Titre: Title:	Multi-Model Assessment of Climate Change Impacts on the Streamflow Conditions and Hydropower Potential in the Kasai River Basin,Central Africa
Auteur: Author:	Samane Lesani
Date:	2022
Type:	Mémoire ou thèse / Dissertation or Thesis
Référence: Citation:	Lesani, S. (2022). Multi-Model Assessment of Climate Change Impacts on the Streamflow Conditions and Hydropower Potential in the Kasai River Basin,Central Africa [Mémoire de maîtrise, Polytechnique Montréal]. PolyPublie. https://publications.polymtl.ca/10315/

URL de PolyPublie: PolyPublie URL:	https://publications.polymtl.ca/10315/
Directeurs de recherche: Advisors:	Musandji Fuamba, & Elmira Hassanzadeh
Programme: Program:	Génie civil

POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Multi-model assessment of climate change impacts on the streamflow conditions and hydropower potential in the Kasai River Basin, Central Africa

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

Génie Civil

Mai 2022

POLYTECHNIQUE MONTRÉAL

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Ce mémoire intitulé:

Multi-model assessment of climate change impacts on the streamflow conditions and hydropower potential in the Kasai River Basin, Central Africa

présenté par **Samane LESANI**

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

a été dûment accepté par le jury d'examen constitué de:

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DEDICATION

I dedicate this work to

my beloved husband, Saeed, who supports me through the ups and down of my life,

sole of my parents, whose love motivates me to pursue my goals,

and to my siblings, who are always supportive of my decisions.

ACKNOWLEDGEMENTS

I would like to sincerely thank Dr. Elmira Hassanzadeh and Dr. Musandji Fuamba for their support and guidance through my research. I also appreciate the collaboration of my lab mates, Ali Sharifinejad and Salomon Salumu Zahera, in this project. I would like to express my gratitude to all employees of Polytechnique Montréal, more specifically Mrs. Adèle El-Murr, who helped us in a supportive way to work efficiently even during the COVID-19 pandemic.

RÉSUMÉ

Les changements climatiques peuvent modifier les caractéristiques de l'écoulement fluvial et son potentiel de production d'hydroélectricité. Par conséquent, comprendre l'impact du changement climatique sur les conditions d'écoulement est essentiel pour promouvoir une gestion durable des ressources en eau et en énergie dans diverses régions. L'approche commune pour évaluer les impacts du changement climatique sur les systèmes de ressources en eau est basée sur l'utilisation des sorties des modèles de circulation générale (MCG) et sur leur introduction dans des modèles hydrologiques pour simuler l'écoulement naturel à l'avenir. Bien que cette méthode soit largement utilisée par la communauté des chercheurs pour l'évaluation des impacts, certaines incertitudes sont attribuées aux modèles hydrologiques et aux MCG. En particulier, dans les régions où les données sont rares, la représentation des bassins versants, même dans des conditions historiques, est très difficile.

L'Afrique centrale est un exemple de ces régions où la qualité des données hydroclimatiques est limitée et médiocre. Avec un potentiel techniquement réalisable d'environ 100 000 MW, le bassin du fleuve Congo possède le plus grand potentiel hydroélectrique d'Afrique et est l'un des plus importants au monde. Cependant, seulement environ 2.5% de ce potentiel a été développé jusqu'à présent. Ce potentiel hydroélectrique dépend entièrement des potentiels des principaux affluents, dont le fleuve Kasaï. Le bassin du fleuve Kasaï (KARB) en Afrique centrale est le principal sous-bassin versant du bassin du fleuve Congo. Il couvre 897 500 km2 mais comprend moins de cinq stations actives avec des données limitées dans le temps. En raison de ses riches ressources naturelles en minéraux, en eau et en terres fertiles, cette région est l'une des zones économiques spéciales de la République démocratique du Congo. Le grand potentiel hydroélectrique du bassin en tant que source d'énergie propre peut accélérer efficacement la croissance économique de la région. Cependant, la fiabilité d'une telle ressource dépendante de l'eau a été sous-étudiée dans le contexte du changement climatique. La faible capacité d'adaptation, le manque de gestion intégrée des ressources en eau et l'économie dépendante de l'eau rendent le KARB vulnérable au changement climatique.

Cette étude évalue les impacts des conditions climatiques changeantes sur le régime d'écoulement et le potentiel hydroélectrique dans le KARB. Un cadre multimodèle basé sur l'utilisation d'un ensemble de MCG, de deux modèles hydrologiques, ainsi que d'un ensemble de données d'entrée est utilisé ici pour répondre aux incertitudes de l'évaluation d'impact dans cette région à données limitées. À cette fin, HBV-MTL et GR4J, deux modèles hydrologiques conceptuels, sont utilisés et calibrés à l'aide des produits de réanalyse de ERA5-Land, CFSR, JRA-55 et MERRA pour simuler le débit à la sortie du KARB pendant la période historique de 1977-1991. Les paramètres optimaux et les ensembles de paramètres qui fournissent des performances de modèle acceptables sont sélectionnés pour chacune de ces configurations de modélisation. Pour la projection des débits futurs, les sorties corrigées du biais de 19 MCG sous deux trajectoires climatiques représentatives (RCP), 4.5 et 8.5, au cours de la période 2021-2099 sont introduites dans les modèles calibrés. En conséquence, les impacts du changement climatique sur les altérations des signatures d'écoulement telles que les débits faibles, médians et élevés sont analysés. De plus, le potentiel hydroélectrique brut au cours des périodes historiques et futures est estimé pour fournir une indication globale des changements relatifs du potentiel hydroélectrique dans le bassin.

Les résultats révèlent que toutes les configurations de modèles hydrologiques dans la période historique peuvent simuler le débit observé avec des performances acceptables aux échelles quotidienne et annuelle selon les critères statistiques considérés. Dans l'ensemble, le modèle calibré avec le jeu de données ERA5-Land a les meilleures performances au cours de la période historique. En outre, compte tenu de toutes les simulations de débit dans le cadre de scénarios de changement climatique, des modifications allant de -18% à +3% du débit annuel moyen à l'exutoire du KARB dans le futur par rapport à la période historique sont projetées compte tenu de toutes les simulations. Fait intéressant, le signe et l'ampleur des changements estimés dans le régime d'écoulement dépendent du modèle hydrologique utilisé et de l'ensemble de données de réanalyse utilisé pour son étalonnage, ainsi que du MCG appliqué et des scénarios futurs envisagés. Plus particulièrement, d'une part, la divergence entre les projections de HBV-MTL et GR4J utilisant la même réanalyse d'ERA5-Land peut atteindre 30%. D'autre part, les différences entre les projections utilisant le même modèle hydrologique, par exemple HBV-MTL mais calibrées à l'aide de la réanalyse ERA5-Land et MERRA peuvent être de 89%. De même, pour le modèle GR4J, la

différence entre les projections compte tenu de deux réanalyses différentes pour l'étalonnage du modèle peut être de 80%. Cela montre que les résultats peuvent être plus sensibles aux données qu'à la structure du modèle. De telles différences révèlent l'importance de considérer le modèle hydrologique et les données climatiques historiques pour l'évaluation de l'impact sur les ressources en eau, ainsi que les valeurs ajoutées de l'approche multi-modèles qui évitent l'erreur d'utiliser un modèle unique.

En plus des changements globaux du volume d'écoulement, des modifications du débit élevé et faible sont projetées. Compte tenu du potentiel hydroélectrique dans le KARB, les changements de débit élevé sont estimés dans le futur, dont, encore une fois, l'ampleur dépend de la configuration de modélisation. Compte tenu de la valeur attendue basée sur l'ensemble de toutes les simulations, une diminution moyenne de 13% du débit élevé annuel est projetée dans la future période à long terme (2071-2099) dans le cadre du RCP 8.5. Cette réduction est importante mais peut ne pas causer de problèmes sérieux pour l'approvisionnement en eau et la production hydroélectrique, compte tenu des valeurs de débit élevées existantes. Le potentiel théorique du bassin diminuera d'environ 14% et 5% sous RCP4.5 et RCP8.5, respectivement, au cours de l'avenir à long terme de 2071 à 2099. Diminution des étiages au taux de 24% sous RCP 4.5 et 9% sous RCP 8.5 sont estimés à long terme (2071-2099) dans le KARB, compte tenu des projections moyennes d'ensemble basées sur tous les modèles. Cette réduction pourrait affecter la satisfaction des demandes croissantes en eau pour divers secteurs tels que l'agriculture et les activités liées à l'eau telles que la navigation. Par conséquent, les gestionnaires de l'eau devraient tenir compte de cette baisse du débit dans l'élaboration des politiques et les allocations d'eau, en particulier pendant les saisons de faible débit (juin-juillet-août). Par conséquent, ces baisses des débits élevés et faibles peuvent avoir des répercussions sur d'autres aspects du système hydrique, comme les écosystèmes aquatiques, l'entretien des canaux et la gestion des inondations.

Pour résumer, cette étude utilise une approche multi-modèle pour évaluer les impacts du changement climatique sur le KARB. Une telle analyse dans le contexte du cadre appliqué peut également être étendue pour analyser la vulnérabilité d'autres bassins versants dans le bassin du fleuve Congo afin de fournir une évaluation d'impact intégrée dans l'ensemble des conditions du bassin. Les résultats de cette recherche peuvent fournir aux décideurs une meilleure compréhension des systèmes hydriques pour proposer des politiques d'atténuation des impacts du changement climatique sur les ressources en eau, l'énergie, l'agriculture et la gestion de l'environnement. Cette étude contribue non seulement à la mise en œuvre de la gestion intégrée des ressources en eau, mais présente également des avantages à valeur ajoutée dans le contexte économique. Par exemple, la conception des barrages et des centrales électriques et d'autres activités socio-économiques est sensible à la disponibilité de l'eau dans des conditions changeantes. Avec une population estimée à 15 millions d'habitants dans la région du Kasaï, le développement économique des communautés rurales et urbaines dépend fortement de la disponibilité de l'eau et de l'énergie. Pour répondre aux besoins industriels, domestiques et commerciaux de la région, une production hydroélectrique fiable et un approvisionnement énergétique adaptatif constituent le principal moteur du développement durable de la région.

ABSTRACT

Changes in climate can alter the characteristics of streamflow and its potential to generate hydroelectricity. Therefore, understanding the impact of climate change on streamflow conditions is essential to promote sustainable water and energy resource management in various regions. The common approach to assess climate change impacts on water resources systems is based on using the outputs of General Circulation Models (GCMs) and forcing them into hydrological models to simulate natural streamflow in the future. While this method is widely used among the research community for impact assessment, there are some uncertainties attributed to both hydrological models and GCMs. In particular, in data scarce regions, representation of catchments even under historical conditions is highly challenging.

Central Africa is an example of such regions with limited and poor hydroclimatic data quality. With a technically feasible potential of about 100,000 MW, the Congo River Basin has the largest hydropower potential in Africa and is one of the largest worldwide. However, only about 2.5% of this potential has been developed so far. This hydroelectric potential depends entirely on the potentials of the main tributaries, including the Kasai River. The Kasai River Basin (KARB) in Central Africa is the main sub-watershed of the Congo River Basin. It covers 897,500 km^2 yet includes less than five active stations with limited data over time. Due to rich natural resources of minerals, water, and fertile lands, this area is one of the Special Economic Zones of the Democratic Republic of Congo. The great hydropower potential within the basin as a clean energy source can effectively accelerate the region's economic growth. However, the reliability of such a water-dependant resource has been understudied under changing climate. The low adaptive capacity, lack of integrated water resource management, and water-dependent economy make the KARB vulnerable to climate change.

This study evaluates the impacts of changing climatic conditions on streamflow regime and hydropower potential in the KARB. A multi-model framework based on using an ensemble of GCMs, two hydrological models, as well as a set of input data is employed here to address the uncertainties of impact assessment in this data limited region. For this purpose, HBV-MTL and

GR4J, two conceptual hydrological models, are utilized and calibrated using reanalysis products of ERA5-Land, CFSR, JRA-55, and MERRA to simulate the flow at the outlet of the KARB during the historical period of 1977-1991. Both optimal and ensemble of parameters that provide acceptable model performance are selected for each of these modeling configurations. For the future flow projection, the bias-corrected outputs of 19 GCMs under two Representative Climate Pathways (RCPs), 4.5 and 8.5, during 2021-2099 are fed into the calibrated models. Accordingly, the impacts of climate change on alterations in streamflow signatures such as low, median, and high flows are analyzed. Moreover, the gross hydropower potential during both historical and future periods is estimated to provide an overall indication of the relative changes in hydropower potential in the basin.

Results reveal that all hydrological model configurations in the historical period can simulate observed streamflow with acceptable performance at daily and annual scales according to the considered statistical criteria. Overall, the calibrated model with the ERA5-Land dataset has the best performance during the historical period. Furthermore, considering all flow simulations under climate change scenarios show alterations ranging from −18% to +3% in mean annual discharge at the outlet of the KARB in the future with respect to the historical period is projected considering all simulations. Interestingly, the sign and magnitude of estimated changes in flow regime depend on the utilized hydrological model and reanalysis dataset used for its calibration, as well as the applied GCM and considered future scenarios. Most notably, on the one hand, the divergence between projections of HBV-MTL and GR4J using the same reanalysis of ERA5-Land can be as high as 30%. On the other hand, the differences between projections using the same hydrological model, e.g., HBV-MTL but calibrated using reanalysis ERA5-Land and MERRA can be 89%. Similarly, for the GR4J model, the difference between projections given two different reanalysis for model calibration can be 80%. This shows results might be more sensitive to the data than to the model structure. Such differences reveal the importance of considering the hydrological model and historical climate data for the water resource impact assessment, as well as multi-model approach added values which avoid the misleading of using a single model.

In addition to overall changes in flow volume, alterations in high and low flow are projected. Considering the hydropower potential in the KARB, changes in high flow are estimated in the future, which, again, its magnitude depends on the modeling configuration. Given the expected value based on the ensemble of all simulations, an average decrease of 13% in annual high flow is projected in the future long-term period (2071-2099) under RCP 8.5. This reduction is important but may not cause serious concern for water supply and hydropower production, given the existing high flow values. The theoretical potential of the basin will decrease by around 14% and 5% under RCP4.5 and RCP8.5, respectively, during the long-term future from 2071 to 2099. Decreases in low flow at the rate of 24% under RCP 4.5 and 9% under RCP 8.5 are estimated in the long-term future (2071-2099) in the KARB, considering the ensemble mean projections based on all models. This reduction might affect the meeting of increasing water demands for various sectors such as agriculture and water-related activities such as navigation. Hence, water managers should consider this decline in flow in policymaking and water allocations, especially in low flow seasons (June-July-August). Accordingly, these declines in high and low flows can have implications for other water system aspects such as aquatic ecosystems, channel maintenance, and flood management.

To summarize, this study employs a muti-model approach to assess the climate change impacts on the KARB. Such analysis in the context of the applied framework can also be extended to analyze the vulnerability of other catchments in the Congo River Basin to provide an integrated impact assessment within the whole basin conditions. The outcomes of this research can provide decision-makers with a better understanding of water systems to propose mitigation policies against climate change impacts on water resources, energy, agriculture, and environment management. This study not only contributes to the implementation of integrated water resource management but also has added-value benefits in the economic context. For instance, the design of dams and power plants and other socio-economic activities are sensitive to water availability under changing conditions. With an estimated population of 15 million in the Kasai region, the economic development of rural and urban communities highly depends on the availability of water and energy. To meet the industrial, domestic, and commercial needs of the region, reliable hydropower production and adaptive energy supply is the major driver of the region’s sustainable development.

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LIST OF SYMBOLS AND ABBREVIATIONS

CSC	Climate Service Center
CDF	Cumulative Distribution Function
CFSR	Climate Forecast System Reanalysis
CICOS	Commission Internationale du bassin Congo-Oubangui-Sangha
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CMORPH	Climate Prediction Center Morphing method
CORDEX	Coordinated Regional Downscaling Experiments
ERA5-Land	Land component of the fifth generation of European Reanalysis
FDC	Flow Duration Curve
GCM	General Circulation Model
GEIDCO	Global Energy Interconnection Development and Cooperation Organization
Geo SFM	Geospatial Streamflow Model
GHG	Greenhouse Gas
GLUE	Generalized Likelihood Uncertainty Estimation
HRR	Hillslope River Routing
IPCC	Intergovernmental Panel on Climate Change
JRA-55	Japanese 55-year Reanalysis
KAR	Kasai River
KARB	Kasai River Basin
KGE	Kling-Gupta Efficiency
MCMC	Markov Chain Monte Carlo
MERRA	Modern-Era Retrospective Reanalysis

NEX-GDDP NASA Earth Exchange Global Daily Downscaled Projections dataset

Para Sol Parameter Solution method

PERSIANN Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks

PSO Particle Swarm Optimization

RCM Regional Climate Model

RCP Representative Concentration Pathway

SCE-UA Shuffled Complex Evolution algorithm

SUFI Sequential Uncertainty Fitting

SWAT Soil Water Assessment Tool

TRMM Tropical Rainfall Measuring Mission

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CHAPTER 1 INTRODUCTION

1.1 Background and problem definition

Water resources play a key role in human life and socio-economic developments (Yevjevich, 1992) by supplying water demands of various sectors, including industry, agriculture, domestic users, and the natural environment (Cai & Rosegrant, 2002; Flint, 2004; Niang et al., 2014). Water resources management is often needed to ensure the availability of water in corresponding time and space to meet these water demands (Kundzewicz, 1997) at the regional scale. (Li et al., 2019; Li et al., 2020). The prerequisite of this action is having enough knowledge about the long-term water budget of the region. In addition to conventional problems of water management, changes in climate due to human activities since the Industrial revolution have posed new challenges due to alterations in the historical patterns of the hydrological cycle (Beck & Bernauer, 2011; Frederick & Major, 1997; IPCC, 2007; Van Rooyen et al., 2011). Most importantly, in recent decades, anthropogenic climate change has modified the characteristics of precipitation and temperature in various regions (Aloysius et al., 2016; Dore, 2005; Sohoulande Djebou & Singh, 2016). Such changes have (and will) lead to alterations in streamflow characteristics such as annual volume, peak flow timing and magnitude, and seasonality, which are important for water resources planning in watersheds (Dai et al., 2018; Hirabayashi et al., 2013; Konapala et al., 2020; Kundzewicz et al., 2014; Wi, 2012). Hence, to make reliable, long-lasting management policies, climate change impacts should be taken into account (Sophocleous, 2004). Although climate change might be seen as a long-term issue, it must be handled now since today's actions will increase the adaptive capacity of societies against changing conditions (IPCC, 2014; Sophocleous, 2004).

Such changes directly affect the performance of water users, such as hydropower plants which have been designed based on historical streamflow characteristics (Basso & Botter, 2012; Falchetta et al., 2019; Hamududu, 2012; Wang et al., 2019). Hydropower is a widely used renewable source of energy that plays a crucial role in the socio-economic development of societies (Falchetta et al., 2019; IEA, 2020). Nevertheless, it is potentially vulnerable to changes in streamflow regime and seasonality (Hamududu, 2012; IEA, 2020). Therefore, a thorough understanding of the possible impacts of climate change on streamflow regime and hydropower potential is essential for a sustainable water resource plan, mitigation actions and more adaptable energy production to changing conditions.

Central Africa will be subject to the effects of climate change by the end of the 21st Century despite low Greenhouse Gas (GHG) emission rates compared to other continents (Collier et al., 2008; Niang et al., 2014). These impacts will be severe due to the high reliance of the population on activities dependent on natural resources (Calzadilla et al., 2013; McCluskey & Strzepek, 2007). Meanwhile, low adaptive capacity makes this region more vulnerable to changing future conditions imposing major challenges to water resources management (Aloysius & Saiers, 2017; Niang et al., 2014; Tilleard & Ford, 2016), which currently has big issues in food and water security (IPCC, 2021; UNEP, 2011b). The Congo River and its tributaries, with high potential for water resources and hydropower (~110 GW), play a crucial role in promoting the sustainable development of the region (Falchetta et al., 2019; Hamududu, 2012; IEA, 2020). However, as discussed earlier, climate change will threaten the reliability of this precious source of clean energy, making it vital to assess how its potential will be affected by the changing future condition.

There are two approaches to assessing climate change impacts: the “Top-down” and “Bottom-up” methods. The first method is a scenario-based technique in which the projections of General Circulation Models (GCMs) are used to evaluate the impacts on the water system (Givati et al., 2019; Hare et al., 2010; Wilby & Dessai, 2010). While the latter is a neutral scenario-led approach, and the system’s behaviour and its vulnerability to climate change are assessed based on the feasible changes of climatic data and the adaptive capacity of the system (Garcia et al., 2014; Lutsey & Sperling, 2008; Nazemi et al., 2020). In some studies, the combination of these two approaches is used for climate change impact assessment (Bhave et al., 2014; Sauquet et al., 2019). The “Top-down” approach is widely used to assess climate change impacts on water systems. In this method, the GCMs outputs either are forced to a hydrological model to estimate the flow or directly analyzed to project watershed conditions under changing climate (Aloysius & Saiers, 2017; Arnell & Gosling, 2013; Bergström et al., 2001; Kundzewicz, 2008). GCMs are useful mathematical tools for projecting the climatic response to global warming by modeling the atmosphere and ocean's physical processes (Hannah, 2015). Different scenarios are considered for future conditions based on factors affecting the rise of greenhouse gas (GHGs) emissions. The assumptions are defined according to the potential population growth, social, economic, and technological developments, Energy system and mitigation strategies taken by countries (IPCC, 2007). Concerning climate modeling, there are major sources of uncertainties attributed to the GCMs, such as the probability of scenario occurrence, large scale, and imperfect conceptualization, which may cause inter-model variability and diverse future projections (Bourdeau-Goulet & Hassanzadeh, 2021; Shackley et al., 1998). Therefore, to address the inherent uncertainties of climate models, the application of multi model ensembles of GCMs projections has been suggested to quantify the climate change impacts on the basin's hydrological conditions (Crosbie et al., 2011; Wang et al., 2020)

Hydrological models are the main components of impact assessment analysis in the Top-down approach (Peel & Blöschl, 2011). They are efficient tools to represent the physical processes in a hydrological cycle and their nonlinear transformation using either simple mathematical equations or more complex structures (Ogden, 2021; Wagener et al., 2001). Briefly, the historical climatic data and outputs of GCMs are forced into these models as input to simulate the flow at the watershed's outlet in the historical and future periods, respectively (Christensen & Lettenmaier, 2007; Tshimanga & Hughes, 2012). Different types of hydrological models have been developed in a wide range of spatiotemporal scales based on the objective of the study and which processes are important to be considered in the model's structures (Beven, 2011; Devia et al., 2015; Pechlivanidis et al., 2011; Tshimanga & Hughes, 2014).

The choice of hydrological models has been a centre of debate in climate change impact studies. While models with a complex structure represent more detailed information about the hydrology of the basin, the need for a large amount of data for parameter estimation affects the model performance (Hughes, 2016; Moges et al., 2021; Orth et al., 2015; Singh & Marcy, 2017). This issue will be exacerbated when hydrological modeling is employed for the uncertain future simulation (Ludwig et al., 2009; Minville et al., 2008; Singh & Marcy, 2017). Due to the lack of available data in the future, the use of models with simple structures is of high interest in the context of climate change impact studies (dos Santos Franciane et al., 2018; Her & Chaubey, 2015; Singh & Marcy, 2017). Given the importance of structural uncertainties of hydrological models (Beven, 2000), applying a multi-model ensemble is highly recommended (Seiller et al., 2012; Viney et al., 2009), so intercomparison between the models results in a more reliable estimation of future flow conditions.

In addition to the structural uncertainty in hydrological modeling, the other major error source is stemmed from observational data inputs affecting model efficiency (Cortés et al., 2011; Moges et al., 2021). Most importantly, if the watershed is located in a data-scarce region, the additional uncertainty would affect the validity of the simulated flow (Cortés et al., 2011; Hughes et al., 2012; Knoche et al., 2014). Use of satellite-derived data (Becker et al., 2018; Huang et al., 2020) and reanalysis of data sets (Abubakari et al., 2018; Ghebrehiwot & Kozlov, 2021; Hua et al., 2019) are common options to tackle this issue in ungauged basins like Congo River Basin (Beven, 2011; Christensen et al., 2007; Hua et al., 2019). Reanalysis products are grid-based climatic data obtained from systematic assimilation incorporating available observational data (Bosilovich et al., 2008; Dee et al., 2014). It is indicated that they are generally of high quality making them a desirable choice for a data-scarce region (Ghebrehiwot & Kozlov, 2021; Trenberth et al., 2008). Nonetheless, the amount of different reanalysis in a specific location may differ due to the inter-model variability, applied assimilation approach, and available observations used in simulations (Lin et al., 2014; Washington et al., 2013). Hence, using an ensemble of these datasets in hydrological modeling may reduce the related uncertainty.

1.2 Research objectives

Despite the importance of the Congo River Basin as the second-largest watershed in the world, containing immense sources of freshwater, integrated water resource management has been hindered in this region. Because of the huge potential of hydropower, the Congo River and its main tributaries play a crucial role in the sustainable development plans of Africa. While limited adaptive capacity makes this strategic region more vulnerable to climate change, a comprehensive understanding of climate change impacts will be helpful in proposing reliable and adaptable plans and making mitigation policies. However, impact study in this region is challenging due to the complexity of the basin's hydroclimatic conditions, data scarcity and low quality of existing data.

This study aims to quantify the impacts of climate change on streamflow conditions and hydropower potential of the main southern watersheds of the Congo River Basin, the so-called Kasai River Basin using a multi-model approach including multiple hydrological models and an ensemble of climate data in the historical and future period. The research questions that we try to address in this study are how vulnerable the future hydropower potential is to the changing climate; how sensitive is the impact assessment to the choice of applied hydrological model with the same input data? Moreover, how sensitive is the impact assessment to the choice of input data using the same hydrological model?

Hence, to achieve the main goal, the following specific objectives are identified:

(1) Employ a multi-model approach to simulate the natural streamflow in the historical period. For this purpose, two hydrological models and an ensemble of input datasets are used to calibrate and validate the models.

(2) Force an ensemble of climate model projections to the calibrated hydrological models to estimate the future streamflow at the watershed outlet.

(3) Assess the possible changes in streamflow characteristics and hydropower potential under changing climate, considering the intercomparison of hydrological models fed by different datasets.

1.3 Case study

The Kasai River Basin (KARB), with a drainage area of 897,500 km^2, is accounted for the principal largest tributary of the Congo River Basin located in Central Africa (Becker et al., 2018; Moukandi et al., 2020). Its source is the Munyango headwaters in Angola, with an altitude around 1500 meters above sea level. The basin is shared between two countries in central Africa; more than 70% in the Democratic Republic of Congo and Angola (Jean Marie et al., 2016). The Kasai ecoregion encompasses the Kasai River (KAR) and its tributaries with complex geomorphology (Roberts et al., 2015). The main tributaries of the KAR are the Lulua River, Sankuru River, Kwilu River, and Kwango River (GEIDCO, 2020), which are free of obstacles to navigate, playing a key role in the transportation and trade sector in the region. The basin is mostly covered by the equatorial rainforest area, making its land infertile enough for agricultural activities (Broadhead, 1992). While the tropical forest occupies the northern part, the basin's south is dominated by dense, dry forest and savannahs (Kisangala & Ntombi, 2012). The main water user in the region is rainfed agriculture which makes food production security highly dependent on the water resources (Brown et al., 2014). Along with agriculture, people’s livelihood in KARB mostly relies on activities such as fisheries, livestock and navigation in which hydroclimatic condition is significant (Bele et al., 2010).

Given the importance of agriculture in the region's economy in the first phase of development plans provided by GEIDCO (2020), the Central Especial Economic Zone, where the KARB is located, is planned to promote the agriculture industry, implying the rise of the regional water demand in the future. On the other hand, with the average flow rate of 11,300 m^3/s in its reach to the Congo River, it constitutes around one-fifth of Congo's mainstream volume (Becker et al., 2018). This huge water resource provides the basin with a remarkable hydropower potential which can significantly contribute to the future energy supply in the region. Accordingly, in the sustainable development plan, hydropower plants with a total installed capacity of 8270 MW within the basin have been considered (GEIDCO, 2020). However, the reliability of the proposed plants, which are based on the water system's historical conditions, is questioned due to their vulnerability to climate change. Hence it is essential to assess the impacts of climate change on this precious source of water and energy under changing climate conditions.

CHAPTER 2 LITERATURE REVIEW

2.1 Hydrological modeling

Sustainable water resource management on a regional scale needs a comprehensive understanding of hydrological conditions over the basin. Estimation of streamflow as one of the main components of the hydrological cycle plays a key role in water resource planning. For this purpose, hydrological models are commonly used to simulate the transformation of rainfall to runoff through various physical processes constituting the water cycle over the basin (Beven, 2012). Important physical processes include evapotranspiration, groundwater recharge, infiltration, interception, and surface and sub-surface flow. Since first emerging about 160 years ago (Mulvaney, 1851), hydrological models (Williams, 1995) have been extensively used in water systems and climate change impact studies. The significant deference of these models is the assumptions and mathematical equations considered to represent physical processes.

Hydrological models have been developed in different spatial scales ranging from basin-scale (Person et al., 1996) to global (Sood & Smakhtin, 2015) and temporal scale (daily Vs. monthly) based on the objective of the study and available hydrological information. In brief, hydrological models are classified into three groups based on their structure and how the processes are represented (Pandi et al., 2021); empirical, physically-based, conceptual and hybrid. Empirical models in which flow is estimated based on its relations to observed rainfall using statistical techniques. While the physically based models employ conservation of mass and momentum equations to simulate streamflow using hydroclimatic variables, the conceptual models use simplified mathematical equations representing the main hydrological processes within the watershed. All these types can be categorized based on the spatial representation of catchment as lumped, semi or fully distributed models (Beven, 2012).

Although physically-based models provide more detailed information about the hydrologic response of the watershed, the complexity of their structure and associated uncertainties is argued in the literature (Beven, 1989; Grayson et al., 1992). The need for a large number of input data and many parameters to calibrate the model will affect the model's performance (Hughes, 2016; Orth et al., 2015). In particular, in the case of climate change impact projections and flow prediction in data-scarce regions, the model complexity will diminish the opportunity to understand the future condition of the water system (Beven, 1989; Ludwig et al., 2009; Minville et al., 2008) thoroughly. Given the lack of data for the future condition, simple hydrological models have been suggested for the flow projection under uncertain future scenarios (Hamududu, 2012; Michaud & Sorooshian, 1994; Singh & Marcy, 2017).

Streamflow estimation in a data-scarce region adds more challenges to hydrological modeling, which is considered a data-driven procedure (Bao et al., 2012; Sivapalan et al., 2003; Sivapalan et al., 2006). The observational hydroclimatic data are required to estimate model parameters through the calibration procedure, while the poorly gauged watersheds lack the required data. As one solution, regionalization is a commonly used approach in which the hydrological information is transformed from a gauged watershed (Blöschl & Sivapalan, 1995; Sivapalan et al., 2003). Among the different methods of regionalization, three techniques have been used widely; spatial proximity, regression, and physical similarity (Beck et al., 2016; Oudin et al., 2008; Tung et al., 1997).

In regression strategy, the model parameters are estimated based on the relationship with watershed characteristics (Abdulla & Lettenmaier, 1997; Young, 2006). This method has uncertainties related to using unrealistic simple equations for the nonlinear relationship between parameters and basin features. Besides, it is sensitive to the potential changes in catchment characteristics due to land-use changes and climate variations (Wagener et al., 2010), criticized by some studies (Bárdossy, 2007; Parajka et al., 2007). In the spatial proximity technique, the parameters obtained from the model calibration in the near gauged catchments are used to estimate the parameters in ungauged catchments by interpolation methods (Vandewiele et al., 1991). This approach assumes that the proximate catchments are similar in hydrological characteristics, which may cause errors (Drogue & Ben Khediri, 2016). In the last method, the donor catchments are chosen based on the physical similarity to the ungauged watershed (Burn & Boorman, 1993;

McIntyre et al., 2005). The performance of these approaches differs among catchments, dependent on the climatic conditions and gauging network density (Parajka et al., 2013).

Given the uncertainties associated with these methods, some studies have combined these approaches with a few available flow measurements in the catchment. The test showed that even a small number of observational data would significantly improve the model performance (Plasse et al., 2014; Pool & Seibert, 2021; Rojas-Serna et al., 2016). Indeed, short time series of streamflow is a valuable source for model calibration (Tachikawa et al., 2012). Given the importance of direct calibration of the model with the available flow, some studies investigated the sensitivity of the model performance to the flow availability. Hence considering at least 5 to 8-year series has been recommended for the calibration to estimate robust parameter sets (Anctil et al., 2004; Yapo et al., 1996).

As another alternative for data-scarce regions, remotely sensed data is available in a wide range of temporal and spatial scales. They have been used widely in hydrological modeling over the globe (Beck et al., 2017; Huang et al., 2020; Stewart & Finch, 1993). In particular, in different ungauged or poorly gauged basins (Asante et al., 2008; Becker et al., 2018; Kim et al., 2021; Kittel et al., 2018; Wanders et al., 2014). However, the variation in the quality of satellite data over the regions can affect the accuracy of hydrological model results applied on a regional scale (Andersen et al., 2005; Liu et al., 2016; Sun et al., 2018). Thus, various approaches have been deployed to make the use of these datasets more accurate such as bias correction (Habib et al., 2014; Stisen & Sandholt, 2010; Zhang & Tang, 2015).

Rainfall is the major climatic component of hydrologic response in a basin, the accuracy of which crucially affects the model performance and, consequently, our understanding of the watershed conditions (Hua et al., 2019). In Central Africa, where the KARB is located, the pattern and variability of this climatic data are known little due to limited in situ meteorological stations (Todd & Washington, 2004; Tshimanga & Hughes, 2014; Washington et al., 2013; Zhou et al., 2014). Many studies have demonstrated large uncertainty in the spatial variability of precipitation over the Congo River Basin (Diem et al., 2014; Malhi & Wright, 2004; Samba et al., 2008; Zhou et al., 2014). This attributed uncertainty is also seen in the future climate model projections among the models in both sign and magnitude of rainfall climatology in Central Africa (Aloysius et al., 2016; Creese & Washington, 2016; Niang et al., 2014; Washington et al., 2013).

Reanalysis datasets assimilated by the climate models using observational data can provide useful grid-based climatic information over the basins in the globe (Bosilovich et al., 2008; Hua et al., 2019; Parker, 2016), particularly for such a data-scarce region like KARB (Parker, 2016). The differences among the reanalysis datasets can be attributed to the data availability, considered assimilation scheme (Lin et al., 2014; SPARC, 2022). The lack of available observational data (Nicholson et al., 2018a; Nicholson et al., 2018b) and large uncertainties in the complex climatology of the Congo River Basin (Raphael M. Tshimanga, 2012) make it difficult to validate these datasets against the gauged rainfall. Thus, using an ensemble of these datasets can contribute to overcoming this issue (Hofer et al., 2012).

Calibration of hydrological models is considered a substantial task in hydrological modeling in which the model parameters are quantified. The performance of the model highly depends on how well it is parametrized. The calibration methods can be divided into two categories, manual and automatic (Yulizar & Singh, 2021). Both methods have merits and demerits, which are discussed widely by many studies (e.g., Yulizar and Singh (2021) and Ndiritu (2009)). Since manual calibration is subjective and time-consuming (Gupta et al., 1999; Ndiritu, 2009), a great deal of research has been conducted to develop automatic calibration and improve the procedure. In automatic calibration, five main components have constituted the procedure: calibration period selection, parameter sets' initial ranges, error measurement between the model outputs and observed data using an objective function, and optimization algorithm (Gupta et al., 1999). Many studies have been conducted to improve the automatic calibration methods (Brazil & Krajewski, 1987; Duan et al., 1992; Gan & Biftu, 1996; Ndiritu & Daniell, 2001; Sorooshian & Gupta, 1983). One of the states of the art of automatic calibrations is Shuffle Complex Evolution (SCE-UA)

(Duan et al., 1993) which has been demonstrated as a rigorous approach for the model parameterization (Chu et al., 2010; Duan et al., 1994; Rahnamay Naeini et al., 2019).

In recent years, the uncertainty analysis of hydrological modeling has been increasingly taken into account (Bosshard et al., 2013; Rafiei Emam et al., 2018). In brief, the error in model outputs stems from different sources, including input data, model structure, and model parameters (Moges et al., 2021). The main goal of uncertainty analysis is to tackle the challenges in model calibration and improve its performance in practice. In this regard, different methods have been developed to quantify the attributed uncertainty, such as Generalized Likelihood Uncertainty Estimation (GLUE) (Beven & Binley, 1992, 2014), Markov Chain Monte Carlo (MCMC, Zheng & Han, 2016), Parameter solution method (Para Sol) (Van Griensven & Meixner, 2006), Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995), and Sequential Uncertainty Fitting (SUFI-2) (Abbaspour et al., 2007). The uncertainty quantification using the mentioned techniques instead of having a single set of outputs provides an ensemble of simulations, contributing to more reliable results than the traditional deterministic model (Tennøe et al., 2018). Therefore, representing the uncertainty analysis beside the optimization technique in model calibration will maximize the model's reliability in practice.

This study uses two conceptual hydrological models, HBV and GR4J, for impact assessment. The detailed description of these models, their equations as well as a schematic of them are presented in Appendix A and B, respectively. The streamflow during the historical period is estimated by forcing the ensemble of reanalysis datasets into the models. It is worth mentioning that potential evapotranspiration is estimated using the Hargreaves method. Besides the models' calibration based on global optimization, the uncertainty analysis is implemented using the GLUE method.

2.2 Climate change impact assessment

Water availability within a basin is highly affected by climatic conditions and variability, leading to challenges for water resource management in decision-making and development planning, such as dams and hydropower plants (Caceres et al., 2021). By affecting the climatic patterns, temperature and precipitation, global warming has caused runoff changes leading to water supply issues (Frederick & Major, 1997; Haddeland et al., 2014; Kundzewicz, 2008; Sophocleous, 2004). Hence it is crucial to assess the possible impacts on the water resources at the watershed level under changing climate to provide decision-makers with a better knowledge of the system reliability in water supply contributing to sustainable development (Kundzewicz, 1997). two approaches have been applied to assess climate-induced impacts on watershed systems, namely “Top-down” and “Bottom-up.” While the first one is scenario-based, the latter is considered a scenario-neutral method, avoiding the uncertainty lying under climate models (Bhave et al., 2014; Wilby & Dessai, 2010). In the bottom-up approach, the system’s behaviour under feasible hydroclimatic changes is evaluated using various available climatic data without considering any specific scenario for future conditions (Garcia et al., 2014; Lutsey & Sperling, 2008; Tra et al., 2018). In this method, the vulnerability of the system and related risks are presented to provide decision-makers with an adequate understanding of future conditions (Borgomeo et al., 2014; Brown et al., 2012; Hassanzadeh et al., 2016; Kim & Kaluarachchi, 2016). Some researchers to analyze the water budget in the system under plausible climatic changes have used hydrological models (e.g., Antonetti et al., 2017; Knighton et al., 2017; Prudhomme et al., 2010; Wilby & Dessai, 2010).

However, to avoid the uncertainties that stemmed from hydrological models, some authors used stochastic streamflow prediction (Borgomeo et al., 2015; Hassanzadeh et al., 2016). Although this method contributes to addressing the climate and hydrological model uncertainties, some studies have argued there are other major sources of uncertainties in the bottom-up approach, which affect the reliability of streamflow estimation (Nazemi et al., 2020; Zscheischler & Seneviratne, 2017). Concerning the attributed uncertainties, the combination of these two approaches has been applied by some researchers (Bhave et al., 2014; Girard et al., 2015; Tra et al., 2018).

The scenario-led top-down approach has two major components: hydrological and global climate models (GCMs) projections. In this method, the outputs of GCMs are fed into the calibrated hydrological models to project the future condition of the water system (Bergström et al., 2001;

Erler et al., 2019; Kour et al., 2016; Sunde et al., 2017; Wang et al., 2012). GCMs are powerful tools for simulating the atmospheric and oceanic physical processes to represent the global climate response to the increasing greenhouse gas emissions. However, they have uncertainties originating from the considered scheme and conceptualization or the large scale, which lead to considerable discrepancies between their outputs even under the same emission scenario (Bourdeau-Goulet & Hassanzadeh, 2021; Hannah, 2015; Hattermann et al., 2018; Liepert & Previdi, 2012; Wang et al., 2020). It is widely acknowledged that the use of multi-model ensembles for climate projections and hydrological models contributes to addressing the related uncertainties in climate change impact studies (Christensen & Lettenmaier, 2007; Ghosh & Mujumdar, 2009; Her & Chaubey, 2015; Tebaldi & Knutti, 2007; Wang et al., 2020).

Concerning the coarse spatial scale of climate model projections, downscaling approaches have been widely used in regional and local water system studies to fit the model outputs in a finer resolution (Chen et al., 2012; Eden & Widmann, 2014; Sunde et al., 2017; Thrasher et al., 2013). These approaches can be categorized as statistical and dynamical downscaling methods (Bergström et al., 2001; Friederichs & Hense, 2007; Gebrechorkos et al., 2019). In the dynamical downscaling technique, regional climate models (RCMs) are employed using GCMs low-resolution outputs as initial and boundary conditions to reproduce a higher-resolution climatic data suited for the regional scale studies. One of the current dynamical downscaling initiatives is Coordinated Regional Downscaling Experiments (CORDEX, Jacob et al., 2014), with a resolution of about 45 km available for the globe. Although the RCMs have a higher resolution than GCMs, they are computationally intensive and multi-model climate simulation with these models for a region is time-consuming and needs super computers. Most importantly, applying this approach may not improve the simulation skill of the GCMs, and they still show biases (Rockel et al., 2008).

On the other hand, in statistical downscaling, the empirical relationship between large-scale GCMs projections and local variables is developed, which is a more cost-effective approach than the dynamical method. As a result, different statistical methods have been established in many projects and are widely used in climate change impact studies. Besides the necessity of downscaling the climate model projection to desired spatial resolution, the outputs of GCMs or RCMs should be bias-corrected (Bruyère et al., 2014). The need for bias correction of climate model projections, particularly for the precipitation data in hydrological modeling, is demonstrated by many studies (e.g., Dosio & Paruolo, 2011; Johnson & Sharma, 2015). In bias correction, typically, a transfer function based on cumulative distribution functions (CDFs) of observed and simulated data is established and employed to correct the climate model projections (Dosio & Paruolo, 2011; Li et al., 2010).

Already, the GCMs outputs have been downscaled into a finer resolution as well as bias-corrected for the globe by some institutions to provide the scientific community with appropriate data at local and regional scales. NASA Earth Exchange Global Daily Downscaled Projections dataset (NEX-GDDP, available at https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp) is downscaled and bias-corrected projections of 21 GCMs from Coupled Model Intercomparison Project Phase 5 (CMIP5) under two emission scenarios, RCP4.5 and RCP8.5. This bias-corrected dataset with a spatial resolution of 25 km has been widely used in climate change impact studies (Abiodun et al., 2020; Guevara-Ochoa et al., 2020; Musie et al., 2020). Accordingly, in this study, the required GCMs projections are derived from this database to feed into hydrological models for estimating future flow conditions.

2.3 Hydropower potential

Hydropower potential is highly dependent on topography and streamflow signatures, including flow volume, timing and seasonal variation (Hamududu, 2012; Killingtveit & Hamududu, 2015). Hence, this water-dependent energy source production is vulnerable to climate change (Caceres et al., 2021; Kling et al., 2015). In this regard, there have been studies focused on assessing the probable climate change impacts on its potential (Falchetta et al., 2019; IEA, 2020; Schaefli, 2015). For this purpose, the ensemble model-based impact assessment has been recommended to evaluate climate-induced impacts on hydropower (Christensen & Lettenmaier, 2007; Manoha et al., 2008; Tebaldi & Knutti, 2007; Yu et al., 2014). Flow Duration Curve (FDC) has had a wide range of applications in water resource-related issues such as water quality, hydropower, and water-use planning (Vogel Richard & Fennessey Neil, 1994; Vogel & Fennessey, 1995). Regarding hydropower, it has been used for design and planning purposes and analysis of the effects of discharge variation on hydropower generation (Basso & Botter, 2012; Hänggi & Weingartner, 2012; Liucci et al., 2014; Reichl & Hack, 2017). Streamflow quantiles extracted from the FDC indicate the design runoff volume used to determine a hydropower plant's energy potential (Hänggi & Weingartner, 2012). Concerning the stream's gross hydropower potential, the quantiles commonly are classified as the low, mean and high potential of power with the exceedance probability of 90, 50% and 10% (Pandey et al., 2015; Wali, 2013). Similarly, in this study, these quantiles extracted from future flow duration curves are analyzed with respect to the long-term historical values to provide an overall indication of the relative changes in hydropower potential under changing climate.

2.4 Studies in the Congo River Basin and its major sub-watersheds

Despite its vital role in the water, energy and carbon cycle, the Congo River Basin has been understudied in hydro-climatology (Aloysius & Saiers, 2017; Laraque et al., 2020). However, in recent years more attention from scientific communities has been turned to this valuable source of water and energy. The course of the river basin and its geology, geomorphology, and flow regime have been explained (Runge, 2008) in detail. One of the important challenges in the Congo River Basin and its tributaries is the limited gauged stations. The number of observational stations has decreased after the colonial era over the recent decades (Bultot, 1971a; Laraque et al., 2020). Laraque et al. (2020) reviewed the history of the hydroclimatic networks in the Congo River Basin and its tributaries. Some authors have studied the hydro climatology of the basin. Riou (1984) investigated potential evapotranspiration over Central Africa using experimental techniques. Rainfall pattern and variability of the basin have been evaluated in many studies (Janicot, 1992; Kazadi & Kaoru, 1996; Lempicka, 1959; Mahé, 1995; Mahé & Olivry, 1995; Mahé et al., 2012; Matsuyama et al., 1994; Samba et al., 2008). However, a large uncertainty has been demonstrated in available precipitation datasets (Diem et al., 2014; Malhi & Wright, 2004; Samba et al., 2008). Zhou et al. (2014) observed a significant decrease in forest greenness over the past decades using the satellite-derived datasets. Matsuyama et al. (1994) investigated the seasonal variation of the water budget, analyzing the monthly hydrometeorological data.

Besides the climatic condition, some studies focused on the flow regime over the Congo River Basin, either the entire basin or at the sub-basin scale (Bricquet et al., 1995; Wesselink et al., 1996). Bricquet et al. (1995) classified the flow hydrographs in the entire basin represented in maps based on the contribution of main tributaries in the flow regime at the basin's outlet at Kinshasa in different months of the year. Bricquet et al. (1997) investigated the water resource variations in African Atlantic River basins over the last two decades of the 20th century. They highlighted a significant reduction in water budget as the long-term effect of the rainfall deficit since the 1970s and the changes in baseflow contributions. Also, some researchers quantified the hydrological dynamics and water level of the Congo River Basin using remote sensing data (Becker et al., 2014; Becker et al., 2018; Lee et al., 2011; Lee et al., 2015). Over a 116-year study period, Laraque et al. (2020) highlighted high flow period of the Congo River was ended in the 1960s, and since then, in almost all tributaries, the year 1970s has been the beginning of the significant downward flow trend. Based on the analysis of rainfall data from 1940 to 1999, they concluded that the precipitation overall decreased in the Kasai, Ubangi and the entire Congo River Basin, with the breaking point around 1970. Also, the same trends and changes have been shown in the streamflow records.

In the context of hydrological modeling in the Congo River Basin region, there has been a great deal of effort focusing on the two major issues in this basin, the limited data and understanding of the physical processes of the basin with a complex hydrologic system. However, there is still a need to improve the approaches in hydrological modeling to have more reliable and practical information at an appropriate scale for water resource management argued to Laraque et al. (2020). Given the lack of in-situ data, studies have tried to address this issue by using different global data sets, including reanalysis and satellite-derived for climatic data and physical characteristics of the basin (Beighley et al., 2011; Hua et al., 2019; Munzimi et al., 2019).

Regarding the process understanding, some research has been conducted to improve the existing models in the Congo region to represent the hydrologic system of the basin better, especially considering wetland and lakes' role in the hydrologic response of the basin and flow routing function of such a large watershed. For instance, Beighley et al. (2011) used three satellite rainfall datasets to estimate streamflow running the Hillslope River Routing (HRR) model. They concluded that TRMM (3B42) is better than the other two datasets by comparing the three precipitation datasets and the simulated streamflow spatially and temporally. While all three datasets result in an acceptable flow estimation, they vary significantly in magnitude. The CMORPH and PERSIANN overestimate the magnitude of precipitation.

Tshimanga and Hughes (2014) established a semi-distributed model, initially calibrated by Tshimanga et al. (2011) and evaluated its streamflow estimation performance at the basin scale using the available data. They argued that their model performance in both high and low flow estimation is satisfying in terms of timing and magnitude, contributing to water resource management in the region. Aloysius and Saiers (2017) investigate how changing climate will affect the hydrologic conditions of the Congo River Basin using the Soil Water Assessment Tool (SWAT). They forced 25 climate model projections under RCP4.5 and RCP8.5 scenarios for future estimation. Their analysis showed that considering the mean of model ensembles, the total runoff over the basin will be increased by 7% by mid-century (2046-2065). However, flow changes at sub-basins are different in both sign and magnitude.

Applying satellite-derived rainfall data, Munzimi et al. (2019) used USGS Geospatial StreamFlow Model (GeoSFM) to simulate the daily flow over the Congo River Basin. They applied a physically based and spatially distributed model to consider better the slowing effects of central wetlands in flow estimation. Calibration and validation of the model were done using the observed flow at the Kinshasa gauge station, and additional evaluation in other sites was done based on monthly data. While the authors stated their model is reliable in discharge estimation in terms of timing and seasonality, the accuracy of flow magnitude is not satisfied in some cases. Recently, some studies have made an effort to develop a model with a better performance in the existing issues of the former models in wetland and routing functions and improve the flow generation within a basin. Kabuya et al. (2020) developed a river-wetland model, namely LISFLODD-FP, to quantify the parameters of the wetland functions of GW- PITMAN. In the new model, the river flow and wetland exchange process can be modelled and used in parameter estimation instead of trial and error calibration techniques. Given the importance of wetlands on watersheds' hydrology and their increasing changes, Datok et al. (2020) studied the role of Congo wetlands, called "Cuvette Centrale," in the water budget within the basin. For this purpose, they used the modified version of SWAT, suitable for tropical regions, forced by monthly gauged flow data. In brief, given that the Cuvette Centrale plays a crucial role in regulating the flow, they highlighted that the groundwater resources should be preserved to make wetlands' water quantity and quality safe against threats.

Currently, climate change impacts are much more than other human-induced impacts within the Congo River Basin (Laraque et al., 2020). Existing hydropower plants, few constructed roads and railways, no bridge over the river course, a vast inaccessible area to reach by humans, and low major industrial activities have caused most of the basin to remain intact. However, mining and agricultural activities and deforestation affect the basin hydrology. Nevertheless, they are currently limited compared to the climate-change-related risks. Besides, the expected surging population growth and its consequences will change the current weak human impacts to intensified stresses on natural resources.

The impact of climate change on the Congolese region has been understudied despite its significant role in the global climatic system. A few studies have focused on this context though some were conducted at continental or regional scales (Hamududu, 2012; IEA, 2020; Mahe et al., 2013; Orange et al., 1997). For example, Orange et al. (1997) investigated the impacts of climate change on river baseflow in Central Africa and found that decreases in runoff and groundwater storage are linked to the rainfall decline since 1971. Mahe et al. (2013) came to the same conclusion. Some authors focused on climate change impact assessment at the basin scale, which is essential for the decision-makers in water resource management. The hydrologic response of the basin to changing climate was investigated by Aloysius and Saiers (2017) using 25 GCMs output forced into the SWAT model. Model calibration was implemented based on 7-year available gauged streamflow in 20 locations over the basin from 1950 to 1957. They analyzed the runoff changes over the entire basin and each of the four main sub-basins considered in their study. Also, besides the total runoff, in their analysis, the variation of accessible flow was evaluated by excluding the flood events.

Given the expected impacts of climate change on African water resources, Sidibe et al. (2020) assessed how changing climate affects hydrological conditions. For this purpose, they downscaled outputs of 9 global climate models using the Rossby Center Regional climate model (RCA4) and then carried out bias correction through a non-parametric quantile mapping technique. The processed data forced two impact models, GR2M and IHACRES. The multi-model ensemble analysis found that overall discharge will increase by 5% across the region by mid-century (2020-2050). However, they highlighted high uncertainties in Central Africa attributed to the climate models and observed data.

In 2010 a joint project was established, namely “Climate Change Scenarios for the Congo River Basin” (CSC, 2013), implemented by cooperation between Gesellschaft für Internationale Zusammenarbeit GmbH, the Climate Service Centre (CSC) in Hamburg and the Wageningen University and Research Centre in the Netherlands. This project considered an Ensemble of 46 projections under SRES and RCPs low emission scenarios and 31 projections for the high emission scenario. While all projections are consistent in significant temperature rise by the end of the century, they do not agree with precipitation changes. Based on the annual analysis, the temperature increase in the low emission will be +1.5 to +3°C, while under high emission, the changes are between +3.5 and +6°C. It is highlighted that the precipitation changes vary, ranging from -10 to +10% and -5 to +10% for the high and low emission scenarios, respectively. Based on a large model ensemble, it is pointed out Congo River Basin is not likely to face significant changes in the water budget by the end of the century. However, the frequency and intensity of extreme events were projected to increase significantly.

As a water-dependent energy source, hydropower is vulnerable to climate change and needs to be investigated adequately in Congo River Basin with huge potential. Nevertheless, GEIDCO (2020), in their development plan for hydropower in the Congo River, disregards the probable impacts of climate change on its potential. A few studies investigate the possible effects of changing future conditions on hydroelectric generation. Killingtveit and Hamududu (2015) investigated the climate change impacts on the hydropower production in Inga plants. Regrading the project of hydropower plant Inga 3, Swanson and Sakhrani (2016) evaluated the climate risks on investment returns of the project. At the continental scale, IEA (2020) assessed the climate impacts on hydropower generation in 13 African countries by the end of the century using global hydrological and climate models under RCP2.6 and RCP4.5 emission scenarios. In brief, considering the region mean hydropower capacity of the considered plants in the period 2060-2090 was projected to decline by around 3% concerning the reference period (2010-2019). Also, the country-based analysis has shown a significant decrease in hydropower production in the Democratic Republic of Congo. While this assessment provides a general vision of future conditions of hydropower production over the continent, there is still needed to conduct an impact assessment at the regional scale using basin-scale hydrological models and high-resolution downscaled climate model projections and an ensemble of local observational data.

Hydrology of the KAR, despite its importance as the largest tributary of the Congo River, contributing more than 25% of mainstream flow, has been studied by a few authors at a sub-watershed scale (Backer, 1932; Devroey, 1939; Jean Marie et al., 2016; Kisangala & Ntombi, 2012; Ntombi & Kisangala, 2002). Among the Congo River Basin sub-watersheds, most studies have focused on the northern ones (Laraque et al., 2013; Laraque et al., 1998; Nguimalet & Orange, 2019; Tshimanga & Hughes, 2012; Wesselink et al., 1996). For instance, Wesselink et al. (1996) analyzed the flow of the Ubangi River. The northern tributary of the Congo River showed a downward trend in hydrological regimes since the 1970s droughts. They demonstrated that this runoff deficit is attributed to the rainfall decrease. According to what has been discussed above, the hydrology of the KARB under changing climate and the subsequent effects on its hydropower potential are investigated in this study.

CHAPTER 3 ORGANIZATION OF THE WORK

Significant changes in water availability and, consequently, pressure on water resources systems are projected in African regions due to human-induced changes in climate. For instance, total runoff within the Congo River Basin is projected to vary between -12% to +24% by mid-century (2046-2065) based on the minimum and maximum changes across model ensembles (Aloysius & Saiers, 2017). Such changes need to be considered in water resource planning to promote sustainable development. