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**Analysis of hydro-hazard extremes hotspots
across Upper Jhelum Basin and possible
mitigation measures**

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Abstract

The two contrasting extremes of the hydrological spectrum have substantial and far-reaching impacts on a wide range of sectors including water resources, agriculture and food security, energy, infrastructure, and ecosystem. The compounding factors of climate change, burgeoning population, and rapid economic development create unprecedented challenges in devising effective and sustainable strategies to cope with these natural disasters and minimize their devastating impacts. To this end, this dissertation aims to advance our understanding of these hydroclimate risks and their compounding in temporal dimension over transboundary Upper Jhelum Basin-South Asia, both in retrospective (i.e. past) or prospective (i.e. future) climate contexts. Additionally, this dissertation also provides a comprehensive overview of the existing and proposed water development projects, their coping capacities, and potential impacts that may be positive or negative in hydrologic, social, economic and environment terms. The basin is located in the foothills of Western Himalaya and shared by Pakistan and India. The climate change signals are quite loud and clear in the region, and it is likely to become more pronounced in coming decades.

The study begins with a comprehensive assessment of the key terrestrial water budget components (precipitation, evapotranspiration, terrestrial water storage and discharge) using observed and gridded datasets (**chapter 3**). The uncertainties in the gridded datasets are firstly evaluated against direct comparison with observed gauge data at monthly, seasonal, and annual scale and subsequently their abilities are assessed in terms of water budget closure. Overall, ERA5-precipitation and DOLCE-evapotranspiration performed relatively better and hence considered to be the most appropriate to present the hydrological spatiotemporal variability across the basin. The imbalance in the water budget is mainly associated with higher uncertainties in precipitation, especially during wet periods. These findings highlighted the need for bias correction (BC) of ERA5 precipitation before their application in subsequent impact assessment studies. Therefore **the 4th chapter** focuses on the ERA5 precipitation BC by four commonly used precipitation BC methods and evaluate their skills to capture various aspects of moderate to rare extreme precipitation events. The four BC methods are linear scaling, local scaling intensity, power transmission, and distribution mapping. Overall, distribution mapping method is found to be a good compromise to correct various aspects of extreme precipitation.

Chapter 5 employs the corrected ERA5 data for spatio-temporal evolution of the regional wet-dry extreme events and their temporal compounding (abrupt transition from one powerful state to another in the adjacent month). The temporally compound events include dry to wet (D-to-W) and wet to dry (W-to-D) events. Meteorological wet and dry conditions, as drivers of hydrologic floods and droughts, are characterized by using a multivariate drought index (namely the Standardized Precipitation Evapotranspiration Index, SPEI). The results of temporal variations in SPEI showed a strong change in basin climatic features associated with El Niño–Southern Oscillation at the end of 1997, with the prevalence of wet and dry events before and after 1997 respectively. The results of spatial analysis showed the southwestern part of the basin, located in the monsoon-dominated region, is found to be the hotspot for extreme wet events. In contrast, the

westerlies-dominated region is found to be the hotspot of dry events with higher duration, severity, and intensity. The average transition time from one extreme type to the other varied spatially, with more pixels transitioning from D-to-W events in a shorter time than W-to-D events. This rapid transition showed the temporal compounding of these extreme events which may provoke greater impacts than those resulting from individual events.

To investigate these extreme events in future climate context, the **chapter 6** intercompare different state-of-the-art BC methods (univariate and multivariate) and BC approaches (direct and component-wise) applied to climate models simulations stemming from three modeling initiatives (namely Coordinated Regional Climate Downscaling Experiment (CORDEX), CORDEX Coordinated Output for Regional Evaluations (CORDEX-CORE), and the 6th Coupled Intercomparison Project (CMIP6)), under low, medium and high emission scenarios for two-time segments i.e., near future (2040-2059) and far future (2080-2099). Based on the performance in present time, two univariate (i.e., Empirical Quantile Mapping-EQM- and Quantile Delta Mapping-QDM) and one multivariate (Multivariate Bias Correction with N-dimensional probability density function transform-MBCn) BC methods are shortlisted for future projections (**chapter 7**). Results show that extreme wet and dry events are projected to be more frequent and severe in the future, however, duration of extreme shows varying change signals depending on the location. Event coincidence analysis used to investigate the statistical interdependency between wet- dry extreme events showed that the basin is more prone to D-to-W CEs than W-to-D CEs. The southwest monsoon-dominated region is identified as the D-to-W CEs hotspot. In context of BC, contrasting climate change signals are found for BC approaches with the direct correction introducing a greater modification of the original change signals. Regarding climate model experiments, CORDEX ensembles (WAS44 and WAS22) show varying climate change signals whereas the CMIP6 ensemble show stronger change signals with specific spatial pattern of occurrence. These findings assert the necessity of integrating mitigation measures targeting the CEs into disaster risk reduction strategies at the identified hotspots.

After locating spatial hotspots for extreme events, the **chapter 8** provides comprehensive overview of the existing, under construction and planned water infrastructure projects (i.e., water storage and hydropower project), their coping capacities, and potential impacts that may be positive and/or negative in hydrologic, social, economic and environment terms. Extensive review and data analysis showed that Pakistan and India, along with state governments, have implemented many water-related projects in the basin, yet have not achieved their goals. Reasons for this include geography, inadequate planning, high flow variability, geopolitical disputes, lack of cooperation, financial issues, and reservoir operation. The study suggests alternative water management strategies that are cost-effective, accessible, and eco-friendly. For instance, subsurface floodwater harvesting techniques (also known as managed aquifer recharge-MAR) and hybridization of existing reservoirs with floating photovoltaic (FPV) system. These measures have the potential to sustainably solve both floods and droughts, fulfill energy needs sustainably and reduce dependency of local communities on forest wood.

Key words: gridded datasets, bias correction, ewxtreme events, floods, droughts, compound events, climate change, SPEI, Upper Jhelum Basin.

Riassunto

Siccità e inondazioni, due estremi contrastanti dello spettro idrologico, hanno enormi impatti su un'ampia gamma di settori tra cui l'acqua, l'agricoltura e la sicurezza alimentare, l'energia, le infrastrutture e l'ecosistema. Le crescenti preoccupazioni per i rischi di siccità e inondazioni dovute ai cambiamenti climatici, insieme alla crescente crescita della popolazione e al rapido sviluppo economico, creano sfide senza precedenti per le società che devono migliorare la loro capacità di resistere a questi disastri naturali, mitigare i loro impatti estremi e ideare strategie pratiche ed efficaci verso uno sviluppo sostenibile. sviluppo. Questa tesi mira a migliorare la nostra comprensione di questi rischi idroclimatici e del loro aggravamento nella dimensione temporale sul bacino transfrontaliero dell'Upper Jhelum (UJB)-Asia meridionale, sia in contesti climatici retrospettivi (cioè passati) che prospettici (cioè futuri). L'UJB si trova ai piedi dell'Himalaya occidentale ed è condiviso da Pakistan e India. I segnali del cambiamento climatico sono piuttosto forti e chiari nella regione, ed è probabile che diventino più pronunciati nei prossimi decenni.

Lo studio inizia con una valutazione completa dei componenti chiave del bilancio idrico terrestre (TWB) (precipitazioni, evapotraspirazione, stoccaggio e scarico dell'acqua terrestre) utilizzando set di dati osservati e grigliati (capitolo 3). Le incertezze nei set di dati grigliati vengono innanzitutto valutate rispetto al confronto diretto con i dati di misurazione osservati su scala mensile, stagionale e annuale e successivamente le loro capacità vengono valutate in termini di chiusura del bilancio idrico. Nel complesso, la precipitazione ERA5 e l'evapotraspirazione DOLCE hanno ottenuto risultati relativamente migliori e quindi considerati i più appropriati per presentare la variabilità idrologica spazio-temporale attraverso UJB. Lo squilibrio nel bilancio idrico è principalmente associato a maggiori incertezze nelle precipitazioni, soprattutto durante i periodi piovosi. Questi risultati hanno evidenziato la necessità di una correzione del bias (BC) delle precipitazioni ERA5 prima della loro applicazione nei successivi studi di valutazione dell'impatto. Pertanto il quarto capitolo si concentra sulla precipitazione BC ERA5 mediante quattro metodi di precipitazione BC comunemente usati e valuta la loro capacità di catturare vari aspetti di eventi di precipitazione estremi da moderati a rari. I quattro metodi BC sono scala lineare (LS), intensità di scala locale (LOCI), trasmissione di potenza (PT) e mappatura della distribuzione (DM). Nel complesso, il metodo DM si è rivelato un buon compromesso per correggere vari aspetti delle precipitazioni estreme, seguito dai metodi LOCI, PT e LS.

Il capitolo 5 utilizza i dati ERA5 corretti per l'evoluzione spazio-temporale degli eventi estremi regionali umido-secco e la loro composizione temporale (transizione successiva/improvvisa da uno stato potente a un altro nel mese adiacente). Gli eventi temporalmente composti (EC) includono eventi da asciutto a umido (da D a O) e da umido a asciutto (da W a D). Le condizioni meteorologiche umide e secche, come fattori che determinano inondazioni idrologiche e siccità, sono caratterizzate utilizzando un indice di siccità multivariato (ovvero l'indice di evaporazione delle precipitazioni standardizzato, SPEI). I risultati delle

variazioni temporali nello SPEI hanno mostrato un forte cambiamento nelle caratteristiche climatiche del bacino associate a El Niño-Oscillazione Meridionale alla fine del 1997, con la prevalenza di eventi umidi e secchi rispettivamente prima e dopo il 1997. I risultati dell'analisi spaziale hanno mostrato che la parte sud-occidentale del bacino, situata nella regione dominata dai monsoni, risulta essere il punto caldo per eventi umidi estremi. Al contrario, la regione dominata dai venti occidentali risulta essere il punto caldo degli eventi secchi con durata, gravità e intensità più elevate. Il tempo medio di transizione da un tipo estremo all'altro variava spazialmente, con più pixel che passavano dagli eventi D a W in un tempo più breve rispetto agli eventi W a D. Questa rapida transizione ha mostrato che la composizione temporale di questi eventi estremi può provocare impatti maggiori di quelli risultanti da eventi individuali.

Per indagare questi eventi estremi nel futuro contesto climatico, il capitolo 6 confronta diversi metodi BC all'avanguardia (univariati e multivariati) e approcci BC (diretti e per componenti) applicati alle simulazioni di modelli climatici derivanti da tre iniziative di modellazione (vale a dire l'esperimento coordinato di riduzione del clima regionale (CORDEX), i risultati coordinati di CORDEX per le valutazioni regionali (CORDEX-CORE) e il sesto progetto di interconfronto accoppiato (CMIP6)), in scenari di emissioni basse, medie e alte per segmenti di due tempi, ovvero il prossimo futuro (2040-2059) e nel lontano futuro (2080-2099). Sulla base delle prestazioni attuali, sono stati selezionati per il futuro due metodi BC univariati (ovvero, mappatura quantile empirica-EQM- e mappatura delta quantile-QDM) e uno multivariato (correzione multivariata del bias con trasformazione della funzione di densità di probabilità N-dimensionale-MBCn). proiezioni (capitolo 7). I risultati mostrano che si prevede che gli eventi estremi di pioggia e di pioggia diventeranno più frequenti e gravi in futuro, tuttavia, la durata degli eventi estremi mostra segnali di cambiamento variabili a seconda della posizione. L'analisi delle coincidenze degli eventi (ECA) utilizzata per studiare l'interdipendenza statistica tra eventi estremi bagnato-asciutto ha mostrato che l'UJB è più incline ai CE da D a W rispetto ai CE da W a D. La regione dominata dai monsoni di sud-ovest è identificata come punto caldo dei CE da D a O. Nel contesto del BC, si riscontrano segnali contrastanti di cambiamento climatico per gli approcci BC con la correzione diretta che introduce una maggiore modifica dei segnali di cambiamento originali. Per quanto riguarda gli esperimenti sui modelli climatici, gli insiemi CORDEX (WAS44 e WAS22) mostrano segnali di cambiamento climatico variabili mentre l'insieme CMIP6 mostra segnali di cambiamento più forti con uno specifico modello spaziale di occorrenza. Questi risultati affermano la necessità di integrare le misure di mitigazione rivolte ai CE nelle strategie di riduzione del rischio di catastrofi negli hotspot identificati.

Dopo aver individuato i punti caldi spaziali per gli eventi estremi, il capitolo 8 fornisce una panoramica completa dei progetti di infrastrutture idriche esistenti, in costruzione e pianificati (ad esempio, progetti di stoccaggio dell'acqua e di energia idroelettrica), delle loro capacità di far fronte e dei potenziali impatti che possono essere positivi e/o negativi. in termini idrologici, sociali, economici e ambientali. Un'analisi approfondita e un'analisi dei dati hanno mostrato che il Pakistan e l'India, insieme ai governi statali, hanno implementato molti progetti legati all'acqua nel bacino, ma non hanno raggiunto i loro obiettivi. Le ragioni di ciò includono la geografia, la

pianificazione inadeguata, l'elevata variabilità del flusso, le controversie geopolitiche, la mancanza di cooperazione, i problemi finanziari e il funzionamento del bacino. Lo studio suggerisce strategie alternative di gestione dell'acqua che siano economicamente vantaggiose, accessibili ed ecologiche. Ad esempio, le tecniche di raccolta delle acque sotterranee (note anche come ricarica gestita della falda acquifera-MAR) e l'ibridazione dei serbatoi esistenti con il sistema fotovoltaico galleggiante (FPV). Queste misure hanno il potenziale per risolvere in modo sostenibile sia le inondazioni che la siccità, soddisfare il fabbisogno energetico in modo sostenibile e ridurre la dipendenza delle comunità locali dal legno forestale.

Parole chiave: set di dati su griglia, correzione di bias, eventi estremi, inondazioni, siccità, eventi composti, cambiamento climatico, SPEI, bacino del Jhelum superiore.

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Statement of Authorship

I **Rubina Ansari** hereby confirm that my PhD thesis entitled “Evaluation of the effect of climate variability on the hydro-glaciological regime in the Upper Indus Basin” is my own work and has been completed by me under guidance of my supervisors. I also certify that.

- Work has not been submitted to any other university for obtaining any degree or diploma.
- I have followed guidelines and norms instructed by University of Brescia in preparing the thesis.
- Whenever I have used materials (data, theoretical analysis, figures, and satellite data) from multiple sources, I have given due credit to them by citing them in the text of the thesis, giving their details in the references.
- All statistical analysis in the thesis and initial draft of published and under-review manuscripts was completed by me. Subsequently, it was circulated among co-authors and underwent peer review before publication, which led to the editing of the manuscript and inclusion of additional analysis.

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Chapter 1

Introduction

1.1 Background and Motivation

Water resources management is challenged by the inherent variability and unpredictability of available freshwater resources, which leads to recurring floods and droughts that hinder progress toward Sustainable Development Goals. According to the Emergency Events Database (EM-DAT), floods account for 38.8% of global natural disasters from 1900 to 2023, causing significant economic and social impacts. Droughts, though less frequent (5.3%), have caused more fatalities. Hydro hazards, including floods and droughts, have affected 86% and 35% of the total affected population and economic losses respectively (catholique de Louvain Brussels-Belgium, 2012). These hazards have also had significant environmental, social, and economic impacts, such as degraded wetland areas, diminished natural biodiversity, destroyed agricultural land and industrial facilities, and high economic costs.

Pakistan is among the countries with the highest frequency and magnitude of natural disasters in the world, including floods, droughts, heatwaves, and high incidences of pests and diseases (Smit and Skinner, 2002). According to Inform Risk Index 2023, Pakistan is ranked 22 out of 191 countries with high exposure to flooding (ranked 7th) and relatively low exposure to droughts (ranked 124th). Common examples of environmental hazards in Pakistan are the prolonged droughts from 1999 to 2003 and the devastating floods in 2010, 2011, 2012, 2014 and 2022 (Abid et al., 2016). The process of measuring and managing the impact of climate change is challenging because it involves balancing the benefits and costs of adaptation, which depends on many factors that have been debated for several decades.

Pakistan is heavily reliant on the Indus River and its tributaries (Jhelum and Chenab) for its water resource, which face contrasting situations of water shortage and abundance separated by time and/or space. The source regions of the Indus River and its tributaries (Jhelum, Chenab) encompass the world's largest reserves of natural snow and ice and are highly sensitive to climate change. The indicators of climate change in the region are quite loud and clear, and it is anticipated that they will become more pronounced in the coming decades (Arias et al., 2021). Therefore, the uncertainty around future glacial and snow change is significant. Thus, there is a clear need to develop better policies and plans to enhance resilience by addressing water variability under changing climate to reduce societal vulnerability to floods and droughts.

Typically, floods and droughts have been considered independently in water resources management and planning. However, these events are inherently interconnected and governed by the same underlying hydrological processes and atmospheric dynamics, which may augment

hydro-climatic variability under the influence of climate change (He and Sheffield, 2020). This can result in overlapped and inconsistent operations and management, which can be inefficient. Further the compounding (consecutive occurrences of floods and droughts) of these extreme events across time may provoke greater impacts than those caused by individual events (Zscheischler et al., 2020, Poschlod et al., 2020, Leonard et al., 2014). Such compounding of two contrasting extremes in temporal dimension reflects a volatile hydrological cycle and makes water resources management more challenging, especially for reservoir operation, as a trade-off should be set between short-term flood-control and long-term water-storage imperatives to satisfy water demand (He and Sheffield, 2020).

A holistic approach that considers both floods and droughts and employs integrated measures and strategies to address them simultaneously is now more necessary than ever. This approach may be more effective than the conventional approach of tackling them individually.

This dissertation aims to quantify and comprehend the evolution of two water-related natural hazards, namely floods and droughts, and their compounding in temporal dimension, both in retrospective and prospective climate contexts. In the present study, meteorological wet and dry conditions, as drivers of hydrologic floods and droughts, are characterized by using a multivariate drought index (namely the Standardized Precipitation Evapotranspiration Index, SPEI). Furthermore, the study aims to address these extreme events together by proposing some integrated strategies and measures.

The proposed framework was implemented with reference to the transboundary watershed, namely Upper Jhelum Basin (UJB), where the relevance of flood-drought events and their temporal compounding have not been assessed yet, despite of clear evidence of climate change in the region. The UJB is located in Western Himalaya and shared by Pakistan and India. The region has already witnessed an increase in extreme hydro-meteorological events in the last few decades, but these events are expected to become even more pronounced in the coming future (Arias et al., 2021).

1.2 Research Objectives

This dissertation studies the meteorological wet and dry extreme events as the drivers of hydrological floods and droughts and their temporal compounding in the present and future projected period. The specific objectives of this study are given below:

- 1) Evaluation of gridded datasets for terrestrial water budget assessment in the Upper Jhelum River Basin.
- 2) Performance evaluation of raw and bias corrected ERA5 precipitation data with respect to extreme precipitation analysis.
- 3) Spatio-temporal evolution of extreme Wet-Dry event characteristics and their abrupt transition.
- 4) Evaluation of bias correction methods for a multivariate drought index in the historical period.

- 5) Changes in the Probability of temporally compound wet and dry events in a warmer world.
- 6) Improving flood and drought management in transboundary Upper Jhelum Basin.

1.3 Organization of the thesis

The study encompasses a multitude of aspects including the selection of suitable gridded datasets for the terrestrial water budget component analysis and their temporal dynamics, bias correction of the data, extreme wet and dry events and their temporal compounding, mitigation measures and strategies. As a result, a significant amount of diverse data is required for analysis, and various methodologies are needed to address each aspect. The findings from each step demonstrate various aspects that contribute to achieving all specific objectives, which eventually lead to achieving the main objective. These elements are structured into nine chapters, as follows:

Chapter 1 provides an introduction, background context and the rationale of the research topic.

Chapter 2 describes the study area – the Transboundary Upper Jhelum Basin, including geography, hydro-climatic conditions and land cover in the basin.

Chapter 3 evaluates the various gridded datasets of key terrestrial water budget component (precipitation, evapotranspiration, terrestrial water storage) against limited in situ observations at multiple time scale and their abilities to close the water budget. Results showed that the ERA5 precipitation performed relatively better to present precipitation behavior over UJB in space and time, despite its overestimation against observed dataset which need to be adjusted before its implication in further impact assessment studies.

Chapter 4 is based on the findings of chapter 3 and reports the bias adjustments methods for ERA5 precipitation estimates. These bias adjustment methods are evaluated in context of moderate to rare extreme precipitation events.

Chapter 5 provides spatio-temporal evolution of the regional wet and dry extreme events and their temporal compounding i.e., abrupt transition of wet-to-dry and dry-to-wet events for the period of 1981-2014. Meteorological wet and dry conditions, as drivers of hydrologic floods and droughts, are characterized by using a multivariate drought index (namely the Standardized Precipitation Evapotranspiration Index, SPEI).

Chapter 6 provides a comparison of different state-of-the-art bias correction (BC) methods (univariate and multivariate) and BC approaches (direct and component-wise) applied to climate model simulations stemming from different experiments at different spatial resolutions (namely CORDEX, CORDEX-CORE and CMIP6).

Chapter 7 builds upon the findings of chapter 6 and provides the future projections of wet-dry extreme events and their temporal compounding in the future climate context under low, medium, and high emission scenarios for two-time segments i.e., near future (2040-2059) and far future

(2080-2099). The three best performing BC methods from chapter 6 are used/selected for the correction of climate model simulations. The findings of this chapter provide meaningful insight into the geographical hotspots of compound extreme events, which could be of practical value to inform a group of stakeholders of the potential risk.

Chapter 8 provides an overview of the existing, under construction and planned water infrastructure projects (i.e., water storage and hydropower project), their coping capacities, and potential impacts that may be positive and/or negative in hydrologic, social, economic and environment terms. Moreover, provide a few suggestions to solve flood and drought problems simultaneously using the integrated mitigation measures and strategies.

Chapter 9 provides the synthesis of this dissertation and an outlook for the future work.

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Chapter 2

Study Area: The Transboundary Upper Jhelum Basin, South Asia

2.1 Course of the Jhelum River

The Jhelum River is the westernmost of the five rivers of the Punjab region and one of the major eastern tributaries of the Indus River. The source of the river lies at the foothills of Pir Panjal in the southeastern part of the Kashmir Valley in the form of spring (Verinag spring). The river receives its flow from 24 major and minor tributaries draining from the slope of the Pir Panjal and southern slopes of the Greater Himalayan range, joining the main river stream on the left and right bank respectively. The Lidder River, Sind River, Poonch River, Nelum River and Kunhar River are the major tributaries of the Jhelum River. The Liddar River (73 km long river originates from the Kolhoi Glacier and joins the Jhelum River at Gurnar Khanabal at an altitude of 1,615 m with an average flow rate of 206 m³/s) and Sind River (108 km long river rises from the Machoi Glacier and joins the Jhelum River at Ganderbal district of Kashmir Valley at an elevation of 4,800 m with 290 m³/s average flow rate with 290 m³/s average flow rate) joins the main stream of the river in Kashmir valley. It meanders through the Srinagar and Wular Lake before entering into Pakistan. The total catchment area up to the Line of Control when it enters into Pakistan is about 18,966 km².

Nearly 130 km downstream of Wular Lake, the largest tributary of the Jhelum River, Neelum River also known as Kishan Ganga, joins it at Domel Muzaffarabad. The 240 km long Neelum River fed by the great Himalaya glaciers with an elevation from 4573 m to 6097 m. About 8 km downstream of Muzaffarabad, the second largest tributary of Jhelum River, Kunhar River merges in it at an elevation of 3950 m. The 166 km long Kunhar River originates from Lulusar Lake and meanders through the entire region of Kaghan and Naran Valleys. The other two major tributaries Poonch River and Kanshi River meet the Jhelum River at Mangla Reservoir in the Mirpur District. The 130 km long Poonch River originates from the southern slopes of Pir Panjal range, in the areas of Neel-Kanth Gali and Jamian Gali while the Kanshi River rises from eroded lowland regions, directly joining the Jhelum River in Mangla Lake.

From Mangla reservoir, the Jhelum River breaks through the Outer Himalayas into broad alluvial plains of Pakistan's Punjab and finally joins the Chenab River at Trimmu Barrage in the Jhang District. The Chenab merges with the Sutlej River, Ravi River and Beas River at Panjnad before joining the Indus River at Mithankot.

2.2 Topography

The Jhelum River catchment area situated upstream of the Mangla Dam is called the Mangla watershed or Upper Jhelum Basin (UJB), lies between latitudes of $33^{\circ} 00' \text{ N}$ - $35^{\circ} 12' \text{ N}$ and longitudes of $73^{\circ} 07' \text{ E}$ - $75^{\circ} 40' \text{ E}$. It covers an area of about 33467 km² and its elevation ranges from 223 m to 6201 meters above mean sea level (MSL). The UJB has a mean elevation of 2353 m with approximately 52.92% (177010 km²) of the area lies below mean elevation. The UJB is a transboundary catchment with 48% (16064.16 km²) of its area situated in India, which makes data collection very difficult due to socio-political issues between the two countries. The hypsometric curve, glaciated area and the climatic stations elevation range is shown in Fig. 2.1B. Based on the topography, the UJB area can be subdivided into four units as follows:

- **Alpine area** at the northernmost area of this region, with an altitude of around 3,500 meters
- **Medium- and high-mountain area** in the northern and central part of this region, with an altitude of about 2,000 meters; to the east is the Kashmir Basin, and to the west the Pansavart Basin
- **Low-to-medium mountain area** in the central part of this region; to the west is the Potowar plateau with an altitude of about 500 meters, and to the east is the Hazara-Kashmir Syntaxis with an altitude of about 2,500 meters
- **Plain area** toward the south of this region, with an altitude of about 200 meters.

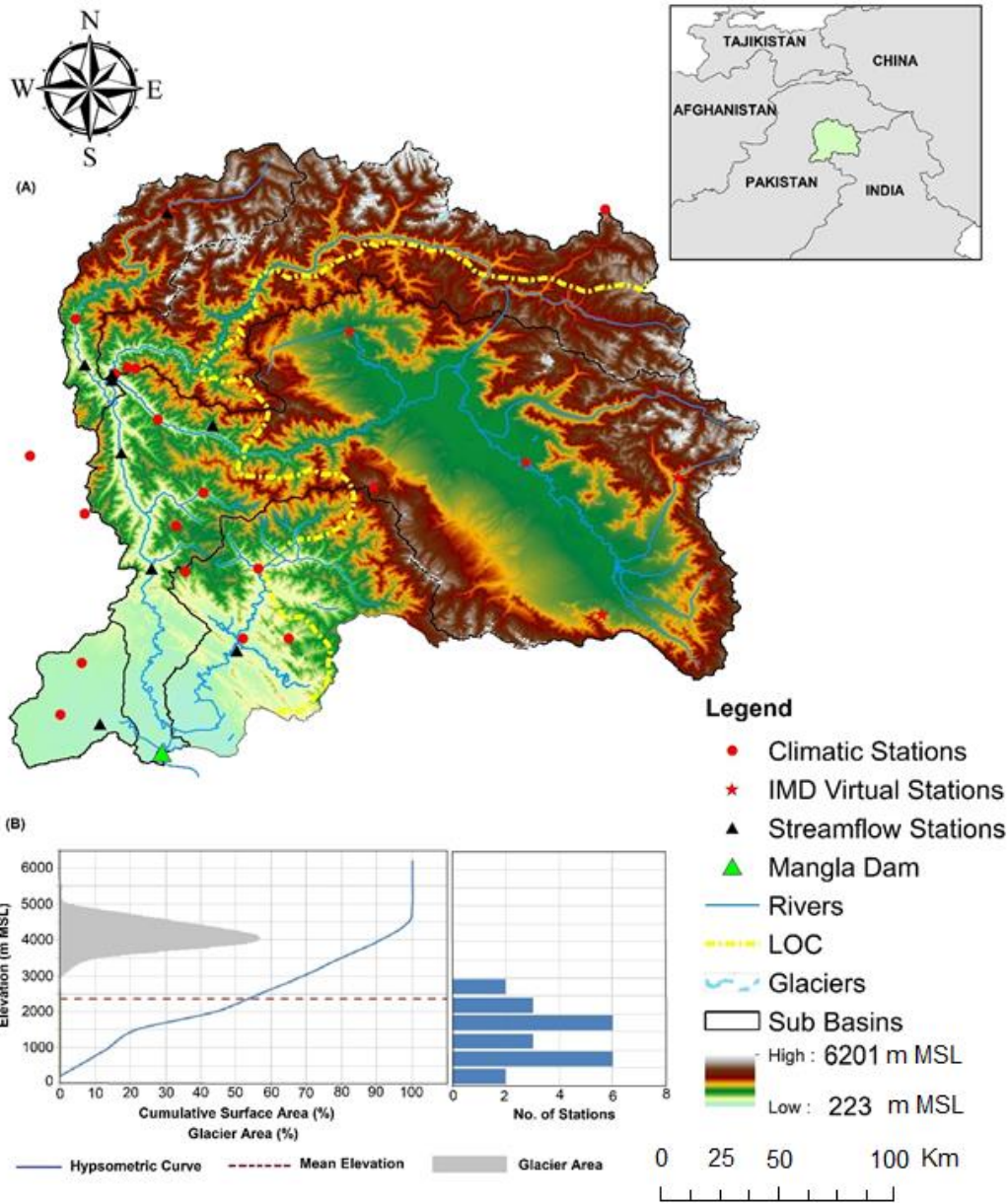


Figure 2.1: (A) Location of UJB with spatial distribution of climatic stations, streamflow stations and glaciers, (B) Hypsometric curve, glaciated area, and no. of stations with respect to elevation.

2.3 Climate

The UJB lies at the edge of the core monsoon region of Pakistan and western Himalaya, experiencing the South Asian summer monsoon, also known as the Southwest monsoon. Orography and the fact that the region is at the north-western extent of the South Asian summer monsoon creates two distinct precipitation regimes in the basin: westerlies (December to March) which transport the moisture from Mediterranean and Caspian sea and fall as snow in the northern part of the basin (high altitude regions) and monsoon precipitation regime which carries moisture from the Arabian sea and Indian ocean to western Himalayas in the southern of the basin (low

altitude regions) which brings heavy rains from June to September (Bookhagen and Burbank, 2006, Lang and Barros, 2004). A distinct dividing line between the two regimes appears at the Pir Panjal Range which restricts the northward penetration of the summer monsoon. However, Archer and Fowler (2004) have shown that winter and spring precipitation, by contrast, is strongly correlated on both sides of the Himalayan divide, resulting from westerly disturbances (Archer and Fowler, 2008). These both rainfall patterns and abrupt change in elevation make hydrology of this catchment peculiar. In the northern part of the basin, there is a single peak in spring precipitation, but the summer peak is weakly developed. In the southern part, the monsoon rains dominate, and the summer peak is better developed (Archer and Fowler 2008). According to the Randolph Glacier Inventory (Consortium and Inventory, 2017), approximately 0.75% (252 km²) of the UJB is covered by perennial glaciers and nearly 63% of the catchment is covered by seasonal snow cover during the winter months (October–March) (Azmat, 2015).

The mean annual P ranges from 836 mm at Srinagar (1587 m MSL) to 1761 mm at Narran (2419 m MSL), while the mean annual minimum and maximum temperature varies from -6.20 °C at Burzil (4100 m MSL) to 29.79 °C at Mangla (265 m MSL) station. Table 2.1 lists the climatic stations within and adjacent to UJB, as well as their characteristics. These stations are located within political boundary of Pakistan which are operated and maintained by the Pakistan Meteorological Department (PMD), Water and Power Development Authority (WAPDA) of Pakistan. Three stations (Burzil, Kakul and Murree) are located outside but near to the UJB are also taken into account. For the Indian side region, Indian Meteorological Department (IMD) daily gridded precipitation and temperature datasets, derived from a dense network of meteorological stations for the Indian mainland (Pai et al., 2014), are extracted at the five stations and used as a reference data for that region.

Table 2.1: Summary of climatic stations located within and adjacent to UJB for the 1981-2014

Basin/Area (km ²)	Climatic Station	Agency	Latitude (°)	Longitude (°)	Elevation (masl)	Tmin (°C)	Tmax (°C)	Precipitation (mm/year)
Neelam (7425.96) 7356	Muzaffarabad	PMD	34.37	73.48	908	13.59	27.64	1424.89
	Burzil*	WAPDA	34.91	75.09	4100	-6.20	0.73	772.51
	Kelash*		34.39	73.52	1643	4.26	12.51	1174.87
	Pir Chanasi*	WAPDA	34.39	73.55	2875	5.56	11.41	847.12
Poonch (4753.24) 4222	Sehr Kakota	WAPDA	33.73	73.95	890	11.24	25.06	1235.80
	Palandri	PMD	33.72	73.71	1761	9.33	23.12	1348.06
	Khandar	WAPDA	33.5	74.05	919	11.44	25.59	988.49
	Kotli	PMD	33.5	73.9	593	11.82	28.37	1249.00
Kunhar (2563.39) 2435	Balakot	PMD	34.55	73.35	1003	12.21	25.16	1492.14
	Naran	WAPDA	34.9	73.65	2419	2.21	11.38	1761.08
Kanshi (1240.06) 1658	Kallar	WAPDA	33.42	73.37	549	16.39	28.50	930.17
	GujarKhan	PMD	33.25	73.3	448	17.01	28.54	855.23

Lower Jhelum (4076.22)	Bagh	WAPDA	33.98	73.77	1042	12.13	23.07	1329.15
	Murree	PMD	33.91	73.38	2213	8.51	17.69	1750.65
	GariDopatta	PMD	34.22	73.62	826	12.31	26.24	1413.06
	Rawalakot	PMD	33.87	73.68	1885	14.52	20.53	1231.92
	Kakul	PMD	34.1	73.2	1215	11.98	21.77	1173.01
	Mangla	PMD	33.12	73.63	265	17.12	29.79	867.15
Indian main Jhelum (13396.34)	Gulmarg	IMD	34.00	74.33	2705	11.23	23.66	1267.67
	Kupwara	IMD	34.51	74.25	1609	9.66	22.10	1119.13
	Pahalgam	IMD	34.00	75.33	2310	9.68	22.08	1236.73
	Quazigund	IMD	33.58	75.08	1690	9.90	22.28	1354.44
	Srinagar	IMD	34.08	74.83	1587	9.66	22.10	836.26

* Time of record is 1995-2014

2.4 Hydrology

The runoff generated from UJB at the Mangla Reservoir is the combination of rapid runoff generated by rainfall in the low altitude part of the basin and delayed runoff generated by snowmelt from the high-altitude part of the basin. Mangla inflows are dominated by the snowmelt during the spring and summer months, along with monsoon rainfall-runoff (Archer and Fowler, 2008). These flows are essential and primary source of irrigation for the downstream flood plains. Since the catchment is not extensively glaciated, as with the Karakoram or the Central Himalaya, therefore contribution of glacial melt to the total flow is negligible. However, a larger number of glaciers are present in the high-altitude areas.

Table 2.2: Summary of gauging stations located within the UJB for the 1981-2013
Station River

Station	River	Latitude (°)	Longitude (°)	Elevation (masl)	Mean Flow (m ³ /s)
Muzafferabad	Neelum	33.73	73.6	697	325.18
Naran	Kunhar	34.9	73.65	2421	45.54
Gari-Habibullah	Kunhar	34.4	73.38	810	103.60
Kotli	Poonch	33.46	73.88	518	129.13
Palote	Kanshi	33.22	73.43	400	5.26
Kohala	Jhelum	34.11	73.5	584	769.98
Chinari	Jhelum	34.2	73.8	1412	289.37
Domel	Jhelum	34.35	73.47	695	317.72
Azad Pattan	Jhelum	33.73	73.6	476	824.00
Mangla	Jhelum				890.75

From Mangla reservoir, the outlet of the UJB, the lower course of the Jhelum River is an arid and semi-arid environment and does not provide a reliable basis for rain-fed agriculture and, until the development of storage and irrigation network systems. The Mangla Dam and Reservoir, the only storage structure constructed on Jhelum River, is a multipurpose hydraulic structure used

for irrigation supplies, power generation and flood control. About 6 million hectares land is irrigated from the supplies of Mangla dam and has an installed hydroelectric capacity of 1,000 MW (Archer and Fowler, 2008). Unfortunately, the recent reservoir storage capacity has been insufficient to meet the water demands for food, domestic use and energy, due to significant increase in the country's population and decrease in storage capacity of dam due to siltation/sedimentation.

2.5 Land Cover

The satellite land cover maps from the Copernicus Climate Change Service (C3S) are used to identify the land cover classes in the UJB for the years 1992 and 2019 (Figure 2.2). The land cover was classified into eight classes including agriculture, forest, grassland, wetland, settlement, bare area, Water and permanent snow and ice. The grass, forest and agriculture are three major dominating features over high, mid, and low elevation areas, respectively. The forest covered 46.50% of the total area of the UJB, followed by agriculture (29.10%) and grass (21.39%) in 1992. Permanent snow and ice covered a negligible area in the northwest of the basin whereas the Mangla reservoir can be seen in the south of the basin in the water body class. The bare land can be observed within the densely grassy mountains of western Himalaya and Pir-Panjaj. The urban settlement class was concentrated in the Kashmir valley.

Clear land cover changes from 1992 to 2019 can be observed in forest, agriculture, urban settlement, and water bodies classes. The changes in land-cover classes are interlinked. For example, a reduction in forests signifies deforestation and a corresponding conversion in agricultural land. The forest area decreased from 46.50% to 41.64% whereas the agriculture land increased from 29.10% to 33.15% during 1992-2019. The change was prominent in Kashmir valley where agricultural land replaced the forest area. The area of large water bodies and urban settlement increased from 0.51% and 0.11% to 0.73% and 0.72%, respectively. The areas under grasses, wetlands, bare land, and permanent snow and ice have remained similar.

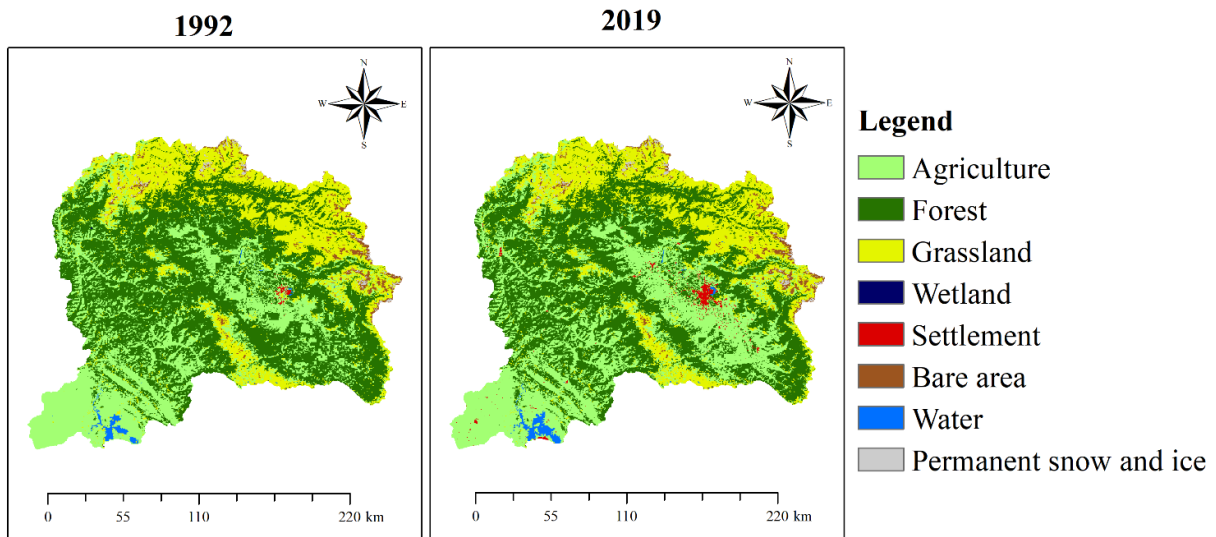


Figure 2.2: Land cover maps of the UJB for the year of 1992 and 2019.

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Chapter 3

Evaluation of gridded datasets for terrestrial water budget assessment in the Upper Jhelum River Basin-South Asia

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Abstract

The study presents a comprehensive assessment of the key terrestrial water budget (TWB) components and their recent temporal trends using observed and gridded datasets across Upper Jhelum Basin (UJB) for the period of 2003-2014. Different gridded datasets were used for precipitation-P (APHRODITE, CHIRPS, PGMFD, ERA-5, and MSWEP), evapotranspiration-ET (MOD16A2, SSEBop, GLDAS-NOAH, TERRACLIMATE and DOLCE), Gravity Recovery and Climate Experiment (GRACE) derived terrestrial water storage (TWS) and observed discharge (Q) measurements. Firstly, gridded P and ET datasets were assessed through detailed spatiotemporal analysis against reference datasets and considering their adequacy to close the TWB. The imbalance in TWB and associated uncertainties of each component were also computed to understand the potential of gridded datasets for water budget studies. Finally, TWB components were subjected to trend analysis to evaluate temporal trends and their statistical significance over the study period. Overall, ERA5-P and DOLCE-ET relatively performed better and hence considered to be the most appropriate to present the hydrological spatiotemporal variability across UJB. The imbalance in the water budget was mainly associated with higher uncertainties in P, especially during wet periods. The results of temporal trend analysis showed a) insignificant mixed trends for annual P with increase and decrease in monsoon and winter P, respectively b) mixed yet statistically significant trends for ET in different parts of basin at annual and seasonal scale c) significant decreasing trends for TWS throughout the UJB in winter and annual scale d) increasing trends for Q in all months of the year except January and February. Despite the imbalance in water budget estimation due to large uncertainties in gridded P, ET, and TWS datasets, the study underlines the important information about TWB dynamics and their spatiotemporal variability over UJB which can be used as the knowledge base for further impact assessment studies.

Key words: Precipitation, Evapotranspiration, terrestrial water storage change, water balance dynamics, Uncertainty

3.1 Introduction

Knowledge of the terrestrial water budget (TWB) components and their dynamics over large spatial scale are crucial to understand the water resources availability and management, the potential risk of hydro hazards (floods and droughts), and the interactions of the land surface with the atmosphere under a changing environment.

Overall, the ground-based measurement of TWB components over large spatial scale has long been a challenge around the world, primarily owing to limited and inconsistent measurement networks and their intrinsic inaccuracies, particularly in mountainous environment like the Upper Jhelum Basin (UJB-33467 km²) where complex climatic and terrain conditions prevail (Franchito et al. (2009)). In addition, the data scarcity for the transboundary river basins may increase due to political issues among the sharing countries. The aforementioned issues motivate practicing hydrologists to look beyond the available ground measurements for alternative data sources providing continuous estimates of TWB components in space and time. In this context, the

regional/global gridded datasets based on observations, reanalysis and satellite remote sensing are unique in their ability to capture spatiotemporal estimates of TWB components at different spatial and temporal resolutions, with the potential to provide data for regions with low-density in situ measurements around the globe (Moreira et al., 2019, Zhang et al., 2018, Oliveira et al., 2014).

To date, several gridded precipitation (P) and evapotranspiration (ET) datasets are available in near real-time with quasi-global to global coverage. The use of these datasets to study TWB components, however, is not straightforward as no single gridded dataset can be said to be perfect for all conditions. In fact, different datasets of the same geophysical variable can include errors and uncertainties particularly at higher altitudes where sources and magnitudes of the variable exhibit large variability, leading to inconsistency between estimates of the same variable (Pellet et al., 2020). These errors and uncertainties could be associated with the way they are developed and/or the lack of calibrated ground observations in remote areas (Jia et al., 2012, Thiemiig et al., 2013). Therefore, a comprehensive performance assessment of these gridded P and ET datasets for the area of interest is necessary before their subsequent use in any studies.

Research conducted in different regions of the world has shown that the performance of these P and ET gridded datasets could vary from region to region (Omonge et al., 2022, Moreira et al., 2019, Baudouin et al., 2020, da Motta Paca et al., 2019, McCabe et al., 2016, Michel et al., 2016, Xie et al., 2019). Over high mountains of Asia (HMA), various studies investigated the performance of different P gridded datasets from reanalysis, models, and remote sensing (Andermann et al., 2011, Hu et al., 2016, Palazzi et al., 2013, You et al., 2015). For example, Ma et al. (2009) and You et al. (2015) evaluated few atmospheric reanalysis P datasets in Tibetan Plateau and found large negative biases in these datasets. Though the gauge-based datasets such as Asian Precipitation - Highly-Resolved Observational Data Integration Toward Evaluation (APHRODITE), have a better match with in-situ observation, they feature P under catch at higher altitudes which significantly impact the P trends and quality (Andermann et al., 2011, Hu et al., 2016, Immerzeel et al., 2015). The research conducted on Upper Indus Basin (UIB) by Immerzeel et al. (2015) also stated that APHRODITE underestimates the P for snow and glacier fed basins. The errors and uncertainties in the satellite-based datasets are attributed to photon scattering associated with terrestrial snow cover (You et al., 2015). For instance, the Tropical Rainfall Measuring Mission (TRMM) has been found to reproduce rainfall well in wet regions and in warm seasons in East Asia (Shen et al., 2010), but the dataset largely overestimates extreme rainfall in South Asia (Hu et al., 2016). These studies, in general, endorse the biases and uncertainties in existing gridded P datasets, especially over the Himalayas Mountain ranges.

In addition to gridded P datasets, hundreds of ET algorithms have been developed since 1970s and the availability of the global-scale ET datasets has increased. Some reviews of ET algorithms from earth observation data can be found in (Kalma et al., 2008, Karimi and Bastiaanssen, 2015, Wang and Dickinson, 2012). Like P, gridded ET datasets are also subjected to discrepancies due to deficiencies in the model structure, input datasets and model parameter related errors, scale expansion problems and limited flux tower data for validation (Jia et al., 2012, Xia et al., 2015a). The previous studies of the comparison of gridded ET datasets in different regions of the world

(da Motta Paca et al., 2019, McCabe et al., 2016, Michel et al., 2016) generally concluded that variations among ET datasets can lead to significantly different estimates of annual runoff, water storage change and irrigation requirements, demanding for a thorough evaluation of the available datasets for the study area.

The Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE-Follow-on (GRACE-FO) (Tapley et al., 2004) are an active remote sensing (RS) satellite. It measures change in mass gravity field variation over large spatial scale to infer vertically integrated estimates of terrestrial water storage (TWS) at the monthly basis. The TWS from both GRACE and GRACE-FO missions includes all terms of storage on the land surface (glacier, snowpack, vegetation canopy, lakes, wetlands, rivers, etc) and subsurface (soil moisture, groundwater). Many researchers integrate GRACE observations with hydrological data from variety of sources, including global land data assimilation system (GLDAS) models (Rodell et al., 2004), in situ measurements, and RS data, to provide improved descriptions of water fluxes such as groundwater storage changes-GWSC (Scanlon et al., 2012a), surface water consumption (Anderson et al., 2012), regional flood potential (Long et al., 2014b, Reager and Famiglietti, 2009), drought monitoring (Long et al., 2014b, Sun et al., 2018), reservoir storage changes (Yi et al., 2017), ice mass loss (Sasgen et al., 2010), and water budget closure (Lv et al., 2017, Pellet et al., 2020, Sheffield et al., 2009). These studies concluded that GRACE data can well monitor the variations in terrestrial water storage.

Initially, GRACE data applications are limited to large basins with drainage area of more than 200,000 km² due to its coarse spatial resolution (4 degree) and higher potential of errors for small basins (lower signal to noise ratio). However, the finer spatial resolution of GRACE mascon solutions in release 6 (RL06) makes it applications possible for small basin studies. Moreover, GRACE observation is sensitive to total mass changes concentrated within a smaller area if the magnitude is sufficient (Longuevergne et al., 2013, Scanlon et al., 2012b, Scanlon et al., 2016). Abou Zaki et al. (2019) monitored depletion in ground water storages from GRACE observations in Bakhtegan catchment (31511 km²), Iran and found good agreement between GRACE derived ground water storage change and observations at wells. Similarly, Ouma et al. (2015) found consistent and close correlation between GRACE derived TWSC and observed GWSC in the Nzoia River Basin (12709 km²) in Kenya. Further application of GRACE data for smaller basins can be found in the following studies: (Becker et al., 2010, Swenson and Wahr, 2009, Wang et al., 2011).

Understanding the origin of uncertainties in gridded datasets and their spatial variability is another critical issue that deserves comprehensive study. Investigation of the errors that can exist in these datasets is important for achieving future water-cycle observation missions with fewer errors regarding water balance closure (Gao et al., 2010, Sahoo et al., 2011, Penatti et al., 2015). The current study is conducted keeping in mind the hydrological applications to create awareness about uncertainties and biases in gridded P, ET and TWS datasets over transboundary UJB, located at the foothills of Western Himalayas, a most affected mountainous range by climate change. The region already witnessed an increase in extreme hydro-meteorological extreme events in the last few decades (Ansari et al., 2022), and are expected to become even more pronounced in the coming

future (Pachauri et al., 2014). In this context, TWB components estimations from gridded datasets become important tools for comprehensively understanding the water dynamics in the region. Although a number of studies have already been conducted on the performance evaluation of gridded P datasets and their associated uncertainties, however, the ET component has received less attention and remains unexplored. As far as the GRACE satellite TWS is concerned, the coarse spatial resolution (1 degree) of spherical Harmonics (SH) solutions restricts its application in hydrological studies over UJB. With the improvement in spatial resolution of GRACE mascon solution in RL06, GRACE data can be used also for small basin (e.g., area<200,000 km²) studies. The same goes for the trend analysis which have been carried out only for essential climatic variables e.g., P and temperature (Saddique et al., 2020a, Shafiq et al., 2020).

In this regard, the current study is the first attempt to evaluate a number of gridded P, ET and TWS datasets for water balance studies over UJB. The uncertainties in these gridded datasets are firstly evaluated against direct comparison with observed gauge data at monthly, seasonal, and annual scale and subsequently their abilities are assessed in terms of water budget closure. Finally, trend analysis is carried out for each TWB component with a more accurate and reliable gridded P, ET, TWS and observed discharge (Q) to check its statistical significance for the period 2003-2014.

Table 3.1: Summary of climatic stations located within and adjacent to UJB for the 2003-2014.

Climatic Station	Latitude (°)	Longitude (°)	Elevation (masl)	Mean Tmin (°C)	Mean Tmax (°C)	Precipitation (mm/year)
Muzaffarabad	34.37	73.48	908	13.46	28.03	1236.53
Kelash	34.39	73.52	1643	4.09	12.48	1174.87
Pir Chanasi	34.39	73.55	2875	5.43	11.23	804.56
Sehr Kakota	33.73	73.95	890	11.34	25.71	1049.21
Palandri	33.72	73.71	1761	10.14	23.05	1334.12
Khandar	33.5	74.05	919	11.53	26.20	863.33
Kotli	33.5	73.9	593	12.87	28.63	1198.23
Balakot	34.55	73.35	1003	11.97	25.73	1375.80
Naran	34.9	73.65	2419	1.26	10.52	1925.54
Kallar	33.42	73.37	549	16.26	28.38	900.35
GujarKhan	33.25	73.30	448	16.40	28.09	904.39
Bagh	33.25	73.77	1042	12.25	19.46	1050.55
Murree	33.91	73.38	2213	8.62	18.16	1564.23
GariDopatta	34.22	73.62	826	12.35	26.83	1377.12
Rawalakot	33.87	73.68	1885	12.00	19.72	1068.60
Kakul	34.1	73.20	1215	11.26	22.31	1273.67

Mangla	33.12	73.63	265	16.82	30.20	889.05
Gulmarg*	34.00	74.33	2705	11.23	23.66	1121.14
Kupwara*	34.51	74.25	1609	9.66	22.10	1022.99
Pahalgam*	34.00	75.33	2310	9.68	22.08	1204.86
Quazigund*	33.58	75.08	1690	9.90	22.28	1290.21
Srinagar*	34.08	74.83	1587	9.66	22.10	840.66

* IMD stations

3.2 Datasets

3.2.1 Reference P and ET data

Ideally, the in-situ data from well-distributed measurement networks are a good reference to assess the performance of the global gridded P and ET datasets at basin scale. In case of UJB which is subject to dual data scarcity issue (i.e., low density unevenly distributed network lying at low altitudes and Transboundary River basin), the limited availability of observed data at least helps the researchers to know the varying range of performances of the global datasets and their spatiotemporal distribution at basin scale. In this study, the observed daily P and temperature data from seventeen climatic stations located within political boundary of Pakistan were used as a reference dataset. These stations are operated and maintained by the Pakistan Meteorological Department (PMD) and Water and Power Development Authority (WAPDA) of Pakistan. For the Indian side region, Indian Meteorological Department (IMD) daily gridded P and temperature datasets, derived from a dense network of Meteorological stations for the Indian mainland (Pai et al., 2014), were extracted at the five stations and used as a reference data for that region. A detailed summary of these stations is given in Table 3.1.

Regarding ET, different methods are available for its computation either direct or indirect. Since there is not a single flux tower ET measurement in the studied region, the reference data for actual ET (hereafter referred as evapotranspiration-ET) was calculated using an indirect method. Indirect ET estimation from TWB equation depends on the accuracy of other hydrological variables, for example, precipitation, runoff, and total water storage change. As there are few precipitation stations constrained by uneven distribution at low altitudes, this approach can provide uncertain estimates. Another indirect ET estimation makes combined use of RS based vegetation indices (VIs) and in situ or remotely sensed meteorological data. This method has been widely used for the estimation of actual evapotranspiration and crop water use efficiency. This hybrid approach used vegetation fractional cover (Fc) (Johnson and Trout, 2012, Trout et al., 2008, Glenn et al., 2010, Verger et al., 2009) and crop coefficient (Kc) derived from remotely sensed VIs (Pôças et al., 2020, Calera et al., 2017, Kamble et al., 2013, Jayanthi et al., 2007) along with reference evapotranspiration-ET_o (or potential evapotranspiration -PET) for the estimation of actual evapotranspiration. Crop coefficients (Kc) primarily depend on the dynamics of canopies (cover fraction, LAI, greenness). Since satellite data can help to estimate some key-variables related to vegetation phenology (Myneni et al., 1997, Duchemin et al., 1999, Gutman, 1999, Bastiaanssen et

al., 2000), they offer opportunities for monitoring the space and time variability of K_c . The method is similar to $ET = ETo * K_c$ where K_c is the function of VI. K_c obtained from VIs are more robust than conventional K_c values since they estimate current vegetation conditions in space and time (Maselli et al., 2014, Marcial-Pablo et al., 2021, Kullberg et al., 2017).

In the present study, green vegetation fraction-based K_c values were used along with PET to calculate ET. Since green vegetation fraction is a scalar value for multiplication by PET, it is functionally the same as a crop coefficient (Allen et al., 1998a, Groeneveld and Baugh, 2007, Groeneveld et al., 2007). The PET was calculated using Hargreaves (1994) equation due to data limitation. The present study used maximum green vegetation fraction, a global dataset (spatial resolution= 1 km) derived from Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI (Broxton et al., 2014).

3.2.2 Gridded precipitation datasets

Five different gridded P datasets (i.e., APHRODITE, CHIRPS, PGMFD, ERA-5, and MSWEP) were evaluated against reference data at monthly, seasonal, and annual scale. These datasets can be distinguished by the way they assimilate observations and produce distributed P fields. Table 3.2 offers a brief overview of the chosen datasets. The Asian Precipitation - Highly-Resolved Observational Data Integration Toward Evaluation (**APHRODITE**) is based on a dense network of up to 8000 daily rain-gauge data for monsoon Asia region with spatial resolution $0.25^\circ \times 0.25^\circ$ provided by Data Integration and Analysis System (DIAS), Japan (Yatagai et al., 2012). The Climate Hazards Group Infrared Precipitation with Stations (**CHIRPS**) dataset is developed by Climate Hazards Group (CHG) and the United States Geological Survey (USGS), which has a spatial resolution of 0.05° and temporal resolution at daily and monthly scale. It was developed with combined use of ground-based gauge measurements and cold cloud duration measurement by the synergistic use of satellite thermal infrared band (Funk et al., 2015). The Princeton Global Meteorological Forcing Dataset for Land Surface Modelling (**PGMFD** (Sheffield et al., 2009); was developed by Terrestrial Hydrology Group at Princeton University and is based on the observed and NCEP/NCAR Reanalysis I data. The dataset is currently available at 1.0° (plus 0.5° and 0.25°), 3-hourly (plus daily and monthly) resolution globally for 1961-2016. The **ERA5**, a relatively new reanalysis data launched by European Centre for Medium-Range Weather Forecasts (ECMWF) (Saha et al., 2006). The data is developed by using advanced 4Dvar assimilation scheme and provides various atmospheric variables at 139 pressure levels for 1979-present time period. The Multi-Source Weighted-Ensemble Precipitation (**MSWEP**) is a new global historic P dataset (1979–2017) developed by merging 18 P datasets at a 3-hourly temporal and 0.1° spatial resolution (Beck et al., 2017, Beck et al., 2019). It takes advantage of the complementary strengths of in situ measurements, satellites observations and reanalysis data and validated at global scale using observations from ~70,000 discharge gauges and hydrological modelling for ~9000 catchments, with daily gauge corrections.

Table 3.2: Summary of Gridded Precipitation Datasets used in this study.

Dataset	Type	Spatial-Temporal resolution	Coverage	Period	Algorithm/Assimilation schemes	Institute	Data Sources	References
Asian Precipitation - Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE)	Observation	0.25°/ 3,6 h and daily	Asia	1951-2015	Interpolation with rain gauge gridded precipitation	Meteorological Research Institute Japan	Data Integration and Analysis System (DIAS)	(Yatagai et al., 2012)
Climate Hazards Centre InfraRed Precipitation with Station (CHIRPS)	Observation & Satellite	0.05°/daily, Monthly	Global	1981-Present	Smart Interpolation Tech	University of California, Santa Barbara	USGS, CHG	(Funk et al., 2015)
ERA-5	Reanalysis	0.25° / hourly, Monthly	Global	1979-Present	4D-Var	ECMWF	ECMWF	(Tarek et al., 2020, Saha et al., 2010)
Princeton Global Meteorological Forcing Dataset for Land Surface Modeling (PGMFD)	Reanalysis & Observation	0.25°, 0.05°, 1°/3 hourly, daily, Monthly	Global	1961-2016	Correction of NCEP/NCAR reanalysis data with observed and WMO solid precipitation data	Terrestrial Hydrology Research Group, Princeton University	NCAR-DSS	(Sheffield et al., 2006)
Multi-Source Weighted-Ensemble Precipitation (MSWEP)	Observation, satellite, and reanalysis (Hybrid of 18 datasets)	0.1°/3,6 hourly, daily	Global	1979–2017	Ensemble weighting and merging technique	Princeton University and Princeton Climate Analytics	On request to producer	(Beck et al., 2017, Beck et al., 2019)
Indian Metrological Department (IMD)	Observation	0.25° /Daily	Indian mainland	1980–Present	Weighted Interpolation of rain gauge station	Indian Metrological Department, Pune	IMD, Pune	(Pai et al., 2015)

3.2.3 Gridded evapotranspiration datasets

ET estimations from five global datasets (MOD16A2, SSEBop, GLDAS-NOAH, TERRACLIMATE and DOLCE) were evaluated against the reference ET data. These datasets differ in their input data source and production mechanism. Table 3.3 gives a brief summary of the selected datasets. The Moderate Resolution Imaging Spectroradiometer product (**MOD16A2**) is a widely used global terrestrial ET dataset that has been computed using an algorithm proposed by (Mu et al., 2011), which employs the logic of the Penman–Monteith equation (Monteith, 1965). The input parameters includes the daily meteorological reanalysis data of the Global Modelling and Assimilation Office (GMAO) (Hu et al., 2015) along with MODIS remotely sensed data

products. The land surface models (**LSMs**) in the Global Land Data Assimilation System-2.1 (**GLDAS-2.1**) such as **NOAH (Ek et al., 2003)** produce optimal fields of the terrestrial water and energy fluxes through the combined use of ground-based observations, remote sensing, and modelled datasets. This dataset is available at a spatial resolution of 0.25° and 1.0° and temporal resolution of 3-h and monthly. The Operational Simplified Surface Energy Balance (**SSEBop**) ET dataset was generated using single source energy balance model (Senay et al., 2013). The algorithm integrates the standardized version of Penman–Monteith equation (Allen et al., 1998b) and ET fractions generated from remotely sensed MODIS thermal imagery, using a thermal index approach to account the topographical impacts on surface temperature. The Derived Optimal Linear Combination Evapotranspiration (**DOLCE**) is a new hybrid ET dataset derived by merging eleven available global ET datasets. The contribution of each merging dataset to DOLCE is defined by its ability to represent ground ET measurements at 260 sites as well as its dependence on the other parent datasets (Hobeichi et al., 2018) . **TERRACLIMATE** ET is estimated using a one-dimensional modified Thornthwaite-Mather climatic water-balance model (Abatzoglou et al., 2018). Inputs for the water balance calculation include P, reference ET and satellite derived plant extractable soil water capacity at 0.5° resolution (Wang-Erlandsson et al., 2016).

Table 3.3: Summary of the Gridded ET datasets used in this study.

Dataset	Type	Spatial-Temporal resolution	Coverage	Period	Algorithm/Assimilation schemes	Institute	Data Sources	References
Moderate Resolution Imaging Spectroradiometer (MOD16A2)	Satellite (Red, NIR)	500 m/8 days	Global	2003-2014	3-layer Penman-Monteith	Numerical Terra dynamic Simulation Group NTSG, University of Montana (UMT)	NASA's MODIS Adaptive Processing System (MODAPS)	(Mu et al., 2011)
Operational Simplified Surface Energy Balance (SSEBop)	Satellite (Red, NIR, TIR)	0.25°/ Monthly	Global	2003-2014	1-layer Penman – Monteith	National Water Census, USGS	United States Geological Survey (USGS)	(Senay et al., 2013)
Global Land Data Assimilation System (GLDAS-NOAH v2.1)	Observations, Satellite, and modelled	0.25°, 1°/ Monthly	Global	2000-2020	Land Surface Model	Goddard Earth Sciences Data and Information Services Centre (GES DISC)	NASA Land Information System and Goddard Earth Sciences Data and Information	(Ek et al., 2003)

							n Services Centre	
Derived Optimal Linear Combination Evapotranspiration (DOLCE v2)	Observation, satellite, and reanalysis (Hybrid of 11 datasets)	0.25°/ Monthly	Global	1980- 2018	Ensemble weighting and rescaling technique	University of New South Wales, Sydney, Australia	NCI geonetwork catalogue	(Hobeichi et al., 2020)
TERRA CLIMATE	Modelled	0.05°/ Monthly	Global	1958- 2019	1-D Modified Thornthwaite -Mather climatic water- balance model	University of California, Merced	Climatolog y Lab	(Abatzoglu et al., 2018)

3.2.4 GRACE Data

The GRACE derived total water storage anomaly (TWSA) data from two institutes Center for Space Research (CSR) and Jet Propulsion Laboratory (JPL) of released 6 (RL06) mascon (mass concentration) solutions were used in this study (Save et al., 2016). The mascon solutions are available at a spatial resolution of 0.25 ° and 0.5° in cm of equivalent water height for CSR and JPL, respectively. The two mascon solutions via derived TWSA differ slightly due to different approaches for the application of spatiotemporal constraints and scale of the grid cells (<https://grace.jpl.nasa.gov/data/choosing-a-solution/>). Table 3.4 gives a brief overview of the used datasets. The few missing months in GRACE data are due to “battery management”. These missing epochs were filled by linear interpolation from the previous and following months of the missing data. This method was considered as rational because it keeps a good seasonal cycle at the monthly temporal resolution (Long et al., 2014a, Sheffield et al., 2009).

In this study, GRACE mascon solutions were preferred instead of spherical harmonic (SH) solutions due to two reasons: firstly, the finer spatial resolution and secondly, reduced leakage from land to ocean and application of geophysical data constraints during processing with little empirical post processing requirements(Pellet et al., 2020) .

Table 3.4: Summary of GRACE derived TWSA Datasets used in this study.

Dataset	Type	Spatial- Temporal resolution	Coverage	Period	Institute	Data Sources	References
CSR GRACE/ GRACE-FO RL06 Mascon Solutions V 2.0	Satellite	0.25°/ Monthly	Global	April 2002- Present	Center for Space Research (CSR)	Physical Oceanography Distributed Active Archive Centre (PODAAC)	Save, (2020)
(CSR-M) JPL GRACE/ GRACE-FO	Satellite	0.5°/ Monthly	Global	April 2002- Present	Jet Propulsion Laboratory (JPL)	Physical Oceanography Distributed Active Archive	Wiese et al. (2018)

RL06 Mascon Solutions V 2.0 (JPL-M)						Centre (PODAAC)	
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3.2.5 In situ river discharge data

The daily flow at Mangla station (outlet of UJB) were obtained from Surface Water Hydrology Project of WAPDA, Pakistan for the period of 2003-2014. From daily data, monthly aggregates of flow were calculated and converted to water depth (mm) to keep compatible with the other components in water budget equation.

3.3 Methods

3.3.1 Performance evaluation of gridded P and ET datasets

The performance of gridded P and ET datasets were evaluated against the reference data for a period of twelve years (2003-2014) at monthly, seasonal, and annual scale. The lower and upper limit of the study period was limited by the availability of GRACE data and consistent and complete records of reference data respectively. The evaluation was made on station basis to avoid the uncertainties and errors induced by conversion of observed point data to gridded format and spatial scale matching (Hu et al., 2016). The spatial discrepancies among gridded datasets and reference data were assessed by visualization. The disparities in time series were analyzed via the Taylor Diagram which incorporate correlation coefficient (r), normalized standard deviation (NSD) and centered root mean square error (CRMSE).

3.3.2 TWB dynamics and uncertainty characterization

The equation (1) presents the simplified form of water budget, based on the principle of mass conservation. The equation was used to analyze the TWB dynamics at monthly time step over UJB.

The TWSC was calculated as a residual of equation (1) using observed and gridded datasets and compared with GRACE mascon derived TWSC. As GRACE provides mass anomalies of TWS at irregular space intervals, the storage changes were calculated by the simple difference time derivative of TWS anomalies as presented in equation (3.1) (difference between two sub sequent time steps of the GRACE data, representing the average variation of the TWS).

$$\frac{\Delta S}{\Delta t} \approx \frac{\Delta TWS}{\Delta t} \approx \frac{TWS_{t+1} - TWS_t}{\Delta t} \dots \dots \dots (3.1)$$

Where $\Delta S/\Delta t$ is terrestrial water storage change for month (t); TWS (t+1) and TWS (t) are terrestrial water storage anomalies for month t+1 and t, respectively. In agreement with (Moreira et al., 2019, Rodell et al., 2004, Sheffield et al., 2009) , monthly averages between two-time steps of P, ET and Q variables were used to make these components comparable with the TWS change (equation 3.2).

$$\frac{\Delta S}{\Delta t} = \left(\frac{P_{t+1} + P_t}{2} \right) - \left(\frac{ET_{t+1} + ET_t}{2} \right) - \left(\frac{Q_{t+1} + Q_t}{2} \right) \dots \dots \dots (3.2)$$

Here subscripts (t+1) and (t) denote the month of the respective variable.

The uncertainty analysis was conducted on the basis of the principle of Gaussian error propagation. Since the present study used observed discharge data which is relatively more accurate than gridded datasets therefore uncertainties contributions of these gridded TWB components towards discharge were calculated as one standard deviation via the principle of Gaussian error propagation, assuming that the components are independent of each other (no covariance between any two components) (Long et al., 2014a, Lv et al., 2017, Sheffield et al., 2009). The assumption makes it simpler to calculate the uncertainty contribution of each component separately. This approach is particularly useful when the error in the input data is known. In fact, it has been applied in numerous hydrological studies that use RS data for water balance analysis and produce reliable estimates (Long et al., 2014a, Lv et al., 2017) . Therefore, the uncertainty of total basin Q (σ_Q) is computed as follows:

$$\sigma_Q = \sqrt{\sigma_P^2 + \sigma_{ET}^2 + \sigma_{TWS}^2} \dots \dots \dots (3.3)$$

Where σ_P , σ_{ET} , σ_{TWS} are the uncertainty in monthly P, ET and TWS, respectively. The uncertainty in P and ET were estimated as the standard deviation (σ) of the observed and selected gridded P and ET datasets at each station. The uncertainties of these stations were then averaged to calculate basin level uncertainties. The uncertainty of JPL-M derived TWSA can be calculated from the original GRACE data and are available at <http://grace.jpl.nasa.gov>, while a rigorous uncertainty analysis of CSR-M is still in progress (http://www2.csr.utexas.edu/grace/RL05_mascons.html). Therefore, the method described by (Scanlon et al., 2016, Wahr et al., 2006) was used to calculate the uncertainties in CSR-M. The method involves the calculation of uncertainties from the residuals after decomposition of the time series into long-term trends, and inter-annual, annual, and semi-annual amplitudes as presented in equation (3.4). The detailed description of the method can be found in (Scanlon et al., 2016, Wahr et al., 2006) .

$$S_{total} = S_{long-term} + S_{annual} + S_{semiannual} + Residual \dots \dots \dots (3.4)$$

Inter-annual signals were estimated by fitting 13 month moving averages to the residuals in equation 4. The root mean square (RMS) of the residual approximates the measurement uncertainty in CSR-M. Because of the high grid resolution of CSR-M (0.25°) leakage errors were assumed to be negligible and were neglected.

3.3.3 Trend Analysis

The annual and seasonal trends in each TWB components were analyzed for each pixel using the robust nonparametric regression techniques, Mann–Kendall (MK) test (Kendall, 1948, Mann, 1945) in conjunction with Theil–Sen (Theil, 1950) estimates, at 0.05 and 0.1 significance level (95% and 90% confidence level). The MK test was carried out using R package “modifiedmk” after removing lag-one serial correlation if present. For this purpose, trend free pre-

whitening (TFPW) method was employed on serially correlated time series before trend analysis. The MK test results were used to create trends maps using ArcGIS 10.1 software.

3.4 Results & Discussion

3.4.1 Comparison and performance evaluation of gridded precipitation datasets

The spatiotemporal comparison of selected gridded P datasets against reference dataset was carried out at monthly, seasonal, and annual scale employed over the twelve years of period (2003-2014). The basin average reference P was estimated through interpolation of unevenly distributed twenty-two meteorological stations (mostly installed at low elevation areas) considering topography as a predictor, known as “Kriging with external drift (KED)” (Goovaerts, 2000). To check the robustness of the interpolated precipitation, cross validation has been applied to annual reference precipitation by the leave-one-out approach. Cross-validation is a common method for validating the accuracy of interpolation techniques (Voltz and Webster, 1990). In this technique, information regarding one point is removed temporarily, the removed information is estimated from the remaining data points, and the difference between the actual and estimated values is calculated. This operation is repeated for the remainder of the points. One objection to using cross-validation is that the whole data sample is often used to define the interpolation model, and that the validation therefore might be considered not to be totally independent (Tveito et al., 2008). In order to avoid the limitation of using cross-validation, an independent validation procedure was used that consists of splitting the data sample into two parts. Hence, 18 stations were used for interpolation purposes, while the remaining 4 stations were used for independent validation. This procedure is repeated three times with different combinations as shown in Fig. A.1. The results show that the RMSE is higher when one station at high altitude (Gulmarg at 2705 meters) is taken out for validation purposes. Overall, the RMSE range between 51.83-64.80 mm/year. (Rata et al., 2020) compared three interpolation methods for mean annual rainfall in the Cheliff watershed, Algeria and found RMSE 49.5, 54.0 and 61.4 mm/year for KED, regression kriging and ordinary kriging respectively. (Borges et al., 2016) also found RMSE in the range of 50.12-70.35 mm/year for different interpolation methods in Distrito Federal, Brazil. Although the accuracy of interpolation methods depends on the geographical location and the density of measurement station network as evident in our study, these studies showed better results of KED for annual precipitation and comparable errors.

The average annual and seasonal spatial distribution of reference and gridded P datasets are shown in Fig. 3.1. The spatial distribution shows that the average annual reference P was highest over the northwest of the UJB (snow fed sub-basin and/or high-altitude areas) and the lowest annual P was observed in Kashmir valley and the southern part of the basin (low altitude areas). The significant uncertainties in the spatial distribution of mean annual P of the selected gridded P datasets were observed against reference dataset. The spatial patterns of MSWEP and ERA5 were somewhat similar but overestimated to reference data. The PGMFD presents the worst performance in terms of spatial distribution on an annual scale.

On a seasonal scale, overall reference and all selected gridded P datasets showed higher P over northern part of the UJB in all seasons except summer season, in which the highest P was received over southern part of the basin in the form of monsoon rainfall. In winter and spring seasons, a clear distinctive divide line (Himalayas divide line), in the middle of the UJB at Pir Panjal mountainous range, was seen in reference dataset, restricting the downward penetration of westerlies P. However, the effect of westerlies P was dominated in the surrounding downward regions of the divide line in winter season. In summer season, the southwest part of the basin received the highest P. The least influence of southwest monsoon was observed in Kashmir valley which is encapsulated between two mountain ranges. The Pir-Panjal mountains acts as a barrier in the way of monsoonal winds transported from the Indian Ocean. However, the valley experiences the influence of monsoon during late summer with typically low magnitude and intensity (Sen et al., 2017) . A similar spatial pattern was captured with MSWEP and ERA5 datasets. The PGMFD, APHRODITE and CHIRPS were unable to perform good in all seasons.

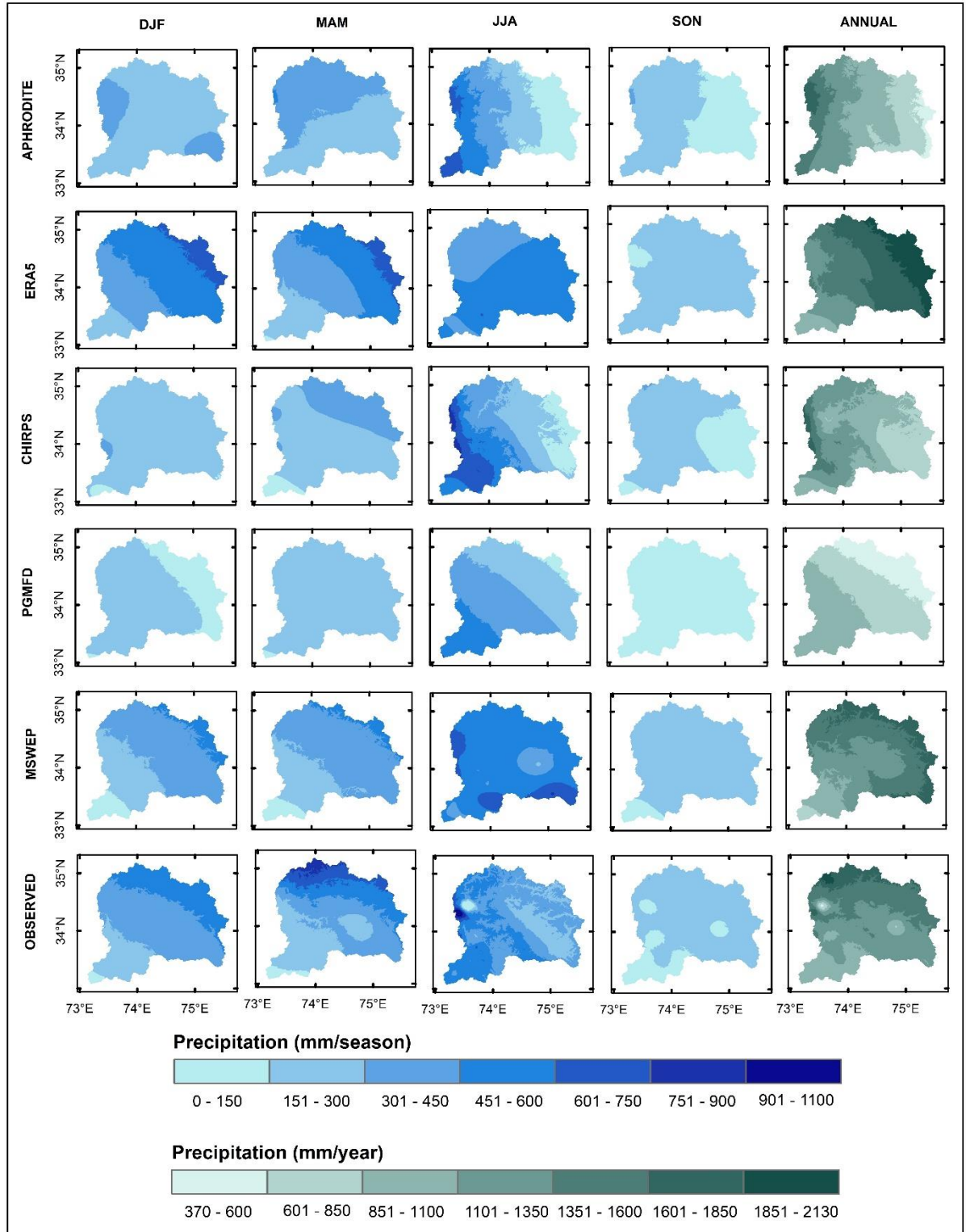


Figure 3.1: Spatial distribution of average annual and seasonal precipitation over UJB for all datasets for 2003-2014.

The average annual reference P was 1150 mm/year over the entire UJB. However, mean annual P varied widely between the reference and gridded P datasets (Fig. 3.2A). Among all gridded datasets, ERA5 and PGMFD showed the highest and lowest mean annual P in UJB. The ERA5 and MSWEP overestimated mean annual P by 37% and 14% comparative to reference data, respectively. On the other side, APHRODITE, CHIRPS and PGMFD underestimated the mean annual P by 5%, 15% and 28% comparative to reference data, respectively. The seasonal distribution of P showed little variation among reference and gridded P datasets except CHIRPS and PGMFD (Fig. 3.2B). The autumn season contributed the least to annual P among all seasons for all datasets. The combined contribution of winter and spring P to annual P was more than 50% for all datasets except CHIRPS and PGMFD, which showed larger contribution of summer season P.

Monthly P distribution for reference and gridded P datasets are shown in Fig. 3.2C. Overall, all datasets present more or less bimodal regime of P, with peaks in February and end of July highlighting the dominance of westerlies and monsoon P, respectively. The northern and eastern parts of the UJB lie in the Himalayas and Pir Panjal ranges and receive more than 50% of its annual P in the winter and spring seasons as a result of westerlies regime. The second peak in July is the result of summer monsoon, prevailing in the southern part of the basin. The shape of the second peak of all gridded datasets varied from reference data, which showed a slight declining plateau from mid of July to end of August. A similar but fairly stable plateau was captured by CHIRPS dataset, from mid of July to mid of September. In addition, ERA5 and APHRODITE datasets produced slightly higher peaks in spring season whereas PGMFD, MSWEP and CHIRPS datasets generate higher peaks in summer monsoon season. The temporal disparities in gridded P datasets against reference data were evaluated on station basis. A Taylor diagram (Fig. 3.2D) summarizes the main statistical metrics (NSD, r , CRMSE) at monthly, seasonal, and annual scale. The proximity of gridded datasets to reference data indicates a good performance. The colors in Fig. 3.2D represent the different gridded datasets and the shape represents the temporal scale at which comparison was made. The performance of all gridded P datasets was relatively better at monthly time scale, while it was found to be worst at annual scale except PGMFD, which showed a relatively better correlation coefficient ($r=0.5$). Overall, ERA5 relatively outperformed over other datasets at monthly and seasonal scale ($r=0.7-0.8$, CRMSE=0.6-0.7, normalized standard deviation=0.9-1.0).

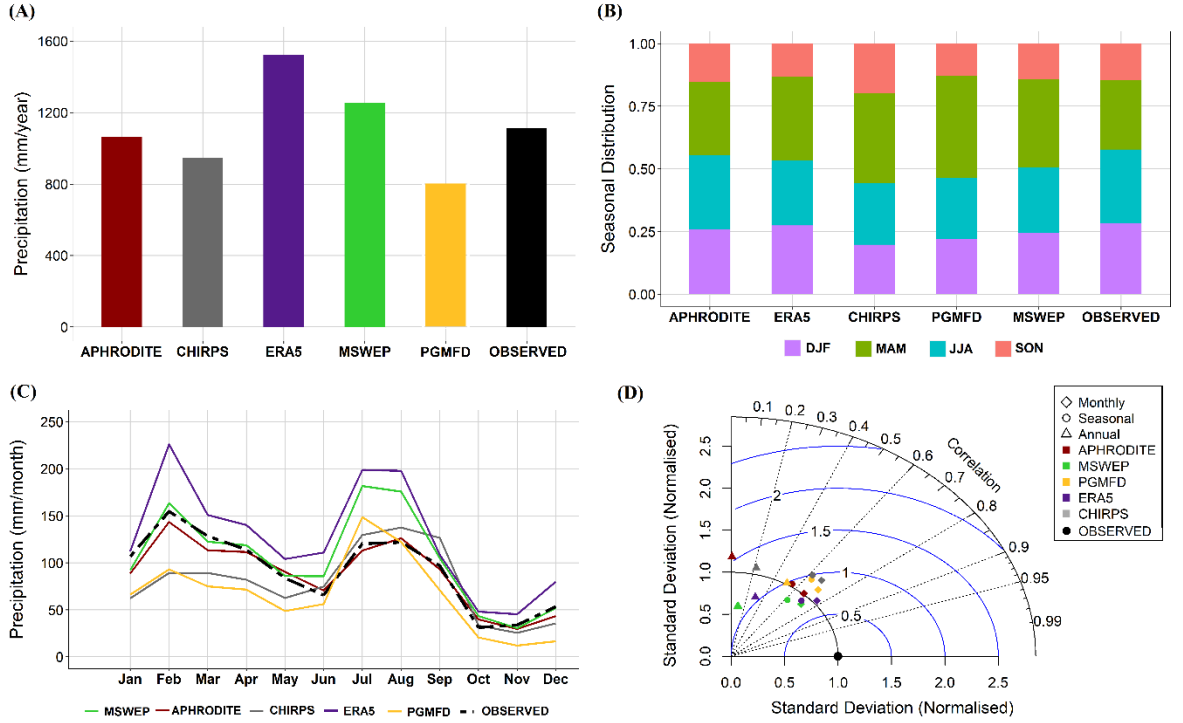


Figure 3.2: (A) Average annual precipitation, (B) their seasonal distribution for all datasets, (C) Mean monthly precipitation distribution and (D) Taylor diagram showing the statistical error metrics (NSD, CRMSE, r) of selected gridded precipitation dataset against reference at monthly, seasonal, and annual scale.

Regarding the selection of suitable gridded P dataset for UJB, one also needs to consider the uncertainties in reference dataset. Despite considering the effect of local topography in interpolation, the basin average P estimates still have uncertainties due to low density station network. Contrasting reviews are reported in literature about the performance of KED technique for P. For instance, Masson and Frei (2014) reported considerable improvement in interpolation accuracy with KED compared to other linear regressions without any predictor in high mountainous regions. On the other hand, (Berndt and Haberlandt, 2018, Ly et al., 2011) argue that, topographical impact was indispensable for only temperature reconstruction at all temporal resolutions and station densities, but it was less clear for daily to monthly P. Furthermore, all spatial interpolation techniques can perform poorly in regions with insufficient high-elevation data, due to inaccurate estimation of local lapse rates (Ruelland, 2020). Considering all above reviews, it can be concluded that the basin average observed P estimates are underestimated owing to the under-catch P and unevenly distributed low-density (approx. 1 gauge/2235 km²) climate station network especially at high altitude areas which are the main active parts of the basins (Azmat, 2015, Grossi et al., 2017, Ranzi et al., 2003, Winiger et al., 2005). Moreover, the P increases with elevation up to 4500 meters in Himalaya mountainous range and then start to decrease (Immerzeel et al., 2015) whereas the climatic stations are installed up to 3000 meters elevation. For this reason,

gridded datasets have been used across a wide range of hydrological modeling research around the world. These gridded datasets have substantial differences with reference as well as among themselves (Fig. 3.1-3.2), and these differences are mostly due to the deficiencies in their data sources and generation mechanisms.

Overall, the performance of ERA5 dataset was considered to be best with higher correlation, even though it overestimates the reference P especially during wet months (Fig. 3.2A and 3.3C). The PGMFD and CHIRPS datasets have been found to be highly underestimated and unable to capture spatial patterns when compared to the reference P. The APHRODITE and MSWEP both perform well in terms of magnitude and capture the monthly and seasonal P cycle (Fig. 3.2A: 3.2C); however, APHRODITE underestimate the basin average P like reference P. Various authors also reported the underestimation of APHRODITE over high mountains of Asia. The meteorological stations used to produce APHRODITE dataset (Yatagai et al., 2012) are probably located at lower elevations and cannot represent the high-altitude P. The underlying explanation for APHRODITE & CHIRPS' underestimation is that the low-altitude measurement network and satellite-based estimates only observe liquid P, whereas ERA5 estimates both liquid and solid P (Immerzeel et al., 2015, Shafeeque et al., 2019) . Moreover, ERA5 is built on a data assimilation scheme and the ECMWF IFS forecast model, which includes fully coupled components for atmosphere, land surface and ocean waves, with closure of atmospheric water balance (Copernicus, 2019) . Our selection of ERA5 for UIB was supported by (Baudouin et al., 2020) who cross validated 20 gridded P datasets across Indus River and suggested that ERA5 provides better P estimates in terms of magnitude, temporal distribution, and variability, from daily to multi-annual scale (Immerzeel et al., 2015). corrected the APHRODITE P data based on glacier mass balance over UIB from 1998 to 2007 and found it very close to ERA-Interim, the third generation of ECMWF which is replaced by fifth generation reanalysis ERA5 with improved parameterizations and higher resolution (Nogueira, 2020) .

3.4.2 Comparison and performance evaluation of gridded evapotranspiration datasets

The spatiotemporal comparison of gridded ET datasets against reference dataset were conducted at monthly, seasonal and annual scale. The annual and seasonal spatial distribution of reference and gridded ET datasets averaged over twelve years of period (2003-2014) are presented in Fig. 3.3. As compared to P, larger discrepancies were observed among ET datasets in terms of magnitude as well as spatial distribution at an annual scale. The land use land cover (LULC) maps for the starting and ending year of the study period are shown in Fig. 3.4 to explain the spatial distribution of ET with reference to LULC because of its direct association with ET. The LULC was classified into seven classes including Agriculture, Forest, Grass, Water bodies, permanent snow and ice, built-up lands, and barren land. The grass, forest and agriculture are three major LULC dominating over high, mid, and low elevation areas, respectively. Permanent snow and ice covered a negligible area in the northwest of the basin whereas the Mangla reservoir can be seen in the south of the basin in the water body class. The barren land can be observed within the densely grassy mountains of western Himalaya and Pir-Panjaj. The urban settlement class was

concentrated in the Kashmir valley. Major LULC changes from 2003 to 2014 can be observed in agriculture (decrease) and forest (increase) class. The change was prominent in Kashmir valley where afforestation replaced agricultural land.

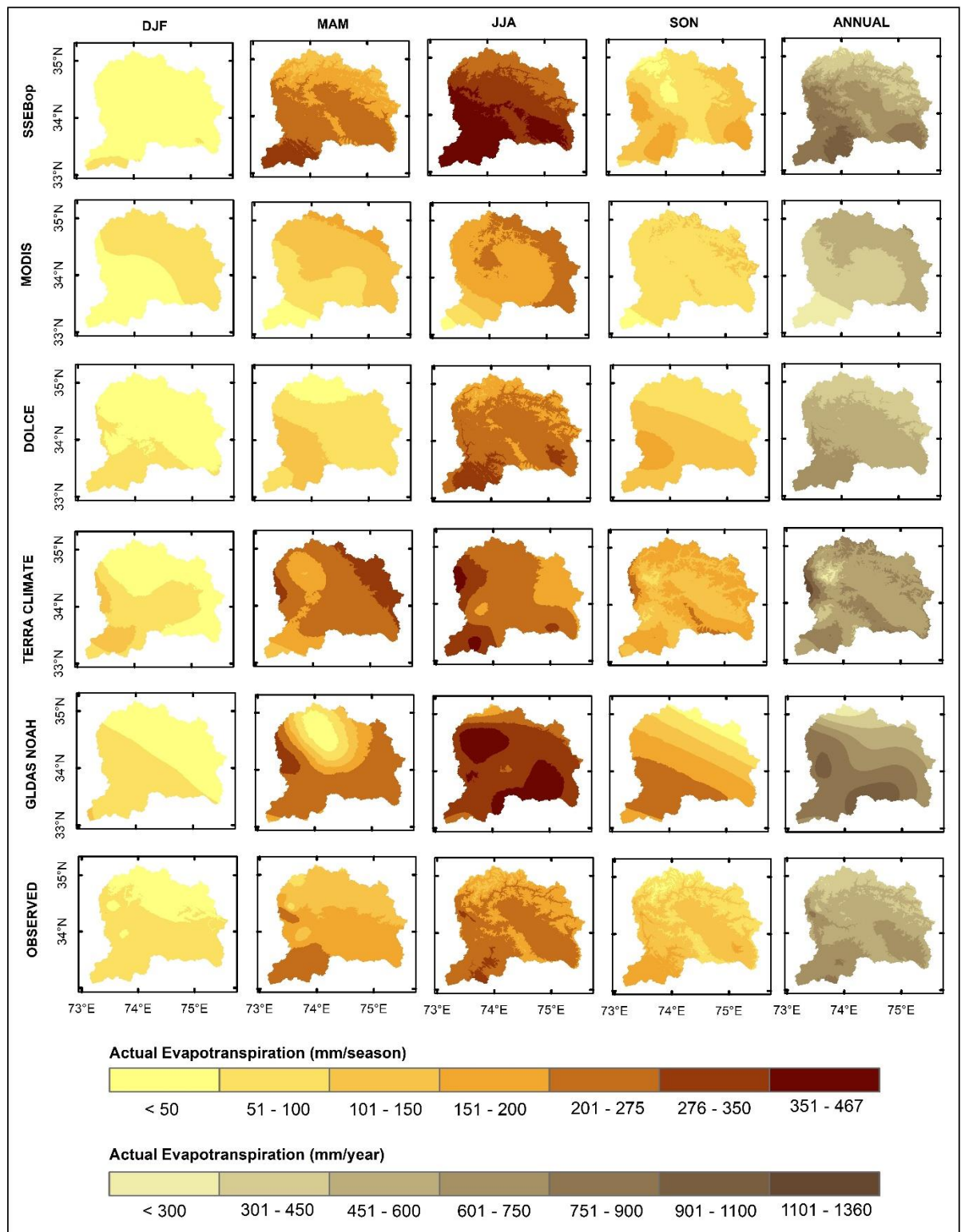


Figure 3.3: Spatial distribution of average annual and seasonal ET over UJB for all datasets for 2003-2014.

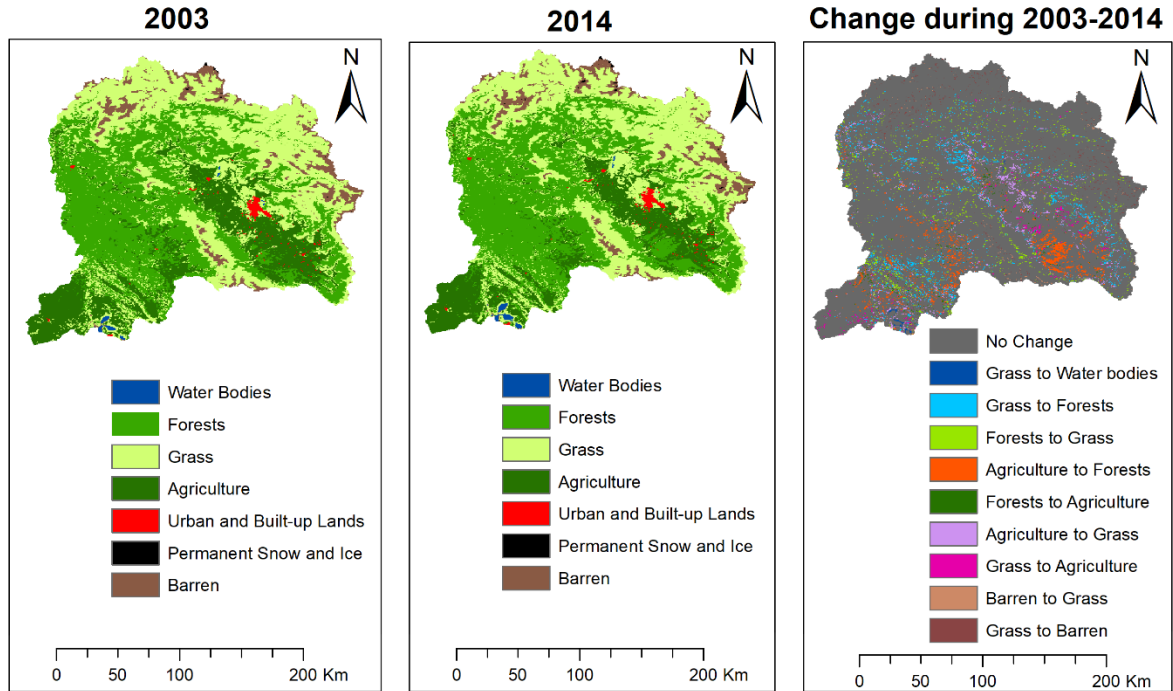


Figure 3.4: Land use land cover (LULC) of the UJB for the year 2003 and 2014.

Concerning spatial distribution at annual scale, the reference ET dataset shows a decrease in ET rates with increase in elevation. The highest ET rates of reference dataset can be observed in Kashmir valley and southern part of the basin which correspond to the agricultural land (Fig. 3.4). The part of the basin which hosts western Himalaya shows the lowest ET rates. The Pir-Panjal Mountains show higher ET rates as compared to Western Himalaya. The difference in ET rates despite of the same land cover (densely grassed area with small patches of barren land) is due to the temperature difference corresponding to different elevation. Moreover, ET at high elevation mountainous regions of Himalaya only plays a minor role in overall water budget and is generally less than 10% of total hydrological budget (Bookhagen, 2010, Khan and Koch, 2018). This also applies to UJB where only lower altitude areas have higher ET contribution, while the high elevation sub-catchments have only minor annual ET due to their low average temperatures. The spatial inhomogeneity of ET among the forest, grass and agricultural land covers were caused by the spatial inhomogeneous soil water content under these land covers. The spatial inhomogeneity of ET over cultivated land could be a potential indicator of making reasonable and effective irrigation schedule for different crops on the farmland. Regarding the spatial distribution of gridded datasets, SSEBop spatial patterns were somewhat similar yet overestimated the reference dataset. The MOD16A2 and TERRACLIMATE datasets present contrasting spatial patterns with higher ET rates at higher elevation and vice versa. Among all ET datasets, the DOLCE reasonably well

captures the magnitude as well as the spatial distribution at annual scale, however it is unable to reproduce higher ET rates of Kashmir valley, encapsulated between two mountainous series. Similarly, at seasonal scale, the SSEBop dataset shows higher ability to present spatial patterns with overestimation in all seasons except winter where ET rates are underestimated. Apart from autumn season, the performance of DOLCE dataset is better than other gridded datasets in terms of magnitude and spatial patterns.

The average annual reference ET for the period (2003-2014) was 550 mm/year over entire UJB (Fig. 3.5A). The GLDAS-NOAH and MOD16A2 showed higher discrepancies with 33% and 27% positive and negative biases, respectively. The other three datasets (DOLCE, SSEBop, TERRACLIMATE) performed better with biases in the range of 7.6-12.6%. For seasonal distribution in terms of magnitude, ET datasets show less consistency (Fig. 3.5B) than the P datasets (Fig. 3.2B), especially for winter season. The summer season contributes for the largest part to annual ET due to availability of sufficient energy and moisture in the form of temperature and monsoon P, respectively. The contribution of spring season to annual ET reduces slightly due to slight reduction in energy availability for extraction of water from water bodies and soil moisture. In comparison, the seasonal distribution of TERRACLIMATE, DOLCE AND GLDAS-NOAH are similar to the reference ET dataset (Fig. 3.5B).

Similarly, temporal distribution of reference and all gridded ET datasets vary in terms of monthly evolution and magnitude as shown in Fig. 3.5C. Generally, all datasets perform better in relatively cold months (from November to February) than warm months (from April to September). Moreover, all datasets underestimate ET at the lower end (winter months) but overestimate ET at the higher end (summer season), except MOD16A2, which underestimates ET at both the low and high ends (Fig. 3.5C). The TERRACLIMATE and DOLCE datasets show similar evolution of ET as reference with one month delayed in peak values. MOD16A2 shows the largest discrepancy with reference ET in terms of temporal distribution and magnitude, mostly dampens monthly variations with underestimation of ET ranges by approximately 70%. The statistical error metrics for ET gridded datasets are presented via Taylor diagram (Fig. 3.5D). The colors in Fig. 3.5D represent the different gridded datasets and the shape represents the temporal scale at which comparison was made. At monthly and seasonal scale, all datasets relatively perform well except MOD16A2 whereas none of the gridded datasets is able to develop a good correlation at annual scale. The DOLCE outperformed other datasets with $r=0.78-0.79$, CRMSE=0.75-0.8 and NSD=1.25 at a temporal resolution of month and season. The SSEBop dataset was well correlated with reference dataset ($r=0.82-0.86$) but has higher CRMSE and NSD.

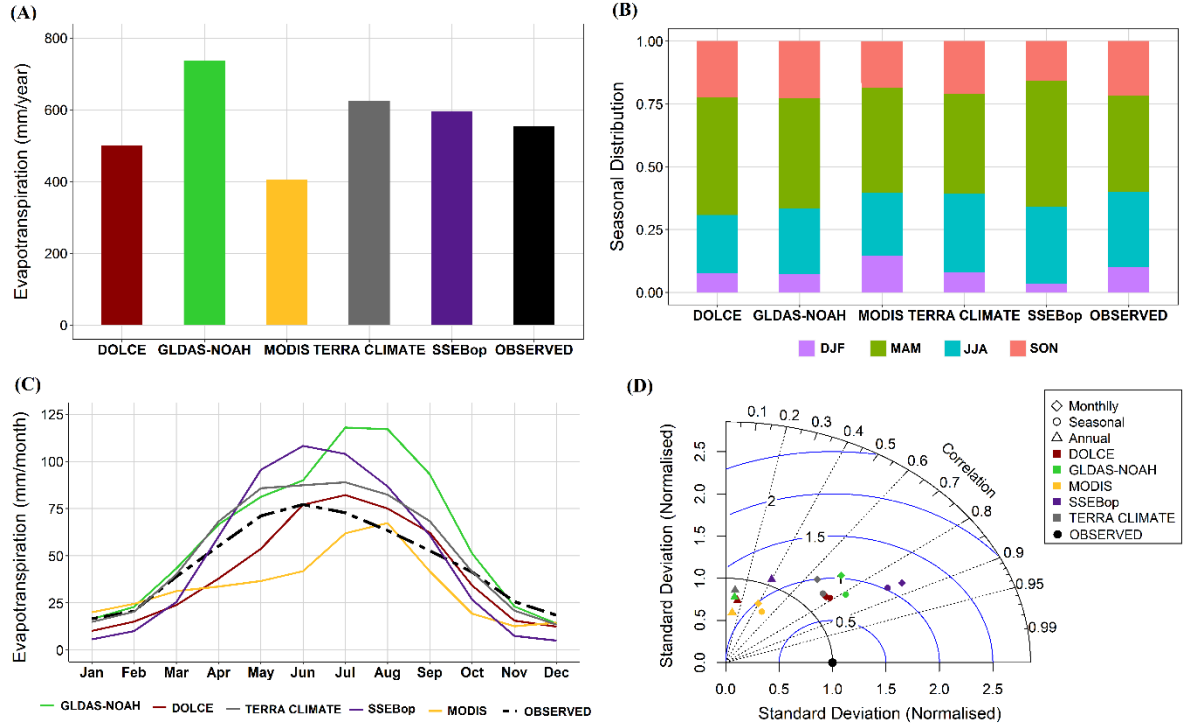


Figure 3.5: (A) Average annual ET, (B) their seasonal distribution for all datasets, (C) Mean monthly ET distribution and (D) Taylor diagram showing the statistical error metrics (NSD, CRMSE, r) of selected gridded ET datasets against reference at monthly, seasonal, and annual scale.

ET across UJB varies in response to atmospheric forcing and moisture availability on snow and earth surfaces. The direct estimation of ET over mountainous regions like the north part of UJB is complicated due to the absence of ground stations at high altitudes and high topographic heterogeneity. For the same reason, absolute ET estimates are very few and highly uncertain, despite its crucial importance in TWB cycle. An indirect approach of estimating ET as a residual of TWB equation has also been applied to alpine high-altitude regions (Builes-Jaramillo and Poveda, 2018, Li et al., 2019). However, the reliability of ET estimated from TWB equation depends on the accuracy of other hydrological variables, for example, P, runoff, and total water storage change. As there are few P stations constrained by uneven distribution at low altitudes, this approach can provide highly uncertain estimates. In this study, a hybrid approach integrating ground-based measurement with RS-based vegetation indices was used to estimate ET. This approach has been widely used for the estimation of ET at large scale (Bryla et al., 2010, Johnson et al., 2016, Johnson and Trout, 2012, Trout et al., 2008). Although results of this method are not as accurate as flux tower estimates, they provide good agreement with lysimetric and flux tower measurement (Bryla et al., 2010, Johnson et al., 2016).

The average annual reference ET for the period (2003-2014) was 550 mm/year over UJB (Fig. 3.5A) which is very close to the ET estimates provided by (Immerzeel et al., 2015, Lutz et

al., 2016) and (Bastiaanssen et al., 2012). Regarding gridded ET datasets, the performance of TERRACLIMATE and DOLCE seems better in terms of magnitude as well as spatial-temporal distribution with higher correlation coefficient. However, the spatial distributions of TERRACLIMATE were found to be inferior to DOLCE whereas the temporal distribution of DOLCE was found to be inferior to TERRACLIMATE. The GLDAS-NOAH and SSEBop datasets overestimated the reference ET which seems unrealistic over partially snow fed basins. The MOD16A2 data was unable to present spatial as well as temporal patterns of ET. The underestimation of MOD16A2 ET was also reported by (Bookhagen and Burbank, 2010) over UIB and other parts of the world. The differences between reference and gridded ET datasets are associated with errors and uncertainties in their forcing input parameters, production mechanism and lack of calibrated ground observations in remote areas (Moreira et al., 2019). For instance, the satellite derived land surface temperature (LST) used in SSEBop and MOD16A2 has larger uncertainties over mountainous region due to cloud cover, snow effect and conversion of instantaneous to daily values (Senay et al., 2013), which further results in significant ET errors. Moreover, MOD16A2 algorithm uses vapor pressure deficit as water stress input instead of P and soil moisture which would be overestimated for higher soil water content, resulting in the underestimated soil evaporation and canopy transpiration (Hu et al., 2015). Although TERRACLIMATE and GLDAS-NOAH land surface model also uses P as forcing input parameter yet P itself present larger uncertainties over mountainous region corresponding to complex topography (Xia et al., 2015b).

3.4.3 GRACE derived terrestrial water storage change.

The GRACE derived TWSA and calculated TWSC time series from JPL-M and CSR-M of RL06 over UJB are shown in Fig. 3.6. These datasets show similar patterns with significant correlation coefficient of $r=0.85$ and $r=0.81$ for TWSA and TWSC, respectively. The slight differences in the two datasets are owed to different approaches for the application of spatiotemporal constraints and scale of the grid cells (<https://grace.jpl.nasa.gov/data/choosing-a-solution/>).

As expected, a strong seasonal fluctuation in TWS with maximum in spring and minimum in winter was observed. The state of gain in TWS was observed after the onset of long P spell. As a bimodal P pattern exists in the basin, two peaks were observed in a year at the positive ends of TWS. The TWS increases with the onset of spring P in the form of snow and reaches its maximum at the end of spring season. Afterwards TWS tends to decrease with the melting of snow. The UJB is known as an “early riser” as its snowmelt season starts in March to April before peaking in June and July, a month earlier than the Indus. The early onset of snowmelt in UJB is attributed to the warming scenarios in western Himalaya. This is consistent with research that claims there has been glacial mass balance loss in the western Himalaya due to an increase in temperature and the retreat has been faster in the Karakorum and Hindukush regions (Lv et al., 2017). The TWS again tends to increase with the start of monsoon P with a smaller peak in August. The decline in TWS from

the end of monsoon P is translated into the removal of water from storage through rapidly generating streamflow, evaporation from water bodies and transpiration from plants.

Overall, both datasets showed slight declining trend in TWS in the basin during the studied period (2003-2014) at the rate of 0.0214 mm/month and 0.0119 mm/month for JPL-M and CSR-M datasets, respectively. This decreasing trend was attributed to land-use changes and changing P pattern due to global warming (Saddique et al., 2020b). The TWSC was calculated using the backward difference equation (Eq. 2). The long term TWSC remained stable during the studied period (2003-2014). The CSR-M data shows more variations in TWSC at both end peaks than JPL-M. The shaded area in Fig. 7 presents the uncertainty in datasets. The higher uncertainty was observed for the JPL-M derived TWSA which may be attributed to the low spatial resolution. The basin averaged uncertainty estimates of CSR-M derived TWSA calculated from residuals of time series decomposition was comparable to the value recommended by CSR institute (2cm in water height in each 0.5° grid globally). The results were also supported by the findings of (Xie et al., 2019) and (Yoon et al., 2019) over Yarlung Tsangpo River Basin and HMA, respectively.

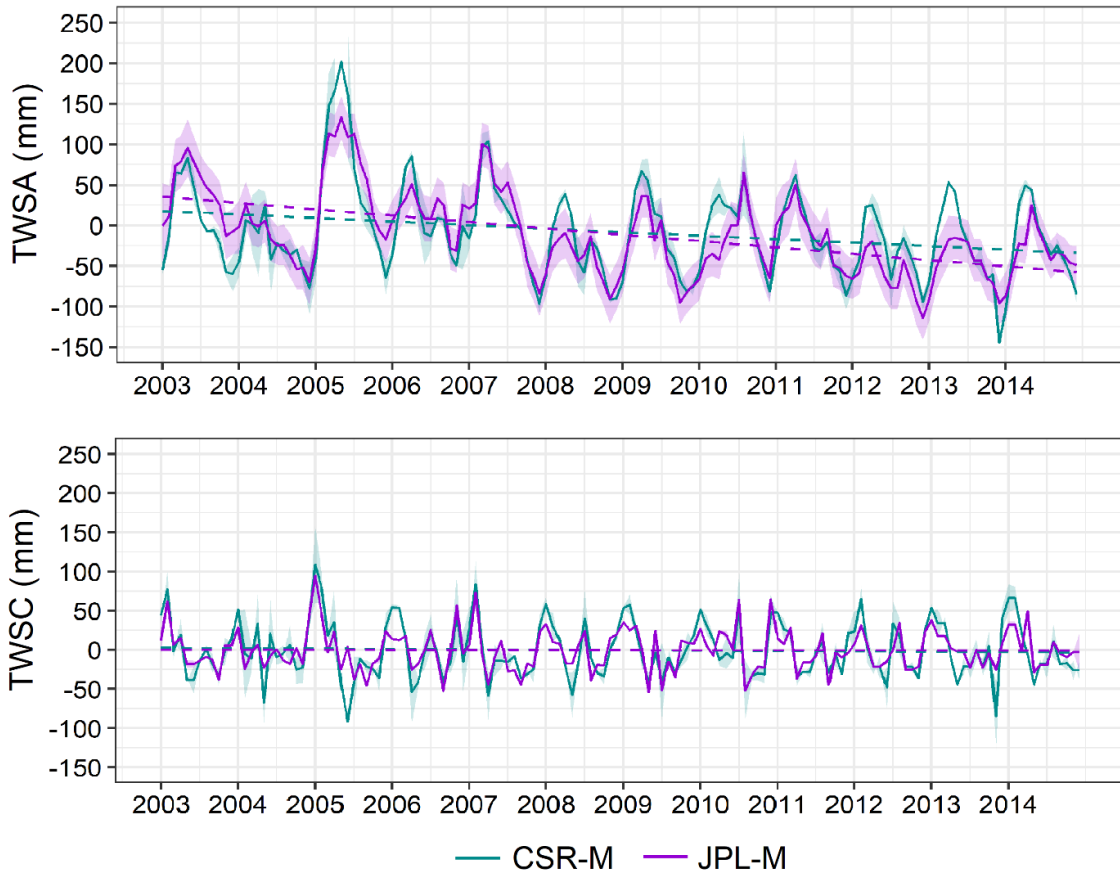


Figure 3.6: Comparisons of monthly time series of TWSA and TWSC during 2003–2014 for UJB. The shaded area represents the uncertainty in TWSA and TWSC.

3.4.4 TWB dynamics and uncertainties in its components

In this section, the adequacy of different combinations of selected gridded P and ET datasets to close the water budget was analyzed. For this purpose, TWSC was calculated as a residual of water budget equation (equation 3.1), hereafter referred as WB-TWSC, and compared with CSR-M and JPL-M derived TWSC. Table 3.5 shows the correlation coefficient between WB-TWSC and two GRACE datasets (CSR-M-TWSC and JPL-M-TWSC). The observed Q time series was used in water budget equation for all P and ET datasets pairs. It is clearly seen that the WB-TWSC was better correlated with CSR-M-TWSC than JPL-M-TWSC for all P and ET datasets. Regarding P datasets, the highest correlation coefficient between WB-TWSC and CSR-M-TWSC was obtained with ERA5 dataset followed by reference P dataset. In context of ET datasets, the use of DOLCE in water budget equation provides better correlation coefficient. The highest correlation coefficient and least imbalance was achieved with the combination of ERA5 and DOLCE datasets. This shows the higher ability of ERA5 and DOLCE to close the water budget than reference datasets.

Table 3.5: Correlation coefficient between WB-TWSC and GRACE derived (CSR-M-TWSC and JPL-M-TWSC) with different gridded P and ET combinations.

GRACE	ET/P	REFERENCE	APHRODITE	MSWEP	CHIRPS	ERA5	PGMFD
CSR-M	REFERENCE	0.68	0.65	0.64	0.58	0.76	0.61
	MOD16A2	0.67	0.60	0.59	0.53	0.78	0.57
	TERRA CLIMATE	0.66	0.62	0.63	0.56	0.77	0.59
	SSEBop	0.65	0.62	0.63	0.56	0.75	0.59
	GLDAS NOAH	0.67	0.64	0.65	0.60	0.78	0.62
	DOLCE	0.70	0.66	0.65	0.63	0.81	0.48
JPL-M	REFERENCE	0.50	0.50	0.51	0.41	0.61	0.47
	MOD16A2	0.49	0.47	0.48	0.35	0.63	0.44
	TERRA CLIMATE	0.47	0.46	0.49	0.36	0.60	0.44
	SSEBop	0.46	0.46	0.49	0.37	0.58	0.44
	GLDAS NOAH	0.51	0.51	0.54	0.44	0.64	0.50
	DOLCE	0.52	0.52	0.54	0.45	0.65	0.52

The graphical representation of CSR-M-TWSC and WB-TWSC along with monthly water fluxes of ERA5, DOLCE and observed Q is shown in Fig. 3.7A. The bimodal P pattern with peaks in winter and summer season was observed. The ET patterns in the basin showed a single peak in

summer season due to availability of sufficient energy and soil moisture in the form of temperature and monsoon P, respectively. During winter season, the limited energy availability for the extraction of water from water bodies and soil moisture lowers the ET rates despite of enough moisture availability. The temporal distribution of Q showed a single peak usually in spring season when snowmelt combines with rainfall runoff. The snowmelt in the UJB starts in March to April, a month earlier than the UIB as a result of increasing warming rates in the western Himalayas. A second smaller peak in the Q was observed in the summer season for the 2006 and 2014 years. These peaks were a result of intense monsoon rainfall which caused flooding conditions in the basin. The TWSC also exhibits two gaining peaks which coincides with the P peaks in winter and summer season. The two losing peaks in TWSC showed relatively dry season than winter and summer season. It can also be seen that basin TWSC exhibits strong seasonal fluctuations, but changes in P are not obvious. A comparison of the WB-TWSC and CSR-M-TWSC as time series reveals that both exhibit seasonal changes and demonstrate a fluctuating feature with a correlation coefficient of 0.81. However, discrepancies are higher at both gaining and losing ends of peaks. The imbalance or non-closure errors ($\text{imbalance} = P - ET - Q - \text{TWSC}$) varies in the range of 141.26 to -81.08 mm/month with the median being close to 17.22 mm/month and shows a seasonal cycle (Fig. 3.7B). Higher values of imbalance were found on the positive side as compared to negative. A higher positive imbalance was observed for the winter season where there are high P and least ET rates. On the other hand, a higher negative imbalance was observed in the summer season where high Q and ET rates respectively produced two peaks in WB-TWSC at losing ends. This may be explained with the higher uncertainties of P during wet seasons, as can be seen in Fig. 3.7C.

The uncertainties of each TWB component and their contribution to the overall uncertainty in basin Q, computed by the error propagation equation are depicted in Fig. 3.7C. The uncertainty of Q is in the range of 22.96 to 118.46 mm per month, with the largest error coming from the P. The higher uncertainties contribution from P was also documented by many researchers around the world (Moreira et al., 2019, Xie et al., 2019, Yoon et al., 2019). In general, ERA5 data tends to overestimate P especially wet seasons when compared to reference dataset (Fig. 3.2C). The P uncertainty varies between 2.99 and 116.17 mm/month. The high values of uncertainties of P are also attributed to the under-catches P and lack of in-situ gauge stations over snow fed parts of the basin. The uncertainty of ET varies from 6.44 to 31.12 mm/month and has been calculated through the same method as P. Irrespective of P, the uncertainty of ET remains consistent throughout the period. Regarding the uncertainties in CSR-M derived TWSC, our estimate of basin average uncertainty is 19.6 mm/month which is near to the value recommended by institute (2cm in water height in each 0.5° grid globally). Similar estimates of uncertainties are reported over Yarlung Tsangpo River Basin, in Southwest of China (Xie et al., 2019) and HMA (Yoon et al., 2019). Xie et al. (2019) estimated the uncertainties in P, ET, and Q to be in the range of 0.7-119.7 mm/month, 1.76-41.0 mm/month and 8.60-122.0 mm/month, respectively. Across the HMA, Yoon et al. (2019) reported mean annual uncertainty to be 0.45, 0.11 and 0.36 mm/day for P, ET, and Q, respectively.

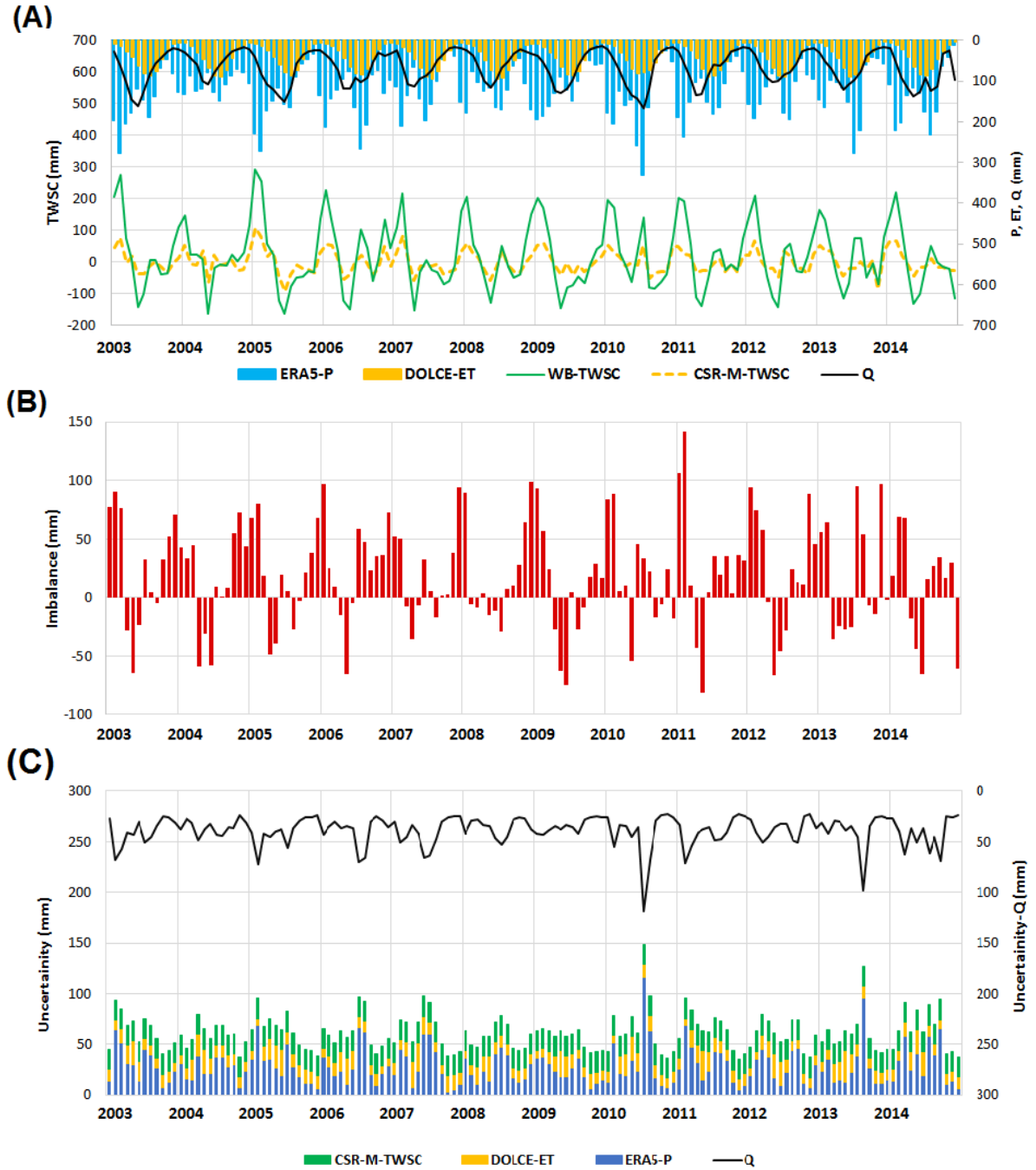


Figure 3.7: (A) Monthly water fluxes, (B) imbalance in TWB and (C) Uncertainties of each water balance component.

3.4.5 Trend Analysis

The annual and seasonal trend maps of P, ET, and TWS were prepared using MK test results. The lag-1 serial correlation coefficients of each pixel time series were calculated before applying MK trend test. Among the 79 pixels of study region, significant lag-1 serial correlation

exists at ten pixels of annual ET. In seasonal time series, significant serial correlations were more pronounced in summer series. The pre-whitening process of serially correlated time series is commonly used to eliminate the effects of serial correlation before trend analysis (Yue et al., 2002). However, the controversies still exist about its utility for hydro meteorological time series as it leads to a loss of important information contained in a time series and reduces the power of the test when a trend exists (Razavi and Vogel, 2018). A simulation study carried out by (Bayazit and Önöz, 2007) documented that pre-whitening should be applied except for large samples ($n \geq 50$), or when the coefficient of variation is very small. As our sample size was small, the pre-whitening of the serially correlated time series was done using (Yue et al., 2002) approach.

The annual and seasonal trend maps of three TWB components is shown in Fig. 3.8. Overall, both upward and downward trends in annual P were detected and their magnitude vary between -21.00 to 48.00 mm/year. Specifically, the annual P tended to increase in the lower part of basin and decrease in the Northwest (higher altitudes) of the basin during the study period. The increase and decrease in P in lower and upper part of the basins was attributed to the increase in summer monsoon and decrease in westerlies P, respectively, as clearly seen in seasonal trend maps. However, these positive and negative changes in P were not significant in most parts of the basin. At seasonal scale, the non-significant mixed trends were found in most part of the basin with a few significant positive pixels for all seasons except winter where significant decreasing trends were detected for most part of the basin at either 0.1 or 0.05 significance level.

Contrasting results of P trends over Greater Himalaya were found in literature. Shrestha (2000) and Archer and Fowler (2004) reported no significant evidence of long-term trend, either increasing or decreasing, over the Nepalese Himalaya and UIB for the period of 1948-1994 and 1895-1999, respectively. Dimri and Dash (2012) and Kumar and Jain (2010) also reported large-scale decadal variation with increasing and decreasing P over Himalaya. However, significant increasing trend were found for winter P (October to March) from 1961 to 1999 (Archer and Fowler, 2004). The results of our study are consistent with (Azmat, 2015) who reported decreasing tendency ($\tau = -0.034$) of snow cover area (SCA) in winter over an altitude of 4000 m in UJB for the period of 2000-2010. The snow cover shrinkage tendency in high elevation areas of the Himalayan range were also found by (Berthier et al., 2007). Recent studies conducted by Zaz et al. (2019) and Shafiq et al. (2020) on Indian side UJB also showed decreasing trends of winter and spring P. The contradictions in P trends are due to the study period as historic trend may not persist in future (Milly et al., 2008). For instance, the inclusion of 2000-2003 severe drought years in (Archer and Fowler, 2004) study may change the statistical significance of the trend.

Regarding ET trends over UJB or even UIB, very few studies were found in literature. The results of MK statistics for ET are presented in Fig. 3.8. A mixed trend for annual ET with a magnitude of -8.0 to 5.50 mm/year was observed. For seasonal trends, winter and spring seasons show decreasing and increasing trends at high and low altitude areas respectively whereas opposite trends are observed for summer season. Low turbulence of air due to a declining trend in wind velocity may be one explanation for dropping ET rates at high altitudes (Akbar and Gheewala, 2020) despite of warming in Himalaya as reported by many researchers (Zaz et al., 2019).

Moreover, the increasing trend in temperature did not necessarily cause an increase in ET (Tamaddun et al., 2019). (Moreira et al., 2019) also observed that the ET rates are regulated by a radiation balance, P rates and vegetation physiological control rather than being exclusively limited by one of these factors.

The annual TWS tended to decrease with a magnitude of -2.32 to -7.25 mm/year in the basin at either 0.1 or 0.05 significance level. Despite the increase in annual P over lower part of the basin (monsoon dominated), TWS shows declining trend even at higher significance level ($p>0.05$). This may be due to the rapidly generating rainfall runoff that leaves less time for recharging groundwater. Moreover, the changes in LULC (reduction in agricultural area in valleys and increase in settlement) also reduce the infiltration to soil (Saddique et al., 2020b, Shafiq et al., 2020). On a seasonal scale, TWS was decreasing during winter and spring seasons, however significant decline was detected only for winter season. For the summer and autumn seasons, nonsignificant increasing trends were observed for most parts of the basin with a few pixels of slightly decreasing slope. The TWS are directly linked to amount and form of P. The decreasing TWS in winter and spring season is directly linked to decrease P of the same seasons. The study area has also witnessed the significant loss in glacierized area with Kolahai receding by around 23.6% from 1962 to 2018 (Rashid et al., 2020) , and Nehnar lost nearly half of its area from 1962 to 2017 (Shafiq et al., 2020).

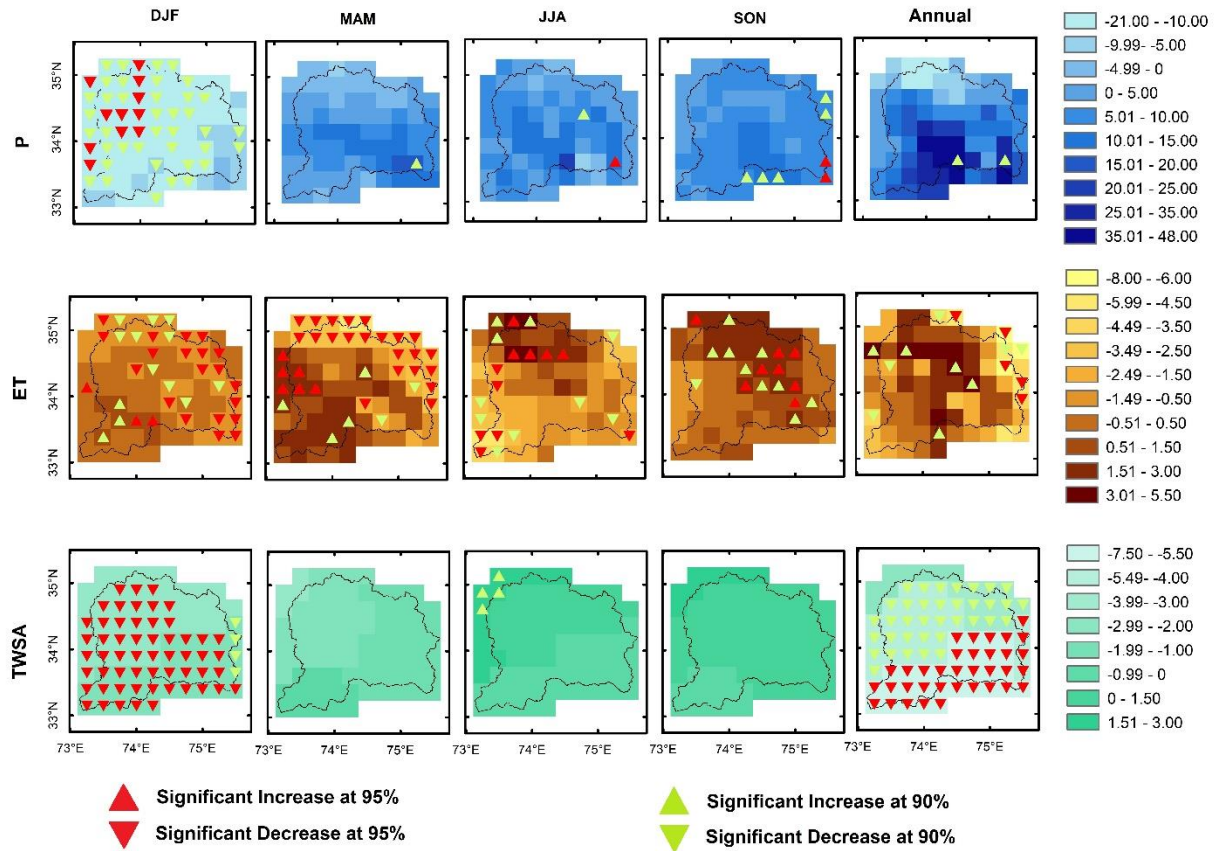


Figure 3.8: Annual and seasonal trends of P, ET, and TWS over UJB from 2003-2014.

The robustness of these gridded P, ET and TWS trends analysis depends on how accurately the given gridded dataset represents the basin behavior in space and time. In the present study, the selected gridded P (ERA5), ET (DOLCE) and TWSA (CSR-M) datasets performed well in direct comparison against reference point data at monthly, seasonal and annual scale. The suitability and reliability of ERA5 has also been reported by many researchers over UJB and surrounding regions (Ansari and Grossi, 2021; Liaqat et al. 2021; Arshad et al. 2021; Baudouin et al., 2020) whereas the DOCE ET estimates are consistent with the previous studies conducted over larger scale than UJB (Lutz et al., 2016, Immerzeel et al., 2015; Bastiaanssen et al., 2012).

Notwithstanding, ERA5 overestimates the observed basin (Fig. 3.2A and 3.2C), it accurately reproduces the seasonal distribution and presents least temporal differences against observed gauge data (Fig. 3.2B and 3.2D). The overestimation of ERA5 against observed data is defensible and can be explained with low density unevenly distributed station network lying at low altitudes which mostly received liquid P whereas the hydrologically active part of the basin remained ungauged (Baudouin et al., 2020; Shafeeque et al., 2019, Khan and Koch, 2018, Immerzeel et al., 2015; Azmat, 2015). Moreover, among all P datasets, ERA5 P has the highest sufficiency to sustain the water balance with DOLCE ET and CSR-M TWS datasets (Table 5). Immerzeel et al. (2015) and Shafeeque et al., (2019) also argue that the observed P over UIB is underestimated and the water balance closure can be achieved only if the P in gridded datasets is 2–8 times greater than the observed P in these datasets at higher altitudes. The overestimation of gridded dataset could be different owing to the use of different P datasets, different size and location of study areas, and different mass balance values.

