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POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Assessing the impact of climate change on an ungauged watershed in the Congo River Basin

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Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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Ce mémoire intitulé:

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présenté par **Stephane MASAMBA**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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DEDICATION

I dedicate this dissertation to

My parents, whose wisdom and sacrifices have paved the way for my success

And to my family, who have always stood by me with their unwavering love and encouragement.

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I would like to sincerely thank Prof. Musandji Fuamba and Prof. Elmira Hassanzadeh for their firm support and invaluable guidance throughout my research. My sincere appreciation also goes to Dr. Salomon Salumu Zahera for his invaluable insights and unwavering encouragement, which greatly facilitated the progress of my work. My heartfelt gratitude extends to all the employees of Polytechnique Montréal for their support and dedication throughout this journey.

RÉSUMÉ

Les changements climatiques sont connus pour perturber les cycles hydrologiques, entraînant des modifications des caractéristiques des bassins versants et du débit des rivières. Pour promouvoir une gestion durable des ressources en eau, il est essentiel de comprendre les impacts des changements climatiques sur les systèmes hydrologiques. L'approche scientifique courante pour l'évaluation des ces impacts sur les systèmes hydrologiques repose sur les projections des Modèles de Circulation Générale (GCM) forcées dans des modèles numériques pour des simulations. Néanmoins, cette approche est sujette à des incertitudes souvent attribuées aux modèles hydrologiques et aux données climatiques. De plus, la représentation des bassins versants peut être une tâche difficile dans les régions où les données sont rares, même dans des conditions historiques.

En raison de la disponibilité limitée de données hydroclimatiques de bonne qualité et à long terme, l'Afrique centrale est souvent décrite comme une région où les données sont rares. Le bassin du fleuve Congo (CRB) en Afrique centrale est l'un des plus grands et des plus importants bassins fluviaux tropicaux du monde. Son principal cours d'eau est le fleuve Congo, qui traverse sept pays sur plus de 4000 km. Par son volume de débit, le fleuve Congo se classe au deuxième rang mondial après l'Amazone en Amérique du Sud. Tout en assurant la sécurité de l'eau et alimentaires dans la région, ce cours d'eau naturel détient un potentiel considérable pour l'hydroélectricité, estimé à environ 100,000 MW. Une partie significative de ce potentiel dépend des principaux affluents du fleuve Congo, y compris sa source, le fleuve Lualaba. Le bassin du fleuve Lualaba (LRB) est le principal sous-bassin du CRB, couvrant 974,140 km^2, avec seulement un nombre limité de stations actuellement actives. Néanmoins, cette région figure parmi les Zones Économiques Spéciales de la République Démocratique du Congo en raison de ses abondantes ressources naturelles, y compris les minéraux critiques, les ressources en eau et les terres fertiles. En particulier, plusieurs secteurs économiques, tels que l'agriculture, l'industrie, l'hydroélectricité et le commerce, dépendent des ressources en eau du LRB. Cependant, l'intégrité de cette précieuse ressource a été peu étudiée dans des conditions climatiques changeantes. En outre, la vulnérabilité du LRB aux changements climatiques est exacerbée par la faible capacité d'adaptation régionale, le manque de gestion intégrée des ressources en eau et la dépendance à l'eau.

Cette étude a évalué l'impact des changements climatiques sur les caractéristiques des débits du fleuve Lualaba. Un cadre multi-modèle a été utilisé, prenant en compte un ensemble de GCM, deux modèles hydrologiques conceptuels (HBV-MTL et GR4J), et divers produits de réanalyse climatique pour répondre à la rareté des données. Spécifiquement, les modèles hydrologiques ont été calibrés en utilisant ERA-5, MERRA-2 et un ensemble de GCM historiques pour simuler le débit à l'exutoire pendant la période historique de 1981 à 2001. Basé sur une performance acceptable des modèles, un ensemble de paramètres optimaux a été sélectionné pour chaque configuration. Par la suite, les sorties biais-corrigées de 19 GCM sous deux Sentiers Socioéconomiques Partagés (SSP) ont été forcées dans les modèles calibrés pour la prédiction des débits. L'impact des changements climatiques sur les signatures des débits tels que les faibles, médians et hauts débits a été analysé sur la base de ces projections.

Les résultats indiquent que les deux modèles hydrologiques (HBV-MTL et GR4J) simulent les débits observés dans le bassin du fleuve Lualaba (LRB) avec une performance acceptable. Les modèles calibrés avec les réanalyses ont surpassé ceux utilisant des observations de jauge, alignant avec les recherches précédentes qui mettent en avant la valeur des données d'entrée de haute qualité et des approches multi-modèles. Les projections futures sous les scénarios SSP245 et SSP585 montrent une augmentation globale des débits, avec des changements dans le débit de pointe et la saisonnalité. Plus précisément, le débit annuel moyen devrait augmenter de 45% à 62%, avec des augmentations plus marquées sous SSP585. Les projections suggèrent un débit de pointe plus précoce pendant Mars-Avril-Mai et un débit de pointe plus tardif en Septembre-Octobre-Novembre, indiquant une probabilité plus élevée d'événements de débit extrême. De plus, les quantiles de débit (Q10, Q50, Q90) devraient augmenter, améliorant les faibles, médians et hauts débits, bien que l'ampleur varie selon les configurations.

Les résultats soulignent la nécessité de stratégies de gestion adaptative de l'eau pour faire face aux impacts potentiels sur les activités économiques, les infrastructures et l'environnement. Ils fournissent aux décideurs des informations pour proposer des politiques d'atténuation pour la gestion des ressources en eau, de l'énergie, de l'agriculture et de l'environnement. Cette recherche soutient la gestion intégrée des ressources en eau et apporte des avantages économiques en informant la conception des barrages, des centrales électriques et d'autres activités socio-économiques sensibles à la disponibilité de l'eau. L'étude met en évidence l'importance d'une approche multi-modèle pour capturer une gamme de conditions futures possibles, assurant une gestion résiliente de l'eau face aux changements climatiques.

ABSTRACT

Climate change is known to disrupt hydrological cycles, leading to changes in the characteristics of watersheds and river flow. To promote sustainable water resource management, it is essential to understand the impacts of climate change on hydrological systems. The common scientific approach for climate change impact assessment on hydrological systems is based on projections of General Circulation Models (GCMs) forced into numerical models for simulations. Nevertheless, this approach is prone to uncertainties often attributed to both hydrological models and climate data. Furthermore, the representation of catchments can be a difficult task in data-scarce regions, even under historical conditions.

Because of the limited availability of good-quality and long-term hydroclimatic records, Central Africa is often portrayed as a data-scarce region. The Congo River Basin (CRB) in Central Africa, is one of the largest and most important tropical river basins in the world. Its main watercourse is the Congo River, which flows across seven countries over more than 4000 km. By discharge volume, the Congo River ranks second in the world after the Amazon River in South America. While ensuring water and food security in the region, this natural stream holds a considerable potential for hydropower, estimated around 100,000 MW. A significant portion of this potential depends on the Congo River's main tributaries, including its headstream, the Lualaba River. The Lualaba River Basin (LRB) is the main sub-watershed of the CRB, covering 974,140 km^2, yet with only a limited number of currently active stations. Nevertheless, this region is among the Special Economic Zones of the Democratic Republic of the Congo because of its abundant natural resources, including critical minerals, water resources, and fertile lands. Particularly, a range of economic sectors, such as agriculture, industry, hydropower, and trade, are dependent on water resources within the LRB. However, the integrity of this valuable resource has been understudied under changing climate conditions. Furthermore, the LRB's vulnerability to climate change is exacerbated by regional low adaptive capacity, lack of integrated water resource management, and water-dependency.

This study assessed the impact of climate change on streamflow characteristics of the Lualaba River. A multi-model framework was employed, considering an ensemble of GCMs, two conceptual hydrological models (HBV-MTL and GR4J), and various climate reanalysis products to address data scarcity. Specifically, the hydrological models were calibrated using ERA-5, MERRA-2, and a set of historical GCMs to simulate streamflow at the outlet during the historical period from 1981 to 2001. Based on acceptable model performance, a set of optimal parameters was selected for each configuration. Thereafter, downscaled bias-corrected outputs from 19 GCMs under two distinct Shared Socioeconomic Pathways (SSPs) were forced into the calibrated models for future streamflow prediction. The impact of climate change on streamflow signatures such as low, median, and high flow was analyzed based on these projections.

Results indicate that both hydrological models (HBV-MTL and GR4J) successfully simulate observed runoff in the Lualaba River Basin (LRB) with acceptable performance. The models calibrated with reanalysis datasets outperformed those using gauge observations, aligning with previous research that emphasizes the value of high-quality input data and multi-model approaches. Future projections under SSP245 and SSP585 scenarios show an overall increase in runoff, with changes in peak timing and seasonality. Specifically, mean annual discharge is expected to rise by 45% to 62%, with more pronounced increases under SSP585. The projections suggest an earlier peak flow during March-April-May and a later peak in September-October-November, indicating a likelihood of more frequent extreme runoff events. Additionally, flow quantiles (Q10, Q50, Q90) are projected to increase, enhancing low, median, and high flows, though the magnitude varies across configurations.

The findings underscore the need for adaptive water management strategies to address the potential impacts on economic activities, infrastructure and the environment. They provide decision-makers with insights to propose mitigation policies for water resources, energy, agriculture, and environmental management. This research supports integrated water resource management and added-value benefits in the economic context by informing the design of dams, power plants, and other socio-economic activities sensitive to water availability. The study highlights the importance of a multi-model approach to capture a range of possible future conditions, ensuring resilient water management in the face of climate change.

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AR6	IPCC Sixth Assessment Report
CMIP6	Coupled Model Intercomparison Project Phase 6
CMORPH	Climate Prediction Center Morphing method
CORDEX	Coordinated Regional Downscaling Experiments
CRB	Congo River Basin
ERA5	European Centre for Medium-Range Weather Forecasts Reanalysis 5
GCM	General Circulation Model
GEIDCO	Global Energy Interconnection Development and Cooperation Organization
Geo SFM	Geospatial Streamflow Model
GLUE	Generalized Likelihood Uncertainty Estimation
GR4J	Génie Rural à 4 paramètres Journalier
HBV-MTL	Hydrologiska Byråns Vattenbalansavdelning Model - Montréal
IPCC	Intergovernmental Panel on Climate Change
JRA-55	Japanese 55-year Reanalysis
KARB	Kasai River Basin
KGE	Kling-Gupta Efficiency
LRB	Lualaba River Basin
MCMC	Markov Chain Monte Carlo
MERRA-2	Modern-Era Retrospective Analysis for Research and Applications, Version 2
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NSE	Nash-Sutcliffe Efficiency
ParaSol	Parameter Solution method

PERSIANN Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks

PSO Particle Swarm Optimization

RCM Regional Climate Models

RCP Representative Concentration Pathway

SSP Shared Socioeconomic Pathway

SUFI Sequential Uncertainty Fitting

SWAT Soil and Water Assessment Tool

TRMM Tropical Rainfall Measuring Mission

WCRP World Climate Research Programme

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CHAPTER 1 INTRODUCTION

1.1 Background and problem statement

Freshwater resources are indispensable for socio-economic development and ensuring the well being of individuals (Yevjevich, 1992). Water resources significance lies in meeting needs in sectors such as agriculture, energy, industry, household usage and environmental aspects (Alam et al., 2022; Garrick et al., 2019; Kaini et al., 2022; Macharia et al., 2020). Efficiently managing water resources is crucial to ensuring an equitable supply that caters to requirements in these sectors, in terms of timing and location (Kundzewicz, 1997; Tavassoli et al., 2014). The availability of water resources differs across catchments, creating regional obstacles and development barriers that urge water management authorities and decision makers to look for sustainable and balanced solutions (He et al., 2020). Major infrastructure projects such as dams, water diversions, hydroelectric power and water treatments plants aim to tackle these challenges, aligning with long-term natural streamflow patterns. Nevertheless, water management problems are becoming more complex due to shifts in hydrological cycles caused by human induced climate change (IPCC, 2007), that led to significant alterations in precipitation and temperatures patterns (Hernandez-Bedolla et al., 2017; Muyambo et al., 2023; Wang, 2022), affecting characteristics such as annual water volume, peak flow timing and magnitude, and seasonality (Chapagain et al., 2022; Kahaduwa & Rajapakse, 2022). For the development and implementation of sustainable and reliable water management policies, Kahaduwa and Rajapakse (2022) emphasized the importance of understanding the long-term regional water balance amidst evolving climatic conditions, as noted by Kolokytha et al. (2017) and Hassanzadeh et al. (2014).

Despite having lower Greenhouse Gas (GHG) emissions in comparison to other continents, Africa is projected to experience significant impacts due to climate change by the end of the 21st century (Alenda-Demoutiez, 2022; Kalu et al., 2021; Papa et al., 2023; Santini & Caporaso, 2018; Thomas & Nigam, 2018; van Houtan et al., 2021). The impacts of climate change are worsened because of Africa's population reliance on natural resources and the limited capacity to adapt (Ahmadalipour et al., 2019; Falchetta et al., 2019b; Yengoh & Ardo, 2020). The Congo River emerged as a cornerstone of Central Africa's identity and development initiatives. Flowing through seven countries, it is the second-longest river in Africa (4,370 km) and the world's second-largest river by discharge volume. Its natural stream ensures regional water and food security, while holding a considerable potential for hydroelectric power. The Congo River Bassin (CRB) is home to diverse flora and fauna that contribute to global climate regulation and serve as carbon sinks. This valuable natural asset faces threats from the changing climate (B. I. Inogwabini, 2020). It is essential to understand the impacts of climate change for developing water management and allocation strategies and minimizing the negative consequences (D. Alsdorf et al., 2016).

The assessments of climate change impacts in the field of hydrology commonly employs two approaches; the "Top-down" and "Bottom-up" methodologies. They each provide a distinct perspective for assessing and understanding how climate change may affect the hydrological cycle. The first is a scenario-based simulation technique, while the latter is a neutral scenario-led approach. The "Top-down" approach relies on General Circulation Models (GCMs). Currently, according to the Intergovernmental Panel on Climate Change (IPCC), GCMs are the most advanced tools available for simulating the response of the global climate system to increasing GHG concentrations. These numerical models represent physical processes of Earth's atmosphere, ocean, cryosphere and land surface (Hannah, 2015). GCMs outputs are directly employed to assess the impacts of climate change (Hare et al., 2010; Krysanova et al., 2018; Wilby, 2010). Hydrological models that depict physical processes in hydrological cycle are forced with GCMs outputs (Arnell & Gosling, 2013; Chun et al., 2013) to simulate river's streamflow, groundwater replenishment rates and other key hydrological parameters. Nonetheless, there are uncertainties associated with GCMs (Brunner et al., 2019), that include the large scale variability in projections and the imperfect conceptualization leading to a range of scenarios (Shackley et al., 1998). To address uncertainties associated with GCMs and improve insights into hydrological conditions, researchers frequently suggest integrating results from an ensemble of GCMs (Bourdeau-Goulet, 2021; Xing et al., 2018; Yang et al., 2017). Unlike the "Top-down" approach that heavily relies on GCMs projections, the "Bottom up" approach is used to assess vulnerabilities and adaptive capacity of hydrological systems based on observed changes in climatic data (Hassanzadeh et al., 2016; Sant'Anna et al., 2022). The "Bottom-up" approach is an assessment of climate change impacts from a localized and scenario driven perspective that begins with the system's behaviour, vulnerabilities, and adaptive capacity (Di Francesco et al., 2020; Nazemi et al., 2020). It is becoming more frequent to blend "Top-down" and "Bottom-up" approaches together (Bhave et al., 2014; Stigter et al., 2017; Tra et al., 2018). The combined approach aims to take advantage of the strengths of each method for addressing their respective weaknesses and improve the credibility of climate change impact assessment (Conway et al., 2019).

Hydrological models are simplifications of water systems, representing the physical processes of hydrological cycles and their nonlinear transformation using either simple mathematical equations or more complex structures (Wagener et al., 2001). They are the principal component of assessment with the top-down approach. Their primary objective is to simulate and quantify the movement of water within the Earth's terrestrial systems (Peel & Blöschl, 2011). The applications of hydrological models span a wide range of phenomena, with popular models like the Soil and Water Assessment Tool (SWAT) and Hydrological Simulation Program-FORTRAN (HSPF) commonly employed for watershed hydrology, water quality, and other complex hydrological processes under changing environment. The choice of hydrological models remains a topic of debate in climate change related research. While complex models provide detailed information about regional hydrology, their reliance on extensive data for parameter estimation poses challenges (Hughes, 2016; Moges et al., 2021a; Orth et al., 2015; Shailesh Kumar & Nelly, 2017), particularly when simulating an uncertain future (Ludwig et al., 2009; Minville et al., 2008). In such cases, simpler models are often preferred (Her & Chaubey, 2015; Santos et al., 2018). Given the importance accorded to structural uncertainties of hydrological models (Beven, 2000), the application of multi-model ensemble is recommended for intercomparison between results (Seiller et al., 2012; Viney et al., 2009).

Besides structural uncertainties in hydrological models, observational data inputs are the other principal source of error affecting the validity of simulations (Johnston & Smakhtin, 2014; McMillan et al., 2018; Silberstein, 2006; Tegegne et al., 2017). Addressing data scarcity with satellite-derived data (Becker et al., 2018; Huang et al., 2020) and reanalysis datasets (Berg et al., 2018; J. Chen et al., 2018; Fuka et al., 2014; Hua et al., 2019a) emerged as viable alternative, especially in ungauged watersheds. Reanalysis products, characterised by high-quality grid-based climatic data obtained through systematic assimilation of available observational data (Bosilovich et al., 2008), are particularly useful in regions with limited data (Beven, 2012; Hua et al., 2019a), such as the Congo River Basin. However, the availability and quality of reanalysis datasets can vary in a specific location depending on several factors including inter-model variability, assimilation approach, and the observational data used in the simulation (Lin et al., 2014; Washington et al., 2013).

1.2 Research objectives

This research aims to measure the impacts of climate change on the streamflow of Lualaba River, a major tributary of the Congo River. Freshwater resources within the Lualaba River Bassin (LRB) fosters regional development, ensuring the well being of populations through water and food security while holding a considerable potential for hydroelectric power. However, the effective and sustainable management of this natural resource was proven challenging due to the complexity and size of the watershed, further complicated by data scarcity that limits the understanding of hydroclimatic conditions in the region. Climate change represents a significant threat to the LRB. This intricacy contributes to the challenges of formulating water resources policies and mitigation strategies. The objectives of the research are:

(1) To simulate the historical streamflow using a multi-model approach consisting of two hydrological models and an ensemble of hydroclimatic input datasets.

(2) To project future streamflow at the watershed outlet by forcing calibrated hydrological models with an ensemble of climate projections.

(3) To assess the changes in streamflow characteristics under changing climate conditions by comparing the results of hydrological models fed with different datasets.

1.3 Research questions

Research questions were identified based on the proposed research objectives. These questions were put forward to guide the research and accordingly provide answers to the thesis:

(1) Is the Lualaba River streamflow vulnerable to changing climate?

(2) How does the choice of hydrological model impact the assessment of climate change impacts?

(3) How does the input data choice affect the assessment results with a particular hydrological model?

1.4 Research scope and limitations

A brief overview of the scope and limitations to achieve the research goals.

Multi-model approach: A multi-model approach including two hydrological models and an ensemble of input datasets was used to simulate the natural streamflow in the historical period.

Climate Model Projections: The calibrated hydrological models were forced with downscaled bias corrected outputs of an ensemble of GCMs from CMIP6 under SSP245 and SSP585 to estimate the future streamflow at the watershed outlet.

Future streamflow Assessment: The intercomparison of hydrological models fed with different datasets was used to assess the possible changes in streamflow characteristics under changing climate.

1.5 Case study

The Lualaba River Basin (LRB), a sub-watershed of the Congo River Basin (CRB) spans about 974,140 squared kilometers, mainly in the Democratic Republic of the Congo (DRC) with extensions into Zambia, Rwanda, Burundi and Tanzania. Covering 27% of the CRBs area, the LRB contributes significantly to its annual water budget (Moukandi N'kaya et al., 2020). With over 30% of DRCs population residing within the LRB, facing conflicts over natural resources and abundant mineral reserves such as cobalt, coltan and copper, the primary economic activities are mining and shifting agriculture that heavily relies on renewable water supply (Brown et al., 2014; C. Chen et al., 2018; Gielen, 2021; Parens, 2022).

The Lualaba River is the principal stream in the LRB. It originates from the Katanga Plateau within the DRC and flows for 1,800 kilometers until it transitions into the Congo River at Boyoma Falls, near the city of Kisangani. The Lualaba River encounters drops and rapids along its path, notably as it flows down into a depression exploited to generate hydroelectric power at the Nzilo Dam (Lukamba-Muhiya & Uken, 2006). The river becomes suitable for navigation at Bukama, passing through lakes filled with marshes that are prone to floods (Bala & Wantzen, 2023). Important tributaries such as the Lufira, Luvua and Lukuga rivers contribute to its natural streamflow. Despite obstacles like gorges and rapids that disrupt navigation, the Lualaba River remains critical for transportation trade and the regional ecosystem. Additionally, the LRB is home to UNESCO World Heritage Sites, including parks that safeguard endangered species and emphasize the areas ecological importance. The reliability and effectiveness of water management policies and practices, as well as proposed hydraulic infrastructure development, which are based on historical conditions of the hydrological cycle, are under concerns of the basin’s vulnerabilities to climate change. It is therefore important to assess the impacts of changing climate conditions on this valuable natural resource.

CHAPTER 2 LITERATURE REVIEW

The literature review explores topics that include the principles and development of hydrological models, challenges presented by climate change, and related hydrological research in the Congo River Basin (CRB). It begins with an overview of hydrological modeling, tracing its evolution from basic empirical formulas to more advanced physically based models. These numerical models are essential tools used for understanding water systems, predicting responses to climate variations and guiding water resource management. The first section emphasizes the significance of calibration, parameterization and incorporating uncertainty analysis to enhance the reliability and efficacy of hydrological models.

Subsequently, the next section reviews measures of climate change impacts on hydrological systems by outlining scientific methods employed for assessment. It differentiates between "Top down" and "Bottom up" approaches while advocating for an integrated approach that combines the strengths of both to improve resilience in water resource assessments. Best practices and methodologies are suggested with emphasis on the necessary tools, such as general circulation models (GCMs), regional climate models (RCMs), downscaling techniques, and bias correction methods for enhancing the assessment framework based on hydrological models.

Lastly, the review highlights related hydrological research specific to the Congo River Basin, a region with importance yet historically overlooked in scientific studies. Recent studies investigate the features, land formations, freshwater streams and lakes in the CRB, despite facing challenges due to limited number of monitoring stations and data availability. To understand the impacts of climate change on the Congo River, researchers are using hydrological models and satellite data to simulate streamflow patterns. The significance of wetlands and lakes, in influencing the basin’s hydrological response and climate change impacts are areas for future studies. Emphasis is given to the importance of incorporating multi-models approaches, climate forecasts, and thorough analysis of hydrological cycles to guide sustainable management of water resources and infrastructure planning amidst shifting weather patterns.

2.1 Advancements in Hydrological Modeling: From Empirical Formulas to Physically-Based Numerical Approaches

The science of hydrology is concerned with water and its behaviour on Earth, which includes its presence, movement, distribution and characteristics (Linsley Jr et al., 1975). It explores how water interacts with the environment and living organism. Understanding phenomena related to water and the hydrological cycle is crucial for grasping the impacts of expansion, industrial development, deforestation, land use changes irrigation practices and other human activities on water systems. Hydrologists analyze stages of the hydrological cycle to comprehend how water interacts with the environment. Consequently, hydrological models were developed to simulate the transformation of rainfall into runoff through physical and mathematical processes that make up the hydrological cycle (Beven, 2000; Clark et al., 2017). Hydrological models can predict how water systems respond to factors such as climate changes and increasing demands for water resources (Wagener et al., 2001). In terms of environmental management, they provide insights for formulating flood prevention strategies and assessing the impacts of alterations in land-use. Hydrological models serve as instruments for managing water resources by providing insights into water availability and associated risks to facilitate informed decision making (Maidment, 2002; Vorosmarty et al., 2000).

The development of hydrological models has evolved over time transitioning from historical data driven empirical formulas in the 19th century to more advanced techniques as highlighted by Clark et al. (2017). Conceptual models emerged with the advancements in computing power, striking a balance between simplicity and accuracy. Technological advancement have significantly enhanced the effectiveness of hydrological models, improving their predictive capabilities and subsequently water resource management practices (Beven, 2012; Maidment, 2002).

According to Person et al. (1996), different spatial and temporal scales have been utilized in developing models based on research objectives and available hydrological data. These models are essential in analyzing the hydrological cycle by simulating fundamental processes like precipitation, evaporation, infiltration and surface runoff (Person et al., 1996). Precipitation is simulated using climatic data while evaporation, which involves returning water to the atmosphere, is influenced by variables such as temperature and humidity. Infiltration into soil is determined by factors such as like soil characteristics and land cover, whereas surface runoff depends on rainfall intensity, topography and land-use patterns. Hydrological models are numerical tools that synthesize these components and their interactions to replicate the natural hydrological cycle in a realistic manner (Dingman, 2015; Xu et al., 2014).

Rainfall-runoff models are classified according to inputs and parameters, as well as the extent to which physical principles are applied (Sitterson et al., 2018). They are categorized into lumped, semi-distributed, and distributed models on the basis of their parameters as a function in space and time, and deterministic and stochastic models on the basis of other criteria. The output of a deterministic model is the same when a single set of input values is applied, but the output of a stochastic model can be different when a single set of input values is applied (Devia et al., 2015). Lumped models treat watersheds as single units, disregarding spatial variability, therefore the outputs are calculated without considering spatial processes, while distributed models are able to predict the state of watersheds by dividing them into smaller units, usually square cells or triangulated irregular networks, thus varying the parameters, inputs and outputs geographically (Moradkhani & Sorooshian, 2008). Static and dynamic models are classified based on time factor. Models that exclude time are static, while models that include time are dynamic. Hydrological models are further categorised either as event-based models that produce output only for a specific time period or continuous models that produce continuous output over time (Sorooshian et al., 2008).

Hydrological models are classified into three important groups based on structure and representation of processes. Empirical models, also referred to as data driven models solely rely on observed data without considering the characteristics and processes of the hydrological system. They employ mathematical equations based on concurrent input and output time series (Devia et al., 2015). Since the accuracy of empirical models is limited to the scope of the data they are built upon, they may lack reliability in ungauged or changing environments due to their simplistic approach (Maidment, 1992). The unit hydrograph is a good example that highlights the approach (Maidment et al., 1996). On the other hand, Regression and correlation techniques are used in statistically based methods to establish functional connections between inputs and outputs. Moreover, advanced machine learning approaches, like artificial neural networks and fuzzy regression are applied in hydro informatics to improve models' predictive abilities (Singh, 2018).

Conceptual models aim to describe all component hydrological processes. They consist of multiple interconnected reservoirs representing the physical elements of watersheds, recharged by rainfall, infiltration, and percolation, and emptied by evaporation, runoff, and drainage (Devia et al., 2015). Conceptual models use semi-empirical equations, and their parameters are determined through both field data and calibration. Also known as parametric models, simplifying hydrological processes for broader applicability with fewer parameters and computational demand, they are particularly effective in general watershed analysis (Beven, 2012). They can vary in complexity; for instance, the Stanford Watershed Model IV (SWM), developed by Crawford and Linsley in 1966 was the first major conceptual model and includes 16 to 20 parameters. Accurate calibration of conceptual models requires a substantial amount of meteorological and hydrological records, often includes curve fitting, which can complicate interpretation and reduce confidence in predicting the effects of land-use changes (Devia et al., 2015).

Physically-based models, also referred to as mechanistic models, provide a mathematically idealized and detailed representations of hydrological phenomena (Devia et al., 2015).They incorporate fundamental physical processes through conservation of mass and momentum equations and utilize state variables that can be measured and vary over both time and space (Liu & Todini, 2002). Subsequently, they provide extensive information that can be applied beyond the immediate study area and are suitable for various hydrological scenarios (Paniconi & Putti, 2015). Unlike other models, physically-based models require a comprehensive evaluation of numerous parameters that describe the physical characteristics of watersheds, and do not necessarily rely on extensive meteorological and hydrological data for calibration (M. B. Abbott et al., 1986). They rather employ parameters with physical interpretations to address many limitations found in other types of model, making them valuable in research and understanding complex hydrological systems (Jakeman & Hornberger, 1993). The SHE/MIKE SHE model is a notable example of a physically-based model (M. Abbott et al., 1986).

Since hydrological modelling is a data-driven process, estimating streamflow in data-scarce regions presents additional challenges (Nyeko, 2015; Sisay et al., 2017; Sivapalan, 2003). In poorly gauged watersheds, observational data is often lacking for calibrating the parameters of hydrological models. Therefore, regionalisation is a common practice that involves the transfer of hydrological information from gauged to ungauged watersheds (Bao et al., 2012; Blöschl & Sivapalan, 1995; Sivapalan et al., 2003). The main regionalization techniques include similarity-based methods, regression methods, and hydrological signature methods (Beck et al., 2016; Oudin et al., 2008; Wagener & Wheater, 2006).

The spatial proximity strategy involves the selection of one or more nearby gauged watershed (references) for parameters estimation of the ungauged watershed (target) through interpolation (Y. Guo et al., 2021). There are two methods of regionalization with spatial proximity: simple proximity and spatial interpolation. The Euclidean distance is often used in simple proximity to identify the closest reference watersheds and uses their hydrological model parameters for calibration of the target watershed (Randrianasolo et al., 2011; Vandewiele & Elias, 1995). Spatial interpolation is a more complex strategy, that uses inverse distance weighting (Shepard, 1968) and Kriging (Stein, 2012) for parameter regionalization. It is widely used in application and research and for some cases generate better results compared to other approaches (Merz & Blöschl, 2004; Parajka et al., 2005; Samuel et al., 2011). However, the spatial proximity approach is based on the assumption of similarity between hydrological characteristics of adjacent watersheds (Blöschl, 2006). This assumption does not hold in regions with significant variability in surface and meteorological conditions (Ali et al., 2012; Reichl et al., 2009). Spatial proximity does not fully capture the consistency of hydrological characteristics for the target watershed, and it is often insufficient to rely on a single nearest neighbor reference watershed for accurate regionalization (McIntyre et al., 2005; Shu & Burn, 2003). Furthermore, the density of stations can affect the accuracy of regionalization (Beck et al., 2016), meaning that acceptable results may not be obtained in areas with sparse streamflow gauges.

The physical similarity method is a regionalization approach that requires classification of one or more reference watersheds based on attributes such as climate type, geological conditions, and land-use, to identify similarities with the target ungauged watershed. This method is based on the assumption that geographic and climatic conditions, as well as the physical distance between reference and target watershed can determine hydrological characteristics of ungauged watersheds (Acreman & Sinclair, 1986; Burn & Boorman, 1993; Oudin et al., 2010). Similarity index and clustering analysis are two primary approaches used to generate model parameters that are applicable to the ungauged watershed. Similarity index, such as the topographic index (Beven & Kirkby, 1979) and soil-topographic index (Beven, 1986) assume that locations with similar index value share the same hydrological response to rainfall, therefore inferring similarities between reference watersheds and ungauged target watershed (Kong & Rui, 2003; Yao et al., 2013). However, the topographic index requires further testing for large-scale regionalization despite its potential (Y. Guo et al., 2021). Promising results were observed from copula-based similarity measures because of their ability to describe the stochastic dependence between watersheds (Chowdhary & Singh, 2010; Samaniego et al., 2010). Clustering is the other approach to physical similarity regionalization. There are two main clustering methods of parameters regionalization that divide watersheds into groups according to their attributes. The first involves the uniform calibration of watersheds within a cluster and a direct transfer of parameters from the most similar reference watershed to the target watershed (Parajka et al., 2005; Zhang & Chiew, 2009). it is suitable for areas with less spatial heterogeneity. The second methods chooses reference watersheds within a threshold and transfers their parameters to the target watershed via a weighted average (Kay et al., 2007). The latter is better suited for areas with complex land cover. Beyond the regionalization of hydrological parameters, research on physical similarity also targets observed runoff (Agarwal et al., 2016; Choubin et al., 2019; Yilmaz & Onoz, 2020), streamflow regime (Solans & Mellado-Díaz, 2015), and hydrological signatures (Chouaib et al., 2019; Elesbon et al., 2015; Westerberg et al., 2016).

The number of reference watersheds in similarity-based regionalization can affect the accuracy of simulation and prediction results for the target watershed. Therefore, it is important to analyse the relationship between the number of reference watersheds and hydrological model's evaluation criteria, such as the Nash-Sutcliffe Efficiency (NSE) coefficient (Y. Guo et al., 2021). Factors that influence the optimal number of reference watersheds include the region under investigation, the density of stations (Yang et al., 2018), the choice of hydrological model (Oudin et al., 2008), and the regionalization method (spatial proximity or physical similarity). Several studies suggest that using 5 or 6 reference watersheds generally yields accurate model predictions (Li & Zhang, 2017; Oudin et al., 2008; Swain & Patra, 2017). Additionally, the use of multiple reference watersheds can reduce random errors compared to using a single reference (Arsenault et al., 2015; Randrianasolo et al., 2011; Zhang & Chiew, 2009).

Regression-based regionalization methods originated in the 1960s with the exploration of the correlations between unit hydrographs and watersheds attributes by Nash (1960), and the proposed flood frequency curve transposition by Dalrymple (1960). Such methods aim to establish regression relationships between model parameters and watersheds descriptors used to predict parameters for ungauged watersheds and simulate runoff (Y. Guo et al., 2021). Regression-based regionalization are categorised into three types (He et al., 2011): two-step regression, sequential regression, and one-step simultaneous regression.

Two-step regression is an intuitive approach to parameter regionalization that involves first calibrating model parameters for reference watersheds and then establishing relationships between these parameters and watersheds descriptors (Beck et al., 2016). Despite its widespread use (Abdulla & Lettenmaier, 1997; Heuvelmans et al., 2006; Xu, 2003), this approach faces challenges such as disregarding high correlations between model parameters (Kuczera & Mroczkowski, 1998), and problems with multicollinearity among watersheds attributes, that undermine results of linear regressions (Blöschl, 2006). Furthermore, equifinality in model calibration is a problem that impact regression accuracy (Kokkonen et al., 2003; McIntyre et al., 2005). Hence, the two-step regression method may poorly predict runoff in ungauged watersheds without clear relationships between parameters and attributes (Fernandez et al., 2000; Kim & Kaluarachchi, 2008).

Sequential regression was developed to address the equifinality problem by calibrating parameters in a specific order based on hydrological mechanisms or their relationships to the objective function (Calver et al., 2005). This approach was inspired by multiple automatic calibration schemes (Hogue et al., 2000), where each parameter is sequentially calibrated and regressed to enhance identifiability (He et al., 2011). However, this approach is less effective than simultaneous calibration of all parameters because it reduces the parameter space once a parameter is selected (Y. Guo et al., 2021).

The one-step regression approach integrates parameters calibration into a single process. Also know as simultaneous regression, it was first introduced for the regionalization of parameters using a monthly water balance model in the southeastern United State (Fernandez et al., 2000). This approach uses an objective function to combine the effects of parameter calibration and regression equations, but studies demonstrated that it does not significantly improve simulation results compared to two-step regression unless a deeper understanding of the mechanisms is achieved (He et al., 2011).

Recent advancements include comprehensive assessments of different approaches, as well as new regression methods. Gaussian process is an example that outperformed linear regression and artificial neural network models in a study of 438 watersheds across the United States (Sun et al., 2014). The multiple linear regression (MLR) was outperformed by the regression tree ensemble approach in predicting streamflow dynamics in 605 watersheds across Australia (Zhang et al., 2018). The constrained hydrologic regression technique shows promise over MLR and stepwise regression in Pakistan (Waseem et al., 2016). Additionally, to further enhance the potential and applicability of regression-based methods, some studies combined them with clustering analysis (Huang et al., 2015), spatial proximity approaches (Steinschneider et al., 2015), and machine learning (Prieto et al., 2019).

The hydrological signature methods are static (average streamflow, streamflow percentile, flood frequency, etc.) and dynamic (FDC slope, flow change rate, baseflow index, etc.) indicators that reflect hydrological characteristics of watersheds on different time scales (Westerberg & McMillan, 2015; Zhang et al., 2018). These methods attracted attention in recent years because of their numerous applications in watershed characterization and classification (Ssegane et al., 2012; Wagener & Wheater, 2006), runoff prediction in ungagged watersheds (Shu & Ouarda, 2012; Zhang et al., 2014), water resource planning and management (Biondi & De Luca, 2015), and ecological and environmental streamflow assessment (Beck & Birch, 2012; Newcomer et al., 2012).

There are two approaches for using hydrological signatures in regionalization. The first approach is a direct transfer of hydrological signatures from references to target watershed, focusing on flow duration curves (Atieh et al., 2017; Chouaib et al., 2019; Viglione et al., 2013; Worland et al., 2018). This approach has the advantage of directly characterizing hydrological conditions across many features and scales, but it is important to select the appropriate hydrological signature depending on the research objectives (Addor et al., 2018). However, a drawback is that using different hydrological signatures may not always provide unique insight. To address this issue, the concept of inter-signature error correlation was proposed to prevent overlooking or duplicating regional information (Almeida et al., 2016). Additionally, certain hydrological signatures, such as the baseflow index, have multiple calculation techniques (Beck et al., 2015). The other approach uses hydrological signatures to constrain model parameter sets used for streamflow predictions in ungauged watersheds (Y. Guo et al., 2021). A regionalization strategy was developed to establish connections between 28 signatures and 13 watershed attributes, in reference watersheds. These relationships were then applied to target watersheds while considering uncertainty, as well as employing Monte Carlo simulation to generate parameter sets (Yadav et al., 2007). Rather than investigating model parameters, the relationship between hydrological signatures and watershed attributes provides clear insight into the hydrological cycle (Y. Guo et al., 2021). This method was employed in several research and it is expected to bring about notable progress in the upcoming years (Costa et al., 2014; Pinheiro & Naghettini, 2013; Shu & Ouarda, 2012; Westerberg et al., 2014).

Remotely sensed data are another alternative for data-scare regions. They are available at various temporal and spatial scales and have been widely utilized in hydrological modeling (Becker et al., 2018; Huang et al., 2020; Stewart & Finch, 1993), particularly for ungauged or poorly gauged watersheds (Asante, 2008; Kim et al., 2021; Kittel et al., 2018; Wanders et al., 2014). Variability in the quality of satellite data across different regions can however impact the accuracy of hydrological model (Andersen, 2008; Stisen & Sandholt, 2010; Xu et al., 2014). Methods such as the bias correction were implemented to address these issues (Habib et al., 2014; Stisen & Sandholt, 2010; Xu et al., 2014)

Precipitation is a primary climatic factor that influence hydrological response, therefore its measurements accuracy are critical for the performance of models and for understanding watershed conditions (Hua et al., 2019a). The knowledge of precipitation patterns is limited in Central Africa due to the scarcity of in situ meteorological stations (Hua et al., 2019b; Todd & Washington, 2004; Tshimanga & Hughes, 2014; Washington et al., 2013). Various studies have pointed out uncertainties in the distribution of rainfall over the Congo River Basin (Douglas Alsdorf, Ed Beighley, Alain Laraque, Hyongki Lee, Raphael Tshimanga, Fiachra O'Loughlin, Gil Mahé, Bienvenu Dinga, Guy Moukandi, & Robert GM Spencer, 2016; Awange et al., 2016; Diem et al., 2014; Laraque et al., 2001; Malhi & Wright, 2004), which also extend to future climate projections, with considerable variability in both the intensity and direction of rainfall forecasts (Aloysius & Saiers, 2017; A Creese et al., 2019; Sidibe et al., 2020; Washington et al., 2013). Reanalysis datasets, which assimilate observational data from climate models, provide valuable grid-based information across watersheds (Bosilovich et al., 2008; Hua et al., 2019b; Parker, 2016). They are particularly valuable for data-scare regions such as the Lualaba River Basin. Variations among reanalysis products arise from differences in data availability and the assimilation schemes used

(Lin et al., 2014). The scarcity of observational data (Nicholson et al., 2018), along with uncertainties in the complex climatology of the Congo River Basin (Tshimanga et al., 2011) exacerbate the validation of reanalysis datasets against gauged measurements. Therefore, employing ensembles of reanalysis data can mitigate the issue (Hua et al., 2019a).

Calibration of hydrological models remains a critical task because parameters are quantified to enhance models' performance (Kumarasamy & Belmont, 2018; Pechlivanidis et al., 2011; Refsgaard & Storm, 1996; Rouholahnejad et al., 2012). The effectiveness of hydrological models depends on the accuracy of its parametrization. Calibration methods are generally classified into manual and automatic categories (Duan et al., 2003; Eckhardt et al., 2005). Both methods have advantages and disadvantages (Boyle et al., 2000). As for manual calibration, it is flexible but subjective and time-consuming (Duan et al., 1994; Efstratiadis & Koutsoyiannis, 2010). Consequently, several research aimed to develop and refine automatic calibration methods (Getirana, 2010; Gupta et al., 1999; Hogue et al., 2000; Madsen, 2003). Automatic calibration consist of five steps: selecting the calibration period, setting initial ranges for parameters sets, measuring the error between model output and observed data with an objective function, and employing an optimization algorithm (Gupta et al., 1999; Van Liew et al., 2005). Numerous research aimed to enhance automatic calibration techniques (Confesor Jr & Whittaker, 2007; Getirana, 2010; Gupta et al., 2003; Yapo et al., 1996). The Shuffle Complex Evolution (SCE-UA) algorithm is amongst the most praised automatic calibration methods for its proven rigorous parametrization (Chu et al., 2010; Duan et al., 1993; Kan et al., 2018; Naeini et al., 2019; Seong et al., 2015; Vrugt et al., 2003).

Recent years have seen a growing interest in uncertainly analysis (Bosshard et al., 2013; Rafiei Emam et al., 2018). Errors in model outputs mainly arise from input data, model structure, and model parameters (Butts et al., 2004; Moges et al., 2021b). The goal of uncertainty analysis is to address these issues in model calibration and improve model's effectiveness in real world scenarios. Various approaches were developed to measure uncertainty, such as Generalized Likelihood Uncertainty Estimation (GLUE) (Beven & Binley, 1992, 2014; Beven & Freer, 2001; Mantovan & Todini, 2006), Markov Chain Monte Carlo (MCMC) (Marshall et al., 2004; Smith & Marshall, 2008; Vrugt et al., 2008; Vrugt et al., 2013), Parameter Solution method (ParaSol) (Abbaspour, 2015; van Griensven & Meixner, 2006; Van Griensven & Meixner, 2007), Particle

Swarm Optimization (PSO) (Gill et al., 2006; Jiang et al., 2007; Kennedy & Eberhart, 1995; Zambrano-Bigiarini & Rojas, 2013), and Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al., 2004; Kumar et al., 2017; Salamon & Feyen, 2009). These methods rely on ensembles of simulations to quantify uncertainty rather than a single set of outputs, resulting in more dependable outcomes compared to deterministic hydrological models (Carpenter & Georgakakos, 2004; Georgakakos et al., 2004; Strauch et al., 2012; Wood & Lettenmaier, 2008). By integrating uncertainty analysis, with optimization techniques during model calibration the reliability and robustness of applications are significantly improved.

2.2 Climate Change Impacts Assessment on Hydrological Systems

The uncertainties and fluctuations in weather patterns and have an impact on the availability of water in a watershed posing challenges in managing water resources and planning for infrastructure projects like dams and hydroelectric power plants (Hamududu & Killingtveit, 2017; Wasti et al., 2022). Changes in precipitation and temperature attributed to global warming have led to shifts in runoff affecting water supplies (Frederick & Major, 1997; Haddeland et al., 2014; Kundzewicz et al., 2008; Sophocleous, 2004). It is essential to assess the impacts of climate change on water resources to help policymakers gauge the sustainability of water resources over time, for sustainable development purposes (Hamududu & Killingtveit, 2017; Kundzewicz, 1997).

Two primary methods are utilized to evaluate the impacts of climate change on the hydrology of watersheds; the "Top-down" and "Bottom up" approaches. The "Top-down" approach is based on scenarios that typically utilize outputs from global climate models to assess future water system impacts, while the "Bottom-up" approach remains scenario neutral to steer clear of uncertainties linked to climate models (Bhave et al., 2014; Conway et al., 2019; Wilby, 2010). In the "Bottom-up" strategy, an assessment is made on how the system behaves under alterations using various climatic data without depending on specific future scenarios (Brown et al., 2012; Lutsey & Sperling, 2008; Tra et al., 2018). This technique showcases the systems susceptibility and associated risks to equip decision makers with insights into the future conditions (Borgomeo et al., 2018; Brown et al., 2012; Eriyagama et al., 2010; Hassanzadeh et al., 2016). Scientists employ models to scrutinize the water balance within the system amidst climatic shifts (Antonetti et al., 2017; Knighton et al., 2017; Prudhomme et al., 2010; Wilby, 2010). However, in order to tackle the uncertainties associated with hydrological models, some researchers have employed stochastic methods for predicting streamflow (Bhave et al., 2014; Hassanzadeh et al., 2016). While this strategy helps address uncertainties linked to climate and hydrological models, other studies have identified sources of uncertainty in the bottom-up approach that could impact the accuracy of forecasts (Bevacqua et al., 2022; Nazemi et al., 2020). To address these uncertainties researchers have integrated both top-down and bottom-up approaches (Bhave et al., 2014; Girard et al., 2015; Tra et al., 2018). This integrated approach aims to leverage the strengths of both techniques to enhance the resilience and reliability of water resource assessments in adapting to changing climate conditions. The top-down approach involves scenarios and consists of two components; hydrological models and projections from global climate models (GCMs). GCMs are tools that simulate atmospheric and oceanic processes to illustrate how the global climate reacts to the rise in greenhouse gas emissions. In this method, the results from GCMs are inputted into calibrated models to forecast water system conditions (Bergström et al., 2001; Erler et al., 2019; Kour et al., 2016; Sunde et al., 2018; Zhang et al., 2013). However, these models come with uncertainties due to their underlying mechanisms, conceptual frameworks or low spatial resolutions leading to variations in outputs with the emission scenarios (Bourdeau-Goulet, 2021; Clark et al., 2016; Hannah, 2015; Krysanova et al., 2018; Wang et al., 2020). To address these uncertainties, it is widely acknowledged that using model ensembles for both climate projections and hydrological models can enhance the reliability of studies on climate change impacts (Christensen & Lettenmaier, 2007; Her et al., 2019; Mujumdar & Kumar, 2012; Tebaldi & Knutti, 2007). This approach helps reduce bias and spread out the risk associated with uncertainties in models providing insights into future scenarios.

Regarding the coarse spatial scale of climate model forecasts, researchers have extensively used downscaling techniques, in regional and local water system studies to refine model results to a finer resolution (Chen et al., 2013; Eden & Widmann, 2014; Sunde et al., 2018; Thrasher et al., 2022). These techniques fall into two categories; statistical and dynamical downscaling methods (Bergström et al., 2001; Friederichs & Hense, 2007; Schmidli et al., 2006; Wood et al., 2004). Dynamical downscaling involves the use of Regional Climate Models (RCMs) that utilize low resolution GCM outputs as starting points to produce higher-resolution climatic data suitable for regional analyses. One notable initiative in dynamical downscaling is the Coordinated Regional Downscaling Experiments (CORDEX) which provides a resolution of approximately 45 km (Jacob et al., 2020). While RCMs offer better resolution than GCMs they are computationally demanding, requiring time and supercomputing resources for multi model climate simulations in a region (Tapiador et al., 2020). Additionally, despite their resolution, RCMs may not always improve upon the simulation accuracy of GCMs and can still display biases (Rockel et al., 2008). Statistical downscaling however, creates a link based on the empirical relationship between large scale GCM forecasts and local variables offering a cost-effective method compared to dynamical downscaling (Landman et al., 2001; Rummukainen, 1997). As a result, various statistical techniques have been widely utilized in research on the impacts of climate change (Busuioc et al., 1999; Chen et al., 2012; Ghosh & Mujumdar, 2008). In addition to the importance of adjusting the resolution of climate model forecasts, it is also essential to correct biases in GCMs or RCMs outputs (Bruyère et al., 2014). The significance of bias correction in climate model forecasts for precipitation data used in modeling has been highlighted by numerous investigations (Dosio & Paruolo, 2011; Mehrotra & Sharma, 2016). Bias correction typically involves creating a conversion function based on the cumulative distribution functions (CDFs) of observed and simulated data, for adjusting the climate model forecasts (Ahmed et al., 2013; Dosio et al., 2012; Fang et al., 2015).

Already, institutions have downscaled and bias-corrected GCM outputs to finer resolutions for global use, providing the scientific community with appropriate data at local and regional scales. One such dataset is the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), which is available at NASA NEX-GDDP. This dataset includes downscaled and bias-corrected projections from GCMs from the Coupled Model Intercomparison Project Phase 6 (CMIP6) under future scenarios. The NEX-GDDP dataset, with a spatial resolution of 25 km, has been widely utilized in climate change impact studies (Abiodun et al., 2020; Guevara-Ochoa et al., 2020; Musie et al., 2020).

The World Climate Research Programme (WCRP) organizes the Sixth Phase of the Coupled Model Intercomparison Project (CMIP6), which involves collaboration among partners and modeling groups to enhance climate model experiments. With the expansion of CMIP participation and the advancement of climate modeling complexity, CMIP has transformed into a framework incorporating Model Intercomparison Projects (MIPs) (Eyring et al., 2016). MIPs consist of experiments and simulations aimed at evaluating aspects of climate models. Each MIP presents a design focused on improving understanding of physical processes in the climate system and the response of the climate system to external factors such as increasing greenhouse gases (O'Neill et al., 2016). CMIP6 encompasses 23 distinct MIPs serving as the coordination hub for future climate change simulations involving contributions from around 30 climate models (O'Neill et al., 2016).

The recent versions of scenarios utilized for CMIP6 and highlighted in the IPCC Sixth Assessment Report (AR6) (2021) are built upon a series of Shared Socio Pathways (SSPs). These SSP driven scenarios represent the ones thus far spanning from highly ambitious efforts to mitigate climate change to projections with continued growth in emissions (Masson-Delmotte et al., 2021). The ambitious mitigation scenario is in line with the objectives of the Paris Agreement aiming to restrict the global temperature rise to below 2°C compared to pre industrial levels with a specific focus on limiting it to 1.5°C (Meehl et al., 2020).

These SSP based scenarios merge elements from narratives outlining societal progress (SSPs) with previous scenario iterations known as the Representative Concentration Pathways (RCPs) (Su et al., 2021). The RCPs depict trajectories of changes in greenhouse gas and aerosol concentrations in the atmosphere, along with alterations in radiative forcing over time (Miao et al., 2014; Ul Hasson et al., 2016). The SSPs offer storylines about societal advancements throughout the forthcoming century if climate policies are not implemented (Kebede et al., 2018). While they do not directly quantify actions taken towards climate change adaptation or mitigation, they reflect the complexities and achievements associated with implementing strategies based on factors like population size, regional cooperation, technological progress and more (Tebaldi et al., 2021). Five different scenarios were established with outlooks on progress such as population trends, education levels, urbanization rates, economic status, technological advancements, greenhouse gas emissions, energy needs and supplies and alterations in land-use. These scenarios are intended to complement the revised versions of the Representative Concentration Pathways (RCPs) which outline the stabilized radiation levels by the end of the century (Riahi et al., 2017). This ultimately influences the type of climate policies needed for each scenario to reach the radiation levels. In this study, the necessary GCM projections are sourced from this database to input into hydrological models for estimating future runoff conditions.

2.3 Hydrological studies within the Congo River Basin

The Congo River Basin (CRB) despite its role, in the water, energy and carbon cycles at the global scale has not received much attention with regards to hydro-climatology historically (Aloysius & Saiers, 2017; Laraque, Moukandi N'kaya, et al., 2020). However, there is a growing interest among scientists in studying this freshwater and renewable energy resource. Recent research investigates aspects such as the course of the river basin, its geology, geomorphology and runoff patterns (Runge, 2022). A notable challenge in the CRB and its tributaries is the inadequate number of gauging stations. A recent study by Laraque et al. (2020) provides insights into the evolution of gauging stations networks within this region. Over time, there were a decrease in gauging stations from the colonial period (Bultot, 1971; Laraque, Moukandi N'kaya, et al., 2020). Several researchers have studied the hydro-climatology of the basin, investigating rainfall trends and fluctuations in the region (Janicot, 1992; Kazadi & Kaoru, 1996; Łempicka, 1971; Lesani, 2022; Mahe et al., 2013; Mahé & Olivry, 1995; Matsuyama et al., 1994; Samba et al., 2008). However there remains uncertainty regarding the precipitation datasets (Diem et al., 2014; Kabuya et al., 2020; Malhi & Wright, 2004; Samba et al., 2008; Tshimanga, 2012). Riou (1984) explored experimental methods for the estimation of evapotranspiration in Central Africa. Matsuyama et al. (1994) explored the changes in the water balance by examining hydro-meteorological information. Zhou et al. (2014) noted a decline in forest vitality over decades based on satellite derived data.

With regards to hydrological modelling, significant attention was directed towards addressing two challenges within the CRB; the insufficiency of data and the complex nature of the basin's hydrological system. With limited on-site data available, researchers utilized datasets like reanalysis and satellite derived information to gather climate specifics and physical characteristics of the basin (Beighley et al., 2011; Hua et al., 2019a; Lee et al., 2011; Munzimi, 2019). Despite these efforts there remains a need to enhance modeling techniques to provide practical insights for water resource management (Laraque, Moukandi N'kaya, et al., 2020).

To enhance the understanding of the hydrological process within the CRB, several studies aimed to improve hydrological models to accurately represent the water systems. Such improvements involve taking into account the roles of wetlands and lakes in the basin's hydrological response as to grasp how this large watershed handles the routing of water. For instance, a study by Beighley et al. (2011) used three satellite rainfall datasets with the Hillslope River Routing (HRR) model to predict streamflow over the CRB. While all three datasets provided estimates of streamflow, there were differences in the magnitudes predicted with CMORPH and PERSIANN tending to overestimate rainfall levels. The study found that the TRMM (3B42) dataset performed better than others, by comparing precipitation data with expected patterns both spatially and temporally.

Aloysius and Saiers (2017) studied the effects of climate change on hydrological conditions in the CRB with the Soil Water Assessment Tool (SWAT). They considered 25 climate models under RCP4.5 and RCP8.5 scenarios for predictions. Their findings suggested that across model ensembles, on average there is a projected 7% increase in runoff over the basin by mid century (2046 2065). However, changes in streamflow at basin levels displayed prominent variations in sign and magnitude. Tshimanga and Hughes (2014) developed a model that was partly calibrated by Tshimanga et al. (2011) to assess how well it could estimate streamflow at the basin level using data from gauge observations. They discovered that the model accurately predicted both low and high flows in terms of timing and magnitude, providing insights for managing water resources in the region. Munzimi et al. (2019) utilized the USGS Geospatial StreamFlow Model (GeoSFM), applying satellite-derived rainfall data to simulate daily streamflow across the CRB. They employed a physically-based and spatially distributed hydrological model to better account for the slowing streamflow effects of central wetlands. Calibration and validation were conducted using gauge observation streamflow data from the Kinshasa station, with additional evaluations at other sites based on monthly data. While the authors reported that their model reliably estimated streamflow in terms of timing and seasonality, the accuracy of runoff magnitude was unsatisfactory in some instances.

There are recent attempts to develop hydrological models aiming to overcome the shortcomings of earlier models, especially in relation to wetland and flow routing functionalities. Research conducted by Kabuya et al. (2020) introduced a river-wetland model named LISFLOOD FP to evaluate the wetland function parameters of the GW PITMAN model. This innovative model allows for simulating river runoff and wetland interaction processes, simplifying parameter estimation without relying on trial-and-error calibration techniques. Recognizing the significance of wetlands to watershed hydrology and their increasing alterations, Datok et al. (2020) examined the role of Congo’s wetlands, specifically the "Cuvette Centrale," in the basin's water budget. They employed a modified version of the SWAT model, adapted for tropical regions, and forced it with monthly gauged streamflow data. Their study underscored the crucial role of the Cuvette Centrale in regulating streamflow and emphasized the need to preserve groundwater resources to protect the quantity and quality of wetland water against various threats.

Currently, the impacts of climate change far outweigh other human-induced effects within the Congo River Basin (Laraque, Moukandi N'kaya, et al., 2020). The region remains relatively intact due to minimal infrastructure, including existing hydropower plants, few roads and railways, no bridges across the river, vast inaccessible areas, and low major industrial activities. However, mining, agricultural activities, and deforestation do affect the basin's hydrology. Additionally, the anticipated population growth and its consequences are likely to transform the current minor human impacts into intensified stresses on natural resources.

The effects of climate change on the CRB have not been thoroughly studied, despite its influence on the global climate system. While there have been some studies in the area, many have focused on regional perspectives (Beyene et al., 2012; Chishugi et al., 2021; Amy Creese et al., 2019; Hamududu, 2012; Bila-Isia Inogwabini, 2020; Karam et al., 2023; Lesani, 2022; Mahé et al., 2013; Orange et al., 1997; Salumu, 2023; Tshimanga & Hughes, 2012). For example, a study by Orange et al. (1997) investigated how climate change impacts river baseflow in Central Africa and found that reduced runoff and groundwater storage were linked to decreased rainfall since 1971, a conclusion also supported by Mahe et al. (2013). Certain researchers have studied the impact of climate change at a localized basin level, which is critical for those involved in water resource management. Aloysius and Saiers (2017) explored the hydrological response of the CRB to changing climate using outputs from 25 GCMs forced into the SWAT model. They calibrated the SWAT model using seven years of available gauged streamflow data from 20 locations across the basin, spanning from 1950 to 1957. Their study analyzed runoff changes across the entire basin and within each of the four main sub-basins considered. In addition to total runoff, they evaluated the variation of runoff while excluding flood events, providing a comprehensive understanding of water availability under future climate scenarios. Sidibe et al. (2020) assessed how changing climate affects hydrological conditions given the expected impacts of climate change on Central African water resources. The outputs from nine global climate models were downscaled using the Rossby Center Regional Climate Model (RCA4) and bias correction was performed through a non-parametric quantile mapping technique. The processed data were then used to force two hydrological models, GR2M and IHACRES. The results of their multi-model ensemble analysis projected an overall increase by 5% of discharge across the region by mid-century (2020-2050). However, the presence of significant uncertainties in Central Africa was emphasized, which are attributed to the variability among climate models and the limitations of gauged asseverations.

In 2010 a collaborative effort named "Climate Change Scenarios, for the Congo River Basin" was launched involving Gesellschaft für Internationale Zusammenarbeit GmbH, Wageningen University and Research Centre in the Netherlands, and the Climate Service Centre in Hamburg (Haensler et al., 2013). This initiative examined 46 projections under SRES and RCPs low emission scenarios and 31 projections for the high emission scenarios, revealing a consistent prediction of rising temperatures by the century’s end. However, there were discrepancies in forecasts regarding precipitation changes. The analysis indicated temperature increases ranging from +1.5 to +3°C under low emission scenarios and between +3.5 and +6°C under high emission scenarios. Estimations of changes in Precipitation varied from -5 to +10% for low emission scenarios, and from -10 to +10% for high emission scenarios. Overall, the study suggested that while significant alterations to the water balance of the CRB are unlikely by the end of the century, based on a large model ensemble, there may be an increase in both frequency and intensity of extreme events.

As an energy solution, Hydropower being reliant on renewable water resources is susceptible to the impacts of climate change. It is important to investigate hydropower potential in the CRB considering this vulnerability. However, there seems to be a lack of consideration for climate change effects in the development plans outlined by the Global Energy Interconnection Development and Cooperation Organization (GEIDCO) in 2020. Limited research has been conducted on how changing environmental conditions might affect power generation in this region. Killingtveit and Hamududu (2015) investigated the implications of climate change on production at Inga plants while Swanson and Sakhrani (2016) assessed climate risks concerning investment returns for the Inga 3 hydropower project. A broader analysis by the International Energy Agency (IEA) in 2020 looked at how climate changes may impact generation across 13 nations by the end of this century using GCMs based on RCP2.6 and RCP4.5 emission scenarios. This research indicated a decline of 3% in hydropower capacity between 2060 and 2090 compared to data from 2010-2019, with a notable decrease expected in hydropower production for the Democratic Republic of Congo. Although these evaluations provide an outlook on hydropower conditions throughout the continent, there is still a necessity for in depth impact assessments on a regional level. This entails utilizing models at the basin scale, climate model projections with adequate resolution, and a combination of local observational data to provide precise and localized insights into hydropower potential of the future.

Research often investigates the impact of climate change on the capacity for hydroelectricity using a combination of models to assess the consequences (Carvajal et al., 2017; Christensen & Lettenmaier, 2007; Falchetta et al., 2019a; Majone et al., 2016; Schaefli, 2015; Wasti et al., 2022; Yu et al., 2014). The Flow Duration Curve (FDC) is commonly used in water resource management for planning and analysis of discharge variations, particularly for hydropower and water-use planning (Basso & Botter, 2012; Hänggi & Weingartner, 2012; Liucci et al., 2014; Reichl & Hack, 2017; Vogel & Fennessey, 1995). Streamflow quantiles derived from the FDC are useful in determining the energy potential of a plant. Usually, streamflow quantiles are divided into low, average and high potentials determined by the likelihood of exceeding 10%, 50% and 90% respectively (Pandey et al., 2015; Wali, 2013). The current research analyzes similar quantiles, extracted from Flow Duration Curves (FDCs) and compares them to historical values to evaluate how hydropower potential may change in response to shifting climate conditions.

While the Lualaba River is well known as a major tributary of the Congo River, contributing more than 30% of its total flow, there is a limited amount of research on its watershed (Behm, 1872; Lemaire, 1902; Mukweze Mulelenu et al., 2020; Ravenstein, 1893; Uhl, 1933). Previous studies have primarily focused on the northern sub-watersheds and tributaries of the CRB, emphasizing trends and rainfall patterns (Douglas Alsdorf, Ed Beighley, Alain Laraque, Hyongki Lee, Raphael Tshimanga, Fiachra O'Loughlin, Gil Mahé, Bienvenu Dinga, Guy Moukandi, & Robert GM Spencer, 2016; Laraque et al., 1998; Nguimalet et al., 2022; Tshimanga, 2012). However, there remains much to uncover about the dynamics and contributions of the LRB. Researchers like Behm (1872), Ravenstein (1893), Lemaire (1902), Uhl (1933), and Mukweze Mulelenu et al. (2020) explored related topics, shedding light on aspects such as runoff and ecological balance in the CRB. Similarly, Laraque et al. (2020) and other scholars explored research themes that provide insights on climate change and human activities impacts on river systems in the CRB.

CHAPTER 3 ORGANIZATION OF THE WORK

Projections indicate that African regions will experience shifts in water availability and increased pressure on water resource systems due to climate changes caused by human activities. For instance, the Congo River Basin is expected to see fluctuations in runoff ranging from 12% to +24% by mid century (2046-2065) based on model predictions (Aloysius & Saiers, 2017). These changes need to be taken into account for the planification of water resources to support equitable and sustainable development. However, assessing the impacts in the CRB poses challenges due to limited availability of spatial data and the regions intricate hydroclimatic conditions.

This research seeks to assess how climate change is affecting the streamflow in a sub watershed of the CRB using a variety of hydrological models. Such conceptual lump models incorporate climate datasets for both past and future time periods, for on the case study of Lualaba River Basin, that holds significance in driving development in the region through activities such as farming, river transport and producing power generation. Far as the author is aware, no similar study has been carried out for Lualaba River Basin, ensuring that the research does not replicate previous work.

Chapter 4 describes the implementation of two conceptual hydrological models, HBV-MTL and GR4J for the simulation of streamflow during historical and future periods. These models were calibrated using temperature and precipitation outputs from two reanalysis products and an ensemble of GCMs for the historical period. Optimal calibration parameter sets were identified using the Generalized Likelihood Estimation method. The ensemble of calibrated models was employed to simulate the streamflow at the watershed's outlet. The performance of hydrological models was assessed on daily and annual scales so that only satisfactory models were retained for the assessment of future streamflow conditions in the LRB. Downscaled and bias-corrected projections from 19 GCMs under two SSPs were employed to simulate future runoff conditions for the period 2021-2100. This chapter has been submitted to the MDPI Water journal (impact factor: 3.0) on 2024-08-13. Chapters 5 and 6 discusses the results and implications of this research, proposing recommendations and conclusion to the implications for water resource management and policy development in the Lualaba River Basin.

CHAPTER 4 ARTICLE 1: ASSESSING THE IMPACT OF CLIMATE CHANGE ON AN UNGAUGED WATERSHED IN THE CONGO RIVER BASIN

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Abstract

This study assesses the impact of climate change on streamflow characteristics in the Lualaba River Basin (LRB), an important yet ungauged watershed in the Congo River Basin. Two conceptual hydrological models, HBV-MTL and GR4J, were calibrated using the reanalysis datasets and outputs of Generalized Circulation Models (GCMs) under CMIP6 during the historical period. The calibrated models were fed with outputs of GCMs under Shared Socio-Economic Pathways (SSPs) 2-45 and 5-85, moderate and high radiative future scenarios. The results demonstrate that hydrological models successfully simulate observed streamflow, but their performance varies significantly with the choice of climate data and model structure. Under future climate, Q10 is projected to increase by 33% under SSP2-45 and 44% under SSP5-85, suggesting high low flow conditions. Q50 is also expected to rise by almost the same rate. However, considerably higher Q90 is projected by 56% under moderate and 80% under high radiative scenario. These indicate overall higher water availability in this watershed to be used for energy and food production and need for flood risk management.

Keywords: Climate Change Impact, Hydrological Modeling, Lualaba River Basin, Streamflow Projections, Reanalysis Datasets, Water Resource Management

4.1 Introduction

The hydrological cycle is greatly influenced by human-induced climate change at multiple spatial scales (Amanambu et al., 2020; Arnell, 1999; Duan et al., 2019; Heidari et al., 2021; Seiller et al., 2017). Changes in precipitation and temperature patterns were observed around the world (Alehu et al., 2022; Arnell, 1999; Bourdeau-Goulet & Hassanzadeh, 2021; Ganguli & Coulibaly, 2017; Oguntunde et al., 2017; Wi, 2012). These alterations can impact characteristics such as the peak flow volume and timing crucial for water resource planning and management (Beven & Westerberg, 2011; Nazemi et al., 2020; Zaerpour et al., 2020). Understanding risks to water systems is essential for developing water resource policies.

The importance of Central Africa is well known at the global scale. Its expansive tropical rainforests play a key role as carbon sinks that help counteract the impacts of global warming (Aloysius & Saiers, 2017; Laraque, Nkaya, et al., 2020; Runge, 2022). The Congo River Basin (CRB) in this area is known as the 2nd world's largest watershed and holds about one third of Africa's freshwater resources. Despite having abundant freshwater resources and a considerable potential for hydroelectricity production, as well as natural wealth, the countries in the CRB region are among the least developed economically and face challenges related to food and water security (Brown et al., 2011; Tshimanga et al., 2021; United Nations Environment, 2011).

Global warming in the region has caused changes in the hydroclimatic conditions, bringing about challenges for development. These alterations include shifts in the frequency and duration of wet periods, reduced water content in rainforests, multidecadal drying trends in streamflow, a rise in temperatures by 0.5 °C (with a more notable increase in minimum temperatures) and a 9% decrease in rainfall during the 20th century (Diem et al., 2014; Haensler et al., 2013; Moukandi N'kaya et al., 2020; Nicholson et al., 2019; Sidibe et al., 2020). These changes could worsen vulnerabilities due to insufficient infrastructure, limited industrialization, resource mismanagement and political instability. Understanding the impacts of climate change on water availability within the CRB is essential for developing water and energy management policies. Because the CRB is a large basin and impacts might differ depending on the regions within it, the effects across its sub-watersheds need to be studied.

Studying the effects of climate change on water systems often involves using "top-down" methods that depend on General Circulation Models (GCMs) (Bhave et al., 2014). Such models mathematically replicate Earth's surface and atmospheric processes to forecast climate patterns (Gizaw et al., 2017; Krysanova et al., 2017; Wilby & Dessai, 2010). These models typically provide outputs at coarse resolutions that may not be ideal for managing regional water resources, thus requiring the use of downscaling methods to refine outputs at the desired resolution (Diallo et al., 2012; Liang et al., 2008; Okkan & Kirdemir, 2016; Sørland et al., 2018). However, discrepancies in GCMs' predictions can arise, prompting the need for a combination of climate models to address various scenarios (Aloysius & Saiers, 2017; J. Chen et al., 2018). Downscaled data are utilized to assess watershed conditions or forecast properties alongside hydrological models (Arnell, 1999; Lauri et al., 2012).

Hydrological modelling in the ungauged CRB can be challenging due to its large size, as well as limited and unreliable data. Issues such as maintenance problems, human errors and environmental factors can lead to compromised and misleading ground-based data (Diem et al., 2014; Samba et al., 2008). Methods such as regionalization, satellite-based information and reanalysis datasets are commonly used because of in-situ data scarcity (Beck et al., 2016; Huang et al., 2020; Kratzert et al., 2019). Reanalysis datasets, developed with data assimilation techniques and multiple observational sources for accuracy and consistency are valuable tools for the assessment of climate change impacts in data-scarce regions (Bosilovich et al., 2008; Parker, 2016). Hydrological models that integrate reanalysis products have demonstrated performance improvement compared to those relying solely on observations from monitoring stations, indicating a better approach for reducing uncertainties (Arsenault et al., 2023; Berg et al., 2018; Fuka et al., 2014).

The complexity, including size and remoteness of watersheds also affects the choice of appropriate models to represent hydrological systems. Simple conceptual models are often recommended for climate change assessment, because they are less complex and involve fewer variables, making them suitable for regions with limited data availability (Chen et al., 2013; Santos et al., 2018). However, as different hydrological models can provide varying runoff predictions, it is suggested to use multiple models when conducting impact assessments in order to cover a broad spectrum of potential outcomes (Ludwig et al., 2009; Seiller et al., 2012), thus ensuring a comprehensive assessment framework geared at providing insights for water resource management and policy development.

This research aims to assess the sensitivity of different representation of hydrological systems in the assessment of climate change impacts on water resources in the Lualaba River Basin (LRB), which is a sub-watershed within the CRB. The LRB spans about 974,140 square kilometers, covering 27% of the CRBs area and contributing significantly to its annual water budget. Two hydrological models were calibrated with a combination of reanalysis products and ensemble of GCMs' outputs during the historical period. Accordingly, changes in streamflow over the course of the century is projected under moderate and high radiative forcings. Section 4.2 provides an overview of the framework for impacts assessment, along with details on the hydroclimatic data and hydrological models employed. Section 4.3 presents the LRB case study, along with the characteristics and challenges related to water resources in the region. Section 4.4 analyzes and discusses models' performance and the behaviour of the hydrological system in both historical and future periods. Lastly, Section 5.5 provides concluding remarks and recommendations based on the results, including implications for managing water resources and shaping policies in the region.

4.2 Materials and methods

In this study, we employed two conceptual hydrological models, HBV-MTL and GR4J to represent streamflow in the basin. The minimal data requirements for the models makes them suitable for data-scarce regions. Gauge observations, while critical, often fail to fully represent hydrological processes and variability due to their confinement to specific locations. This limitation overlooks spatial heterogeneity and local factors that significantly affect streamflow characteristics. Moreover, gauge data are susceptible to measurement errors and uncertainties, potentially leading to biases and inaccuracies in calibration. Therefore, including sophisticated climate reanalysis datasets as primary inputs was essential to enhance the framework's robustness.

Since good-quality data should be used as primary inputs to enhance the reliability and precision of simulations, recommended in the literature, we used an ensemble of reanalysis products and historical GCMs outputs for calibrating these hydrological models (J. Chen et al., 2018; Hua et al., 2019a; Tesfaye et al., 2017). The calibrated models were then forced with outputs from a range of GCMs under two SSP scenarios to project future streamflow up to the end of the century. Historical and projected climate data are detailed in Sections 4.2.1 and 4.2.2, respectively, while the hydrological models, calibration and validation processes are outlined in Section 4.2.3.

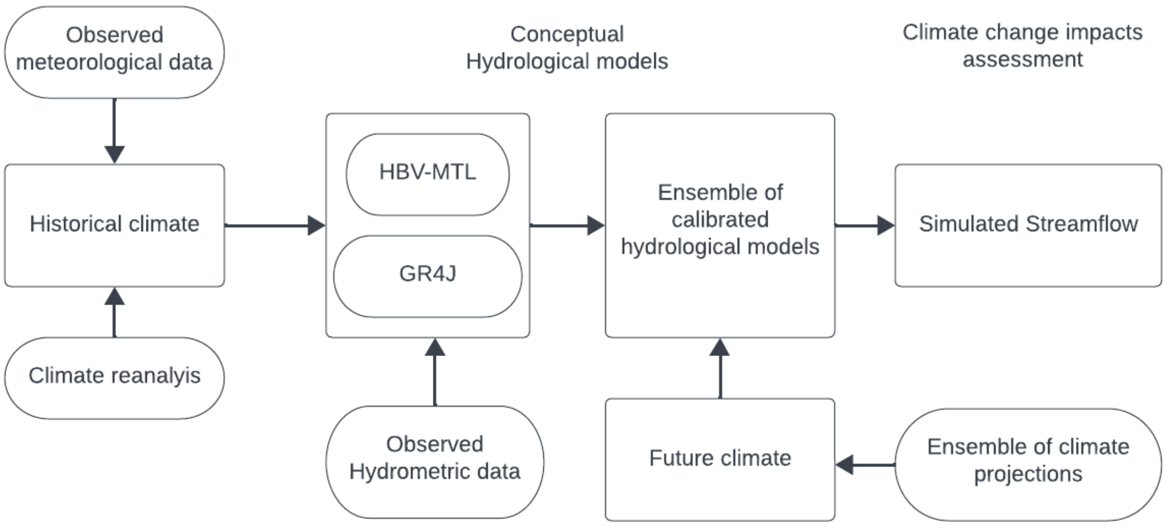

Figure 4.1 Framework for climate change assessment on streamflow in the LRB.

4.2.1 Historical hydroclimatic datasets

The CRB watershed polygon shapefiles and digital elevation models (DEM) were utilized for delineation of sub-watersheds and mapping of the rivers network. The procedures involved using ESRI ArcGIS Desktop (Ormsby, 2004). Land cover data was retrieved based on ENVISAT's Medium Resolution Imaging Spectrometer (MERIS) Level 1B data, acquired in full resolution mode with a spatial resolution of approximately 300 meters (ESA & UCLouvain, 2010). OpenStreetMap (OSM) features under infrastructure, mining, and fabrication were obtained through the UN Humanitarian Data Exchange (Abuoda et al., 2021).

Streamflow observations from the hydrometric station at the watershed's outlet were obtained from the International Commission for the Congo-Ubangi-Sangha Basin (Laraque, Nkaya, et al., 2020). Precipitation and temperature gauge observations from the National Meteorological Agency of the Democratic Republic of Congo. Missing data patterns and mechanisms were analyzed during data preparation. Construct-level missingness in the dataset was the primary consideration when selecting the study period for the calibration and validation of hydrological models. Based on demonstrated reliability over the African continent (Gruber et al., 2022; J. Guo et al., 2021; Johnston et al., 2021), two reanalysis products, ERA5 and MERRA-2, were considered for collecting temperature and precipitation data at acceptable spatial and temporal resolutions over the watershed Table 4.1.

Table 4.1 Climate Reanalysis Datasets.

Dataset	**Source**	**Data type**	**Spatial resolution**	**Temporal resolution**	**Temporal coverage**
ERA5	Copernicus Climate Change Service (C3S) Climate Data Store (CDS)	Atmosphere	0.25° x 0.25°	Hourly	1940 – present
MERRA-2	Goddard Earth Sciences Data and Information Services Center (GES DISC)	Surface land	0.5° x 0.625°	Daily	1981 – present

4.2.2 Climate model projection

NASA Earth Exchange Global Daily Downscaled Projections dataset featured 19 General Circulation Models (GCMs) outputs (NEX-GDDP; accessible at https://cds.nccs.nasa.gov/nex-gddp/) that accounted for bias-corrected daily minimum and maximum near-surface air temperatures and precipitation, at a spatial resolution of 0.25°, based on the outcomes of Phase 6 of the Climate Model Intercomparison Project (CMIP6). Daily downscaled models were generated by adapting the monthly bias correction/spatial disaggregation (BCSD) approach (Thrasher et al., 2022). Future climate projections were covered amongst three timeframes, including near-term (2021–2040), mid-term (2041–2070), and long-term (2071–2100), from SSP245 and SSP585 that respectively represent moderate and predominant mitigation challenges until the end of the century.

The SSPs scenarios were developed to investigate global development trajectories with regards to climate change. They assess the impact of socioeconomic trends and policies on greenhouse gas emissions, climate change and societal resilience (Thrasher et al., 2022). SSP245 depicts global development progresses steadily facing challenges in addressing climate change. Despite some advancements in reducing emissions, it may not be adequate to mitigate the effects of climate change by the end of the century (Su et al., 2021). On the hand SSP585 depicts a high emission scenario characterized by reliance on fossil fuels and limited efforts to tackle climate change. This pathway anticipates an increase in greenhouse gas emissions resulting in climate impacts (Tebaldi et al., 2021). These pathways contribute to climate modeling by projecting how various policy decisions and societal shifts could influence conditions (O'Neill et al., 2016).

4.2.3 Hydrological models

Lumped models are appropriate for data-scarce environments because they require fewer and less spatially detailed input data compared to semi-distributed models. They can effectively simulate hydrological process in the case study without the need for extensive spatial datasets. Furthermore, the lumped approach is suitable for regional-scale assessment since the primary interest is to capture the overall hydrological response of the watershed rather than detailed spatial variations. This approach provides enough details for understanding the broad impacts of climate change on streamflow characteristics across the entire watershed while maintaining manageability in terms of model complexity and data requirements. The computational efficiency of this modelling approach is advantageous given the large scale of the study area and the need to run multiple simulations under various climate scenarios, allowing for extensive sensitivity analyses and uncertainty assessments.

The selected lumped models (HBV-MTL and GR4J) have been used and validated in several hydrological studies, including those conducted in similar environments (Lesani, 2022; Salumu, 2023; Sharifinejad et al., 2022). Their proven reliability and adaptability to different hydrological regimes make them a strong choice for this study. Simplicity and accuracy (Kwakye & Bárdossy, 2020) were the principal criteria for selecting HBV-MTL and GR4J models used in this study to simulate daily streamflow in the LRB. The HBV-MTL model shown in Figure 4.2 represents the hydrological processes using a set of equations and parameters.

Conceptual HBV models are widely used for streamflow estimations at watershed outlets (Lindström et al., 1997; Seibert & Vis, 2012). A variant of the HBV model was introduced by (Sharifinejad et al., 2022) based on (Aghakouchak & Habib, 2010), namely HBV-MTL. This model employs daily temperature and precipitation data as its primary inputs. It differentiates precipitation into categories of rainfall, snowfall, or a mix of both, according to a temperature threshold. Rainfall and any resulting liquid water from melted snow may infiltrate the soil layer, contributing to soil moisture or surface runoff. The amount of the contribution split depends on the current soil temperature and moisture conditions.

Evapotranspiration was calculated based on Hargreaves' method (H. Hargreaves & A. Samani, 1985). This method is widely used and validated in various regions worldwide for its accuracy in estimating evapotranspiration. Numerous studies have compared the process with other models and observed reasonable results, making it a reliable tool for calculating evapotranspiration (Berti et al., 2014; Droogers & Allen, 2002; Hargreaves & Allen, 2003). The method is based on mean, maximum and minimum air temperature and extraterrestrial radiation.

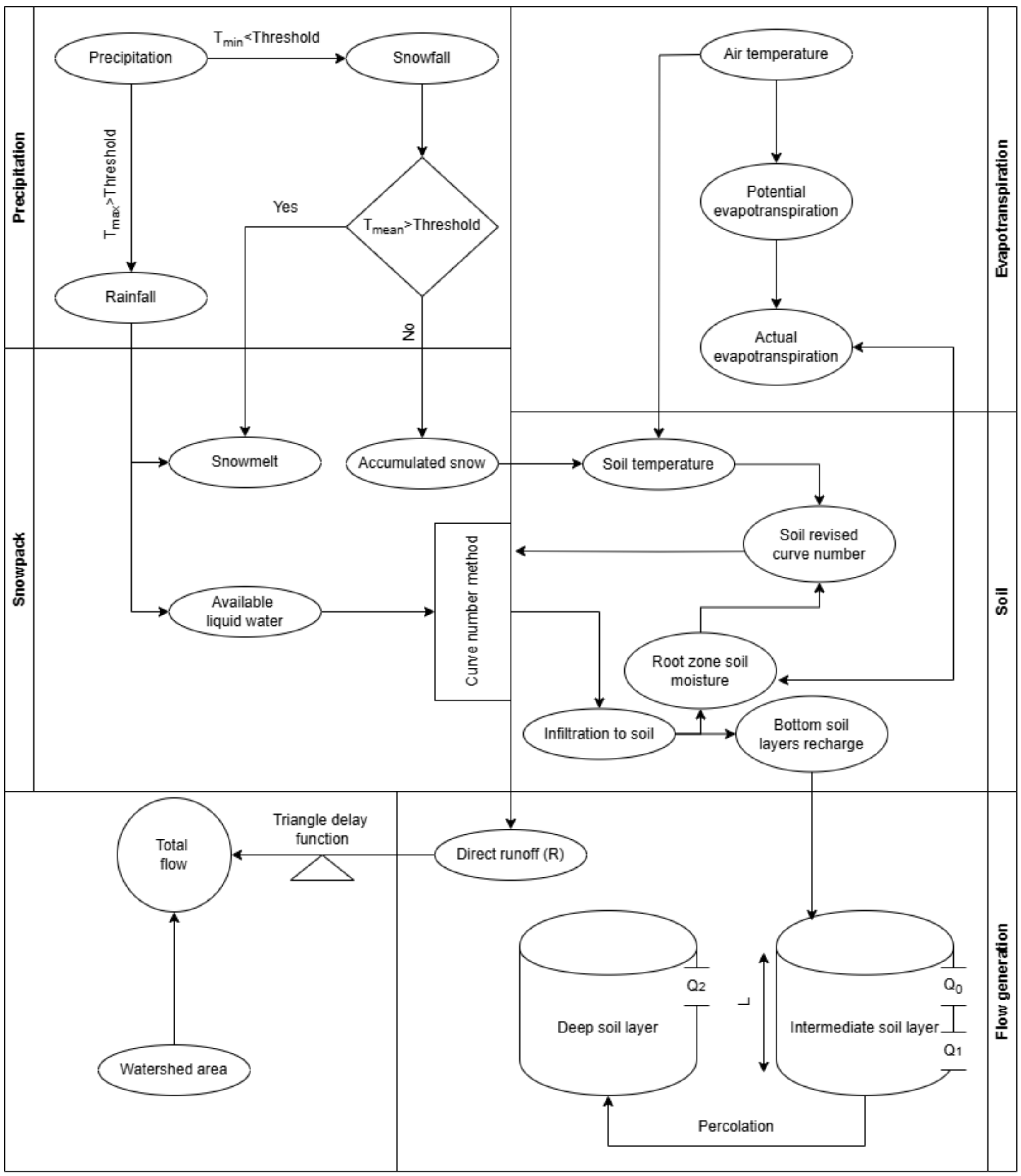

Figure 4.2 Schematic of the HBV-MTL hydrological model.

The remaining water percolates into deeper soil layers contributing to the formation of interflow and baseflow, and replenishing groundwater. Interflow is the lateral movement of water through the subsurface layers of soil, while baseflow refers to the slow and continuous movement of water into streams and rivers (Tarboton, 2003). Total runoff is the sum of surface flow, interflow, and baseflow. It is assigned to a triangular delay function to simulate the daily streamflow at the watershed outlet. A balanced hydrological system regulates water availability, preventing both water scarcity and excessive flooding while maintaining the overall stability and resilience of ecosystems (Gao et al., 2022).

The GR4J model shown in Figure 4.3 is a numerical system that calculates runoff using daily data on precipitation, temperature, and potential evapotranspiration. Distinct from the HBV-MTL model, GR4J partitions the net precipitation, which is derived by deducting potential evapotranspiration from total precipitation, into two segments. This model comprises three primary components: production storage, routing storage, and dual unit-hydrograph functions. Initially, a segment of the net precipitation is allocated to production storage, where it percolates slowly based on soil moisture capacity. Concurrently, a portion of stored water facilitates evapotranspiration through vegetation usage. The remaining net precipitation merges with the water that has percolated from the production storage, and directed to the routing storage via unit hydrographs, which manage the delay between precipitation events and streamflow generation. At this juncture, 10% of the runoff is directly channelled to the outlet using a two-sided unit hydrograph. In contrast, the residual 90% is indirectly routed through interactions with groundwater, employing a one-sided unit hydrograph. Further information on the model's architecture and equations is provided in (Perrin et al., 2003).

The calibration process involves adjusting the parameters of the HBV-MTL and GR4J models to ensure they accurately simulate the historical hydrological processes. This is done by comparing the model outputs with the historical data and iteratively refining the parameter to a satisfactory threshold. Parameterizing hydrological models can be challenging. Selecting suitable values for the model parameters is a key step for this endeavour because parameter values greatly influence the model's behaviour and performance.

Both hydrological models were calibrated against observed streamflow data from gauges at the outlet. As for primary input, an ensemble of climate datasets from the historical period, including station-based observations, an ensemble of GCMs, and reanalysis datasets.

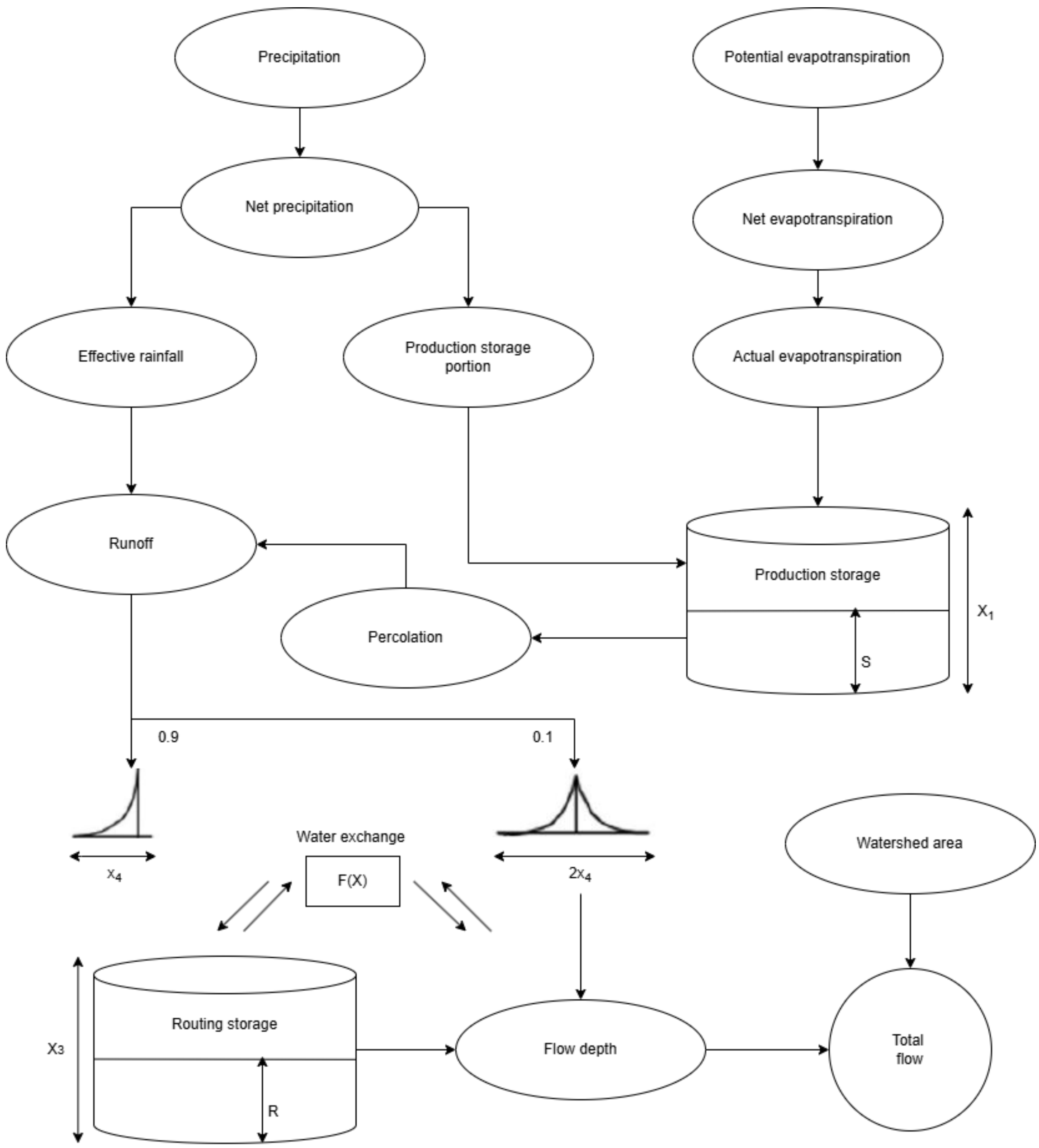

Figure 4.3 Schematic of the GR4J hydrological model.

The Kling-Gupta Efficiency (KGE) measure (Gupta et al., 2009) was used to evaluate the models' performance. It compared the estimated and observed values across many statistical criteria, enabling a thorough assessment of the hydrological models. KGE was used to assess the estimated values from the model using an array of statistical criteria and compared them with the observed values. It comprehensively evaluates the hydrological models, considering several factors, including the correlation, variability, and bias between the observed and estimated values. This aids in assessing the accuracy and precision of simulations and forecasts of hydrological processes.

The criteria for formulating the KGE metric include standard deviation, mean, and Pearson correlation coefficient, represented as α, β, and μ, respectively, in the equations (Eqs. 2.1, 2.2, and 2.3). Compared to other measures such as the Nash-Sutcliffe Efficiency, KGE provides a more balanced assessment by incorporating these criteria via the Euclidean distance measure (Nash & Sutcliffe, 1970). This approach enables a robust assessment of model accuracy and reliability. The calibration and evaluation of the hydrological models are conducted using KGE measures on both daily and annual scales, as outlined in Eq 2.5. The standard deviations of simulated and observed runoff are represented in Eqs 2.1 to Eqs 2.3 as σ_S and σ_O. Meanwhile, $\overline{S}$ and $\overline{O}$ refer to mean values in simulated and observed flow, respectively, whereas S_t and O_t refer to specific instances in simulated and observed flow.

$$\alpha = \frac{\sigma_S}{\sigma_O} \qquad \text{(Eq. 2.1)}$$

$$\beta = \frac{\bar{S}}{\bar{O}} \qquad \text{(Eq. 2.2)}$$

$$\mu = \frac{\sum_t (O_t - \bar{O})(S_t - \bar{S})}{\sqrt{(\sum_t (O_t - \bar{O})^2)(\sum_t (S_t - \bar{S})^2)}} \qquad \text{(Eq. 2.3)}$$

$$KGE = 1 - \sqrt{(1-\alpha)^2 + (1-\beta)^2 + (1-\mu)^2} \qquad \text{(Eq. 2.4)}$$

$$Obj = Min\sqrt{(1 - KGE_{daily})^2 + (1 - KGE_{annual})^2} \qquad \text{(Eq. 2.5)}$$

The Shuffled Complex Evolution algorithm (SCE-UA), developed by Duan et al. (1993) and further explored by Yarpiz (2020), was employed to calibrate the hydrological models. This is a method that integrates both random (Price, 1983) and deterministic strategies (Dixon & Szegö, 1978), along with clustering (Torn, 1987) and competitive evolution (Holland, 1992), to optimise parameter sets. The optimisation occurs through a global search mechanism that mimics natural evolutionary processes (Duan et al., 1994; Kumar et al., 2020). Initially, a population of parameter sets was randomly selected from the feasible space and subsequently divided into several complexes. These complexes evolved independently using a competitive evolution technique. The populations were periodically shuffled to prevent the algorithm from settling into local optima, enabling information interchange between complexes. This iterative procedure continued until the convergence criteria were met. In the specific context of this study, 50 parameter sets were randomly chosen within the defined range and segmented into five complexes. The evolution and shuffling of the complexes persisted through a maximum of 100 iterations to ensure a thorough exploration of the parameter space.

4.3 Case study

The Congo River Basin (CRB) presented in Figure 4.4 is located between latitude 9°N and 14°S and longitude 11°E and 34°E. Extending across Central Africa, ranked after the Amazon River Basin as the second-largest watershed in the world, with an impressive 3.7 million square kilometres and a mean annual discharge of 40,600 m^3/s (Laraque et al., 2001). Surrounding most of the Democratic Republic of the Congo (DRC) territory, the CRB also extends its coverage to eight other countries. These countries include Angola, Burundi, the Central African Republic, Cameroon, the Republic of the Congo, Tanzania, Rwanda, and Zambia. The CRB supports the Congo rainforest, which is one of three major humid tropical regions on Earth (Douglas Alsdorf, Ed Beighley, Alain Laraque, Hyongki Lee, Raphael Tshimanga, Fiachra O'Loughlin, Gil Mahé, Bienvenu Dinga, Guy Moukandi, & Robert G. M. Spencer, 2016).

The Lualaba River Basin (LRB) is amongst the largest of five sub-watersheds, accounting for 27% of the total area of the CRB (Moukandi N'Kaya et al., 2020). It drains approximately 974,140 square kilometres, most of which is located within the DRC. The remaining area coverage is located across Zambia in the southeast and Rwanda, Burundi, and Tanzania in the east. As a major contributor to the CRB annual water budget, the LRB is a principal-agent for water resource management in the region (Becker et al., 2018; Bultot, 1971). However, this region is ranked 177 of 181 on the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index, illustrating countries that are best prepared to deal with global changes brought about by overcrowding, resource constraints and climate disruption (C. Chen et al., 2018). There is an unequal distribution of population in the LRB, accounting for over 30% of the DRC's population, including several conflicted regions that are often portrayed as prominent examples of how violent struggles over natural resources have shaped internal warfare (Parens, 2022).

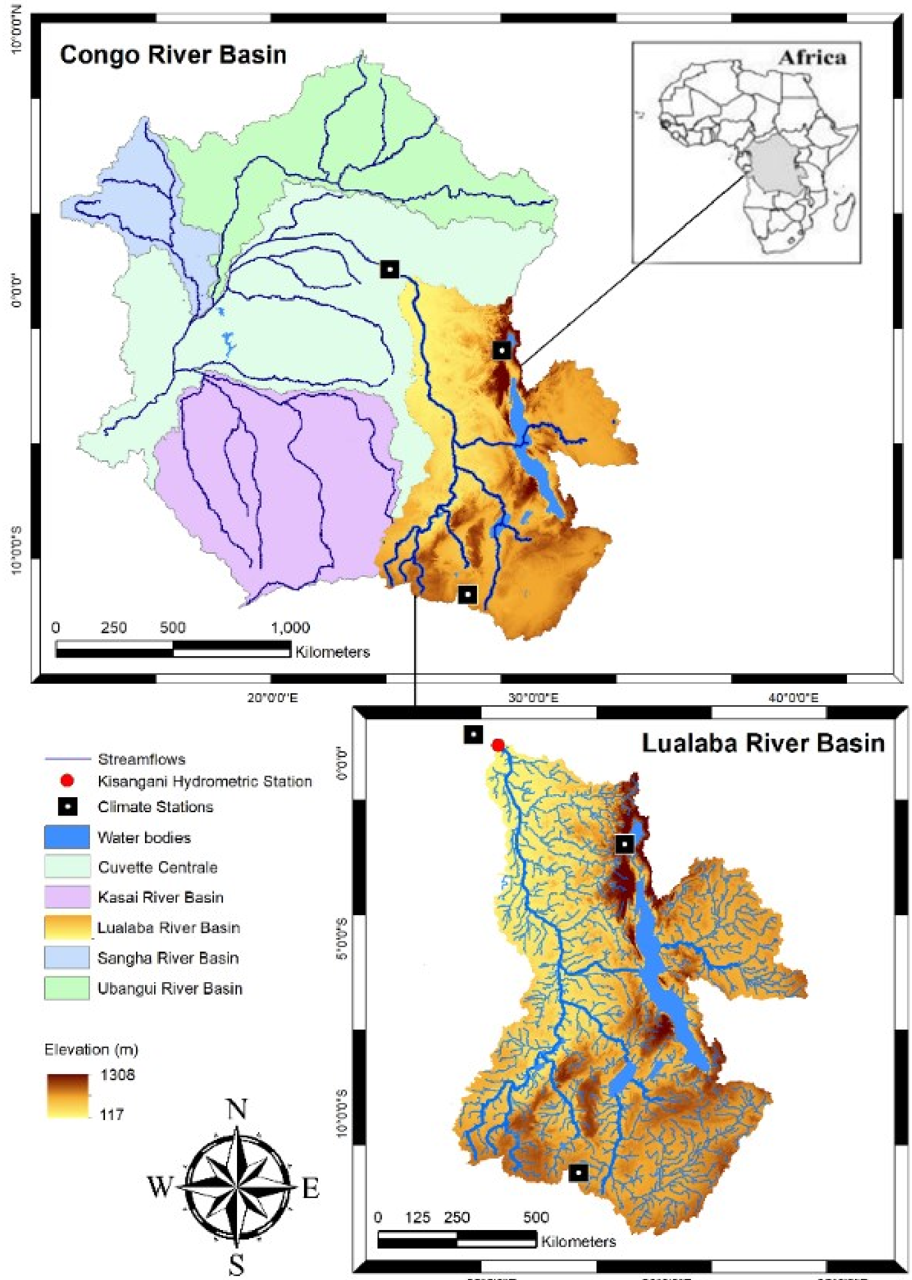

Figure 4.4 CRB sub-watershed, Lualaba River Basin, location of gauges used in case study.

A plethora of critical mineral resources, including cobalt, coltan, copper, and other valuable minerals, exist in this region (Gielen, 2021; Owen et al., 2023; Srivastava & Kumar, 2022). However, the predominant economic activity sustaining local households is shifting agriculture, which is profoundly reliant on the availability of water resources within the region. Notably, agricultural productivity within the LRB is predominantly rain-fed, rendering the basin's water availability critical for ensuring regional food security (Brown et al., 2014). Figure 4.5 illustrates aspects of the LRB land-use distribution, emphasising its water resources, soil and vegetation cover. Water resources are depicted, showcasing the extensive network of rivers and streams within the watershed. Hydraulic infrastructure represents locations of dams or other facilities essential for regulating the flow, hydropower and distribution of water. The soil cover delineates the primary areas of fertile land, while civil and mining activities represent locations of interest where industrial and extractive operations are concentrated. The vegetation cover illustrates the expansive areas of natural flora across the watershed. Furthermore, a UNESCO World Heritage Sites collection is located within the LRB. These National Parks, namely Kahuzi-Biega, Kundelungu, Maiko, Upemba, and Virunga, collectively cover 50,000 square kilometres as a habitat for numerous endangered species of animals and fish, thereby emphasising the LRB ecological significance.

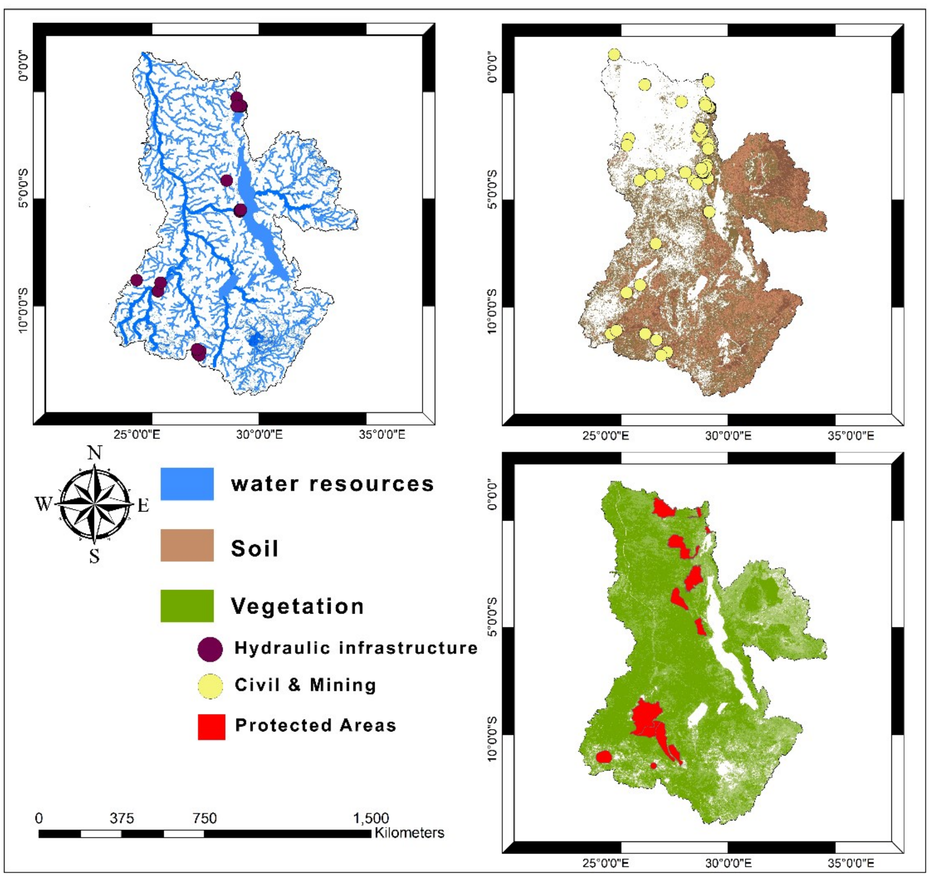

Figure 4.5 LRB land-use classification

The Lualaba River is the principal headstream of the LRB, flowing entirely within the DRC's national borders. It is a testament to the power and beauty of nature and an important asset in the ecosystem of the CRB. Spanning an impressive 1,800 kilometres, The Lualaba River originates at approximately 1,400 meters above sea level on the Katanga (Shaba) plateau near Musofi; the river's early watercourse features a descent across the Manika Plateau, marked by numerous waterfalls and rapids. Notably, the river undergoes a drastic descent into the Upemba depression, dropping about 457 meters over 72 kilometres, a gradient harnessed for hydroelectric production at the Nzilo Dam near the historical Delcommune Falls (Lukamba-Muhiya & Uken, 2006).

The river becomes navigable at Bukama, continuing for roughly 644 kilometres through the channel, where it expands into expansive, marsh-filled lakes like Upemba and Kisale, which are prone to seasonal flooding and dense with aquatic vegetation (Bala & Wantzen, 2023). Along this navigable stretch, the Lualaba River is fed by tributaries such as the Lufira, Luvua, and Lukuga rivers. Downstream, the Lualaba River enters the challenging Portes d'Enfer (Gates of Hell), a narrow and deep gorge that precludes navigation. The river is again navigable for 109 kilometres from Kasongo to Kibombo, although this segment is interrupted by rapids extending to Kindu. Despite some shallow sections and rocky banks toward its outlet near Kisangani, the river remains navigable up to the Boyoma Falls, where a series of seven cascades marks the transition of the Lualaba River into the Congo River (Stanley, 1889). Historical hydro-climatic characteristics of the LRB are presented in Table 4.2.

Table 4.2 Hydro-climatic characteristics of the LRB.

Climate					**Streamflow**		
Data source	Mean annual precipitation (mm)	Average minimum temperature (°C)	Average maximum temperature (°C)	Mean annual ET (mm)	Hydro Station	Average annual discharge (m^3/s)	Drainage area (km^2)
Observed	1526	16.5	27.7	1677	Kisangani	7583	974,140
ERA5	711	22.7	23.4	433			
MERRA-2	1416	18.3	27.6	1555			
GCMs	1385	19.7	30.9	1809			

Daily streamflow and the flow duration curve recorded at the Kisangani hydrometric station are presented in Figure 4.6. The left panel presents the daily streamflow recorded at the outlet for each year from 1981 to 2001, revealing interannual streamflow variations and peak periods that indicate seasonal influences. The right panel presents daily streamflow against exceedance probabilities over the same time period, as the river's perennial characteristic. Low streamflow was recorded around 5000 m^3/s, medium flow at approximately 7,500 m^3/s, and high flow above 11,000 m^3/s.

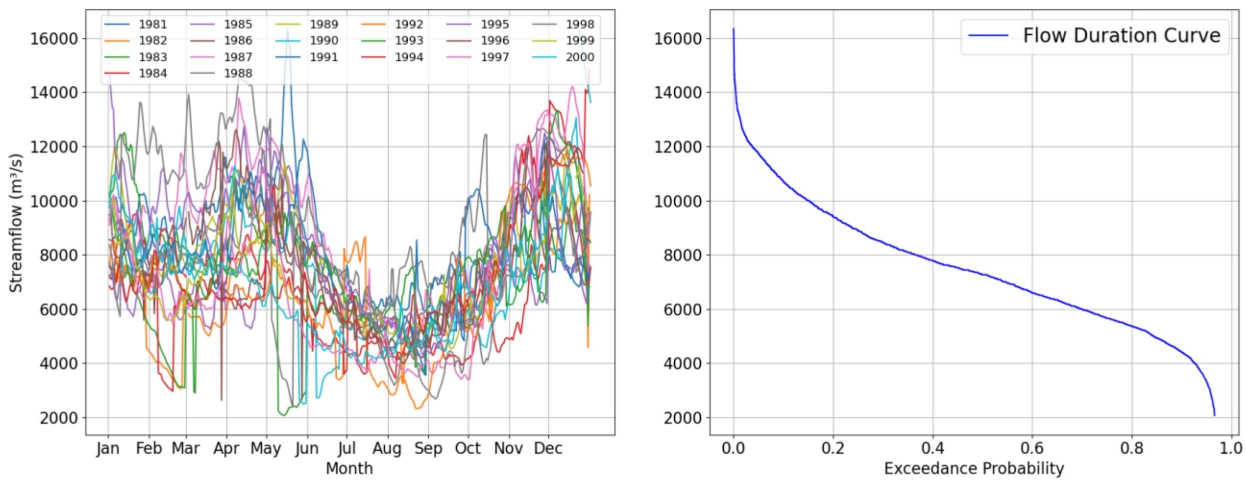

Figure 4.6 LRB outlet, daily Streamflow and flow duration curve (1981-2001).

Historical temperature and precipitation datasets revealed mean annual temperature between 22°C and 25°C, and mean annual precipitation varying from 1385 to 1526 mm over the LRB for a 20-year period (1981 – 2001). Temporal variations in daily mean precipitation and temperature across the LRB, along with seasonal climatic cycles derived from reanalysis products and gauge observations from 1981 – 2001, are detailed in Figure 4.7 that employs boxplots to represent daily values averaged over gauge observations and lines to depict expected daily temperature and precipitation over the 20-year period. The boxplots clearly depict the central tendency and dispersion of the daily precipitation and temperature for each dataset. Notably, the range of values for the reanalysis datasets varies significantly, principally with regard to precipitation. Such discrepancies may stem from differences in assimilation schemes, the ground data incorporated into assimilation processes, and the forecasting climate models (Lin et al., 2014).

Gauge observations revealed a median daily precipitation of approximately 1.8 mm, with an interquartile range (IQR) extending from approximately 0.3 mm to 5.8 mm. The maximum daily precipitation recorded was around 13.8 mm. MERRA-2 dataset had a higher median of 3.2 mm but a slightly narrower distribution, indicating less variability. The IQR ranged from 1.3 mm to 5.6 mm, with a maximum value near 12 mm. ERA5 revealed the lowest median precipitation at around 1.8 mm, with a much narrower distribution. Its maximum daily precipitation was roughly 6 mm, and the IQR ranged between 0.8 mm and 3.1 mm. Temperature, on the other hand, ranged from 19°C to 25°C for the gauge observations, the IQR ranged from 21.4°C to 22.9°C, and a mean of 22°C. MERRA-2 mean daily temperature was 22.9°C, IQR from 22.2°C to 23.8°C, and maximum and minimum of 26°C and 19.6°C, respectively. similarly, a mean temperature of 23°C was recorded by ERA5, however with a narrower IQR.

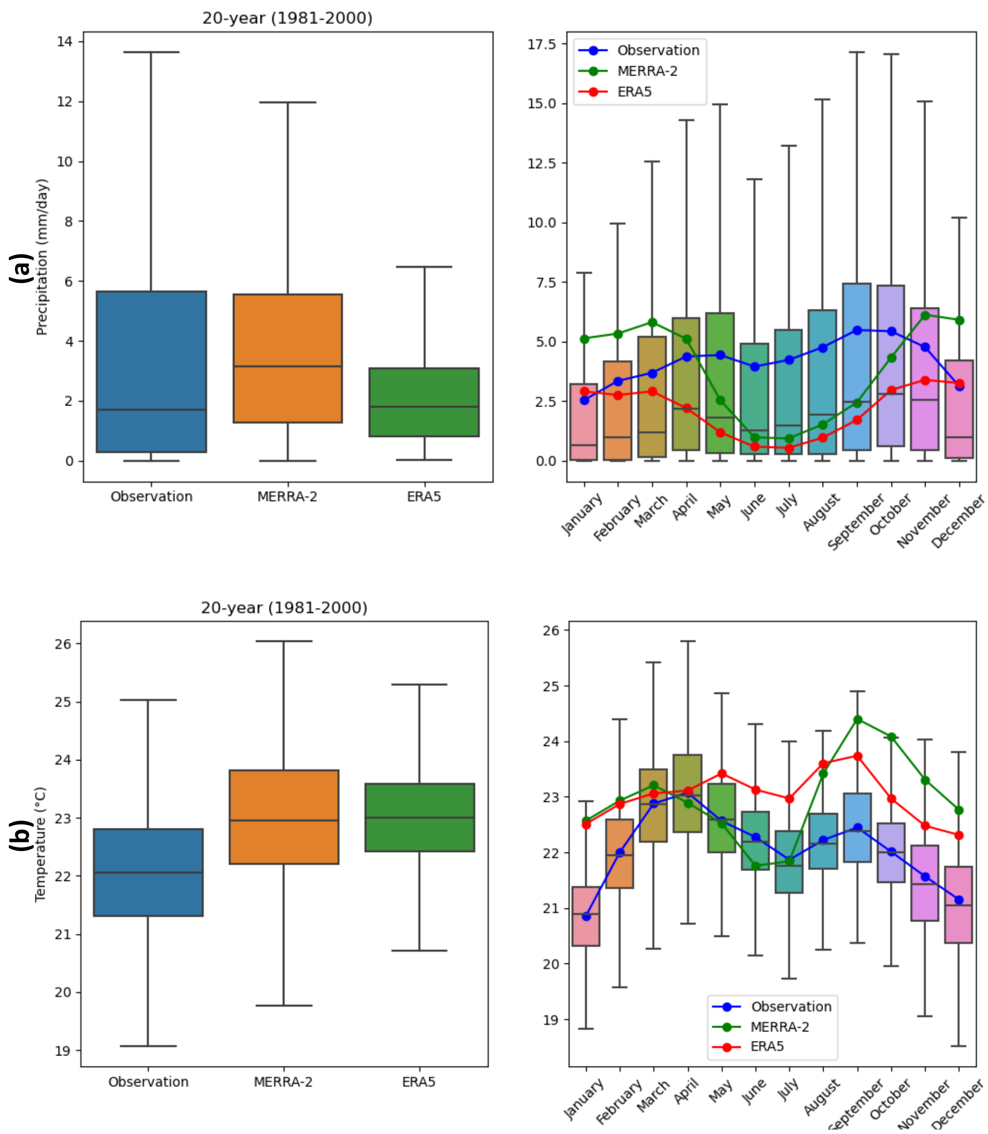

Figure 4.7 Daily precipitation and temperature (left panel). Observed daily (boxplots) and expected values (lines) per month based on observation and reanalyses (right panel).

The right panels of Figure 4.7 highlights seasonal variations, presenting daily precipitation and temperature boxplots for each month. Observation unveiled two high precipitation periods during March-April-May (MAM) and September-October-November (SON), with peaks in April and November exceeding 12 mm/day. MERRA-2 unveiled a lower variability and magnitude in precipitation compared to observed data, with peaks in March, and ERA5 consistently recorded lower precipitation values and less variability throughout the year. For temperature, observation Indicated a distinct seasonal cycle, with temperatures peaking in March and April (over 23°C) and the coolest period from June to August (around 21°C). MERRA-2 captured the seasonal cycle well, generally indicating slightly higher temperatures than gauge observations, while ERA5 Followed the observed seasonal cycle but reported consistently higher temperatures.

The gauge observations unveiled the most variability in precipitation and higher peaks, essential for capturing extreme weather events. MERRA-2 aligned well with the precipitation cycle but overestimated variability, while ERA5 consistently showed lower values. The observed temperature data accurately reflected seasonal dynamics. MERRA-2 showed good alignment to the cycle with slight overestimation, while ERA5 consistently recorded higher temperatures. For the purpose of hydrological model calibration, ERA5 and MERRA-2 reanalysis datasets provided reliable insight into precipitation and temperature over the LRB.

On the basis of Phase 6 CMIP6 results, NEX-GDDP provided bias-corrected daily minimum and maximum near-surface air temperatures and precipitation. SSP245 and SSP585 represented moderate and high-forcing scenarios until the year 2100 over the watershed (2021-2040, 2041-2070, and 2071-2100). A comparison of historical data (1981-2001) with future projections across various time horizons is provided to illustrate the temporal variation in daily precipitation and temperature Figure 4.8. Outputs from 19 GCMs were computed along with gauge observations and reanalysis products from ERA5 and MERRA-2 under two Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5). The magnitudes of daily precipitation and temperature for the historical period are presented in the first panel. (a) Median precipitation recorded by GCMs was 4.1 mm, IQR ranged from 1.9 mm to 5.5 mm, and a maximum of 9.1 mm. (b) Mean daily temperature recorded by GCMs was 25.3 °C, IQR ranged from 25°C to 25.7°C, and maximum and minimum temperatures of 26.7°C and 24.2°C, respectively.

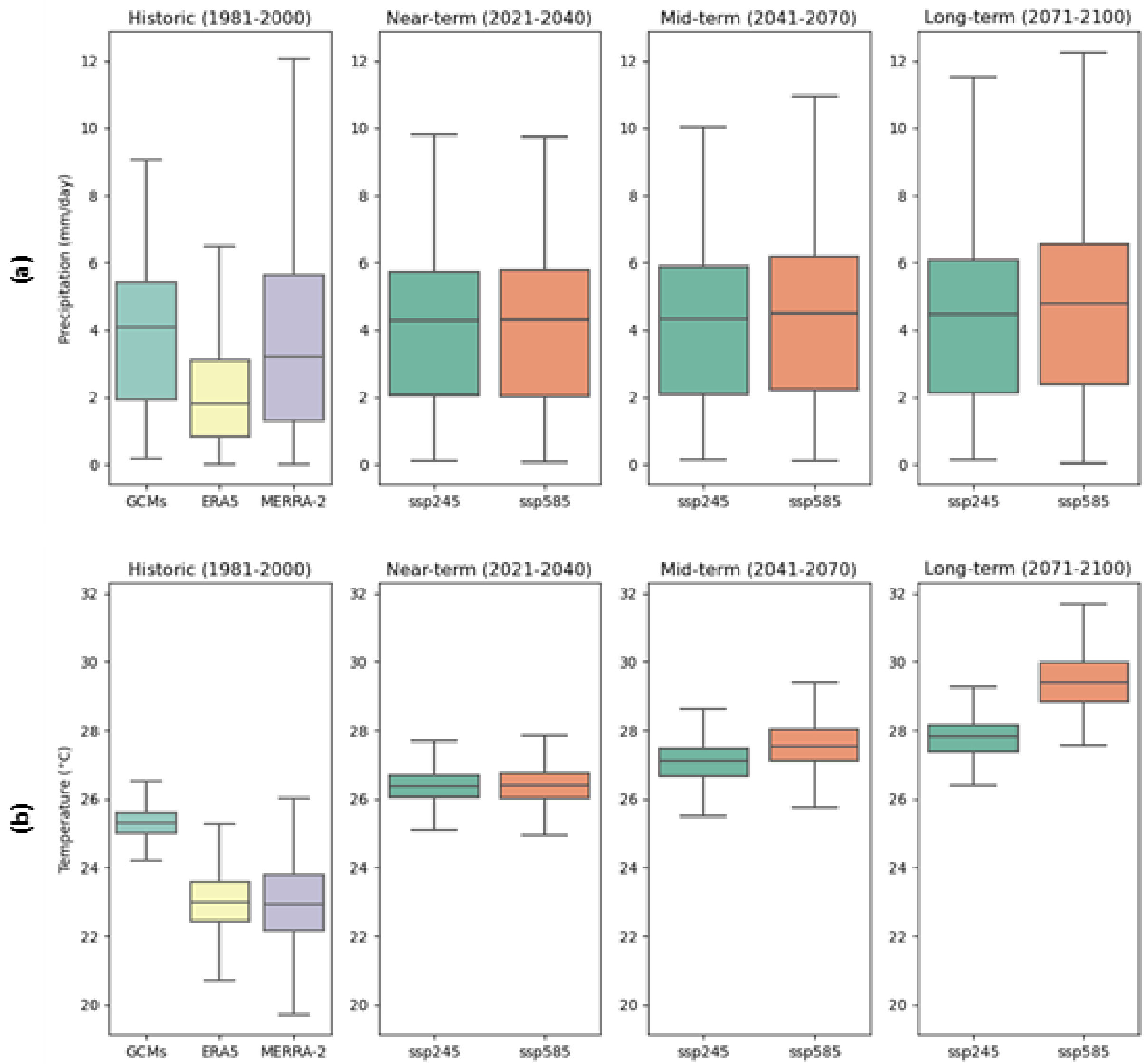

Figure 4.8 Climate models projections under SSP245 and SSP585 compared with historical (a) precipitation and (b) temperature (GCMs and reanalysis in the LRB).

The right panels in Figure 4.8 represent precipitation and temperature projections for near-term, mid-term, and long-term periods under two scenarios: SSP245 and SSP585. (a) Both SSP245 and SSP585 projected a Near-term median daily precipitation of 4.3 mm, IQR from 2 mm to 5.7 mm, and a maximum of 9.8 mm. Mid-term projections under SSP245 maintained a median daily precipitation of 4.3 mm, IQR from 2.1 mm to 5.9 mm, consistent precipitation range, and maximum at 10 mm. SSP585 continued to show similar patterns, with median at 4.5 mm and slightly broader IQR of 2.3 to 6.2, and maximum of 11 mm. As for the long-term climate projections under SSP245, median daily precipitation was 4.4 mm, IQR from 2.1 mm to 6.1 mm, and maximum precipitation of 11.5 mm. SSP585 projected higher precipitation variability, median at 4.7 mm, with maximum reaching 12 mm. (b) Mean daily temperature projections under SSP245 were 26.4°C for the Near-term, with IQR ranging from 26°C to 26.7°C, and a maximum and minimum temperature of 27.7°C and 25.1°C, respectively.

Although there were slight increases in variability, a similar median was projected by SSP585 with maximum and minimum daily temperatures of 28°C and 25°C, respectively. the mid-term projections under SSP245 maintained a mean daily temperature of 27°C, IQR from 26.7°C to 27.5°C, with maximum and minimum temperature of 28.8°C and 25.4°C. Temperature patterns remained similar under SSP585, with a mean of 27.6°C, IQR that was slightly broader, and maximum and minimum temperature of 29.9°C and 25.7. The mean daily temperature under SSP245 for the long-term was 27.8°C, IQR ranged from 27.4°C to 28.2°C. A considerable increase was noticed under SSP585 that projected mean daily temperature of 29.4°C, IQR from 28.8°C to 30°C, and maximum and minimum reaching 32°C and 27.6°C, respectively.

The historical data revealed the differences in rainfall and temperature among various datasets. ERA5 was in closer alignment to MERRA-2, compared to historical GCMs outputs. Looking into the future, both the SSP245 and SSP585 scenarios predicted stable rainfall for all future time frames. However, the SSP585 scenario indicated higher variability. This implies that while average rainfall is likely to remain stable, there could be an increase in extreme rainfall events under higher emission scenarios. Temperature forecasts unveiled an increasing trend over time. Short-term predictions hinted at a rise in temperature. Mid-term and long-term projections under SSP585 pointed to a significant increase, in both average temperatures and variability.

4.4 Results

4.4.1 Hydrological models performance during the historical period

The historical period from 1981 to 2001 was selected based on the availability of climate datasets and streamflow data within the LRB. HBV-MTL and GR4J models were calibrated using temperatures and precipitation from two reanalysis datasets, and the average historical outputs from 19 GCMs. The KGE statistical metric was used to assess the performance of the calibrated hydrological models. The calibration performances of the hydrological models are presented in Table 4.3 and validation performances in Table S.1 under supplementary materials. Any optimal solutions that recorded KGE < 0.4 and KGE < 1.5 for the calibration of HBV-MTL and GR4J, respectively, were considered unsatisfactory and were attributed to low-quality model input data from gauge observations, including streamflow. Models that did not converge to an optimal solution and those that did not meet the calibration thresholds were not considered for the assessment under projected future climate.

Calibrated HBV-MTL models revealed acceptable performance across reanalyses-based configurations, especially under the historical GCMs configuration. On the other hand, calibrated GR4J models systematically returned lower performance in comparison to HBV-MTL models, at the exception of the ERA5-based configuration. Performance assessment indicated that MERRA-2 was the least efficient dataset for the calibration of hydrological models. The GR4J model showed good model performance under the ERA5 configuration (KGE = 0.49), whereas the HBV-MTL performed well under the GCMs configuration (KGE = 0.59). In contrast, ERA5 and MERRA-2 configurations returned negative NSE values, suggesting that they might be less reliable than using the average of the input data as predictors. Across all configurations, there was a positive linear relationship. In addition, the relative bias revealed the tendencies of models to overestimate or underestimate the streamflow for each configuration.

Table 4.3 Calibration performance of HBV-MTL and GR4J models.

criteria	**ERA5**		**MERRA-2**		**GCM**	
	HBV-MTL	GR4J	HBV-MTL	GR4J	HBV-MTL	GR4J
Kling-Gupta efficiency	0.41	0.49	0.45	0.16	0.59	0.41
Nash-Sutcliffe efficiency	-2.98	-0.02	-0.72	-5.75	0.19	0.15
Pearson correlation	0.41	0.61	0.24	0.27	0.35	0.22
Relative Bias	0.45	-0.22	-0.20	-0.58	0.01	0.00

Daily and annual streamflow at the LRB outlet for gauge observation and simulations with HBV-MTL and GR4J are presented in Figure 4.9 (HBV-MTL on the left panel and GR4J on the right panel). Each time series presents the observed and simulated daily streamflow (solid lines), as well as observed and simulated annual streamflow (dashed lines).

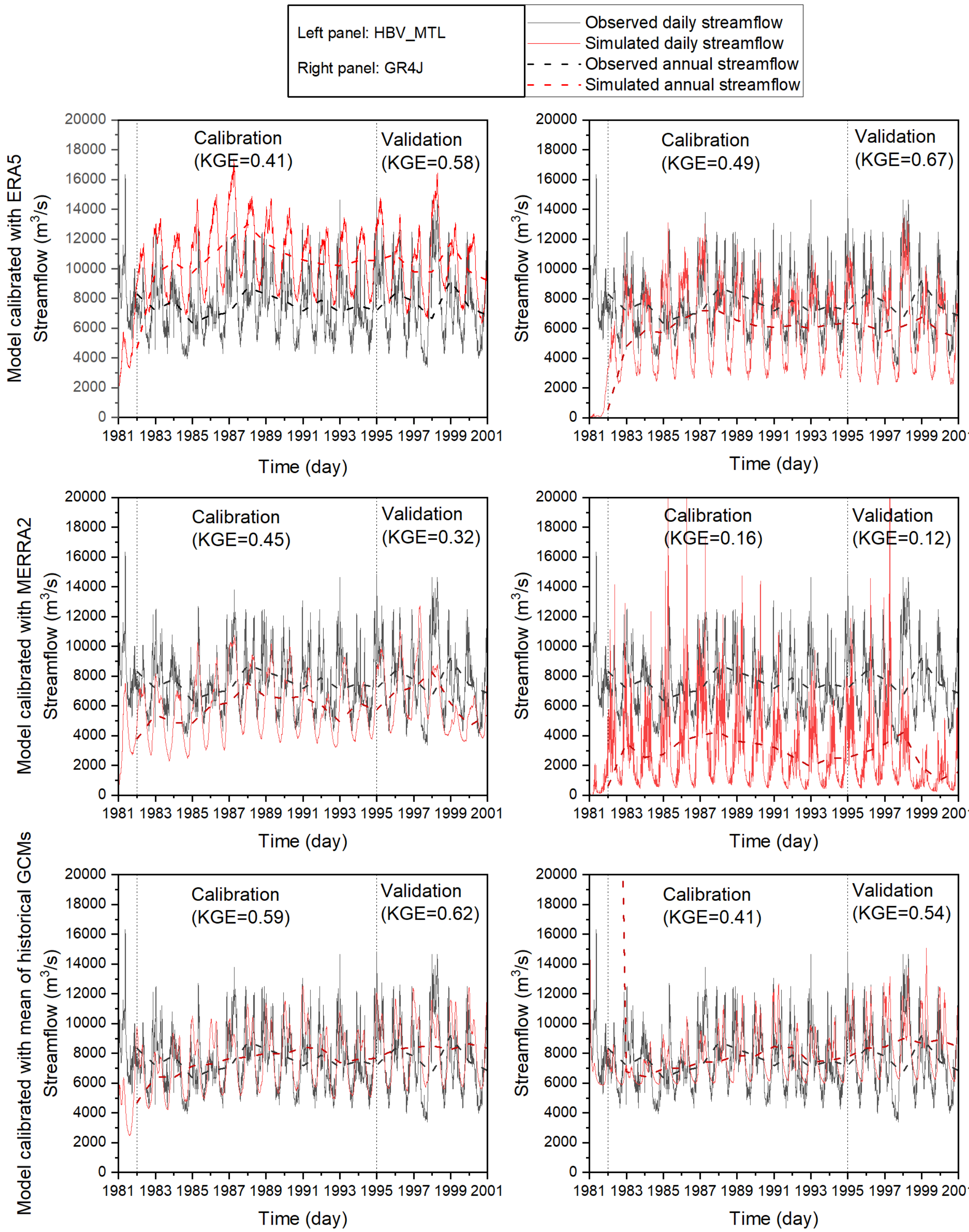

Figure 4.9 Observation and simulation of daily and annual streamflow for the historical period at Kisangani.

The calibration and validation periods are clearly outlined in Figure 4.9, with Kling Gupta Efficiency (KGE) values providing a quantitative measure of model performance. Distinct patterns emerged in the performance of the HBV-MTL and GR4J models during the calibration and validation stages. When utilizing ERA5 reanalysis data for calibration, the HBV-MTL model tends to overestimate observed streamflow. Conversely, under the ERA5 configuration the GR4J model generally underestimates observed streamflow. With MERRA-2 configuration, both HBV-MTL and GR4J models tend to underestimate the observed streamflow. This consistent underestimation hints at biases in MERRA-2 data, or shortcomings in representing certain hydrological processes within these models using this dataset. When the hydrological models were calibrated with historical GCMs they exhibit an alignment with the observed streamflow. This alignment suggests that the calibrated models can effectively reproduce the patterns when historical GCMs data is utilized, highlighting the potential of these models to serve as tools for simulating streamflow under past climate conditions. In general, the results of calibration and validation emphasize the varying performance of the HBV-MTL and GR4J models based on the input data.

The long-term historical annual runoff shown in Figure 4.10 presents observed flow (solid black line), optimal flow for calibration (solid green line), observed flow for validation (solid blue line), and optimal flow for validation (solid red line). Across configurations, both hydrological models captured fluctuations in streamflow, including high and low flow periods, as well as the seasonality. Generally, the ERA5 configuration aligned well with gauge observations for both hydrological models, particularly during the calibration period. Notably, this alignment reflects high flow periods from March to May and September to November, and low flows periods from June to August. Discrepancies were more pronounced in the MERRA-2-based models, especially concerning the HBV-MTL model during low flow months from June to August. The historical GCMs-based models have shown good performance by representing seasonal changes and closely matching the observed and simulated streamflow. The findings underscore the significance of choosing input data for modeling. The ERA5 configurations seemed effective for both the HBV-MTL and GR4J models, whereas adjustments may be required for the MERRA-2 configurations to better capture low flow periods. The historical GCMs based models present a viable option for capturing long-term seasonal variations in streamflow.

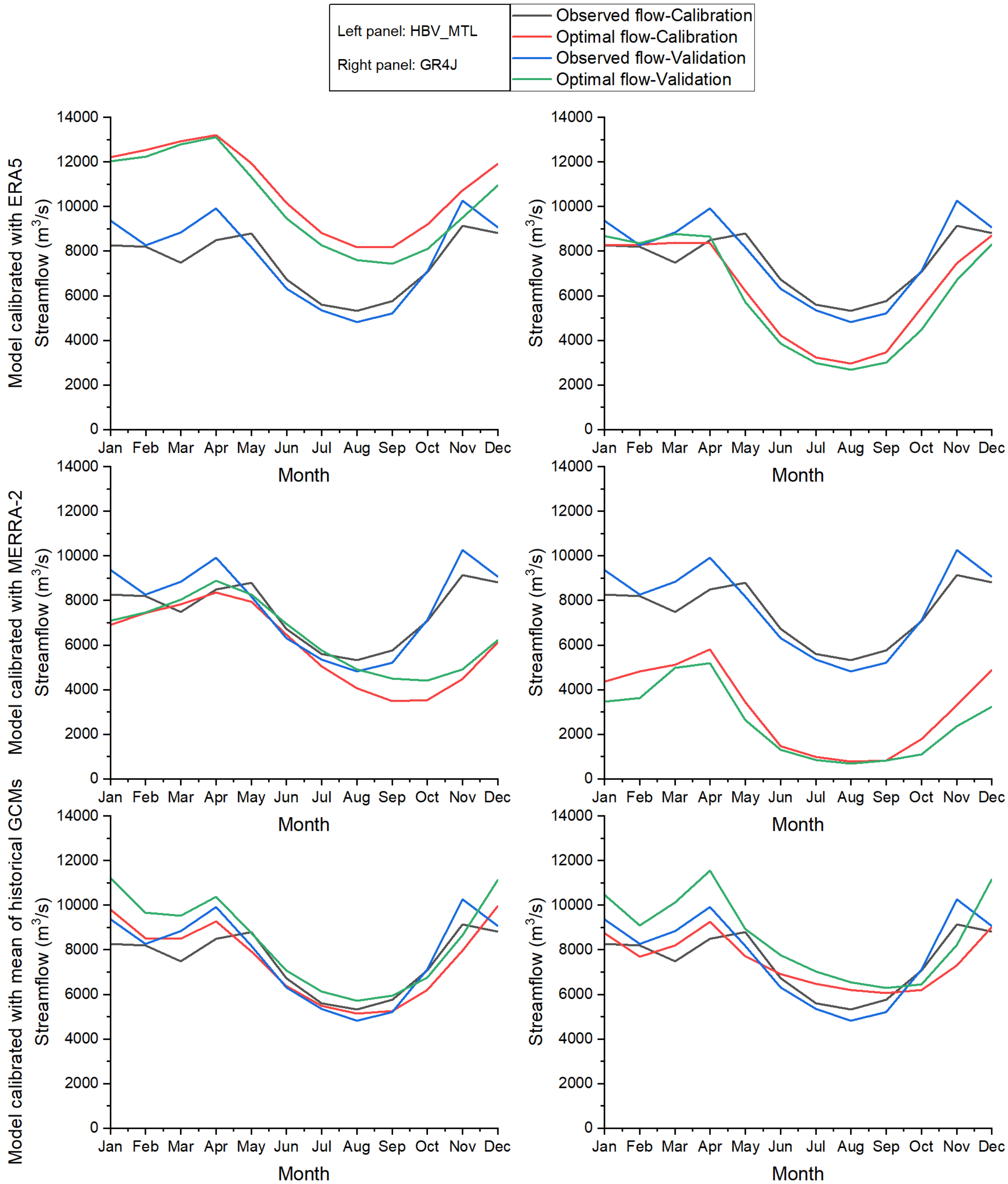

Figure 4.10 Long-term annual hydrograph observation and simulation at the outlet using reanalysis datasets with HBV-MTL (left) and GR4J (right) models.

4.4.2 Streamflow conditions under GCM projections of changing climate

To estimate streamflow at the LRB outlet for future horizons, 19 GCMs under SSP245 and SSP585 were respectively forced into the calibrated hydrological models according to the scenarios. The observed and projected interannual hydrographs using HBV-MTL as presented in Figure 4.11 revealed changes in peak timing and seasonality, as well as an overall increase in the magnitude of runoff across all model configurations. The increase is more pronounced under SSP585 scenario.

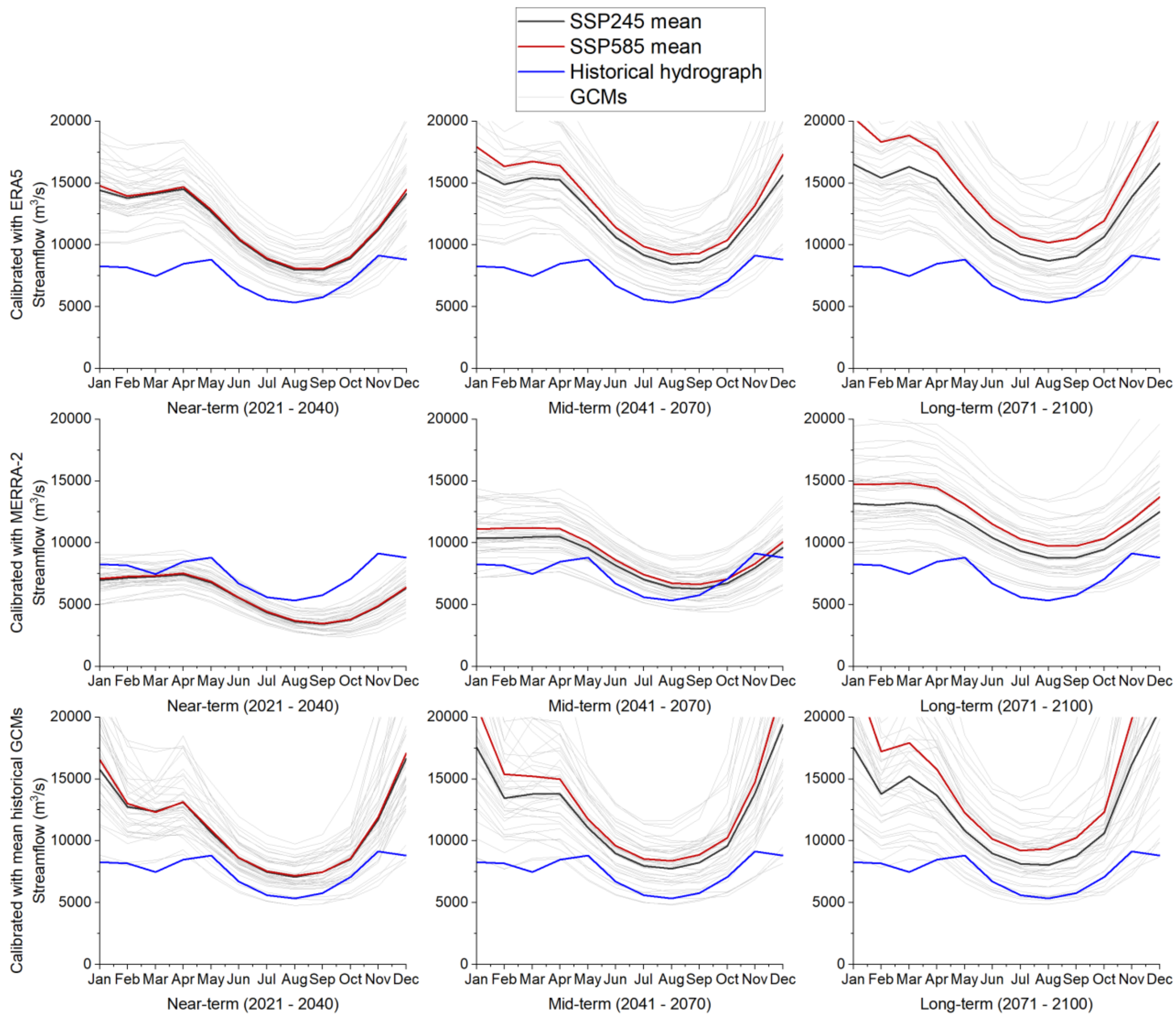

Figure 4.11 Mean annual hydrograph at LRB outlet under SSP245 and SSP585 using HBV-MTL model calibrated with ERA5, MERRA-2, and GCMs.

ERA5-based models revealed a general increase in annual discharge under SSP245 and SSP585 compared to the long-term historical hydrograph across all future horizons. GCMs-based models also displayed an increase in discharge across future time periods. MERRA-2-based models showed a decline in discharge compared to the long-term historical hydrograph for the near future, followed by an increase in the mid to long term future.

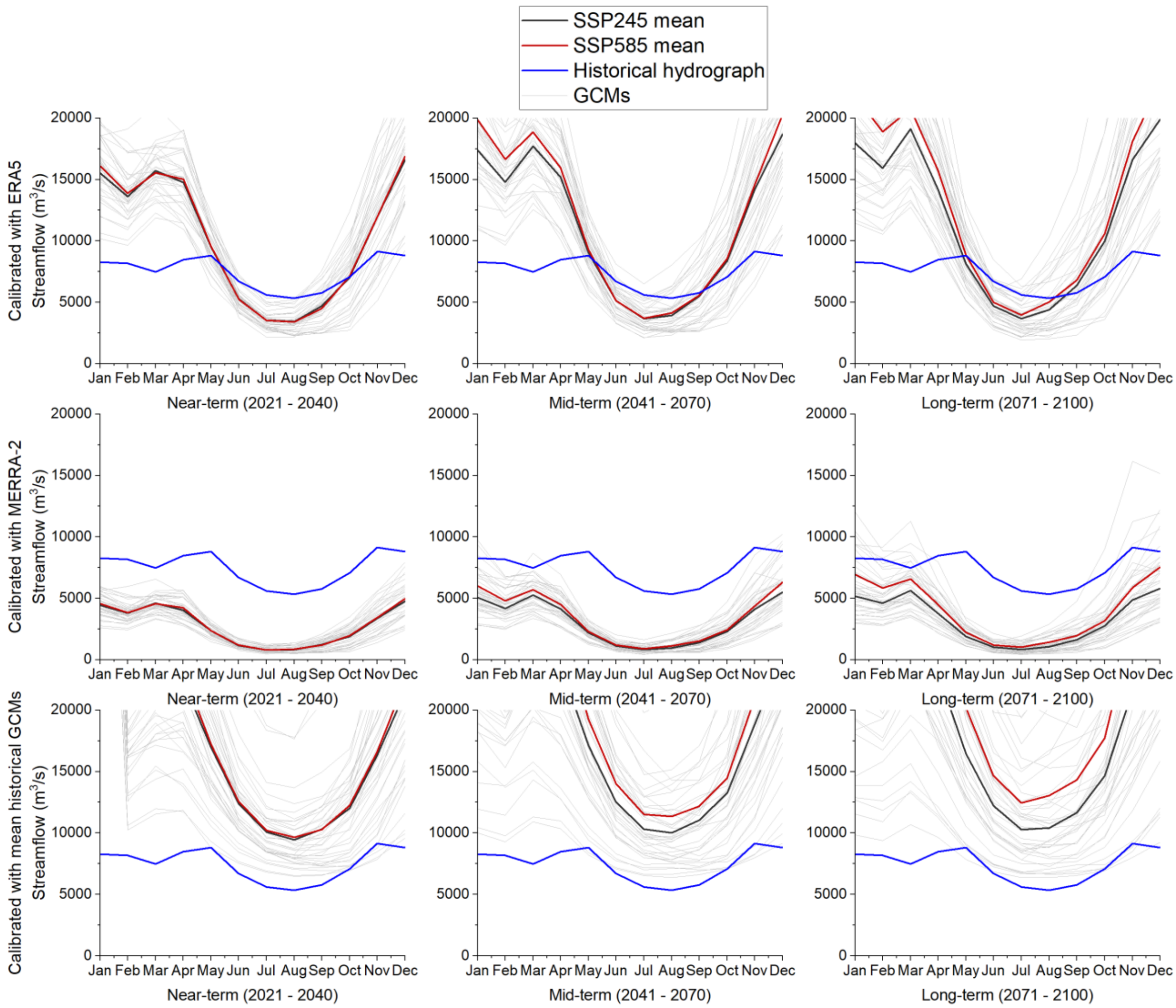

Figure 4.12 Mean annual hydrograph at LRB outlet under SSP245 and SSP585 using GR4J model calibrated with ERA5, MERRA-2, and GCMs.

The observed and projected interannual hydrograph with GR4J models are presented in Figure 4.12. Similar to the projections with HBV-MTL, the hydrographs revealed changes in peak timing and seasonality. However, these patterns differ in high and low flows, which are accentuated in this case. Overall, the annual hydrographs indicated an increase in discharge across future horizons for ERA5 and GCMs configurations, with more pronounced increase under SSP585. MERRA-2 configurations, however, revealed a decrease in discharge compared to the long-term historical hydrographs across all future horizons, where the difference between SSP245 and SSP585 remained more pronounced in the long-term, especially for periods for high flow.

A better understanding of the runoff conditions in the future is provided by analysing the changes in 90th, 50th, and 10th flow percentiles. Thus, observed and simulated annual flow duration curves (i.e., empirical cumulative probability distributions of runoff in each year) were analyzed for historical and future periods. Figure 4.13 and Figure 4.14 illustrate the variability in projected changes in streamflow quantiles under the SSPs scenarios and future time periods, for HBV-MTL and GR4J models, respectively.

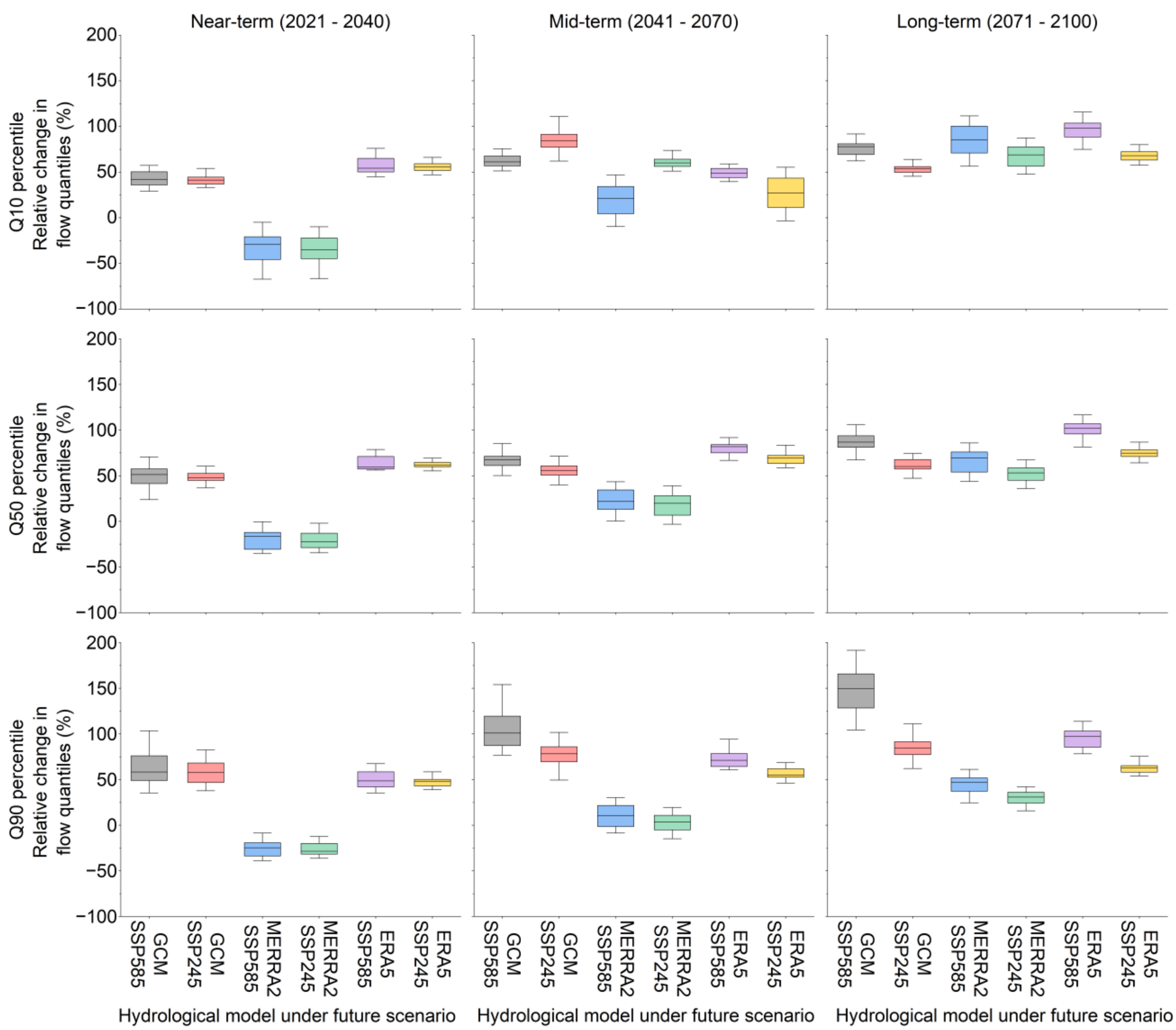

Figure 4.13 Relative changes between simulated annual streamflow quantiles under SSP245 and SSP585 according to the outputs of 19 GCMs projections using HBV-MTL.

Streamflow values were averaged over the historical period to calculate the long-term historical interannual quantiles. Similarly, based on the outputs of SSP245 and SSP585 scenarios, with an ensemble of 19 GCMs, the long-term projected interannual quantiles were calculated for six hydrological model configurations.

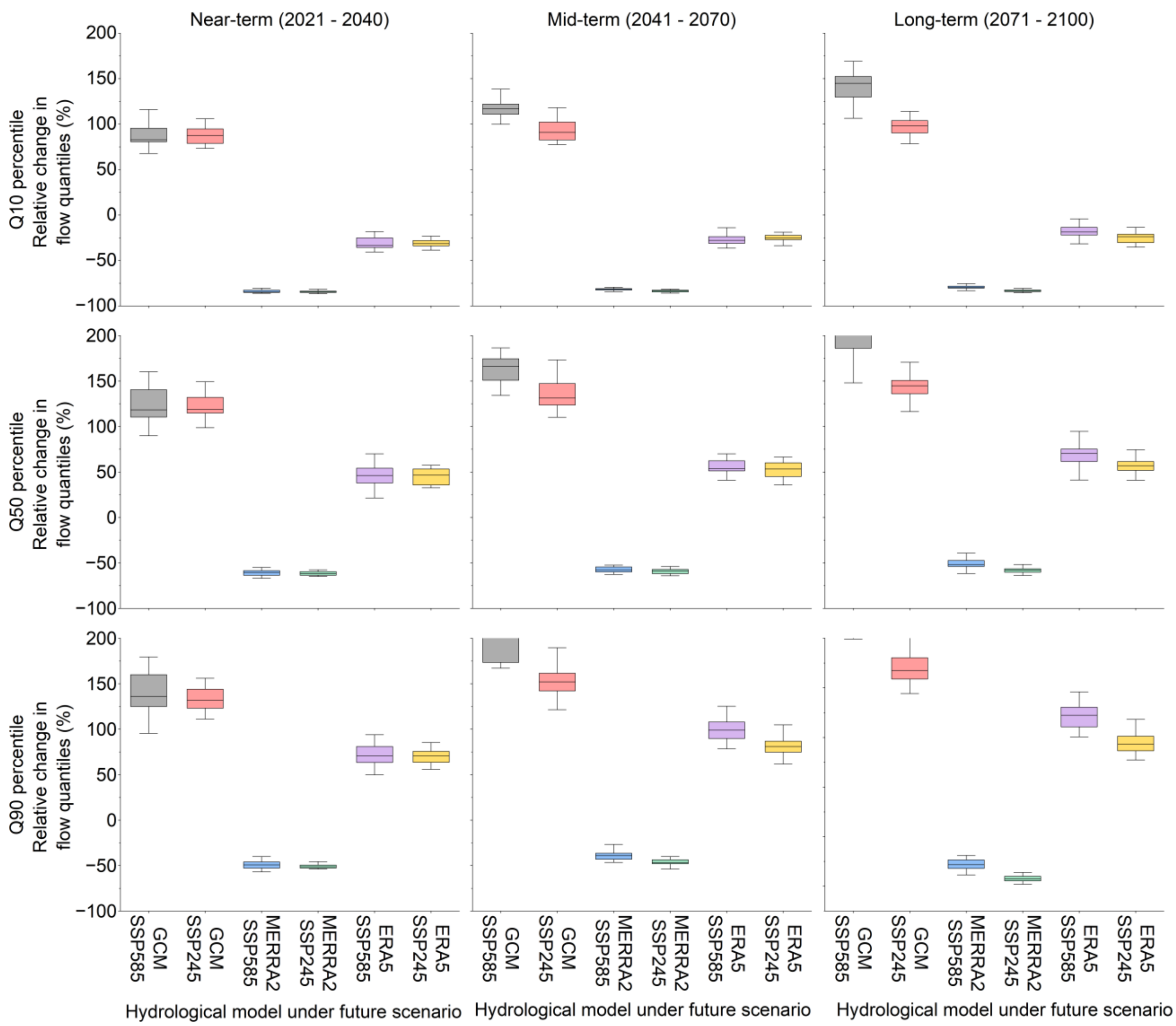

Figure 4.14 Relative changes between simulated annual streamflow quantiles under SSP245 and SSP585 according to the outputs of 19 GCMs projections using GR4J.

The magnitude and direction of relative change in annual flow quantiles varies depending on model configuration and considered future horizon. An overall increase in interannual quantiles for low, median, and high flows was found across all projected time horizons for HBV-MTL and GR4J models, at the exception of the GR4J-MERRA-2 and GR4J-ERA5. In comparison to historical annual flow quantiles, the HBV-MTL models calibrated with MERRA-2, as shown in Figure 4.13, projected a nuanced trend. Specifically, there was an initial decline in Q10, Q50, and Q90 during the near term (2021 – 2040). This decline is followed by a slight increase during the mid-term (2041 – 2070), which then transitions into a more significant rise in long-term (2071 – 2100). These projections indicate that while the near-term may experience reduced streamflow, the latter half of the century could see substantial increases in low, median, and high flows. Conversely, under the ERA5 and GCMs configurations, the HBV-MTL models revealed a consistent increase in annual flow quantiles Q10, Q50, and Q90 across all future periods.

For the GR4J models calibrated with ERA5, as depicted in Figure 4.14, there was a clear pattern where the low flow (Q10) was projected to decrease across all future horizons. In contrast, both the mid flow (Q50) and high flow (Q90) were projected to increase. This potential shift in variability could imply more pronounced extremes runoff events. GR4J models that were calibrated with MERRA-2 projected a decrease in annual flow quantiles Q10, Q50, and Q90 throughout future horizons. Models calibrated with historical GCMs, however, projected a considerable increase in Q10, Q50, and Q9. The increase was observed particularly during the near term (2021 – 2040).

The Mann-Kendall trend test is a nonparametric method often used in climate change impacts assessments (Mann, 1945; Ojo & Ilunga, 2018). This method was applied to analyze trends in annual flow quantiles and determine their significance for future projections. The summary test results of expected future annual Q10, Q50, and Q90 values for all model configurations are presented in Table S.2 of the supplementary materials. The Mann-Kendall trend analysis revealed an increasing trend across all model configurations under both SSP245 and SSP585. Figure 4.15 Highlights trends in projected future high flows (Q90) under SSPs scenarios with respect to specific model configurations. The analysis revealed a significant increasing trend in high flow across all models for both SSP245 and SSP585 scenarios. Notably, the increasing trend was more pronounced under the SSP585 scenario compared to SSP245. Similar trends were observed for projected low flow (Q10) and median flow (Q50) as shown in Figure S.1 and Figure S.2 of the supplementary materials, respectively. Similarly, Figure S.1 and Figure S.2 in the supplementary materials illustrate trends in projected low flow (Q10) and median flow (Q50), respectively. Overall, the results from the Mann-Kendall trend analysis provide strong evidence of significant increases across annual flow quantiles under future climate scenarios.

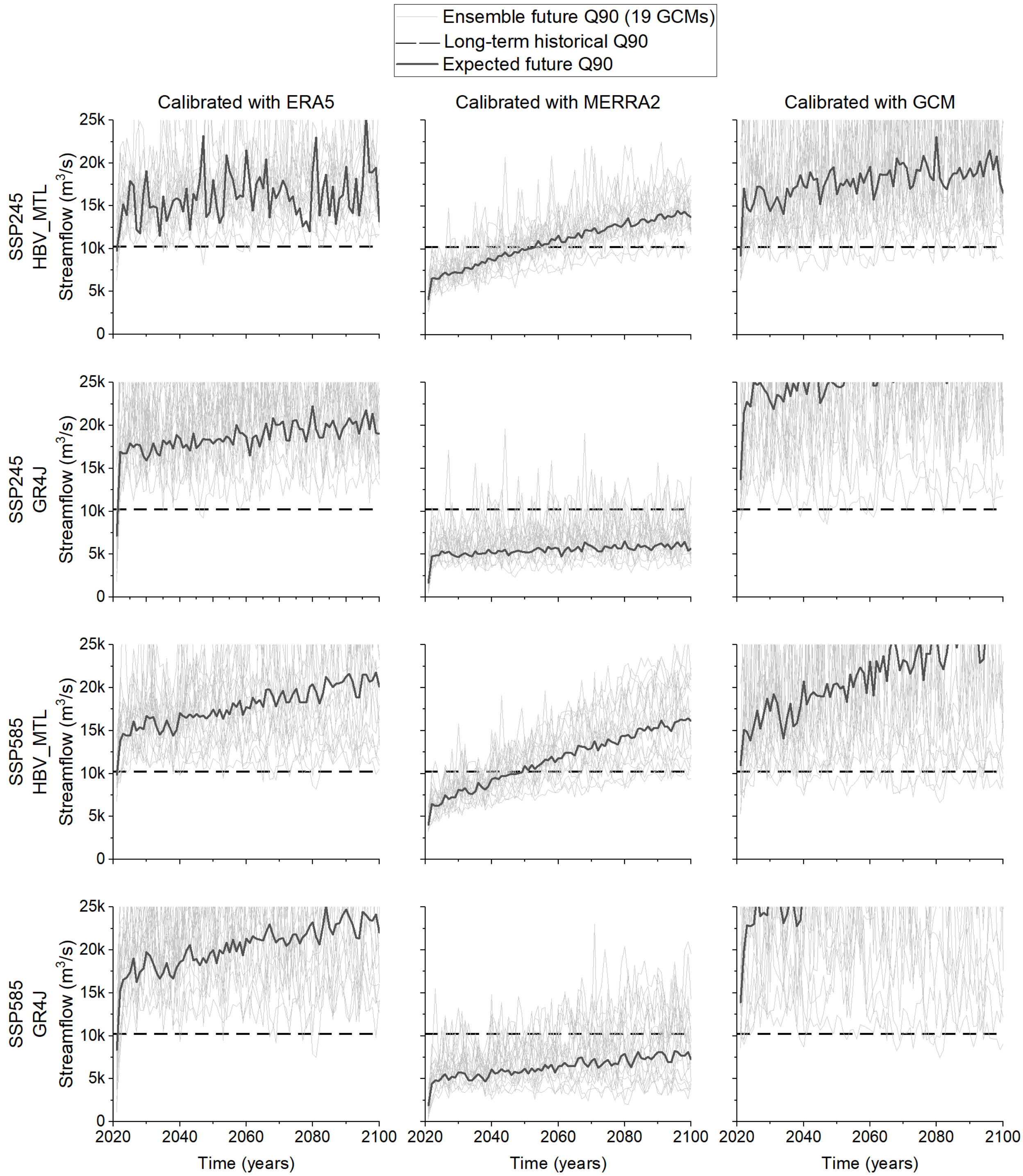

Figure 4.15 Ensemble and expected future values of annual Q90 under SSP245 and SSP585 based on calibrated HBV-MTL and GR4J models using ERA5, MERRA-2 and GCMs reanalyses.

4.5 Discussions and conclusions

This study has assessed the possible impacts of climate change on streamflow characteristics using a multi-model framework over the LRB, an important watershed in the Congo River Basin, Central Africa. For this purpose, two conceptual hydrological models, HBV-MTL and GR4J, were calibrated using two reanalysis products, as well as an ensemble of historical GCMs. Subsequent to the calibration, the hydrological models were fed with downscaled bias-corrected outputs from 19 GCMs under two shared socioeconomic Pathways, SSP245 and SSP585.

Results demonstrate that both hydrological models can simulate the observed runoff in the LRB with acceptable performance. The thresholds considered were demystified in several studies across the overarching CRB (Aloysius & Saiers, 2017; Tshimanga et al., 2011). The KGE values indicated that all 6 configurations of hydrological models based on reanalysis and historical GCMs performed better than their calibrated counterparts that used gauge observations as input data. Such results align with other researcher in demonstrating that the superior performance of hydrological models calibrated with reanalysis products underscores the importance of incorporating an ensemble of data approach into hydrological modeling to improve performance (Dos Santos et al., 2022; Essou et al., 2016; Fuka et al., 2014). Calibration results during the historical period (1981-2001) indicate that the performance of hydrological models is sensitive to the choice of reanalysis dataset and hydrological model structure. The results are consistent with related research (Aloysius & Saiers, 2017; Dakhlaoui et al., 2017; Osuch et al., 2015; Tshimanga et al., 2011) that highlight the importance of using high quality input data along with suitable model structure to achieve satisfactory calibration. Considering annual and daily time series, models that were calibrated with the historical ensemble of GCMs performed better than the others.

Streamflow projections under the SSP245 and SSP585 scenarios provide valuable information on the hydrological response to climate change in the LRB. Overall, the projected simulations under climate change scenarios indicate that runoff is expected to increase with a change in peak timing and seasonality. However, the expected change in magnitude of future annual hydrographs depends on the considered hydrological model configuration. The projected runoff increase is more pronounced under the SSP585 scenario. Based on a comparison between observed and future values, changes in mean annual discharge at the outlet of the LRB are estimated to range from 45% to 62%. Considering the shift in peak timing and seasonality, across model configurations, results suggest a shorter high flow cycle, revealed by earlier peak during March-April-May (MAM) and late peak during September-October-November (SON). These results imply a likelihood of extreme runoff events occurrence in the future. Other studies within the CRB concurred with these findings (Aloysius & Saiers, 2017; Arnell & Gosling, 2013; Beyene et al., 2012; Bola et al., 2022; Nago & Krott, 2020). According to Aloysius and Saiers (2017), decrease in rainfall in the southern headwater areas of the CRB have resulted in prolonged periods of low flow in comparison to the reference period of 1986-2005 and a 10.4% runoff increase was observed over the southwest region under high emission scenarios from 2046 to 2065.

Projected changes in annual flow quantiles (Q10, Q50, Q90) further elucidate the hydrological conditions in response to climate change in the LRB. While an overall increase in annual quantiles was observed based on all model configurations, the magnitude and sign varied among each configuration. The analysis revealed that Q10 is projected to increase by 33% and 44% under SSP245 and SSP585, respectively. These projections suggest a significant rise in low flow conditions, potentially reducing the frequency of extreme low-flow events and improving water availability during dry periods. Similarly, Q50 is projected to increase by 32% under SSP245 and 44% under SSP585. The rise in Q50 implies an uptick in median streamflow, pointing to improved water availability, which could be advantageous for both human needs and the environment. Lastly, Q90 is projected to increase by 56% and 80% under SSP245 and SSP585, respectively. The considerable increase in Q90 indicates a likelihood of more frequent high flow occurrences, which raises the threat of flooding. This projection underscores the need for flood control measures and strategies to safeguard both communities and infrastructure in the LRB.

The expected increase in flow underscores the importance of adaptive water management strategies. Such strategies should account for water storage capacity to guarantee a supply in times of low flow and effective flood protection measures to mitigate the impact of extreme flow events. Considering the environment, these projections may or may not be beneficial for the ecosystem and its habitats, highlighting the need for ecosystem-based management strategies that cater to species and habitats. Ultimately, the different hydrological responses under climate scenarios and models underscores the significance of multi-model approach to guide water management decisions. This method ensures that management strategies can adapt to a range of possible conditions, ultimately enhancing the resilience against climate change.

This study builds upon an existing multi-model assessment of climate change impact in the Congo River Basin. It highlights the importance of hydrological models' structure and the input data used to forecast streamflow in historical contexts and future climate projections. Future research may broaden the investigation by including additional reanalysis products and hydrological models, as well as investigating better representation of catchments (both lumped and semi-distributed models). Incorporating high-resolution regional climate models (RCMs) to capture local-scale climatic variations could improve the performance of hydrological models and help identify localized impacts of climate change on streamflow. Using long-term, high-quality observational data in addition to integrating advance techniques such as machine learning and data assimilation to enhance hydrological model performance and predictive accuracy. Investigations of the sensitivity of hydrological models to different climate data inputs, parameterization, and assumptions could help identify critical factors that influence model outcomes and guide efforts to reduce uncertainties. Exploration of the impacts of climate change on hydrological extremes is suggested, such as detailed studies on the frequency, intensity, and duration of floods and droughts. Better insights could be gained into the challenges facing future water resources by incorporating field data and taking into account socio economic aspects such as population growth and increasing water needs into a holistic approach.

Given the transboundary nature of the LRB, future research should explore collaborative water management approaches, including the development of frameworks for data sharing, joint modelling effort, and coordinated adaptation strategies. Furthermore, investigate potential geopolitical and social implication of hydrological changes, such as water allocation conflicts and the impacts on livelihood and food security. High-quality, long-term database are essential for validating hydrological models and detecting hydrological patterns over time; therefore, it is a necessity to establish and maintain monitoring programs for the collection of continuous data on streamflow, precipitation, temperature, and other relevant variables.

By focusing on high-resolution climate models, improved hydrological modeling, integrated scenarios, extreme events analysis, ecosystem impacts, transboundary water management, and long-term monitoring, future research can provide critical insights and tools to support sustainable water resource management and climate adaptation in the region. These efforts will help ensure the resilience of the LRB's water systems and the communities that depend on them.

4.6 Supplementary materials

Table S.1 Validation performance of HBV-MTL and GR4J models.

Criteria	**Gauge observation**	**ERA5**		**MERRA-2**		**GCM**	
	GR4J	HBV-MTL	GR4J	HBV-MTL	GR4J	HBV-MTL	GR4J
Kling-Gupta efficiency	-0.14	0.58	0.67	0.32	0.12	0.62	0.54
Nash-Sutcliffe efficiency	-3.31	-0.58	-0.02	-0.43	-4.88	0.34	0.16
Pearson correlation	0.00	0.55	0.61	0.13	0.20	0.45	0.35
Relative Bias	-0.27	0.32	-0.22	-0.17	-0.67	0.09	0.12

Table S.2 Mann-Kendall summary trend analysis results for annual Q10, Q50, and Q90 based on ERA5, MERRA-2, and GCMs under SSP245 and SSP585.

Reanalyses	**SSPs**	**Criteria**	**HBV-MTL**			**GR4J**		
			q10	**q50**	**q90**	**q10**	**q50**	**q90**
ERA5	SSP245	P-value	2.9E-11	1.3E-12	2.5E-14	4.6E-06	6.6E-07	2.2E-14
		Trend	increase	increase	increase	increase	increase	increase
		Slope	1.3E+01	1.9E+01	2.8E+01	7.3E+00	2.0E+01	4.6E+01
		Intercept	8.0E+03	1.2E+04	1.5E+04	3.5E+03	1.1E+04	1.7E+04
	SSP585	P-value	0.0E+00	0.0E+00	0.0E+00	3.8E-11	1.7E-09	0.0E+00
		Trend	increase	increase	increase	increase	increase	increase
		Slope	3.7E+01	4.9E+01	8.8E+01	1.3E+01	3.1E+01	9.3E+01
		Intercept	7.8E+03	1.2E+04	1.4E+04	3.5E+03	1.0E+04	1.7E+04

Table S.2 Mann-Kendall summary trend analysis results for annual Q10, Q50, and Q90 based on ERA5, MERRA-2, and GCMs under SSP245 and SSP585 (continued).

Reanalyses	SSPs	Criteria	HBV-MTL			GR4J		
			q10	q50	q90	q10	q50	q90
MERRA-2	SSP245	P-value	9.71E-01	9.61E-01	**9.25E-01**	4.97E-14	6.8E-13	0.0E+00
		Trend	increase	increase	increase	increase	increase	increase
		Slope	9.4E+01	9.8E+01	1.0E+02	1.3E+00	5.3E+00	1.6E+01
		Intercept	3.2E+03	5.5E+03	7.1E+03	8.1E+02	2.9E+03	4.9E+03
	SSP585	P-value	0.0E+00	0.0E+00	0.0E+00	5.0E-14	6.8E-13	0.0E+00
		Trend	increase	increase	increase	increase	increase	increase
		Slope	1.1E+02	1.2E+02	1.3E+02	4.2E+00	1.3E+01	4.1E+01
		Intercept	2.9E+03	5.3E+03	6.8E+03	8.2E+02	2.7E+03	4.8E+03
GCMs	SSP245	P-value	1.0E-13	6.5E-12	9.9E-10	4.9E-05	1.7E-07	1.6E-14
		Trend	increase	increase	increase	increase	increase	increase
		Slope	1.3E+01	2.0E+01	5.0E+01	1.2E+01	3.2E+01	7.1E+01
		Intercept	7.3E+03	1.1E+04	1.6E+04	9.7E+03	1.6E+04	2.3E+04
	SSP585	P-value	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00
		Trend	increase	increase	increase	increase	increase	increase
		Slope	3.2E+01	5.1E+01	1.6E+02	5.1E+01	1.0E+02	2.0E+02
		Intercept	7.2E+03	1.1E+04	1.5E+04	9.5E+03	1.6E+04	2.3E+04

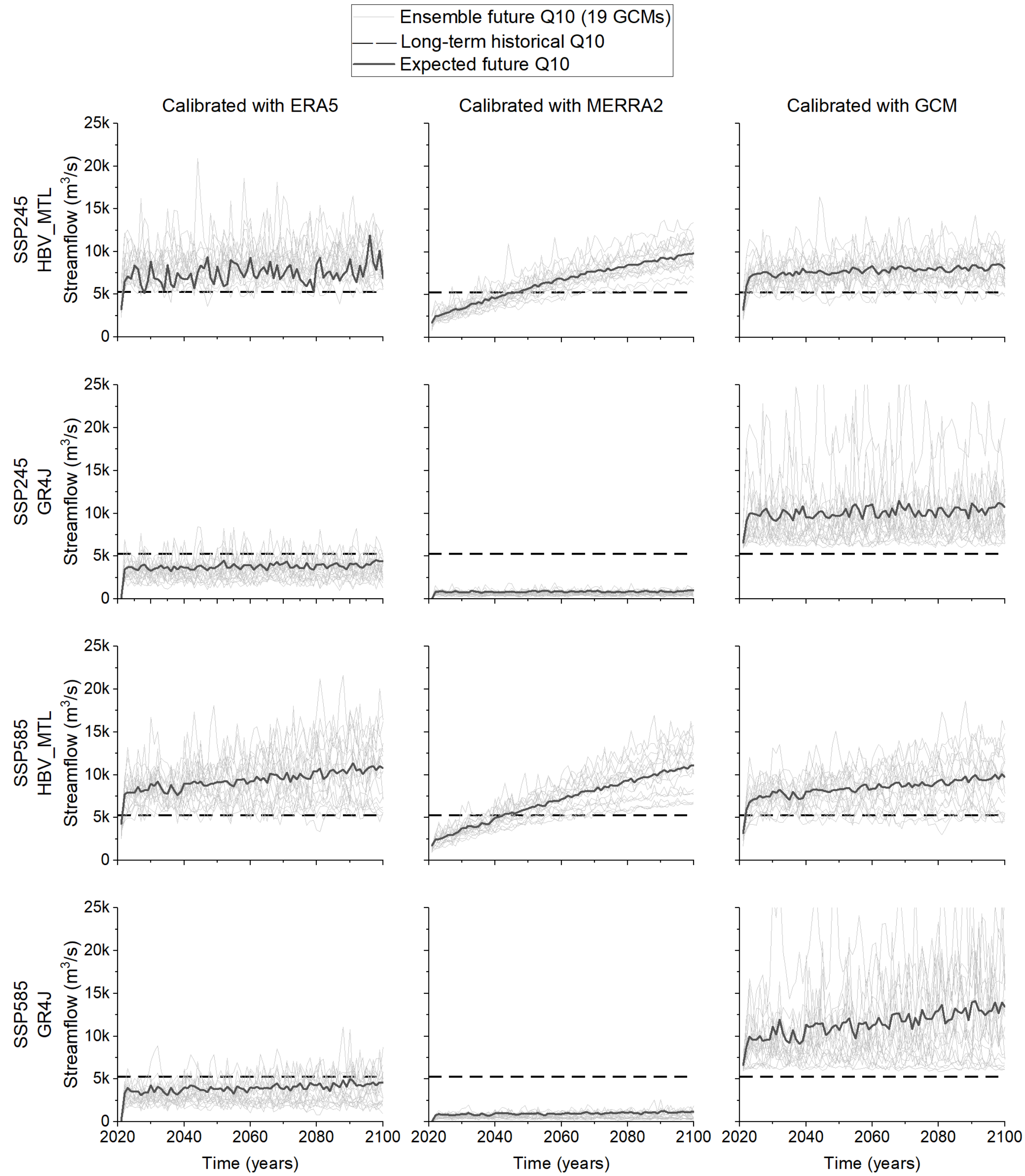

Figure S.1 Ensemble and expected future values of annual Q10 under SSP245 and SSP585 based on calibrated HBV-MTL and GR4J models using ERA5, MERRA-2 and GCMs reanalyses.

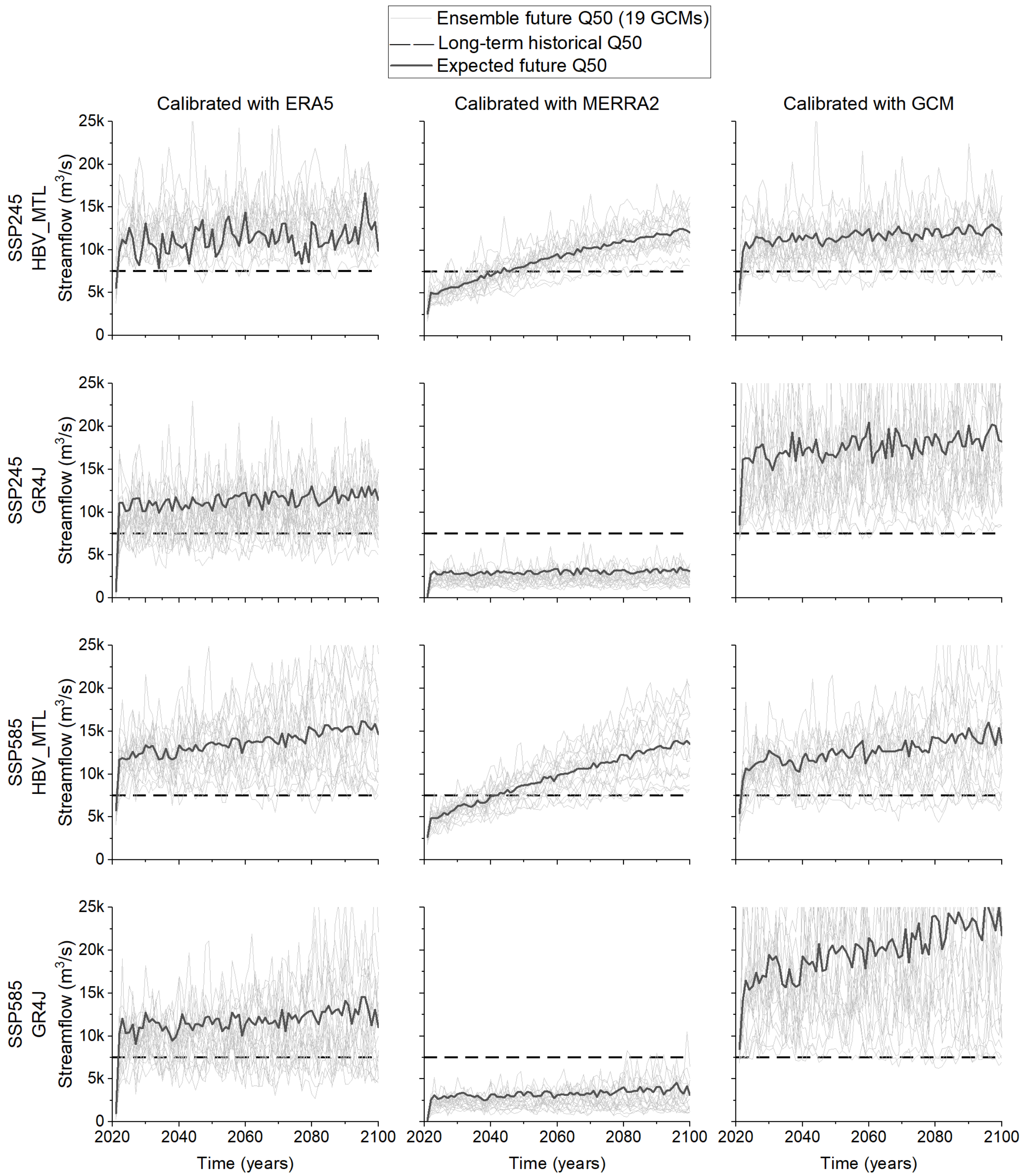

Figure S.2 Ensemble and expected future values of annual Q50 under SSP245 and SSP585 based on calibrated HBV-MTL and GR4J models using ERA5, MERRA-2 and GCMs reanalyses.

Author Contributions

Conceptualization, M.F. and E.H.; methodology, S.M. and E.H.; formal analysis, S.M.; data curation, S.M.; writing—original draft preparation, S.M.; writing—review and editing, S.M., M.F. and E.H.; visualization, S.M.; supervision, M.F. and E.H.; project administration, M.F. All authors have read and agreed to the published version of the manuscript

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Data Availability Statement

The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding authors.

Conflicts of Interest

The authors declare no conflicts of interest.

CHAPTER 5 GENERAL DISCUSSION

The challenges of hydrological modeling in the Congo River Basin include data availability and the intricate nature of hydrological processes in the area, aggravated by the scarcity of measurement stations and inconsistent observational data (Bultot, 1971; Laraque, Moukandi N'kaya, et al., 2020). Researchers often employ datasets such as reanalysis and satellite derived data to bridge these data gaps (Beighley et al., 2011; Hua et al., 2019a; Munzimi, 2019). For instance, the use of satellite derived rainfall information in developing runoff estimation models like the USGS GeoSFM (Munzimi, 2019). To enhance comprehension of hydrological processes scientists are improving models to better capture the hydrology of river basins, particularly the role wetlands and lakes (Beighley et al., 2011). New modeling techniques like the river model LISFLOOD FP by Kabuya et al. (2020) are showing potential in refining parameters estimation and representing hydrological responses accurately.

The effects of climate change on water systems have received attention, as seen in research by Aloysius and Saiers (2017) who utilized the SWAT to predict hydrological conditions under different climate scenarios. Their results indicate differences in runoff patterns among sub basins underscoring the importance of conducting assessments tailored to specific regions. Similarly, Sidibe et al. (2020) pointed out uncertainties in forecasting discharge rates due to variations in climate models. Research on hydropower potential in the CRB suggest that future hydropower capacity may decrease due to climate change (SDG, 2021) and that considering FDCs in the design and planification of hydropower plants (Vogel & Fennessey, 1995) is key to understanding the effects of streamflow variability on energy production. However, relying on a single hydrological model may lead to inaccurate forecasts, highlighting the significance of ensemble modeling approaches (Christensen & Lettenmaier, 2007). The Climate Service Centre project from 2013 (Haensler et al., 2013) and various other research studies by Falchetta et al. (2019) and Schaefli (2015) suggested using ensemble model approaches to assess the effects of climate change. This research further emphasizes the importance of multi-model frameworks to effectively address the uncertainties and intricacies present in hydrological and climate systems.

The methodology and case study of this research distinguish it from other significant research conducted in the CRB, particularly the studies by Salumu (2023) and Lesani (2022). Salumu (2023) contributed to the understanding of climate change impact on river runoff for the CRB, with a particular emphasis on the semi-distributed representation of the CRB. His work highlighted the challenges of using reanalyses products and GCMs output to simulate hydrological processes for each sub-watershed of the CRB. The study employed a semi-parametric regression model in conjunction with traditional HEC-HMS and GR4J hydrological models to improve discharge calculations, particularly in the context of hydraulic infrastructure design. The regression model was developed to capture the complex relationship between various factors, such as water level and flow velocity, and river discharge. This model was designed to ensure the reliability of the rating curve used for discharge calculations, while a simultaneous discharge measurement campaign was conducted from June to August 2019 at the Kinshasa station on the Congo River. The results of this method emphasized the non-linear dependence between the factors and river discharge, highlighting the effectiveness of the semi-parametric regression model in improving discharge calculations (Salumu, 2023).

In contrast, the present study provides a more comprehensive examination of the LRB's unique hydrological dynamics, utilising the Shuffled Complex Evolution (SCE-UA) algorithm to calibrate and optimise parameter sets for the HBV-MTL and GR4J hydrological models. This algorithm combines random, deterministic, clustering, and competitive evolution strategies, allowing the calibration process to explore a broader range of potential solutions, increasing the likelihood of finding an optimal set of parameters. Compared to simpler or less integrated calibration methods, the SCE-UA approach provides a more robust framework for handling the complexities and uncertainties inherent in hydrological modeling, particularly in data-scarce regions like the LRB. This robustness directly contributes to the improved reliability and depth of insights gained from the simulations.

On the other hand, Lesani (2022) applied the multi-model approach on the Kasai River Basin (KARB), another major sub-watershed of the CRB, to evaluate the impacts of climate change on streamflow regimes and hydropower potential. The KARB has different hydrological characteristics and challenges compared to the LRB. While both studies employed similar hydrological models (HBV-MTL and GR4J), this study introduced the latest generation of climate models (CMIP6) to the LRB, integrating high-resolution GCMs under SSP245 and SSP585 scenarios. In Lesani (2022), the RCPs from the previous generation of climate models (CMIP5) outline possible trajectories of changes in greenhouse gas and aerosol levels in the atmosphere, as well as shifts in radiative forcing over time (Miao et al., 2014; Ul Hasson et al., 2016). In contrast, the SSPs utilised in this study provide narrative descriptions of societal evolution over the next century, assuming no additional climate policies are enacted (Kebede et al., 2018). Although they do not directly quantify measures taken for climate change adaptation or mitigation, they illustrate the challenges and progress related to implementing such strategies, considering factors such as population growth, regional collaboration, and technological advancements (Tebaldi et al., 2021). This approach provides a more nuanced and up-to-date understanding of potential shifts in streamflow patterns, peak timing, and average interannual flow quantiles in the LRB, thereby offering critical insights that are essential for effective water resource management in the region.

Rapid changes in climate conditions are altering the hydrological cycle in the Lualaba River Basin and exerting pressure on current regional water management and allocation plans. A multi-model framework was employed for assessing vulnerabilities of the LRB affected by shifts in climate patterns. The hydrological response was sensitive to numerical models, historical climatic data used for calibration, and climate projections. Based on multi-models instead of single-model approach, the results emphasized the significance of choosing an ensemble of climate projections and historical input data while fine tuning hydrological models. A significant finding was the inconsistencies in reanalysis products with regards to capturing rainfall fluctuations over the LRB, which is consistent with related studies carried out in Central Africa (Abdrabo et al., 2014; Aloysius & Saiers, 2017; Ghebrehiwot & Kozlov, 2021). These discrepancies underscore the difficulties in accurately predicting future hydrological conditions. The variations in projected streamflow conditions between two SSPs scenarios also demonstrate the sensitivity of streamflow projections to shared socioeconomic pathways. Overall uncertainty was addressed by considering projections from 19 GCMs across two shared socioeconomic pathways reducing errors by averaging of results from an ensemble of models.

Based on the findings, multiple hydrological models calibrated with two reanalysis datasets and an ensemble of historical GCMs rather than a single model, may improve the robustness of assessments by portraying a broader range of probable watershed conditions. This approach strengthened the reliability of forecasts by encompassing a spectrum of potential hydrological formulations. Even though ensembles of hydrological parameter sets were not obtained during the calibration the hydrological models, optimal parameter sets led to a satisfactory estimation of uncertainties in simulations. Compared to a deterministic calibration approach, such technique may reduce misleading streamflow projections while improving understanding of uncertainties in simulations. Nevertheless, estimations of low, median, and high flows were dependent on the structure of the hydrological models. For instance, the simulated Q10, Q50, and Q90 by HBV-MTL models were in accordance regardless of the historical input reanalysis used for calibrations, in comparison to GR4J models. In the long-term (2071-2100), HBV-MTL models projected a significant increase in streamflow signatures regardless of historical input data and future shared socioeconomic Pathways, while the outputs of GR4J models varied such as streamflow signatures were projected to decrease based on MERRA-2 configuration.

By referencing the detailed calibration parameters provided in the appendices, this study ensures that the models are calibrated in transparent manner and provides a clear understanding of the complex hydrological processes in the LRB. Appendix A provides an in-depth description of the HBV-MTL model that was adapted to simulate hydrological processes such as infiltration, soil moisture dynamics, and groundwater flow. Key physical parameters such as the percolation coefficient and the soil moisture coefficient were calibrated to reproduce the specific hydrological characteristics of the watershed, ensuring that the model accurately represents groundwater recharge and infiltration processes for the LRB. Appendix B describes the GR4J model and its parameters, which was calibrated in a similar manner to the HBV-MTL for capturing the interactions between precipitation, evapotranspiration, soil moisture, and groundwater within the LRB. Specifically, the maximum production storage and the routing storage capacity were fine-tuned during the calibration process to ensure that the model accurately simulate the storage and release of water in the soil and subsurface layers that are essential for predicting runoff in the LRB. The calibration results, detailed in Appendix C, revealed the variability in model performance depending on the choice of model structure and reanalysis datasets. For instance, the soil moisture capacity and the potential evapotranspiration (ET) coefficient showed significant variation across different datasets, with the ET coefficient ranging from 0.20 to 0.90 depending on the reanalysis product used. These differences highlight the sensitivity of the models to the input data and underscore the importance of precise parameter calibration, particularly in tropical regions where evapotranspiration plays a crucial role in the hydrological cycle.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS

The LRB is well known for its considerable freshwater resources, fostering development opportunities for sustainable growth across various sectors like energy, transportation, fishing, agriculture, manufacturing and tourism in Central Africa. However, the looming threat of climate change affects this natural resource and the surrounding ecosystems. Key challenges related to water management in the region include ensuring water access for drinking and sanitation purposes, generating hydropower, promoting irrigation projects, facilitating river transport, and tackling water pollution stemming from operations such as mining activities and agricultural practices. Furthermore, as an element of the growth strategy in the CRB, notably the LRB hydroelectric power generation is influenced by varying river runoff patterns, extreme occurrences and seasonal fluctuations. The LRB area holds importance in prioritizing development along the upper reaches of the Congo River main watercourse. Thus, gaining an understanding of streamflow conditions plays a crucial role in holistic water management that supports sustainable progress in the region. Effectively addressing these concerns necessitates adopting an integrated approach to water resource management amidst shifting climate conditions (von Lossow, 2020).

The top-down approach used in this research combined hydrological models and climate model forecasts of precipitation and temperature to gauge the effects of climate change on future streamflow conditions in the LRB. To address the variations based on the choice of hydrological and climate forecasts models, a multi-model framework was applied, thus reducing uncertainties linked with the structure of hydrological models and GCMs. Two conceptual lumped hydrological models, HBV-MTL and GR4J were considered under this approach, along with 19 downscaled bias-corrected climate model projections, as well as two reanalysis datasets to leverage the observational data scarcity. During the historical period (1981-2001), each hydrological model was calibrated and validated with two reanalysis products and an ensemble of GCMs as climatic input data. Future streamflow at the outlet was methodically simulated by forcing GCMs climatic projections into the calibrated hydrological models. The downscaled bias-corrected outputs of the ensemble of GCMs under both SSP245 and SSP585 shared socioeconomic Pathways were fed into each calibrated hydrological model configuration. Given the significance of parameter uncertainty in hydrological modeling, optimal parameters were derived from a rigorous calibration and uncertainty analysis, ensuring a comprehensive and satisfactory simulation of streamflow projections.

Findings from model calibration with reanalysis products and GCMs in the historical period, conducted between 1981 and 2001, revealed that the hydrological models effectively depicted the daily and annual runoff patterns and adequately captured features of the streamflow regime such as the timing of peak flows and seasonal variations. However, The HBV-MTL and GR4J models returned different levels of performance across datasets, underscoring that the selection of reanalysis products and hydrological model significantly impacts the accuracy and precision of streamflow predictions. The GR4J model returned the best performance under ERA5 configuration, while the ensemble of historical GCMs was the configuration that yielded the best performance for the HBV-MTL model. The KGE metric emphasized these differences by showcasing superior performances with ERA5 and GCMs compared to MERRA-2 respective configurations. The latter model configurations consistently returned lower performance, along with negative NSE values. Nevertheless, these results are consistent with studies (Aloysius & Saiers, 2017; Dakhlaoui et al., 2017; Tshimanga & Hughes, 2014) highlighting the importance of utilizing high quality input data and appropriate hydrological model structures for achieving calibration and validation requirements.

The multi-mode assessment revealed that overall future streamflow projections under SSP245 and SSP585 scenarios provides insights into the hydrological response of the LRB to climate change. Both the HBV-MTL and GR4J models predicted an overall increase in mean annual discharge, especially in the SSP585 scenario. However, the estimated rate of change in runoff depends on the considered modeling configuration. The significant increasing trend in flow signatures hints at a likelihood of extreme streamflow events occurrence, particularly noticeable with the historical GCMs configurations. ERA5-based model configuration consistently predicted a rise in mean annual discharge, for both SSPs scenarios. As for MERRA-2 configuration, models projected a declined in the near term before rebounding over the medium to long term. This variability emphasizes the sensitivity of hydrological models and stresses the significance of integrating multiple data sources to capture a wide range of potential future scenarios.

The analysis of flow quantiles (Q10, Q50, Q90) further clarifies the expected hydrological response. While most model configurations showed an overall increase in interannual quantiles, MERRA-2-based models projected a decline in low and median flows (Q10 and Q50) during the near term, followed by an increase in the mid to long term. This variability emphasized the complex relationship between climatic drivers and hydrological responses, necessitating detailed analyses to inform water resource management strategies. Despite some predictions of streamflow decreases (MERRA-2), the Mann-Kendall trend test showed a rising trend in streamflow from 2021 to 2100, indicating that increasing occurrences of extreme streamflow may offset certain effects of reduced average annual flows. The expected increase in the Lualaba River runoff characteristics highlights the importance of adapting water management strategies, such as to develop plans that improve water storage flood control measures. Furthermore, these results underscore the need for ecosystems-based management plans to address the needs of species and habitats considering both the potential advantages and challenges for the environment.

This research expands upon the existing assessment of climate change impacts in the Congo River Basin while emphasizing the importance of the structure of hydrological models and input data for the assessment of river runoff. Diverse hydrological responses under climate scenarios and numerical models stress the significance of using the multi-model approach in guiding water management decisions. Future studies should incorporate additional sources of reanalysis data and hydrological models, as well as explore various watershed representations, such as lumped and semi distributed approaches. Moreover, integrating high-quality observational data with methodologies to enhance model accuracy and predictive capabilities. Nevertheless, studying the sensitivity of hydrological models to climate data inputs and assumptions to identify factors that affect model outcomes and guide efforts to minimize uncertainties. It is also recommended to conduct research on the effects of climate change on extremes, such as floods, droughts, including their frequency, intensity and duration. Furthermore, to integrate field data and take into account socio economic factors such as population growth and increasing water demand. A collaborative approach to water management should be explored. This includes sharing data and developing adaptation strategies. Additionally, it is important to assess social consequences of hydrological changes, such as conflicts over water allocation, impacts on livelihoods and food security. Building and maintaining databases for collecting streamflow, precipitation, temperature and other pertinent variable. To support sustainable water resource management and climate adaptation in the region, climate models, hydrological modeling techniques, scenarios analysis, ecosystem impacts, and long-term monitoring can provide valuable insights to future research.

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APPENDIX A DESCRIPTION OF THE HBV-MTL MODEL

In this study the HBV MTL model, which is a modified version of the HBV model is used. Precipitation is classified as rainfall, snowfall or a combination of both based on an air temperature threshold (Eq. A.1) (Turcotte et al., 2007). When precipitation falls as snow, the depth of accumulated snow is determined using Eq. A.2. For snowfall, the water equivalent is included in the model as liquid water. The model assumes that snow density is 10% of water density for converting snow into water. Snowmelt is calculated using the degree day method (Seibert & Vis, 2012) taking into account ambient temperature, degree day factor and melting threshold (Eq. A.3). The degree day coefficient can vary between 1.6 to 6 mm/°C depending on watershed characteristics (NRCS, 2009). In some research studies it has been approximated based on air temperature and accumulated snow levels (Bergstroem, 1975). The melting threshold is commonly considered to be zero with consideration, for variations influenced by altitude and catchment characteristics.

The model assumes that melted snow exits the snowpack once the pores are filled with water (Eq. A.4). If air temperature drops below the threshold, retained water in the pores will refreeze, using the same threshold as the snowmelt (Eq. A.5). At the end of the precipitation module, available liquid water is estimated based on rainfall, snowmelt, refrozen water, and water leaving the snowpack (Eq. A.6). In the case of the Lualaba River Basin, located in a tropical region, precipitation is always in the form of rainfall, so snow processes do not occur.

In the next stage, available liquid water either flows over the surface or infiltrates into the soil, depending on soil moisture and temperature. Soil temperature is dynamically estimated at each time step as a function of initial soil temperature, the eleven-day average air temperature, and any available snowpack (Eq. A.7). The modified SCS method is used for infiltration (Neitsch et al., 2011). Based on soil moisture relative to the wilting point, infiltration and runoff amounts are determined, and the soil curve number (CN) is revised (Eq. A.8). In cold regions with frozen soil, the CN is adjusted based on soil saturation and other characteristics (Eq. A.9). Using the revised CN, retention and initial abstraction are calculated (Eq. A.10 and A.11), followed by runoff and infiltration estimates (Eq. A.12 and A.13).

In the soil medium, water absorbed by soil particles contributes to soil moisture (Eq. A.15), while free water infiltrates deeper layers, feeding intermediate and deep groundwater reservoirs (Eq.

A.14). Water in the soil is also utilized by vegetation through evapotranspiration, which affects soil moisture. Actual evapotranspiration is estimated based on potential evapotranspiration and existing soil moisture using Eq. A.16. The Hargreaves and Samani (1985) method is used for estimating potential evapotranspiration due to its minimal data requirements. Soil moisture is dynamically estimated based on evapotranspiration rate and soil moisture recharge (Eq. A.17).

Infiltrated water in deeper soil layers is stored in intermediate and deep soil reservoirs, gradually released as interflow and base flow (Eq. A.18, A.19, and A.20). Water content in these layers is calculated using water balance equations (Eq. A.21 and A.22). The combined flow from interflow, baseflow, and near-surface runoff generates streamflow at the watershed's outlet (Eq. A.23). Flow is routed based on the watershed's physical characteristics using a triangular weighting function to simulate flow at the outlet (Eq. A.24). The total watershed flow is estimated by multiplying the catchment area by the generated flow per unit area (Eq. A.25). All equations are detailed below, and variable and calibration parameters are explained in Table A.1 and Table A.2. The subscript 't' indicates the time step for each variable.

Table A.1 Variables used in HBV-MTL equations.

Variables					
Variable	**Abbreviation**	**Variable**	**Abbreviation**	**Variable**	**Abbreviation**
Precipitation	P_t	Snow cover coefficient	M_t	Actual evapotranspiration	ETA_t
Rainfall	$Rain_t$	Soil moisture	SM_t	Shallow groundwater storage	SS_t
Snowfall	$snow_t$	Soil temperature	ST_t	Interflow	IF_t
Maximum temperature	T_{max}	Soil revised curve number	$CN_{soil,t}$	Baseflow	BF_t
Minimum temperature	T_{min}	Initial abstraction	IA_t	Percolation	$PERC_t$

Table A.1 Variables used in HBV-MTL equations (continued).

Variables					
Variables	**Variables**	**Variables**	**Variables**	**Variables**	**Variables**
Average temperature	$T_{ave,t}$	Soil retention	SR_t	Streamflow	F_t
Accumulated snow	S_{P_t}	Infiltration	I_t	Deep groundwater storage	DS_t
Refrozen water in the snowpack	R_{f_t}	Direct runoff	DR_t	Routed flow	RF_t
Snowmelt	S_{m_t}	Soil moisture recharge	SMR_t	Total flow	TF_t
Retained water in the snow medium	S_{w_t}	Groundwater recharge	GWR_t		
Water output of snow medium	LW_t	Potential evapotranspiration	ETP_t		

Table A.2 Calibration parameters used in HBV-MTL equations.

Calibration parameters					
Parameter	**Abbreviation**	**Parameter**	**Abbreviation**	**Parameter**	**Abbreviation**
Snow gauge correction factor	SCF	Soil curve number	CN	Wet-period interflow coefficient	K_0
Snowfall temperature threshold	$T_{a,thres}$	Soil field capacity	FC	Wet-period threshold	L

Table A.2 Calibration parameters used in HBV-MTL equations (continued).

Calibration parameters					
Parameter	**Abbreviation**	**Parameter**	**Abbreviation**	**Parameter**	**Abbreviation**
Degree-day coefficient	DD	Moisture coefficient	β	Normal interflow coefficient	K_1
Snowmelt temperature threshold	$T_{m,thres}$	Wilting point coefficient	WP	Percolation coefficient	K_p
Snow's retaining capacity coefficient	$Snowcap$	Frozen soil temperature threshold	ST_{thres}	Baseflow coefficient	K_2
Refreeze coefficient	F	Frozen soil coefficient	FSC	Delay length	$delay$

$$\begin{cases} rain_t = P_t; snow = 0 & T_{min,t} \geq T_{a,thres} \\ rain_t = \dfrac{T_{max,t} - T_{a,thres}}{T_{max,t} - T_{min,t}} \times P_t; snow_t = SCF \times (P_t - rain_t); & T_{min,t} < T_{a,thres} AND T_{max,t} > T_{a,thres} \\ rain_t = 0; snow_t = SCF \times P_t & T_{max,t} \leq T_{a,thres} \end{cases}$$

(Eq. A.1)

$$S_{P_{t=T}} = S_{P_{t=t_0}} + \int_{t_0}^{T} (snow_{t=s} + R_{f_{t=s}} - S_{m_{t=s}}) ds \quad \text{(Eq. A.2)}$$

$$S_{m_t} = \min\left(S_{P_{t-1}}, DD \times \max\left(0, T_{ave,t} - T_{m,thres}\right)\right) \quad \text{(Eq. A.3)}$$

$$LW_t = \max\left(0, S_{w_{t-1}} + rain_t + S_{m_t} - R_{f_t} - Snowcap \times S_{p_t}\right) \quad \text{(Eq. A.4)}$$

$$R_{f_t} = \min\left(S_{w_{t-1}}, F \times DD \times \max\left(0, T_{ave,t} - T_{m,thres}\right)\right) \quad \text{(Eq. A.5)}$$

$$S_{w_{t=T}} = S_{w_{t=0}} + \int_{t_0}^{T} (rain_{t=s} + S_{m_{t=s}} - R_{f_{t=s}} - LW_{t=s}) ds \quad \text{(Eq. A.6)}$$

$$ST_t = \left(\overline{T_{ave,t-10:t}} - ST_{t-1}\right) \times M_t + ST_{t-1} \;\; where\; M_t = \begin{cases} 0.1 & S_{P_t} > 0 \\ 0.25 & S_{P_t} = 0 \end{cases} \quad \text{(Eq. A.7)}$$

$$ST_t \leq T_{s,thres}: CN_{soil,t} = \begin{cases} CN - \frac{20\times(100-CN)}{100-CN+\exp(2.533-0.0636\times(100-CN))} & SM_t < WP \times FC \\ CN \times (0.00673 \times (100 - CN)) & SM_t > 0.95 \times FC \\ CN & WP \times FC \leq SM_t \leq 0.95 \times FC \end{cases} \quad \text{(Eq. A.8)}$$

$$ST_t \geq T_{s,thres}: CN_{soil,t} = CN + (100 - CN) \times \min\left(1, \frac{SM_t}{FC}\right)^{FSC} \quad \text{(Eq. A.9)}$$

$$SR_t = 25.4 \times \left(\frac{1000}{CN_{soil,t}} - 10\right) \quad \text{(Eq. A.10)}$$

$$IA_t = 0.2 \times SR_t \quad \text{(Eq. A.11)}$$

$$DR_t = \begin{cases} \frac{(LW_t - IA_t)^2}{LW_t - IA_t + SR_t} & LW_t > IA_t \\ 0 & LW_t \leq IA_t \end{cases} \quad \text{(Eq. A.12)}$$

$$I_t = LW_t - DR_t \quad \text{(Eq. A.13)}$$

$$GWR_t = \left(\frac{SM_{t-1}}{FC}\right)^{\beta} \times I_t \quad \text{(Eq. A.14)}$$

$$SMR_t = I_t - GWR_t \quad \text{(Eq. A.15)}$$

$$ETA_t = ETP_t \times \min(1, SM_{t-1} \times WP) \quad \text{(Eq. A.16)}$$

$$SM_{t=T} = SM_{t=t_0} + \int_{t_0}^{T}(SMR_{t=s} - ETA_{t=s})ds \quad \text{(Eq. A.17)}$$

$$IF_t = K_0 \times \max(0, SS_{t-1} - L) - K_1 \times SS_{t-1} \quad \text{(Eq. A.18)}$$

$$PERC_t = K_p \times SS_{t-1} \quad \text{(Eq. A.19)}$$

$$BF_t = K_2 \times DS_{t-1} \quad \text{(Eq. A.20)}$$

$$SS_{t=T} = SS_{t=t_0} + \int_{t_0}^{T}(GWR_{t=s} - IF_{t=s} - PERC_{t=s})ds \quad \text{(Eq. A.21)}$$

$$DS_{t=T} = DS_{t=t_0} + \int_{t_0}^{T}(PERC_{t=s} - BF_{t=s})ds \quad \text{(Eq. A.22)}$$

$$F_t = DR_t + IF_t + BF_t \quad \text{(Eq. A.23)}$$

$$RF_t = \sum_{i=1}^{N_{delay}} TD(i) \times F_{t-i+1} \; where \;\; TD(i) = \int_{i-1}^{i} \frac{2}{N_{delay}} - \left|x - \frac{N_{delay}}{2}\right| \times \frac{4}{N_{delay}} dx \quad \text{(Eq. A.24)}$$

$$TF_t = RF_t \times Area \quad \text{(Eq. A.25)}$$

APPENDIX B DESCRIPTION OF THE GR4J MODEL

The GR4J model is an enhanced version of the GR3J model (Michel, 1989), proposed by Perrin et al. (2003). This model is a conceptual four-parameter rainfall-runoff model operating on a daily timescale. The primary inputs for this model are precipitation and maximum and minimum air temperatures. As with the HBV model discussed earlier, potential evapotranspiration in this study is estimated using the Hargreaves method (H. Hargreaves & A. Samani, 1985) .

In the initial step, net precipitation and net evapotranspiration are calculated by subtracting potential evapotranspiration from precipitation (Eq. B.1 and B.2). If net precipitation is positive, a portion of it contributes to filling the production storage, which represents the soil layer in this model. This portion is determined by a parabolic function of the water level in the production storage (Eq. B.3, Michel, 1989). The remaining portion directly contributes to surface runoff. For net evapotranspiration, actual evapotranspiration is calculated based on the water level in the production storage (Eq. B.4). The available water content in the production storage is dynamically calculated at each time step, considering the initial water level, actual evapotranspiration, and the portion of net precipitation entering the production storage (Eq. B.5). It is important to note that the water level in the production storage cannot exceed its maximum capacity.

The remaining water in the soil layer (production storage) percolates to the deeper layer, modeled by a power function of the reservoir water content (Eq. B.6). The water content in the production storage is then updated accordingly (Eq. B.7). The percolated water, along with direct runoff, proceeds to the routing stage (Eq. B.8). In the GR4J model, flow routing is simulated using a linear function with two unit hydrographs that account for the time lag between precipitation and streamflow generation. The water reaching the routing storage is split into two components: 90% is routed through a one-sided unit hydrograph and a non-linear routing store, while the remaining 10% is routed through a two-sided unit hydrograph. The ordinates of the unit hydrographs are derived from their respective S-curves (Eq. B.9 to B.17).

The model also estimates the exchange of water between the catchment and groundwater, affecting both flow components (Eq. B.18). The water level in the routing reservoir is dynamically updated based on the initial water level in storage and the outflow from the unit hydrograph (Eq. B.19). The outflow from the routing reservoir is then estimated based on the updated water content in each time step (Eq. B.20), and the water level is adjusted accordingly (Eq. B.21). Similar to the routing storage outflow, the two-sided hydrograph output is also subject to water exchange with groundwater (Eq. B.22). Finally, the total flow, based on the two calculated components, is estimated (Eq. B.23). The variables and parameters used in model calibration are presented in Table B.1 and Table B.2.

This detailed description of the GR4J model highlights the various processes and equations involved in simulating daily streamflow, emphasizing the dynamic interactions between precipitation, evapotranspiration, soil moisture, and groundwater exchange. The comprehensive approach ensures accurate representation and simulation of hydrological processes within the catchment area.

Table B.1 Variables used in GR4J equations.

Variables					
Variable	**Abbreviation**	**Variable**	**Abbreviation**	**Variable**	**Abbreviation**
Precipitation	P	Groundwater exchange term	F	Time	t
Evapotranspiration	E	Actual evapotranspiration	E_s	Water level in the routing store	R
Net precipitation	P_n	Percolation from the production store	$Perc$	Outflow from UH1	Q_9
Maximum temperature	T_{max}	Water entering the routing stage	P_r	Outflow from UH2	Q_1
Minimum temperature	T_{min}	One-sided unit hydrograph	UH_1	Outflow from routing reservoir	Q_r

Table B.1 Variables used in GR4J equations (continued).

Variables					
Variables	**Variables**	**Variables**	**Variables**	**Variables**	**Variables**
Net evapotranspiration	E_n	Two-sided unit hydrograph	UH_2	Total direct runoff	Q_d
Portion of net precipitation entering production store	P_s	S-curve corresponding to UH1	SH_1	Total streamflow	Q
Water level in the production store	S	S-curve corresponding to UH2	SH_2		

Table B.2 Calibration parameters used in GR4J equations

Calibration parameters					
Parameter	**Abbreviation**	**Parameter**	**Abbreviation**	**Parameter**	**Abbreviation**
Maximum capacity of the production store (mm)	x_1	One day ahead maximum capacity of the routing store (mm)	x_3	The time base of unit hydrograph UH1 (days)	x_4
Groundwater exchange coefficient (mm)	x_2				

$$P_n = P - E \quad and\ E_n = 0 \quad if\ P \geq E \tag{Eq. B.1}$$

$$E_n = E - P \quad and\ P_n = 0 \quad if\ P < E \qquad \text{(Eq. B.2)}$$

$$P_s = \frac{x_1\left(1-\left(\frac{S}{x_1}\right)^2\right)tanh\left(\frac{Pn}{x_1}\right)}{1+\frac{S}{x1}tanh\left(\frac{Pn}{x_1}\right)} \qquad \text{(Eq. B.3)}$$

$$E_s = \frac{S\left(2-\frac{S}{x_1}\right)tanh\left(\frac{En}{x_1}\right)}{1+\left(1-\frac{S}{x_1}\right)tanh\left(\frac{En}{x_1}\right)} \qquad \text{(Eq. B.4)}$$

$$S = S - E_s + P_s \qquad \text{(Eq. B.5)}$$

$$Perc = S\left\{1 - \left[1 + \left(\frac{4}{9}\frac{S}{x1}\right)^4\right]^{-1/4}\right\} \qquad \text{(Eq. B.6)}$$

$$S = S - Perc \qquad \text{(Eq. B.7)}$$

$$P_r = Perc + (P_n - P_s) \qquad \text{(Eq. B.8)}$$

$$SH_{1_t} = 0 \qquad \text{for } t \leq 0 \qquad \text{(Eq. B.9)}$$

$$SH_{1_t} = \left(\frac{t}{x_4}\right)^{5/2} \qquad \text{for } 0 < t < x_4 \qquad \text{(Eq. B.10)}$$

$$SH_{1_t} = 1 \qquad \text{for } t \geq x_4 \qquad \text{(Eq. B.11)}$$

$$SH_{2_t} = 0 \qquad \text{for } t \leq 0 \qquad \text{(Eq. B.12)}$$

$$SH_{2_t} = \frac{1}{2}\left(\frac{t}{x_4}\right)^{5/2} \qquad \text{for } 0 < t \leq x_4 \qquad \text{(Eq. B.13)}$$

$$SH_{2_t} = 1 - \frac{1}{2}\left(2 - \frac{t}{x_4}\right)^{5/2} \qquad \text{for } x_4 < t < 2x_4 \qquad \text{(Eq. B.14)}$$

$$SH_{2_t} = 1 \qquad \text{for } t \geq 2x_4 \qquad \text{(Eq. B.15)}$$

$$UH_{1_j} = SH_{1_j} - SH_{1_{j-1}} \qquad \text{(Eq. B.16)}$$

$$UH_{2_j} = SH_{2_j} - SH_{2_{j-1}} \qquad \text{(Eq. B.17)}$$

$$F = x_2\left(\frac{R}{x_3}\right)^{7/2} \qquad \text{(Eq. B.18)}$$

$$R = \max\,(0; R + Q_9 + F) \qquad \text{(Eq. B.19)}$$

$$Q_r = R\left\{1 - \left[1 + \left(\frac{R}{x_3}\right)^4\right]^{-1/4}\right\} \quad \text{(Eq. B.20)}$$

$$R = R - Q_r \quad \text{(Eq. B.21)}$$

$$Q_d = \max\left(0; Q_1 + F\right) \quad \text{(Eq. B.22)}$$

$$Q = Q_r + Q_d \quad \text{(Eq. B.23)}$$

APPENDIX C MODEL CALIBRATION PARAMETERS OBTAINED DURING THE HISTORICAL PERIOD

Table C.1 Calibration parameters obtained for HBV-MTL model during the historical period. The values are presented for ERA5, MERRA-2, and GCMs configurations.

Parameters	**ERA5**	**MERRA-2**	**GCMs**
Degree-day coefficient	1.01	2.17	1.36
Snow correction factor	1.00	0.98	0.91
Potential ET coefficient	0.36	0.50	0.20
Low soil moisture coefficient	0.13	0.02	0.05
Snow capacity to retain water	0.10	0.00	0.12
Topmost outlet's coefficient	0.02	0.00	0.02
Intermediate outlet's coefficient	0.00	0.00	0.00
Bottom outlet's coefficient	0.05	0.01	0.04
Percolation coefficient	48.52	36.36	44.94
Topmost outlet's trigger	499.90	471.57	118.52
Soil moisture capacity	1.05	2.72	4.00
Base of triangle delay function	1.00	1.00	1.01

Table C.1 Calibration parameters obtained for HBV-MTL model during the historical period. The values are presented for ERA5, MERRA-2, and GCMs configurations (continued).

Parameters	**ERA5**	**MERRA-2**	**GCMs**
Soil's water absorption coefficient	80.93	52.98	74.87
Soil's curve number	4.59	4.17	1.33
Frozen soil coefficient	-1.56	0.33	0.04
Soil frost temperature threshold	1.82	-0.32	-0.87
Melting temperature threshold	0.70	0.83	0.69

Table C.2 Calibration parameters obtained for GR4J model during the historical period. The values are presented for ERA5, MERRA-2, and GCMs configurations.

Parameters	**ERA5**	**MERRA-2**	**GCMs**
Degree-day coefficient	3.74	2.90	3.19
Melting temperature threshold	-0.32	1.51	0.59
Snow capacity to retain water	0.12	0.05	0.18
Potential ET coefficient	0.30	0.30	0.90
Maximum production storage	1381.54	1500.00	1323.08
Water exchange coefficient	-10.00	-10.00	2.57
Routing storage capacity	52.48	7.39	26.23
Unit hydrograph delay time	4.00	4.00	1.49
Snow correction factor	1.08	0.86	0.82
Degree-day coefficient	3.74	2.90	3.19