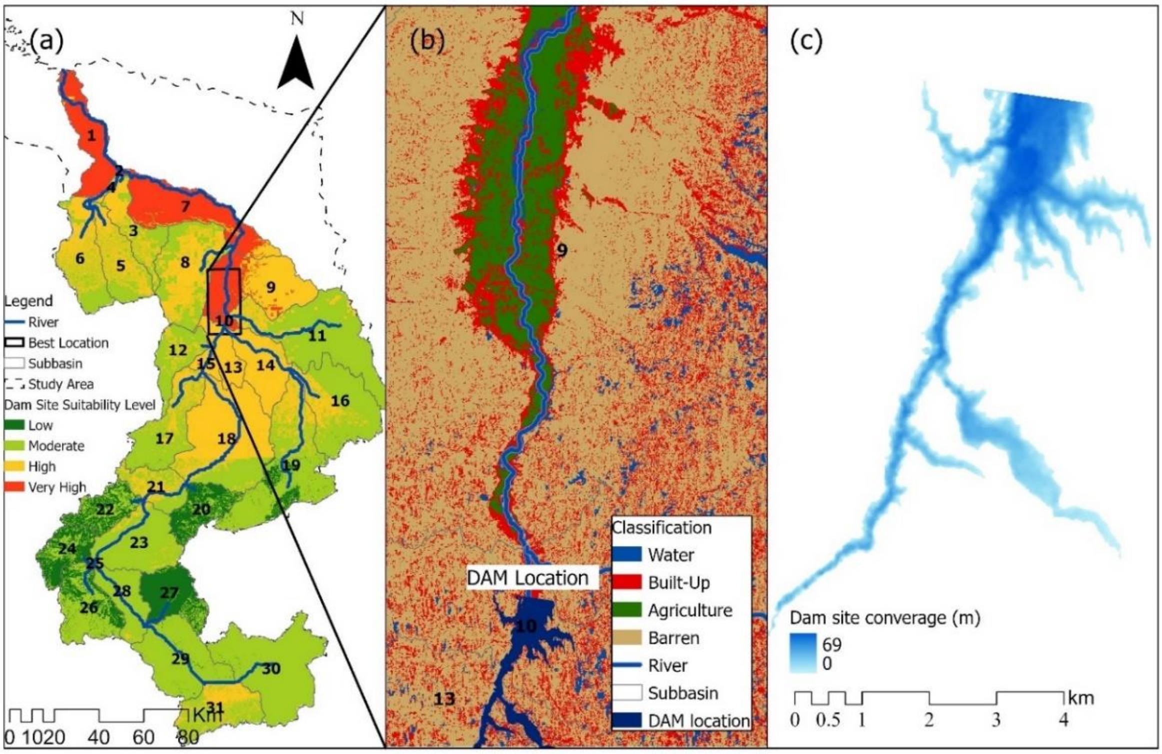

Figure 7.1 Dam site suitability map using AHP; (a) Dam site suitability level map on the subbasins level, (b) Land Use Land Cover map created using Landsat 8 satellite images using support vector machine, (c) spatial extension of water in-case of dam construction in subbasin 10.

The AHP process output for dam site suitability analysis is depicted in **Figure 7.2**. In **Figure 7.2(a)**, the suitable area for dam construction is highlighted in red based on specified criteria and their respective importance. Subbasins 10, 9, 7, and 1 were identified as most suitable for dam construction, with subbasin 10 tentatively selected as the preferred location. This choice is motivated by the mountainous nature of the southern part of the BRB, with the flat agricultural land predominantly in the northern part. Placing the dam upstream offers greater opportunities for downstream land development. **Figure 7.2(b)** presents the land use and land cover (LULC) derived from Landsat 8 level 1 imagery, providing detailed information about the area and dam location.

The decision to locate the dam in the southern part minimizes agricultural and built-up land, focusing instead on barren land to reduce construction costs. As shown in **Figure 7.2(c)**, the dam in subbasin 10 is estimated to have a water height of 69 meters, with a storage capacity of 197,900,938 cubic meters and a submergence area of approximately 748 hectares and a length of 1600 meters. This capacity is chosen to address irrigation water shortages during February, March, and April, estimated at 131,820,480 cubic meters under current conditions. Additional storage will serve flood control and surplus water storage purposes.

Table 7.3 Monthly water allocations required for 11 downstream irrigation canals compared with allocations under the proposed irrigation scheme scenario. Cells with a white background indicate water requirements for the new irrigation scheme, accounting for a 20% loss in the irrigation system, while cells with a gray background show current water allocations by BRB.

No.	Canal name	Irrigation land (ha)	Required canal water allocation (m^3/s)											
			Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
1	Imam Sahib	7741.9	0.74	1.34	1.97	3.65	3.13	1.34	1.53	1.23	0.50	0.11	0.21	0.39
			1.37	1.47	1.92	3.51	4.30	2.46	1.64	1.24	1.22	1.28	1.39	1.37
2	Nahar-i-Shahi	14005.2	1.34	2.42	3.57	6.60	5.65	2.42	2.77	2.22	0.91	0.20	0.38	0.70
			3.84	4.12	5.39	9.84	12.05	6.91	4.59	3.47	3.41	3.60	3.91	3.85
3	Sia Gird	7702.0	0.74	1.33	1.96	3.63	3.11	1.33	1.52	1.22	0.50	0.11	0.21	0.38
			1.03	1.10	1.44	2.63	3.22	1.85	1.23	0.93	0.91	0.96	1.05	1.03
4	Balkh	8086.6	0.77	1.40	2.06	3.81	3.26	1.40	1.60	1.28	0.52	0.11	0.22	0.40
			0.48	0.51	0.67	1.23	1.50	0.86	0.57	0.43	0.43	0.45	0.49	0.48
5	Moshtaq	9207.1	0.88	1.59	2.35	4.34	3.72	1.59	1.82	1.46	0.60	0.13	0.25	0.46
			1.43	1.54	2.01	3.67	4.50	2.58	1.71	1.29	1.27	1.35	1.46	1.44
6	Chemtal	8003.4	0.77	1.38	2.04	3.77	3.23	1.39	1.58	1.27	0.52	0.11	0.22	0.40
			1.12	1.21	1.58	2.88	3.53	2.02	1.34	1.01	1.00	1.05	1.14	1.13
7	Abdullah	22866.3	2.19	3.95	5.83	10.77	9.23	3.96	4.52	3.62	1.48	0.32	0.62	1.14
			4.80	5.15	6.73	12.29	15.06	8.63	5.74	4.33	4.26	4.50	4.88	4.82
8	Dawlat Abad	38728.2	3.71	6.69	9.88	18.25	15.64	6.70	7.65	6.13	2.51	0.54	1.06	1.93
			5.14	5.52	7.21	13.17	16.13	9.25	6.15	4.64	4.56	4.82	5.23	5.16
9	Char Bolak	36078.3	3.46	6.23	9.20	17.00	14.57	6.24	7.13	5.71	2.34	0.51	0.99	1.80
			5.14	5.52	7.21	13.17	16.13	9.25	6.15	4.64	4.56	4.82	5.23	5.16
10	Fayaz Abad	17180.5	1.65	2.97	4.38	8.10	6.94	2.97	3.39	2.72	1.11	0.24	0.47	0.86
			4.11	4.42	5.77	10.54	12.91	7.40	4.92	3.71	3.65	3.86	4.19	4.13
11	Aqcha	88706.0	8.50	15.31	22.62	41.80	35.81	15.35	17.52	14.05	5.75	1.24	2.42	4.42
			7.54	8.10	10.58	19.33	23.67	13.57	9.02	6.81	6.70	7.08	7.68	7.57
Total		258305.5	24.75	44.59	65.87	121.71	104.28	44.70	51.01	40.90	16.74	3.62	7.06	12.87
			36.00	38.66	50.51	92.26	113.00	64.78	43.06	32.50	31.97	33.77	36.65	36.14

7.3.2 Irrigation water management in the BRB

As per Hussainzada & Lee (2022), BRB allocated irrigation water on the basis of the farmer tax payment, agricultural land area, and available water in the BRB river for each month (please refer to **Table 4.8** for the percentage of water allocation at each canal in the downstream of BRB). The comparison between the existing and proposed irrigation scheme by this study reveal a significant water shortage for the irrigation in BRB during February, March, April, July, and August and surplus water in the downstream during other months with respect to the irrigation water consumption. The most severe water scarcity happens in the three consecutive months in February, March, and April with shortage of $138{,}820{,}480\ m^3$ for irrigation. The annual mean streamflow in subbasin 10 was estimated as $1.578 \times 10^9\ m^3$ by the SWAT model from 2013 to 2018. Additionally, the irrigation water requirement in the BRB was estimated to be $1.395 \times 10^9\ m^3$ including 20% loss in the irrigation channels (Hussainzada & Lee, 2022). Construction of dam can regulate the water flow and fill the gap between consumption and available water in the BRB for the irrigation purposes.

Figure 7.2 dedicates the hydrograph in the downstream subbasin 7 under three different scenarios, (1) the blue line showing the river discharge in the subbasin 7 under current condition, (2) the red line illustrate the river flow controlled by dam constructed in the subbasin 10 and regulating the water flow based on the crop water requirements and an additional 20% water loss in the irrigation canals and releasing of a minimum 20 m^3/s during non-irrigation months to maintain the downstream ecosystems , (3) Gray line represent the ideal case of no water loss in the irrigation canals. The estimations based on **Table 7.3** and considering the scenario of maintaining at least 20 m^3/s of water during the non-irrigation seasons shows that the Balkhab river can irrigate all the farmland as well as storing a surplus water of approximately $84 \times 10^6\ m^3$. The surplus water can be used for different means, as a possible scenario the surplus water can be used for the developed 17,180.5 ha of new agricultural land in the BRB (Hussainzada & Lee, 2022).

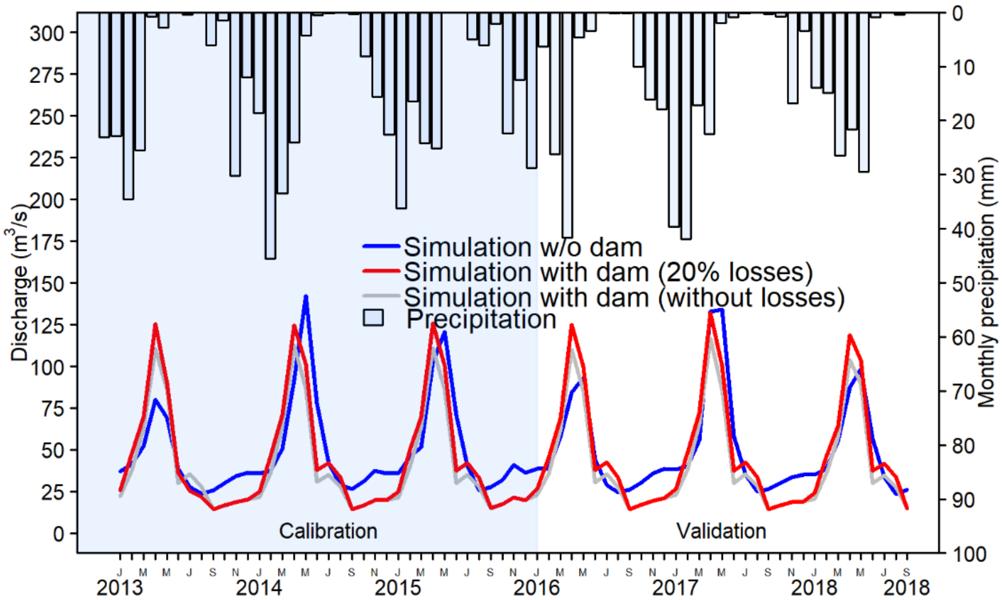

Figure 7.2 Resulting hydrographs from subbasin 7 with (red) and without (blue) dam inclusion in subbasin 10 (Hussainzada & Lee, 2022).

7.3.3 Hydro-electricity generation

Dam structures could be used for multiple purposed and hydropower generation is one of them. The investigation in this study shows that BRB authority can build a dam with 69 m heads and annual flow of $1.578 \times 10^{9}\ m^{3}$. This dam has theoretical capacity for generation of 25.4 MW or 609.6 MWh of energy based on **Equation 7.2.** Considering the dam outflow schedule in **Table 7.3,** the minimum and maximum discharge are 31.97 m^{3}/s and 131 m^{3}/s which can generate 66.5 MW and 16.23 MW respectively. The residential energy consumption in the biggest city in the BRB, Mazar-i-Sharif, has been calculated to be 236,526.3 kWh for cooling, heating, domestic hot water, and lightening according to Ahady et al. (2022). The population of Mazar-i-Sharif is 584,886 (NISA, 2020).

$$P = g \times H \times Q \times Efficiency \qquad (7.2)$$

where P is the power generated in KW, g is the gravitational acceleration (9.81 m/s^{2}), H is the effective head (m), Q is the amount of water flow (m^{3}/s), and the efficiency is how well the turbine and generator convert the power of falling water into electric power. The average flow from the dam is 50.04 m^{3}/s, and the efficiencies of the turbine and generator are between 95 and 75%. To ensure safety, the lower range was included in the estimation.

7.3.4 Water supply for BRB

The river has a surplus flow of $84 \times 10^6 m^3$ after irrigating the existing lands. This study targets the urban population living in the BRB as the consumer of the water supply system. The urban population in the BRB was reported to be 584,886, with a growth rate of 2.14% (NISA, 2020). Using the geometric population growth formula in **Equation 7.3**, the projected population of the BRB in 50 years will be 1,686,024. According to the Afghanistan Ministry of Urban Development and Land, the per capita water demand is 140 liters per day. It is estimated that 86,155,856 m^3 will be sufficient for the urban population's water consumption in 2070. The surplus water in the BRB is nearly sufficient for a water supply project with a 50-year lifespan.

$$P_t = P_0(1 + r)^n \qquad (7.3)$$

where P_t is the projected population at time t, P_0 is the initial population, r is the population growth rate, and n is the number of years for the future projection.

7.3.5 Flood control

The Balkhab River experiences the highest flow in May ($113\ m^3/s$) due to rapid snowmelt and rainfall (Hussainzada & Lee, 2022). September is the driest month in the basin, with an average total monthly flow of 31.97 m^3/s. The most extreme flood event was recorded at the Rabat-i-Bala station in May 2014, with a peak flow of 1190 m^3/s and an accumulated daily water volume of 102 million m^3 (**Figure 4.3**). The dam's capacity is approximately 192 million m^3, meaning the volume of water from this extreme event is only 53% of the dam's capacity. Adding 84 million m^3 as surplus water, based on the results in subsection 4.3.1, the total volume reaches 196 million m^3. Thus, the overflow is only 4 million m^3, which the dam's outflow rate can manage. Dams can effectively control water flow during extreme events, reducing downstream damage.7.3.6 Cost-benefit analysis (CBA)

The estimated costs and benefits of the dam are presented in **Table 7.4**. The construction cost was estimated based on similar dams constructed in Afghanistan. In western Afghanistan, Salma dam construction was completed in 2016 with a capacity of 640 million m^3, and electricity generation of 42 MW costs 290 million USD (BBC, 2016). Compared to the Salma dam reservoir capacity and electricity generation capacity, the BRB dam is almost one-third in size and will cost approximately 89.6 million USD. The operation and maintenance of the dam will cost 1.5-2.5%

of the construction cost (Paul Lako, Giorgio Simbolotti, 2010). The price for a single hectare of land was determined based on interviews with local people to be 10,130 USD/ha in subbasin 10.

On the other hand, the electricity price is 0.056 USD/kWh. The prices of agricultural products were estimated based on the market price in Afghanistan, and the agricultural products were estimated based on the yield of agricultural products per hectare of land. The average revenue of 20% was considered farmer profits. The municipal and industrial water supply price is currently 0.36 USD/m^3 and 20% profit margin for the services was included in the estimation. There is no record of flood damage at the regional scale. However, the annual flood damage in Afghanistan is estimated at 54 million USD, and we consider the flood damage as the total damage divided by the number of provinces over 50 years. The revenue for the fishery was compared with that of the Darunta dam located in eastern Afghanistan.

Table 7.4 CBA results for the dam construction with an effective life span of 50 years.

	Cost	
No	Description	Amount (USD)
1	Construction	89,600,000
2	Land Acquisition	3,550,889
	Total	**93,150,889**
	Operation and maintenance	
3	Operation and Maintenance (2.5% of construction costs)	2,241,846
	Total	**2,241,846**
	Benefit	
No	Description	Annual amount (USD)
6	Hydroelectric Energy	12,460,224
7	Irrigation Water	4,536,540
8	Municipal and Industrial Water Supply	6,203,221
9	Reduction of Flood Losses	1,588,235
10	Fishery and Recreational Benefits from Reservoirs	151,410
	Total[1]	**18,736,409**
	Total[2]	**20,403,090**

Note: Total[1] consider the irrigation water use and Total[2] consider surplus water to be used for the municipal and industrial water supply.

Considering the discount rate in the CBA of dam project with a 50-year lifespan is crucial due to the time value of money and uncertainty in the future. Inclusion of the discount rate allows for the present value of future costs and benefits to be reflected in the economics estimation of the project over time. Otherwise, the future benefits might appear unduly attractive, and long-term costs may be highly underestimated leading to misallocation of the resources in a project. Giving the lengthy time horizon of the 50 years even small difference in the discount rate can significantly affect the analysis result. The discount rate for Afghanistan was considered based on the International Financial Statistics and data provided by the world bank between 2007 and 2017. The discount rate in Afghanistan varies between 2007 to 2017 and the most recent rate is reported 12.1% and used for the estimations here (World Bank, 2024).

Net present value (NPV) is the key financial metrics to evaluate the profitability of an investment. NPV calculates for the sum of the present value for all cash inflow minus operation and maintenance costs and initial investment over the project's life. Positive NPV indicates the project profitability exceed the anticipated costs. Negative NPV implies that initial costs outweigh the benefits and makes the project unattractive. The project payback period is the year when the cumulative cash flow turns positive. NPV can be estimated using the **Equation 7.4**.

$$NPV = \sum_{t=1}^{n} \left(\frac{B_t - O_t}{(1+r)^t}\right) - C_0 \qquad (7.4)$$

where, B_t is benefits in year t, O_t is the operation and maintained cost in year t, r is the discount ratio, C_0 is initial investment, and t is time period in year.

Figure 7.3 is representing the NPV estimation for the 50-years lifespan dam project considering two cases in the CBA, Case-I using the surplus water for the irrigation of newly developed land and Case-II using the surplus water as the source for the municipal and industrial water supply. Financial assessment depicted in the **Figure 7.3** is showing the project is profitable for both cases. The payback period for the project is 10.07 and 8.5 years for Case-I and Case-II, respectively. The NPV for the Case-I and Case-II is 42.7 and 56.4 million US dollars respectively which means the project is profitable in either case. The internal rate of return (IRR) for the Case-I is 17.7% and 19.5% for the Case-II.

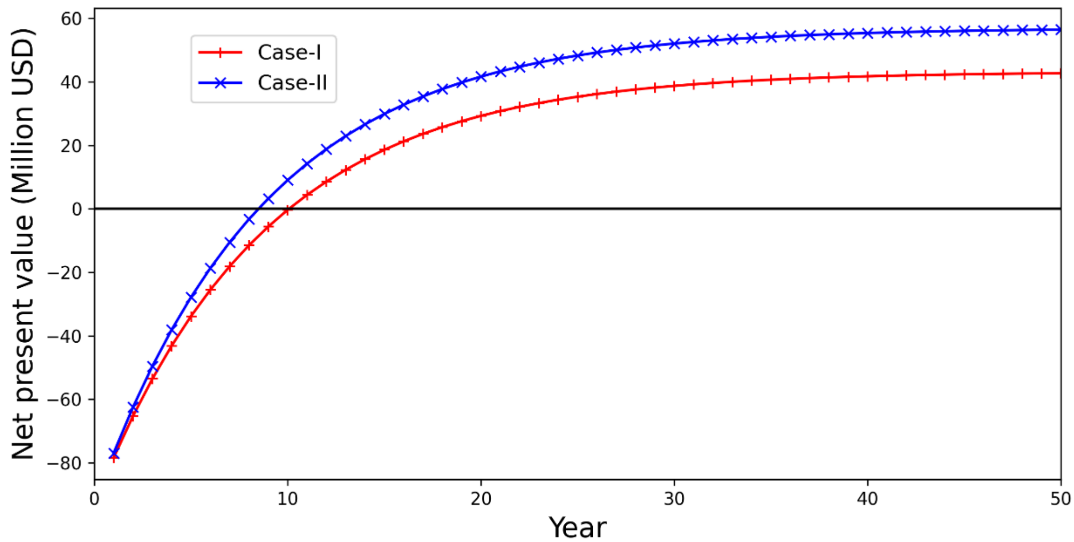

Figure 7.3 Net present value for the dam project with lifespan of 50-years considering irrigation water consumption (Case-I), and municipal and industrial water supply (Case-II).

Meanwhile, inclusion of the climate change impact in dam CBA is essential for ensuring the long-term viability and effectiveness of the dam are accurately assessed. In order to account for climate changes, the following should be considered:

i. **Assessment of climate change impacts:** It is essential to consider the changes in the hydrological cycle due to changes in the temperature and evaporation under the climate changes scenarios, changes in the sediment regime, and extreme weather and rainfall events changes in the future.

ii. **Scenario analysis**: Analysing future water condition under different scenarios (e.g., high, medium, and low) for better understanding of the future condition and estimation of the cost for adaptive measures such as spillway modification, reservoir reoperation, or additional construction costs.

iii. **Risk and Uncertainty Analysis:** Given the high level of uncertainty in future climate change projections, it is vital to incorporate flexibility into the project design. Recent studies highlight the increasing severity and frequency of flood and drought events, suggesting that unanticipated costs may arise, further contributing to the project's uncertainty.

7.4 Irrigation water management in ARB

The northeastern region of Afghanistan (Kunduz, Baghlan, Takhar, and Badakhshan provinces) is known as the food basket of Afghanistan. The basin is the largest in terms of surface water availability and agricultural activities in Afghanistan. In this section, we analysed the irrigation sector water consumption from 2014 to 2019. The irrigation sector water consumption was calculated based on the crop type map generated for each year and the CWR for the individual crops. The analysis was conducted on three river basins in the ARB, namely, Kokcha, Khanabad, and Kunduz. The points for the generation of the discharge data were incorporated into the WRF-Hydro model for the midstream region of all three rivers. The locations of the selected points on the mid-streams are shown in **Figure 7.4**.

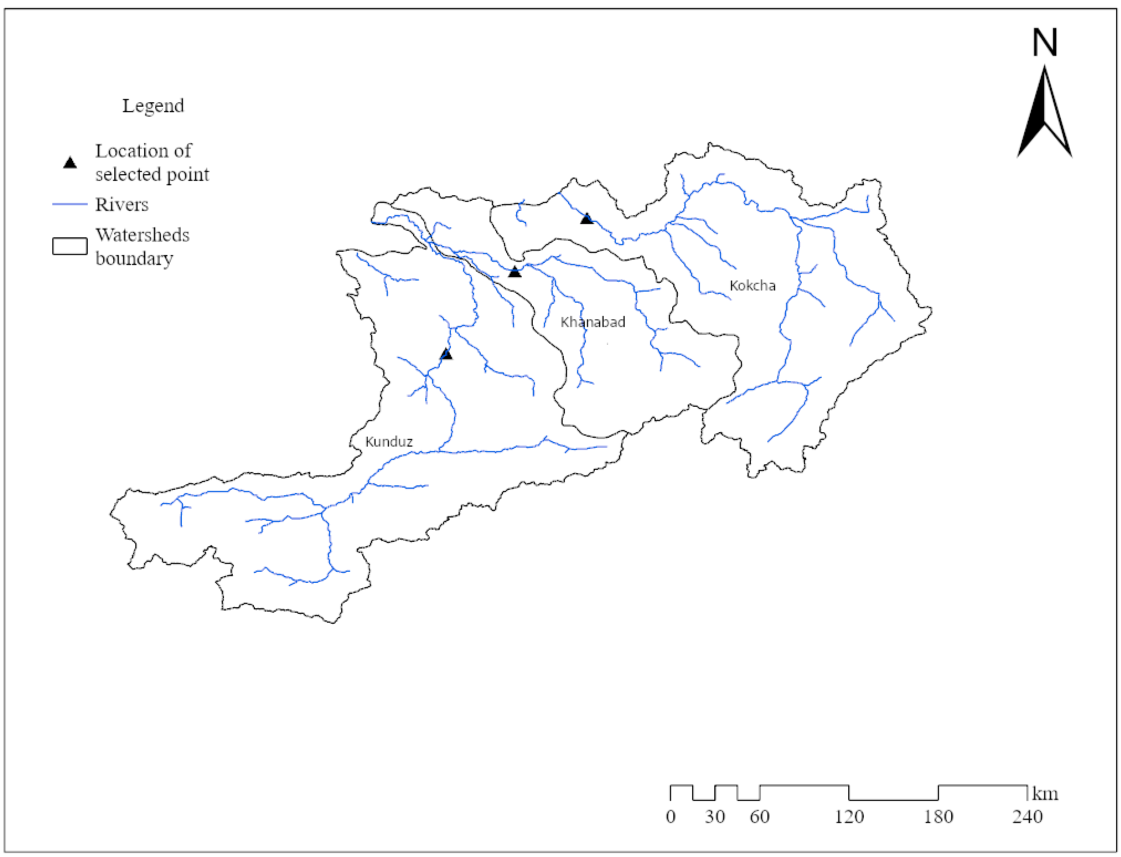

Figure 7.4 Location of the selected point for discharge data generation using WRF-Hydro model.

The losses of irrigation water in irrigation canals (conveyance) and agricultural land (field application) are very high in Afghanistan. Conveyance loss refers to the amount of water naturally lost through conveyance between two points in irrigation canals. The conveyance losses are 20% for canals longer than 2000 m and clay soil. The field application efficiency refers to the amount of water applied in the field. The amount of field application efficiency for the surface irrigation schemes, namely, border, furrow, and basin irrigation, is determined to be 60%, and 40% of the water cannot reach the root zone due to evaporation, deep percolation, or application to the soil area where roots are not present. **Equation 7.5** represents the irrigation water efficiency formula (RG, 1998).

$$e = \frac{e_c \times e_a}{100} \tag{7.5}$$

where e is the scheme irrigation efficiency, e_c is the conveyance efficiency (80%), and e_a is the field application efficiency (60%).

In this study, we consider three scenarios for the irrigation scheme in the ARB. **Scenario-1** represents the current irrigation scheme, where the conveyance efficiency is 80% due to earth canals and the field application efficiency is 60%, representing surface irrigation for all crops. Substituting the values in **Equation 7.5** the irrigation efficiency of the current irrigation system will be 48%.

Scenario-2 represents the case of improving irrigation canals from traditional earth canals to lined canals with concrete to avoid infiltration. In this case, the conveyance efficiency increases to 95%, and the irrigation water efficiency in the system increases by 9% with respect to scenario-1. Substituing the values into **Equation 7.5** the irrigation efficiency will be 57%.

Scenario-3 represents the case of improvement in irrigation canals as well as improvement in the irrigation scheme in the ARB. In this scenario, we assumed that the irrigation scheme improved from surface irrigation to sprinkler irrigation. In this case, the field application efficiency will be 75%, an improvement of 15%. It should be noted that rice fields still use traditional surface irrigation. However, there have been attempts to improve the irrigation efficiency of rice, but most countries still use traditional surface irrigation. By substituting the conveyance and field irrigation efficiency values into **Equation 7.5** the scheme irrigation efficiency will be 71.25%.

Figure 7.5 shows the availability of water in the three main rivers of the ARB midstream. The locations of the selected points for the streamflow were selected based on the existence of the majority of agricultural land downstream of those points. The majority of lands in the ARB are cultivated in two seasons, with the first season starting in October with the cultivation of wheat and ending in May and the second season starting in June and ending at the start of October. The hydrographs of the available water in Figure 7.4 are presented at a monthly temporal resolution and are compared with those of irrigation water consumption in each watershed. The Kokcha River has a significant amount of surplus water during the high-flow seasons of May, June, July, August, and September. The hydrograph and irrigation water consumption are very close during the months of April. Comparison between the hydrographs of the Kokcha River and irrigation water consumption showing the availability of water for the entire study period except for the start of the irrigation season in 2018. However, scenario 3 almost resolved the issue of water shortages in 2018.

The behaviour of the Khanabad River is very similar to that of the Kokcah River, with high flows occurring from May to September. The irrigation water consumption curve is very close to the hydrographs in the month of April. As shown in **Figure 7.5**, Khanabad experienced water shortages in April 2017, April and May 2018 and September 2018. The mitigation scenarios eliminate water shortages in April 2017. However, the Khanabad watershed experienced water shortages even after the implementation of the mitigation scenarios. It should be noted that Afghanistan experienced severe drought in 2018. Reports show a 28% decline in wheat production below the five-year average and a greater than 30% reduction in milk production (FAO, 2019).

Based on the analysis of this study, the Kunduz River basin experienced water shortages during April, May, and September 2014, 2017, and 2019, respectively. The mitigation scenarios reduced the gap between available water in the river and irrigation water consumption. The mitigation scenario-3 shows significant improvements during the first season of cultivation. Overall, improving irrigation canals can reduce the consumption of irrigation water by 9%. Analysis revealed that agricultural land development is mostly based on the availability of water during April, when the consumption of irrigation water and available water are almost equal. With improvements in canals, ARBs can develop 9% more land to arable land downstream. **Figure 7.6** shows the agricultural land area from 2014 to 2019 for all three watersheds. The irrigation land area changes slightly every year for the Khanabad and Kokcha watersheds. The changes in agricultural land area are more significant in the Kunduz watershed. The average agricultural land areas between 2014 and 2019 for the Kokcha, Khanabad, and Kunduz watersheds were 158151, 167361, and 249400 ha, respectively.

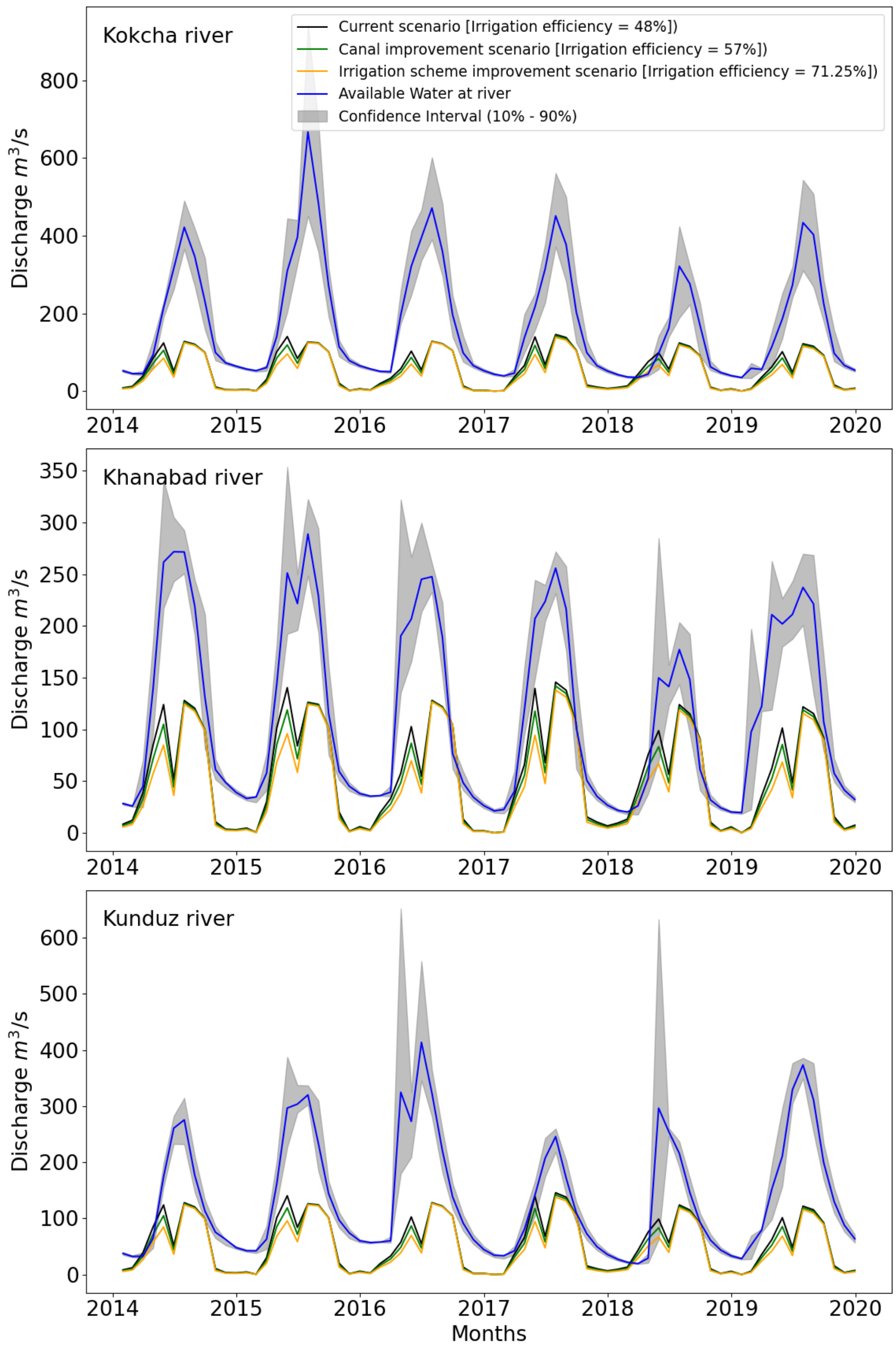

Figure 7.5 Midstream flow hydrographs for the three rivers in the ARB and irrigation water consumption under three scenarios: current irrigation system conditions with 52% losses, improvement of irrigation canals with 43% losses, and improvement of irrigation canals and irrigation schemes with 28.75% losses.

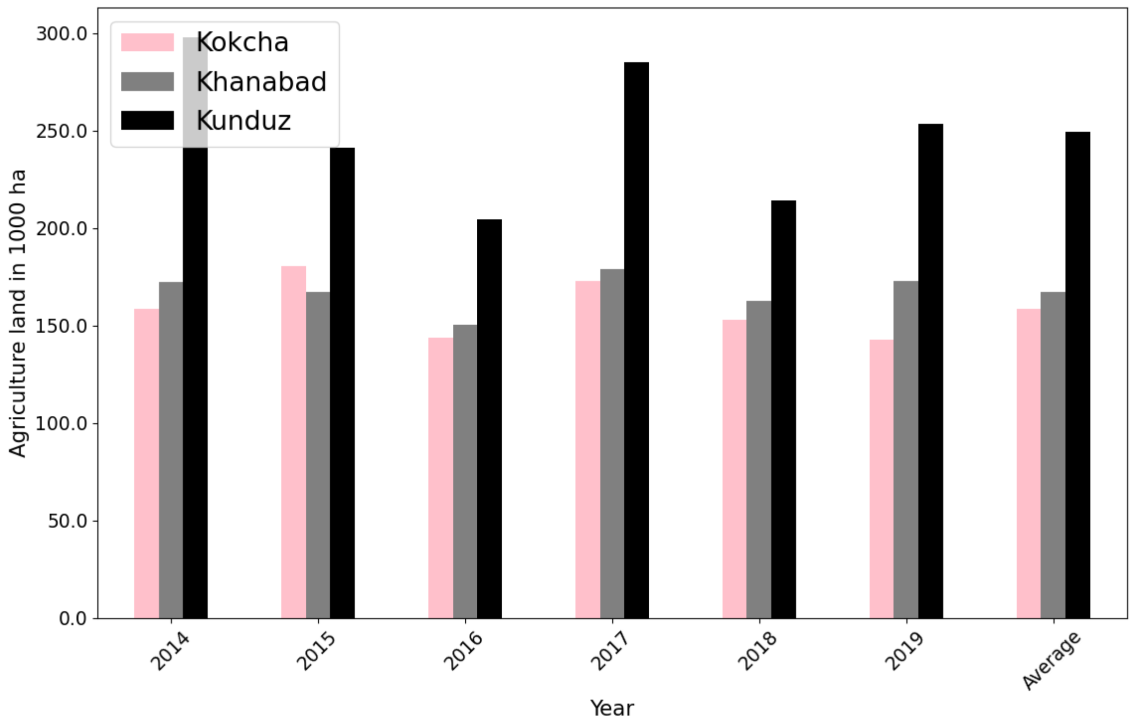

Figure 7.6 The agricultural land area for three watersheds in the ARB and their average for 2014 to 2019.

7.5 Domestic water management

The water supply demand was estimated for three provinces in Afghanistan, namely, Badakhshan, Takhar, and Kunduz, at 422333, 438507, and 45802 m^3/day, respectively, as shown in **Table 4.12**. The water supply demand estimates the projection of the water supply consumption 50 years from now. **Figure 7.7** represents the surplus water in the three rivers after the deduction of the irrigation water required for the agricultural sector. The flow rate in the Kokcha watershed was greater than the required irrigation water consumption and water supply of 4.88 m^3/s except in the extreme drought year of April 2018. The Khanabad River should provide 5.07 m^3/s of water to satisfy the water supply demand. The analysis revealed that the river is capable of providing enough water to satisfy the water supply demand except for one month in 2016 and three months in 2018, with two months in each row. The Kunduz watershed showed the greatest shortage in terms of water supply demand, with four months in 2014, 5 months in 2017, and four months in 2018. This finding supports the existence of enough surplus water in all three rivers. We suggest the construction of storage facilities to meet at least two months of water demand. The storage facilities could be filled during the high-flow seasons and can be used during months where the irrigation intensity is very high.

7.6 Discussion

7.6.1 Economical development of dam reservoir in BRB

Most BRB residents depend on the agricultural sector and related activities. Farming is a low-income activity in the country, contributing 18.6% to the national GDP, while 80% of the population is directly or indirectly involved in agriculture (Hussainzada & Lee, 2021). Farmers often lose their crops near harvest time due to water shortages, or they do not fully utilize their land's capacity from the start. Severe water shortages force farmers to relocate to large cities and seek labor jobs for their livelihood. Constructing a BRB dam could improve farmers' economic conditions by providing adequate water, allowing them to shift to more profitable crops and fully utilize their land. Regulated water through a controlled hydraulic structure could encourage farmers and investors to invest more in agriculture. Currently, farmers rely on traditional techniques for farming and irrigation, using cheap labor instead of agricultural machinery. Open earth channels and surface irrigation are the most common irrigation systems. A stable water source could modernize the agriculture sector, introducing mechanized techniques and increasing crop yields.

The cost-benefit analysis indicates that constructing the dam is economically viable. Dam construction can significantly impact residents' daily lives by providing sustainable irrigation and water supplies. A reliable irrigation source can enhance farmers' economic status, reducing the need for them to migrate to urban areas by increasing agricultural income. The power generated by the dam can supply energy to local residents and, if connected to the power grid, to neighboring provinces as well. The revenue from energy generation alone could cover the dam's costs. Additionally, the dam can significantly reduce downstream flood risks, which often result in fatalities and losses of agricultural products, livestock, and homes. Residents could also benefit from improved fisheries and recreational activities at the dam site and in surrounding areas.

7.6.2 Water resource development in BRB

Proper water resource management in basins with limited water supply is crucial for sustainable development and enhancing residents' livelihoods. Scholars have employed similar approaches for effective water resource management. For instance, Talebi et al. (2019) utilized the SWAT model analytical network process (ANP) to determine the suitable location of underground dams for subsurface flow in Iran. Another study evaluated a rainwater harvesting system using the

SWAT model and MCDA in Iran (Doulabian et al., 2021). In this study, SWAT was used as a tool to simulate streamflow and test the proposed solution. In the present study, SWAT modelling was coupled with MCDA to address irrigation water management issues at the basin level.

On the other hand, the dam can be used for power generation. In 2020, Afghanistan's installed capacity was $1030.87\ GWh$, while the country's imports from neighbouring countries were $5151.87\ GWh$. The construction of multipurposed dams can fulfil the country's energy requirements and improve the country's economy through job creation and power independence. As discussed in section 4.3.2, the capacity of power generation from the dam is 37 times greater than the demand in the urban area located in the BRB.

BRB residents rely on groundwater for their water supply, using shallow to deep wells for domestic use. High demand in recent decades has led to groundwater degradation and a reduction in the groundwater table, especially in densely populated urban areas. The local government could potentially use surplus irrigation water to meet urban water supply needs. As estimated in section 4.3.3, the Balkhab River can fulfill the domestic water demand for the population until 2070, though more detailed studies on water quality and project feasibility are required.

Constructing a dam will mitigate downstream flood risks, decreasing losses of agricultural products, livestock, and reducing casualties. BRB will benefit directly from the dam through increased agricultural productivity, a stable water supply, renewable energy production, and flood control. Indirectly, dam construction will generate numerous jobs in construction, operation, and maintenance. Additional benefits include enhanced food security, increased local community income from recreational activities and fisheries, and reduced CO_2 emissions.

However, the dam site selection for the current study represents a preliminary feasibility study from hydrological point of view. Dam construction and design is complicated time-consuming process requires multiple years of the observation and field study. Ecology and biodiversity are one of the important aspects that should be carefully considered during the dam construction. Unfortunately, currently there is limited information about the spatial distribution of the wildlife in Afghanistan. **Figure 7.8** is representing Afghanistan's tectonic setting and its surrounding regions. The current proposal location of the dam is not located on the fault lines, however a careful consideration of the earthquake during the design process are required to be considered.

7.6.3 Water resource development in the ARB

As shown in **Figure 7.6,** the agricultural land area in the three ARB watersheds differs every year based on the water availability and flow in the main rivers. Farmers cannot use the full potential of arable land in low-flow years. On the other hand, the analysis revealed high losses in irrigation canals and agricultural fields during the irrigation period. Current agricultural land development is influenced by water availability at the start and end of the irrigation seasons in April and September. All three watersheds have enormous amounts of surplus water during the high-flow seasons between June and August. In the case of improved irrigation system efficiency, the development of new land areas is possible in all watersheds of the ARB. When improving the conveyance canal efficiency in the ARB, 9% of the losses will be eliminated. The concrete lining of irrigation canals will provide the opportunity to develop more land. The average irrigated land areas in the Kokcha, Khanabad, and Kunduz watersheds are 158519, 167361, and 249400 ha, respectively, and in the case of saving 9%, the new land area in each watershed could be approximately 14266, 15062, and 22446 ha, respectively, for the three watersheds.

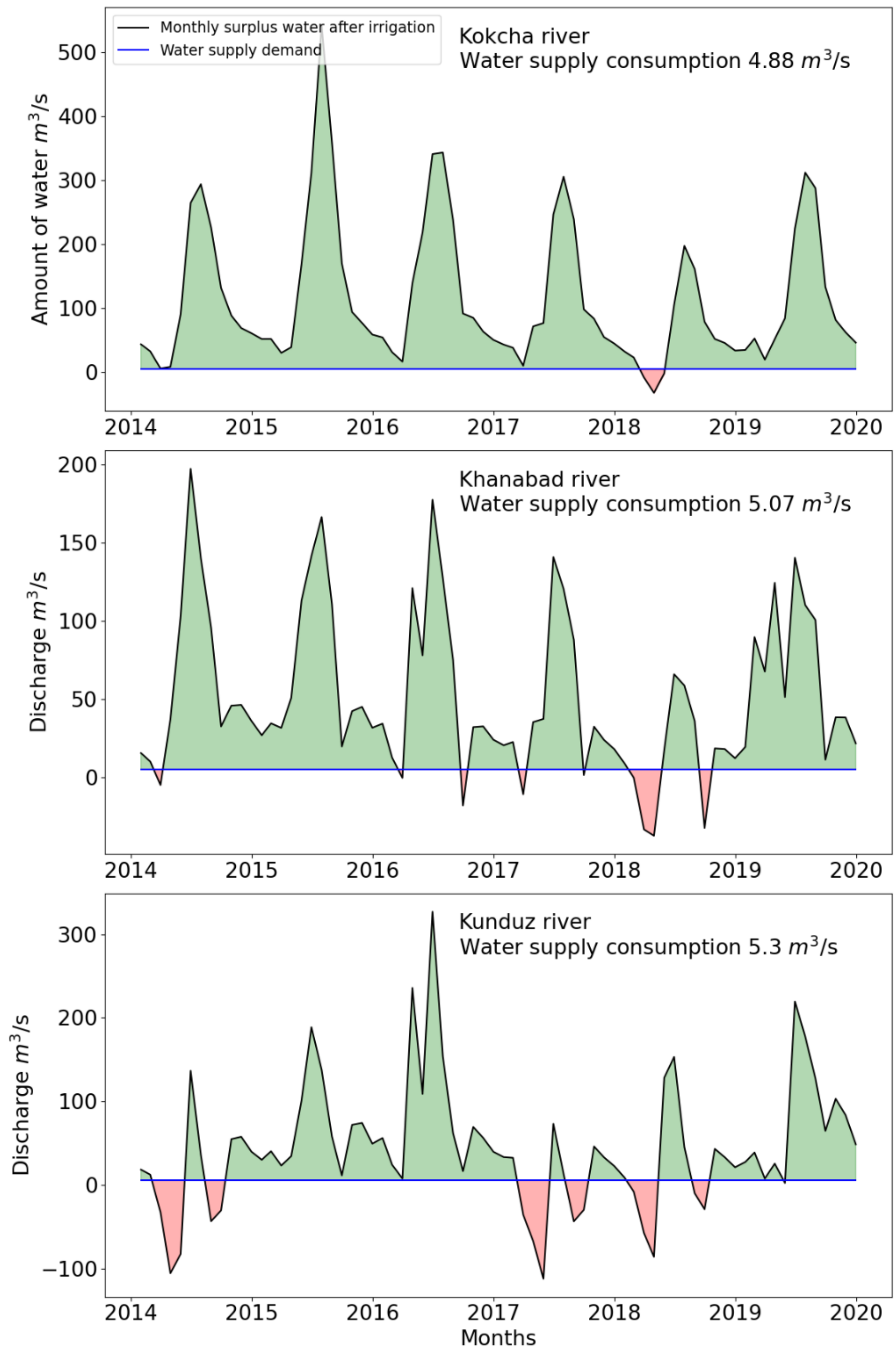

Figure 7.7 The surplus water in the three rivers of Kokcha, Khanabad, and Kunduz after deduction of irrigation water demand.

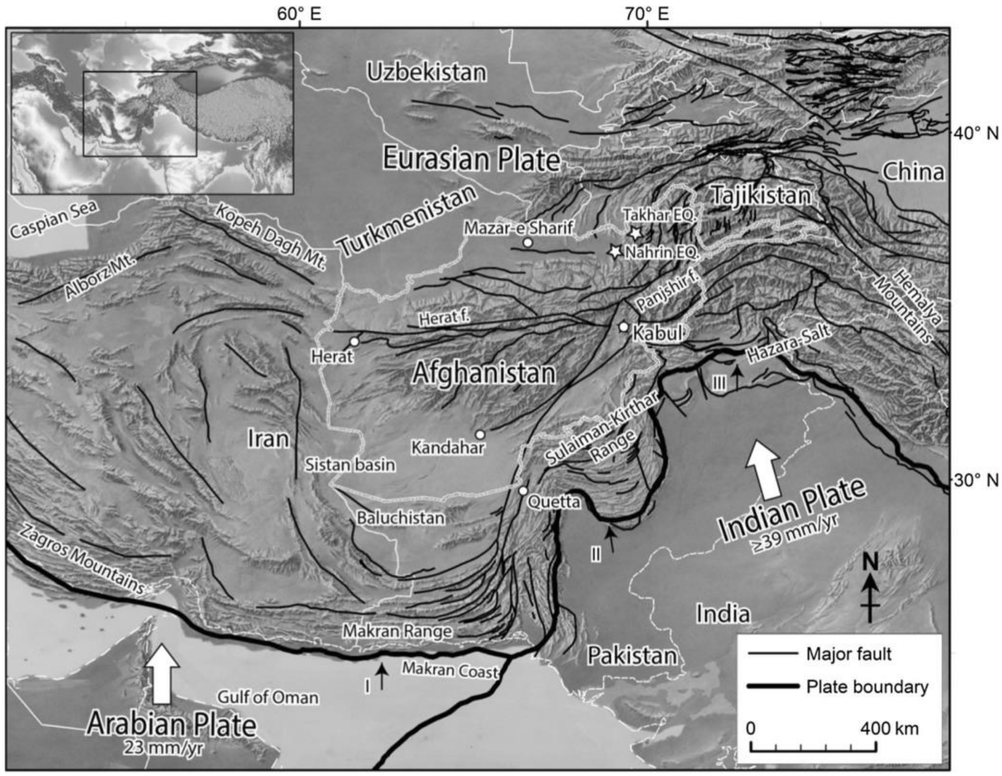

Figure 7.8. Tectonic setting of Afghanistan and surrounding regions. White arrows show relative plate motion directions of the Arabian and Indian plates with respect to the Eurasian plate (plate velocities from Ambraseys and Bilham 2003) adopted from (Shnizai, 2020).

ARBs have great potential for supplying water for domestic water consumption. Currently, residences rely on groundwater sources from individual water wells dug up on their personal property, community wells, springs, or water flowing through irrigation canals. Rivers could be a sustainable alternative source of supply for municipal water consumption. A sufficient water supply is available for the entire year except for the period when the irrigation water consumption almost reaches the available water curve in the river. Every water treatment plant and system should be designed to store at least two months of municipal water during low-flow years and for April and September of each year. The management of surface water in the ARB can benefit users by increasing food security in the region and providing access to sustainable healthy sources of drinking water.

7.7 Conclusion

This study presents a package for water resource management in less developed basins. The study starts with hydrological modelling in the basin and, consequently, other studies on sustainable water resource management in the basin with low precipitation and limited water resources. The basin's hydrological model is used to determine the basin's hydrologic regime and find the strong and weak points of the stream flow. Consequently, current water management practices in the basin were analysed to identify gaps in management. After identifying the problems and evaluating the resources, engineering-based solutions were proposed and tested in the basin using the previously prepared hydrological models. After testing the proposed mitigation measures, further detailed studies were conducted to develop possible management practices for the existing resources.

In this study, we focused on addressing water-related issues in Afghanistan. This study presents a comprehensive package and series of studies on the sustainable and comprehensive management of water resources in the country. The focus of this study is to propose engineering-based solutions to enhance water justice, the efficient use of water resources, economic development, water governance, and the conservation of natural resources. The outcome of this study is the first attempt at a detailed analysis of water resources and solutions to water scarcity issues in Afghanistan. The main focus of this study is on agricultural water resource management, as 98% of the water resources are currently consumed in this sector.

Chapter 8

Discussion and conclusion

8.1 Discussion on a water resources management

Water resource management in arid and semiarid regions of the world has always been challenging due to sparse precipitation and limited water resource availability. Recent developments in science and technology have provided deeper insight into the hydrological dynamics and climatological cycle of water resources. Modern civilization has made significant improvements in the utilization, mobilization, and use of natural resources during the past few centuries. However, water issues are the most challenging with respect to other natural resources, and all the challenges associated with other natural resources are related to water issues. An integrated approach from all sectors and stakeholders is required to develop water resource management policies and strategies. Interorganizational collaboration and coordination make this process more challenging.

Afghanistan, which has limited water resources and is highly dependent on the agricultural sector, is highly vulnerable to water shortages and stress. The preliminary steps for the sustainable and integrated management of water resources were taken by the central government and international organizations. The current study suggests the following issues in the current management scheme in Afghanistan.

- Water allocation and distribution among water users are not equitable among users. Downstream water users especially faced difficulty irrigating their lands during the peak of the irrigation season and during low-flow years.
- The irrigation system in Afghanistan is inefficient, with almost 50% water loss in irrigation canals and irrigation fields during water application.

- The government is following the traditional mirab water allocation system to avoid rising water conflicts among users. However, modernization of the irrigation system requires reform of the current irrigation system, which leads to more interference from the local and central governments.
- WAML 2020 excludes the private sector from the stakeholders. The private sector is more capable of generating large amounts of investment in the agricultural sector. Responsible and regulated supply chains could benefit small-scale procedures, workers, and consumers.
- There is a lack of scientific approaches to decision-making and policy development in Afghanistan.

8.1.1 Pathway to the sustainable irrigation water management

As discussed earlier, the current water management policy suffers from a lack of scientific approaches for the decision-making process and policy development. The current water management framework was developed to avoid conflict, and informal irrigation systems with temporary infrastructure and control systems are being used. To modernize and regulate irrigation water management, the construction of large-scale control and conveyance infrastructures is essential. As evidenced by the BRB case study, the construction of multipurpose large-scale dams is highly beneficial for watersheds with lower flows, especially in the Northern River basin where there are no transboundary water challenges. The construction of large-scale multipurpose structures requires a high degree of coordination among governmental organizations engaged in water management, irrigation, energy, disaster management, recreation, economic development, etc.

The main purpose of the current study is to construct a pathway for sustainable irrigation water resource management to improve food security and the livelihoods of farmers in Afghanistan through the equitable distribution of water. This study proposes some scenario-based engineering solutions for improving the current irrigation scheme. The roadmap for sustainable irrigation water resource management is presented below:

1. Extensive scientific studies are required to determine the capacity of each watershed separately. Hydrological modelling approaches are cost-effective and require less

time. The output of hydrological modelling can provide general insight into the potentials and weaknesses of water resources at the watershed level.

2. Determination of water consumption through scientific approaches can provide insight into water consumption, and economic benefits can be expected at the watershed level.

3. Water consumption and available water resources should be balanced. This approach determines the regions with high potential for investment, the type of investment, the types of structures required for water resource management, and vulnerable regions that require special and immediate actions.

4. The first three steps of the development of strategies and policies based on the outcomes. Since water issues are unique for each watershed, a single strategy will not be effective. A separate development plan is required for each river considering the current conditions.

5. Continuous and extensive monitoring of the water quality, quantity, and consumption of water resources is required to improve and update plans for water resource management. The MEW is responsible for the collection of hydrological and meteorological data in the country. However, the quality and quantity of the data should increase. A comprehensive temporal and spatial database of agricultural land, crop type, and CWR is needed.

6. The management of water resources is interdisciplinary and requires investment and cooperation between all stakeholders. The policy and planning should include all the stakeholders and regulate the interactions between them clearly to avoid later conflicts and misunderstandings.

7. Detailed planning requires more extensive and detailed field studies prior to releasing the development plan and policies.

8. It should be noted that Afghanistan does not have a treaty for its transboundary water except for the Helmand River. Currently, decision making and planning for water resources are subject to uncertainty, which complicates the process for water planners.

9. Water resources are vulnerable to climate change and global warming. Prior to any decision and planning, the impact of climate change on water resources should be quantified and accounted for in the planning and decision-making process. Unfortunately, this study is limited to the analysis of current conditions and cannot cover the impact of climate change on water resource quality and quantity.

8.1.2 Rethinking water demand

Given the limitations on water resources in Afghanistan and the large area of unused agricultural land due to the unavailability of water resources, reducing water demand by increasing the efficiency of the system is the most logical solution. The investment in improving irrigation canals could reduce irrigation water demand by 9%. Considering that irrigation systems consume 98% of the water resources, avoiding water loss in irrigation canals makes room for the development of new agricultural land. Traditional surface irrigation has been the least expensive irrigation practice used for irrigation throughout history. Moreover, recent technological advancements in irrigation have led to the introduction of more efficient irrigation techniques, such as sprinklers or drip irrigation systems, with higher field efficiency. Advanced irrigation methods are costly and require initial investment by farmers. Afghan farmers are poor and cannot afford to develop new irrigation systems. The international aid or subsidies provided by the government could help increase field application efficiency. The active engagement of private sector companies in the agricultural sector could inject more investment into the system and improve the efficiency of the irrigation system.

8.1.3 Rethinking water distribution

As stated in the earlier sections, water allocation in Afghanistan is based on the informal traditional system. The water allocation is decided based on the tax payment in the BRB and the area of land. A formal modern system with efficient and permanent infrastructures requires regulating the water in the system, and more accurate allocation of water should be decided among water users. The water distribution should be equitable among users from upstream to downstream considering the land area, crop type, and climatological conditions of the region to ensure even economic development and enhance the country's food security and nutritional conditions. The surface water of Afghanistan is transboundary, and not only Afghan citizens but also neighbouring countries are shareholders of these valuable resources. Afghanistan declared the water issue for the Helmand River with Iran only in the Helmand River Treaty 1973. However, Afghanistan never has a treaty for other transboundary waters with neighbouring countries. Declaring water rights with neighbouring countries is essential prior to planning and strategy development. To use the full potential of water resources, these issues should be addressed and resolved.

Mirab is traditional way of water allocation in the secondary and tertiary irrigation canals where the local community appoint one person in-charge of water allocation, system maintenance, and resolving water conflicts in return of specific amount of payment annually. The farmers adopted to this traditional system for the centuries but considering rapid increases in water demand and urgent needs for the food requires more optimum and modern way of the water allocation. The *Mirab* system has its limitations and shortages such as inefficient water distribution, lack of flexibility, social and power dynamics, lack of integration with modern water management, and inadequate response to climate change effect. The government should impose to the water allocation in the field level and use modern methods to optimize the water allocation and effectiveness using scientific approaches. Modern water allocation systems can support the overall modernization of agriculture by enabling the adoption of high-efficiency irrigation systems, precision agriculture, and other advanced farming techniques. This can lead to higher yields, reduced water consumption, and greater resilience to environmental stresses.

8.1.4 Integration of climate change impact

The impact of climate change on water resources should be considered in planning and decision-making processes. As stated earlier, Afghanistan originated in a vulnerable region of the world with frequent extreme drought events. Recent evidence suggests that the frequency and severity of drought increase in Central Asia, Afghanistan, and Iran. The future status of the water resources affects the decision and development of the current water resources management infrastructure. The system should be designed to act efficiently under uncertain future climate change conditions. A recent study conducted over the Kokcha River found changes in the hydrological regime, with earlier peak flows occurring during April and May. Any planning for water resources should satisfy the current needs of the watershed, while the system should have the flexibility to adapt to plausible changes in the hydrological regime and water cycle (Alawi & Özkul, 2023).

Water resources are vulnerable to the climate changes impact. High uncertainty regarding future projection of the streamflow exists. Meanwhile, increase in the average temperature is the main driver of the climatic changes' scenarios. In case of changes in the average temperature, water resource manager and planner should expect increase in the CWR and IWR for the future. In the other hand increase in the temperature may cause earlier melting of the snow on the high elevation causing shift in the peak flow season and hydrological regime of the mountainous watershed. The rapid melting process may increase the flood frequency and volume in the early spring causing damages to the agricultural land and resident's property. Considering all possible challenges the decision-makers should be alerted about upcoming changes in the water resources and hydrological regime and undertake the proper mitigations.

One of the widely used climate models used for simulations of the response to the greenhouse gas (GHG) concentration in the future are Global Climates Models (GCMs) (S. Pal et al., 2023). During simulation of the climate changes impact on the water resources the high levels of uncertainty in the output should be considered. Mandal et al. (2019) identifies six sources causing uncertainty namely, (1) selection process of GCMs, (2) choice of GCMs, (3) downscaling techniques, (4) emission scenarios, (5) model structure, and (6) hydrological model structure. Among the six the GCMs are the dominant source of uncertainty (Bosshard et al., 2013). However, most of the current GCMs have coarse resolution in the horizontal gridding from about 70-250 km. This coarse resolution are often unable the GCMs to capture the regional or local scale climatic and weather features, while for simulation of the climate changes impact on the water resources management we need horizontal grid of 10-50 km (S. Pal et al., 2023). As limitation of current study, we could not include the climate changes impact due to huge simulations time and limited resources.

8.2 Summary and conclusion

This study investigated irrigation water management over four watersheds in northern and northeastern Afghanistan. The goals of this study are to determine water availability using long-term hydrological models, quantify irrigation water consumption using remote sensing data, and develop an engineering-based solution to overcome water shortage issues considering the sustainability and conservation of the environment. The findings of this study can be used to construct a pathway for sustainable irrigation water management in the study region. The following are the main findings and conclusions for the series of studies conducted.

- WRF-Hydro was utilized to simulate the surface water flow over the three rivers of Kokcha, Khanabad, and Kunduz in the northeastern parts of Afghanistan. The model simulates the hydrological process. Model calibration and validation were performed on a daily time scale with a fine resolution of 3 km for the entire study region.
- The sensitivity of the Noah-MP land surface model was determined to enhance the snowmelt and snow accumulation processes within the model. The Noah-MP LSM showed a high sensitivity to the snowmelt process within the model. Calibration of the LSM model enhanced the timing of the peak flow. In addition, it significantly improved the delay gap for the start of the melting season in the observation and simulation.
- The crop type map for the period from 2014 to 2019 was generated using the MODIS NDVI product with a spatial resolution of 250 m for the entire study region. The NDVI products were classified using three machine learning algorithms, RF, SVM, and GBM, and their ensemble. RF model performance was the best among all three models, while assembling three models improved the accuracy slightly. The ensemble model performance is greater than 80% for all eight elevation zones of the study region. An existing crop type map for 2020 with a 10 m resolution was adopted as the ground truth for the training and testing of the model.
- The CWR and IWR for the entire study region were estimated based on the Penman–Monteith evapotranspiration procedure by UNFAO. The observation station data across the study area were used as the source of meteorological data input for the estimation of the reference evapotranspiration. The crop water requirement and IWR integrated with the crop type map were used to estimate the agricultural water consumption for the study region.
- The municipal water supply consumption for the study region was estimated based on the current population of the watersheds, and the population was projected for 50 years to estimate the water supply demand load on the surface water and included in the water consumption.

- An irrigation water management scenario-based analysis was conducted on the four rivers included in the current study. The analysis revealed that the BRB is capable of irrigating an extra 84,000 ha of agricultural land. The three rivers in the ARB can irrigate an extra 14266, 15062, and 22446 ha in the Kokcha, Khanabad, and Kunduz Rivers, respectively.

- Water resources in Afghanistan are not equally distributed among water users. The factors that should be included in the water allocations are the area of agricultural land, type of common crop, agricultural practices in the area, climate conditions, population, and climatic conditions of each region.

- The irrigation efficiency in Afghanistan is very low, at 48%. Irrigation canals are earth canals where 20% of the water is lost due to evaporation and infiltration into the ground. Afghans use the traditional irrigation scheme of surface irrigation with the highest water loss due to evaporation and percolation into the ground with an overall efficiency of 75%. Lining irrigation canals can increase system efficiency by 9%, while changing irrigation schemes to more efficient methods can save up to 23.25% of the water in irrigation systems.

8.3 Future works and limitation

This study addresses the lack of scientific approaches to water resource management in data-scarce areas of the world by identifying four rivers in Afghanistan. However, this study is limited in the following ways:

1. The hydrological models used for the current study are associated with uncertainty, similar to any other model. Various sources can introduce uncertainties into conceptual snowmelt runoff hydrological models. These sources can be identified as the structure of the hydrological models, parameters, robustness, calibration approaches, and input and output datasets that can lead to considerable uncertainty in the prediction of the hydrological process (Shafqat Mehboob et al., 2022).

2. The accuracy of the estimation of crop water and irrigation water requirements relies on the quality of the input data. The majority of the stations in Afghanistan are

located in lowland areas near rivers. Any inaccuracies or limitations in these data can propagate errors in the estimation process.

3. MODIS NDVI data and machine learning techniques are valuable for generating crop type maps and spatial distributions. However, the lack of observation data for the study period and the temporal transfer of the model may introduce some errors into the results. Addressing this limitation can improve the accuracy of crop type maps and their byproducts.

4. The scenario-based solutions proposed to address water shortages involve simplifications and assumptions about socioeconomic factors, policy interventions, and stakeholder behavior. Incorporating more realistic and nuanced scenarios can enhance the robustness and applicability of the proposed solutions.

Nevertheless, the outcomes of the current study and the output of the current study may help decision-makers and policy makers. In this study, we constructed a pathway for water resource management and defined the strengths and weaknesses of surface water in the study region. The findings of this study emphasize the following for BRBs and ARBs in Afghanistan.

- The construction of large dams is difficult for BRB water resource management systems because large dams accumulate water during the nonirrigation period and use water later during the peak irrigation period.

- ARB has high surface water availability, especially from June to September, when irrigation water consumption is at its peak. The limitation against new agricultural land development is the start of the irrigation period in April and October, when the discharge in the river declines and the available water and consumption are almost equal.

- Water loss in irrigation systems in Afghanistan is extremely high, and the government should make serious efforts to reduce water loss in irrigation canals. New policies and strategies should be developed to increase irrigation scheme efficiency in the country.

Prior to the adoption of any policy and plans, further studies are needed. The authors suggest the following studies.

- The quantification of the impact of climate change on water resources.
- Socioeconomic and environmental impacts assessment of new policies and plans for managing water resources.
- We explored agricultural management strategies by transitioning from conventional crops to less water-intensive alternatives with comparable economic yields while assessing the public acceptability of such policy interventions.

By addressing these limitations and exploring avenues for further study, this research can contribute to advancing scientific knowledge and informing evidence-based decision-making in water resource management and agricultural sustainability.

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List of Publication

Peer-Reviewed International Journal papers

1. **Hussainzada, W**., and Lee, H.S. (2024). Impact of Land Surface Model Schemes in Snow-Dominated Arid and Semi-Arid Watersheds using the WRF-Hydro modelling Systems. *AIMS Geosci.* 10(2): 312-332. DOI: 10.3934/geosci.2024018
2. **Hussainzada, W**., et al (2023). Water resource management for improved crop cultivation and productivity with hydraulic engineering solution in arid northern Afghanistan. *Applied Water Science* 13.2, 41. DOI: 10.1007/s13201-022-01850-w
3. **Hussainzada, W**., and Lee, H.S. (2022). Effect of an improved agricultural irrigation scheme with a hydraulic structure for crop cultivation in arid northern Afghanistan using the Soil and Water Assessment Tool (SWAT). *Scientific Reports* 12.1, 5186. DOI: 10.1038/s41598-022-09318-2
4. Samim AT, Nayyer F, **Hussainzada W**, and Lee HS (2024). Intercomparison of gridded global precipitation data for arid and mountainous regions: A case study of Afghanistan. *J. Hydrol.-Reg. Stud.*, 53: 101837. DOI: 10.1016/j.ejrh.2024.101837
5. **Hussainzada, W**., & Lee, H. S. (2021). Hydrological modelling for water resource management in a semi-arid mountainous region using the soil and water assessment tool: A case study in northern Afghanistan. *Hydrology*, 8(1), 16. DOI: 10.3390/hydrology8010016
6. **Hussainzada, W**., Lee, H. S., Vinayak, B., & Khpalwak, G. F. (2021). Sensitivity of snowmelt runoff modelling to the level of cloud coverage for snow cover extent from daily MODIS product collection 6. *Journal of Hydrology: Regional Studies*, 36, 100835. DOI: 10.1016/j.ejrh.2021.100835

Peer-Reviewed Conference Proceeding papers

7. **Hussainzada, W**., Lee, H. S., & Vinayak, B., (2020). Snow cover mapping for sustainable water resource management in the Balkhab River Basin in Afghanistan using MODIS satellite normalized difference snow index (NDSI) products. Proceedings of the IAHR-APD 2020 (pp. 1-7).
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Conference Presentations

1. **Hussainzada, W.**, & Lee, H. S. (2024, June 23-28). Sustainable Water Resources Management Using WRF-hydro Hydrological Model Over the Amu River Basin, Afghanistan. Paper presented at the Asia Oceania Geoscience Society (AOGS) 21st Annual Meeting, Incheon, South Korea.
2. **Hussainzada, W.**, et al. (2023, July 30-August 4). Sustainable Water Resources Management Using Soil and Water Assessment Tool (SWAT) and Analytical Hierarchy Process (AHP) for Water-scarce Northern Afghanistan. Paper presented at the Asia Oceania Geoscience Society (AOGS) 20th Annual Meeting, Singapore.
3. Samim, A. T., et al. (2023, July 30-August 4). Inter-comparison of Thirteen Gridded Global Precipitation Dataset for Natural Resources Management. Paper presented at the Asia Oceania Geoscience Society (AOGS) 20th Annual Meeting, Singapore.
4. **Hussainzada, W**., & Lee, H. S. (2021, August 1-6). Agricultural Water Resource Management Using Soil and Water Assessment Tools (SWAT) in Northern Afghanistan. Paper presented at the Asia Oceania Geoscience Society (AOGS) 18th Annual Meeting, Singapore.

5. **Hussainzada, W**., et al. (2021, August 1-6). Effects of the Cloud Coverage Level in Snow Cover on Snowmelt Runoff Modelling in Northern Afghanistan. Paper presented at the Asia Oceania Geoscience Society (AOGS) 18th Annual Meeting, Singapore.
6. Trošelj, J., et al. (2021, August 1-6). Hydrometeorological Real-time Forecasting for Flash Flood Early Warning Systems in the Chugoku Region of Japan. Paper presented at the Asia Oceania Geoscience Society (AOGS) 18th Annual Meeting, Singapore.
7. **Hussainzada Wahidullah**, Han Soo Lee, and Vinayak Bhanage. Snow cover mapping for SUSTAINABLE water resource management in the Balkhab River basin in Afghanistan using MODIS satellite normalized difference snow index (NDSI) products. *The 22nd IAHR-APD Congress (2020) virtual conference*, Hokkaido, Japan, 15-16th September.