Overall, because of the limited number of climatic stations at high altitudes of the UJB, the ERA5 proves to be a good alternative of observed precipitation for further implications in impact studies, which needs continuous precipitation estimates in space and time.

The results of MK statistics for monthly, seasonal, and annual Q time series are shown in Fig. 3.9. The increasing trends were detected for all months of the year except January and February where runoff shows decreasing trend. However, this increase or decrease in monthly Q is insignificant but for September which is significant at 0.05 significance level. In terms of seasonal trends, statistically insignificant upward and downward trends were observed for summer, autumn and winter, and spring seasons, respectively. The possible reason behind the insignificant increase in March to May months Q was attributed to the early onset of snow melting due to warming scenarios in western Himalaya as reported by many researchers (Rashid et al., 2020, Shafiq et al., 2020, Zaz et al., 2019). Wescoat Jr et al. (2018) also reported the expected shift of Jhelum hydrograph to earlier Q, about one month earlier than the Indus River whereas the insignificant decreasing trend over spring season may correspond to the decreasing trend of winter P. For the annual Q time series, a positive yet insignificant trend with a magnitude of 5.7 mm/year was observed. Primarily the increase in annual Q is predominantly caused by increasing monsoon P from low altitude areas. The results of annual Q trend are concurrent with (Wescoat Jr et al., 2018) who found increase in Q for the period 2001-2016, despite of overall decreasing trend for the 1922-2016.

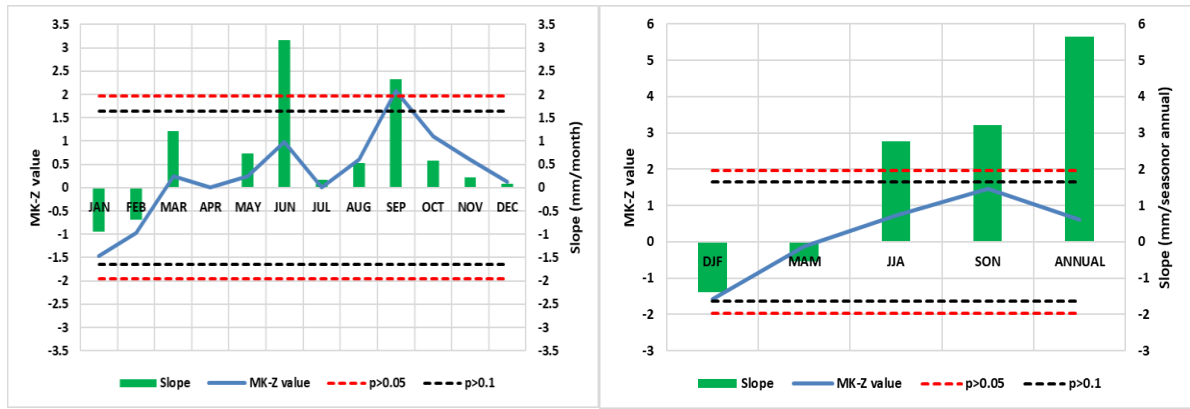


Figure 3.1: MK statistics for monthly, seasonal, and annual discharge at Mangla from 2003-2014.

3.5 Conclusion

With reference to above analysis, the major conclusions of this study can be summarized as follows:

The spatial patterns and seasonal distribution of P were reasonably well captured by all gridded P datasets. However, huge discrepancies in the mean estimates were found across these datasets. ERA5-Pdataset was considered to be the most appropriate to present P behavior over UJB in space and time, despite its overestimation against reference dataset. The underlying reasons for this selection lie in its better performance in terms of time series disparities (r, NSD & CRMSE), while the observed average P due to lack of climate stations over snow fed parts of the basins.

Governing ET, its absolute estimates are very few and highly ambiguous over entire UIB including UJB, due to absence of flux towers and high topographic heterogeneity. High discrepancies were observed spatially and temporally for all gridded ET datasets, as compared to P datasets. Among all gridded ET datasets, DOLCE performed reasonably well in terms of magnitude, as well as of spatiotemporal distribution, yet it is unable to represent the high ET rates of Kashmir valley, encapsulated between two mountainous series.

Small differences were found in TWSC derived from CSR-M and JPL-M of RL06 ($r=0.89$), however, the CSR-M shows higher correlation coefficients when compared to water balance derived TWSC for all P and ET combinations. The results indicate that the GRACE mascon solutions, with finer spatial resolution, also provide a satisfactory result for small basins.

High uncertainties in TWB estimates cause imbalance or non-closure errors. The major contribution to imbalance arises from P, mainly during the wet seasons. This shows the significant need to adjust P estimates before using it for impact assessment studies.

Contradictions in P trends over Greater Himalaya are present in the literature. These contrasting results might be due to different datasets and study periods used for trend analysis in each work. In the present study, non-significant mixed trends in annual P at a rate of -21.00 to 48.00 mm/year were observed with increase and decrease in monsoon and winter P, respectively. The

decrease in winter P was found to be significant throughout the basin at either 0.1 or 0.05 significance level. Whereas statistically non-significant increasing trends were observed for all other seasons.

In context to ET, mixed yet statistically significant trends were detected in different parts of the basin at annual and seasonal scale. The mixed trends despite of the increasing temperature in western Himalaya demonstrate that higher ET rates do not correspond to higher temperature rates and vice versa, but they are influenced by a number of factors such as balance of radiations, P rates and vegetation physiological control.

The TWS shows a significant decreasing trend throughout the UJB in winter and annual scale at either 0.1 or 0.05 significance level. The decreasing trend in winter season is directly linked to the decreasing trend of winter P and loss of glacier mass due to global warming in Western Himalaya. However, the decreasing trend in annual TWS, despite of the increasing P in low altitudes areas, is due to rapidly generating runoff that leaves less time for recharging groundwater.

The Q at Mangla station showed increasing trends in all months of the year except January and February during the 2003-2014 period, corresponding to precipitation trends. The early snow melting in combination with increasing P trends, especially in monsoon dominated regions, are primarily reasons of Q increase.

3.6 References

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Chapter 4

Performance evaluation of raw and bias corrected ERA5 precipitation data with respect to extreme precipitation analysis: case study in Upper Jhelum Basin, South Asia

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Abstract

The application of gridded precipitation datasets as a substitute for limited ground observation over mountainous regions is challenging due to considerable biases and need adjustments before their application in subsequent impact models. In this study, four commonly used precipitation bias correction (BC) methods were evaluated for their skills to capture various aspects of extreme precipitation over Upper Jhelum Basin (UJB) for a period of 34 years (1981-2014). The four BC methods i.e linear scaling (LS), local scaling intensity (LOCI), power transmission (PT) and distribution mapping (DM) were applied on ERA5-reanalysis precipitation dataset and evaluated using nine extreme precipitation indices. First, it was found that the raw/original ERA5 overestimate observed precipitation and number of wet days with little precipitation and thus inevitability need correction in raw estimates. Second, more or less all BC methods improved the raw ERA5 estimates especially magnitude, however, clear discrepancies exist in their skills to correct wet-day frequency. Overall DM method was found to be a good compromise to correct various aspects of extreme precipitation and followed by LOCI, PT and LS methods. This study provides twofold potential benefits, firstly, extreme precipitation information tailored the need of relevant decision makers to devise appropriate mitigation and adaptation strategies, and secondly, provides a certain reference for evaluation, correction, and application of gridded datasets for extreme precipitation analysis in data sparse region.

Key words: Precipitation, bias correction, extreme precipitation indices, return levels.

4.1 Introduction

The Jhelum River, being one of the major tributaries of Indus River, supplies water to downstream semi-arid climate to run the largest irrigation network in the world, the mainstay of Pakistan's economy. The source region of Jhelum River (Upper Jhelum Basin-UJB) lies in the foothills of Himalayas, a region that is severely vulnerable to climate change. The basin witnessed an increase in frequency, magnitude, and duration of extreme events during the last few decades (Bhat et al., 2019, Himayoun and Roshni, 2019, Azam et al., 2018, Nasim et al., 2018, Siddiqui et al., 2018, Rasmussen et al., 2015, Commission, 2014). Most of these extreme events (floods, flash floods, landslides, or droughts) are triggered by extreme precipitation events more than any other meteorological event which in turn disrupt human society as well as natural environment (Miao et al., 2019, Yucel et al., 2014). Apart from these direct impacts, extreme precipitation has implications on water management practices by affecting the function, planning, and operation of existing and planned water infrastructure and watershed development activities.

As the key component of the water budget cycle, precipitation holds a crucial importance not only for extreme events analysis but also for studies related to agriculture, hydrometeorology, environment etc. Accurate and reliable precipitation data in terms of amount, intensity, occurrence, pattern and seasonality, are therefore essential for success of these studies, both in retrospective (i.e., past) or prospective (i.e., future) climate contexts (Foufoula-Georgiou et al., 2020). Ideally, the ground-based precipitation measurement from a well distributed rain gauge and/or Radar networks over longest time period is considered to be the most reliable information. However, in

real world conditions, these measurements are limited in space and time especially for the vast and complex terrains of High Mountains of Asia (HMA) and thus hamper accurate characterization of spatiotemporal precipitation patterns (Tang et al., 2018, Shen and Xiong, 2016).

Gridded precipitation datasets constructed on the basis of satellite remote sensing (e.g. the Tropical Rainfall Monitoring Mission-TRMM; (Huffman et al., 2007), ground observations (e.g. APHRODITES; (Yatagai et al., 2012) and Reanalysis (e.g. ERA5; (Tarek et al., 2020, Saha et al., 2010) are widely used as an alternatives of the ground based measurements. These gridded datasets differ in their production mechanism, input forcing datasets, spatial temporal resolution and domain size, leading to inconsistency between an estimate of the same variable (Pellet et al., 2018). Considerable differences exist in these gridded datasets in context of general climatology (Henn et al., 2018, Gampe and Ludwig, 2017, Isotta et al., 2015, Palazzi et al., 2013) and the representation of extremes (Herold et al., 2017). Furthermore, performance of these datasets could vary for different regions and consequently their applicability in different scientific disciplines studies. Various studies investigated the performance of different gridded precipitation datasets over HMA (Baudouin et al., 2020, Nguyen et al., 2018, Song et al., 2016, Rana et al., 2015, Ma et al., 2015, You et al., 2015, Palazzi et al., 2013, Andermann et al., 2011). These studies in general, endorse the biases and uncertainties in existing gridded precipitation datasets and conclude that no single gridded precipitation dataset consistently ranks first in reproducing the spatiotemporal variability of all hydrological processes. This shows the significant need to adjust precipitation estimates before they can be used as input in subsequent impact models.

To date, various bias correction (BC) methods have been developed for precipitation ranging from very simplistic such as “Linear Scaling-LS”, only correcting the statistical mean, to more sophisticated nonlinear ones such as distribution mapping, based on distribution functions (Teutschbein and Seibert, 2012, Haerter et al., 2011). Usually, these methods have been used for BC of GCM or/and RCM outputs but can be used for gridded datasets in sparsely gauged mountainous basins (Ji et al., 2020, Luo et al., 2020, He et al., 2017). The typical biases in the modelled and/or gridded precipitation are the occurrence of too many wet days with low precipitation (Ines and Hansen, 2006), general under- or overestimation and incorrect seasonal variations (Teutschbein and Seibert, 2010, Terink et al., 2009). Various researchers adjusted these biases by employing different BC methods and found variations in their performance for different parent datasets and subsequent implications in different scientific disciplines. For example, (Soo et al., 2020) stated that different gridded precipitation datasets adjusted for biases using same method in a catchment may not necessarily provide similar results. They found that IMERG and TRMM datasets performed better in terms of rainfall and streamflow simulation when bias adjusted using LS and LOCI methods, respectively. (Luo et al., 2020) reported that LOCI and DM performed better than LS and PT for extreme precipitation analysis across Yarlung Tsangpo–Brahmaputra River basin. (Ji et al., 2020) reported that even though distribution-based BC methods performed well, especially for extreme precipitation, their correction effects also depend on the spatial consistency of the bias, which is even more important than frequency matching. Another study conducted by (Smitha et al., 2018) found superior performance of nonlinear methods (DM

and modified PT) than other linear methods (LS and LOCI) for hydrological simulation across six catchments in India. In general, improvement in statistical mean and standard deviation was observed with all BC methods while clear differences exist in their ability to correct skewness and kurtosis (Ji et al., 2020, Luo et al., 2020, Smitha et al., 2018, Vrac and Friederichs, 2015, Fang et al., 2015, Lafon et al., 2013, Teutschbein and Seibert, 2012).

With reference to above introduction, reliability of hydro-meteorological studies on relevant scales depends on accuracy of precipitation data not only with respect to mean but also with respect to intensity (especially extremes), occurrence, intermittency (Ines and Hansen, 2006) as well as spatial-temporal variability across regions and seasons (Maraun et al., 2010). The aim is then to transform the gridded precipitation dataset to have adjusted values with statistical properties/distribution close to those shown by observations, so that they can be used as input into impact assessment models. As extremes are located at the tails of the variable distribution with low probability, its modelling and/or correction are a challenging task. Moreover, understanding of precipitation extreme values in UJB has a number of gaps because of its complex topographical interactions with atmospheric flows, lack of observations, and data-sharing issues, which hinder effective natural resources and disaster management. To the best of our knowledge, no prior studies have been reported to date that investigate the simulation skills of BC methods for aspects that are important for the analysis of extreme precipitation events over UJB.

This study addresses this research gap by investigating the simulation skills of different BC methods in context of moderate to rare extreme precipitation events. Firstly, daily ERA5 reanalysis gridded precipitation dataset is corrected using four BC methods (LS, LOCI, PT DM) with respect to observed data. Then extreme precipitation indices of various aspects that are relevant to extreme precipitation events, are computed using observed, raw and differently corrected ERA5 estimates. The performance of the BC methods is evaluated in terms of biases (difference between observed and corrected data indices) in each index.

4.2 Data Acquisition and Methods

4.2.1 Observed Precipitation

The daily observed precipitation data for the period of 34 years (1981 to 2014) were used as a reference to correct the ERA5 precipitation estimates. The observed precipitation data of 15 climate stations located inside or adjacent to UJB within the political boundary of Pakistan, were acquired from Water and Power Development Authority (WAPDA) and Pakistan Meteorological Department (PMD). In addition, Indian Meteorological Department (IMD) daily gridded precipitation dataset was extracted at the exact locations of five climatic stations to cover the Indian side region of the basin. This dataset is derived from a dense network of meteorological stations for the Indian mainland and available at 0.25° resolution (Pai et al., 2015). The basic information is of these climatic stations are listed in Table 3.1.

4.2.2 Gridded Precipitation Datasets

Five gridded precipitation datasets including Princeton Global Meteorological Forcing Dataset for Land Surface Modeling (PGMFD) (Sheffield et al., 2006), Asian Precipitation Highly Resolved

Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) dataset (Yatagai et al., 2012), Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015), ERA5, reanalysis data by European Centre for Medium-Range Weather Forecasts (ECMWF) (Tarek et al., 2020, Saha et al., 2010) and Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al., 2019, Beck et al., 2017) were evaluated against the observed precipitation at monthly, seasonally and annual scale for a period of 1981- 2014 (Ansari and Grossi, 2021). A brief overview of these datasets is presented in Table 3.2. Based on performance evaluation (Ansari et al. 2023), ERA5 is found to capture the precipitation behavior reasonably well over UJB in space and time, even though it overestimates precipitation, especially during wet seasons. The suitability yet slight overestimation of ERA5 precipitation over the UJB and surrounding basins, especially mountainous region are also reported in literature ((Baudouin et al., 2020). Baudouin et al. (2020) cross-validated 20 gridded precipitation datasets across Indus River including UJB and suggested that ERA5 provided better precipitation estimates in terms of magnitude, temporal distribution, and variability, from daily to multi-annual scale. Despite the better performance of ERA5 in space and time, its overestimation needs to be adjusted before using it for subsequent impact models.

4.2.3 Bias Correction Methods

Four BC methods covering the major types of existing methods were tested for their skills to adjust the biases of ERA5 precipitation estimates over UJB. These BC methods can be broadly classified into two categories: linear methods and nonlinear methods (Table 4.1). The linear methods (LS, LOCI) use monthly correction factors calculated as a ratio between observed and gridded precipitation and correct statistical mean (Teutschbein and Seibert, 2012, Schmidli et al., 2006). The nonlinear methods include PT and DM. The PT method uses exponential form to adjust coefficient of variation along with statistical mean values as in linear scaling method (Leander and Buishand, 2007). The DM method adjusts the cumulative distribution function (CDF) of gridded precipitation to match with the observed precipitation CDF using a transfer function (Sennikovs and Bethers, 2009) and is commonly used to correct the systematic distributional biases (Cannon et al., 2015). The best fit distribution to precipitation time series could be site specific but usually comes from the exponential family of distribution (Foufoula-Georgiou et al., 2020, Balistrocchi et al., 2013, Wan et al., 2005). The Gamma distribution (Thom, 1958) with shape parameter α and scale parameter β (Table 1) from exponential family was found to be suitable for precipitation distributions in the study region (Azmat et al., 2018). The effectiveness of gamma distribution for precipitation analysis has been documented in various studies conducted all around the world (Ji et al., 2020, Luo et al., 2020, Smitha et al., 2018, Teutschbein and Seibert, 2012, Piani et al., 2010, Ines and Hansen, 2006). The LOCI and DM also use gridded data specific precipitation threshold for which lower gridded data (below this threshold) are put to zero to adjust the number of wet days (Sennikovs and Bethers, 2009, Schmidli et al., 2006). This threshold is selected such that the number of days exceeding this threshold for gridded precipitation is same as the number of days with observed precipitation greater than 0 mm. The mathematical equations and parameter

description of BC methods is presented in Table 4.1 along with respective references explaining in detail these methods.

Table 4.1: Mathematical expression of bias correction methods

Method	Equation	Description	References
Linear Scaling (LS)	$P_{Grid,d}^* = P_{Grid,d} \times \left(\frac{\mu_m(P_{obs,d})}{\mu_m(P_{Grid,d})} \right)$	$P_{Grid,d}^*$ and $P_{Grid,d}$ = daily corrected and raw gridded precipitation, respectively.	(Leander and Buishand, 2007)
Local Intensity Scaling (LOCI)	$s = \frac{\mu_m(P_{obs,d} P_{obs,d} > 0)}{\mu_m(P_{Grid,d} P_{Grid,d} > P_{th,Grid}) - P_{th,Grid}}$ $P_{Grid,d}^* = \begin{cases} 0, & \text{if } P_{Grid,d} < P_{th,Grid} \\ (P_{Grid,d} - P_{th,Grid}) \times s & \text{otherwise} \end{cases}$	$P_{obs,d}$ = daily observed precipitation $\mu_m(P_{obs,d})$ and $\mu_m(P_{Grid,d})$ = mean monthly observed and gridded precipitation in the mth month $P_{th,Grid}$ = adjusted threshold for gridded data s = linear scaling factor	(Teutschbein and Seibert, 2012, Schmidli et al., 2006)
Power Transformation (PT)	$P_{Grid,d}^* = a \times (P_{Grid,d})^b$ $f(b_m) = 0 = CV_m(P_{obs,d}) - CV_m(P_{Grid,d}^{b_m})$ $a = \frac{\mu_m(P_{obs,d})}{\mu_m(P_{Grid,d})}$	a and b = parameters of the power transformation CV_m = Coefficient of variation of mth month	(Leander and Buishand, 2007)
Distribution Mapping (DM)	$f_\gamma(x \alpha, \beta) = x^{\alpha-1} \times \frac{1}{\beta^\alpha \times \Gamma(\alpha)} \times e^{-\frac{x}{\beta}}; \quad x \geq 0; \alpha, \beta > 0$ $P_{Grid,d}^* = F_\gamma^{-1}(F_\gamma(P_{Grid,d} \alpha_{Grid,m}, \beta_{Grid,m}) \alpha_{obs,m}, \beta_{obs,m})$	α = shape parameter β = scale parameter F_γ and F_γ^{-1} = Gamma CDF and inverse, respectively $\alpha_{Grid,m}$ and $\beta_{Grid,m}$ = shape and scale parameter of raw gridded data in the mth month, respectively $\alpha_{obs,m}$ and $\beta_{obs,m}$ = shape and scale parameter of observed data in the mth month, respectively	(Sennikovs and Bethers, 2009)

4.2.4 Extreme Precipitation Indices

To characterize the extreme precipitation events, different descriptive indices proposed by the Joint CCI/Clivar/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) (Karl et al., 1999) were computed at each station using the RclimDex package (Zhang and Yang, 2004). These indices condense information from the distribution of daily data and have been widely used

as a standard tool to assess and monitor changes in extremes around the world. These indices only refer moderate to severe extreme events typically occurring several times in a year (Data, 2009).

Apart from these indices, the probable maximum and minimum annual precipitation for 20 years return levels (20 RL-HIGH and 20 RL-LOW) were also considered in the present study, assuming stationarity in time series. The 20 RL-HIGH and 20 RL-LOW refer to exceeding and non-exceeding probability of annual precipitation and represent the values at the two tails of the distribution. The return period of a given event is the average time elapsing between two successive realizations of the event itself or alternatively the return level is the value expected to be exceeded on average, once every return period, or with probability $1/(\text{return period})$ in any given year (Vezzoli et al., 2012, Data, 2009). In this study, a standard method known as “Plotting order-ranked data” was used to estimate return levels of specified return period from observed data (Chow, 1964). The method includes following steps, (i) rank the annual precipitation data of a period of N years in order of magnitude; (ii) calculate cumulative probability (P) for each data point using the Weibull plot position formula ($P = m/(N + 1)$), where m is the rank and N is the total number of years; (iii) calculate return period (T) from cumulative probability (P) by using the formula ($T=1/P$); (iv) plot annual precipitation (y-axis) versus return period (x-axis) and fits a suitable model/line; (v) interpolates or extrapolates from the graph to estimate the return level of the interested return period (Risley et al., 2008, Makkonen, 2006).

The brief summary of selected precipitation indices covering different aspects are presented in Table 4.2. The indices were computed at each station for the observed, raw, and bias corrected gridded data. Regarding threshold indices, authors preferred to use percentile thresholds rather than fixed thresholds. The underlying reason is that the exceeding percentile thresholds is more evenly distributed in space and is meaningful in every region. Moreover, percentile thresholds indices allow for spatial comparisons because they sample the same part of the probability distribution of precipitation at each location (Data, 2009).

Table 4.2: Detailed description of extreme precipitation indices used in this study.

Aspect	Index	Description	Unit
Absolute	PRCPTOT	Annual total precipitation from days ≥ 1 mm	mm
	SDII	Simple daily intensity index (ratio of annual total precipitation to the number of wet days ≥ 1 mm)	mm/day
	WDP	wet day probability (Number of wet days in a specified time period)	%
Threshold-based	R95p	Very wet days (Annual total precipitation of days in >95th percentile)	mm
	R95pTOT	Contribution to total precipitation (PRCPTOT) from very wet days (R95p)	-
Duration	CWD	Consecutive wet days (Annual maximum number of consecutive days with precipitation ≥ 1 mm)	Days
	CDD	Consecutive dry days (Annual maximum number of consecutive days with precipitation below 1 mm)	Days
	20 RL-HIGH	Probable maximum annual precipitation for 20 years returns levels.	mm

Return Levels (RL)	20 RL-LOW	Probable minimum annual precipitation for 20 years returns levels	mm
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4.2.5 Performance evaluation

The four BC methods were evaluated regarding their skills to capture various aspects of extreme precipitation from reanalysis precipitation dataset (ERA5) for the period of 1981-2014. The selection of the time period is motivated by the availability of the observational data and whole analysis was carried out at station basis since interpolation of the station data can introduced uncertainties and hence results of bias correction may biased due to interpolation. The calibration and evaluation of BC methods were carried out over the same time period. However, our approach can be considered independent since the evaluation was carried out against various aspects of descriptive extreme precipitation indices from ETCCDI and 20-years return levels, which is not directly corrected by the BC methods (Casanueva et al. 2019). The indices computed from raw and corrected datasets were compared with those calculated from observed data in space and time. For the evaluation of BC method in a more quantitative way, biases were calculated over spatially and temporally averaged values of indices. For each index, BC methods were ranked according to biases (lower the rank, the better the performance). The indices and ranks were also computed on the raw ERA5 estimates to assess the added value of the four BC methods. Note that same ranks were assigned when the relative absolute difference between two values of a given index (i.e., $100 \times |\text{value1} - \text{value2}| / |\text{value1}|$) was lower than 10%. The averaged rank was calculated as a ratio of sum of ranks awarded to number of indices for each BC method, which allows summarizing the various indices.

4.3 Results

4.3.1 Temporal Variation of Extreme Precipitation Indices

Temporal variations (1981-2014) in multi station average time series of each index calculated from observed, raw and corrected datasets are presented in Fig. 4.1. Based on observed data, annual total precipitation from days with greater than 1 mm (PRCPTOT) shows a slight increasing trend in the first half of the period (1981-1997) with small fluctuations. A deep dip in PRCPTOT from 1998 to 2003 shows the severe drought period in the history of Pakistan. Afterwards, PRCPTOT shows small fluctuations around its long term mean value. Raw ERA5 overestimates the PRCPTOT as also reported by many authors around the world (Baudouin et al., 2020). In context to adjustments in PRCPTOT, all BC methods improve the PRCPTOT estimate during the whole study period except for the period of 1995-1996, where comparatively larger difference exists than in other time periods.

The 20 RL-HIGH and 20 RL-LOW for the observed dataset are 1973 mm and 550 mm which were well simulated by DM corrected dataset. Interestingly, the raw ERA5 estimate for 20 RL-HIGH was closer to observed estimate than LS, LOCI and PT methods, meaning that these methods can degrade some extreme analysis values of the data to be corrected. In case of 20 RL-LOW, only DM method performed well whereas the raw and other three BC methods (LS, LOCI and PT) were unable to satisfactorily represent the observed values.

Simple daily intensity index (SDII) from the observed dataset varies between 8.96 to 17.01 mm/day with small fluctuations around its long-term mean (11.93 mm/day). These fluctuations in SDII values well correspond to the extreme events that occurred in the basin during study period. For instance, the longest period for the SDII values lower than the long-term mean represents the longest drought observed in the basin. Whereas the notable floods events ranging from moderate to severe occurred in the years of 1988, 1992, 1994, 1997, 2007 and 2014 and are well captured by the observed data. The raw ERA5 data under and over-estimate the SDII and WDP respectively, due to too many wet days with low precipitation amount. Regarding the BC methods performance, clear differences exist in their abilities to adjust the SDII and WDP values. The LOCI and DM outperformed the LS and PT method. The higher skills of DM and LOCI methods in improving the SDII and WDP correspond to the adoption of a threshold approach for the adjustment of the number of wet days.

Percentile threshold-based index R95p, which represents the amount of precipitation in a year from very wet days, varies between 160-525 mm with long term mean of 305 mm for the observed dataset. R95pTOT, which shows the fraction of precipitation from these very wet days, ranges from 0.14 to 0.34 with long term mean of 0.23 for the observed dataset. Both indices (R95p and R95pTOT) follow similar temporal patterns with large inter-annual fluctuations. Regarding raw and bias corrected datasets, the performance of LOCI and DM based corrected datasets were found to be superior to raw and other bias corrected datasets. The PT method shows large differences for R95pTOT even more than raw dataset, meaning that this method can degrade some statistical properties of the gridded data to be corrected.

Length of wet and/or dry spells (CWD and/or CDD) are obviously important features in many domains that BC methods have to reproduce correctly. The observed values of CWD and CDD amount to 6-15 and 25-74 days, respectively. Overall, CDD tended to increase slightly with large fluctuations whereas CWD remained stable with small variations. Too many wet days in original ERA5 precipitation datasets lead to over and under estimation of CWD and CDD, respectively. Likewise, overestimation of CWD was disseminated to LS and PT corrected datasets as no wet day frequency correction was applied in these methods. Again, temporal distribution of CWD is well represented by DM and LOCI methods with small overestimation, pointing to the added value to the original ERA5 in reducing the drizzle effect (too many wet days with small amount of precipitation). In the case of CDD, a small difference was found among DM, PT and LOCI methods while LS implied negligible improvement in raw ERA5 data.

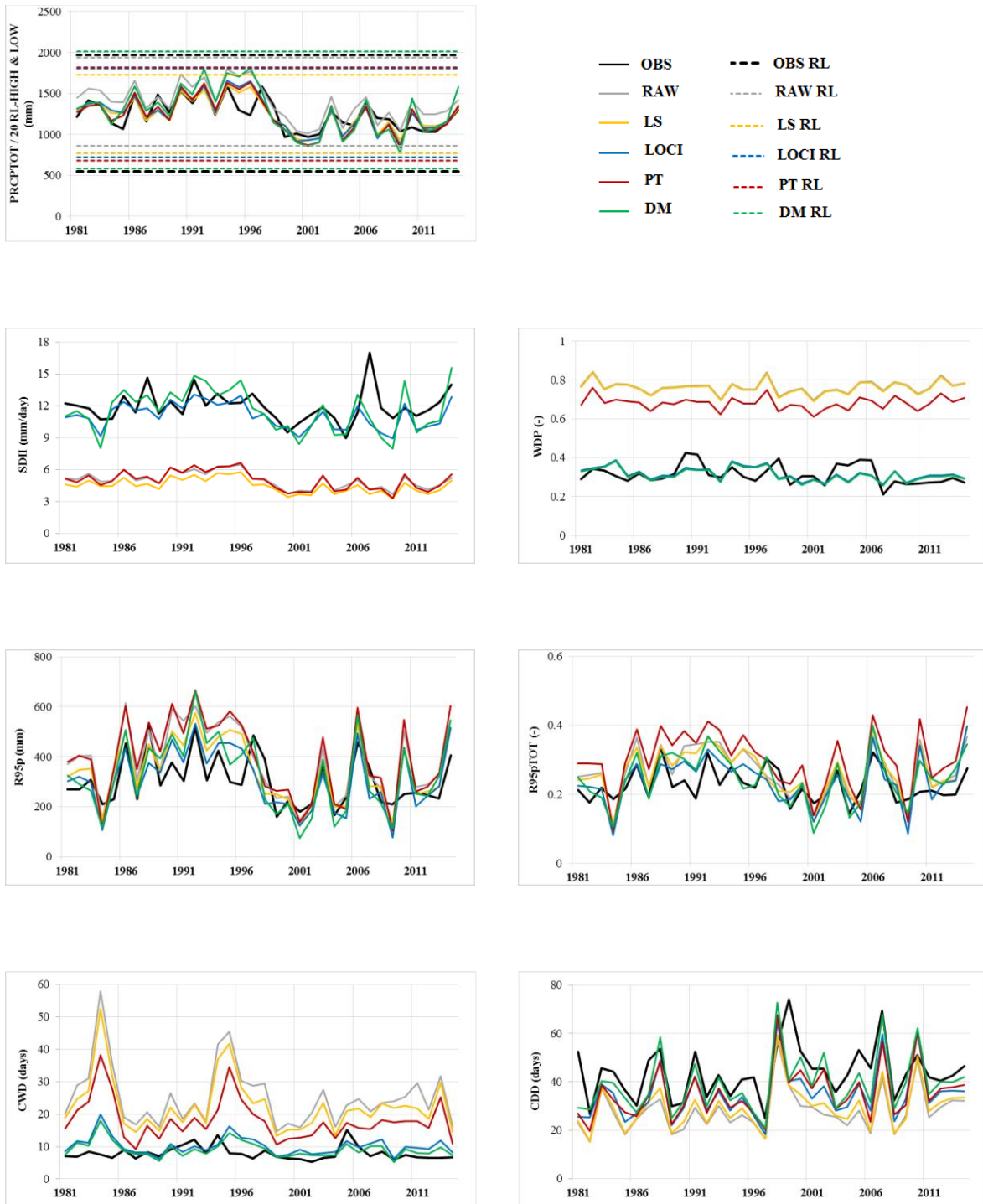


Figure 4.1: Temporal variation of extreme precipitation indices calculated from observed, raw and bias corrected ERA5 estimates for the period of 1981–2014

4.3.2 Spatial Distribution of Extreme Precipitation Indices

Spatial distributions of different extreme precipitation indices calculated from observed, raw and corrected datasets for the period of 1981–2014 are shown in Fig. 4.2. Based on the 20 local station observations located inside and adjacent to basin, PRCPTOT showed an increasing tendency from low to high elevation areas. The raw ERA5 shows larger discrepancies in PRCPTOT especially at those stations located in low elevation areas. The post correction values of PRCPTOT with each BC method were much closer to that of observed one which shows their higher skills to correct yearly averaged PRCPTOT values. Regarding SDII and WDP, it is generally expected to have inverse relation (Casanueva et al., 2014), which can also be seen in present study (Fig. 4.2). The higher values of SDII at lower and higher altitudes stations primarily correspond to monsoon and winter season precipitation, respectively. These indices obtained from raw ERA5 data show huge discrepancies throughout the basin due to drizzling effect which further propagated to LS and PT methods. The LOCI and DM methods proved to have significant value addition in raw ERA5 output.

The mean annual precipitation amount from very wet days (R95p) is found to be in the range of 220–420 mm/year for the observed dataset. The stations located at middle elevation areas of the basin were found to record more intense values whereas less intense values were observed for the valley-based stations. The performance of raw and all corrected datasets varies spatially for R95p. Visually LOCI corrected dataset presents relatively better performance followed by DM. The performance of LOCI was found to be inferior to DM at low and high-altitude stations whereas for mid elevation stations LOCI performance was better than DM. The contribution of precipitation from very wet days to the annual precipitation (R95pTOT) was in the range of 0.15–0.26- for observed dataset. R95pTOT presents a similar pattern across the whole basin with little variations. The major contribution of precipitation from very wet days to annual precipitation was from monsoon and winter precipitation at lower and higher altitudes, respectively. Similar to R95p, LOCI and DM reasonably simulate spatial patterns of R95pTOT with small differences at few stations.

Overall spatial distribution of mean annual CWD showed north to south decreasing tendency whereas the spatial distribution of mean annual CDD was exactly opposite. The station (Naran) located in northwest of the basin showed/holds highest number of CWD resulting in highest value of PRCPTOT and at the same time comparatively lower occurrences of very wet precipitation days resulting in lower values of R95p and R95pTOT. The raw ERA5 data highly overestimated the CWD over mid to high altitude regions of the basin whereas exactly opposite spatial distribution was seen for CDD. The over and under-estimation of CWD and CDD are the result of drizzling effect (too many days with negligibly small amount of precipitation). As expected, CWD index was well represented by datasets adjusted using LOCI and DM methods. On the other hand, more or less all BC methods except LS present satisfactory results for CDD.

The spatial patterns of 20 RL-HIGH are similar to those of PRCPTOT with higher magnitude. Whereas spatial patterns of 20 RL-LOW showed variation with those of PRCPTOT at few stations. For instance, Naran station located at the northwest of the basin receives the highest amount of PRCPTOT (1761 mm) and shows the highest (3283 mm) and lowest (225 mm) values

of 20 RL-HIGH and 20 RL-LOW, respectively. In contrast, Murree stations almost receives similar amount of annual precipitation as Naran station but exhibit many differences in 20-year return levels especially for the lower end. This depicts that the higher PRCPTOT does not necessarily correspond to higher return levels at both ends. The spatial pattern of 20-year return levels from observed dataset were in the range of 1260-3283 mm/year and 225-1096 mm/year for the high and low end, respectively. High ends return levels are found to be more intense at mid to high elevation stations/areas of the basin whereas low ends return levels were more intense at low and high elevation stations. The high-end return level from raw ERA5 data was relatively better simulated than low end return levels. All BC methods reproduce somewhat similar spatial patterns of 20 RL-HIGH with slight differences among themselves as well as with respect to observed. In context to 20 RL-LOW, performance of nonlinear methods (PT and DM) was found to be better than linear methods (LS and LOCI), however none of the BC method reproduce the lowest value of 20 RL-LOW at Naran station.

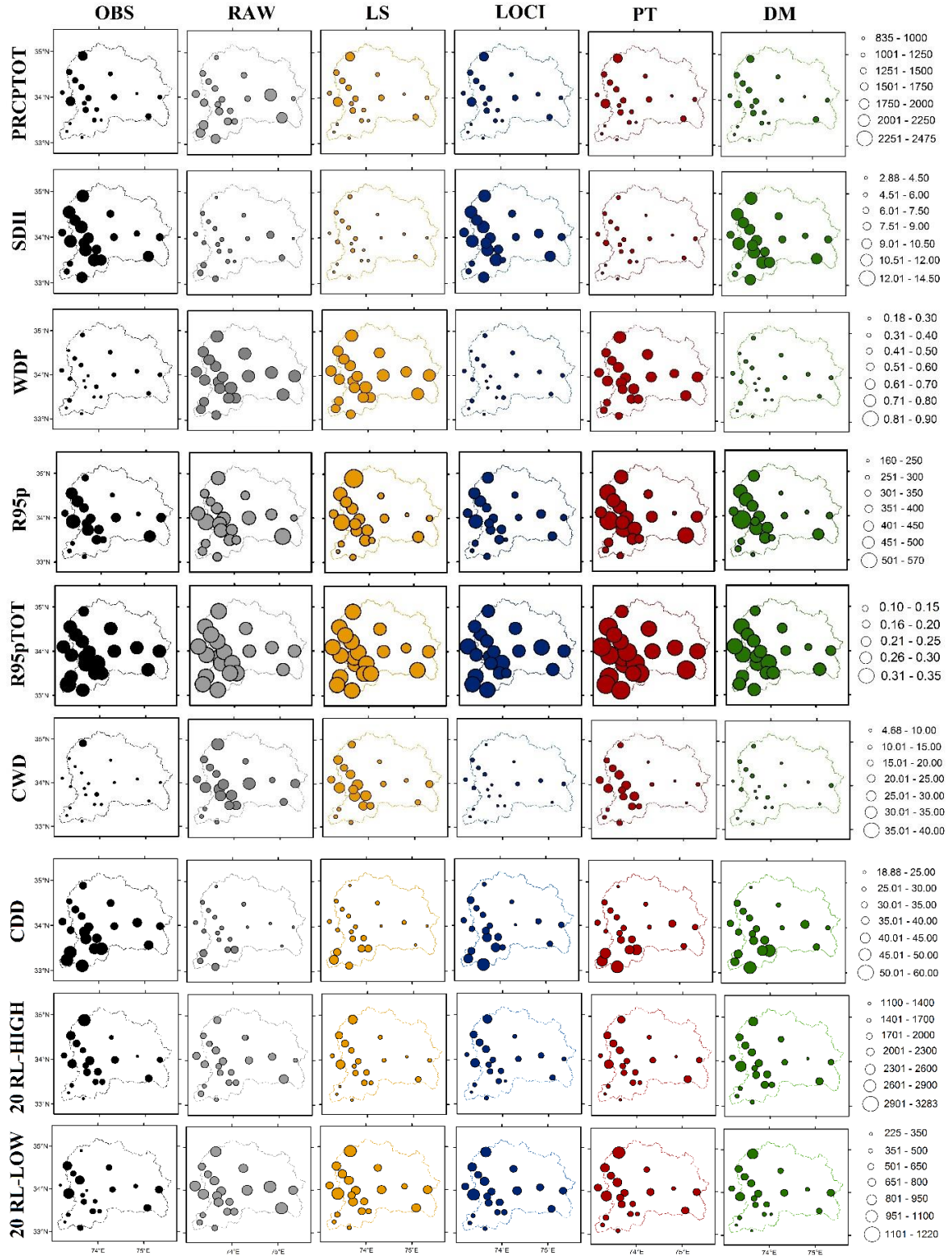


Figure 4.2: Spatial distribution of extreme precipitation indices calculated from observed, raw and bias corrected ERA5 estimates across UJB

4.3.3 Vertical Distribution of Extreme Precipitation Indices

The distribution of extreme precipitation indices with respect to elevation are depicted in Fig. 4.3. Based on the 20 local station observations located inside and adjacent to basin, all indices showed slight increase or decrease in values from low to high elevation stations which depicts weak correlation of precipitation with elevation. The PRCPTOT, SDII, WDP, R95p and 20 RL-HIGH were increasing with low to high elevation stations whereas CDD index decreased with increase in elevation. The CDD and R95pTOT indices changed a little with elevation except for the Naran station which showed irregular behaviour with respect to other stations. The 20 RL-LOW showed higher fluctuations with no specific pattern. Regarding raw ERA5 and bias corrected datasets, DM and LOCI methods performed better than raw ERA5, LS and PT methods for most of the indices. However, none of the BC method well reproduced the vertical distribution of 20 RL-LOW as of observed one.

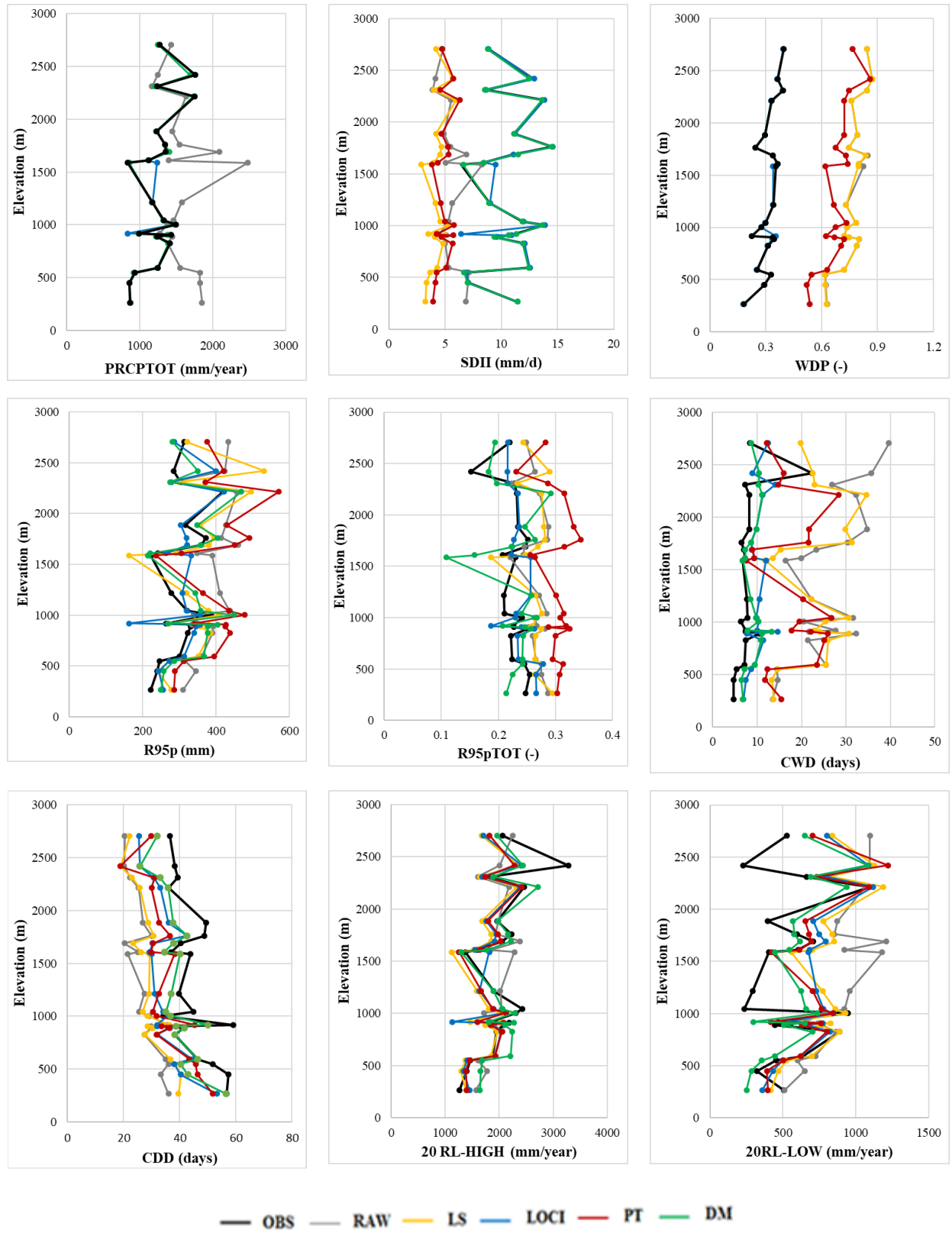


Figure 4.3: Vertical distribution of extreme precipitation indices calculated from observed, raw and bias corrected ERA5 estimates across UJB.

4.3.4 Evaluation of extreme precipitation indices

The quartiles of the stations' biases as difference between the observed and raw/corrected values for each BC method are given in Fig. 4.4. These biases are calculated from the temporally averaged indices at all stations. The raw ERA5 estimates present huge biases (mainly overestimation) for PRCPTOT, ranging from -1000 to 500 mm/year. All BC methods significantly reduce the biases in PRCPTOT with mean bias in the range of -12 to 10 mm per year. The raw ERA5 dataset highly under and overestimate the SDII and WDP indices with biases in range of -1.89 to 9.0 mm/day and -0.29 to -0.51 respectively. Since no wet day frequency correction has been made in LS and PT methods, they show a bias propagation of approximately same magnitude as in raw ERA5 estimates. The LOCI and DM methods matched gridded data wet day frequency with observed one by adopting a threshold, resulting in much lower biases in SDII and WDP. The biases in R95p and R95pTOT indices for the raw ERA5 estimates were in the range of -166.84 to 47.54 mm and -0.112 to 0.009, respectively. Biases were reduced by each BC method except PT which showed no improvement for R95p and even degraded the R95pTOT values. Similar to SDII and WDP, the CWD index was also highly overestimated by raw ERA5 data and approximately similar magnitude of biases transferred to LS and PT methods. Although both LS and PT methods do not apply any adjustment to wet day frequency, PT based corrected dataset shows slight lower biases than raw and LS corrected datasets. This means that very low precipitation frequency was adjusted during variance correction step of the PT method. For raw ERA5, underestimation of CDD was in the range of 5-24 days. More or less some improvement was seen in corrected datasets. DM method was found to be least biased followed by PT, LOCI and LS. In case of return levels, raw ERA5 have biases in the range of -903 to 583 mm/year and -870 to 162 mm/year for 20 RL-HIGH and 20 RL-LOW, respectively. DM corrected dataset shows least biases followed by PT, LOCI and LS for both indices. The absolute mean values of bias in 20 RL-HIGH were -41.43, 155.59, 170.38 and 245.82 for DM, PT, LOCI and LS, respectively. Whereas absolute mean values of bias in 20 RL-LOW were -32.35, -133.23, -175.18 and -220.34 for DM, PT, LOCI and LS, respectively.

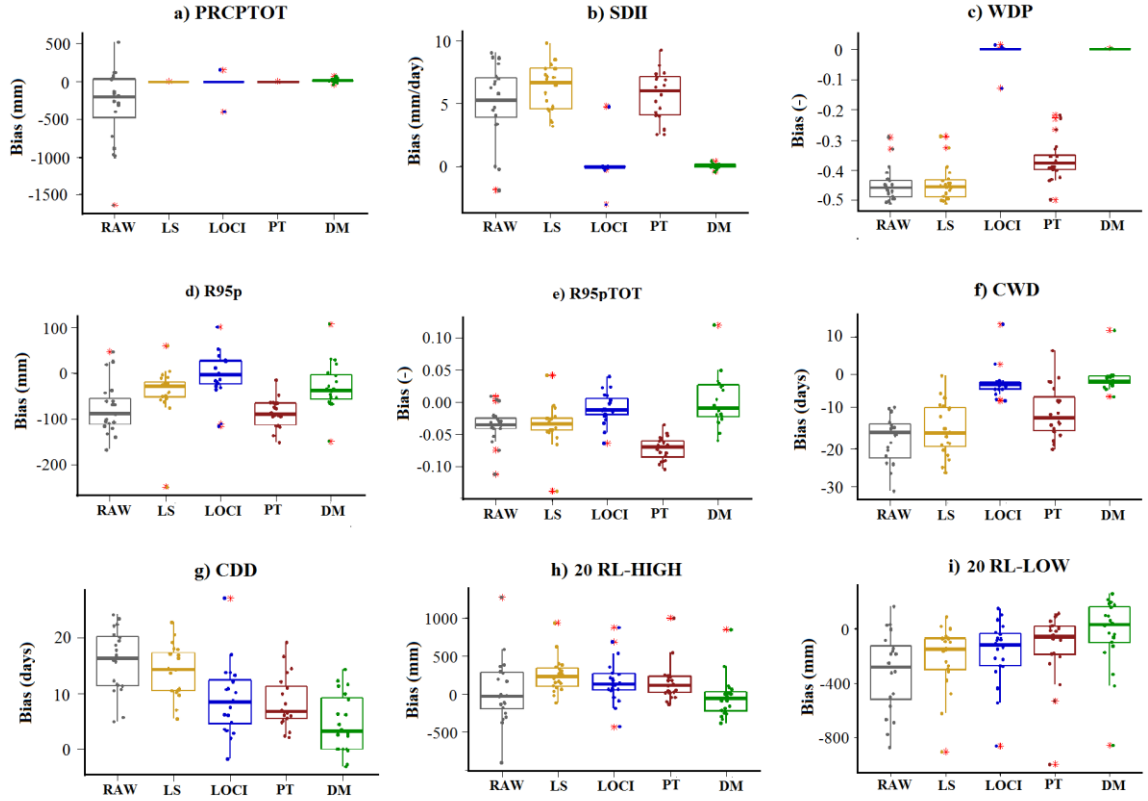


Figure 4.4: Box-whisker-plot summary of biases in each index for the raw and corrected ERA5 estimates

In order to provide a more quantitative assessment of spatial-temporal visual evaluations, Table 4.3 presents the spatial and temporally averaged values of biases in indices calculated from raw and corrected datasets. For each index, a ranking among the BC method is indicated in brackets: the lower the ranking, the better the performance. The numerical values in Table 3 outline some differences between BC methods. For most of the indices, DM got lower ranks except PRCPTOT where it ranked at 3. On the other side, LS method could be able to get higher ranks for all indices except PRCPTOT which ranks at 2. In context to different aspects of precipitation correction, lowest average ranks were assigned to DM method whereas the highest ranks were assigned to raw ERA5 dataset, except return levels where LS method has highest rank, degrading, on average, the raw ERA5 output. There was a tie in the average ranks between LOCI and PT for the absolute aspects and LOCI and DM for the percentile-based indices. Overall DM has the best rank (1.44), followed by LOCI (2.22), PT (2.89), LS (3.44) and raw/original ERA5 (3.67).

Table 4.3: Spatially and temporally averaged biases in indices computed from raw and BC corrected datasets

Aspects	INDCIES	RAW	LS	LOCI	PT	DM
Absolute	PRCPTOT	-324.399 (5)	-0.004 (2)	-12.366 (4)	0.003 (1)	10.900 (3)
	SDII	5.033 (2)	6.262 (4)	0.020 (1)	5.672 (3)	0.019 (1)
	WDP	-0.448 (4)	-0.446 (4)	-0.004 (2)	-0.367 (3)	0.002 (1)
	Average rank	3.67	3.33	2.33	2.33	1.67
Percentile-based	R95p	-75.730 (4)	-38.924 (3)	-4.967 (1)	-87.173 (5)	-28.040 (2)
	R95pTOT	-0.036 (3)	-0.036 (3)	-0.009 (2)	-0.072 (4)	0.003 (1)
	Average rank	3.50	3.00	1.50	4.50	1.50
Duration	CWD	-17.338 (5)	-14.613 (4)	-2.188 (2)	-10.124 (3)	-1.178 (1)
	CDD	15.837 (4)	14.196 (3)	9.060 (2)	8.404 (2)	4.576 (1)
	Average rank	4.50	3.50	2.00	2.50	1.00
Return	20 RL-HIGH	35.463 (1)	245.819 (4)	170.377 (3)	155.599 (3)	-41.839 (2)
Levels	20 RL-LOW	-315.557 (5)	-220.344 (4)	-175.175 (3)	-133.228 (2)	-32.351 (1)
	Average rank	3.00	4.00	3.00	2.50	1.50
	Overall rank	3.67	3.44	2.22	2.89	1.44

4.4 Discussion and Conclusion

In present study, two linear and two nonlinear BC methods have been evaluated regarding their skills to capture station based local climate, regarding different aspects of precipitation extremities from reanalysis precipitation dataset (ERA5). The study was conducted over UJB located in the foothills of western Himalaya for a period of 1981-2014. The high vulnerability of the region to the changing climate and consequently increasing rate of extreme events demands more efforts towards sustainable water resources management and mitigation measures in the basin. The raw ERA5 dataset estimates too many wet days with low precipitation instead of substantial dry days leading to large biases when compared against station based observed data. This shows the clear necessity of bias adjustment/correction before its application in subsequent impact models. Regarding the descriptive extreme precipitation indices, the raw ERA5 estimates showed large overestimation in most instances except SDII and CDD. The underlying reason of over/under estimation of raw ERA5 output is the spatial mismatch, as ERA5 provides area averaged values which cause inaccuracy in presentation of extremes with respect to point information at the station (Donat et al., 2013). Similar limitations are also presented by other gridded datasets (Ji et al., 2020, Luo et al., 2020, Soo et al., 2020). Moreover, most extremes occur from a complex interplay of large and local scale factors involving small-scale thermodynamic processes, which are not assimilated and modelled to the full extent by reanalysis such as ERA5 (Hertig et al., 2019). This is especially true for the diagnostic variable precipitation, and thus precipitation extremes. For instance, limited information of small-scale process and spatial

mismatches and/or scale gap between ERA5 and station data result in a strong drizzle effect. Consequently, wet spells (CWD) and wet day probability (WDP) are overestimated, whereas dry spells (CDD) and precipitation intensity (SDII) are generally underestimated in ERA5.

Currently various bias correction methods have been employed ranging from very simplistic linear scaling to sophisticated one (Teutschbein and Seibert, 2012). More or less all BC methods were able to improve the raw ERA5 output in most instances. All BC methods show slight differences in mean precipitation values, however considerable differences exist for other indices. Linear BC methods (LS and LOCI) employed a single correction factor for both mean and standard deviation (Leander and Buishand, 2007), yielding suspicious precipitation variability. Whereas nonlinear BC methods (PT and DM) adjusts coefficient of variation along with mean values (Teutschbein and Seibert, 2012), resulting in more reliable estimates. To reduce the drizzling effect, present in raw ERA5 data, LOCI and DM employed a threshold exceedance for raw ERA5 output to match the wet day frequency to the observed dataset, whereas no adjustment has been made in LS and PT methods regarding this context. This leads to major discrepancies among BC methods for various indices such as SDII, WDP, CWD and CDD and consequently have significant added value in raw/original ERA5.

Apart from the descriptive indices for moderate extreme events, BC methods also evaluated for rare events that lie far in the tails of the probability distribution. Although the extremes in the tails of the distribution are not necessarily related to environmental disasters, it is very likely that a systematic change in weather extremes will also be escorted by a systematic change in extreme impact events (Hertig et al., 2019). The present study also evaluated all BC methods for probable maximum and minimum annual precipitation that expected to be exceeded on average, once every 20 years, i-e 20 RL-HIGH and 20 RL-LOW. The raw ERA5 which overestimated the PRCPTOT performed better for 20 RL-HIGH, whereas exactly opposite results were found for the 20 RL-LOW. Regarding BC methods, DM shows higher skills to capture similar patterns of 20 RL-HIGH and 20 RL-LOW, as observed. Interestingly, raw ERA5 simulations provide better results than LS method that even degrade the raw ERA5 output.

The spatial distribution of biases in raw ERA5 estimates were consistent in terms of overestimation in number of rainy days throughout the basin, however, the precipitation amount is highly overestimated at lower altitudes stations and underestimated at few high-altitude stations. This showed the spatial variation in ERA5 performance for two distinguish regions, i-e westerlies dominated sub basins (Neelam and Kunhar) and monsoon dominated sub basins (Poonch and Kanshi). The regional differences in ERA5 performance are due to the unusual mountainous terrain in the UJB, which is in the vicinity of the Western Himalaya. All BC methods brought significant improvement in under and/or over estimation of precipitation amount only, but not for the case of frequency of wet days. Overall, not a single BC method are able to reproduce the similar spatial patterns as observed data for all indices.

The temporal variation of extreme precipitation indices well corresponds to the extreme events occurred in the basin during study period. For instance, the longest drought period occurred from late 1990s to early 2000s, as evident in Fig. 2 (PRCPTOT, CWD, and CDD). The drought

started in 1998 and was considered to be the worst in the history of Pakistan, affecting agricultural growth by 2.6% during 2000-2001 (Ahmad et al., 2004). The drought spell 2001-2002 resulted in water shortage of up to 51% of normal supplies as against 40% of the previous year (Ahmad et al., 2004). Likewise, the notable flooding events ranging from moderate to severe occurred in the years of 1988, 1992, 1994, 1997, 2007 and 2014 (Bhat et al. 2019) were well represented by the DM and LOCI corrected data which proves significant added value of these BC methods. The vertical distribution of extreme precipitation indices showed a slight increased or decreased in indices values with increase in station elevation. Whereas some indices showed irregular vertical distribution with fluctuations. There might be two possible reasons for such distribution. The first is that all stations are located at low elevation up to 2705 m ASL whereas the basin elevation ranges from 223 m to 6210 m ASL. The other possible reason is the weak correlation of basin precipitation with elevation. A study conducted by (Qamar et al., 2017) found homogeneity in terms of statistical characteristics of rainfall extremes over UJB and overlooked the elevation in TRMM precipitation correction. About raw ERA5 and bias corrected datasets, DM and LOCI methods performed better than raw ERA5, LS and PT methods for most of the indices except 20 RL-LOW which none of the BC method able to reproduce.

Findings of our study reaffirmed the previous studies that evaluated the BC methods in context of hydrological simulations using different gridded datasets. For instance, (Smitha et al., 2018) found better performance of nonlinear methods (DM and modified PT) than other linear methods (LS and LOCI) for hydrological simulation across six catchments in India. (Jakob Themeßl et al., 2011) also evaluated an ensemble of seven empirical-statistical methods to adjust daily precipitation estimates in Alpine region and found superior performance of DM, particularly at high quantiles, which is favorable for applications related to extreme precipitation events. (Ji et al., 2020) reported the underestimation of extreme runoff in Yarlungzangbu-Brahmaputra River basin when VIC hydrological model was driven by LS, LOCI corrected APHRODITE precipitation estimates whereas the correction method combining LS and DM reproduce the extreme runoff closest to the observed runoff. This study further confirms the conclusions of (Luo et al., 2020) and (Teutschbein and Seibert, 2012).

Overall, these results tend to conclude that based on these indices covering different aspects of extreme precipitation, DM is the most reliable method among those tested to obtain bias-corrected precipitation closest to that of observed dataset, when gridded datasets and/or model obey traditional assumption of “too many wet days”. Moreover, the performance of these BC methods may vary for other regions, parent datasets and their subsequent implications in different scientific disciplines. The study provides a certain reference for evaluation, correction, and application of gridded datasets for extreme precipitation analysis in data sparse region, which could be of practical value to inform policymakers and local stakeholders on the potential hydro-meteorological risk and therefore more effective water resources management practices and climate change adaptation plans.

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Chapter 5

Spatio-temporal Evolution of Extreme Wet-Dry Event Characteristics and their Transition across Upper Jhelum Basin (UJB)-South Asia

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Abstract

The increasing rate of occurrence of extreme wet and dry events (drivers of hydrological floods and droughts) and their rapid transition magnifies the associated socio-economic impacts with respect to those caused by the individual event. Understanding of spatio-temporal evolution of extreme wet-dry events collectively, their characteristics and transition i.e., wet to dry (W-to-D) and dry to wet (D-to-W) is therefore significant to identify and locate most vulnerable hotspots, providing the basis for the adaptation and mitigation measures. The Upper Jhelum Basin (UJB)-South Asia is selected as a case study, where the relevance of extreme wet-dry events and their transition have not been assessed yet, despite clear evidence of climate change in the region. The Standardized Precipitation Evapotranspiration Index (SPEI) at the monthly time scale is applied to detect and characterize wet and dry events for the period 1981-2014. The results of temporal variations of SPEI showed a strong change in basin climatic features associated with El Niño Southern Oscillation (ENSO) at the end of 1997, with the prevalence of wet and dry events before and after 1997 respectively. The results of spatial analysis show a higher susceptibility of the monsoon-dominated region towards wet events, with more intense events occurring in the eastern part, whereas a higher severity and duration is featuring in the southwestern part of the basin. In contrast, westerlies dominated region is found to be the hotspot of dry events with higher duration, severity, and intensity. Moreover, the surrounding region of the Himalaya divide line and the monsoon-dominated part of the basin are found to be the hotspots of rapid wet-dry transition events.

5.1 Introduction

There is growing evidence that recent warming is leading to significant alteration in hydrological cycle, exacerbating extreme weather events in general (Peterson et al., 2012) in many regions of the world. Meteorological wet and dry extreme events (drivers of hydrological floods and droughts) and their rapid successions (recurrent spells) during the past few decades have taken a heavy toll on both life and property. Moreover, such events can have large impacts on water availability, agriculture and food security, power production, and natural ecosystems (He et al., 2019, Sheffield and Wood, 2012). These events are projected to regionally intensify and be more frequent within the context of global warming, underscoring the importance of research on wet–dry extreme weather events collectively. The climate change projections for Asia continent in the sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) reported that during the 21st century South Asia is likely to face more intense and frequent heatwaves and humid heat stress, whereas both annual and summer monsoon precipitation will increase, with enhanced inter-annual variability (medium confidence) (Zhongming et al. 2021). Various studies at local, basin, national and regional scale already documented and acknowledged the vulnerability to climate change of that region (He and Sheffield, 2020; Zhao et al. 2020; Visser-Quinn et al. 2019; He et al. 2017).

Typically, extreme wet and dry events are generally considered independently in water resources management and planning. However, these events are inherently interconnected and governed by the same underlying hydrological processes and atmospheric dynamics, which may

augment hydro-climatic variability under the influence of climate change (He and Sheffield, 2020). A number of wet-dry rapid altered events in the last decade acknowledged the relevance of sequences of wet and dry events. For example, the California's large scale flood event in 2017 occurred at the offset of prolonged drought (2011-2016) (He et al., 2017, Information, 2018). South Carolina observed an abrupt transition (within a week) from drought to flood in September 2015 (He and Sheffield, 2020). Other examples include the successive drought and flood events of 2010–2012 and 2015–2016 in the UK (Parry et al., 2013) and Tasmania, Australia respectively (CSIRO, 2018). Such abrupt flood-drought transitions put a substantial risk for water management practices, especially for reservoir operation, as a trade-off should be set between short-term flood-control and long-term water-storage imperatives to satisfy water demand (He and Sheffield, 2020). This has aroused widespread concern in the scientific community to understand the wet-dry interplay under a changing environment.

During the past few decades, significant effort is put forward towards the adoption of multi-hazard approach (consideration of both types of extreme hydrological conditions at the same time) in developing resilience to climate change. (Kourgialas, 2021) analyzed floods and droughts collectively in the Mediterranean agricultural region, and proposed water-saving and flood protection measures for adapting to the inevitable adverse effects of climate change. (Visser-Quinn et al., 2019) identified hotspots regions in UK where spatio-temporally concurrent increase in the number of flood and drought events are projected. (Zhao et al., 2020) investigated the rapid transition of flood and drought events under present and future climate change in the Hanjiang Basin and found more frequent drought to flood rapid transition events of higher intensity in the 21st century. Other examples include the analysis of rapid drought to flood transitions in river basins in China (Yan et al., 2013) and in England and Wales (Parry et al., 2013). These studies employed the peak over threshold (POT) method and various indices recommended by the World Meteorological Organization (WMO) for the detection and characterization of wet-dry extreme events.

Some commonly used indices are the Standardized Precipitation Index (SPI) (McKee et al., 1993), Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010), Palmer Drought Severity Index (PDSI) (Palmer, 1965), normalized difference vegetation index (NDVI) (Tucker, 1979), Standardized Drought Indices (SDI) (Svoboda and Fuchs, 2016), and Standardized Anomaly Index (SAI) (Katz and Glantz, 1986). Among these indices, SPI and SPEI are more widely accepted for the following reasons: a) simple to calculate, b) require few input data (precipitation and temperature), that are easily accessible in most cases, c) standardized indices, which facilitate the comparison of different climatic zones, and d) can be calculated at multiple timescales, depending on the objective. For instance, SPI and SPEI at short timescales (1, 2, 3 or 6-month) better reflect the meteorological and agricultural drought, while longer time scales (12, 24 or 48 months) are usually considered in hydrology (Kourgialas, 2021). The calculation of SPI and SPEI is mathematically similar, but it differs in the input parameters. The SPI index only uses precipitation, whereas SPEI is based on the climatic water balance. Many studies advocate the use of SPEI, rather than SPI, due to its link to potential evapotranspiration

(PET), which makes it more sensitive in the context of global warming (Himayoun and Roshni, 2019, Yao et al., 2018, Huang et al., 2017, Vicente-Serrano et al., 2010).

In this study, attempts are made to understand the regional evolution of extreme wet-dry events collectively (as drivers of hydrological floods and droughts), their characteristics and transition (W-to-D and D-to-W) for different severity levels ranging from moderate to extreme. Here, the term “wet and dry events” does not necessarily imply observed flood and drought events, unless explicitly mentioned. There exists a basic difference between a flood and a wet event. The former has a short duration effect (e.g., a few hours or days) while the latter is regarded as a long period without precipitation shortage (e.g., several months or years) (Wu and Chen, 2019).

The proposed framework is implemented with reference to the Upper Jhelum Basin (UJB), where the relevance of wet-dry events and their transition have not been assessed yet, despite clear evidence of climate change in the region. The UJB is located in Western Himalaya and shared by Pakistan and India. The region already witnessed an increase in extreme hydro-meteorological events in the last few decades, but these events are expected to become even more pronounced in the coming future (Pachauri et al., 2014). A study conducted over the Northern Highlands of Pakistan investigated the trends in time distribution patterns (TDPs) and return periods for event based extreme precipitation for a period of 1961 to 2014 and found maximum values of 20 and 50-year return levels of TDP for the UJB (Zaman et al. 2020). Another study conducted on a portion of UJB located in Kashmir, India, uses SPEI index for spatio-temporal characterization of drought events only (Himayoun and Roshni, 2019). (Akhtar et al., 2020) investigated the correlation of meteorological and hydrological drought using SPEI and standardized streamflow index (SSI) over the Upper Indus Basin (UIB), including UJB. They validated the results with historically prolonged drought event observed in Pakistan (1999-02). Another study employed locally weighted SDI index and compared it with SPI and SPEI on ten meteorological stations within Pakistan (Ali et al., 2019). (Ullah et al., 2021a) evaluated four reanalysis products for drought assessment in Pakistan using SPI and SPEI at multiple time scales. All above mentioned studies put focus towards drought event characteristics only, whereas the wet events and transition of wet-dry events were overlooked. This study attempts to fill this gap by addressing the following specific points:

1. How does climate change influence the evolution of regional wet-dry events?
2. How comparatively frequent were wet or dry events in the past?
3. What is the average transition time from W-to-D and D-to-W events?
4. Which parts of the basin are hosting hotspots for rapid wet-dry transition events?

The most widely used index, SPEI, is here adopted to detect and characterize wet and dry events of different severity levels (moderate, severe, and extreme). The analysis is carried out both at each grid cell and averaged over the basin, using corrected ERA5 precipitation and observed temperature data for a period of 35 years (1981-2014).

5.2 Data description

The daily observed precipitation and temperature data of 15 climatic stations located within the political boundary of Pakistan are collected from Pakistan Meteorological Department (PMD) and Water and Power Development Authority (WAPDA). For the Indian side region, Indian Meteorological Department (IMD) daily gridded precipitation and temperature datasets, derived from a dense network of meteorological stations for the Indian mainland (Pai et al., 2015), are extracted at five stations and used for that region. The analysis is carried out for a period of 34 years (1981-2014), due to the availability of observed data. In fact, there are only a few climatic stations where data are available starting from 1971, but the number of stations would not be enough for the spatial analysis. The observed temperature data is used to calculate potential evapotranspiration (PET) using the Thornthwaite equation (Thornthwaite, 1948) due to data limitation. A study conducted by Beguería et al. (2014) compared the SPEI values calculated with three different methods (Penman-Monteith, Hargreaves, and Thornthwaite) and found small differences in humid regions. Mavromatis (2007) also reported similar outcomes of PET methods for drought indices calculation. Afterwards PET values are interpolated at 0.25° using Kriging with External Drift (KED), considering elevation as a predictor (Goovaerts, 2000). For the precipitation, contrasting reviews are reported in the literature about the performance of KED technique. For instance, (Masson et al., 2014) reported considerable improvement in interpolation accuracy with KED compared to other linear regressions not accounting for any predictor in high mountainous regions. On the other hand, (Berndt and Haberlandt, 2018, Ly et al., 2011) argue that topographical impact is indispensable for only temperature reconstruction at all temporal resolutions and station densities, but its influence is less clear for daily to monthly precipitation. Furthermore, all spatial interpolation techniques can perform poorly in regions with insufficient high-elevation data, due to inaccurate estimation of local lapse rates (Ruelland and Sciences, 2020). Therefore, the distribution mapping (DM)-corrected ERA5 precipitation estimates (0.25° horizontal resolution) are used in the present study. ERA5 is a relatively new reanalysis launched by European Centre for Medium-Range Weather Forecasts (ECMWF) (Saha et al., 2010). The data are developed by using advanced 4Dvar assimilation scheme and provide various atmospheric variables at 139 pressure levels for the period 1979-present time. The suitability of ERA5 to the UJB and surrounding region is also reported by Liaqat et al. (2021) and Baudouin et al. (2020). The DM method adjusts the cumulative distribution function (CDF) of modelled precipitation to match with the observed precipitation CDF using a transfer function (Sennikovs and Bethers, 2009) and it is commonly used to correct the systematic distributional biases (Cannon et al., 2015). The Gamma distribution (Thom, 1958) with a shape and a scale parameter is found to be suitable for the precipitation distribution in the study region (Azmat et al., 2018). The suitability of ERA5 precipitation and bias correction method with respect to extreme precipitation analysis is checked against observed station data (Ansari et al. 2023; Ansari & Grossi, 2023).

5.3 Methods

5.3.1 Wet and Dry Events Identification

SPEI, the most widely used index is adopted to detect and characterize wet and dry events of different severity levels (moderate, severe, and extreme). The SPEI index supports comparisons over time and space, as proxies of wet and dry conditions from both the meteorological and agricultural perspectives. Although the SPEI is originally proposed for drought monitoring, it can also be used as a tool to detect flood risk. The calculation procedure of SPEI involves two steps: fitting a log-logistic distribution to the monthly climatic water balance (P-PET) time series and then transforming the cumulative probability of the fitted distribution to a standard normal distribution (with mean zero and variance one). According to this distribution method, the probability distribution function of a variable x is expressed as:

$$F(x) = [1 + (\frac{\alpha}{x-\gamma})^\beta]^{-1} \quad (5.1)$$

Where α , β and γ are the shape, scale, and origin parameters, respectively. In the second step, SPEI is calculated as the standardized value of $F(x)$ as follows:

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad (5.2)$$

Where

$$W = \sqrt{-2 \ln(F(x))} \quad \text{for } F(x) < 0.5 \quad (5.3)$$

(3)

$$W = \sqrt{-2 \ln(1 - F(x))} \quad \text{for } F(x) > 0.5 \quad (5.4)$$

The parameters C_0 , C_1 , C_2 , d_1 , d_2 , d_3 are SPEI constants (Vicente-serrano et al., 2010). The log-logistic distribution for SPEI calculation is used and recommended by many researchers (Ullah et al., 2021a, Akhtar et al., 2020, Himayoun and Roshni, 2019, Vicente-Serrano et al., 2010). The detailed description of the SPEI calculation procedure can be found in (Vicente-Serrano et al., 2010). In this study, SPEI is calculated using “SPEI” package in R environment (Beguería et al., 2017). The severity levels of wet and dry events based on SPEI values are classified according to (Chen et al., 2020), results are listed in Table 5.1. Positive and negative values of SPEI represent the severity of wet and dry events, respectively.

Table 5.1: SPEI Classification of Dry and Wet Events (from Chen et al., 2020)

SPEI value	Description
> 1.99	Extreme Wet

1.99 to 1.50	Severe Wet
1.49 to 1.00	Moderate Wet
0.99 to -0.99	Normal
-1.00 to -1.49	Moderate Dry
-1.50 to -2.00	Severe Dry
-2.00 <	Extreme Dry

5.3.2 Wet and Dry Events Characteristics

In this study, three characteristics (severity, duration, and intensity) of wet and dry events are calculated for each pixel. Following (Spinoni et al., 2014), the duration (D) of a wet/dry event is the length of time (months) that the index is consecutively above or below a truncation value; the Severity (S) refers to the cumulative value of the index from the first month to the last month of the wet/dry event and it represents the water surplus and deficit, respectively ; the intensity (I) of an event is the ratio of severity (S) to duration (D). These characteristics are computed for each event and then further the total wet/dry event duration (TWD and TDD), total wet/dry severity (TWS and TDS), total wet/dry intensity (TWI and TDI), average wet/dry event duration (AWD and ADD), average wet/dry severity (AWS and ADS), average wet/dry intensity (AWI and ADI), maximum wet/dry event duration (MWD and MDD), maximum wet/dry severity (MWS and MDS), maximum wet/dry intensity (MWI and MDI) are calculated for a period of 34 years (1981-2014).

5.3.3 Wet-Dry (WD) ratio

Wet-Dry (WD) ratio is defined as the natural logarithm of the ratio of the total number of wet months (N_w) to the total number of dry months (N_d) (Luca et al., 2020). The WD ratio is calculated for different levels of severity (moderate, severe, and extreme) at each pixel for the studied period (1981–2014) using Eq. (5.5):

$$WD \text{ ratio} = \ln \left(\frac{N_w}{N_d} \right) \quad (5.5)$$

The WD ratio provides information about the susceptibility of a given area to be more affected by wet or dry events. A WD ratio greater than 0 implies the prevalence of wet events whereas a WD ratio lower than 0 shows a dominance of dry events. The natural logarithm is used to narrow the range of WD ratio values and to separate the wet-dominated versus dry-dominated regions by sign.

5.3.4 Wet-Dry Transition Time

The total number of transitions and their average transition time (T_t) in months for wet-to-dry and dry-to-wet events is computed for each grid cell for the period 1981–2014, as described by (Luca et al., 2020). The calculation procedure of wet-to-dry transitions time (T_t) involves four steps: (i) extraction of wet and dry events and arrange them in an ascending order of time (from the oldest to the most recent); (ii) in case of consecutive dry and wet months, keep only the first and the last month value, respectively; (iii) calculate the difference in months between wet to dry

events within the time series; and (iv) take the average of the time interval. The same procedure is applied for calculating dry-to-wet transitions time (T_t), with the only difference being in step (ii) in which the first and last month of wet and dry event are kept, respectively and in step (iii) in which the time interval is calculated between dry to wet events. The wet-to-dry and dry-to-wet transition time are calculated separately for each level of severity (moderate, severe, extreme).

5.3.5 Wet-Dry Rapid Transition Events

The wet-dry rapid transition event is defined as the consecutive occurrence of wet and dry months/events. For instance, a dry (or wet) event occurring in the i th month abruptly altered to wet (or dry) event in the $i + 1$ st month. In this study, the frequency of W-to-D (wet event followed by dry event) and D-to-W (dry event followed by wet event) rapid transition events are calculated for each pixel to identify the geographical hotspot for compound extreme events. Unlike the wet/dry average transition time which are calculated separately for each severity level, the wet/dry rapid transition events are calculated considering all levels of severity together.

5.4 Results

5.4.1 Change trends of the Wet-Dry Events

The basin average SPEI time series at 1-month (SPEI-1), 3-month (SPEI-3), 6-month (SPEI-6) and 12-month (SPEI-12) time scale is presented in figure 5.1. It can be seen that the study domain mostly experienced moderate-to-severe wet/dry events, whereas the extreme wet/dry events ($\text{SPEI} > 2$ or $\text{SPEI} < -2$) rarely occurred during the study period. For the SPEI-1, the wet (blue) and dry (red) events changed more frequently than accumulated SPEI (at 3-, 6- and 12-month) and there is no extended dry or wet period. The reason might be that the precipitation and temperature of each new month has a substantial impact on the accumulative values of that period. By contrast, with the increase in SPEI time scale (SPEI-1 to SPEI-12), a clear change/shift of basin climate from wet to dry conditions can be seen (Figure 5.1), showing the stability in the frequency of incidence of wet/dry events over the study domain. This could be explained as the slow and consistent response of SPEI towards changes in climatic variables, indicating strong and clear durations of annual and multiple-year dry and wet conditions. This means that at longer time scales of SPEI the number of occurrences of wet/dry events will decrease, but the duration will increase.

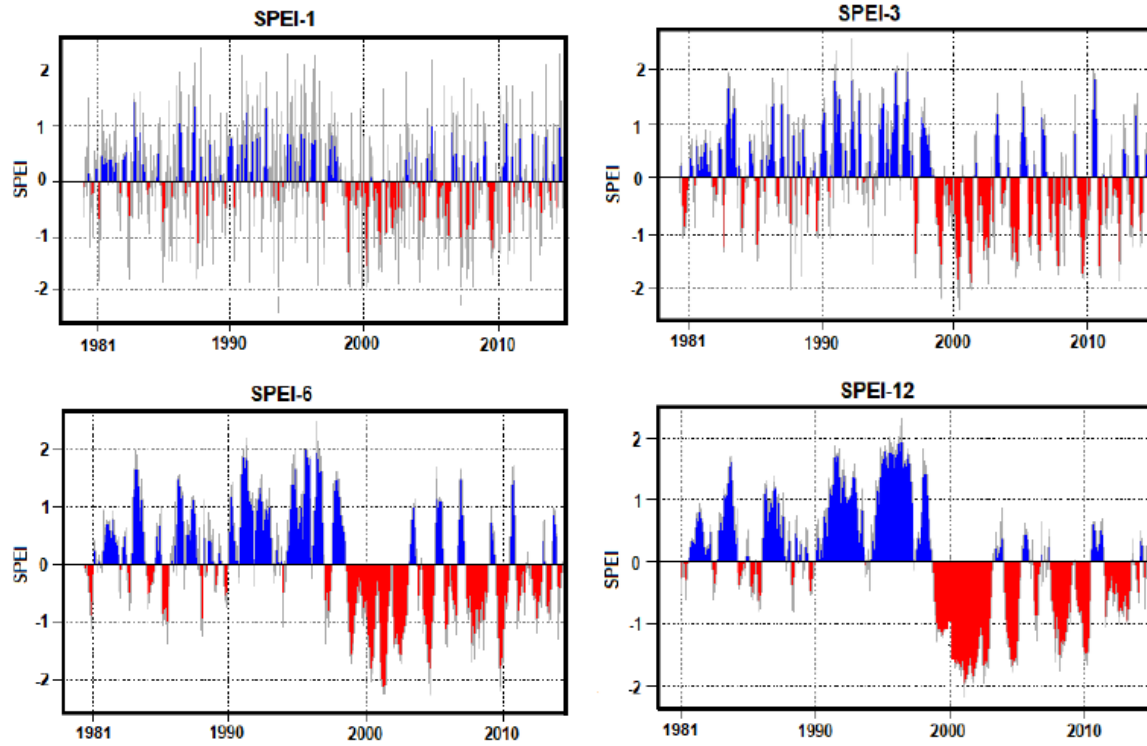


Figure 5.1: Temporal variations of SPEI at 1-, 3-, 6- and 12-month time scale over UJB for the period 1981-2014

This study focuses on the short time scale conditions to analyze frequent variations in climatic conditions and their interplay; therefore, more detailed analysis is carried out at the monthly time scale. Moreover, floods and flash droughts are not clearly associated with long term SPEI, because the averaging effect of long-term accumulated precipitation and temperature surpasses the signal of extreme precipitation and temperature over a short period. Flash drought is relatively a new type of drought. Currently, there is not a universally accepted definition or criteria for flash drought, though there is general consensus on the principle of rapid onset or intensification characterized by moisture deficits and abnormally high temperatures for a period lasting at least 3 weeks (Lisonbee et al. 2021, Otkin et al. 2018, Hunt et al. 2009). This highlights the usefulness of SPEI at the monthly scale in representing flood and flash drought events. It is noted that the terms “wet-dry events” or “wet-dry months” present similar meaning for our study, as the analysis is made at the monthly time step. A clearer picture of the monthly evolution of wet/dry events of different severity levels and their variability can be seen in Table 5.2. The SPEI-1 values fluctuate remarkably from one month to another. For example, an extreme wet October in 1987 is followed by a severe dry November, and a severe wet June occurred at the tail of the longest drought spell in May 2001. Such rapid transition from wet to dry and from dry to wet events is more prominent during the first half of the study period (before the year 1997). Another interesting observation concerns the strong change in the basin climatic features which can be

noticed around the year 1997/1998. During the first half of the study period (1981-1997), the dominance of wet events of different categories prevails whereas the basin conditions lean towards dryer conditions during the second half of the period (1998-2014).

Table 5.2: Temporal variations of monthly SPEI over UJB from 1981-2014. The brown, blue and white colors present dry, wet and normal months, respectively. Different shades of the colors define the different severity levels (EW-extreme wet, ED-extreme dry, SW-severe wet, SD-severe dry, MW-moderate wet, MD-moderate dry). The red line between 1997 and 1998 indicates the strong change in the basin climatic features

Year/ Months	1	2	3	4	5	6	7	8	9	10	11	12
1981							MW					
1982						MD	SD			MW	SW	MW
1983			SW	MW				MW				
1984									MW	MD		
1985		SD				MD	MW		MD			SW
1986	MD		SW	MW							SW	MW
1987	MD			MW	EW		SD	MD		EW	SD	
1988			MW	MD	MD		SW				MD	
1989					MW						MW	
1990					MD							EW
1991				SW	MW	SD			MW			
1992	SW		SW			MD			SW			
1993			MW	SD			SW	ED			MW	MD
1994				EW			MW	SW			MD	SW
1995				SW			EW	MW	MD			
1996			MW		SW	EW		MW	SD	SW		
1997		MD			MW	MW		SW		MW		
1998		MW									SD	SD
1999	MW	MD								SD	MW	SD
2000		MD	MD	SD	SD					MD		
2001	SD	SD	MD		SD	SW	MW					
2002					MD		SD				MD	
2003	MD	SW				MD						
2004		MD	SD		MD		MD			MW		
2005		EW						SD				MD
2006	SW		MD		SD			SW			MW	MW
2007	SD			ED		SW		MD		SD	MD	
2008	SW		SD			MW						MW
2009							MD		SD			
2010	MD	SW	MD		MW		SW	MW			MD	MD

2011		SW			MD				MW			
2012						SD	SD		SW			
2013			MD	MD				EW				
2014			MW						EW			MD

Annual variations in the number of months affected by dry/wet events ($SPEI \leq -1$ and $SPEI \geq 1$) are displayed in figure 5.2. Usually, every year encountered at least one dry and wet month of any severity level. Approximately 35% of the total number of months experienced anomalous dry or wet conditions. The proportion of wet months (18.1%) is slightly higher than that of dry ones (16.9%).

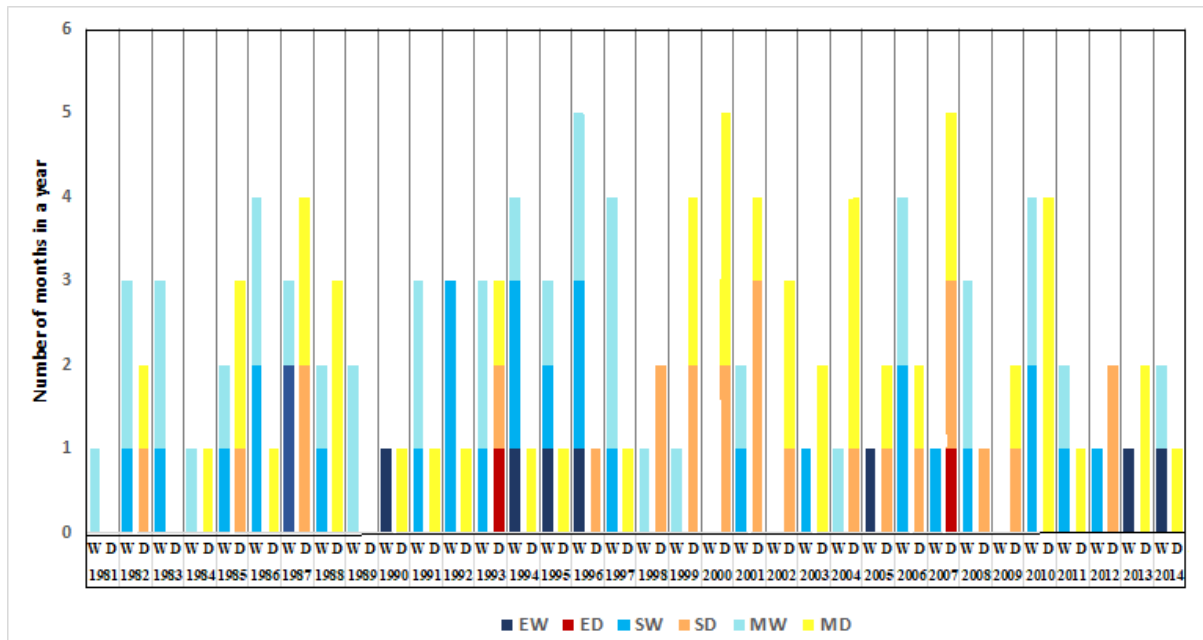


Figure 5.2: Annual variations in the number of months affected by wet/dry conditions during 1984-2014. The brown and blue colors present dry and wet months, respectively. Different shades of the colors define the different severity levels (EW-extreme wet, ED-extreme dry, SW-severe wet, SD-severe dry, MW-moderate wet, MD-moderate dry)

5.4.2 Wet/Dry Event Analysis

The wet/dry event characteristics (duration, severity, and intensity) are computed for each pixel to analyze their spatial distribution. Pixel based analysis shows the location of the most vulnerable parts of the basin, providing the basis for future decisions on adaptation and mitigation measures. In this study, the total, average and maximum value of duration, severity, and intensity are computed for the study period (1981-2014). The maps of wet and dry duration are displayed in figure 5.3. Overall, the study area encountered relatively more wet months than dry months

during the whole study period. The total wet duration (TWD) and the total dry duration (TDD) vary from 66 to 80 and from 61 to 65 months respectively for most parts of the basin. The low elevation parts in the south of the basin show the highest value of TWD whereas the TDD is higher across Himalaya divide line than in other parts of the basin. The Himalayas divide line is a line in the middle of the UJB at Pir Panjal mountainous range, separating the dominance of the two precipitation patterns: westerlies in the north-facing and monsoon in the south-facing slopes of the line (Archer and Fowler, 2008).

The average wet and dry event durations (AWD & ADD) are found to be similar throughout the basin with a slight difference in the range of 1-2 weeks. However, their spatial patterns are found to be mostly complementary. Maximum wet and dry event durations (MWD & MDD) exhibit high values in two distinct parts of the basin. The MWD is about 6-7 months in the east of the basin, which is located in Kashmir, India, whereas it varies between about 4-5 months and 2-3 months in the northwest and southwest parts of the basin. For the MDD, the northwest and central parts of the basin show higher values (4-5 months) than the remaining parts (2-3 months).

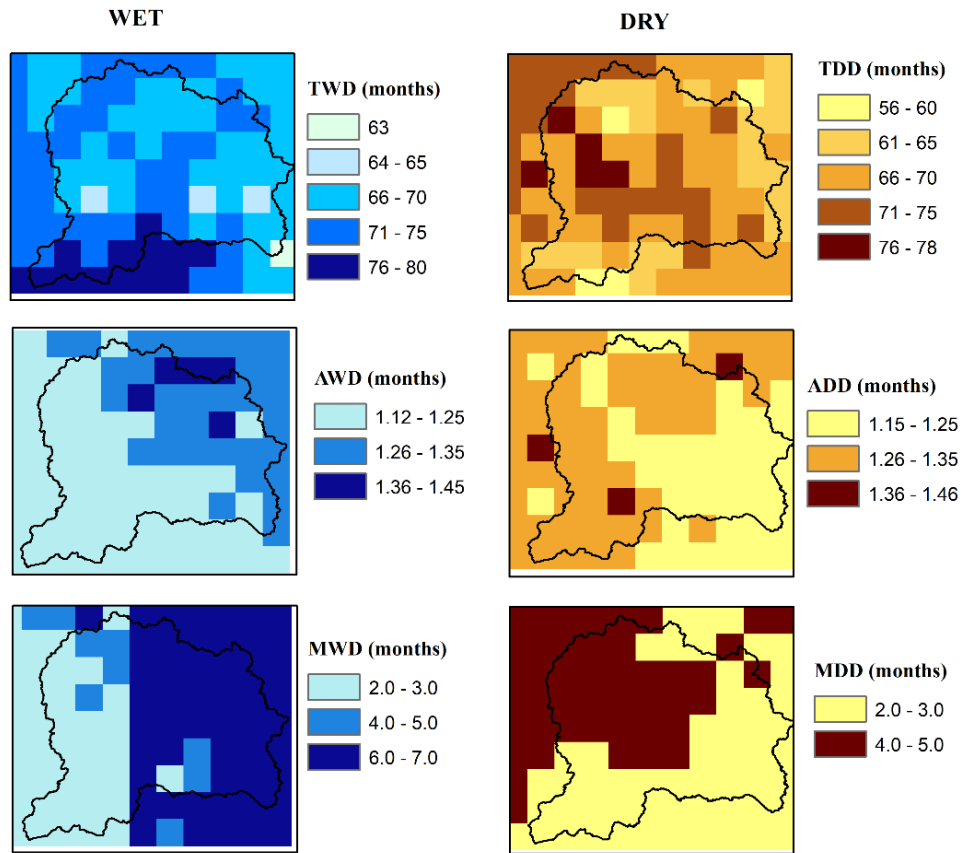


Figure 5.3: Spatial distribution of total wet duration (TWD), total dry duration (TDD), average wet duration (AWD), average dry duration (ADD), maximum wet duration (MWD) and maximum dry duration (MDD) for the period 1981-2014

The spatial distribution of total, average and maximum severity of wet/ dry events is presented in figure 5.4. All wet/ dry severity maps show similar spatial patterns as wet/dry duration maps. In terms of total wet severity (TWS) and total dry severity (TDS), the wet and dry hotspots are located in the south and middle (across Himalaya divide line) of the basin, respectively. Unlike the spatial patterns of TDD, the TDS is relatively higher in the north of the basin above Himalaya divide line. This shows more intense dry events in this part of the basin. The underlying reason for higher TDS could be the higher warming rates in western Himalaya, hosted in the north of the basin. The average severity of wet and dry events is categorized from moderate to severe level. The average wet severity (AWS) exhibits random spatial patterns, whereas the average dry severity (ADS) is relatively higher in the north of the basin. Observed spatial patterns of maximum wet severity (MWS) and maximum dry severity (MDS) are similar to those of MWD and MDD. The eastern part of the basin experienced wet events of higher severity than the western one, whereas the most severe dry events affected the northwest and central parts of the basin.

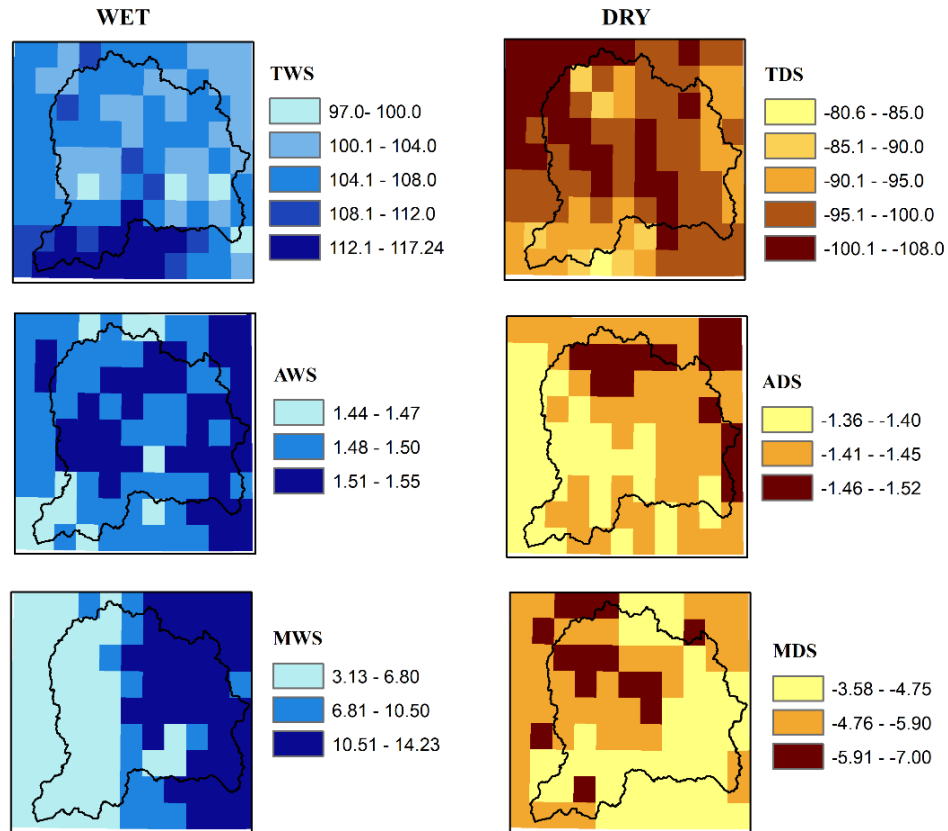


Figure 5.4: Spatial distribution of total wet severity (TWS), total dry severity (TDS), average wet severity (AWS), average dry severity (ADS), maximum wet severity (MWS) and maximum dry severity (MDS) for the period 1981-2014

Figures 5.6 illustrate the spatial distribution of intensities of wet/dry events, calculated as the ratio of severity to duration. The total wet intensity (TWI) and total dry intensity (TDI) varies from moderate to severe with noted range of 1.44 to 1.55 and -1.36 to -1.52 for wet and dry events, respectively. Irrespective to TWD and TWS, which is highest in the south of the basin, TWI is more intense in the middle and northeast of the basin. The TDI is found to be more intense over western Himalaya Mountains, north of the basin. The average wet intensity (AWI) and average dry intensity (ADI) vary within the moderate class of hazard. However, their spatial patterns are much different from average duration (AWD & ADD) and average severity (AWS & ADS) patterns. Regarding maximum intensity, the spatial patterns of maximum wet intensity (MWI) well resemble the patterns of MWD and MWS, whereas the maximum dry intensity (MDI) exhibits much different spatial patterns from MDD and MDS. The dry events are found to be more intense than wet events, but only for a few pixels in the southwest of the basin. On the other hand, wet events with higher intensities are found to be more widespread than dry events.

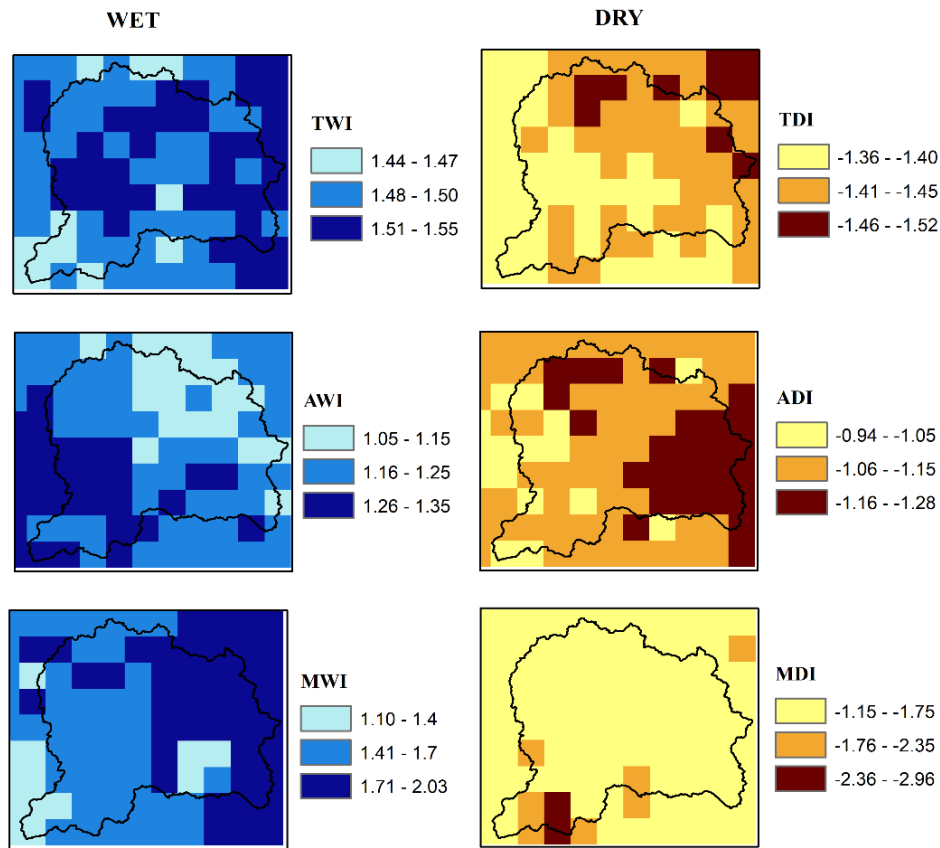


Figure 5.5: Spatial distribution of total wet intensity (TWI), total dry intensity (TDI), average wet intensity (AWI), average dry intensity (ADI), maximum wet intensity (MWI) and maximum dry intensity (MDI) for the period 1981-2014

5.4.3 Wet-Dry Ratio

The WD ratio features the dominance of wet or dry events for the period of 34 years (1981-2014). The WD ratio for the three severity levels (moderate, severe, and extreme) at pixel basis is presented in figure 5.6. The positive and negative value of WD ratio depicts the prevalence of wet and dry events, respectively. As the figure shows, higher frequencies of moderate dry events with respect to moderate wet events are found throughout the basin except for a few pixels in the south. By contrast, severe to extreme wet events are more frequent for most parts of the basin. The highest positive values of WD ratio for extreme level of hazard are found in the southwest of the basin, which shows the higher susceptibility of the area towards extreme wet events. Moreover, the analysis of wet/dry event characteristics also revealed the prevalence of wet events with higher duration and severity over monsoon dominated regions.

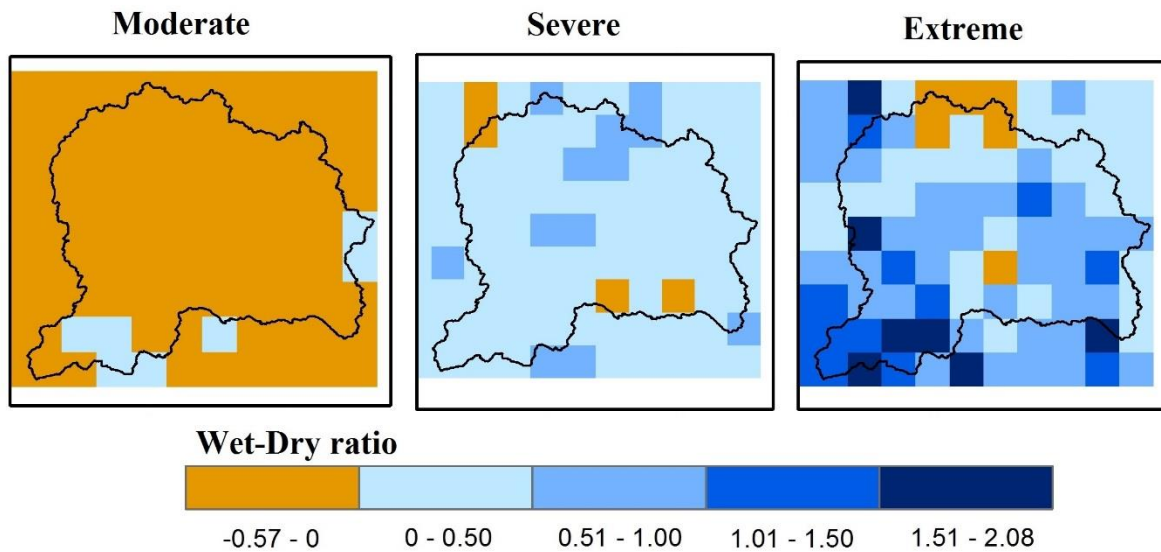


Figure 5.6: Spatial distribution of wet–dry (WD) ratio derived for three levels of severity (moderate, severe and extreme) during the period 1981-2014. Blue (WD ratio>0) means that the area experienced more wet than dry events. Brown (WD ratio<0) indicates the opposite.

5.4.4 Wet-Dry Transition Time

The number of transitions and their average transition time for wet-to-dry and dry-to-wet events for the period 1981–2014 is presented in figure 5.7 and figure 5.8. As expected, the number of transitions for W-to-D and D-to-W events is the highest for the moderate level of events, followed by severe and extreme levels of events. Consequently, the average transition time from W-to-D and D-to-W event is found to be the highest for the extreme level of event followed by severe and moderate levels of events. The number of transitions for moderate, severe, and extreme levels of events varies from 15 to 26, from 6 to 16, and from 1 to 5 respectively. Overall, the number of transitions for D-to-W events is larger than the W-to-D event for severe and extreme levels of events, whereas the opposite is found for the moderate level of events. The transition time

for moderate, severe, and extreme levels of events varies from 1.8 to 6.5, from 1.8 to 16.75 and from 3.5 to 187.0 months, respectively. Overall, 53.57% and 17.86% of pixels in the UJB showed longer transition time from W-to-D than from D-to-W for moderate and extreme levels, whereas the opposite is seen for severe events.

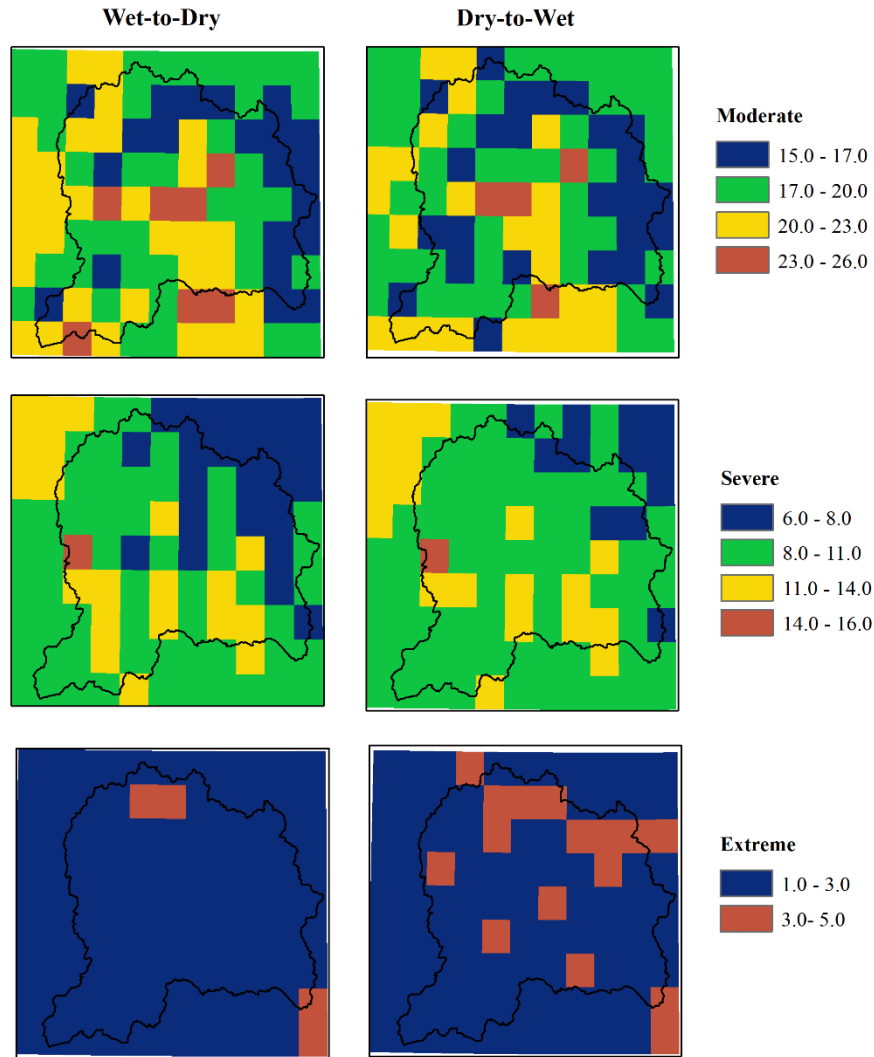


Figure 5.7: Number of transitions from wet-to-dry (left) and dry-to-wet (right) events for three levels of severity (moderate, severe, extreme) for the period 1981-2014

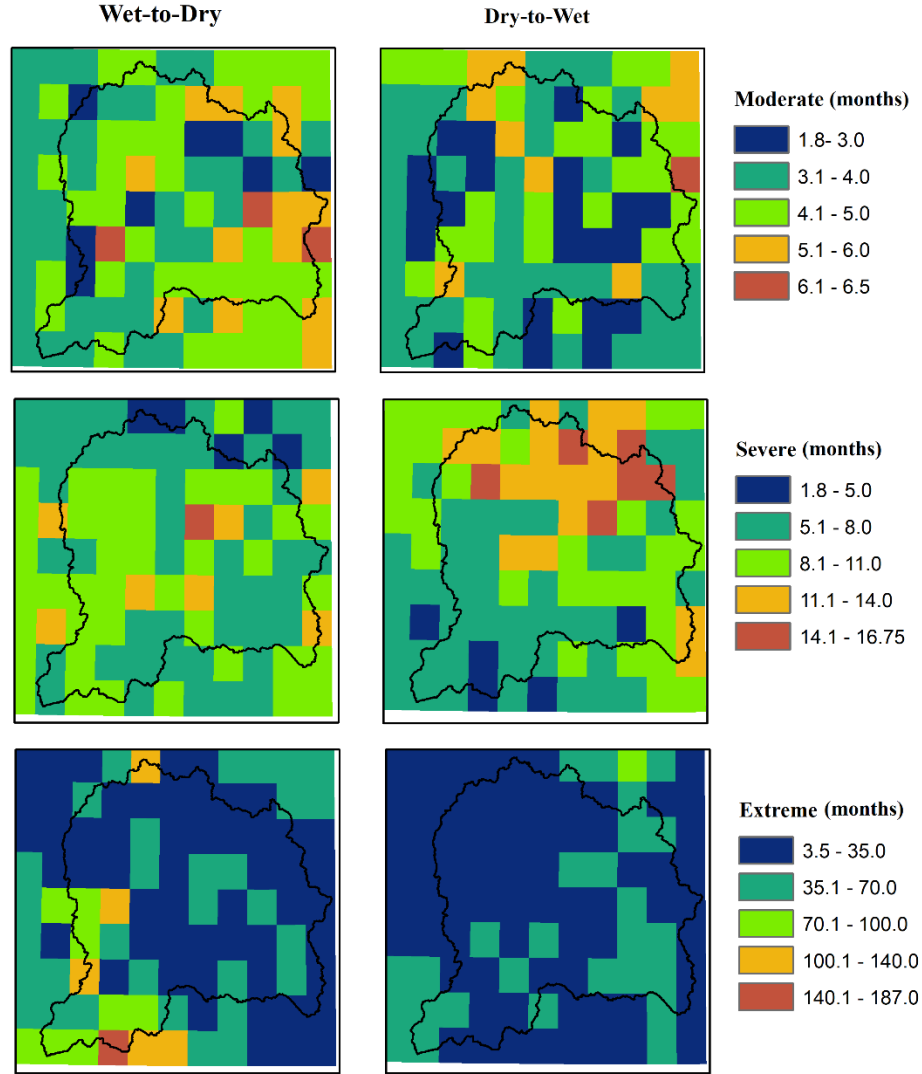


Figure 5.8: Average transition time (T_t) intervals in months for wet-to-dry (left) and dry-to-wet (right) events for three levels of severity (moderate, severe, extreme) for the period 1981-2014

5.4.5 Wet/Dry Rapid Transition Events

The wet/dry rapid transition is the consecutive occurrence of wet and dry months of any severity level. The frequency of W-to-D (wet month followed by dry month) and D-to-W (dry month followed by wet month) rapid transition events are computed for each grid cell and are shown in figure 5.9. The frequency of wet/dry transition events varies/ranges from 5 to 20 events during 34 years of study period. About 50% pixels in the UJB encountered a greater number of wet events terminated at dry months. The spatial distribution of frequency of wet/dry rapid transition events revealed that the W-to-D events are less frequent over the westerlies dominated region of the basin, whereas the southwestern part of the basin is more affected by the W-to-D abrupt altered events. By contrast, D-to-W abrupt altered events are found to be more frequent

over pixels surrounding the Himalaya divide line, whereas the remaining part of the basin depicts less incidence of D-to-W altered events.

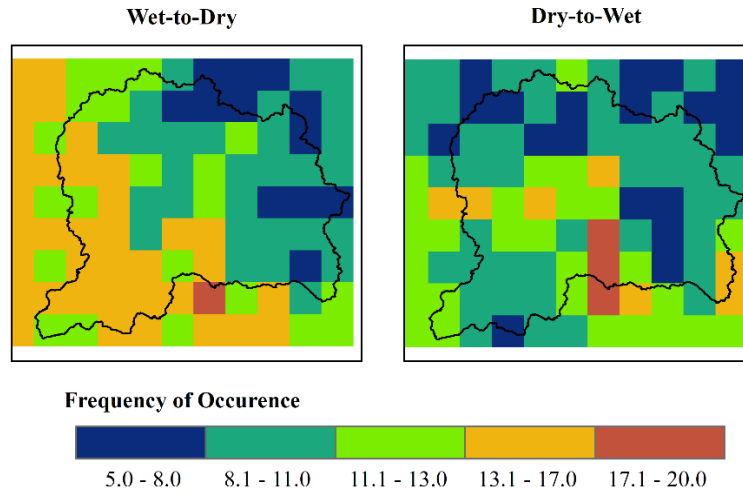


Figure 5.9: Frequency of occurrence of abrupt altered events, wet-to-dry (left) and dry-to-wet (right) during the period 1981-2014

5.5 Discussion and Conclusion

This study attempts to investigate the spatiotemporal variations of wet-dry events collectively, their characteristics (duration, severity, intensity) and transition from W-to-D and D-to-W events during the period 1981-2014 in the Upper Jhelum Basin (UJB)-South Asia. The SPEI index, which incorporates both precipitation and potential evapotranspiration, is used to extract and analyze wet-dry events. The whole analysis is carried out at the monthly time scale, but the temporal evolution of the basin averaged index is also simulated at multiple time scales (1-, 3-, 6- and 12-months).

The results of temporal variations of SPEI showed that the study domain mostly encountered moderate to severe wet-dry events, whereas the extreme wet-dry events rarely occurred during the study period. The results of basin average SPEI at multiple time scales revealed that the response of SPEI to the deviations in climatic features varies with the accumulation time. Therefore, shorter time scales are more appropriate for detecting frequent seasonal and inter-annual variations, whereas longer time scales provide useful information regarding the signature of the events over the region (Ayugi et al., 2020, Du et al., 2013). Furthermore, the SPEI time-series plots well capture the observed extreme floods and drought events occurred in the basin during the study period: for instance, the longest drought event occurred from late 1990s to early 2000s, as evident in Figure 5.1 and Table 5.2. The drought started in 1998 and is considered to be the worst in the history of Pakistan. The drought spell 2001-2002 resulted in water shortage of up to 51% of normal supplies (Ahmad et al., 2004). Likewise, the notable flooding events, usually flash floods ranging from moderate to severe, occurred in the years 1988, 1992, 1994, 1997, 2007

and 2014 (Bhat et al., 2019) and are well captured by SPEI index, confirming its valuable contribution to this type of analysis.

An interesting clue to the changing climate is the strong change that occurred in the basin at the end of 1997 (Table 5.2). Before this change (1981-1997), wet events of different severity levels predominated in the basin, whereas dryer conditions prevailed after 1997. However, it still needs to be investigated whether dryer conditions are expected to continue in the future, or a large multi-decadal variation is taking place. This strong change in the basin climate coincides with the strongest El Niño Southern Oscillation (ENSO) event in the winter season of 1997-1998, where the Oceanic Niño Index (ONI) peaked at 2.3, and influenced the climate conditions all over the world (MRCC, 2021). The 1998-2002 drought in southwestern Asia, accompanied by the most severe drought conditions in the last 50 years, is also a result of this strong ENSO event (Ain et al., 2020, Ahmed et al., 2018). The ENSO is the primary mode of inter-annual variability having great influence on global weather and climate via atmospheric circulations (Ullah et al., 2021a). Many researchers reported the close association between variations in atmospheric circulation patterns and climatic variables, extreme weather phenomena like drought and flood (Luca et al., 2020, Omidvar et al., 2016, Sun et al., 2015). (Kenyon and Hegerl, 2010) examined the response patterns of hydroclimate extremes to ENSO over global land areas and stated a significant decrease in precipitation extremes over Southeast Asia, Indonesia, Australia, and the northernmost region of South America during El Niño phases, whereas in the southern tier of the United States and the region from Argentina to southern Brazil heavy precipitation increased during El Niño phases, and vice versa during La Niña phases. The strength of such connections for Pakistan is also demonstrated in several studies. El Nino suppresses monsoon rainfall activity over Pakistan, while La Nina has a negative impact on winter precipitation over Pakistan (Farooqi et al., 2005, Azmat, 2003). (Ullah et al., 2021a) found significant impacts of three large scale climate indices, i.e Niño4-SST Index, Sea Surface Temperature (SST), and multivariate El Niño-Southern Oscillation (ENSO4.0) on seasonal droughts across Pakistan.

The results of wet-dry event characteristics (duration, severity, intensity) at pixel basis outline the greater susceptibility of westerlies dominated region towards dry events with higher duration, severity, and intensity. The dryer conditions in this region could be explained with the increasing rates of global warming over the mountainous region of the basin, also reported by many researchers (Rashid et al., 2020, Shafiq et al., 2020, Zaz et al., 2019). Studies by (Negi et al., 2018) and (Dimri and Dash, 2012) also confirm that most of the western Himalayan region recorded a significant warming trend especially from 1975 onwards. This is also supported by the tree-ring chronologies of the region which indicate a rapid growth of the tree rings in the recent decades especially at higher altitudes (Borgaonkar et al., 2009). The impact of global warming on short term dry event (soil moisture drought) is not straightforward as rising temperature did not necessarily cause increase in actual ET, especially in arid and semiarid regions (Trenberth et al., 2014, Sheffield et al., 2012). In fact, the rate and amount of ET results from a complex interaction of temperature, radiation balance, precipitation rates and vegetation physiological control, rather than being exclusively limited by one of these factors. For flash drought, the rapid soil moisture

decline should be a result of the intensification of ET driven by higher temperature, which is very common in humid and semi-humid regions, where soil moisture can sustain higher ET amounts up to a few weeks (Yuan et al., 2019). Further decrease in winter and spring precipitation leads to water deficit conditions in this part of the basin. The worst drought event period (2000-2001), partially induced by a stronger ENSO in winter, is also due to the low winter and spring precipitation, as shown in Table 5.2. During 2000-2001, winter and spring seasons are moderate-to-severe dry, whereas the monsoon and autumn seasons observed normal months. By contrast, the higher duration and severity of wet events are detected in the monsoon dominated region, implying that floods mainly occurred during monsoon season with heavy rainfall along with snowmelt. However, the eastern part of the basin is the hotspot of more intense wet events. The above discussion is also supported by the historic database of observed flood events, as most of these events occurred during monsoon season.

The results of WD ratio showed the prevalence of severe to extreme wet events for most part of the basin, while the dry events of moderate severity level are more frequent in the study domain. The southwestern part of the basin, located in the monsoon-dominated region is found to be the hotspot for extreme wet events. Moreover, the analysis of wet/dry event characteristics also revealed the prevalence of wet events with higher duration and severity over the same monsoon dominated region. The spatial patterns of average transition time from one extreme type to the other type are found to be heterogeneous and different for the three severity levels. Overall, a greater number of pixels took shorter time to switch from dry to wet event than from wet to dry events. Apart from the average transition period, the study domain also experienced rapid transition of wet-dry events. In general, the surrounding region of the Himalaya divide line and the monsoon-dominated part of the basin are found to be the hotspots of rapid wet-dry transition. The rapid wet-dry swings could be explained in the context of global warming. In a warmer climate, increased evapotranspiration rates in response to increased temperature could elevate the drought risk and frequency. At the same time, prospect of localized heavy precipitation causing floods is expected to increase in response to increased atmospheric moisture content due to increased evapotranspiration rates (He and Sheffield, 2020, Krishnan et al., 2020). Further warming-induced changes in global climate variability, such as El Niño and La Niña can cause more inter-annual variability or persistence in global weather and climate, significantly affecting regional precipitation and temperature distribution in space and time (Ullah et al., 2021b). Further compelling scientific evidence of human interventions, such as boosted human water intake and land use changes, exacerbate the extreme flood and drought risk hazard.

To conclude, knowledge of wet-dry events characteristics and their rapid transition provides meaningful insight into the geographical hotspots of compound extreme events, which could be of practical value to inform a group of stakeholders (researchers, local authorities, policy makers, relief agencies, non-governmental organizations (NGOs) and (re)insurance companies) on the potential risk. However, greater caution should be taken in analyzing the rapid transition of extreme wet-dry events using drought indices such as SPEI-1. This is because the interpretation of the SPEI values at 1 month may be sometimes misleading, particularly for regions with low precipitation during a month. In such cases, large negative or positive SPEI values may emerge, despite the actual departure from the mean being relatively modest and could misclassify the

conditions as extremely dry or extremely wet. Future work should explore to what extent future wet-dry event frequency will respond to anthropogenic forcing, internal atmospheric processes, and human interventions.

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Chapter 6

Evaluation of bias correction methods for a multivariate drought index: case-study of the Upper Jhelum Basin

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Abstract

Bias correction (BC) is often a necessity to improve the applicability of global and regional climate model (GCM and RCM, respectively) outputs to impact assessment studies, which usually depend on multiple potentially dependent variables. To date, various BC methods have been developed which adjust climate variables separately (univariate BC) or jointly (multivariate BC) prior to their application in impact studies (i.e., the component-wise approach). Another possible approach is to first calculate the multivariate hazard index from the original, biased simulations, and bias-correct the impact model output or index itself using univariate methods (direct approach). This has the advantage of circumventing the difficulties associated with correcting the inter-variable dependence of climate variables which is not considered by univariate BC methods.

Using a multivariate drought index (i.e., SPEI) as an example, the present study compares different state-of-the-art BC methods (univariate and multivariate) and BC approaches (direct and component-wise) applied to climate model simulations stemming from different experiments at different spatial resolutions (namely CORDEX, CORDEX-CORE and CMIP6). The BC methods are calibrated and evaluated over the same historical period (1986-2005). The proposed framework is demonstrated as a case study over a transboundary watershed, i.e., the Upper Jhelum Basin (UJB) in the Western Himalaya.

Results show that (1) there is some added value of multivariate BC methods over the univariate methods in adjusting the inter-variable relationship, however, comparable performance is found for SPEI indices. (2) The best performing BC methods exhibit a comparable performance under both approaches with a slightly better performance for the direct approach. (3) The added value of the high-resolution experiments (CORDEX-CORE) compared to their coarser resolution counterparts (CORDEX) is not apparent in this study.

Key words: Bias correction, CMIP6, CORDEX, CORDEX-CORE, SPEI indices, model evaluation

6.1 Introduction

Weather and climate related extreme events (floods, droughts, heatwaves, storms, etc.) that arise from complex interactions of various physical processes across multiple scales in space and time, are projected to be amplified under global warming conditions and thus are expected to create huge societal and ecological impacts (Kopp et al., 2017, Zscheischler et al., 2018, Raymond et al., 2020, Zscheischler et al., 2020). Such projected climate assessments are usually undertaken using impact models or hazard indices under different global warming scenarios. Those hazard indices and impact models have been developed according to the needs of different sectors and they are usually based on one or more essential climate variables (ECV). For instance, maximum consecutive five-day precipitation and the number of days with minimum temperature above 20 °C rely on one ECV only i.e., precipitation and temperature, respectively, while some require more complex calculations (e.g., the river flow index using runoff based on the results of hydrological model simulations).

Several studies employ such indices and impact models for the assessment of the sectorial impacts of climate change. For instance, drought indices (standardized precipitation index-SPI and standardized precipitation evapotranspiration index-SPEI) with implication in water related sectors, especially agriculture, hydrology and water management (Maru et al., 2021, Ansari and Grossi, 2022), snow indices (Snow days and Mean winter snow depth) in the context of water management, ecology, tourism, or road maintenance (Schmucki et al., 2017), river flow indices (100-year return level of daily high streamflow and 10-year return level of 7-day average low streamflow) for reservoir operation, energy production, flood and drought management (Naz et al., 2018), etc. To assess the climate change impacts through such indices or any impact models, there is the need to have good quality observations and an adequate number of climate model simulations to characterize uncertainties at sufficiently high resolution to provide tailored regional to local climate information for impact assessments.

Global climate models (GCMs), that are the major source of knowledge about future climate change, represent a substantially simplified form of physical processes connecting the atmosphere, ocean, sea ice, land surface, and biogeochemical system. However, they typically present systematic biases with respect to observations (Christensen et al., 2008). These biases may be due to the temporal and spatial discretization (Teutschbein and Seibert, 2012), imperfect and unresolved representation of basic physical processes (Stevens and Bony, 2013) and parametrizations of unresolved sub-grid-scale processes (cloud formation, temperature inversion, convection, and precipitation, etc.). Even though regional climate models (RCMs) improve the representation of regional-scale processes up to some extent, their horizontal resolution is still coarser than the required for impact studies, and additionally suffer from substantial biases, partly inherited from the driving GCMs (Maraun et al., 2017). The use of raw GCM and RCM output for subsequent impact studies without any post processing could lead to biased adaptation decisions for the foreseeable future (Piani et al., 2010, Haerter et al., 2011, Argüeso et al., 2013). Nowadays global models from the 6th Coupled Intercomparison Project (CMIP6, (Eyring et al., 2015)) and regional counterparts from the Coordinated Regional Downscaling Experiment (CORDEX, (Giorgi et al., 2009, Jones, 2010)) constitute the state-of-the-art simulations for global and regional climate, respectively. Within CORDEX, standard simulations are developed on a $0.44^\circ \times 0.44^\circ$ grid (approximately 50x50 km) for many spatially distributed domains and, more recently, the Coordinated Output for Regional Evaluations (CORDEX-CORE, (Teichmann et al., 2021)) provides a reduced set of models on a higher resolution grid (approx. 25x25 km) covering most of the continental domains.

Bias correction (BC, also known as bias adjustment) is commonly applied to climate model output as a post-processing step to render climate model output more useful for climate impact studies. Over the recent years, a number of bias correction methods have been developed, varying from simple adjustments of the mean to correction of all quantiles, either univariate or multivariate, trend-preserving or not. These methods can only reduce systematic biases resulting from subgrid-scale parameterizations and unresolved orography under the current climate, but their efficiency is constrained by the misrepresentation of basic physical processes in the models, such as large-

scale atmospheric circulation (Eden et al., 2012, Addor et al., 2016, Maraun et al., 2017). Further, BC constitutes an additional source of uncertainty in century-long climate change projections when applied under the stationarity (time invariance) assumption (Christensen et al., 2008, Ehret et al., 2012) and thus may induce physically implausible climate future signals (Maraun et al., 2017). Since BC might introduce inconsistencies in the bias-corrected data considerable attention should be paid towards its evaluation not only in terms of simulated statistical moments but also regarding trend preservation and inter-variable physical coherence. The latter is especially important for any climate index or impact model whose calculation depends on more than one variable (e.g., multivariate drought indices, fire weather indices, ecological and hydrological models, etc.). For example, the physical coherence between precipitation and temperature determines the available water for evaporation over arid and tropical watersheds and affects the snow accumulation and melting processes (Chen et al., 2018, Guo et al., 2020).

The physical coherence among several meteorological variables and their dynamic nature in the projected climate is confronted with growing discussion under the BC framework. Contrasting reviews are found in literature. Various researchers advocate the use of multivariate BC methods to reconstruct the inter-variable coherence of the observations to the simulated climatic data (Zscheischler et al., 2019, François et al., 2020, Guo et al., 2020). For instance, François et al. (2020) report the added value of multivariate BC methods over univariate ones and conclude that the choice of the BC method should be based on the end user's goal. Conversely, Rätty et al. (2018) find that the univariate and multivariate methods perform similarly, while Wilcke et al. (2013) show that univariate bias adjustment is able to retain the quality of the temporal structure and the inter-variable dependencies of the uncorrected data. However, it is also argued that the ability of climate models to respond in a physically consistent way to external forcings is one of their basic foundations (Wilby et al., 2000) and that relationships between climate variables are not constant over time (time-invariant) (Mahony and Cannon, 2018, Hao et al., 2019). Another alternative approach in practice is the direct correction of the multivariate index (Casanueva et al., 2014, Casanueva et al., 2018, Li et al., 2019, Chen et al., 2021). This direct approach allows the preservation of the physical and temporal coherence among the primary variables as represented in the original climate model output. However, it may hide compensating biases in the contributing variables, particularly in the case of complex indices bearing in their formulation non-linear relationships between components (Casanueva et al., 2018, Van de Velde et al., 2022).

In this work we intercompare different state-of-the-art BC methods (univariate and multivariate) and BC approaches (direct and component-wise) applied to climate model simulations stemming from three modeling initiatives (CMIP6, CORDEX -WAS-44 domain- and CORDEX-CORE -WAS-22 domain) for a multivariate drought index (namely the Standardized Precipitation Evapotranspiration Index, SPEI). The performance of BC and climate model simulations is examined in terms of inter-variable physical coherence of involved key essential variables i.e., precipitation (Pr), maximum temperature (Tmax) and minimum temperature (Tmin), and characteristics of extreme events (duration, severity and frequency of wet and dry events) during the historical period 1986-2005. The proposed framework is demonstrated as a case study

over a transboundary watershed, namely the Upper Jhelum Basin (UJB) located at the foothills of Western Himalaya, one of the most affected mountainous ranges by climate change. The region has already witnessed an increase in extreme hydro-meteorological events in the last few decades (Pachauri et al., 2014), and hence the projection of these extreme events cannot be left apart in the development of the climate change adaptation strategy for the region. The use of SPEI over other drought indices such as SPI is preferred due to its link to potential evapotranspiration (PET), which makes it more sensitive in the context of global warming (Vicente-Serrano et al., 2010, Huang et al., 2017, Yao et al., 2018).

The specific objectives of the study are:

- To assess the added value of multivariate bias correction methods with respect to the univariate bias correction methods in the context of physical coherence of two variables, i.e., multivariate dependency.
- To assess the applicability of the direct and component-wise bias correction of a multivariate index (SPEI).
- To assess the added value of the CORDEX-CORE simulations compared to the CORDEX counterparts, as well as the added value of CORDEX compared to CMIP6 after bias correction.

6.2 Data and Methods

6.2.1 Standardized Precipitation Evapotranspiration Index (SPEI)

A multivariate drought index i.e., standardized precipitation evapotranspiration index-SPEI (Vicente-Serrano et al., 2010), is widely used to monitor and assess drought and their sectorial impacts under global warming conditions. It can be interpreted as the number of standard deviations by which the observed anomaly deviates from the long-term mean. Various researchers highlighted its suitability to detect the onset and spatio-temporal evolution of drought at the regional to global scales (Wang et al., 2014, Ansari and Grossi, 2022), and recommended it for operational drought monitoring (Vicente-Serrano et al., 2010).

In the present study, SPEI is calculated using a 30-day accumulation period at daily time step which can be used for short- or long-term extreme events analysis. The calculation and application of daily SPEI are similar to that of monthly SPEI except for the temporal resolution of input climatic data. Its calculation requires two parameters i.e., precipitation and potential evapotranspiration (PET). The latter involves numerous variables, including air surface temperature, air humidity, shortwave incoming radiation, water vapor pressure, and ground-atmosphere latent and sensible heat fluxes (Allen et al., 1998), which hinders its correct estimation. Various methods (physical or empirical) have been developed to indirectly estimate PET from meteorological variables. These methods also vary in their input data requirement. The data-intensive methods such as the Penman-Monteith method, in general, provide better results than others for PET quantification (Droogers and Allen, 2002). However, the purpose of including PET in the drought index calculation is to obtain a relative temporal estimation, and therefore the method used to calculate the PET is not critical (Vicente-Serrano et al., 2010). A study conducted by Beguería et al. (2014) compared the SPEI values using three different methods for PET

estimation (Penman- Monteith, Hargreaves, and Thornthwaite) and found small differences in humid regions. Mavromatis (2007) also found similar results for a drought index (i.e., Palmer Drought Severity Index-PDSI) when considering simple and complex PET methods. Therefore, the present study employs a simple temperature-based Hargreaves-Samani method (involves T_{max} and T_{min}) (Hargreaves and Samani, 1985) due to data availability. The extraterrestrial radiation ($\text{mm} \cdot \text{day}^{-1}$) used in Hargreaves-Samani method was calculated from the latitude of each grid box and day of the year. The SPEI calculation involves two further steps: aggregation of daily climatic water balance time series at different time scales (30 days in the present study), and then its normalization into a log–logistic probability distribution to obtain the SPEI index series. The log-logistic distribution for SPEI calculation is used and recommended by many researchers (Vicente-Serrano et al., 2010, Wang et al., 2015, Himayoun and Roshni, 2019, Ansari and Grossi, 2022). A more detailed description of the SPEI calculation procedure can be found in Vicente-Serrano et al. (2010) and Wang et al. (2015).

6.2.2 Identification of extreme events and their characteristics

The wet and dry extreme events are identified by using monthly SPEI values (computed from daily SPEI values, see Sect. 2.1). Although the SPEI was originally proposed for drought monitoring, it can also be used as a tool to detect flood risk, since it quantifies both positive and negative anomalies representing wet and dry conditions, respectively. In the present study, wet and dry extreme events are defined as the positive ($\text{SPEI} \geq 1$) and negative SPEI ($\text{SPEI} \leq -1$) for at least two consecutive months, respectively. The thresholds for the wet and dry extreme events based on SPEI values are taken from previous literature (Svoboda et al., 2012). Three event indices (severity, duration, and frequency) are considered to characterize the wet and dry extreme events during the historical period (1986-2005). The duration of a wet and dry event (denoted hereafter as wet duration -WD- and dry duration-DD) is the number of consecutive months with SPEI above 1 and below -1, respectively; severity (wet severity -WS- and dry severity-DS) refers to the cumulative value of the index from the first month to the last month of the wet/dry event and it represents the water surplus and deficit, respectively; and the absolute frequency (wet frequency -WF- and dry frequency-DF) is the total number of events in the historical period. Since duration and severity are obtained for individual events, we consider the median value across all the identified events as a single index.

6.2.3 Reference Dataset

Because of complex orography, severe weather, and harsh environmental conditions in the High Mountains of Asia (HMA), observations from meteorological stations are rare in this region. Available weather stations are usually sparse and unevenly distributed. Gridded data, satellite observations and reanalysis are mostly used as an alternative, even though they are affected by the uncertainties inherent to the observations and to statistical post processing (e.g., interpolation). In the present study, the W5E5 dataset (Lange, 2019) is used as the observational reference for training the bias correction methods during the historical period (1986-2005). We use these 20

years of calibration to maximize the number of climate model simulations and to align to other climate change studies, such as the IPCC Fifth Assessment Report, which considered it as baseline for future changes. The W5E5 dataset was developed under the Phase 3b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) and was used as reference to bias-correct the climate models output which serve as input data to carry out the impact assessments under ISIMIP3b. The W5E5 is a merged dataset, developed using version 2.0 of WFDE5 data (WATCH forcing data methodology applied to ERA5 data (Weedon et al., 2014, Cucchi et al., 2020) over land and ERA5 (Hersbach et al., 2020) over the ocean. W5E5 is a global daily dataset available at 0.5° horizontal resolution covering the period 1979–2016. The W5E5 dataset provides twelve meteorological variables. However, the present study employed three variables i.e., precipitation, daily maximum near surface air temperature and daily minimum near surface air temperature.

The use of W5E5 (WFDE5 data over land and ERA5 over ocean) for the present study is motivated by numerous previous studies. For instance, the suitability of ERA5 and its slightly overestimation of precipitation over the study region (UJB), especially over the mountainous part of the basin, have been evaluated and acknowledged by several researchers (Baudouin et al., 2020, Arshad et al., 2021, Liaqat et al., 2022, Ansari et al., 2022). These studies recommend performing the bias correction of ERA5 with localized data before its application in impact studies. Moreover, the WFDEI dataset, which is the predecessor of WFDE5 but based on ERA-Interim reanalysis, has also been applied to the UJB and surrounding regions to alleviate the data scarcity issue across the transnational border (Lutz et al., 2016, Dahri et al., 2016, Azmat et al., 2018). The WFDE5 benefits from the higher spatial and temporal resolution and better representation of spatial variability of ERA5, compared to WFDEI which was generated by interpolating the lower-resolution ERA-Interim reanalysis. An evaluation of both products against meteorological observations shows that, on average, WFDE5 has lower mean absolute error and higher correlation than WFDEI for all variables (Cucchi et al., 2020). W5E5 has also been used as the reference observational dataset for bias correction in the IPCC Interactive Atlas in the 6th Assessment Report (Gutiérrez et al. 2021).

6.2.4 Climate model simulations

In the present work, we consider climate model historical simulations from 2 GCMs of the 6th Coupled Intercomparison Project (CMIP6, (Eyring et al., 2015)), 17 RCM simulations (3 RCMs unevenly driven by 10 GCMs) of the coordinated Regional Climate Experiment (CORDEX, (Giorgi et al., 2009, Jones, 2010)) and 9 RCM simulations (3 RCMs unevenly driven by 6 GCMs) of the CORDEX-Common Regional Experiment (CORDEX-CORE, (Teichmann et al., 2021)). For the RCM simulations, the south Asian domain (denoted as WAS) is considered. In particular, we use all available simulations by November 2021 for WAS-44 and WAS-22 domains (simulations conducted at horizontal resolutions of 0.44° and 0.22° on rotated grids, approximately 50km and 25km) for CORDEX and for CORDEX-CORE, respectively. The selection of this particular subset of GCMs from CMIP6 is motivated by the availability of models with high spatial resolution (Table 6.1), approximately similar to the CORDEX counterparts. Coarser GCMs are not

considered due to the small size of the catchment under study. More details on the considered climate models are given in Table 6.1 and 6.2.

Table 6.1: Details of the CMIP6 GCMs used in the present study

Model	Institute (country)	Horizontal resolution
CNRM-CM6-1-HR	CNRM-CERFACS (France) Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	$0.5^\circ \times 0.5^\circ$
EC-Earth3	EC-Earth-Consortium	$0.7^\circ \times 0.7^\circ$

Table 6.2: Details of the CORDEX and CORDEX-CORE RCMs used in the present study

Experiment	RCM	RCM description	Contributing CORDEX modelling center	Driving CMIP5 GCM
CORDEX (WAS-44)	RegCM4-4	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climate Model version 4 (RegCM4; (Giorgi et al., 2012))	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India	CCCma-CanESM2
				CNRM-CERFACS
				CSIRO-QCCCE-CSIRO
				IPSL-IPSL-CM5A-LR
				MPI-M-MPI-ESM
				NOAA-GFDL-GFDL-ESM2M
	RCA4	Rossby Centre Regional Atmospheric Model version 4 (RCA4; (Samuelsson et al., 2011))	Rossby Centre, Swedish Meteorological and Hydrological Institute (SMHI), Sweden	CCCma-CanESM2
				CNRM-CERFACS
				CSIRO-QCCCE-CSIRO
				ICHEC-EC-EARTH
				IPSL-IPSL-CM5A-MR
				MIROC-MIROC5
				MOHC-HadGEM2-ES
				MPI-M-MPI-ESM
				NCC-NorESM1-M
				NOAA-GFDL-GFDL-ESM2M
	REMO2009	MPI Regional model 2009 (REMO2009; (Teichmann et al., 2013))	Climate Service Center (CSC), Germany	MPI-M-MPI-ESM
CORDEX-CORE (WAS-22)	COSMO-crCLIM-v1-1	(Consortium for Small scale Modelling) model (Baldauf et al., 2011)	Climate Limited-area Modelling (CLM) Community	ICHEC-EC-EARTH
				MPI-M-MPI-ESM-LR
				NCC-NorESM1-M

	RegCM4-7	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climate Model version 4 (RegCM4; (Giorgi et al., 2012)	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India	MIROC-MIROC5
				NCC-NorESM1-M
				MPI-ESM-MR
	REMO2015	Climate Service Center Germany (GERICS).	Climate Service Center Germany (GERICS).	MOHC-HadGEM2-ES
				MPI-M-MPI-ESM-LR
				NCC-NorESM1-M

6.2.5 Bias Correction methods

Several univariate and multivariate bias correction methods are used in this study. A comparison between five univariate bias correction methods and three multivariate bias correction methods is performed with respect to their ability to reproduce observed univariate distributions and inter-variable relationships. The univariate methods are applied to climate model simulations following two approaches: (1) individually to all involved essential climatic variables (i.e., the component-wise approach) and (2) directly to the uncorrected SPEI (i.e., the direct approach). All BC methods make a common assumption of stationary biases by applying the same calibrated transfer function in the calibration period (1986-2005) to the future projected climate which may lead to modifications of the raw model climate change signals for non-trend preserving methods. Table 6.3 summarizes the considered BC approaches and methods.

Table 6.3: Bias correction approaches and methods employed in the present study

Approach	Method	Name	Reference
Component-wise	Univariate	Empirical quantile mapping (EQM)	(Déqué, 2007)
		Parametric quantile mapping (PQM)	(Piani et al., 2010)
		Generalized Pareto parametric quantile mapping (GPQM)	(Vrac and Naveau, 2007)
		Quantile Delta Mapping (QDM)	(Cannon et al., 2015)
		Detrended quantile mapping (DQM)	(Cannon et al., 2015)
	Multivariate	Multivariate Bias Correction: Pearson version (MBCp)	(Cannon, 2016)
		Multivariate Bias Correction: Spearman version (MBCp)	(Cannon, 2016)
		Multivariate Bias Correction with N-dimensional probability density function transform (MBCn)	(Cannon, 2018)
Direct	Univariate	Empirical quantile mapping (EQM)	(Déqué, 2007)
		Parametric quantile mapping (PQM)	(Piani et al., 2010)
		Generalized Pareto parametric quantile mapping (GPQM)	(Vrac and Naveau, 2007)
		Quantile Delta Mapping (QDM)	(Cannon et al., 2015)
		Detrended quantile mapping (DQM)	(Cannon et al., 2015)

Univariate Bias Correction Methods

Five univariate methods (either parametric or empirical) are considered in this study. The present study uses the implementation included in the R package downscaleR (Bedia et al., 2020) which is part of the R bundle climate4R (Iturbide et al., 2019).

Empirical quantile mapping (EQM): This method calibrates an empirical transfer function that matches all quantiles of model empirical cumulative distribution function (CDF) to those of reference dataset. The values lying outside the calibration range are adjusted through constant extrapolation (first and last percentile corrections for values below and above the calibration range, respectively) (Thiemeßl et al., 2012). The method also adjusts the overestimation of wet or dry days frequency (defined as days with precipitation above or below 1mm in the reference dataset) in the model using, respectively, adjusted wet-day threshold and frequency adaptation proposed by (Thiemeßl et al., 2012, Wilcke et al., 2013). If a model produces too many wet days, then the wet-day frequency is corrected in such a way that it matches the observed wet-day frequency. In case of overestimation of dry days in the model, then the frequency adaptation is made through the random sampling of the observed Gamma distribution into the simulated first bin (0–1 mm) in order to generate wet days.

Parametric quantile mapping (PQM): This method adjusts the theoretical CDF of the model output onto the corresponding observed distribution via a parametric transfer function calibrated over the training period (Piani et al., 2010). Assumptions are made about the distribution of a particular variable (i.e., precipitation and temperature follow the Gamma and Gaussian distribution, respectively). As for EQM, in the considered implementation the overestimation of wet or dry days in the model data is also adjusted using wet-day frequency correction and frequency adaptation approach, respectively.

Generalized Pareto parametric quantile mapping (GPQM): The method is specifically designed to adjust the extremes of the distribution. It fits two different parametric distributions to adjust the extreme and non-extreme values separately. The Gamma or Gaussian distribution (for precipitation and temperature, respectively) adjust the central part whereas Generalized Pareto distributions are applied above the 95th and below 5th percentiles (Vrac and Naveau, 2007). As for EQM, the wet-day frequency correction and frequency adaptation are applied.

The Quantile Delta Mapping (QDM): The method was first developed by (Li et al., 2010) and (Wang and Chen, 2014) as ‘equidistant’ and ‘equiratio’ quantile matching, respectively. The main idea is to preserve the trends of all quantiles of the simulated distribution. Later, (Cannon et al., 2015) termed both methods as QDM due to its similarity to a quantile delta change method. Firstly, model projections are detrended by quantile and quantile mapping is applied to adjust systematic distributional biases relative to the observations. Then the removed projected trends are reintroduced to the bias-corrected quantiles. Thus, it ensures that the sensitivity of the underlying climate model remains unaffected by the bias correction (at least so far as quantiles are concerned).

Detrended quantile mapping (DQM): The method is similar to QDM, except that absolute or relative changes in the simulated mean are accounted for, rather than all modeled quantiles (Cannon et al., 2015). Hence, the long-term mean (linear) trend is removed, and bias

correction is applied to the detrended series by empirical quantile mapping using all quantiles to adjust systematic distributional biases relative to observation. Then the mean trend is reintroduced to the bias-corrected series. As DQM only preserves long-term mean trends, it does not ensure to preserve the simulated model trends at the tails of the distribution that define climate extremes (Casanueva et al., 2020).

Multivariate Bias Correction Methods

The three MBC methods used to adjust the inter-variable structure in this study are **MBCp**, **MBCr** (Cannon, 2016) and **MBCn** (Cannon, 2018). The MBCp and MBCr methods are the combination of two approaches: firstly, quantile delta mapping is applied to each variable individually, in order to correct the marginal distribution of the variables including the preservation of absolute (in case of temperature) or relative (in case of non-gaussian variables like precipitation) raw climate change signal, and, secondly, multivariate linear rescaling is applied (Bürger et al., 2011), in order to adjust the dependence structure through an iterative application of the Cholesky decomposition of the covariance matrix. The Pearson correlation and Spearman rank correlation are used as covariance matrix in the MBCp and MBCr methods, respectively. These two steps are repeated until both the marginal distributions and specified correlation matrix converge to those of the reference dataset.

The MBCn algorithm, which is based on the N-dimensional probability density function transform, is adopted from an image processing algorithm used to transfer color information (Pitié et al., 2005, Pitié et al., 2007). Unlike MBCp and MBCr methods, MBCn permits to transfer all statistical characteristics of the observed multivariate distribution to those of the climate model outputs. In MBCn, random orthogonal rotation matrices are applied to the observed and climate model data to partially decorrelate the climate variables before the QDM. It is then rotated back with the inverse random matrices. The process of rotation, QDM and back rotation are repeated iteratively until the multivariate distribution of the historical climate model data converges to that of the reference data. In the present study, the MBCn algorithm is iterative 30 times to get bias corrected output. The present study uses the implementation included in the R package “MBC” (<https://cran.r-project.org/web/packages/MBC>).

6.2.6 Experimental framework

In this study, the BC methods presented above are applied to adjust daily maximum temperature, minimum temperature and precipitation of 28 (global and regional) climate model simulations (Tables 6.1 and 6.2) towards the W5E5 reference dataset. All BC methods are calibrated in the period 1986–2005 using daily time series, being the correction functions calculated separately for each month in order to account for biases varying throughout the year. These corrections are then applied to the same period on a monthly basis in order to evaluate their performance in the present climate. Although the calibration and evaluation periods are the same, our approach can be considered independent since the evaluated aspect (i.e., SPEI indices) is not directly adjusted by the BC methods. All analyses are carried out at the spatial resolution of the W5E5 grid (regular 50×50 km). For this reason, all model simulations are remapped into the W5E5

grid. For this purpose, CORDEX-CORE simulations are conservatively remapped into the observational grid in order to guarantee the representation of areal averages. For CMIP6 and CORDEX simulations, the nearest neighbor gridbox to each observational gridbox is taken, since the resolution mismatch is small. This interpolation method maintains the higher spatial variability of the topographical areas whereas bilinear or cubic interpolation would smooth the spatial patterns. As a consequence, there will be aspects of the added value of the higher-resolution WAS-22 experiments (related to better-resolved, fine-scale processes) that can be smoothed out, but they may still be present after remapping them onto a coarse resolution. Thus, we address the added value of the high resolution at its skillful scale (Grasso, 2000), which is coarser than the scale in which the simulation was developed.

For all BC methods, daily maximum temperatures, minimum temperature, and precipitation from each GCM/RCM are corrected independently at each grid box. Due to the multivariate nature of the SPEI, daily maximum temperature, minimum temperature and precipitation are corrected separately (in case of univariate BC methods) and jointly (in case of multivariate BC methods) prior to the SPEI calculation (i.e., the component-wise approach; (Casanueva et al., 2018)). An alternative to this approach is to first calculate the SPEI index from the original, biased simulations (i.e. original modeled intervariable relationships remain) and, secondly, bias-correct the index itself using univariate methods (direct approach; Casanueva et al. (2018)). Note that normal distribution is assumed for the direct correction of SPEI through the PQM method. In addition to the evaluation of BC methods and approaches performance, the added value of higher spatial resolution in the modeled data (CORDEX-CORE over CORDEX and CMIP6) is assessed. Both assessments are performed in terms of the ability to simulate the mean spatio-temporal distribution of SPEI and its derived indices over the study region.

6.2.7 Evaluation metrics

The performance of the raw and bias-corrected climate model simulations (component-wise approach) is first evaluated in terms of univariate indices related to temporal aspects not calibrated specifically by any of the BC methods. For this purpose, we consider indices defined by the EU-COST Action VALUE (Maraun et al., 2019), representing day-to-day characteristics (transition probability of a wet day given that the previous day was dry, longest dry spell and longest warm spell) and monthly/annual features (amplitude of the annual cycle and interannual variance). Secondly, we evaluated inter-variable relationships by using two statistical metrics, namely the correlation coefficient (Pearson, 1895, Wilks, 2011) and Perkins skill score (Perkins et al., 2007). The correlation coefficient between daily time series of two variables (Spearman for Pr vs Tmax and Pr vs Tmin and Pearson for Tmax vs Tmin) is computed at each grid cell to measure the relationship between pairs of variables. Since Pearson and Spearman correlation coefficients imply a linear and non-linear relationship, respectively, are hence recommended for temperature and precipitation respectively (Wilcke et al., 2013). The Perkins skill score is a quantitative measure of the similarity between two probability density functions (PDFs) by measuring the common area between them. A value of 0 indicates no overlap and a value of 1 indicates

distributions are identical. In the present study, an extended version of the Perkins skill score with two dimensions is used, that accounts for the similarity (overlap) between the modeled joint distribution of two meteorological variables and the observed counterpart (Casanueva et al., 2019). Further, the raw and bias-corrected climate model data (component-wise and direct approaches) are evaluated by using the mean bias (ratio of model to reference) of the SPEI indices (median duration, median severity, and absolute frequency; see Sect. 2.2).

6.3 Results

6.3.1 Evaluation of temporal properties

The ability of the BC methods to represent the marginal properties of the individual variables is expected, since they are related to parameters which have been calibrated by the methods explicitly (Casanueva et al., 2016). They might, however, deteriorate temporal properties, as it is case for multivariate BC methods (e.g., François et al., 2020) since they have not been adjusted by any of the methods. Figures B1-B5 show the overall improvement of temporal properties after BC, with a systematic reduction of model biases and no clear benefit of multivariate methods. Raw models present an overall overestimation of dry-to-wet transition probability, which is reduced after BC especially for QDM, MBCn and MBCp (Fig. B1). Annual longest dry and warm spells are underestimated and overestimated, respectively, in the raw models, and biases are largely corrected after most BC methods. Overall, DQM presents the largest departures from the reference dataset. The above-mentioned statistics and their inadequate representation in the BC data might lead to biases in the SPEI, which relies on daily values of the input variables. Similar conclusions hold for temporal properties at longer time scales, such as the amplitude of the annual cycle (Fig. B2) and interannual variance (Figs. B3-B5). The amplitude of the annual cycle is largely improved by most BC methods, except for the annual cycle of precipitation which is overestimated by GPQM and underestimated by DQM (Fig. S2). The interannual variance for monthly precipitation is well represented after BC, except for the overestimation by GPQM in some months (Fig. B3). The large overestimation of the interannual variance of maximum and minimum temperatures is not completely solved by BC, since important overestimations remain for all BC methods (Fig. B4-B5).

6.3.2 Evaluation of inter-variable relationships

To evaluate the inter-variable structures, correlation coefficient (COR) and Perkins skill score (PSS) between daily maximum and minimum temperatures are computed at each grid cell to measure the relationship between the two physical variables (Fig. 6.1). The heat map shows the spatially averaged values of Pearson correlation (size of the marker) and Perkins skill score (colored scale) for the raw and bias-corrected model output, i.e., the larger the marker the stronger the relationship between the two variables, and the yellower the color the more similar the joint PDFs are to the reference dataset. The Spearman correlation coefficient between the other pairs of variables (Pr vs Tmax and Pr vs Tmin) for the reference dataset is found to be negligible (Fig. B6). Therefore, the ability of the BC methods to adjust the inter-variable dependencies is evaluated only

for maximum and minimum temperature. Note that we focus on inter-variable relationships at daily timescales, since this is when they are expected to be relevant for the SPEI used in the present work. However, more important correlations between precipitation and temperatures are found at the monthly scale in the reference data (up to -0.54, Fig. B7), which are not present in most of the raw models but are improved after BC (except for GPQM, Fig. B8).

Overall, small differences in terms of correlation are found for raw and bias-corrected model output, compared to the reference value (Fig. 6.1). Maximum and minimum temperature showed strong positive correlation exceeding 0.9 in W5E5, which is also evident in the raw models and preserved after BC. However, one climate simulation (REMO2009 RCM driven by MPI GCM) shows weaker correlation for the raw model output and improves with all BC methods.

Regarding PSS, low values for the raw model outputs show the differences in the joint PDF of Tmax and Tmin compared to the reference data, meaning that the inter-variable dependencies in the reference dataset are not well presented by the raw model output. However, this inter-variable physical coherence improves to some extent with the application of all BC methods. Among univariate BC methods, the empirical ones (EQM, DQM and QDM) performed better than the parametric counterparts in terms of the inter-variable physical coherence between maximum and minimum temperature. As expected, all MBC methods performed well and improved upon the univariate ones. Among the three MBC methods, MBCn outperformed the other two methods, with a very similar joint PDF to the reference data.

All the above holds for most of the different climate model simulations, regardless of the RCM, driving GCM, original spatial resolution (CORDEX vs CORDEX-CORE) and modelling experiment (CMIP vs CORDEX). Although the differences among different climate model simulations from three modelling experiments exist for parametric methods (PQM and GPQM), no specific pattern is found. Thus, no evident added value of the higher resolution experiment models (WAS-22) is observed over low-resolution experiment models (WAS-44 and CMIP6), either in correlation or Perkins skill score. However, a clear added value of multivariate BC methods is apparent.

To further explore the ability of raw and BC datasets to reproduce the reference full joint probability distribution of maximum temperature and minimum temperature, two-dimensional kernel density plots together with marginal histograms (Fig. 6.2) are developed for a single grid box of an RCM (highlighted red box in Fig. 6.1 and Fig. 6.2). The selection of this particular grid box is motivated by the low values of correlation and PSS for the raw simulation and subsequent improvement after BC, in order to investigate whether low PSS values can be attributed to biases in maximum temperature or minimum temperature or both. Higher density values in the reference dataset (Fig. 6.2, first row and second column) take place around 20°C and 7°C for maximum and minimum temperature, respectively. For the raw model output, the shape and location of the joint distribution and maximum probability are biased at both ends of the distributions, as evident in low PSS value i.e., 0.641. This low PSS value of the raw simulation is attributed to both variables, but especially to the misrepresentation of the minimum temperature distribution. Likewise, the temporal correlation between the two variables is slightly lower than in the reference. Correlation

and PSS improve after BC regardless of the BC method with least improvement in the joint distribution with GPQM (PSS=0.707). Higher density values are well located with parametric methods i.e., PQM and GPQM (this would be expected, because they fit the mean and standard deviation in the calibration phase), but for GPQM they are not so differentiated as in the reference data. Other three univariate BC methods (i.e., EQM, DQM and QDM) and multivariate methods improve the representation of the joint distribution in a similar way, although maxima are not so differentiated as in the reference data.

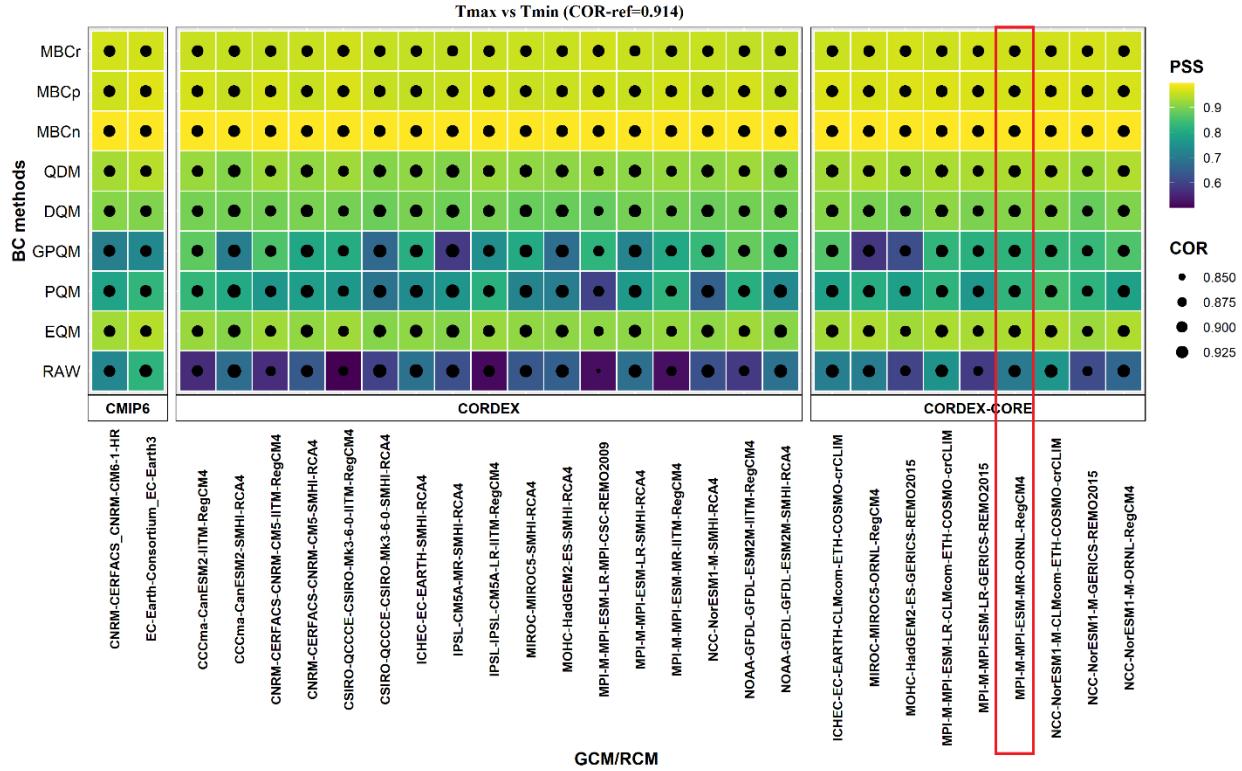


Figure 6.1: Pearson correlation coefficient (COR, circle) between maximum and minimum temperatures and Perkins skill score (PSS, colored scale) of the joint PDFs for the raw and bias-corrected climate model data (only component-wise approach). Correlation for the reference dataset is shown on top of the panel. The highlighted RCM (red square) is selected for further analyses in Fig. 6.2.

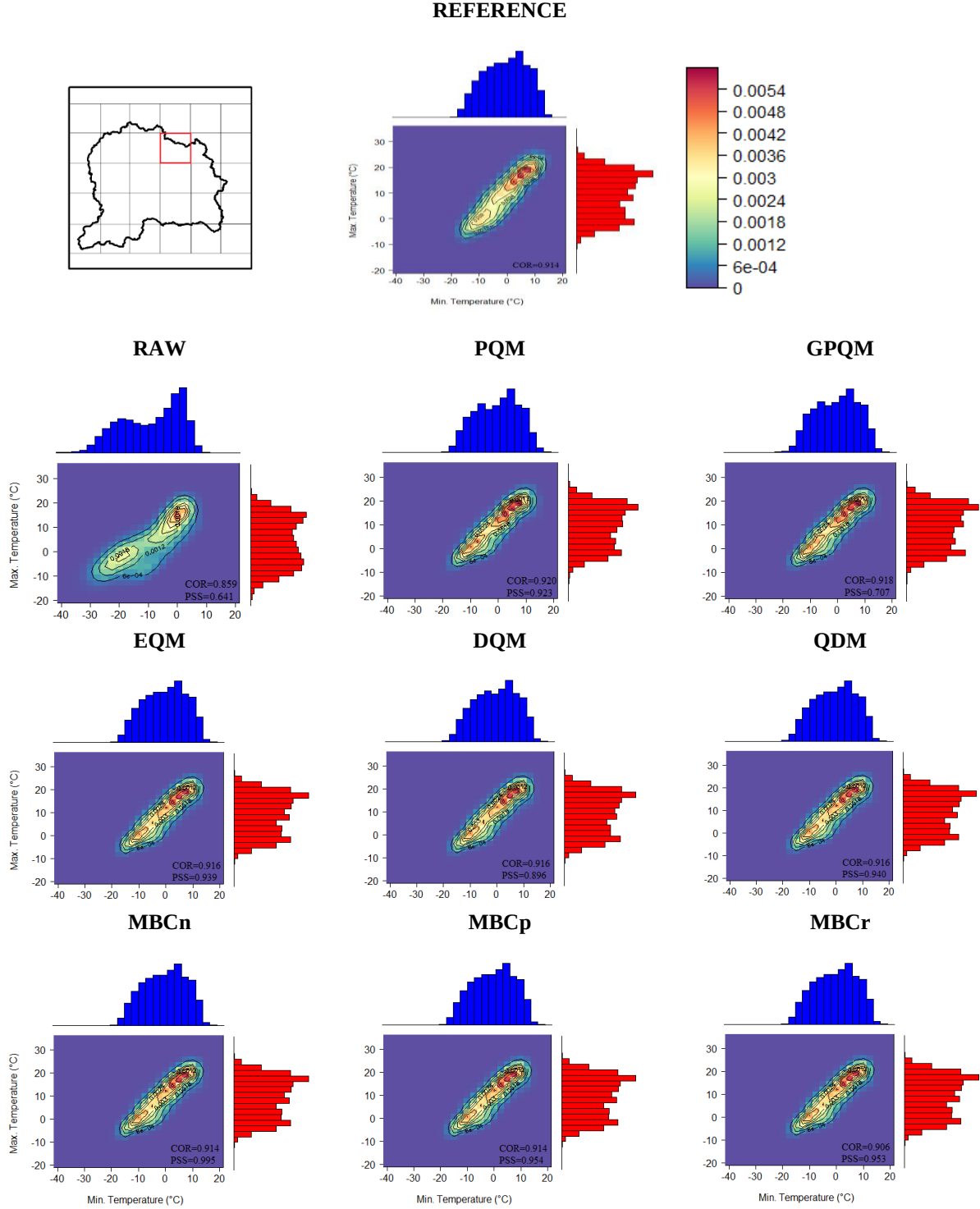


Figure 6.2: Two-dimensional kernel density plots for the highlighted grid box (red box). Blue histograms (and X-axis) refer to minimum temperature and red histograms (and Y-axis) refer to maximum temperature. Shadings represent the 2-D density distribution for the reference, raw and eight BC methods. Contour lines represent the probabilities in the reference dataset, which are overlaid on the model probabilities for the sake of comparison. COR depicts the Pearson

correlation coefficient between daily minimum and maximum temperatures and PSS represents the two-dimensional Perkins skill score of distributional similarity.

6.3.3 Evaluation of SPEI characteristics

The performance of the raw and bias-corrected climate model simulations is evaluated in terms of mean biases (ratio of model to reference dataset) in SPEI indices (duration, severity, and frequency, see Sect. 6.2.2) during the historical period (1986-2005). The spatial distribution of biases calculated from multi-model ensemble mean SPEI indices, separately for CMIP6 (2 simulations), CORDEX (17) and CORDEX-CORE (9) are presented in Figs. 6.3-6.4 and B9-B12. Results show that the northeast part of the region, located at the foothills of Western Himalayas, is found to be more affected by wet and dry events with higher severity and duration (see the upper left panel in each Figure). The higher susceptibility of the region towards more extreme events could be explained with the increasing rates of global warming over mountainous region i.e., Western Himalayas, also reported by many researchers (Pachauri et al., 2014, Zaz et al., 2019, Rashid et al., 2020, Shafiq et al., 2020, Ansari and Grossi, 2022). Studies by Negi et al. (2018) and Dimri and Dash (2012) also confirm that most of the western Himalayan region recorded a significant warming trend especially from 1975 onwards. This is also supported by the tree-ring chronologies of the region which indicate rapid growth of the tree rings in the recent decades especially at higher altitudes (Borgaonkar et al., 2009).

In the context of biases, different sign biases are found depending on the location and SPEI index. The underestimation of all SPEI indices is higher in the northeast part of the region which shows that raw climate models' performance is relatively poor over mountainous regions. Overall, larger biases are found in frequency indices as compared to duration and severity indices. These under- and overestimations are partly alleviated by most of the bias correction methods. Regarding severity indices (Fig. 6.3 and 6.4), remaining biases after BC are similar across BC methods, with underestimation of WS in the mountainous region and no specific pattern for DS. In the case of duration indices (Fig. B9 and B10), the overestimation at lowlands is improved by all BC methods, however that improvement is not only negligible but also degrade the raw CMIP6 ensemble in the northeast of the basin (mountainous region). The underestimation of frequency indices over high mountains (Fig. B11 and B12) is partially reduced by all BC methods with slightly better performance under the direct approach. However, bias correction induces an overestimation in WF over lowlands which is not present in raw ensembles of all datasets. Overall, GPQM is found to bring the least improvement for most of the SPEI indices and the added value of MBC methods is not evident over remaining univariate methods.

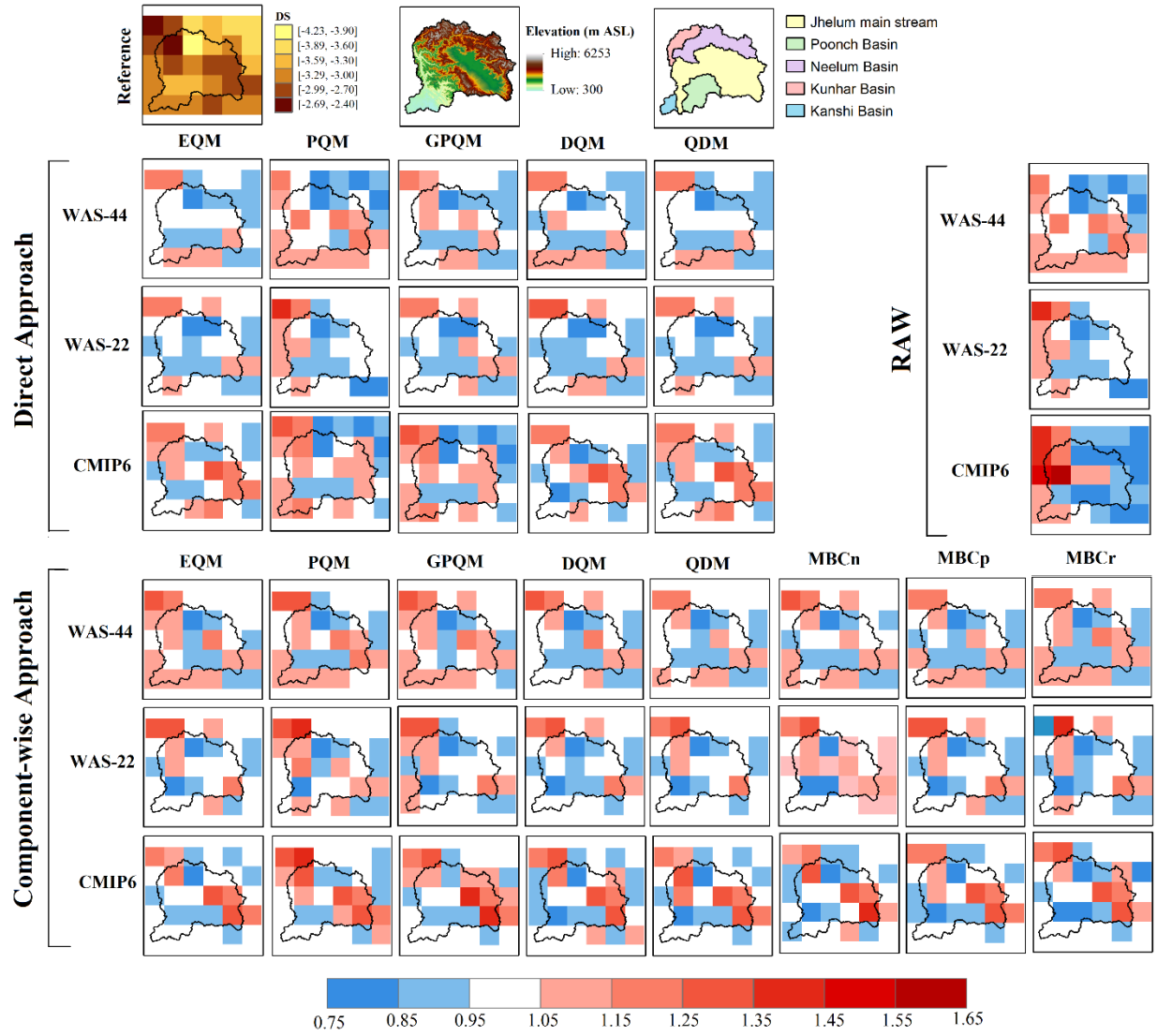


Figure 6.3: Median dry severity (DS) in the reference dataset expressed in accumulated SPEI units (first row, left), digital elevation model in meter above sea level (first row, center and location of sub-basins (first row, right), and biases (as a ratio of model to reference) of DS for the multi-model raw and bias-corrected ensembles, for the two bias correction approaches and all methods (columns).

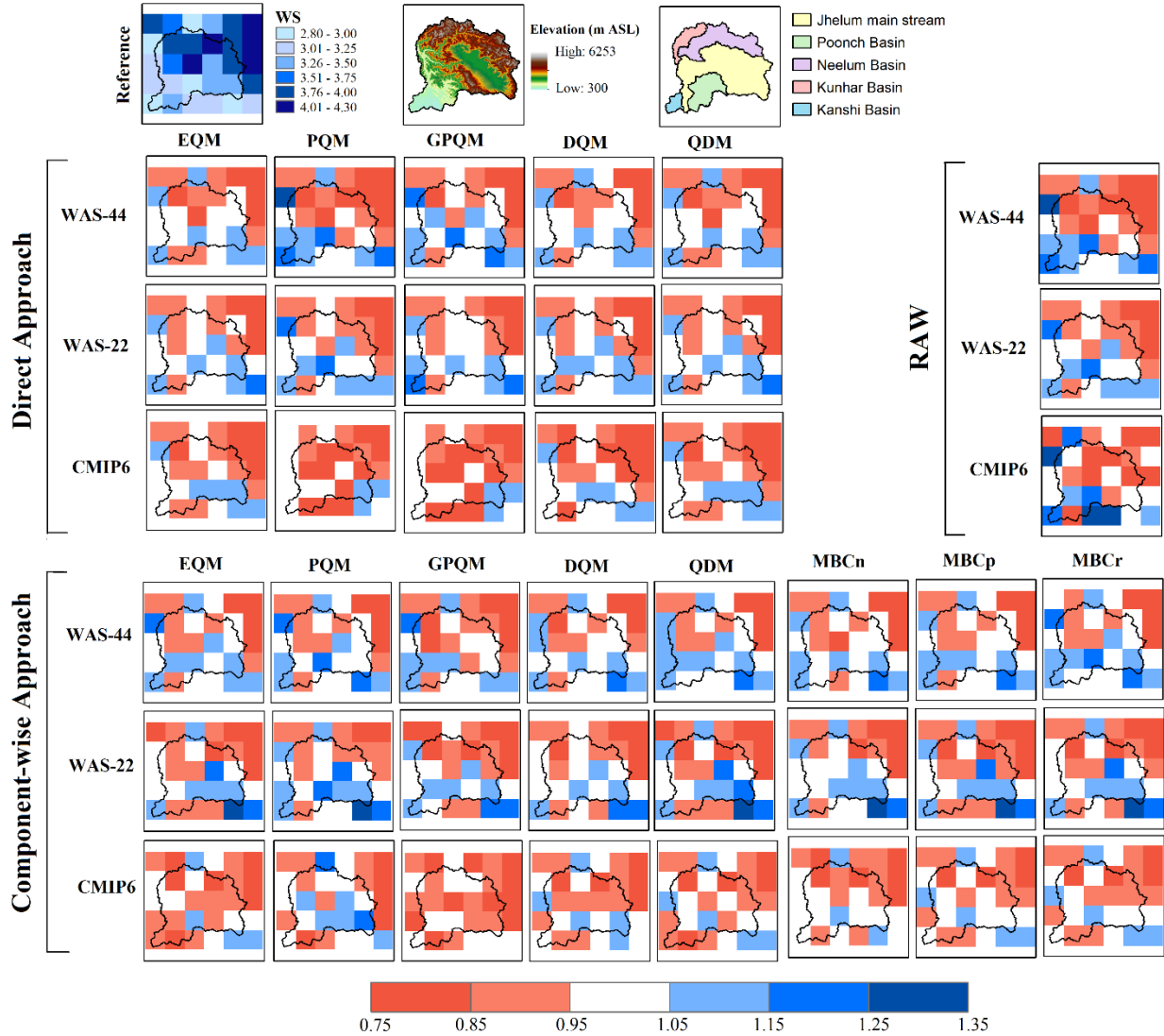


Figure 6.4: Same as figure 6.3, but for median wet severity (WS), expressed in accumulated SPEI units.

The regionally averaged biases in median duration and severity, and absolute frequency of dry and wet events for all individual climate simulations (CORDEX-CORE, CORDEX and CMIP6) are summarized in Fig.6.5. Overall, results show that raw models generally underestimate all SPEI indices and bias correction alleviates this for frequency and severity indices, but shorter events than in the reference dataset are found after the corrections. The conclusions drawn from the spatial plots also relate to climate models spread. For instance, the small improvement in duration indices over high mountains is in line with a slight reduction of the model spread after bias correction, yet the underestimation of the DD and WD remains. Similarly, for WF the reduction in the underestimation over high mountains and induction of overestimation over

lowlands by all BC methods is in agreement with changes in the models spread after bias correction (Fig. B12 and 6.5).

In general, all BC methods under the direct approach present similar improvements for all SPEI indices, except PQM for dry extremes which shows smaller improvements for some simulations. Regarding the component-wise approach, the empirical BC methods i.e., EQM, DQM and QDM performed relatively better than PQM and GPQM for most of the models and SPEI indices. Small differences are found in the performance of three MBC methods.

Regarding the spatial resolution, no obvious benefit of the higher resolution (CORDEX-CORE vs. CORDEX and CMIP6) is apparent. Raw model outputs from CORDEX-WAS44 show more spread than the CMIP6 and CORDEX-CORE experiment models, which could be due to the number of simulations. After BC, the spread of CORDEX and CORDEX-CORE is similar and thus, no clear added value of higher resolution is found.

Overall, the performance of BC methods and climate models are found to be relatively better for drought indices than for flood indices. Most of the models underestimate wet duration and severity over the region before and after bias correction.

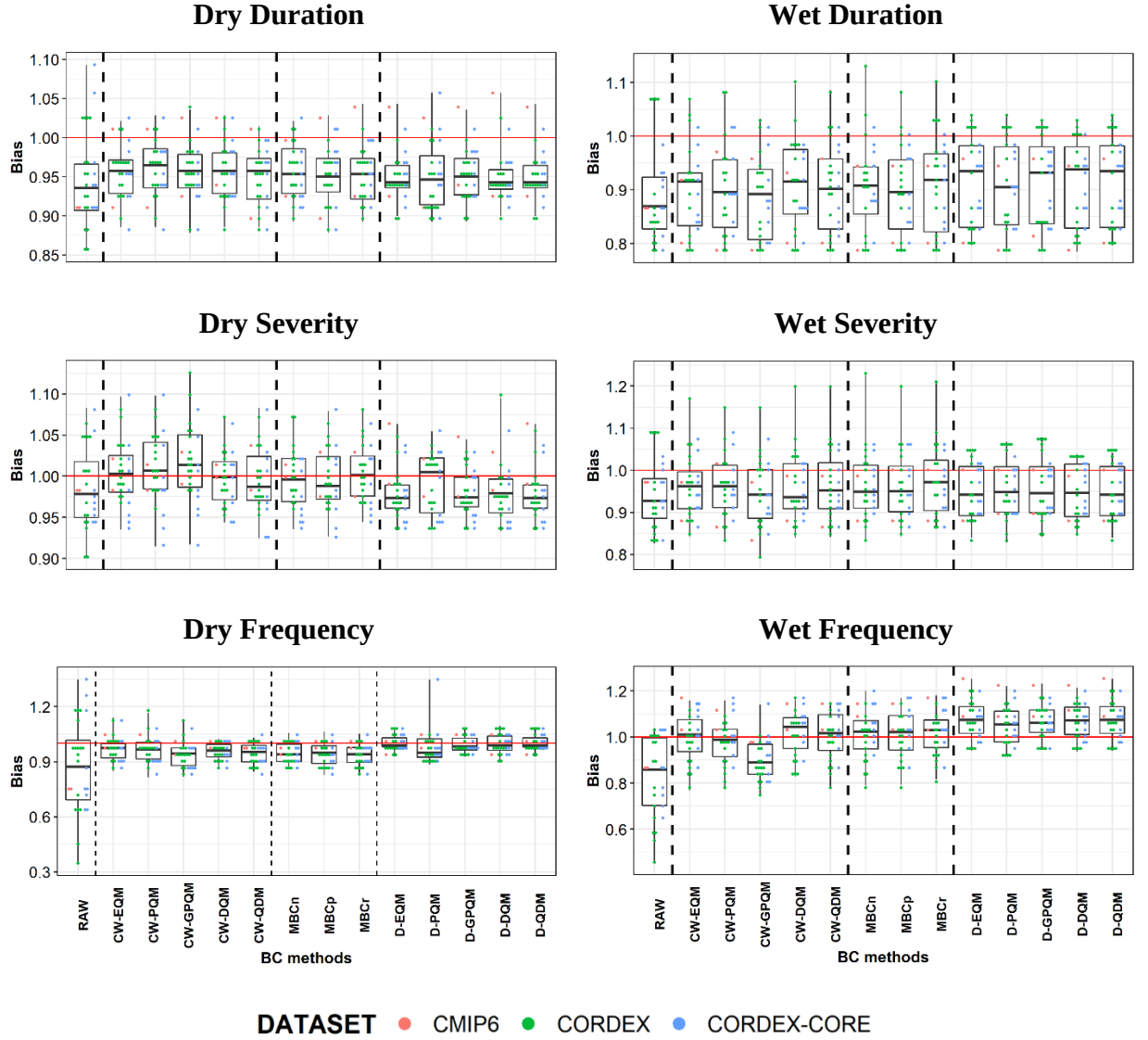


Figure 6.5: Biases (as a ratio of model to reference) in spatially averaged SPEI indices over Upper Jhelum Basin computed from the raw (first box in each panel) and bias corrected data (rest of boxes; CW: component-wise, D: direct). Each box represents the interquartile range of biases across all models, which are depicted individually with colored dots (CMIP6 in red, CORDEX in green, CORDEX-CORE in blue), whiskers expand the full range of biases. Red horizontal lines depict perfect performance, for reference.

6.3.4 Effect of bias correction on the spatial pattern of SPEI characteristics

The ability of the BC methods under both approaches to represent the spatial structure of SPEI indices (median duration and severity and absolute frequency of dry and wet events) in the historical period (1986-2005) for the UJB is explored by Taylor diagrams (Figure 6.6). These Taylor diagrams (Taylor, 2001) show the degree of agreement between the spatial pattern of raw and bias-corrected data and the observed counterpart for SPEI indices, by means of spatial Pearson

correlation coefficient (dotted lines), (centered) root mean squared error (blue curves) and normalized standard deviation (black curve denotes perfect performance). Note that correlations below 0.5 might not be statistically significant given the small sample size (30 grid boxes; (Bujang and Baharum, 2016).

The Taylor diagrams indicate that overall, all BC methods improve upon the raw model output for all datasets and SPEI indices. The correlation coefficient is much lower for duration and severity SPEI indices (typically lies between 0.1 to 0.8) whereas it amounts to between 0.5 and 0.9 for WF and over 0.8 for DF. Concerning the normalized standard deviation (nSD) most of the bias-corrected results underestimate the spatial variability in all SPEI indices. This underestimation amounts up to 50% (nSD between 0.5 to 1.0) except for WD and DF, which show maximum and minimum underestimation, respectively. The centered root mean square errors between BC and reference SPEI indices are found to be in the range of 0.3 to 1.2, being the lowest for frequency indices especially for DF (0.3 to 0.6). Overall, the spatial pattern for the frequency SPEI indices indicates better agreement with the reference dataset than for the duration and severity SPEI indices for most of the BC methods and datasets.

The performance of BC methods is rather consistent for most of the SPEI indices regardless of the statistical measure (i.e., correlation coefficient, normalized standard deviation and centered root mean square error). More specifically, all BC methods under direct approach show better agreement than component-wise approach for most of the SPEI indices and datasets. The EQM, PQM and QDM under the direct approach grouped together for all SPEI indices and datasets. For the component-wise approach, no systematic difference between the best-performing univariate methods and the multivariate ones is found.

Regarding the spatial resolution of the original model data, no clear benefit of the higher resolution (CORDEX-CORE vs. CORDEX and CMIP6) is found, results vary with the SPEI indices and depend more on the BC method than on the model ensemble. The degree of agreement of CORDEX and CORDEX-CORE experiments with reference data is comparable and they tend to group together for the frequency indices, however, differences exist with CMIP6 models. For the best performing BC methods, the CORDEX ensemble presents the largest correlation and smallest root mean square error for dry events and WD, whereas the CORDEX-CORE ensemble represents better the spatial variability. For the dry SPEI indices, CMIP6 falls behind both CORDEX experiments, even for the best performing BC methods. For WS, most datasets present correlation coefficients of 0.4-0.6 and the spatial variability is larger for CORDEX-CORE and CMIP6. For WF, datasets group by BC method, regardless of the model ensemble. Note that here the multi-model ensemble mean is considered, which might hinder the potential added value of individual simulations.

To further explore the inner-ensemble variability and potential added value of individual simulations of CORDEX and CORDEX-CORE experiments, Fig. 6.7 shows the performance of bias-corrected (using D-EQM) individual climate model simulations from the two experiments. Interestingly, there is no clear best performing driving GCM or RCM for all SPEI indices and large discrepancies with the reference data remain for some individual simulations after bias correction.

In general, CORDEX simulations show higher correlation coefficient and smaller root mean squared error and CORDEX-CORE presents more accurate spatial variability. The RCM and GCM combination also matter. For example, the performance of REMO2015 is poor when driven by MPI (which is its typical driving GCM) but it is one of the best with HadGEM2 for most of the indices. On the other hand, HadGEM2-driven RCM under CORDEX-CORE experiment (REMO2015) performed well as compared to CORDEX experiment (RCA4). Similarly, the added value of higher spatial resolution (CORDEX-CORE over CORDEX) can also be seen with RegCM4 driven by MPI under both experiments (dark brown filled and non-filled circle). However, the added value of CORDEX-CORE experiment does not hold for all simulation pairs. For instance, NorESM1-driven RCMs under both experiments do not show a clear behavior (filled and non-filled dark green shapes).

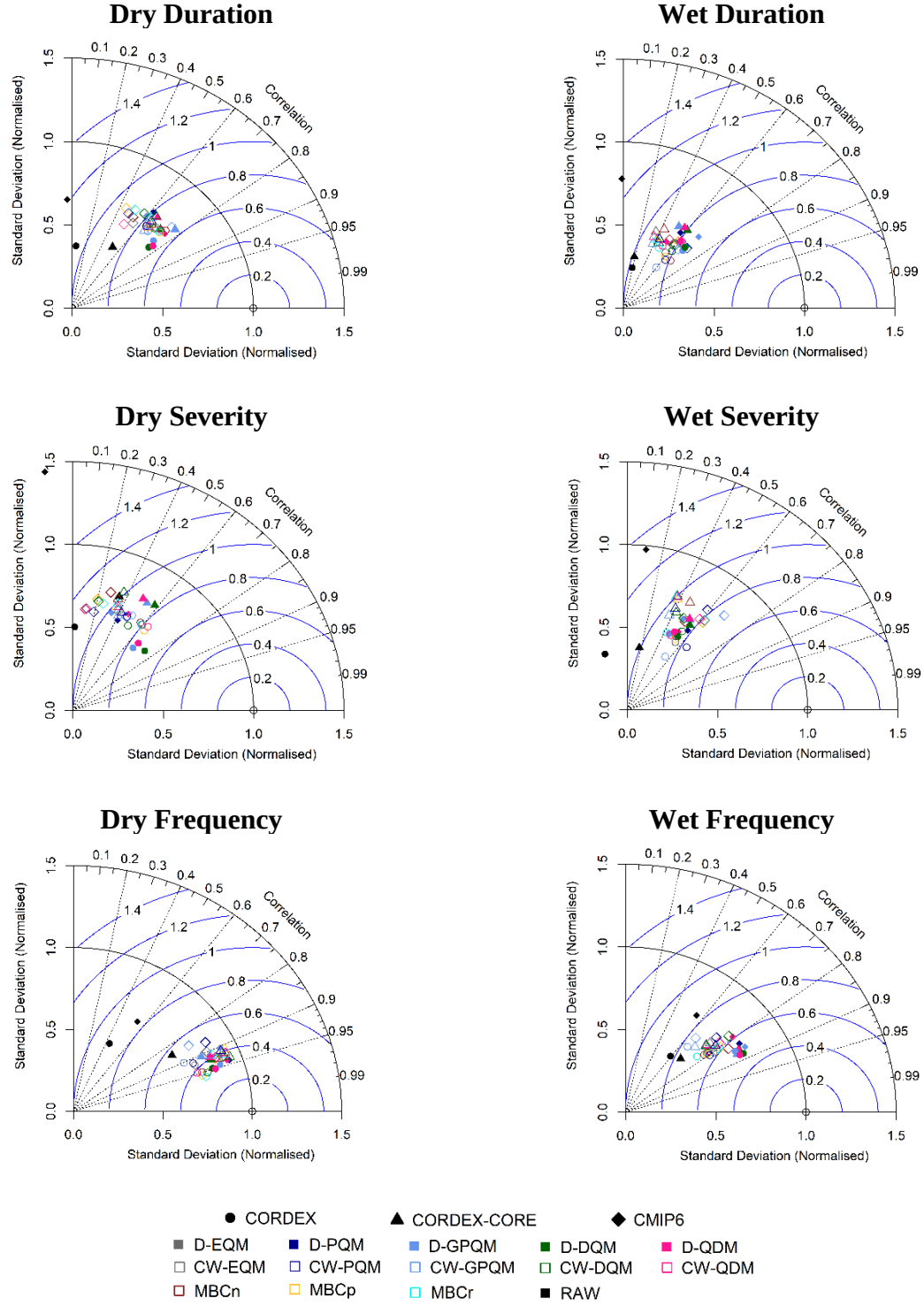


Figure 6.6: Taylor diagrams showing the performance of BC methods (colors) and datasets (markers) with respect to the spatial variability of the SPEI indices in the historical period (1986-2005) for the UJB. Each marker represents the evaluation measures for the multi-model ensemble mean SPEI indices, for the three modelling experiments (CORDEX in circles, CORDEX-CORE in triangles, CMIP6 in diamonds). Filled markers: Direct BC approach, non-

filled markers: component-wise BC approach, black marker: raw model output. Note: In the case of CMIP6, D-EQM (filled grey diamond) and D-PQM (filled dark blue diamond) are grouped together for all SPEI indices. Note: In case of CMIP6, D-QDM (filled pink diamond) and D-DQM (filled dark green diamond) are grouped together for all SPEI indices. Note: In the case of CORDEX and CORDEX-CORE experiments, D-EQM (filled grey marker), D-PQM (filled dark-blue marker) and D-QDM (filled pink marker) are grouped together for all SPEI indices.

spatial pattern of SPEI indices in the historical period (1986-2005) for the UJB. Filled markers: CORDEX models, non-filled markers: CORDEX-CORE models, 3 different markers show the 3 RCMs under both experiments (i.e., RegCM4, RCA4, REMO2009 from CORDEX and COSMO, REMO2015, RegCM4-7 from CORDEX-CORE); colors show the driving GCMs (same color means same driving GCM); plus marker and cross in black shows the multi-model ensemble mean (MME_m) for CORDEX and CORDEX-CORE experiment, respectively. **Note:** RCA4 driven by CSIRO (filled blue triangle) and ICHEC-EC-EARTH (filled maroon triangle) are grouped together for all SPEI indices. **Note:** RCA4 driven by MIROC (filled yellow triangle), RCA4 driven by MOHC-HadGEM2 (filled grey triangle), RCA4 driven by MPI (filled cyan triangle) and REMO2009 driven by MPI (filled cyan square) are grouped together for all SPEI indices. **Note:** RegCM4 driven by MPI (filled brown circle) and RCA4 driven by NCC-NorESM1 (filled dark green triangle) are grouped together.

6.4 Discussion and Conclusion

This study assesses the performance of two BC approaches (direct and component-wise) and eight methods (univariate and multivariate) for an impact relevant, multivariate drought index (SPEI) that characterizes wet and dry extreme events over the Upper Jhelum Basin, in the Western Himalaya.

From obtained results, most of the univariate BC methods under both direct- and component-wise approaches exhibit a comparable performance in current climate, with a slightly better performance for the direct approach. The direct approach with univariate methods provides also comparable results to more sophisticated multivariate methods, which could be due to the weak relationship among the input variables of SPEI in this region at daily time scales. The spatial pattern is better reproduced by the direct approach than component-wise approach (see Taylor diagrams in Sec. 3.4). This is expected from the experimental design, since under the direct approach, the SPEI is corrected as a single variable, regardless of the biases in the input essential climatic variables and in their interdependencies. Concerning univariate methods, the performance of parametric methods (i.e., PQM and GPQM) is found to be the worst especially in terms of inter-variable physical dependencies. Among the univariate empirical BC methods, both QDM and DQM exhibit a similar performance for the SPEI indices and inter-variable physical dependencies. Regarding the performance multivariate BC methods, all methods show comparable performance. Overall, the best performing univariate (i.e., empirical methods) are comparable to the multivariate ones. Overall, biases are reduced with all BC methods up to some extent but still SPEI indices are not well resolved. Reasons for this could be the remaining biases after BC in temporal properties of the individual variables (Figs. B1-B5 in the Supplementary Material), which have not been calibrated by any of the methods, together with the non-linear, multivariate nature of the SPEI, which is not directly calibrated by BC either.

Findings on the limited performance of few univariate BC methods, especially parametric (PQM and GPQM) under both approaches are admittedly based on the inadequate representation of temporal properties and inter-variable physical relationships. The direct correction of SPEI using univariate BC methods, that does not consider the dependencies between variables, has the

advantage of adjusting a single variable instead of several variables with different statistical properties, and in this work shows slightly better performance than correcting individual climatic variable prior to the SPEI calculation. Nevertheless, the advantages of direct approach over component-wise, multivariate over univariate BC methods, and trend-preserving methods over non-trend-preserving methods still need to be evaluated for the projected future conditions (Casanueva et al., 2018). Moreover, our findings may differ from other multivariate hazards or impacts-related indices in different regions of the world. Since the individual variables in a multivariate hazard index are interlinked differently, the contribution of their individual biases to the associated multivariate hazard index may lead to different results. For instance, biases in wet-bulb globe temperature (WBGT) are found to be smaller than Chandler Burning Index (CBI) for a given model output, yet both indices are based on temperature and relative humidity (Villalobos-Herrera et al., 2021). This is attributed to the construction of the index since bias in CBI is mainly driven by the bias in relative humidity whereas bias in WBGT interplays between biases in temperature and relative humidity which compensate each other.

Contrasting conclusions are found in the literature about the added value of multivariate BC methods over univariate ones in impact relevant studies. For example, Guo et al. (2020) reported the regionally dependent added value of MBC methods over univariate methods in reproducing observed inter-variable dependencies and observed streamflow using GR4J hydrological model. Similar findings also have been identified with the Canadian Fire Weather Index (Cannon, 2018), heat-stress (WBGT) and fire risk (CBI) indicators (Zscheischler et al., 2019), and snowmelt-driven streamflow (Meyer et al., 2019). On the other hand, Eum et al. (2020) reported marginal improvement of MBC methods in reproducing the extreme climatic indices and hydrological indicators over Alberta, Canada. Rätty et al. (2018) also indicated that it is difficult to demonstrate that multivariate methods may significantly reduce biases in hydrologic indicators. Van de Velde et al. (2020) stated that the simpler univariate BC methods are better to use for climate change impact assessment as the MBC methods failed to handle non-stationary climate conditions. François et al. (2020) reported the added value of multivariate BC methods over univariate ones and concluded that also multivariate methods can deteriorate temporal aspects and that the choice of the BC method should be based on the end user's goal. In the present study, the added value of multivariate BC methods over univariate ones is only evident for inter-variable physical coherence whereas comparable results are found in terms of biases in temporal properties and SPEI indices. The comparable performances for SPEI indices could be attributed to the weak relationship among the input variables (precipitation and temperature) of SPEI in this region for the daily time scale and to biased temporal properties. In comparison with the direct BC approach, Chen et al. (2021) found similar performance of MBC and the direct correction of hydrological model output i.e., streamflow in present climate, however both are sensitive to non-stationary biases during the validation period. They recommended the MBC especially for streamflow projections under strong anthropogenic signature on the climate. They also reported that biases in streamflow simulations depend on the climate model output, hydrological model, streamflow metrics and region. Similar conclusions were also made by Casanueva et al. (2018), who state that

the direct correction of the Canadian Fire Weather Index (FWI) presents similar performance as the FWI calculated from individually corrected climate variable in present climate but found a more robust behavior for the component-wise approach under future climate change.

The added value of higher climate model resolution (CORDEX-CORE vs. CORDEX and CMIP6) is not evident in the evaluation step, either in terms of inter-variable physical coherence or SPEI indices. There is some indication of added value of CORDEX-CORE with respect to CORDEX and CMIP6 in terms of the representation of spatial variability. However, the CORDEX ensemble performs best in terms of correlation and root mean squared error of the spatial patterns. Nevertheless, the absence of obvious benefits of a finer grid resolution in the present work does not rule out such an added value in general. For instance, a study conducted by Maharana et al. (2021) on Indian summer monsoon precipitation found improved representation of mean precipitation climatology of individual CORDEX-CORE models from the CORDEX experiment. Moreover, the 0.5° resolution of the gridded observational reference (W5E5), coarser than that of the 0.22° CORDEX-CORE simulations, allows us to draw conclusions concerning a lack of large-scale bias improvements by the 0.22° CORDEX-CORE experiments, but hinders the identification of benefits at a smaller scale. The added value of finer spatial resolution could be more obvious if the evaluation is carried out at their original resolution (Prein et al., 2016, Casanueva et al., 2019) especially for the processes over complex terrains where abrupt orographic changes cause much larger spatial variability. Although the uncertainty due to the spatial resolution of the reference dataset is out of scope of the present study due to limited availability of reliable finer resolution observational datasets for the studied region, many other studies acknowledge its greater impact especially for extreme precipitation indices (Casanueva et al., 2019, Casanueva et al., 2020). Kotlarski et al. (2014) also stated that the obvious added value of finer resolution simulations over its coarser counterpart is strongly dependent on the availability and accessibility of fine-gridded and high-quality observational data sets.

To summarize, there is some added value of multivariate bias correction with respect to univariate BC methods in the representation of the inter-variable structures but comparable results to the best performing univariate BC methods are found in terms of biases in SPEI indices. Present climate evaluation shows limited added value of higher spatial resolution simulations, mainly due to the experimental design (both resolutions are remapped onto the 50×50 km observational grid). Future work will explore to what extent current results of bias correction are robust under projected climate. Moreover, the application of bias-corrected climate model outputs to identify geographical hotspots prone to wet and dry extreme events as well as their temporal compounding under different warming levels will be very useful for stakeholders (researchers, local authorities, policy makers, relief agencies, non-governmental organizations (NGOs) and (re)insurance companies) working on the potential risk and associated development of adaptation strategies to climate change in this region.

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Chapter 7

Changes in the Probability of temporally compound wet and dry events in a warmer world: case study in the Upper Jhelum Basin

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Abstract

The temporal compounding of two contrasting extremes of the hydrological spectrum (droughts and floods) reflects a volatile hydrological cycle and makes water resources management more challenging. To this end, the present study examines extreme wet-dry events and their temporal compounding over the Upper Jhelum Basin (UJB) in the future climate context based on climate models simulations stemming from three modeling initiatives (namely Coordinated Regional Climate Downscaling Experiment (CORDEX), CORDEX Coordinated Output for Regional Evaluations (CORDEX-CORE), and the 6th Coupled Intercomparison Project (CMIP6)), bias corrected with three different methods, under low, medium and high emission scenarios for two time segments i.e., near future (2040-2059) and far future (2080-2099). Meteorological wet and dry conditions, as drivers of hydrologic floods and droughts, are characterized by using a multivariate drought index (namely the Standardized Precipitation Evapotranspiration Index, SPEI), which is derived from daily precipitation and maximum and minimum temperatures. The temporally compound event (CE), which is defined as a successive transition from one powerful state to another, includes dry to wet (D-to-W) events and wet to dry (W-to-D) events in the adjacent month.

Results show that (1) extreme wet and dry events are projected to be more frequent and severe under warming conditions whereas duration of the events shows varying change signals depending on the location. (2) The basin is more prone to D-to-W CEs dominated in the southwest of the region, which was not found to be hotspot historically neither for dry nor for wet extreme events. (3) Contrasting climate change signals are found for BC approaches with the direct correction introducing a greater modification of the original change signals. (4) For most of the indices, CORDEX ensembles (WAS44 and WAS22) show varying climate change signals with no specific spatial pattern whereas the CMIP6 ensemble show stronger change signals and divide the region into two distinct parts i.e., northeast and southwest.

Key words: Temporal compounding, bias correction, CMIP6, CORDEX, CORDEX-CORE, future projection

7.1 Introduction

Climate change is predicted to intensify the global hydrological cycle and cause extreme events (floods and droughts) with increasing frequency and severity, pushing the limits of society's ability to prepare for these extreme events through prediction and effective adaptation. It is expected that more severe droughts, larger precipitation events, and more frequent anomalous wet and dry spells will become the "new normal" for many ecosystems (Lewis et al., 2017, Seneviratne et al., 2021). Further compounding (concurrent or consecutive occurrences of multiple weather and climate drivers) of these extreme events across space or/and time may provoke greater impacts than those caused by individual events, even when the contributing variables themselves are not extreme (Leonard et al., 2014, Poschlod et al., 2020, Zscheischler et al., 2020). These extreme events have put a strain on society's ability to predict and adapt effectively to these extreme phenomena.

The most important and commonly studied compound events (CEs) in hydro-climatology are those associated with precipitation and temperature. The occurrence of CEs may be induced by a common external factor (e.g., changes in regional warming), mutual reinforcement of two extremes (e.g., land surface feedback) or conditional dependence (e.g., antecedent soil moisture and precipitation conditions leading up to droughts and floods).

The definition and classification of CEs has received significant attention over the past few decades. To aid the framing and development of new research on CEs, Zscheischler et al. (2020) proposed four distinct classes of CEs and their different physical characteristics (modulators, drivers, hazards and impacts) that form a CE. Such events can occur in multiple ways due to the complex nature of the climate system, for example, “Preconditioned” events for which a weather- or climate-driven background can exacerbate the impact; “Multivariate” events for which the simultaneous co-occurrences of individual drivers and/or hazards at the same location result in impacts; “Temporally compound” events for which impacts are due to the consecutive occurrences of hazards within a particular geographical region, and “Spatially compound” events for which synchronized occurrences of individual hazards across several regions lead to an impact.

CEs drivers and their additive impacts on regional and global scales have been the subject of several studies. For instance, the combinations of quasi-synchronous extremes across multiple regions can lead to amplifying effects on connected global systems (Raymond et al., 2020). A severe drought that occurred concurrently in Asia, Brazil and Africa during 1876-1878 resulted in synchronous crop failures in these regions, posing a threat to food security (Singh et al., 2018). Other studies have examined the enhanced risk of concurrent regional droughts and heatwaves with variability in large scale circulation modes under warming scenarios (Kornhuber et al., 2020, Singh et al., 2021, Singh et al., 2022) and the following synchronized crop failures across major breadbasket regions of the world (Tigchelaar et al., 2018, Anderson et al., 2019, Gaupp et al., 2020).

Temporal CEs can be of the same type such as, multiple consecutive heatwaves (Baldwin et al., 2019), droughts (Hari et al., 2020, Bastos et al., 2021, van der Wiel et al., 2023) or consecutive heavy- precipitation events (Kopp et al., 2021, Fish et al., 2022), or different hazards, for example, concurrent precipitation and wind extremes (Raveh-Rubin and Wernli, 2015, Martius et al., 2016), compound flooding due to storm surge and heavy precipitation in coastal areas (Zheng et al., 2013, Wahl et al., 2015, Bevacqua et al., 2019), a flood followed by a heatwave or drought (He and Sheffield, 2020, Zhang et al., 2021), simultaneous drought and heatwave (Mazdiyasni and AghaKouchak, 2015, Manning et al., 2019, Sutanto et al., 2020, Zscheischler and Fischer, 2020), co-occurrence rate of heavy precipitation and snowmelt to estimate the risk of rain-on-snow events (Musselman et al., 2018, Poschlod et al., 2020), epidemics followed by floods (Donges et al., 2016).

A quantification of the CEs is important for assessing the risk of associated impacts, both in retrospective (i.e. past) or prospective (i.e. future) climate contexts. A number of above studies have focused primarily on the concurrent occurrence of CEs, but a limited number have examined the consecutive occurrence of contrasting extremes (i.e., floods and droughts or extreme wet and

dry events). Often an increase in floods is aligned with a decrease in droughts as a result of more abundant rainfall, and the opposite is the case as rainfall becomes scarcer (Gudmundsson et al., 2021). However, some models suggest a joint increase in the severity of floods and droughts (Kreibich et al., 2022), a phenomenon referred to as acceleration of the terrestrial component of the water cycle.

In this context, we have specifically considered CEs for a situation where two contrasting extremes, namely extreme wet and dry events, occur consecutively at the same location (as a subset of the broader CE definition). The consecutive occurrence of these extreme events can exacerbate adverse impacts resulting from individual hazards alone, as recently witnessed in Pakistan, 2022 (Wang et al., 2023), Queensland-Australia, 2010 (Beard et al., 2011), United Kingdom, 2012 (Parry et al., 2013), India, 2016 (Roxy et al., 2017), California-United States, 2017 (Huang et al., 2018), Peru, 2017 (Son et al., 2020), Japan, 2018 (Wang et al., 2019) and Mozambique, 2019 (Brida et al., 2013). The effects of compound floods and droughts (extreme wet and dry conditions) have also been studied under current and warming climate conditions. For instance, Visser-Quinn et al. (2019) and Zhao et al. (2020) identified geographical hotspots for spatio-temporally concurrent floods and droughts in UK and Hanjiang River Basin, China, respectively. Other examples include the analysis of rapid transitions of wet-dry extreme events in river basins in China (Yan et al., 2013), in Upper Jhelum Basin-Pakistan (Ansari and Grossi, 2022) and in England and Wales (Parry et al., 2013).

It is therefore important to analyze the temporal compounding of extreme dry and wet events in a changing environment, thereby fully characterizing their impacts on water-related sectors and understanding possible adaptation strategies, such as developing more efficient reservoir operation rules or agricultural planning.

The present study builds upon Ansari et al. (2023), which shows a comprehensive present-climate evaluation of bias-corrected climate model simulations regarding the main characteristics of wet and dry events in the Upper Jhelum Basin (UJB). The extreme wet and dry events were quantified using a multivariate drought index, namely the Standardized Precipitation and Evapotranspiration Index-SPEI (Vicente-Serrano et al., 2010) with potential evapotranspiration based on daily maximum and minimum temperature. Here we examine the extreme wet-dry events and their temporal compounding over UJB in the future climate context based on climate model simulations from three modeling initiatives (global climate models from CMIP6, regional climate models from CORDEX and CORDEX-CORE), bias corrected with three different methods under low, medium and high emission scenarios for two-time segments i.e., near future (2040-2059) and far future (2080-2099).

The specific objectives of the study are to assess:

- the projected changes in the characteristics of wet and dry extreme events (i.e., duration, severity, and frequency) and in the probability of temporal CEs (consecutive occurrence of wet and dry extreme events).
- the uncertainty associated with different bias correction (BC) methods and approaches in the climate change signal of wet and dry extreme events characteristics and CEs.

7.2 Material and Methods

7.2.1 Identification of extreme events and their characteristics

Wet and dry events are quantified using a multivariate drought index, i.e., SPEI (Vicente-Serrano et al., 2010). In the present study, SPEI is calculated using a 30-day accumulation period of climatic water balance (precipitation minus potential evapotranspiration) at daily time step with potential evapotranspiration estimated using the Hargreaves-Samani method (Hargreaves and Samani, 1985) based on daily maximum and minimum temperature. The extraterrestrial radiation used in Hargreaves-Samani method is calculated from the latitude of each grid box and day of the year. The detailed description of the SPEI calculation procedure can be found in Vicente-Serrano et al. (2010) and Ansari et al. (2023). The daily SPEI is then aggregated at monthly scale to identify wet and dry extreme events. The wet and dry extreme events are defined as positive ($SPEI \geq 1$) and negative SPEI ($SPEI \leq -1$) for at least two consecutive months, respectively. The thresholds for the wet and dry extreme events based on SPEI values are taken from previous literature (Svoboda et al., 2012). To characterize the wet and dry extreme events, three event indices (duration, severity, and frequency) are considered. The duration of a wet/dry event (denoted hereafter as wet duration-WD- and dry duration-DD) is the number of consecutive months with SPEI above 1 and below -1, respectively; severity (wet severity-WS- and dry severity-DS) refers to the cumulative value of the index from the first month to the last month of the wet/dry event and it represents the water surplus and deficit, respectively; and the absolute frequency (wet frequency-WF- and dry frequency-DF) is the total number of events in a specified time period. Since duration and severity are obtained for individual events, we consider the median value across all the identified events as a single index.

7.2.2 Temporally Compound Event and Event Coincidence Analysis

The temporal CEs, which are defined as consecutive transitions from one powerful state to another, include D-to-W events and W-to-D events in the adjacent month. Therefore, the minimum duration of a CE is 2 months. D-to-W CE is defined as a dry spell ($SPEI_i \leq -1$) abruptly changing into a wet spell ($SPEI_{i+1} \geq 1$) in the next month. Conversely, a W-to-D CE is defined as a wet spell ($SPEI_i \geq 1$) abruptly changing into a dry spell ($SPEI_{i+1} \leq -1$) in the next month.

To investigate the statistical interdependency between wet and dry extreme events and their statistical significance, the present study employs Event Coincidence Analysis-ECA (Donges et al., 2016, Siegmund et al., 2017). ECA is an effective framework for characterizing the lagged and time-varying responses between two events (i.e., wet and dry extreme events in this study). It calculates how frequently dry events are followed by wet events and vice versa, with a mutual delay (a time lag parameter τ) given a certain temporal window (ΔT) through the calculation of the so-called trigger coincidence rate (r):

$$r^{D \Rightarrow W}(\Delta T, \tau) = \frac{1}{N_D} \sum_{j=1}^{N_D} \Theta \left[\sum_{i=1}^{N_W} 1_{[0, \Delta T]} \left((t_i^W - \tau) - t_j^D \right) \right] \dots \dots \dots (7.1)$$

$$r^{W \Rightarrow D}(\Delta T, \tau) = \frac{1}{N_W} \sum_{j=1}^{N_W} \Theta \left[\sum_{i=1}^{N_D} 1_{[0, \Delta T]} \left((t_i^D - \tau) - t_j^W \right) \right] \dots \dots \dots (7.2)$$

Where Θ is the Heaviside function

$$\Theta(x) := \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$$

And $1_{[0,\Delta T]}(\cdot)$ is the indicator function of the selected window $[0,\Delta T]$:

$$1_{[0,\Delta T]}(x) := \begin{cases} 1 & \text{if } x \in [0, \Delta T] \\ 0 & \text{if } x \notin [0, \Delta T] \end{cases}$$

t_1^W and t_1^D represent the wet and dry event timing with total number of events N_w and N_d , respectively. Here we choose $\tau=1$, as this represents the rapid transition of two contrasting extremes in adjacent months. To further assess the robustness of the statistical interrelationship between wet and dry extreme events, an analytical significance test is performed based on the assumption of a Poisson process with the null hypothesis that the successive occurrence of wet and dry extreme event is randomly distributed. The significance level (p-value) is calculated for each grid cell to assess whether the estimated probability of CE is statistically significant or not.

7.2.3 Climate Model Simulations and bias correction

We used climate model simulations from 2 Global Climate Models (GCMs) of the CMIP6, (Eyring et al., 2015), 17 Regional Climate Models (RCM) simulations (3 RCMs unevenly driven by 10 GCMs) of the CORDEX, (Giorgi et al., 2009, Jones, 2010) and 9 RCM simulations (3 RCMs unevenly driven by 6 GCMs) of the CORDEX-CORE, (Teichmann et al., 2021) under low, medium and high emission scenarios.

For the RCM simulations, the south Asian domain (denoted as WAS) is considered. In particular, we use all available simulations for WAS-44 and WAS-22 domains (simulations conducted at horizontal resolutions of 0.44° and 0.22° on rotated grids, approximately 50km and 25km) for CORDEX and for CORDEX-CORE, respectively. The selection of the particular subset of GCMs from CMIP6 is motivated by the availability of models with high spatial resolution (Table 7.1), approximately similar to the CORDEX counterparts. Note that the driving GCMs of both CORDEX and CORDEX-CORE experiments are CMIP5 GCMs, thus emission scenarios vary across the different datasets, namely two shared socioeconomic pathways (SSPs) for the CMIP6 GCMs (SSP1-2.6 and SSP5-8.5) and all available representative concentration pathways (RCPs) for CORDEX and CORDEX-CORE. In particular, 8 RCMs provide climate projections under RCP2.6 and 9 RCMs RCP8.5 within CORDEX-CORE, and 6 RCMs provide climate projections under RCP2.6 and 17 RCMs under RCP4.5 and RCP8.5 within the CORDEX experiment. Although some differences are found between SSPs and RCPs, the selected pairs approximately target a similar level of aggregated radiative forcing (Tebaldi et al., 2021). More details on the considered climate models and scenarios are given in Tables 7.1 and 7.2.

Climate models represent a substantially simplified form of physical processes and are typically prone to systematic biases. BC is typically applied as a post processing step to overcome

this issue, especially for threshold-based derived indices. In present study, climate model simulations are bias corrected by two univariate (Empirical Quantile Mapping-EQM- and Quantile Delta Mapping-QDM) and one multivariate (Multivariate Bias Correction with N-dimensional probability density function transform-MBCn) BC methods using W5E5 as reference dataset. The W5E5 is a merged, global dataset, developed at 0.5° horizontal resolution using version 2.0 of WFDE5 data (WATCH forcing data methodology applied to ERA5 data (Weedon et al., 2014, Cucchi et al., 2020) over land and ERA5 (Hersbach et al., 2020) over the ocean, covering the period 1979–2016. EQM is an empirical method, which calibrates a transfer function that matches all quantiles of the model empirical cumulative distribution function (CDF) to those of reference dataset (Déqué, 2007). Out-of-sample values are adjusted through constant extrapolation. The method also adjusts the overestimation of wet or dry days frequency (defined as days with precipitation above or below 1mm in the reference dataset) in the model using, respectively, adjusted wet-day threshold and frequency adaptation proposed by (Thiemeßl et al., 2012, Wilcke et al., 2013). QDM is also an empirical method which preserve the trends of all quantiles of the simulated distribution. Firstly, model projections are detrended by quantile and quantile mapping is applied to adjust systematic distributional biases relative to the observations. Then the removed projected trends are reintroduced to the bias-corrected quantiles (Cannon et al., 2015). The MBCn method transfers all statistical characteristics of the observed multivariate distribution to those of the climate model outputs and uses random orthogonal rotation matrices to partially decorrelate the climate variables before QDM are applied to the marginal distributions. The process is repeated iteratively until the multivariate distribution of the historical climate model data converges to that of the reference data (Cannon, 2018).

The univariate BC methods are calibrated and applied to climate model simulations following two approaches: (1) separately to all involved essential climatic variables (i.e., the component-wise approach-CW) and (2) directly to the uncorrected SPEI (i.e., the direct approach-D). All BC methods are calibrated in the period 1986-2005 and applied in two future periods (2040-2059 and 2080-2099). They all make a common assumption of stationarity by applying the same calibrated transfer function in the calibration period to the future projected climate which may lead to modifications of the raw model climate change signals for non-trend preserving BC methods (here EQM). The selection of these BC methods is based on Ansari et al. (2023), which intercompare different state-of-the-art BC methods (uni- and multi-variate) and BC approaches (direct and component-wise) in terms of inter-variable physical coherence of involved key essential variables, namely precipitation, maximum temperature and minimum temperature, and characteristics of extreme events (duration, severity, and frequency of wet and dry events) during the historical period (1986-2005).

Table 7.1: Description of the CMIP6 GCMs used in the present study.

Model	Institute (country)	Horizontal resolution	SSP126	SSP245	SSP585
CNRM-CM6-1-HR	CNRM-CERFACS (France) Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	0.5° × 0.5°	×		×
EC-Earth3	EC-Earth-Consortium	0.7° × 0.7°	×		×

Table 7.2: Description of the CORDEX and CORDEX-CORE RCMs used in the present study.

Experiment	RCM	RCM description	Contributing CORDEX modelling center	Driving CMIP5 GCM	RCP26	RCP45	RCP85
CORDEX (WAS-44)	RegCM4-4	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climate Model version 4 (RegCM4; (Giorgi et al., 2012))	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India	CCCma-CanESM2		×	×
				CNRM-CERFACS		×	×
				CSIRO-QCCCE-CSIRO		×	×
				IPSL-IPSL-CM5A-LR		×	×
				MPI-M-MPI-ESM		×	×
				NOAA-GFDL-GFDL-ESM2M		×	×
	RCA4	Rossby Centre Regional Atmospheric Model version 4 (RCA4; (Samuelsson et al., 2011))	Rossby Centre, Swedish Meteorological and Hydrological Institute (SMHI), Sweden	CCCma-CanESM2		×	×
				CNRM-CERFACS		×	×
				CSIRO-QCCCE-CSIRO		×	×
				ICHEC-EC-EARTH	×	×	×
				IPSL-IPSL-CM5A-MR		×	×
				MIROC-MIROC5	×	×	×
				MOHC-HadGEM2-ES	×	×	×
				MPI-M-MPI-ESM	×	×	×
				NCC-NorESM1-M	×	×	×
				NOAA-GFDL-GFDL-ESM2M		×	×
	REMO2009	MPI Regional model 2009 (REMO2009;	Climate Service Center (CSC), Germany	MPI-M-MPI-ESM	×	×	×

		(Teichmann et al., 2013)					
CORDEX-CORE (WAS-22)	COSMO-crCLIM-v1-1	(CONsortium for Small scale MOdelling) model (Baldauf et al., 2011)	Climate Limited-area Modelling (CLM) Community	ICHEC-EC-EARTH			×
				MPI-M-MPI-ESM-LR	×		×
				NCC-NorESM1-M	×		×
	RegCM4-7	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climate Model version 4 (RegCM4; (Giorgi et al., 2012)	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India	MIROC-MIROC5	×		×
				NCC-NorESM1-M	×		×
				MPI-ESM-MR	×		×
	REMO2015	Climate Service Center Germany (GERICS).	Climate Service Center Germany (GERICS).	MOHC-HadGEM2-ES	×		×
				MPI-M-MPI-ESM-LR	×		×
				NCC-NorESM1-M	×		×

7.3 Results

7.3.1 Future changes in SPEI indices

The climate change signals of SPEI indices (median duration, median severity, and absolute frequency of dry and wet events, see Sect. 2) relative to the baseline period (1986-2005), for the raw and bias-corrected climate model simulations, for the near (2040-2059) and far (2080-2099) future periods under low (RCP2.6/SSP1-2.6), medium (RCP4.5/SSP2-4.5) and high (RCP8.5/SSP5-8.5) emission scenarios, separately for CMIP6, CORDEX and CORDEX-CORE are presented in Figs. C1-C6. Results show contrasting climate change signals for both BC approaches with the direct correction introducing a greater modification of the original (raw) change signals especially for severity and frequency indices. This modification by the direct approach is usually towards positive change signals. Further, given a particular approach, BC methods present similar climate change signals regardless of SPEI indices, emission scenarios and time period.

Regarding climate model experiments, WAS44 and WAS22 ensembles present opposite sign climate change signals for duration indices (DD and WD) with no specific spatial pattern whereas the change signals from CMIP6 ensemble divide the region into two distinct parts i.e., northeast (which host foothills of western Himalaya) and southwest (relatively plain region with dominance of monsoon precipitation system). These results regarding the spatial patterns hold for most of the SPEI indices, emission scenarios and time segments. For instance, dry event indices (i.e., DD, DS and DF) and WF show negative and positive climate change signals in northeast and southwest regions, respectively under high emission scenarios. Differences between the different ensembles also exist for the spatial distribution of the changes in severity indices (DS and WS).

For instance, for CMIP6 WS is projected to increase over the whole basin and mixed signals are found for DS, whereas the opposite is found for WAS44 and WAS22.

The climate change signals for regionally averaged SPEI indices for all individual climate simulations (CORDEX-CORE, CORDEX and CMIP6) are summarized in Figs.7.1 and 7.2. Overall, climate models from all considered experiments present larger spread for wet indices compared to dry indices. The spread is usually determined by WAS-44 climate models for most of the SPEI indices under considered BC methods, time segments and emission scenarios which could be due to the largest number of simulations. However, there are exceptions for CMIP6 and WAS-22, especially for duration and severity indices (particularly for DD and DS) under different BC methods. The reduction in model spread is evident after BC under the component-wise approach and the multi-variate method, whereas the modification of the signals by the direct approach leads to a slight increase in climate model spread. These findings are consistent with all considered time periods and emission scenarios.

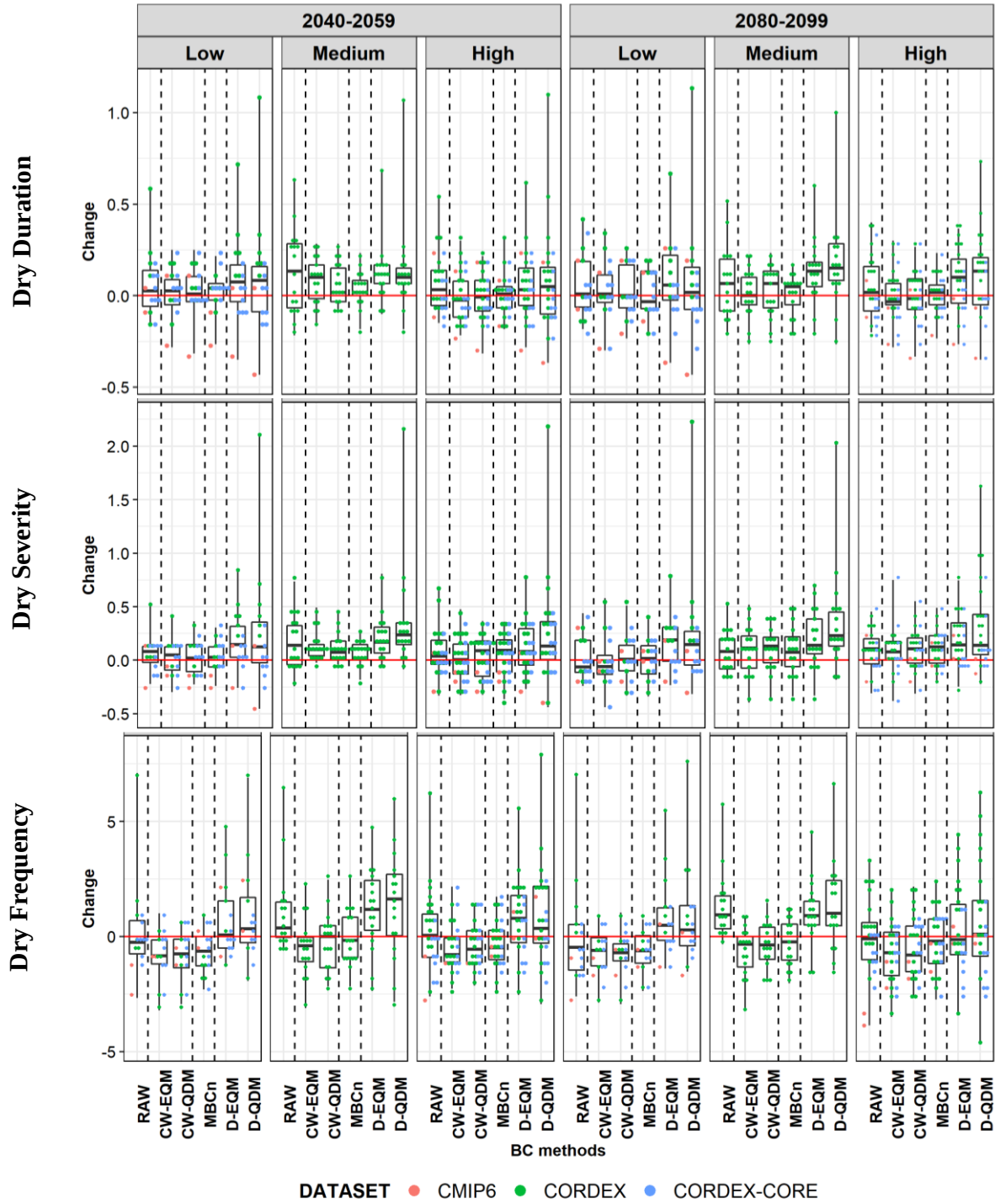


Figure 7.1: Absolute climate change signals of spatially averaged SPEI derived dry indices (duration: upper row; severity: middle row; frequency: lower row) over the Upper Jhelum Basin for the near future (2040-2059) and far future (2080-2099) with respect to 1986–2005 under low (RCP2.6/SSP126), medium (RCP4.5/SSP545), high (RCP8.5/SSP585) emission scenarios, computed from the raw (first box in each panel) and bias corrected data (rest of boxes). Each box represents the interquartile range of change across all models, which are depicted individually

with colored dots (CMIP6 in red, CORDEX in green, CORDEX-CORE in blue), whiskers expand the full range of biases. Red horizontal lines depict no change from baseline period.

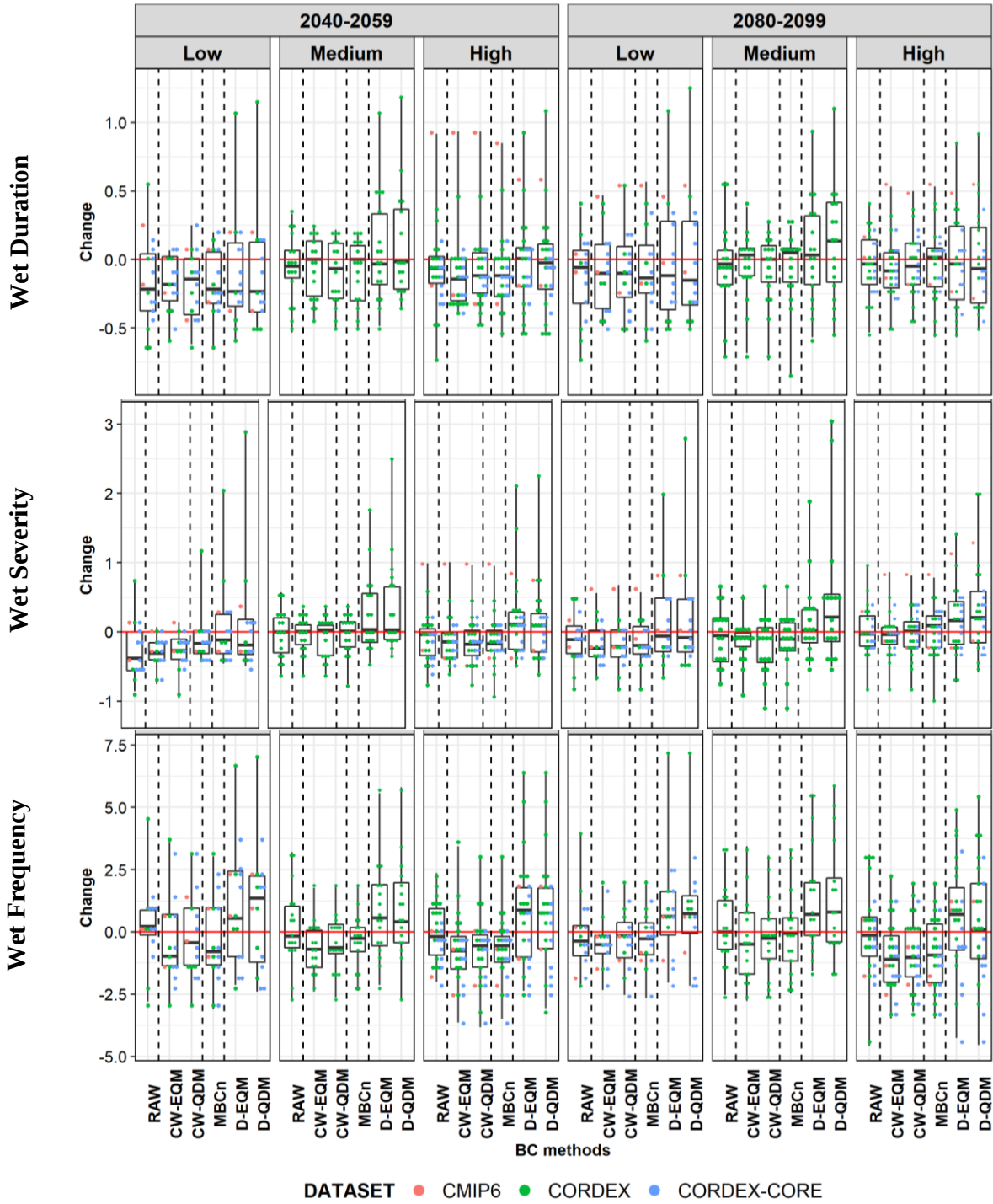


Figure 7.2: Same as Figure 7.1 but for SPEI derived wet indices.

7.3.2 Temporal Compound Events

Next we examine the spatial distribution of probability of temporally compound events (D-to-W and W-to-D, see Sect. 3) and their statistical significance for the historical (according to W5E5) and projected future climate, for the raw and bias-corrected climate model simulations for the near (2040-2059) and far (2080-2099) future periods under low (RCP26/SSP1-2.6), moderate (RCP45/SSP2-4.5) and high (RCP85/SSP5-8.5) emission scenarios.

Results show that the probability of D-to-W CEs (Fig. 7.3) is much higher than the W-to-D CEs (Fig. C7) under both retrospective (i.e. past) and prospective (i.e. future) climate contexts. Specifically, the observed probability of D-to-W CEs is high in the southwest of the basin (up to 60 %, statistically significant at 5% level), whereas W-to-D CEs are found to be statistically non-significant for a 95% confidence level with no clear pattern of occurrence during the historical period. The reference probability of D-to-W CEs is statistically significant over 23.33% of the domain (with p-value less than 0.05), located in the southwest of the basin, which is a monsoon-dominated region. It is interesting to note that this region is not found to be a hotspot neither for dry nor for wet events (Ansari et al. 2023) but a high probability (up to 60%) of dry events that are followed by wet events is found during the historical period. The northeast part of the basin with high mountains of western Himalayas (under westerlies precipitation pattern) is found to be least effected by CEs despite of its higher susceptibility towards wet and dry extreme events with higher severity and duration (Ansari et al. 2023).

Regarding future projections, the spatial patterns of projected probability of CEs are consistent with those for the historical period and show the hotspot for the D-to-W CEs in the southwest of the basin. However, there are some differences among the climate model ensembles. Particularly, CORDEX models (WAS-44 and WAS-22) show slightly decreasing probability of D-to-W CEs from near to far future especially under the lowest emission scenario, whereas the CMIP6 ensemble shows an increase in probability of D-to-W CEs by the end of century under all emission scenarios and time periods. Further, the probabilities of D-to-W CEs are found to be statistically significant with medium to high models' agreement (i.e., number of models agreeing on the statistical significance of the CEs).

The three raw climate model ensembles show decreasing probabilities of D-to-W CEs relative to baseline period under all emission scenarios and time segments. This is especially true for CORDEX and CORDEX-CORE ensembles with also lower models' agreement in terms of statistically significant probabilities. Conversely, the southwest of the basin is a hotspot for the D-to-W CEs for the raw CMIP6 ensemble with medium models' agreement. Overall, none of the BC methods under both approaches preserves the raw climate change signals except for CMIP6 ensemble which show a slight preservation of raw climate change signals in terms of spatial patterns. In general, BC modifies the probabilities of the raw models by increasing the probability of D-to-W CEs and model agreement, for both future periods and all emission scenarios. Similar to SPEI indices, the BC methods under the direct approach (i.e. D-EQM and D-QDM) present similar climate change signals whereas the climate change signals projected by MBCn are somewhat similar to those projected by BC methods under the component-wise approach (i.e. CW-EQM and CW-QDM).

The climate change signals for regionally averaged probabilities of D-to-W for all individual climate simulations (CORDEX-CORE, CORDEX and CMIP6) are summarized in Fig. 7.4. Similar to SPEI indices, a reduction in model spread is found after BC under the component-wise approach and the multi-variate method, whereas the direct approach increases climate model spread by increasing the probability of CEs. These findings are consistent for all considered time periods and emission scenarios.

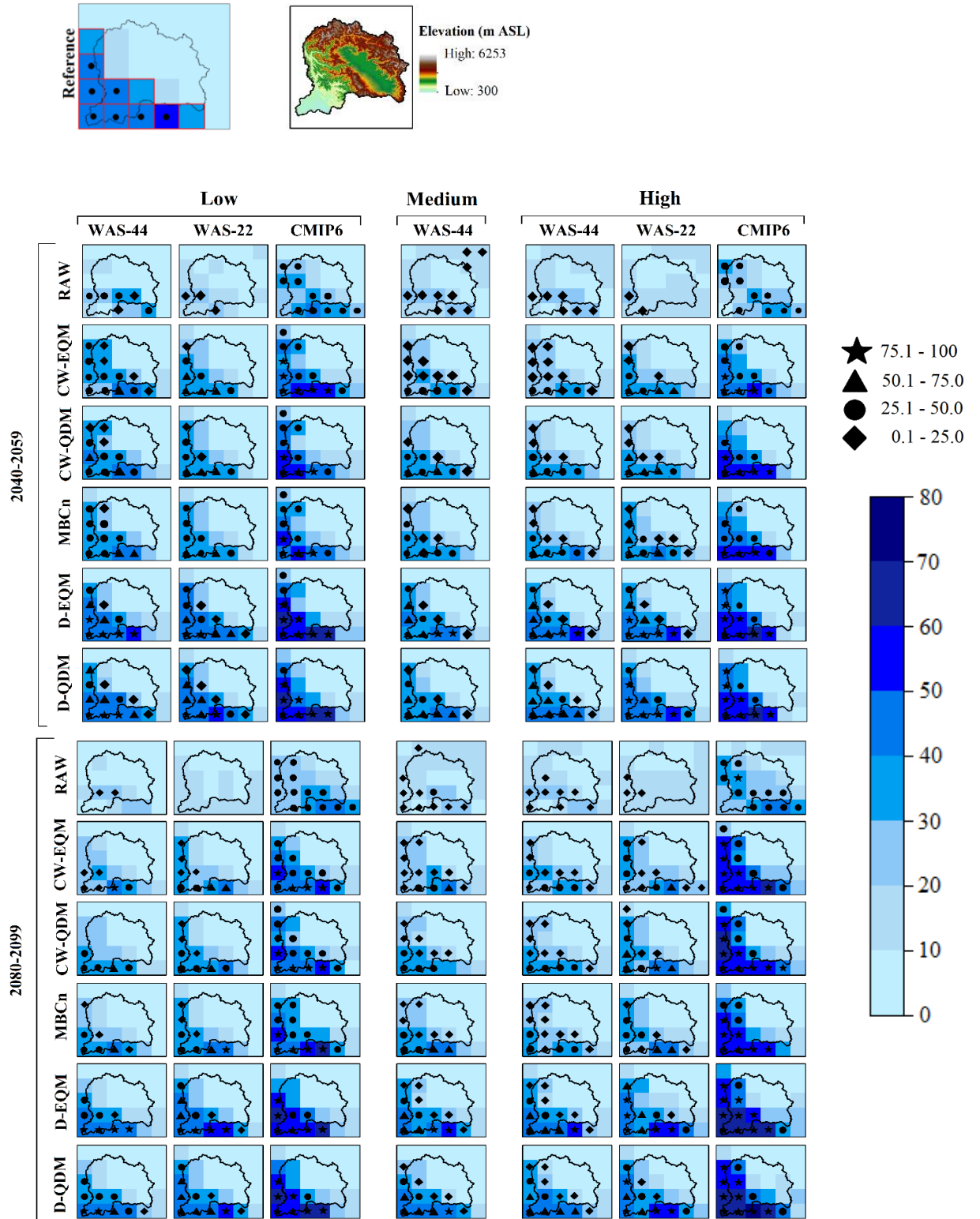


Figure 7.3: Probability of temporal compound dry-to-wet events (%), in the historical reference dataset (1986-2005, first row, left), digital elevation model in meters above sea level (first row, right) and future projected probabilities under low (RCP2.6/SSP126), medium

(RCP4.5/SSP545), high (RCP8.5/SSP585) emission scenarios for the multi-model ensemble mean raw ensembles (second row) and bias-corrected ensembles, for the two bias correction approaches and three BC methods (rows). The probability of temporal compound event is calculated for the near future (2040-2059) and far future (2080-2099). In the projections, the different shapes denote the percentage of ensemble members with statistically significant probability at the 5% level. The highlighted grid boxes are used for further analyses in Fig. 7.4.

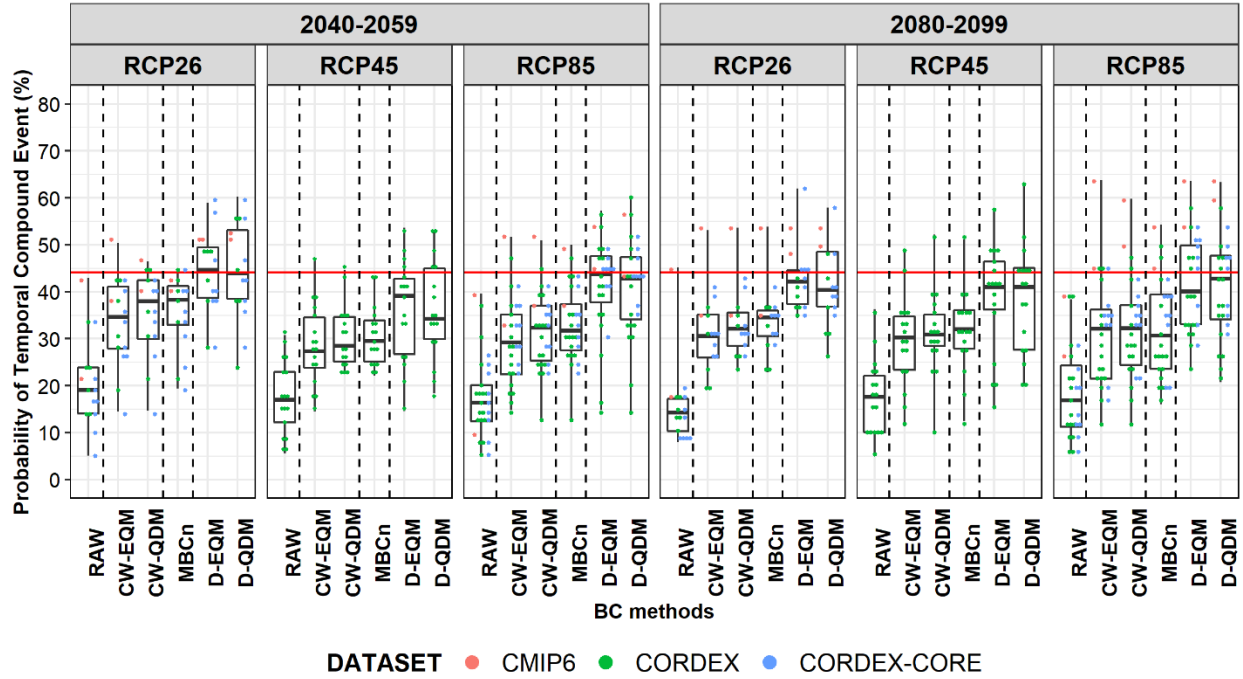


Figure 7.4: Probability of temporal compound dry-to-wet events (%), spatially averaged over ten grid boxes highlighted in Figure 7.3, for the near future (2040-2059) and far future (2080-2099) under low (RCP2.6/SSP126), medium (RCP4.5/SSP545), high (RCP8.5/SSP585) emission scenarios, computed from the raw (first box in each panel) and bias corrected data (rest of boxes). Each box represents the interquartile range of change across all models, which are depicted individually with colored dots (CMIP6 in red, CORDEX in green, CORDEX-CORE in blue), whiskers expand the full range of biases. Red horizontal lines depict the probability of temporal compound events in the baseline period (1986-2005) according to the observations.

7.4 Discussion and conclusions

This work presents future climate projections of wet and dry extreme events and their temporal compounding using climate models simulations from three modelling initiatives (CMIP6, CORDEX WAS-44 domain and CORDEX-CORE WAS-22 domain) bias corrected by two univariate BC methods (i.e., EQM and QDM) under two bias correction approaches (component-wise-CW- and direct-D) and a multivariate BC method (N-dimensions-MBCn). The wet-dry events are characterized by SPEI derived indices (namely duration, severity, and frequency) and climate change signals are estimated for the near future (2040-2059) and far future (2080-2099)

with respect to the baseline period (1986–2005). As CEs such as consecutive occurrence of wet and dry extreme events challenge water resources management and can be particularly impactful, the present study has also been focusing on temporal compounding of wet and dry extreme events, both in retrospective (i.e. past) and prospective (i.e. future) climate contexts. For this purpose, ECA is used to characterize the lagged and time-varying responses between two events. Such assessments could serve as a resource for policymakers and local stakeholders for understanding potential risks and designing more effective water management policies and mitigation plans, such as developing more efficient reservoir operation rules or agricultural planning.

Future projections of the individual wet and dry extreme events (in terms of duration, severity, frequency) show varying climate change signals for all SPEI indices under all considered BC methods, BC approaches, emission scenarios and time segments. Specifically, extreme wet and dry events are projected to be more frequent and severe, which is expected under warming conditions and was reported by many researchers. For example, frequency and intensity of extreme rainfall events are projected to increase across the Himalayan-Tibetan Plateau mountains throughout the 21st century, particularly during the summer monsoon (Panday et al., 2015, Sanjay et al., 2017). Another study indicates an increase in frequency, spatial extent and severity of droughts over India during the twenty-first century while flood propensity is projected to increase over the major Himalayan River basins e.g., Indus, Ganga and Brahmaputra (Mujumdar et al., 2020).

Regarding temporally CEs, the observed probabilities of D-to-W and W-to-D CEs are found to be high up to 60% and 30%, respectively. The probability of D-to-W CEs is projected to increase from 60% to 80% (for specific grid boxes and model simulations) whereas the probability of W-to-D CEs approximately remains unchanged under warming conditions. This low to moderate increment in the D-to-W CEs under anticipated future conditions is in agreement with the Gu et al. (2022) who found a clearer increment in the fraction of CEs (number of CEs to total flood events) in the tropical regions, followed by arid, temperate, cold regions, and polar zone (note that low and high-altitude areas of UJB lie in the temperate and polar climate regions, respectively). Conversely, (Zhang et al., 2021) found a decrease in the probability of such CEs in the tropics albeit with increased frequency of heavy rainfall events. A global study conducted by Zhang et al. (2021) highlighted the spatial hotspots for the compound drought and extreme rainfall events under a warming world. According to that study 66% of CMIP5 models showed a decreased future probability of such CEs in the second half of century (2051-2100) over the southern Asia (SAS) under the worst-case scenario i.e., RCP8.5. Another global study found a historical (1950–2016) probability of 21.6% and 20.7% for drought-pluvial seesaw with 3-month lag period over SAS for the boreal spring-summer and fall-winter, respectively (He and Sheffield, 2020). The differences among these studies could be due to the settings of the proposed framework, such as the definition of wet and dry extreme events relative to the threshold (e.g., high vs. low), the choice of the index (e.g., variables involved in the calculation of the index), the predefined time lag (which determines the rapidness of event transition), and the selected temporal window size (which characterizes the uncertain timing of event occurrence). Because each study addresses a specific sector and impacts

and, hence, has a different methodological framework, it is not possible to draw direct comparisons between the results in this work and these studies. However, our results agree with the general findings of these studies, showing that dry events are often linked to an increase in subsequent wet extremes.

In terms of spatial extent, in the present work about 23% of the total study region has experienced statistically significant ($p < 0.05$) D-to-W CEs during the historical period and it is projected to increase for most of the considered datasets, emission scenarios and time segments after BC. Although the overall percentage area of D-to-W CEs occurrence is small, we identify the spatial hot spots, located in the southwest of the basin where precipitation is dominated by the monsoon system, which was not found to be a hotspot neither for dry nor for wet extreme events separately (Ansari et al., 2023). Although the seasonality of CEs is out of scope of the present work, it is more likely that the D-to-W CEs will occur during summer season because the hotspot region usually receives heavy precipitation during summer season under monsoon system (Archer and Fowler, 2008, Mahmood, 2013, Azmat, 2015, Ansari et al., 2022). Depending on the BC method, datasets, emission scenarios and time segments, a negligible to large increase in most of the (individual) wet and dry events indices are expected in this hotspot in the anticipated future. Particularly, the CMIP6 ensemble presents strong climate change signals (either positive or negative) under the strong emission scenario with a clear pattern of occurrence and the southwest of the basin stands out as a hotspot for the more frequent wet and dry extreme events with an increase in DF and WF of up to eight events relative to the baseline period, respectively. In contrast, the northeast part of the basin which hosts foothills of western Himalayas (under westerlies precipitation pattern) is found to be least effected by CEs despite of its higher susceptibility towards wet and dry extreme events with higher severity and duration during the historical period (Ansari et al., 2023). The increase in CEs may even emerge in the regions with projected decreases in the extreme dry and/or wet events (Gu et al., 2022, Zhang et al., 2021). For instance, Zhang et al. (2021) found that 27–41% of the global land area in Northern China and Southern Africa is projected to experience fewer drought events but to suffer higher probabilities of consecutive drought-flood hazards. In contrast, 4–13% of the global land area, such as the southwestern US, Northern Mexico, Southern Africa, Australia, and Southwest coast of South America, are projected to experience a higher probability of droughts followed by floods but less occurrence of heavy rainfall, which indicates that heavy rainfall is projected to occur more frequently after drought, albeit with a decreased overall frequency of heavy rainfall.

In contrast to D-to-W CEs, the W-to-D CEs are found to be less apparent (statistically non-significant for a 95% confidence level) with no specific pattern of occurrence in the historical period as well as in future climate conditions, in agreement with previous studies (e.g. Qiao et al. (2022) in China).

Explaining the patterns of CEs from a physical perspective is difficult, since individual types of events are complicated, let alone the interdependent relationship between them. In general, these compound events are a result of the complex, combined effect of the local climate system, large-scale circulation structure changes, and even climate change. However, different sequences

involve different physical drivers and may response divergently to global warming. Specifically, D-to-W CEs are usually associated with the disturbed energy budget and could be explained in the context of global warming. In a warmer climate, increased evapotranspiration rates in response to increased temperature could elevate the drought risk and frequency. At the same time, the prospect of localized heavy precipitation causing floods is expected to increase in response to enhance atmospheric instability and promote convective development due to increased evapotranspiration rates (He and Sheffield, 2020, Krishnan et al., 2020, Fowler et al., 2021). Further abrupt transition from dry to wet extreme events may also be driven by large-scale thermodynamics, circulation shifts and land-sea atmospheric feedbacks (Deng et al., 2020, Raghavendra et al., 2019). In contrast, W-to-D CEs are typically linked to major tropical cyclones and is prevalent in coastal regions, including southeast China, Japan, and northwest Australia (Matthews et al., 2019, Liao et al., 2021). This is also evident from our study which shows non-significant probability of occurrence for W-to-D CEs. Major tropical cyclones can trigger devastating flooding and leave sustained heat that compensate for the fall in air temperature, contributing to the development of a consecutive extreme hot event (Liao et al., 2021, Matthews et al., 2019). Further compelling scientific evidence of human interventions and land use changes such as increased human water consumption, urbanization, agricultural practices, levee and dam construction could exacerbate the extreme drought and flood risk hazard (He et al., 2017, Yang et al., 2013, Villarini and Strong, 2014, Munoz et al., 2018).

In the context of BC, none of the BC method under both approaches retain the change signal of the raw counterparts for SPEI indices and CEs except for CMIP6 ensemble where all BC methods show a slight preservation of raw climate change signals for the D-to-W CEs in terms of spatial patterns. The probability and its statistical significance increased remarkably after all BC methods. Further, the BC methods under direct approach (i.e. D-EQM and D-QDM) modify to a larger extent the raw signals compared to MBCn whose signals are somewhat similar to those projected by BC methods under component-wise approach (i.e. CW-EQM and CW-QDM), especially for SPEI indices.

The comparable performance of the direct and component-wise approaches is evident in evaluation experiments with slightly better for direct approach (Ansari et al., 2023). However, remarkable differences in the climate change signals are found between both approaches with the direct correction introducing a greater modification of the original change signals especially for the SPEI indices, in agreement with previous literature (Chen et al., 2021, Casanueva et al., 2018).

The similar climate change signals projected by MBCn and CW-QDM is primarily attributed by construction as MBCn uses QDM to correct the marginal distributions of the individual variables and associated with the ability of univariate quantile mapping methods to implicitly adjust the joint probability distribution in a multivariate context (Casanueva et al., 2019). The small difference between the projected climate change signals by these two BC methods shows limited added value of multivariate BC method over univariate BC methods. Ansari et al. (2023) also found little added value of multivariate BC methods during the evaluation step which could be due to the weak relationship among the input variables of SPEI (i.e., precipitation and temperature) in

this region. Further, the present study found no remarkable difference between trend-preserving i.e., QDM and non-trend preserving i.e., EQM BC method under both approaches. Nevertheless, the absence of clear difference between these two BC methods in the present work does not rule out the added value of trend preserving BC over non-trend preserving BC methods.

To summarize, extreme wet and dry events are projected to be more frequent and severe with an increase in the frequency and severity up to eight events and 2.50 SPEI units relative to baseline period, respectively. The duration of extreme wet and dry events shows varying change signals depending on the location. Further results indicate that the UJB is more prone to D-to-W CEs than to W-to-D CEs and identify the monsoon-dominated region located in the southwest of the basin as the hotspot for the D-to-W CEs. Our findings assert the necessity of integrating mitigation measures targeting the CEs into Disaster Risk Reduction strategies at the identified hotspots. These findings provide invaluable insights for a wide range of decision makers including the dam reservoir operators and water resources managers. However, there remain several unanswered questions which need to be addressed in future work. For instance, the characteristics of compound events such as severity, duration, spatial extent and seasonality and the possible physical mechanisms associated with them.

7.5 References

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Chapter 8

Improving flood and drought management in transboundary Upper Jhelum Basin- South Asia

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Abstract

The two contrasting extremes of the hydrological spectrum have substantial and far-reaching impacts on a wide range of sectors including water resources, agriculture and food security, energy, infrastructure, and ecosystem. The compounding factors of climate change, burgeoning population, and rapid economic development create unprecedented challenges in devising effective and sustainable strategies to cope with these natural disasters and minimize their devastating impacts. This study identifies the geographical areas that are prone to extreme wet-dry events, as drivers of hydrologic floods and droughts, and their compounding over time in the transboundary Upper Jhelum Basin. Additionally, the study provides a comprehensive overview of the existing and proposed water development projects, their coping capacities, and potential impacts that may be positive or negative in hydrologic, social, economic and environment terms. Extensive review and data analysis revealed that the both Pakistan and India, along with state governments, have implemented a significant number of water-related projects across the basin, however significant progress towards achieving their stated goals remains elusive. The primary factors that impede the realization of expected benefits from these projects are geography, high flow variability across seasons, climate change, insufficient planning, geopolitical disputes, lack of transboundary cooperation, financial limitations, and reservoir operation. Based on these factors, the present study suggests some alternative water management measures that offer flexibility, cost-effectiveness, accessibility, and a low environmental impact. These solutions include implementation of sub-surface floodwater harvesting system, augmentation of existing hydropower reservoirs with floating photovoltaic technology, and non-structural measures, including early warning systems, ecosystems-based adaptation, and green infrastructure interventions such as restoring headwater forests, reclaiming floodplains, and wetlands. This will result in reduced flood and drought impacts at local and downstream areas and reduce the reliance of local communities on forest wood.

Key words: Floods; Droughts; Climate Change; transboundary Upper Jhelum Basin

8.1 Introduction

Water resources management is confronted with the formidable challenges posed by two contrasting/opposing extremes of the hydrological spectrum (i.e., floods and droughts) that hinder/impede progress towards achieving the Sustainable Development Goals. According to OFDA/CRED International Disaster Database, the 38.8% of the natural disaster events occurred in the world during 1900 to 2023 are floods whereas droughts are less frequent (5.3% of the total natural disasters) but have a greater impact in terms of fatalities. Combined, the hydro hazards account for 86% and 35% of total affected population and economic losses respectively (catholique de Louvain Brussels-Belgium, 2012). These natural disasters can lead to far-reaching consequences that extend beyond the immediate physical damage and can impact communities' socio-economic well-being and the environment in various ways.

Pakistan is among the world's most disaster-prone countries, ranked 22 out of 191 countries by the 2023 Inform Risk Index, with high exposure to flooding (ranked 7th) and low to droughts

(ranked 124th). Over the past decade, Pakistan has experienced/undergone an increase in the frequency and severity of natural disasters, such as floods, droughts, heatwaves, and pest diseases outbreak (Smit and Skinner, 2002). According to global climate risk index, Pakistan is among the top 10 countries globally/worldwide that have experienced/faced significant flooding between 2000 and 2019 (Eckstein et al., 2019) and among top 7 countries in terms of its high susceptibility to climatic hazards (Kreft and Eckstein, 2013). Prolonged droughts from 1999 to 2003 and devastating floods in 2010, 2011, 2012, 2014, and 2022 are some instances of the natural disasters that have struck Pakistan (Abid et al., 2016). Balancing the benefits and costs of adaptation to climate change is challenging, as it involves assessing and managing the impact of multiple factors that have been addressed for decades.

While the frequency and severity of floods and droughts are anticipated/expected/projected to increase in Pakistan, however the outlook for country's water resources is uncertain in the long run. Specifically, uncertainty surrounding projections of change in annual rainfall, some shifts in seasonality are expected. Given Pakistan's heavy reliance/dependence on the Indus River and its tributaries (Jhelum and Chenab) for its water resource, the uncertainty surrounding future glacial and snow melt is particularly significant. The headwaters/source region of these rivers contain/encompass the world largest natural snow and ice reserves and are highly vulnerable/susceptible to climate change.

The Jhelum River (JR) is the second-largest tributary of the Indus River, joining it from the eastern side, and contributes approximately 16.1% of the mean annual flow of the Indus River. The headwaters of the JR (also known as Upper Jhelum Basin-UJB) are located in the foothills of Western Himalayas and Pir-Panjal mountainous series, severely affected mountainous ranges by climate change. The climate change signals in the basin are already evident and are expected to become more pronounced in the future/coming decades (Arias et al., 2021). Perhaps most significantly, the intensity and duration of precipitation are likely to continue changing and exacerbating extremes in water variability. Furthermore, accelerated melting of Himalayan snow and ice may lead to frequent and higher magnitude floods in the upper reaches of the receiving river basins (Briscoe and Qamar, 2006, Romshoo et al., 2015). The consequences of climate change are severe and complex across the region, and the rural population, which primarily depends on agriculture, will be particularly affected. Most of the agriculture in the region is rainfed and heavily dependent on the monsoons. Further the downstream irrigated floodplains are highly dependent on the supply of the rivers which usually/often inundate during flooding in July and August.

Natural disasters cannot be prevented; however, their impacts can be reduced through the implementation of sustainable water resource management strategies to safeguard/protect the affected communities. Given that the UJB is a transboundary basin shared by Pakistan and India, there is need to cooperate with each other at all the possible levels, i.e., exchange of expertise in the respective field, monitoring and sharing of the scientific data related to hazards, co-operation in issuing warnings about floods, landslides, avalanches etc. There are various water resources development projects under consideration by both governments, including water storage and

hydropower production, aimed at mitigating flood problems and improving/enhancing water availability during the dry season, particularly in downstream irrigated floodplains. However, the achievement is still far from their stated goals. Despite these efforts, progress towards their stated goals remains elusive.

The current study provides a comprehensive overview about existing, ongoing, and planned water resources development projects (structured only) by both governments in the UJB and their impacts that may be positive and/or negative in hydrologic, social, economic and environment terms. Additionally, the study recommends some alternative water management strategies that are flexible, less expensive, easily accessible, and have a low environmental impact/footprints. To the best of our knowledge, it is the first kind of study to analyze all dimensions of floods and droughts in the UJB across the borders.

8.2 Precipitation pattern and hydro-hazard (flood and drought) mechanism

8.2.1 Precipitation pattern

The topography and the geographical position of the basin/region at the north-western edge of the South Asian summer monsoon creates two distinct precipitation patterns within the basin: westerlies (December to March) and monsoon (June to September) precipitation pattern. The westerlies system transported moisture from the Mediterranean and Caspian seas, leading to snowfall in the high-altitude areas of the basin, which accumulates until rising air temperatures cause it to melt and deplete from March to June. The snowmelt gives rise to the high-sustained river flows at Mangla, which normally reach their maximum in June. Conversely, the monsoon system brings moisture from the Arabian Sea and Indian Ocean to the low-altitude regions in the southern part of the basin, resulting in heavy rainfall.

8.2.2 Floods

Floods in JR and its tributaries are primarily driven by sustained heavy and concentrated monsoon rainfall in the catchment area. The intensity and duration of monsoonal rainfall can generate flashy flood peaks with very short lag times, particularly in the hilly areas and steep valleys of the basin. The UJB flow is also influenced by the snow and glacier melt during the summer season. The proportion of glacier melt to total flow is negligible. However, snowmelt plays a significant role in generating the high-sustained river flows at Mangla, which normally peak in June. This glacial melt and snowmelt can lead to both floods and droughts, depending on the timing and magnitude of the melting. Rapid glacial melt can cause sudden flooding, while a delayed or reduced melt can contribute to water scarcity during the dry season.

Discharge and rainfall data of JR in the Indian administrative Kashmir (IAK) is of limited use in the context of real time flood forecasting of Jhelum at Mangla reservoir because the flood waves generated in the Kashmir valley substantially attenuated in the Wular Lake and the surrounding swamp area which continues to expand and may reach up to Baramula under the conditions of high flows (NESPAK and Deltares, 2019). Thus, the Wular Lake acts like a big (natural) reservoir, which performs a positive flood mitigation role by dampening down the incoming flood hydrographs. However, the capacity of Wular Lake to regulate flows has been drastically diminished due to reclamation, sedimentation, and interventions to improve drainage

capabilities of upstream flood mitigation measures. Over the last three decades, about twenty percent of the water holding capacity has been diminished due to sedimentation from degraded catchments and wetland conversions to agricultural land. The overall decrease in the lake area is approximately 45%, primarily due to agricultural conversion (28%) and plantation (17%) between 1911-2007. Furthermore, associated marshes have experienced a 70% reduction due to agricultural conversion and settlements (Asia, 2007). The lake currently accumulates water during winter season when the flows are in the lean phase and fails to tap the high flows during the summer season. This situation has resulted in increased floods in the valley, as well as extended idling periods for the hydropower projects located downstream of Wular Lake.

8.2.3 Droughts

The South Asian region often experience severe drought conditions during the pre-monsoon and post-monsoon seasons; however, the pre-monsoon droughts occasionally persist throughout the monsoon season due to delayed onset of monsoon and suppressed monsoon activity (Nandargi et al., 2010). Hence, the monsoon precipitation system plays a substantial role in determining the sustenance of drought conditions in the region and affects the majority of the rural population whose livelihood is dependent on water related sectors/activities. More than 70% of the population in IAK are directly or indirectly dependent on agriculture for livelihood. Whereas about six-million-hectare land is irrigated downstream of Mangla reservoir in Pakistan (Archer and Fowler, 2008). Once in every three years, deficiency in rainfall is usually observed in the erstwhile state (Khan et al., 2020). Recently, the basin has experienced a significant decrease in snowfall (Ansari et al., 2022, Romshoo et al., 2015). This decrease in snowfall coupled with the accelerating retreat of glaciers has led to water shortage for irrigation and hydropower generation, especially in winter season (Romshoo et al., 2020). The research conducted by Naumann et al. (2018) shows increase in the frequency of severe drought in northern regions of Pakistan with shorter return period. For instance, extreme drought occurring once every 100 years under the present climate may have a return period of 50 years under a 1.5°C warming scenario or 20 years under a 3°C warming scenarios.

8.2.4 Geographical hotspots

Meteorological wet and dry extreme events, as drivers of hydrologic floods and droughts, are identified by using Standardized Precipitation Evapotranspiration Index (SPEI). The SPEI index facilitates comparisons across space and time and acts as a proxy for wet and dry conditions from both the meteorological and agricultural perspectives. It is computed from the monthly climatic water balance (precipitation minus potential evapotranspiration) with potential evapotranspiration is estimated using simple temperature-based Hargreaves-Samani method (Hargreaves and Samani, 1985). The wet and dry extreme events are defined as positive ($SPEI \geq 1$) and negative ($SPEI \leq -1$) values persisting for at least two consecutive months, respectively. Three features of these events are considered: duration, severity, and absolute frequency. The duration and severity are computed for each identified event and their median value is taken as a single index. The duration of an extreme event is defined as the length of time (months) during which the SPEI index is consecutively above 1 or below -1, respectively. The severity is the cumulative value of the SPEI

index during the whole duration of the extreme event. The absolute frequency is the total number of events in a given time period.

The maps of wet and dry extreme events features (median duration, median severity, and absolute frequency) for the period of 1986-2005 are presented in figure 3. The results reveal that the northeast region of the basin, which hosts the high mountains of western Himalayas, is found to be particularly vulnerable to wet and dry extreme events with higher severity and duration (Ansari et al., 2023a). The higher vulnerability of this region to more extreme events may be attributed to the accelerating rates of warming over Western Himalayas, as documented in numerous studies (Pachauri et al., 2014, Zaz et al., 2019, Rashid et al., 2020, Ansari and Grossi, 2022). Research conducted by Negi et al. (2018) and Dimri and Dash (2012) also corroborates the finding that most of the western Himalayan region has experienced a significant warming trend, particularly since 1975. These findings are further supported by the tree-ring chronologies of the region, which show a marked increase in the growth of tree rings in recent decades, particularly at higher elevations (Borgaonkar et al., 2009). These extreme events are projected to become more frequent and severe throughout the basin under warming conditions whereas duration of the extreme events shows varying change signals depending on the location (Ansari et al. 2023b).

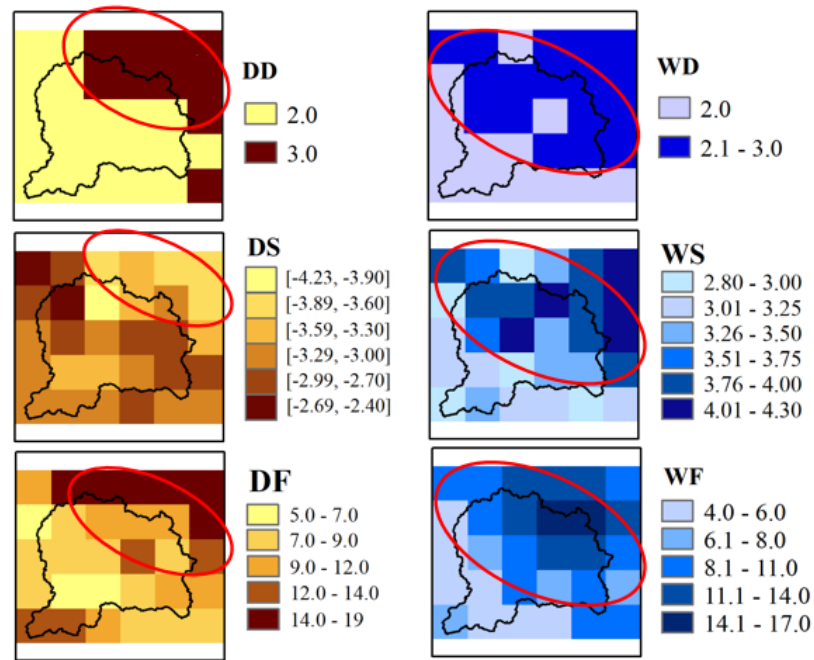


Figure 8.1: Spatial distribution of wet and dry extreme events characteristics (duration in months; severity in accumulated SPEI units and absolute frequency) for the period of 1986-2005. DD: median dry duration; WD: median wet duration; DS: median dry severity; WS: median wet severity; DF: absolute dry frequency; WF: absolute wet frequency.

Further the temporal compounding of these contrasting extreme events (i.e., consecutive occurrence of wet and dry extreme events in the adjacent months) may provoke greater impacts than individual events (Zscheischler et al., 2020) and pose significant challenges for water

resources management. Figure 4 presents the probability of temporal compound, including D-to-W events (extreme dry event is followed by extreme wet event in the following month) and W-to-D events (extreme wet event is followed by extreme dry event in the following month) for the period of 1986-2005, estimated using Event Coincidence Analysis-ECA (Donges et al., 2016). Temporal compound events where an extreme wet event rapidly changes to extreme dry event in the following month is found to be statistically non-significant with no clear pattern of occurrence. In contrast, the southwest of the basin is found to be the hotspot of temporal compound events where there is a high probability (up to 60 %, statistically significant at 5% level) of extreme dry events that are followed by extreme wet events in a close succession. It is interesting to note that this region is not found to be a hotspot neither for extreme dry nor for extreme wet events. The northeast part of the basin with high mountains of western Himalayas is found to be least affected by compound events, despite its higher susceptibility to both wet and dry extreme events with higher severity and duration (Ansari et al. 2023).

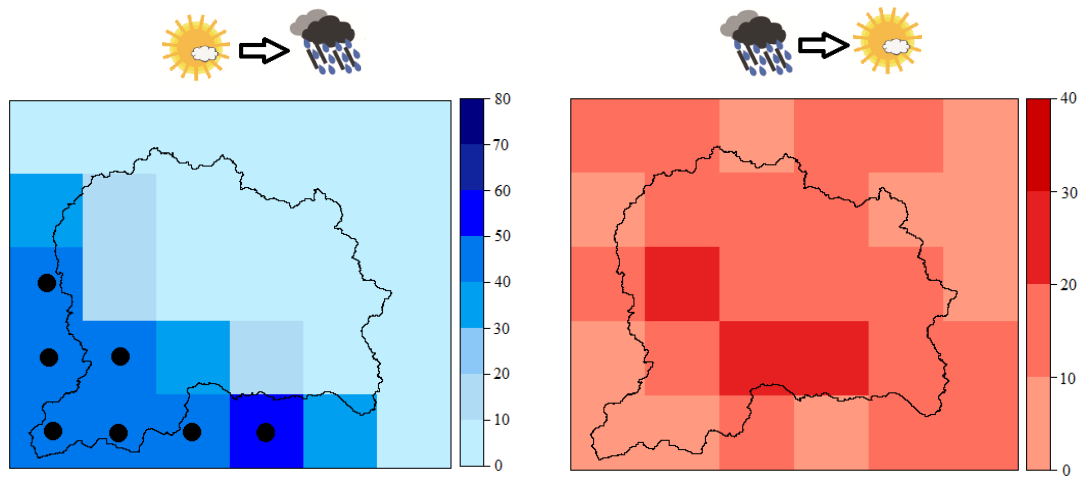


Figure 8.2: Probability of temporal compound dry-to-wet events (left) and wet-to-dry events (right) for the period of 1986-2005. Black circles indicate the statistically significant probability at the 5% level.

8.3 Water Development Projects on Jhelum River

The role of dams and reservoirs in flood management is of paramount/utmost importance, as evidenced by the historical flood events of 2010 and 2014, which highlighted their significance. It will act as safety valves during the flood season and maintain a steady flow of water in the river basin. Furthermore, the increased water storage capacity can be used for agricultural purposes during dry months and will also contribute to resolving the severe energy crisis by generating hydroelectric power.

Considering the precipitation pattern of the region, the water resources management through reservoir construction is ideal for the JR and its tributaries, however, there are no big/significant storage sites on JR, after Mangla Reservoir construction (Agha, 2010). The Mangla Dam, the outlet of the UJB, was built in 1967 under the Indus water treaty (IWT) and is the only reservoir over

Jhelum River. Floods on the upper reaches of JR have been attenuated/reduced through Mangla reservoir which has reduced the intensity of large floods (about 100-year return period) by approximately 20% (NESPAK and Deltares, 2019). Although the storage capacity of the reservoir is decreasing due to sedimentation, it still plays an important role in flood management. The useful life of the dam is anticipated to expire in 2050 (Haq and Nasir, 2003, Strategy, 2002). The effectiveness of the Dam in flood control is subject to their storage capacities, reservoir operation practices, and flood intensities. For instance, the flood peak of 2014 flood released from Mangla could have been reduced by approximately 40%, if the reservoir had been filled up to 1,242 ft instead of 1,241 ft (NESPAK and Deltares, 2019). Although Mangla is a multipurpose dam, their primary objective is to store water for irrigation with power generation as a secondary objective. The dam's operation planning has not been optimized to control floods downstream.

Further, Water and Power Development Authority (WAPDA) has conducted a comprehensive study on western rivers (i.e., Indus, Jhelum, Chenab) and identified different locations on River Indus and River Jhelum along with their tributaries for the development of multipurpose projects. The Jhelum River is considerably less attractive than Indus and the average annual runoff in the Jhelum reaching upstream of Mangla reservoir is about 35% of that of Indus River (IZHAR-UL-HAQ and SHEIKH, n.d). The poor and complex geological conditions in most of the Jhelum Basin do not favor construction of high dams. The geological formations comprise weak friable sandstones and limestones with frequent out-crops of shales. Repeated cycle of wetting and drying cause these to disintegrate and form steep slopes which become unstable in wet conditions. In addition, the sandstone beds are not wide enough to provide continuous rock foundations for spillway or intakes. Therefore, generally dam heights would be restricted to about 70 meters (IZHAR-UL-HAQ and SHEIKH, n.d). The practical solution appears to be the construction of low concrete gravity dams in the river channel with as little excavation as possible in the abutments. The tunneling operation in the Jhelum basin would be more difficult and expensive due to poor geology. Consequently, schemes on JR are smaller and less cost effective than those on Indus. The Jhelum valley is consistently narrow throughout its length. No sites are available where the spillway and power intake could be continued within the width of the valley. Sites are therefore, located near nullah openings where more space would be available and where valley sides to lower elevations. Table 2 & 3 show the potential of small dams in Pakistan Administrative Kashmir (PAK).

Table 8.1: List of proposed dams/reservoirs in PAK Jhelum basin (Package I)

Sr. #	Dam	Type of Dam	Command Area (acres)	Height (ft)	Type of spillway	Width of spillway (ft)	Storage capacity (acre-ft)	Power generation (kW)
1	Nihala, Bhimber	Earth Core rockfill Dam	314	49	Sloping Baffled Apron	50	100.5	3.4
2	Barali, Kotli	Earth Core rockfill Dam	164	49	Sloping Baffled Apron	75	85.35	1.9
3	Sona Sabzpir, Bhimber	Concrete Gravity	872	46	Free overflow Ogee Type	160	138.72	10.8
4	Bal-Brahmana, Kotli	Concrete Gravity	620	49	Free overflow Ogee Type	50	75.56	12.0
5	Naval, Bagh	Concrete Gravity	880	47	Free overflow Ogee Type	150	40.80	3.7

6	Earn, Bagh	Concrete Gravity	380	43	Free overflow Ogee Type	125	12.51	3.7
7	Baroora, Muzaffarabad	Concrete Gravity	225	47	Free overflow Ogee Type	75	12.74	2.75
8	Kardala, Muzaffarabad	Concrete Gravity	550	46	Free overflow Ogee Type	150	60.79	9.0
9	Tahi, Poonch	Concrete Gravity	225	46	Free overflow Ogee Type	100	38.96	1.8
10	Numb, Sudhnoti	Concrete Gravity	570	47	Free overflow Ogee Type	75	63.8	2.8
11	Nakkar, Sudhnoti	Concrete Gravity	222	45	Free overflow Ogee Type	58	109.44	2.7

Table 8.2: List of proposed dams/reservoirs in PAK Jhelum basin (Package II)

Sr. #	Dam	Type of Dam	Command Area (acres)	Height (ft)	Type of spillway	Width of spillway (ft)	Storage capacity (acre-ft)	Power generation (kW)
1	Dudnaya, Neelum	Concrete Gravity	3020	52.23	Free overflow Ogee Type	203.12	210	25
2	Palri, Neelum	Concrete Gravity	3761	53	Free overflow Ogee Type	78	21.76	6
3	Nowshera, Muzaffarabad	Concrete Gravity	5477	53	Free overflow Ogee Type	153	152	10
4	Pursacha, Muzaffarabad	Concrete Gravity	1711	54	Free overflow Ogee Type	10	12.54	2
5	Nawan Pur, Bagh	Concrete Gravity	3237	50.54	Free overflow Ogee Type	103	57.64	5
6	Madar Pur, Poonch	Concrete Gravity	2361	49.75	Free overflow Ogee Type	128	54.6	5
7	Bal Mandhole, Poonch	Concrete Gravity	819	47	Ogee Type	83	47	1
8	Saher, Sudhnoti	Concrete Gravity	4790	54	Ogee Type	103	106	6
9	Bhimber, Bhimber	Zoned Earthfill Dam	18000	36.64	Sloping Baffled Apron	602	4930	10
10	Bindi Nakka, Bhimber	Concrete Gravity	384	45.2	Free overflow Ogee Type	23	11.22	-
11	Abshar, Bhimber	Concrete Gravity	1917	48	Ogee Type	53	222	5
12	Andral Tarala, Kotli	Concrete Gravity	1016	53	Free overflow Ogee Type	38	43	2
13	Banala Nakayyal, Kotli	Concrete Gravity	3397	47.28	Ogee Type	93	72.58	6
14	Bilal Kund, Kotli	Concrete Gravity	696	47	Ogee Type	78	82.82	1
15	Chilayar, Mirpur	Concrete Gravity	819	47	Ogee Type	83	40.58	1

Apart from these storage projects, the topography and terrain in Jhelum basin offers numerous promising sites for run-off- river (RoR) type hydropower projects (HPP). Steep river gradients to produce/create large heads for hydropower production can be harnessed by tunnel construction. For the last several years the Government of Pakistan and Government of PAK has encouraged the private sector investments in such projects, which initially generated a lot of interest, and a number of potential project sites were identified. A number of feasibility studies have been conducted, but somehow no private sector projects have been built/implemented to date. Table 4 provides a list of the projects in different stages of completion, their capacity, and the responsible agency. Hydro Electric Board-HEB (public sector) and Private Power Cell-PPC (private sector) are the two government agencies in PAK, established in 1989 and 1995, respectively. They are responsible for the implementation of HPP in PAK with capacities up to 50

MW, in accordance with the Power Policy of 2002. WAPDA (public sector) and Private Power and Infrastructure Board-PPIB (private sector) are responsible for projects greater than 50 MW.

Table 8.3: List of operational and upcoming hydro power projects in PAK Jhelum basin

Sr. no	Name	Power Capacity (MW)	Agency	Status
1	Mangla	1000	WAPDA	Operational
2	New Bong Escape	84	PPC	Operational
3	Jari	1	PPC	Operational
4	Chinari	0.2	PPC	Operational
5	Patikka	0.50	HEB	Operational
6	Changan	0.05	HEB	Operational
7	Kel	0.4	HEB	Operational
8	Kathai	1.6	HEB	Operational
9	Leepa	1.6	HEB	Operational
10	Kundal Shahi	2	HEB	Operational
11	Sharian	3.2	HEB	Operational
12	Jagran – I	30.4	HEB	Operational
13	Neelum-Jhelum	969	WAPDA	Operational
14	Kohala	1124	WAPDA	Under construction
15	Patrind	147	PPIB	Operational
16	Halmat	0.32	HEB	Under construction
17	Hillan	0.6	HEB	Under construction
18	Dhanna	1.5	HEB	Under construction
19	Hajira	3	HEB	Under construction
20	Sharda	3	HEB	Under construction
21	Rerah	3.2	HEB	Under construction
22	Battar	4.8	HEB	Under construction
23	Chamfall	6.4	HEB	Under construction
24	Jhing – I	14.40	HEB	Operational
25	Jagran- II	43.5	HEB	Under construction
26	Naghdar	39	HEB	Planning or feasibility stage
27	Doarian	46	HEB	Planning or feasibility stage
28	Jari II	2.5	PPC	Planning or feasibility stage
29	Dakhari	2.2	PPC	Planning or feasibility stage
30	Kathai – III	1.0	PPC	Planning or feasibility stage
31	Hotteri	5.40	PPC	Planning or feasibility stage
32	Jhing – II	4.0	PPC	Planning or feasibility stage
33	Riali – III	3.7	PPC	Planning or feasibility stage
34	Riali-II	7.08	PPC	Under construction
35	Riali-I	1.6	PPC	Planning or feasibility stage
36	Ashkot	40	PPC	Planning or feasibility stage
37	Jagran-III	35	PPC	Planning or feasibility stage
38	Khoja Seri	2	PPC	Planning or feasibility stage
39	Kundian	48	PPC	Planning or feasibility stage
40	Madar Batdara	10.2	PPC	Planning or feasibility stage
41	Samani	1.6	PPC	Planning or feasibility stage
42	Sarhota	1.0	PPC	Planning or feasibility stage
43	Sarswah	0.7	PPC	Planning or feasibility stage
44	Pothi	1.0	PPC	Planning or feasibility stage
45	Barar	1.0	PPC	Planning or feasibility stage
46	Gumot Nar	40.0	PPC	Planning or feasibility stage
47	Changan-II	9.0	PPIB	Planning or feasibility stage

48	Taobat	10.0	PPIB	Planning or feasibility stage
49	Janawahi	12.0	PPIB	Planning or feasibility stage
50	Shontar	52	HEB	Planning or feasibility stage
51	Luat	63	HEB	Planning or feasibility stage
52	Rajdhani	132	PPIB	Planning or feasibility stage
53	Gulpur	100	PPIB	Planning or feasibility stage
54	Kotli	100	PPIB	Planning or feasibility stage
55	Karote	720	PPIB	Planning or feasibility stage
56	Azad Pattan	222	PPIB	Planning or feasibility stage
57	Kohala	1100	PPIB	Planning or feasibility stage
58	Mahl	511	PPIB	Planning or feasibility stage
59	Hari-ghal	53	PPIB	Planning or feasibility stage
60	Abbasian	360	PPIB	Planning or feasibility stage
61	Kundal Shahi – II	600	WAPDA	Planning or feasibility stage
62	Dudhnial	960	WAPDA	Planning or feasibility stage

Sources: Annandale and Bailly (2014)

The part of the UJB in the IAK is also rich in water resources and has huge potential for hydropower generation. However, the water utilization and hydro-power generation in the IAK are largely subject to the provisions of the Indus Water Treaty signed in 1960 between Pakistan and India. As per the IWT, Pakistan is entitled to the unrestricted use of the flows of the three main west-flowing rivers, namely the Indus, the Jhelum, and the Chenab, while India retains exclusive rights to the waters of the eastward flowing rivers, namely the Ravi, the Sutlej, and the Beas. However, India has the right to utilize the water from the Western Rivers for various purposes mostly in the State of Jammu & Kashmir, including domestic use, non-consumptive use, agricultural use (as outlined in IWT Annexure C), and hydropower (as specified in Annexure D).

As per the treaty, India can create aggregate storage capacity up to 1.50 MAF (general storage: 0.50 MAF; power storage: 0.25 MAF; flood storage: 0.75 MAF) on the JR excluding the Jhelum Main. In context of irrigated area, India was irrigated 6.42 lakhs acres from the three Western Rivers as on effective date of IWT (01-04-1960) and is allowed to irrigate an additional 7.01 lakhs acres cropped area/land, including 4.00 lakhs acres from the JR. However, the treaty prohibits/forbids the construction of storage reservoirs on the three western rivers, except RoR projects which are subject to specific design and operational criteria. India has managed to produce around 2400 MW of hydropower, amounting to approximately 12.5% of the estimated power potential (20,000 MW) in IAK (Nisar and Monroy, 2012). Table 5 shows the HPP along with power generation capacity, responsible agency, and their status in IAK.

In context of surface water storage, Central Water Commission, India conducted survey and studies and found that there were not many feasible storage sites in the tributaries of JR. The Irrigation and Flood Control Department of Jammu and Kashmir has proposed 14 potential storage sites that could irrigate approximately 80000 acres of land. Nonetheless, these sites must be further surveyed and investigated as a small height of dam, about 20 meters, could relate to serious problems such as submergence of forest, land and villages (SAPCC: J&K, 2022).

Table 8.4: List of operational and upcoming hydro power projects in IAK Jhelum basin

Sr. no	Name	Power Capacity (MW)	Agency	Status
1	Lower Jhelum (LJHP)	105	State sector	Operational

2	Upper Sindh USHP-II Kangan	105	State sector	Operational
3	Upper Sindh USHP-I	22.60	State sector	Operational
4	Ganderbal	15.00	State sector	Operational
5	Pahalgam	3.00/4.50	State sector	Operational
6	Karnah	2.00	State sector	Operational
7	Uri –I	480	Central Sector	Operational
8	Uri-II	240	Central Sector	Operational
9	Athwattoo	10.00	Private Sector	Operational
10	Brenwar	7.50	Private Sector	Operational
11	New Ganderba	93.00	State sector	upcoming
12	Parnai	37.50	State sector	upcoming
13	Achoor Gurez	7.00	State sector	upcoming
14	Kishenganga	330	Central Sector	upcoming

Source: Ahmad (2019)

8.4 Discussion on existing and planned projects

Although both countries along with state government have implemented (operational, under construction, and planned) an immense number of water development projects across the basin, significant progress towards achieving their stated goals remains elusive. The primary factors that hinder the realization of anticipated benefits from these projects are geography, high flow variability across seasons, climate change, insufficient planning, geopolitical disputes, lack of transboundary cooperation, financial limitations, and reservoir operation. The following section provides a more detailed explanation of these factors.

8.4.1 Social-economic and Environmental Impacts

The water development projects (water storage reservoirs and RoR HPPs) are considered to be extremely important in enhancing socio-economic conditions on both local and national scales. Strong power sector infrastructure boosts the growth of other sectors, such as agriculture, industries, tourism, education, health etc while also eradicate the problem of deforestation by providing an alternative source of energy for local communities, whhve relied on forest wood. The local communities of PAK have traditional rights in terms of use of the forests. In the absence of alternative energy sources, it is estimated that one household burns/utilize on average of three trees annually for fuel purpose, and that about five trees are required to construct a house, with the wooden roofs need to be replaced every 8-10 years (D, 2015, Termizi and Rafique, 2001). Like PAK, the region of IAK also experiences an ongoing process of deforestation due to the significant reliance of local communities on forests for timber and fuel wood. In addition, the huge demand of fodder for the 9.90 million livestock population in the IAK resulting in deforestation (SAPCC: J&K, 2022). Additionally, the water storage reservoirs and the provision of electricity can uplift and boost the agricultural sector. This is achieved by increasing the cultivable land and adding value to agricultural products through processing and preservation methods. Approximately 20-30% of the fruits and vegetables are wasted from the farm to consumer due to poor marketing infrastructure in PAK (Atiq-ur-Rehman and Anis, 2008).

No doubt, the HPPs are considered to be eco-friendly and sustainable sources of energy. However, there are numerous factors that must be taken into account before embarking on such projects to ensure that their development is aimed at providing a long-term, sustainable source of

energy. For instance, the construction of surface storage reservoirs and HPPs in relatively small areas may pose significant environmental hazards, particularly during the construction and post-construction phases. (Annandale and Bailly, 2014). These hazards include increased pollution and environmental damage to both aquatic and terrestrial ecosystems, such as impacts on fish, algae, and other aquatic organisms due to modification in flow regimes, as well as on mammals and reptiles due to modification in flow regimes and construction of transmission lines. Furthermore, the development of such projects in areas already under threat from climate change and degraded watershed systems is a cause for concern.

Although small-scale RoR type HPP with little or no storage, are generally considered to have minimum impacts on the downstream river ecosystem but in practice it is different. Large RoR dams fragment the river's natural flow by forcing water through tunnels to hydel power plants before releasing it back into the river. The bypass path between dams and power plant usually is quite long, and up to 90% of the wintertime river discharges are diverted through these paths. This is evident in case of 330-MW Kishenganga Hydroelectric Project on the Neelum River (also known as Kishenganga), where a 24-km long tunnel was dug through the mountains to divert water of Neelum river to JR through Wular Lake in Baramulla district in IAK, which otherwise join each other at Domail near Muzaffarabad, PAK. This project deprives 27% of the natural flow of Neelum river, thereby impacting aquatic ecology, and causing damage to the existing 133,000 ha of irrigated land in the Neelum valley and 11% reduction in power generation capacity of Neelum Jhelum project in PAK (Dar, 2011). Apart from ecological impacts, these developmental actions also have significant socio-economic, demographic, and cultural impacts on the local communities, demanding a trade-off between competing interests to ascertain the optimal flow regimes in a river basin for the long-term sustainability of the riverine ecosystem. This is crucial for maintaining/ensuring food security and livelihoods in the region (Assessment, 2005).

8.4.2 Climate Change

Water scarcity in the Indus River Basin, which is often attributed to water mismanagement, is also substantially shaped by the impacts of climate change. Climate change altered the hydrological cycle, impacting the spatial and temporal distribution of hydrological components and resulting in an increased frequency of both floods and droughts. A number of authors have reported that Western Himalayan glaciers will retreat over the next 50 years, causing an increase flow of Indus and its tributaries, followed by a decrease of 30% to 40% by the end of the century (Ahsan et al., 2016, Briscoe and Qamar, 2006). The UJB also has witnessed/experienced a marked/significant reduction/decrease in snowfall in recent decades. This decline in snowfall coupled with the accelerated receding/melting of glaciers has resulted in water scarcity for irrigation and hydropower generation, particularly during winters season and thus hinders/impedes the efforts of Pakistan and India to become energy-secure countries. At the same time, heavy rains during the monsoon season are expected to become more irregular, bringing additional challenges to manage potential flood risks (Stolbova et al., 2016). This is likely to exacerbate existing tensions related to distribution and management of water flows, in particular with regard to low flows during the dry season and higher flows during the wet season. Moreover, the projected

hydrological regime for the Himalayan rivers is expected to have more silt deposits which could pose a threat to reservoirs, as well as larger flood waves that could potentially lead to dam bursts. Given these circumstances, constructing additional dams for hydropower or flood control is a risky endeavor.

8.4.3 Geopolitical disputes

Kashmir is a region of contention between India and Pakistan for over a half century and resulting in three wars between the two countries. The state of Kashmir is divided by the Line of Control (LoC) into Pakistan administered Kashmir (PAK) and Indian administered Kashmir (IAK). The core issue of Kashmir conflict is the water insecurity of two countries with swiftly increasing populations. The Kashmir dispute and dispute over the sharing of water resources are intertwined and have been the two major challenges when it comes to normalizing relations between the two countries. While military and political conflicts over Kashmir in the early years of independence were largely about ideology and sovereignty, it seems that the resolution of the water dispute may have a direct influence/impact on the Kashmir problem as negotiations on water were being held.

As a result of negotiations, both countries signed the IWT in September 1960. As per the treaty, Pakistan is entitled to the unrestricted use of the flows of the three main west-flowing rivers, namely the Indus, the Jhelum, and the Chenab, while India retains exclusive rights to the waters of the eastward flowing rivers, namely the Ravi, the Sutlej, and the Beas. With the World Bank as guarantor, the signed treaty has endured three wars, rapid decolonization, and uneven geographical development. However, between 2007 to 2017, several disputes arose as a result of continuous upstream interventions such as the Baglihar, Wullar, and Kishan Ganga projects. Pakistan's complete dependence on the Indus River system, unlike India, is a geographical reality. Even though the construction of RoR type hydropower plants may not significantly impact the amount of water reaching Pakistan, the natural timing of these flows is a crucial concern. Reduced flows resulting from filling dams during low flow seasons could potentially damage/destroy the rabi crops in Pakistan (Tariq, 2010), thereby exacerbating political tensions among both countries.

One noteworthy fact is that during the negotiations and signing of the IWT between both countries did not involve the representation from Jammu and Kashmir states, despite the treaty significantly impacting their utilization of water resources. Additionally, Jammu and Kashmir has not yet received compensation from the government of India for the losses incurred as a result of the treaty. In June 2011, a Chinese news agency reported that the government of Kashmir was seeking the assistance of reputable multi-national consultancies to determine the precise financial loss suffered by Kashmir due to this treaty, with the intention of presenting this information to the Indian federal government.

The outlook for resolving the water issue between India and Pakistan do not appear optimistic, given the ongoing energy and water crises in both countries, the lack of progress on the Kashmir dispute, and the exacerbating effects of climate change and rapid population growth.

8.4.4 Cooperation and Coordination at national and international level

The IWT is considered one of the most enduring and successful international water-sharing mechanisms. However, new challenges are emerging with clear and loud signals of climate change in the region. The treaty currently lacks appropriate guidelines to effectively address this issue, which necessitate an integrated approach. The cooperation mechanism outlined in the treaty is limited and does not encourage riparian countries to collaborate and build mutual trust for common good. Although the treaty includes a provision for future cooperation, experts from both countries agree that building cooperation on a treaty of division is difficult. Majority of the experts in both countries criticized the treaty as outdated and acknowledge that there are good reasons to supplement and expand the treaty using scientific knowledge to address issues that have emerged after IWT, such as climate change, environmental flows, sustainable watershed management, groundwater, design of water infrastructures etc. This would modernize the implementation of the treaty and the dispute resolution mechanism, thereby promoting peaceful relations between the two countries (Romshoo, 2016).

Additionally, cooperation and coordination between different stakeholders is also lacking at the national level. For instance, the HPPs development plan in PAK is highly fragmented and lacks an integrated approach. There are four proponent agencies, namely WAPDA, PPIB, HEB, and PPC, which are involved in HPPs development in PAK. These agencies are mainly focused on individual project implementation without adequate institutional coordination. This often leads to overlapped or overlooked service areas, inconsistent strategies, and other obstacles to effective water management and project goals achievement. The coordination between the different proponent agencies would provide a prospect to identify joint capacity building goals and objectives for managing the cumulative effects of the hydropower plan. For example, where multiple projects are being planned in close proximity of the same tributary or river segment, developers have the chance to collaborate and adopt a synergistic approach to redesign their projects. This will not only optimize positive outcomes but also mitigate adverse environmental impacts.

8.4.5 Financial Limitations and Constraints

The development of water reservoirs and hydropower projects in UJB/Kashmir is hampered by several financial challenges/constraints. The mountainous rugged terrain and challenging geographical conditions significantly escalate construction and transportation costs and poses logistical challenges. The challenge of land acquisition and population displacement for these projects, maintenance, and up-gradation of the transmission system need/demand substantial investment/budget allocation. Securing adequate funding from both national and international sources for such large-scale projects has been a persistent issue, especially in the face of competing demands for resources in other sectors. Moreover, geopolitical factors and administrative complexities can further hinder the timely allocation of funds for water reservoirs and hydropower initiatives.

A report by Kristoff (2022) stated that achieving long-term goals to have hydropower meet 46% of Pakistan's power generation needs by 2030 appears increasingly unlikely, due to increased

frequency of extreme weather events and significant cost overruns resulting from schedule delays. (Hanif et al., 2016) found that the errors and omissions in project design, changes in scope and changes in design are three main contributing factors that resulted in 20%-time delay and 31% cost overruns of the hydropower project in Pakistan. For example, the Neelum Jhelum hydropower project with a capacity of 969 MW, proposed in 1987, demonstrates the non-availability of funds and engineering challenges, resulting in unprecedented cost escalation and significant schedule delays. The project was finally completed in 2018 at a cost of \$4.1 billion, which is 600% higher than its initial estimate and a 21-year schedule delay. Despite the potential benefits these projects offer in terms of water for agriculture, power generation and disaster management, overcoming these financial constraints remains a critical aspect in realizing their full potential for the development and sustainability of the region.

8.4.6 Reservoir operation

Mangla, a multipurpose reservoir is located at the outlet of the UJB in PAK and plays a crucial role in both flood and drought mitigation. The primary function of the reservoir is to store water to irrigate the downstream floodplains with power generation as the secondary objective. The fact that dams and reservoirs serve different purposes makes it difficult to manage conflicting interests and priorities which may result in unintended impacts. In instances of flooding, water levels in the reservoirs need to be lowered, whereas to manage droughts conditions, they need to retain water at their maximum capacity in the reservoirs. Balancing the needs for flood control and drought mitigation/relief can be a delicate task, especially in the face of unpredictable weather patterns and changing climate conditions. This problem is further compounded by the occurrence of flash floods between drought periods, due to misperception of security (Mediero et al., 2007). This situation is particularly evident in the UJB where southwest of the basin experiences a rapid transition of dry spells into heavy rainfall events (Ansari et al. 2023b). Therefore, careful coordination and monitoring of weather patterns, river flow data, and sedimentation levels are essential to optimize its performance. Addressing these issues and adopting adaptive management strategies are imperative to optimize the Mangla Reservoir's role in effectively mitigating both flood and drought challenges in the region.

8.5 Potential Solutions

8.5.1 Water Storage

Fostering sustainable water resource management in a transboundary river basin poses a multifaceted challenge, particularly when considering the compounding impacts of climate change, hydropower development, population growth, and evolving water governance paradigms (Mohammed et al., 2022). Given the higher seasonal precipitation and discharge variability within the transboundary UJB, it is imperative be made transformational changes to existing water management practices to simultaneously address the challenges posed by floods and droughts, while minimizing the adverse environmental impacts. Previously flood and drought mitigation measures in JR basin have focused on surface water storage and the role of groundwater has been overlooked in scientific studies and management plans, despite its critical importance amidst climate change. The buffering capacity of groundwater (subsurface water in the saturated zone)

may provide resiliency against climate change-induced hydrologic changes in high mountains by retaining water during wet periods and releasing during dry periods. Compared to conventional surface storage options (i.e., surface reservoirs) with larger environmental and infrastructure implications, groundwater reservoirs offer better water quality, resilience to climate fluctuations, reduced evaporation losses, and enhanced ecosystem services (Dillon et al., 2019, Maendly, 2018). Therefore, overlooking the groundwater resources impedes an effective response to the challenges that must be addressed in catchments headed by temperate glaciers and their subsequent downstream areas worldwide.

Groundwater in high mountain regions is recharged by precipitation in the form of rain, snowmelt, and glacier melt. The amount of groundwater recharge varies in space and time, and is influenced by climate (i.e., precipitation forms, patterns, magnitude and timing), vegetation, geology, and topography (Somers and McKenzie, 2020, Urióstegui et al., 2017, Smith et al., 2014, Smerdon et al., 2009). Despite its importance, understanding of the groundwater process in the Himalayan region is limited due to lack of research, security concerns, under development, scarcity of available data, challenging topography, and other factors. Few recent studies have emphasized the significant potential of groundwater storage and discharge in mountain watersheds, as well as its buffering capacity in the face of climate change (Liu et al., 2004, Uhlenbrook et al., 2002, Soulsby et al., 2000).

A study conducted by Lone et al. (2021) investigated the sources of recharged water in high mountains of the Upper Indus Basin and found that annually groundwater is primarily replenished from glacier melt (44%), snowmelt (39%) and with a smaller contribution from rainfall (17%) on an annual basis. Another study assesses the groundwater recharge in Neelum watershed (sub-basin of UJB) and revealed that, on average, 46% of the annual rainfall converts to surface runoff, 35% loss to atmosphere through evapotranspiration, and remaining 18% infiltrates and contributes to groundwater recharge. The process of infiltration and groundwater recharge in Neelum watershed occurs over two distinct periods – from December to March and July to August. The amount of groundwater recharged during these periods ranges from 45 to 176 mm, with peaking in August. The groundwater discharge during the remaining six months of the year in the form of oozing springs and contributes to base-flow of the streams (Khan et al., 2021). The groundwater recharge that takes place in the mountains region can have substantial implications for distal groundwater systems in adjacent lowlands, extending up to several hundred kilometers. Furthermore, there is a great potential for preserving the flood flows of hill torrents in the basin, estimated to be approximately 493 million cubic meters per year. This water could potentially be utilized to cultivate 33,600 hectares of cultivable waste land in the basin rather than being wasted and causing damage to the land and population.

Subsurface floodwater harvesting system, also known as managed aquifer recharge (MAR), is part of the palette of solutions to flooding, water scarcity, water security, lowering water tables, declining water quality, and endangered groundwater-dependent ecosystems (Dillon et al, 2019). It is the practice of strategically recharging water to replenish subsurface storage at subbasin scale. To date, a variety of MAR techniques have been designed/implemented all around the world

(Dillon, 2005). Nonetheless/However, the potential of these MAR techniques remains relatively untapped/ underexplored compared to conventional surface water infrastructure, despite the growing evidence of their effectiveness (Gleeson et al., 2016, MacDonald et al., 2012). Dillon et al. (2019) quantified MAR efforts from 15 countries with available data and found that MAR capacity increased from 1 to 10 km³/year from 1965 to 2015. The successful implementation of MAR demands careful tailoring according to local needs and limitations. The choice of technique depends on factors such as local hydrogeology, soil properties, water quality considerations, land availability, and the specific objectives of the floodwater harvesting system. Each technique has its advantages and limitations, but collectively, they contribute to sustainable water management, aquifer recharge, and flood mitigation.

Implementation of MAR techniques in the upstream tributaries of the Jhelum River basin will result in fewer/reduced flood impacts at local and downstream areas. This, in turn, would ensure the availability of groundwater not only within the upstream basin but also for the distant groundwater systems in adjacent lowlands, facilitating productive utilization and enhancing livelihoods. Thus, the adverse impacts that would be felt/experienced/encountered across one part of the system could be offset to generate/create opportunities/ potential advantages in another part.

The MAR concepts suggested in this context are deemed deserving of additional exploration. Prospective avenues for future endeavors encompass:

- Appraisal/availability of non-committed surplus monsoon runoff in space and time/spatial and temporal dimension.
- Comprehensive research/investigations to identify the suitable hydrogeological environment and sites for establishing subsurface reservoirs.
- engagement between the farming community, water resources authorities and local government to formulate a practical implementation framework.
- Creation of pilot sites to illustrate the technical and economic feasibility, as well as to develop/formulate guidelines incorporating feasible institutional structures.

8.5.2 Power

Both, Pakistan and India have a tremendous potential for hydropower production on the Indus River System including UJB. For instance, IAK has a potential of about 20,000 MW (Nisar and Monroy, 2012), while the PAK has a potential of about 18,000 MW (Ranjan, 2020). Such potential could not be fully exploited because of geography, extreme weather conditions, financial limitations and transboundary issues as discussed in previous sections. Despite a renewable source of energy, hydropower also faces unique environmental challenges, such as disruption of required environmental flows, damage to aquatic habitat, degradation of water quality, deforestation, emissions of greenhouse gases and population displacement.

Given the burgeoning energy demands for economic growth and challenges associated with the hydropower generation, it is crucial to shift the emphasis from “generation driven” planning to more holistic solutions that integrate smaller, more financially viable, faster to build more agile technologies (Kristoff, 2022). For example, instead of investing in new hydropower projects

(especially large RoR), the government should focus on supplementing existing hydropower reservoirs with floating photovoltaic (FPV) derived power which would perhaps be a promising solution/appropriate approach to address the state and country's energy demands sustainably. By harnessing the synergy between the constant hydropower generation and the intermittent nature of solar energy, this innovative approach can enhance energy production while optimizing land and water resource utilization. The key advantages of this approach include land conservation, improved water quality by reducing algae growth, reduced evaporation losses, increased PV efficiency due to temperature regulating effect of water, reduced shading effects on PV modules, reduced construction and transmission cost, and reduced capital costs as compared to isolated hydropower or solar PV system (Jin et al., 2023, Vidović et al., 2023, Rauf et al., 2020, Farfan and Breyer, 2018). Conversely, this hybrid system may have adverse impacts on aquatic ecosystem due to reduced dissolve oxygen level, direct contact between water bodies and floating devices and electromagnetic fields generated (Château et al., 2019, Pimentel Da Silva and Branco, 2018). However, the extent to which these negative impacts can be mitigated depends largely on the specific baseline conditions of the reservoir, which is often lacking in available information (Jin et al., 2023). Therefore, there is an immediate need for research aimed at determining the optimal size and coverage rate of FPV systems to maximize electricity generation while minimizing environmental impacts. This research is essential for the further development and adoption of this technology.

Developing countries like Pakistan and India, which characterized by high population densities and increased competition for land and water resources, could potentially benefit from FPV systems to enhance water, energy, and food security as a part of achieving sustainable development goals. India has already begun to leverage this technology and has huge potential. The Energy and Resources Institute of India assess that the country has the potential to install 280 GW of FPV technology (Acharya and Devraj, 2019) which could reduce surface evaporation losses by an estimated 11 km³yr⁻¹ (Jin et al., 2023). Although there have not been many large-scale installations in India in the past, various projects have been announced in recent years. The largest FPV plant in India, located at Omkareshwar dam on the Narmada River, has a capacity of 600 MW and is expected to be the largest plant of its kind globally (Vidović et al., 2023).

Pakistan also possesses substantial/considerable potential for energy generation through FPV technology, particularly in the central and northwest regions, which are rich in both hydro and solar energy resources and well-suited/suitable for the installation of large hybrid hydro-FPV systems. Pakistan is in the process of installing his first FPV system with a capacity of 300 MW at Tarbela Ghazi Hydropower Generation Complex. The World Bank has been advocating for such projects and recently approved a loan of 341.5 million USD for this project/endeavor. The world bank believes that incorporating the FPV system can enhance the generation capacity of hydropower plants by 5-10%. The world bank also plans to support FPV installation on smaller hydropower plants through the Khyber Pakhtunkhwa Hydropower and Renewable Energy Development Program for which a loan of 450 million USD is being provided (Kristoff, 2022).

8.5.3 Non-structural measures

Besides the suggested MAR strategy, non-structural measures from early warning systems to ecosystems-based adaptation and green infrastructure interventions like restoring headwater forests, reclaiming floodplains and wetlands should be considered. While these measures may offer numerous benefits and be preferable to conventional hard infrastructure solutions in many instances, their effectiveness primarily depends on the countries' ability to implement and manage them successfully. (Mohammed et al., 2022). Capacity building of local communities and stakeholders is crucial for effective response and adaptation against climate change. However, this bottom-up approach (i.e., community-based climate change adaptation and solutions) necessitates a concurrent top-down approach with effective policies at the government or highest level to ensure its success and effectiveness, especially in developing countries where local communities lack awareness, technical education, and financial resources (Qamar and Archfield, 2023). For example, the Green Pakistan program, launched by the Ministry of Climate Change, in collaboration with the provincial Forest and Wildlife Departments, with an estimated cost of 3.652 billion Pakistani rupees for a period of five years, aimed to mitigate climate change impacts (GOP, 2017). This initiative not only succeeded in raising public awareness about the issue, but also facilitated the establishment of a community-level framework for its long-term sustainability (Kamal et al., 2019). Both of these outcomes are essential for translating community-driven adaptation measures into practice. To achieve this, a collaborative and coordinated efforts among governmental institutions, policymakers, officials, environmental organizations, and community members is vital for formulating strategies and approaches for climate change mitigation and adaptation.

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Chapter 9

Synthesis

9.1 Summary and Conclusions

Droughts and floods are two of the most common and devastating natural hazards, affecting a wide range of sectors including water, agriculture and food security, energy production, infrastructure, and ecosystem health. This dissertation aims to quantify and understand the evolution of these two water-related natural hazards and their compounding in temporal dimension over transboundary Upper Jhelum Basin-South Asia, both in retrospective (i.e. past) or prospective (i.e. future) climate contexts. Throughout the dissertation, this framework has been developed with each chapter emphasizing one particular aspect. The outcomes of each chapter are presented and summarized below:

To begin with, it's imperative to acquire knowledge of the terrestrial water budget (TWB) components and their dynamics within the study area to better understand the water resources availability, effective management, and the potential risk of hydrological hazards (floods and droughts) under a changing environment. Therefore, the **3rd chapter** presents a comprehensive assessment of the key TWB components and their recent temporal trends using observed and gridded datasets across Upper Jhelum Basin (UJB) for the period of 2003–2014. Different gridded datasets were used for precipitation-P (APHRODITE, CHIRPS, PGMFD, ERA-5, and MSWEP), evapotranspiration-ET (MOD16A2, SSEBop, GLDAS-NOAH, TERRACLIMATE and DOLCE), Gravity Recovery and Climate Experiment (GRACE) derived terrestrial water storage (TWS) and observed discharge (Q) measurements. The uncertainties in these gridded datasets are firstly evaluated against direct comparison with observed gauge data at monthly, seasonal, and annual scale and subsequently their abilities are assessed in terms of water budget closure. Finally, trend analysis is carried out for each TWB component with a more accurate and reliable gridded P, ET, TWS and observed discharge (Q) to check its statistical significance for the period 2003–2014. Overall, ERA5-precipitation and DOLCE-evapotranspiration relatively performed better and hence considered to be the most appropriate to present the hydrological spatiotemporal variability across UJB. The imbalance in the water budget was mainly associated with higher uncertainties in precipitation, especially during wet periods. The results of temporal trend analysis showed a) insignificant mixed trends for annual precipitation with increase and decrease in monsoon and winter precipitation, respectively b) mixed yet statistically significant trends for ET in different parts of basin at annual and seasonal scale c) significant decreasing trends for TWS throughout the UJB in winter and annual scale d) increasing trends for Q in all months of the year except January and February. Contradictions in precipitation trends over Greater Himalaya are present in the literature. These contrasting results are attributed to different datasets and study periods used for trend analysis in each work.

The **4th chapter** is based on the findings of chapter 3, which highlighted/showed that the application of gridded precipitation datasets as a substitute of limited ground observation over mountainous regions is challenging due to considerable biases and needs adjustments before their application in subsequent impact assessment studies. Therefore, this chapter evaluates four commonly used precipitation bias correction (BC) methods for their skills to capture various aspects of moderate to rare extreme precipitation events over Upper Jhelum Basin (UJB) for a period of 34 years (1981–2014). The four BC methods, i.e., linear scaling (LS), local scaling intensity (LOCI), power transmission (PT), and distribution mapping (DM), were applied on ERA5 reanalysis precipitation dataset and evaluated using nine extreme precipitation indices. Results show that, more or less all BC methods improved the raw ERA5 estimates especially magnitude; however, clear discrepancies exist in their skills to correct wet day frequency. Overall, the DM method was found to be a good compromise to correct various aspects of extreme precipitation, followed by LOCI, PT, and LS methods.

Chapter 5 provides spatio-temporal evolution of the regional wet and dry extreme events and their abrupt transition of wet-to-dry and dry-to-wet events for the period of 1981-2014. Meteorological wet and dry conditions, as drivers of hydrologic floods and droughts, are characterized by using a multivariate drought index (namely the Standardized Precipitation Evapotranspiration Index, SPEI). The use of SPEI at monthly scale for analyzing the abrupt transition of these extreme events needs greater caution. This is because the interpretation of the SPEI values at 1 month may sometimes be misleading, particularly for regions with low precipitation during a month. In such cases, large negative or positive SPEI values may emerge, despite the actual departure from the mean being relatively modest and could misclassify the conditions as extremely dry or extremely wet. The results of temporal variations in SPEI showed a strong change in basin climatic features associated with El Niño–Southern Oscillation (ENSO) at the end of 1997, with the prevalence of wet and dry events before and after 1997 respectively. The results of spatial analysis showed the prevalence of severe to extreme wet events for most of the basin, while the dry events of moderate severity level were more frequent in the study domain. The southwestern part of the basin, located in the monsoon-dominated region, was found to be the hotspot for extreme wet events. In contrast, the westerlies-dominated region was found to be the hotspot of dry events with higher duration, severity, and intensity. The spatial patterns of average transition time from one extreme type to the other type was found to be heterogeneous, however, a greater number of pixels took a shorter time to switch from dry to wet events than from wet to dry events. The switch/transition from dry to wet events within a shorter time interval showed the temporal compounding of these extreme events which may provoke greater impacts than those resulting from individual events.

Chapter 6 and 7 examines extreme wet-dry events and their temporal compounding in the future climate context based on climate models simulations stemming from three modeling initiatives (namely Coordinated Regional Climate Downscaling Experiment (CORDEX), CORDEX Coordinated Output for Regional Evaluations (CORDEX-CORE), and the 6th Coupled Intercomparison Project (CMIP6)), under low, medium and high emission scenarios for two time

segments i.e., near future (2040-2059) and far future (2080-2099). **Chapter 6** compares different state-of-the-art bias correction (BC) methods (univariate and multivariate) and BC approaches (direct and component-wise) for an impact-relevant, multivariate drought index (SPEI). The BC methods are calibrated and evaluated over the same historical period (1986–2005). The results found that, there is some added value of multivariate bias correction with respect to univariate BC methods in the representation of the inter-variable structures but comparable results to the best performing univariate BC methods are found in terms of biases in SPEI indices. These results were held under both BC approaches with a slightly better performance for the direct approach. The present climate evaluation shows limited added value of higher spatial resolution simulations (CORDEX-CORE) compared to their coarser resolution counterparts (CORDEX), mainly due to the experimental design (both resolutions are remapped onto the 50×50 km observational grid).

Chapter 7 builds upon the findings of chapter 6 and provides the future projections of wet-dry extreme events and their temporal compounding for the near future (2040-2059) and far future (2080). The climate model simulations are bias corrected by two univariate BC methods (i.e., EQM and QDM) under two BC approaches (component-wise-CW- and direct-D) and a multivariate BC method (N-dimensions-MBCn). The selection of these BC methods is based on their performance in present time climate, presented in Chapter 6. Results show that the extreme wet and dry events are projected to be more frequent and severe with an increase in the frequency and severity up to eight events and 2.50 SPEI units relative to baseline period, respectively. Wet duration of extreme wet and dry events shows varying change signals depending on the location. The results of ECA indicate that the UJB is more prone to D-to-W CEs than to W-to-D CEs and identify the monsoon-dominated region located in the southwest of the basin as the hotspot for the D-to-W CEs. In context of BC, contrasting climate change signals are found for BC approaches with the direct correction introducing a greater modification of the original change signals. Regarding climate model experiments, CORDEX ensembles (WAS44 and WAS22) show varying climate change signals whereas the CMIP6 ensemble show stronger change signals with specific spatial pattern of occurrence. The findings of this chapter provide meaningful insight into the geographical hotspots of compound extreme events, which could be of practical value to inform a group of stakeholders for understanding potential risks and designing more effective water management policies and mitigation plans, such as developing more efficient reservoir operation rules or agricultural planning.

Chapter 8 provides comprehensive overview of the existing, under construction and planned water infrastructure projects (i.e., water storage and hydropower project), their coping capacities, and potential impacts that may be positive and/or negative in hydrologic, social, economic and environment terms. Extensive review and data analysis revealed that the both countries (Pakistan and India) along with state government have implemented (operational, under construction, and planned) a tremendous number of water-related projects across the basin, however, the achievement is still far from their stated goals. The main reasons the expected benefits from the projects have not materialized are geography, insufficient planning, high flow variability across seasons/climate change, geopolitical disputes/constraints, lack of transboundary

cooperation, financial constraints, and reservoir operation. Considering all the above, the present chapter/study suggests some alternative water management strategies that are flexible, less expensive, easily accessible, and have a low environmental footprint. For instance, the implementation of subsurface floodwater harvesting techniques (also known as MAR) in the upstream tributaries of the Jhelum River basin will result in reduced flood impacts at local and downstream areas. This, in turn, would ensure the availability of groundwater not only within the upstream basin but also for the distant groundwater systems in adjacent lowlands, facilitating productive utilization and enhancing livelihoods. Thus, the adverse impacts that would be encountered across one part of the system could be offset to create opportunities in another part. Further the present study suggests that instead of investing in new hydropower projects, particularly large run-of-river (RoR) plants, government should focus on augmenting existing hydropower reservoirs with floating photovoltaic (FPV) technology. This could be a promising solution for addressing the state and country's energy demands sustainably and reducing the dependency of local communities on forest wood.

9.2 Future Direction

The findings of this dissertation would provide invaluable insights for a group of stakeholders (researchers, local authorities, policy makers, relief agencies, non-governmental organizations (NGOs), and (re)insurance companies) on the potential risk. However, there are several promising avenues for further investigation that could uncover valuable insights and new knowledge.

- 1) The present study locates the hotspot for temporal compound events within the UJB, however, the underlying physical mechanisms which lead to occurrence of temporal compound events, such as large-scale drivers (e.g., sea surface temperature, sea ice), regional and local scale feedback (e.g., land-atmosphere coupling), and natural variability (e.g., El Nino Southern Oscillation) will need further exploration/investigation. This can help increase the hydrological predictability and reduce the forecast uncertainty. A detailed analysis on a range of recorded instances of such temporal compound events would help to identify the favorable synoptic conditions for these events.
- 2) The regional climate model simulation that we use to project the future projections of extreme events are based on the 5th phase of the Coupled Model Intercomparison Project (CMIP5). Although we also use two global climate models from 6th phase of the Coupled Model Intercomparison Project (CMIP6) with high spatial resolution, however, we recommended to assess the future projections of the extreme events with the regionally downscaled climate model simulations from CMIP6 experiment, whenever available.
- 3) Bias correction is a mere statistical post-processing and cannot overcome fundamental climate model errors (e.g., inadequate representations of processes). BC may distort the climate change signal in the raw model output and produce physically implausible results. However, if the climate model simulates a credible climate change signal, and no clear physical argument exists then trend-preserving methods are a preferable choice (Maraun,

2016). Otherwise, process-based bias correction that explicitly considers relevant climatic phenomena should be explored.

- 4) The proposed mitigation measures have been selected based on their proven effectiveness elsewhere and should be further evaluated through pilot projects or by model simulations within the study area. A comprehensive cost-benefit analysis that accounts for social, economic, and environmental impacts should also be carried out for these measures. Furthermore, eco-system-based disaster risk reduction measures like restoring headwater forests, reclaiming floodplains and wetlands should be studied and locating suitable sites for their implementation. Moreover, eco-system-based disaster risk reduction measures such as restoring headwater forests, reclaiming floodplains, and wetlands, which are already being implemented on the Indus River under the "Recharge Pakistan" project, should also be carried out for the Jhelum River.
- 5) Investigating how and to what extent human interventions impact drought and flood risks under current and projected climate scenarios, and understanding the associated physical mechanisms behind these extremes, is crucial for addressing a broader problem across the human-environment interface.

Appendix A: Chapter 3 supplementary material

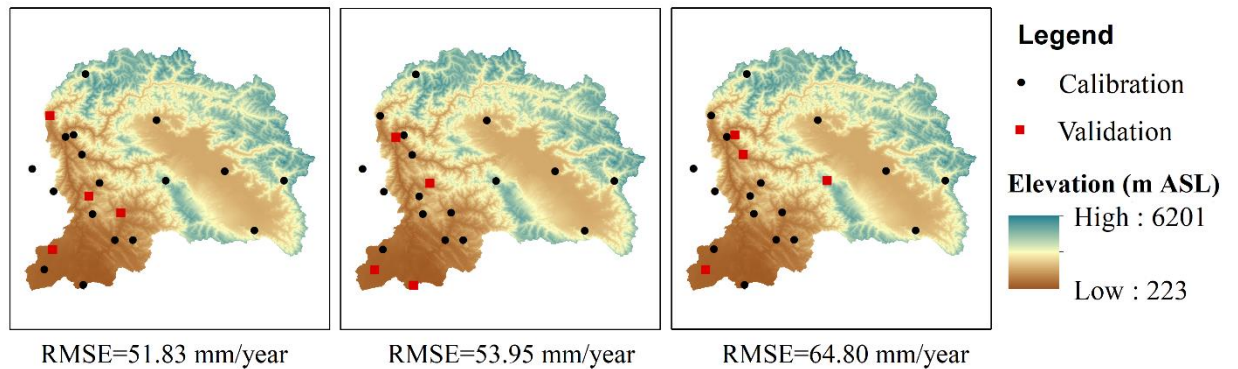


Fig. A.1: Cross validation results of interpolation technique (i.e., kriging with external drift-KED) for annual reference precipitation. In each figure 4 different stations (in red) were selected for validation

Appendix B: Chapter 6 supplementary material

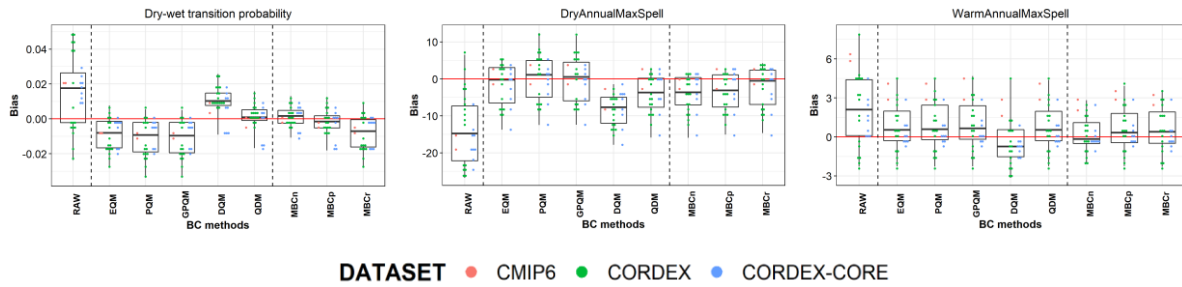


Figure B.1: Spatially averaged bias (model minus reference) over the UJB in transition probability of a wet day given that the previous day was dry (left), annual longest dry spell (middle) and annual longest warm (above 90th percentile) spell (right) computed from the raw (first box in each panel) and bias corrected data (rest of boxes). Each box represents the interquartile range of biases across all models, which are depicted individually with colored dots (CMIP6 in red, CORDEX in green, CORDEX-CORE in blue), whiskers expand the full range of biases. Red horizontal lines depict perfect performance, for reference.

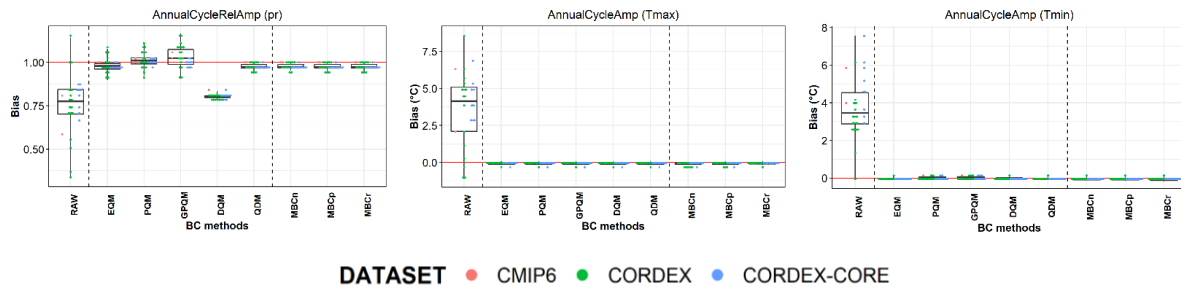


Figure B.2: Spatially averaged bias (as a ratio and delta for precipitation and temperatures, respectively) over the UJB in the relative amplitude of seasonality for precipitation (left), amplitude of seasonality for maximum temperature (middle) and minimum temperature (right) computed from the raw (first box in each panel) and bias corrected data (rest of boxes). Each box represents the interquartile range of biases across all models, which are depicted individually with colored dots (CMIP6 in red, CORDEX in green, CORDEX-CORE in blue), whiskers expand the full range of biases. Red horizontal lines depict perfect performance, for reference.

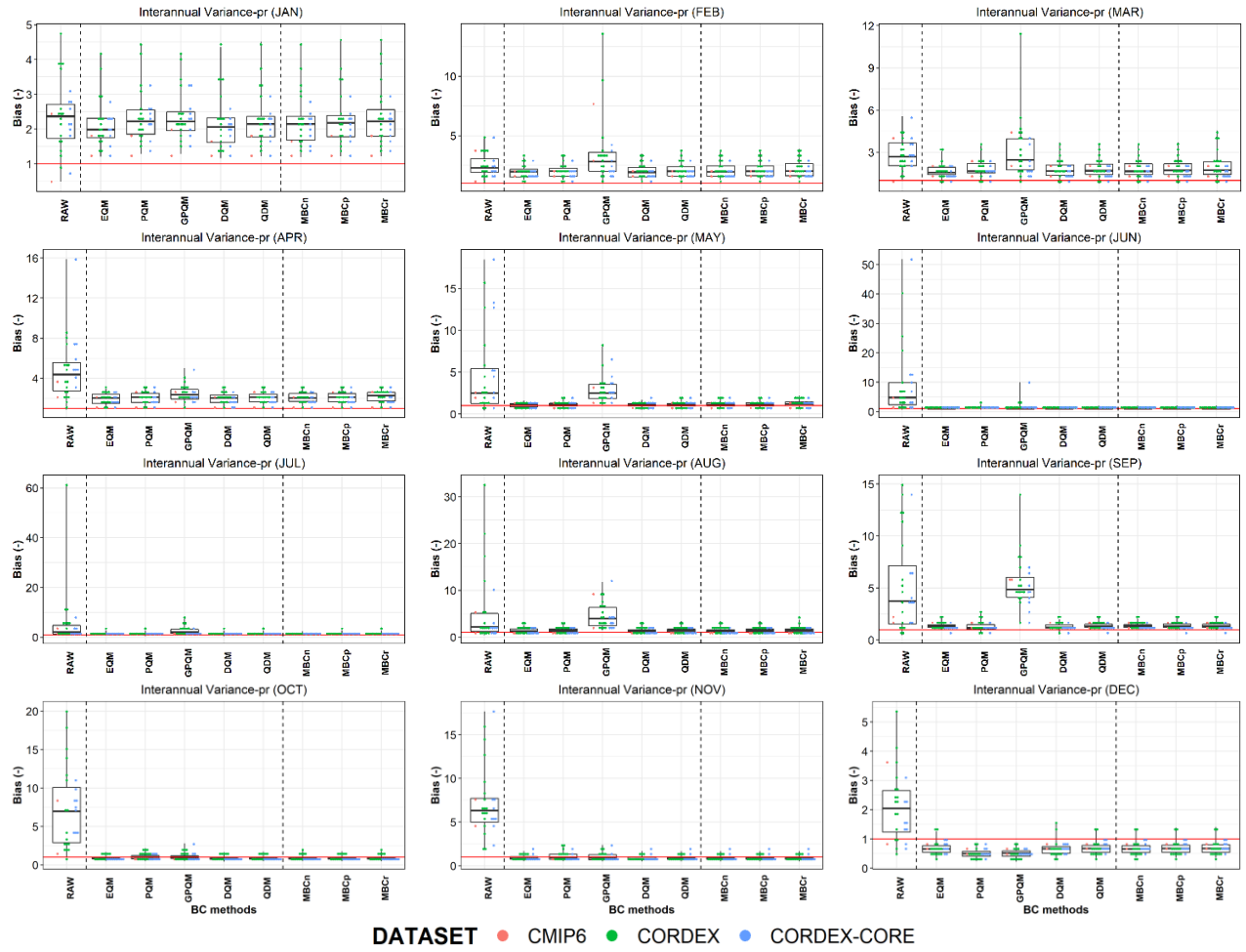


Figure B.3: Spatially averaged bias (as a ratio of model to reference) over the UJB in interannual variance of precipitation for each month, computed from the raw (first box in each panel) and bias corrected data (rest of boxes). Each box represents the interquartile range of biases across all models, which are depicted individually with colored dots (CMIP6 in red, CORDEX in green, CORDEX-CORE in blue), whiskers expand the full range of biases. Red horizontal lines depict perfect performance, for reference.

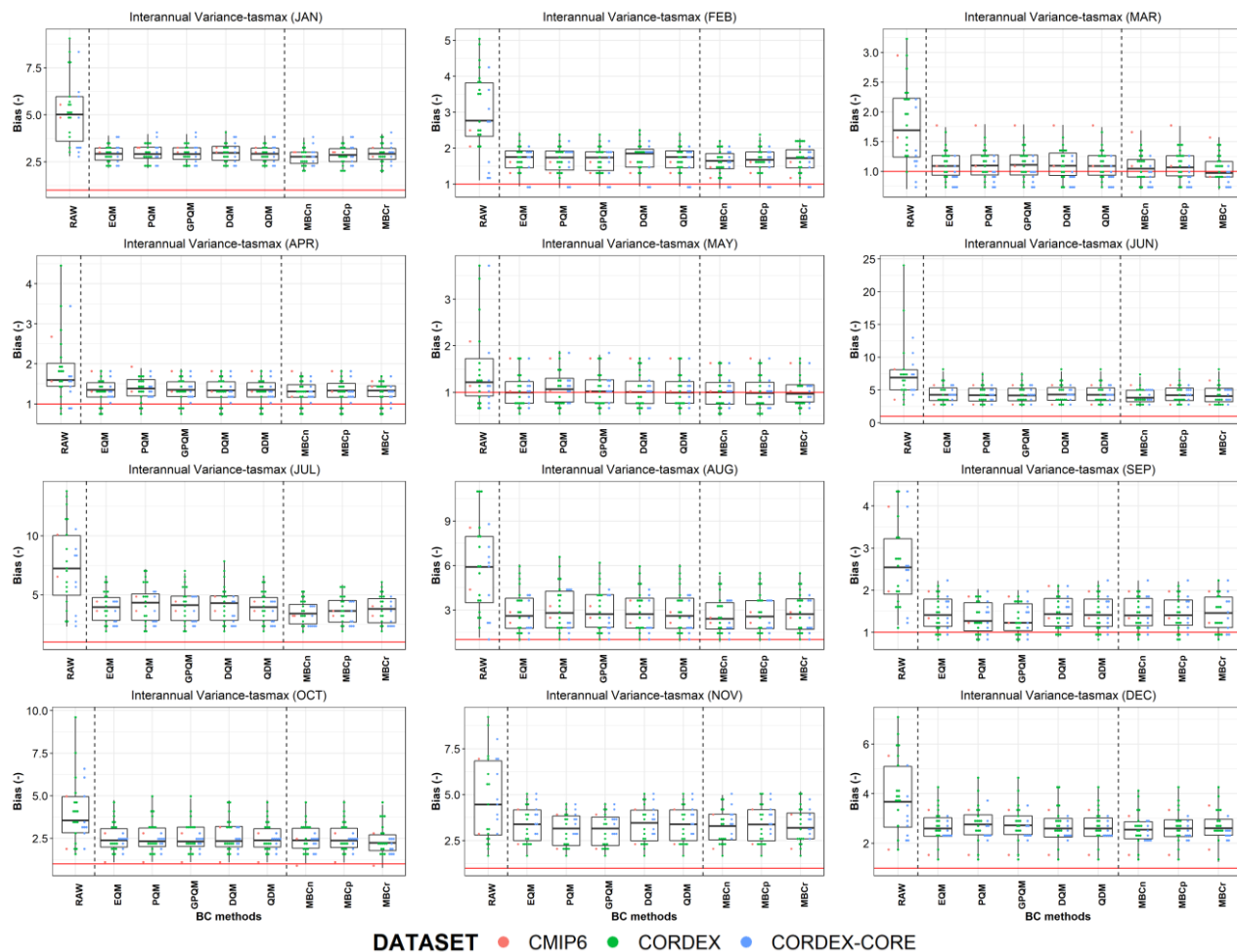


Figure B.4: Same as figure B.3, but for maximum temperature.

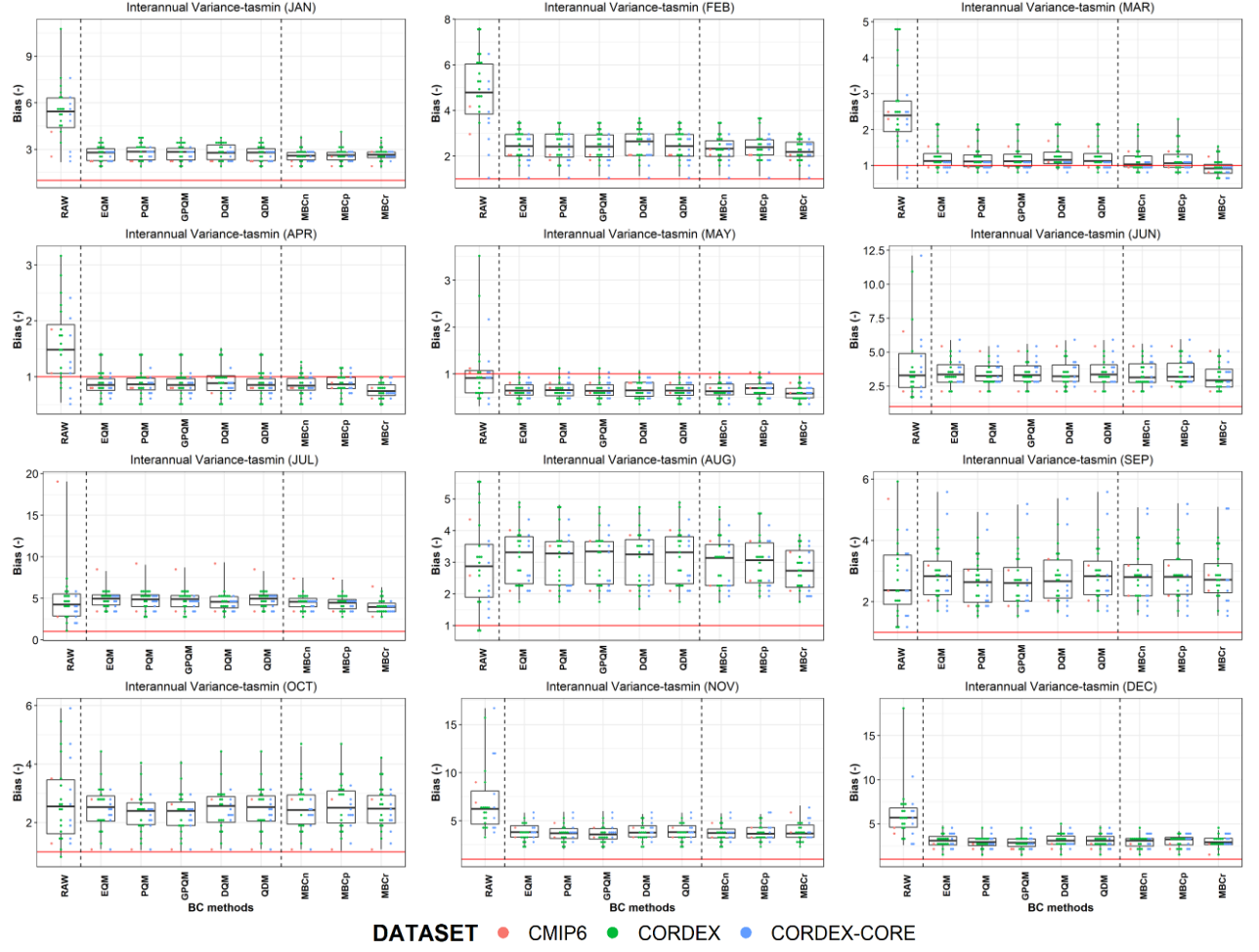


Figure B.5: Same as figure B.3, but for minimum temperature.

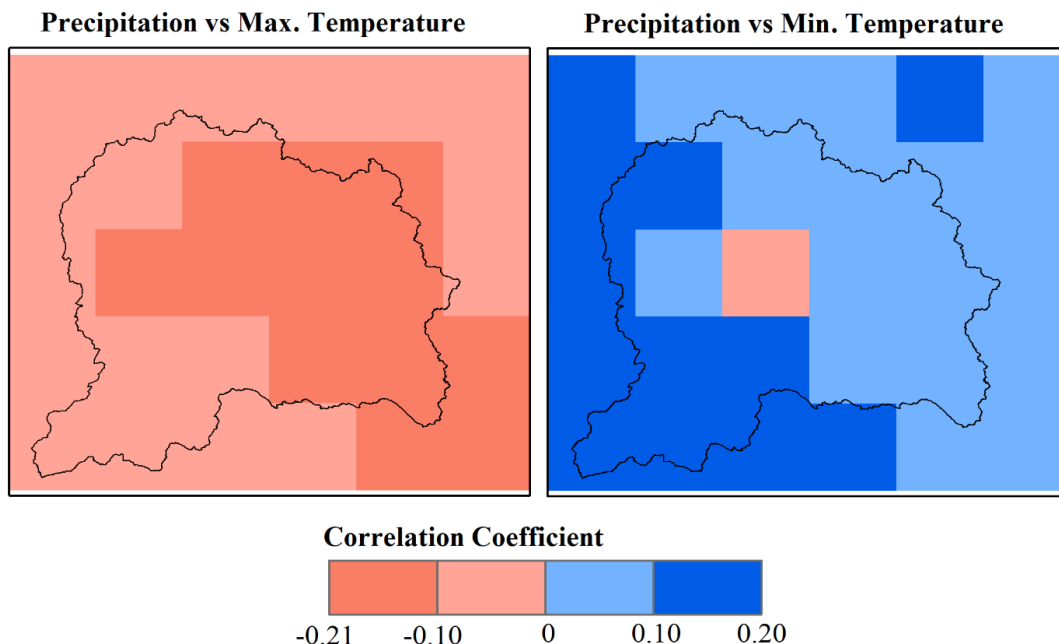


Figure B.6: Spearman correlation coefficient between daily precipitation and maximum temperature (left panel) and between daily precipitation and minimum temperature (right panel) for the reference data.

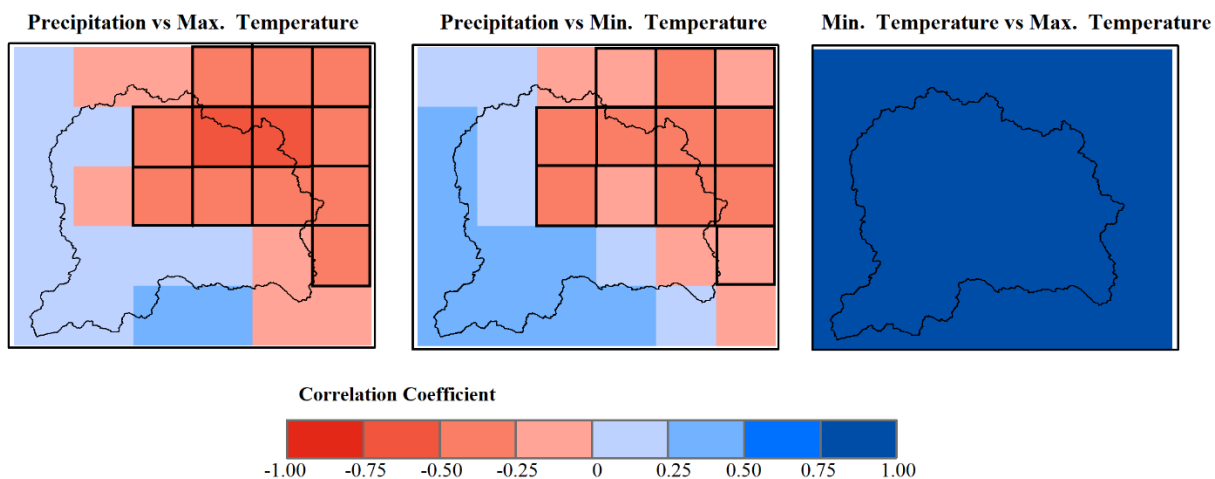


Figure B.7: Spearman correlation coefficient between monthly timeseries of precipitation and maximum temperature (left), precipitation and minimum temperature (center) and Pearson correlation coefficient between minimum temperature and maximum temperature (right) for the reference data. The marked/highlighted grid boxes are used for further analyses in Fig. B.8.

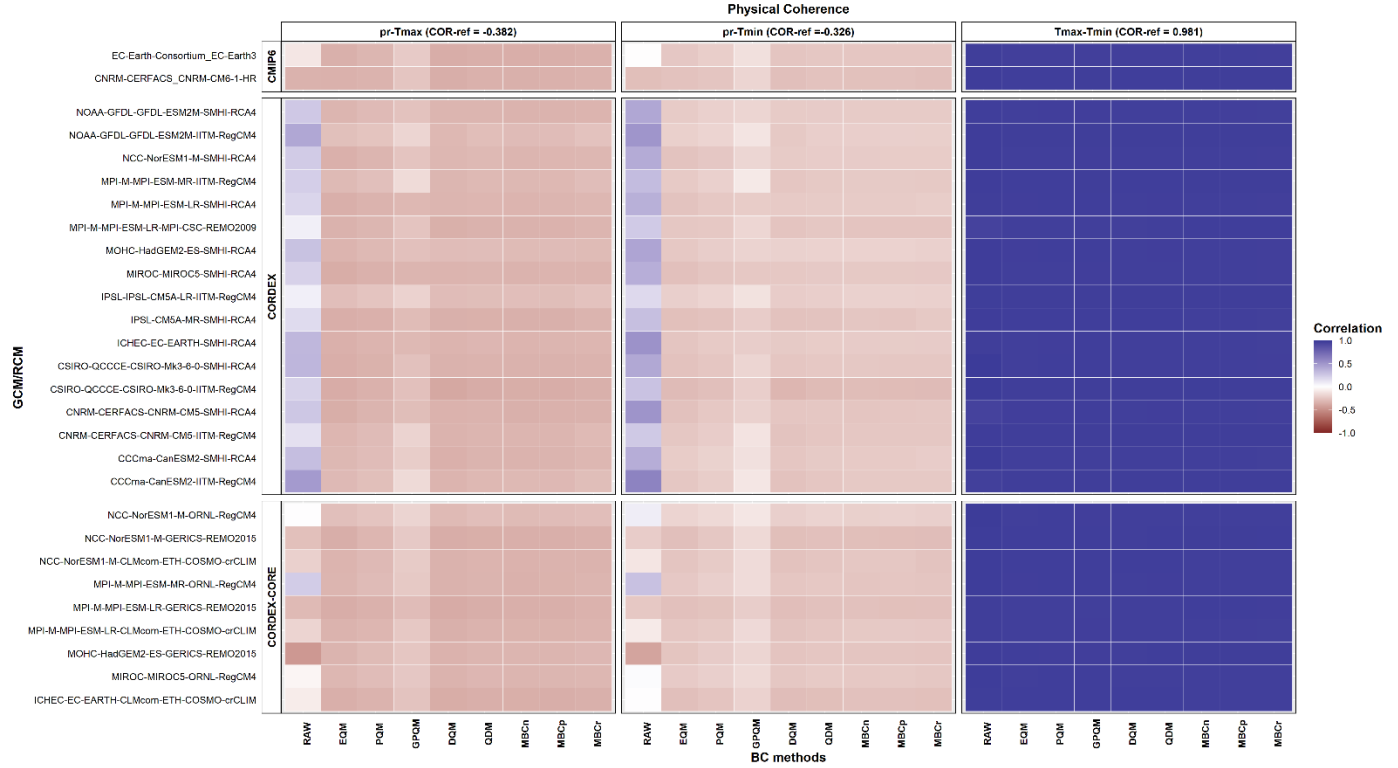


Figure B.8: Spearman correlation coefficient between monthly timeseries of precipitation and maximum temperature (left), precipitation and minimum temperature (middle) and Pearson correlation coefficient between minimum temperature and maximum temperature (right) for the raw and bias corrected climate model data (only component-wise approach). Correlation for the reference data is shown on top of each panel. Correlation values between precipitation and temperature (left and middle panels) are spatially averaged over a few grid boxes in the northeast part of the domain with negative correlation in the reference data (marked grid boxes in Fig. B.7). Correlation between max. and min. temperature is spatially averaged over the whole domain.

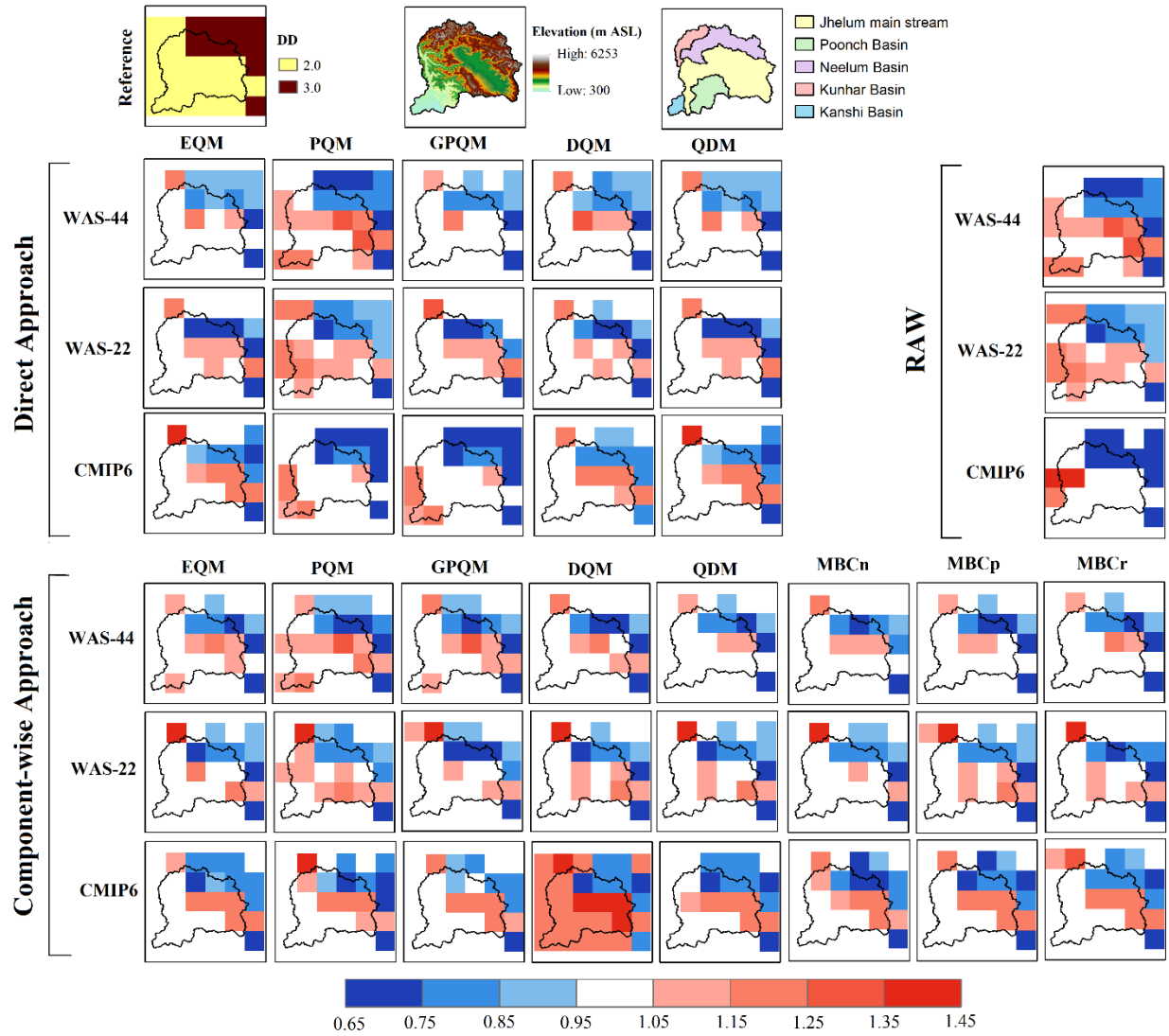


Figure B.9: Median dry duration (DD) expressed in months in the reference dataset (first row, left), digital elevation model in meter above sea level (first row, center) and location of sub-basins (first row, right), and biases (as a ratio of model to reference) for the multi-model raw ensembles and bias-corrected ensembles, for the two bias correction approaches and all methods (columns).

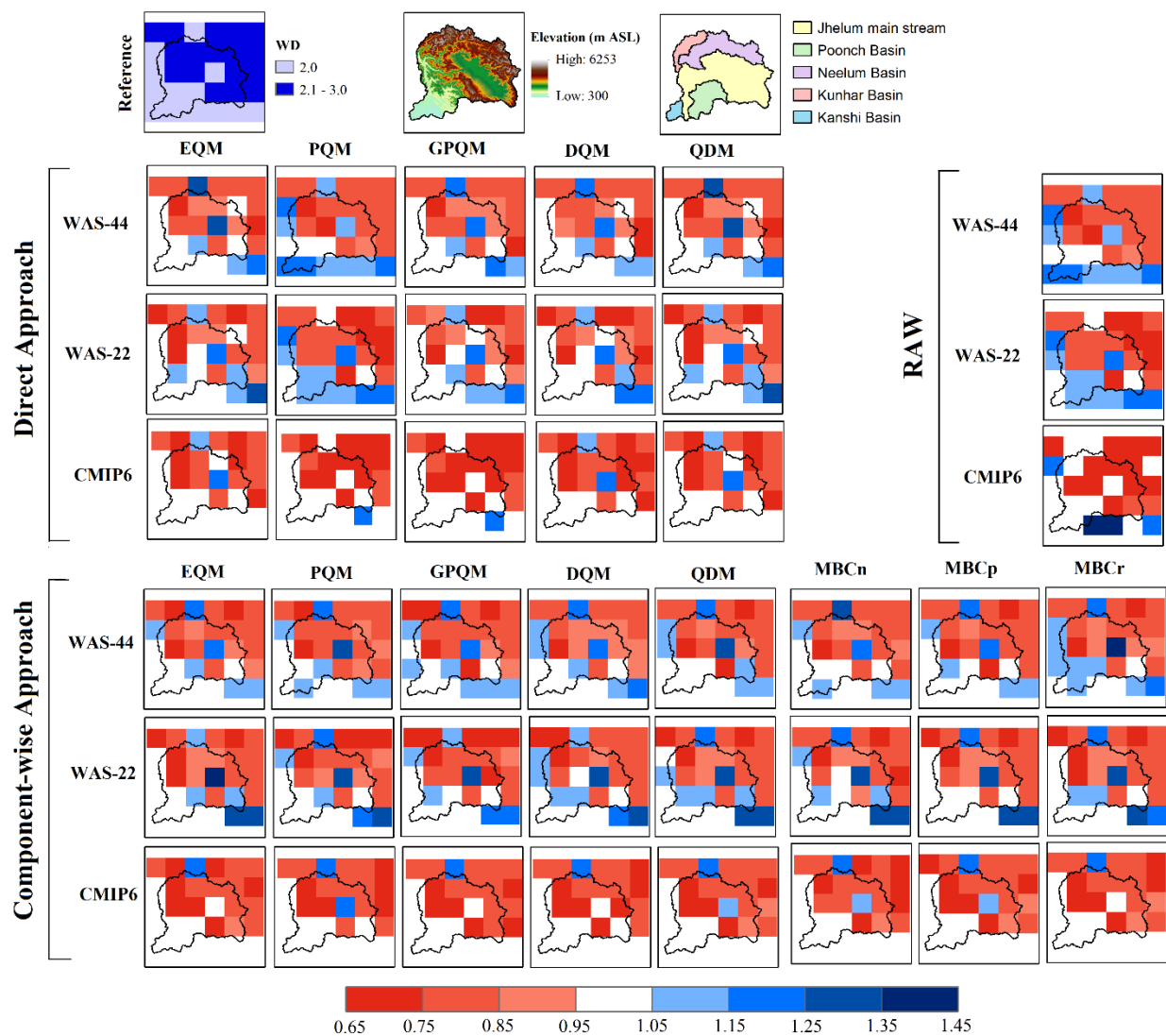


Figure B.10: Same as figure B.9, but for median wet duration (WD) expressed in months.

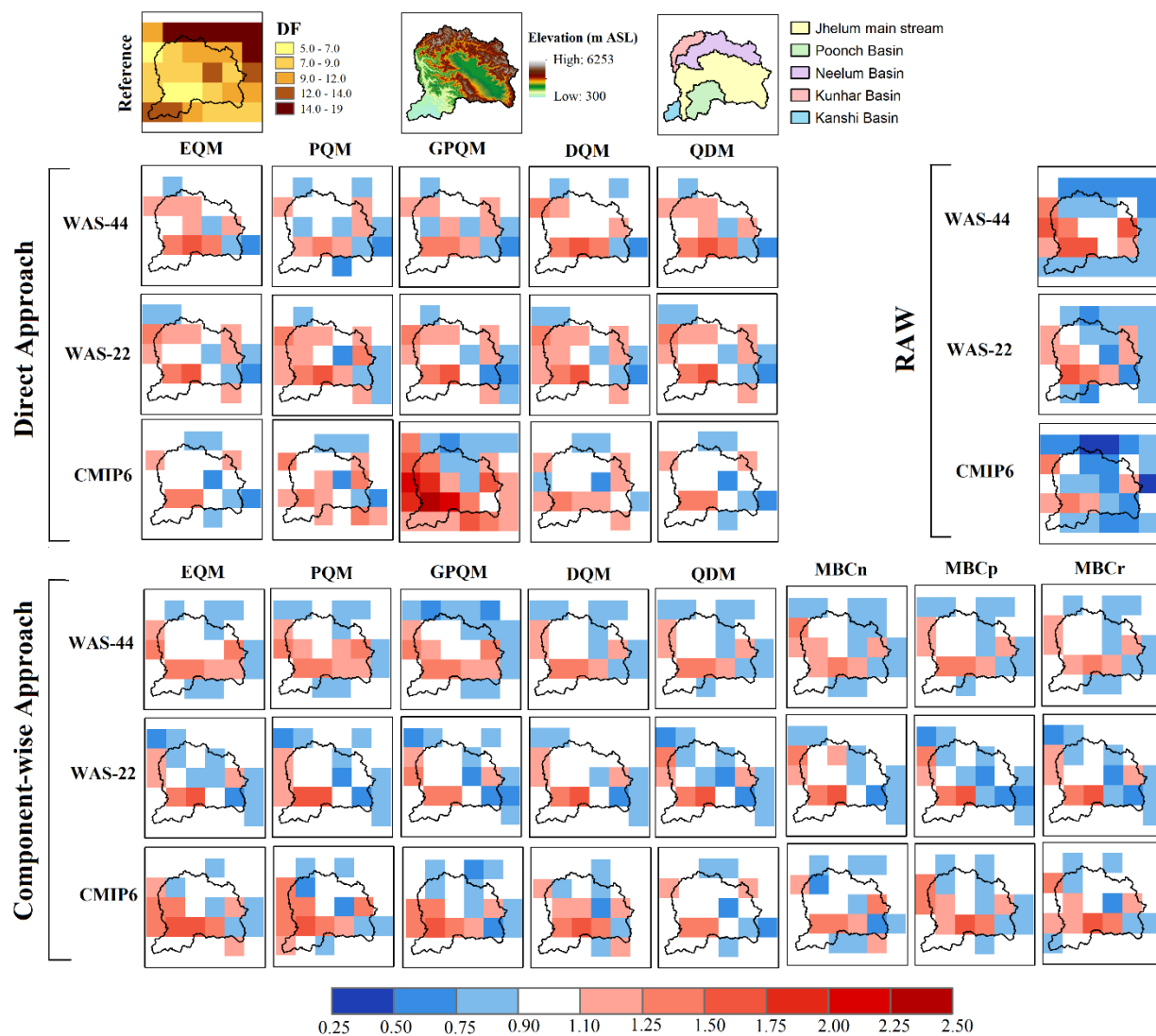


Figure B.11: Same as figure B.9, but for absolute dry frequency (DF) expressed as total number of dry events.

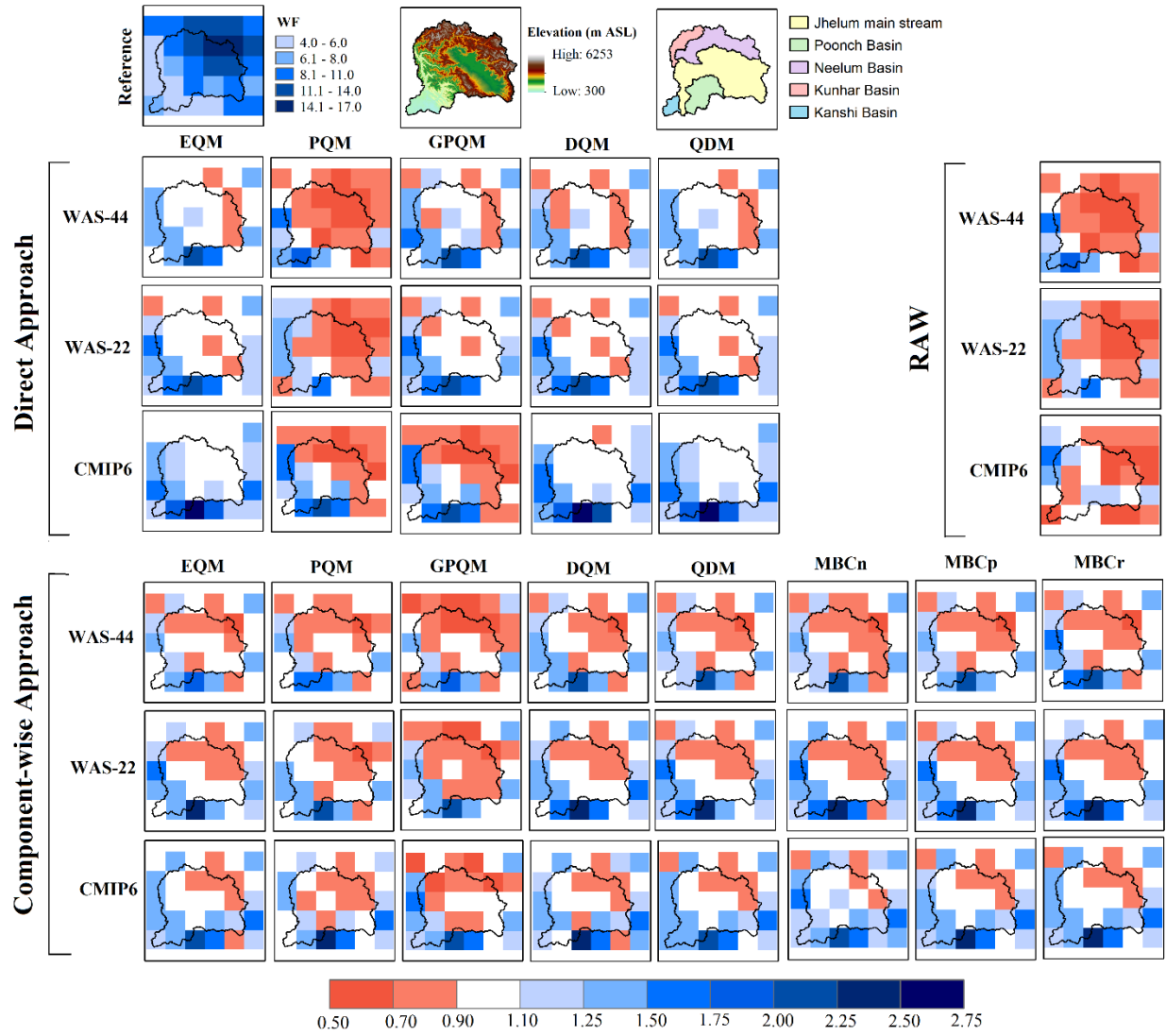


Figure B.12: Same as figure S9, but for absolute wet frequency (WF) expressed as total number of wet events.

Appendix C: Chapter 7 supplementary material

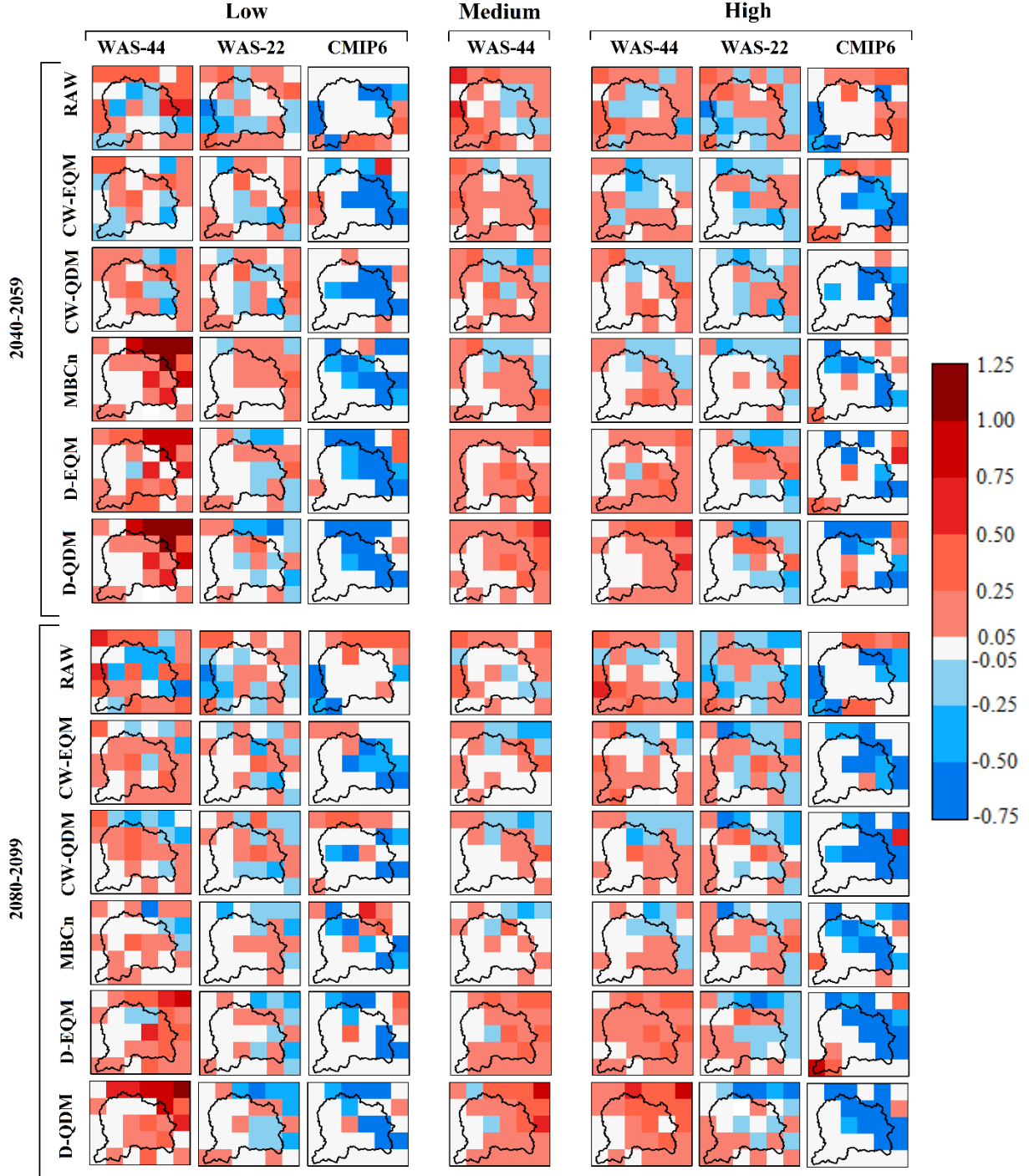


Figure C.1: Spatial distribution of climate change signals of median dry duration (DD), expressed in months, under low (RCP2.6/SSP126), medium (RCP4.5/SSP545), high (RCP8.5/SSP585) emission scenarios for the multi-model raw ensembles (first row) and bias-corrected ensembles, for the two bias correction approaches (direct -D- and component-wise -CW) and three BC methods. The climate change signals are calculated for the near future (2040-2059) and far future (2080-2099) with respect to baseline period (1986–2005).

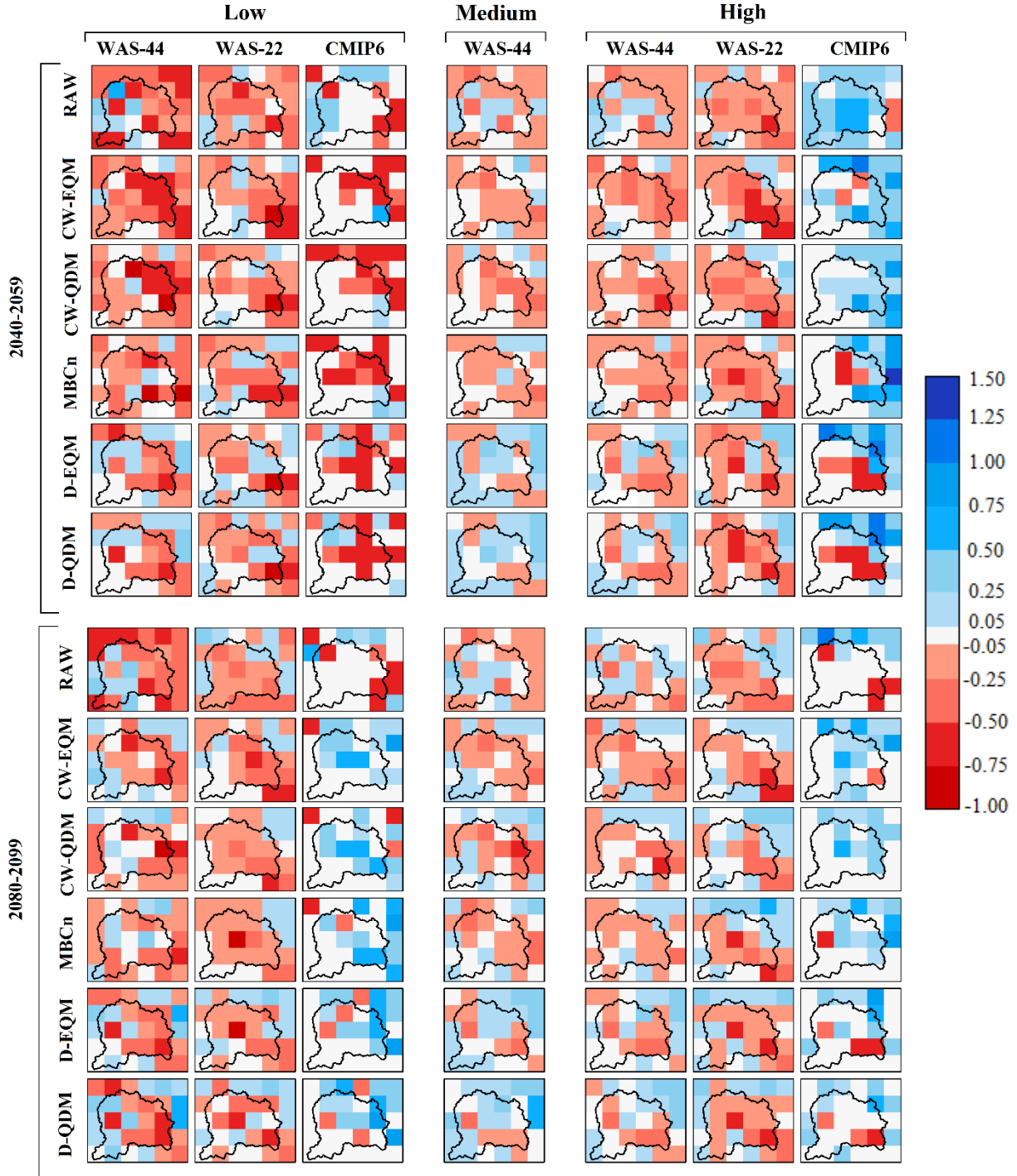


Figure C.2: Same as Figure C.1, but for median wet duration (WD) expressed in months.

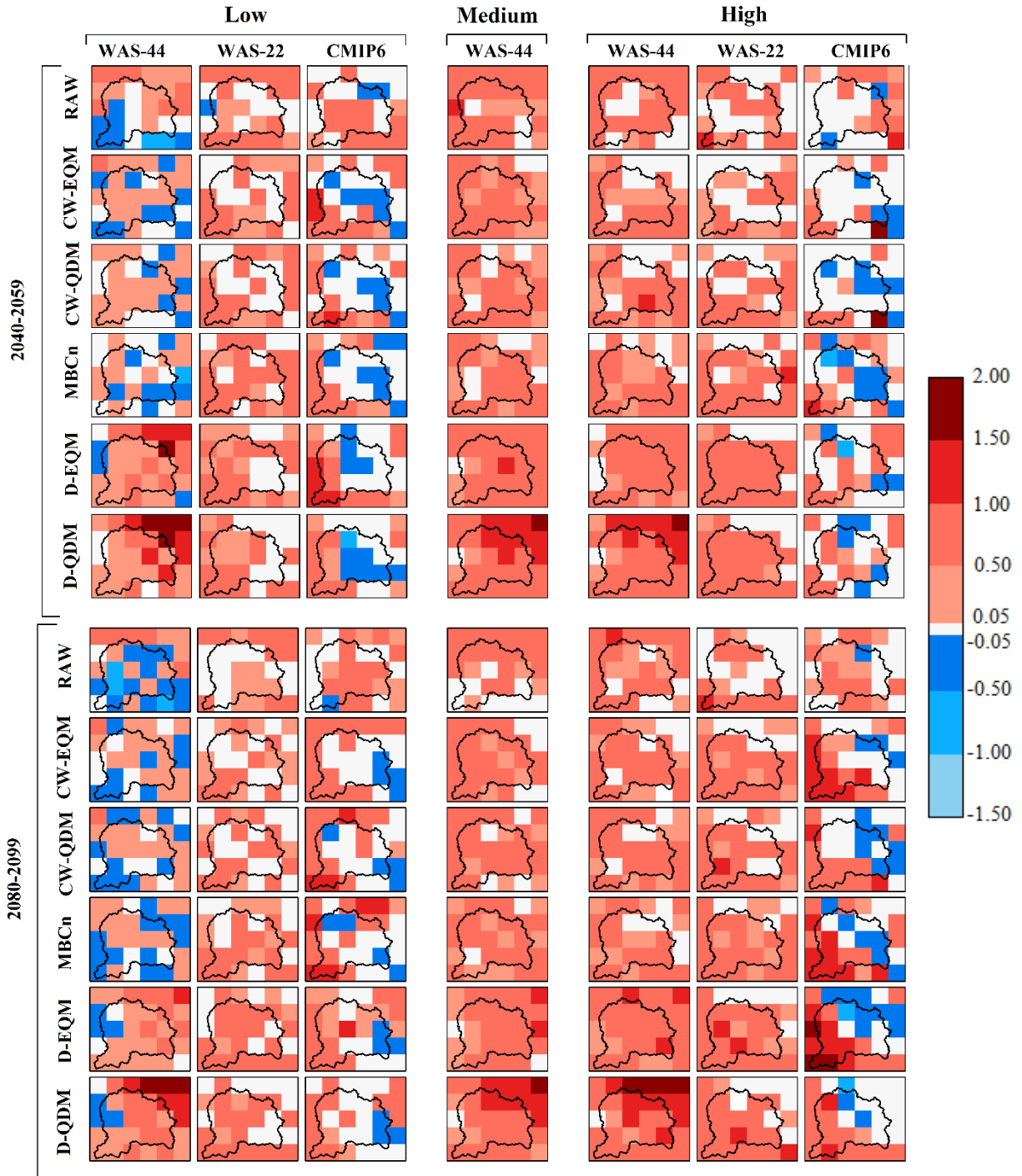


Figure C.3: Same as Figure C.1, but for median dry severity (DS), expressed in accumulated SPEI units.

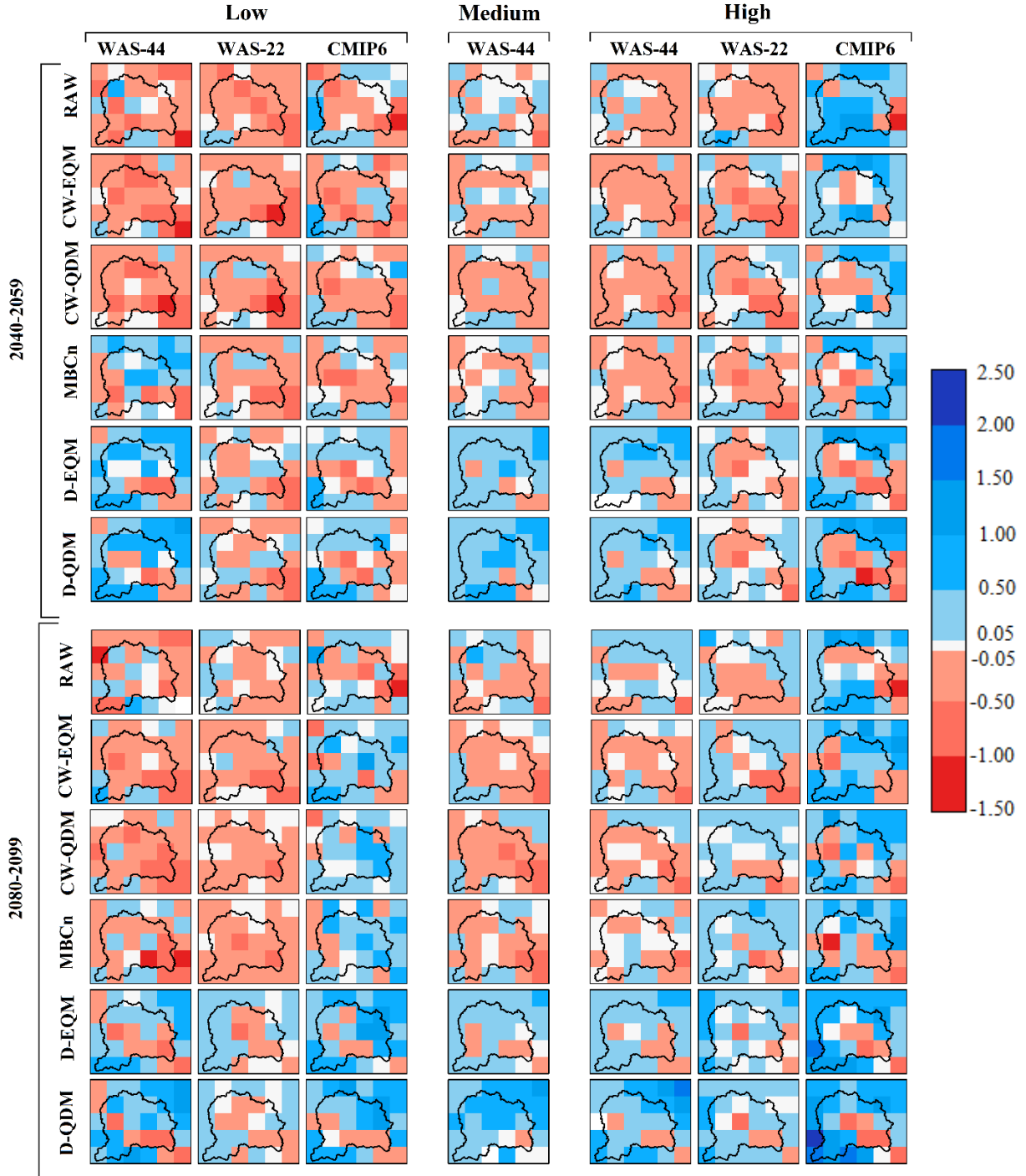


Figure C.4: Same as Figure C.1, but for median wet severity (WS), expressed in accumulated SPEI units.

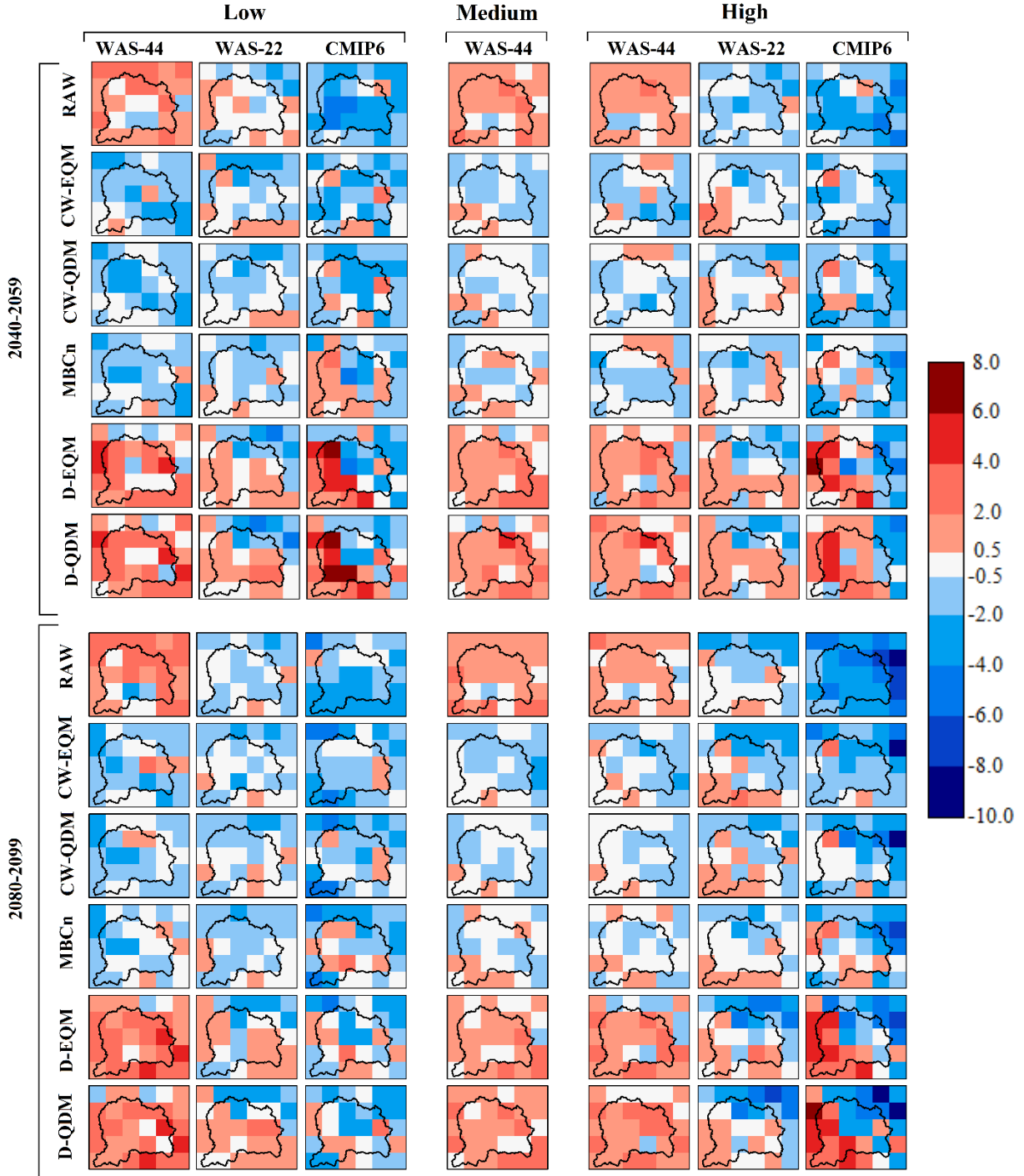


Figure C.5: Same as Figure C.1, but for absolute dry frequency (DF) expressed as total number of dry events.

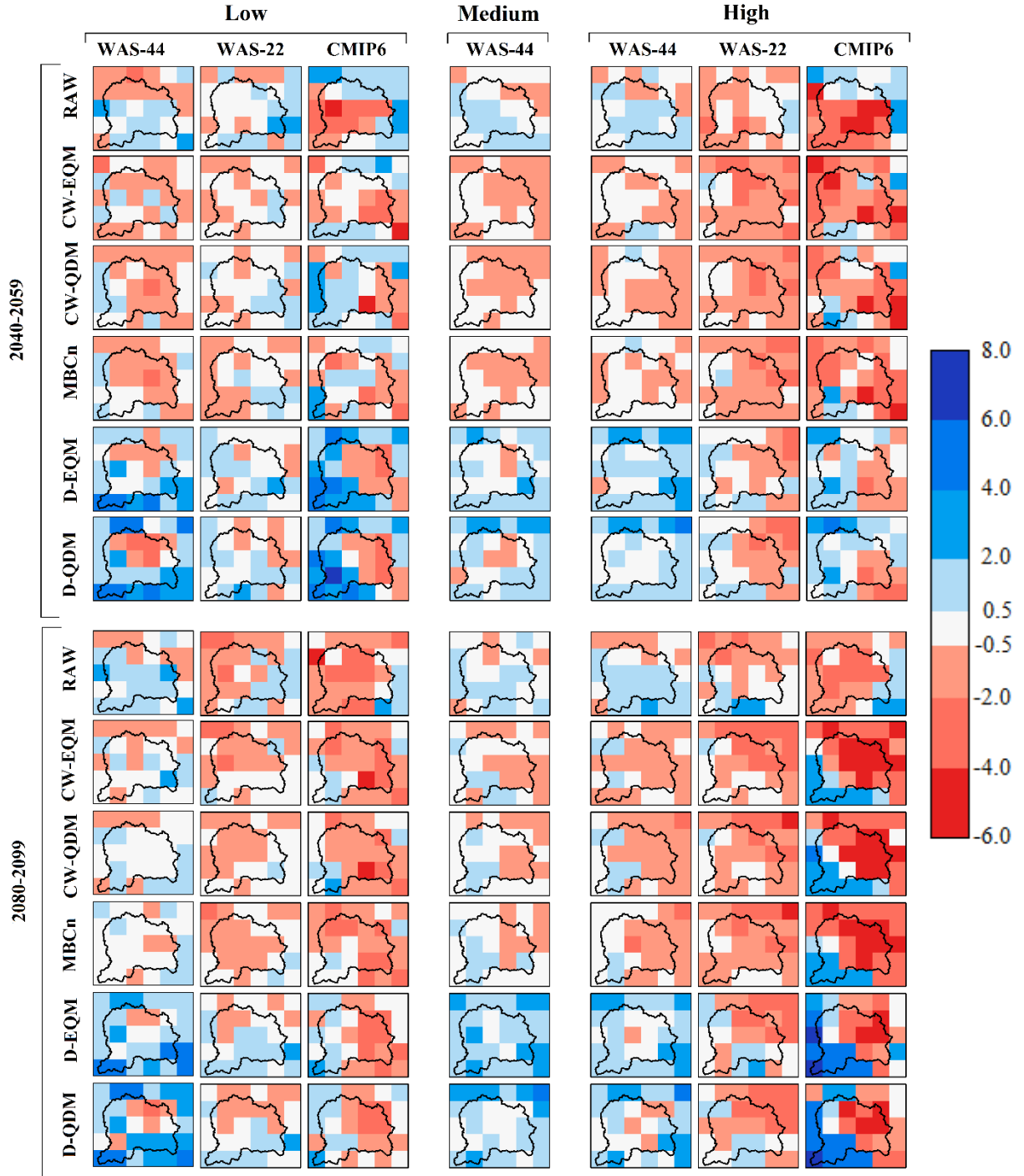


Figure C.6: Same as Figure C.1, but for absolute wet frequency (WF) expressed as total number of wet events.

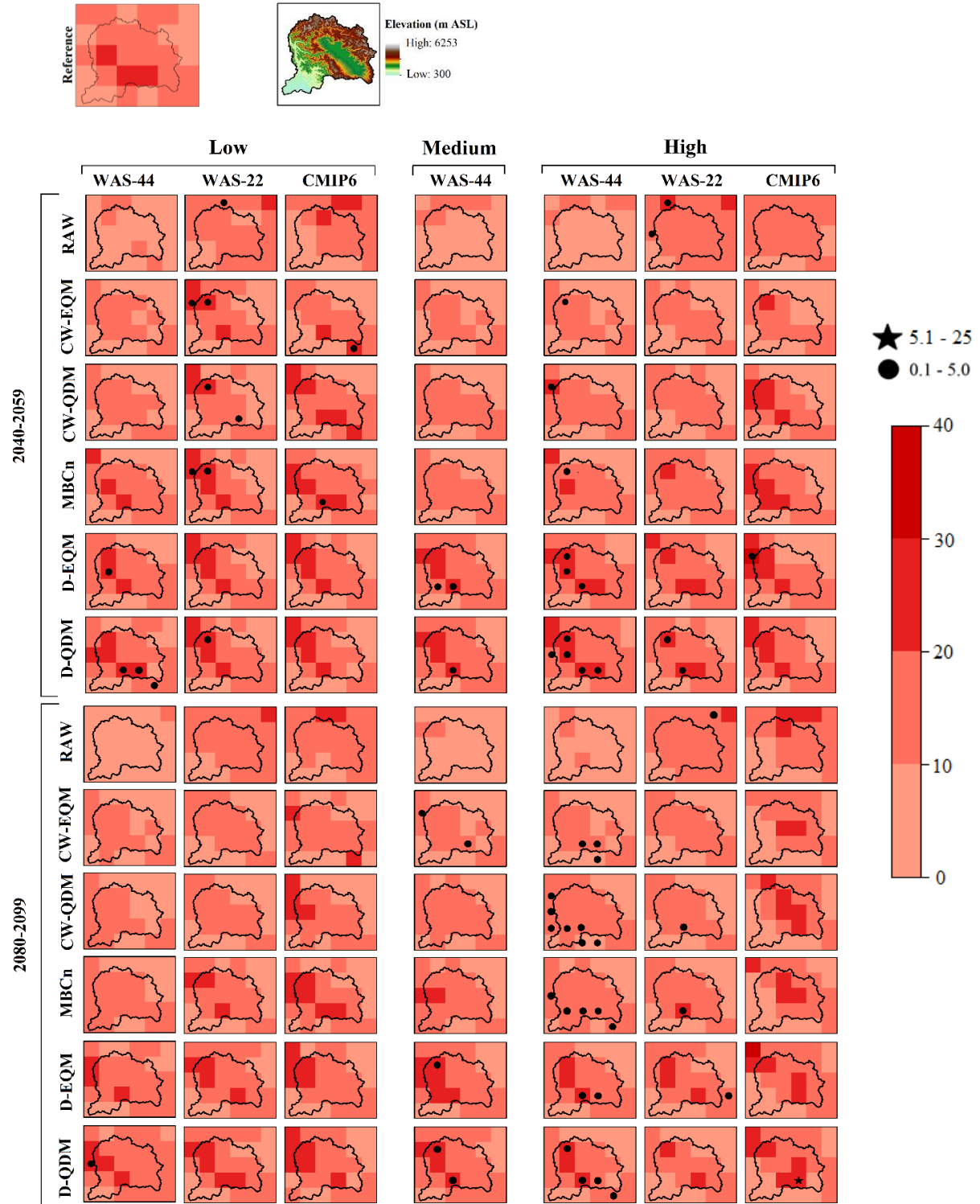


Figure C.7: Same as Figure 7.3 but for the probability of temporal wet-to-dry compound events (%).

Details of scientific activities performed during Ph.D.

International mobility

Erasmus plus traineeship at Meteorology Group of the Dept. Applied Mathematics and Computer Science, University of Cantabria, Spain from October 2021 to December 2021 (three months).

Courses

I hugely benefited from attending following valuable courses:

- “IS-ENES3 virtual Autumn School on Climate data use for impact assessments”.
(November 4th, 2020 – December 10, 2020)
- “IS-ENES3: Virtual clinic on bias-adjustment of climate model data”.
(14th and 21st October 2021)

Conferences/Workshops/ Symposium

- SciShops Symposium. 30-31 January 2020. SciShops Symposium in the framework of the SciShops.eu project, “Enhancing the Responsible and Sustainable Expansion of the Science Shops Ecosystem in Europe” Brescia (Italy).
- EGU virtual General Assembly 2021, 19-30 April. Session: HS4.2– Drought and water scarcity: monitoring, modelling and forecasting to improve hydro-meteorological risk assessment. “Evolution of Dryness/Wetness conditions and their characteristics (duration and severity) using standardized Index across Upper Jhelum Basin”.
- AGU, 2021, 13-17 December. Session: C55D –Cryosphere Changes and Their Impact on the High-Mountain Water Cycle. “Modelling Hydrological Vulnerability to Climate Change in the Glacierized Naltar Catchment (Pakistan) Using a Distributed Energy Balance Model”
- EGU 2022, 23-27 May. Session: HS2.4.4 –Hydrological extremes: from droughts to floods. “Climate projections of spatio-temporally compound extreme events (floods and droughts) using a multivariate drought index”.
- AICS-PFK Final Workshop in Procida, 5-9 October 2022
- EGU 2023, 23-28 April. Session: NH11.2 –Predictions and projections of weather and climate hazards around the world on seasonal to centennial scales “Changes in the Probability of temporally compound wet and dry events in a warmer world”
- World Water Week 2023: 20 –24 August (online attendee)

Journal Publications

- **Ansari, R.** and Grossi, G., 2024. Improving flood and drought management in transboundary Upper Jhelum Basin-South Asia, Science of Total Environment, STOTEN-D-24-03573 (Under review).

- **Ansari, R.**, Casanueva, A., Liaqat, M.U. and Grossi, G., 2023. Changes in the Probability of temporally compound wet and dry events in a warmer world: case study in the Upper Jhelum Basin. Weather and Climate Extremes, WACE-D-23-00430 (Under Review).
- Liaqat MU, Grossi G, Casanueva A, **Ansari, R.**, Ranzi R (2023) Energy balance modelling of snow and ice melt for the Naltar Catchment Pakistan in the Future Climate, Journal of Hydrology (Accepted with revision).
- **Ansari, R.**, Casanueva, A., Liaqat, M.U. and Grossi, G., 2023. Evaluation of bias correction methods for a multivariate drought index: case study of the Upper Jhelum Basin, Geosci. Model Dev., 16, 2055–2076.
- **Ansari, R.** and Grossi, G., 2022. Performance evaluation of raw and bias corrected ERA5 precipitation data with respect to extreme precipitation analysis: case study in Upper Jhelum Basin, South Asia. Theoretical and Applied Climatology, 150(3-4), pp.1409-1424.
- **Ansari, R.**, Liaqat, M.U. and Grossi, G., 2022. Evaluation of gridded datasets for terrestrial water budget assessment in the Upper Jhelum River Basin-South Asia. Journal of Hydrology, 613, p.128294.
- **Ansari, R.**, & Grossi, G. (2022). Spatio-temporal evolution of wet–dry event features and their transition across the Upper Jhelum Basin (UJB) in South Asia. Natural Hazards and Earth System Sciences, 22(2), 287-302

Conference proceedings

- **Ansari, R.**, Liaqat, M. U., Grossi, G. and Ranzi, R. 2023, December. Role of International Cooperation Development for Water Resources Management under Climate Change in Pakistan. XX International Conference "HUMAN DEVELOPMENT, HEALTH and ENVIRONMENT: Partnerships for International Development Cooperation".
- **Ansari, R.**, Casanueva, A. and Grossi, G., 2023, April Changes in the Probability of temporally compound wet and dry events in a warmer world. In EGU General Assembly Conference Abstracts, pp. EGU23-6223.
- **Ansari, R.**, Casanueva, A. and Grossi, G., 2022, May. Climate projections of spatio-temporally compound extreme events (floods and droughts) using a multivariate drought index. In EGU General Assembly Conference Abstracts (pp. EGU22-10376).
- Liaqat, M. U., Grossi, G., **Ansari, R.**, & Ranzi, R. (2021, December). Modeling Hydrological Vulnerability to Climate Change in the Glacierized Naltar Catchment (Pakistan) Using a Distributed Energy Balance Model. In AGU Fall Meeting 2021. AGU.
- **Ansari, R.** and Grossi, G., 2021, April. Evolution of Dryness/Wetness conditions and their characteristics (duration and severity) across Upper Jhelum Basin, Pakistan. In EGU General Assembly Conference Abstracts (pp. EGU21-12550).

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The undersigned..... Rubina Ansari Born on..... December 12, 1989.....
in (specify the foreign country, where applicable)..... Pakistan
province of (or abbreviation of the foreign country)..... Punjab
PhD in Civil and Environmental Engineering, International cooperation and Mathematics
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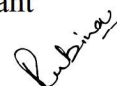
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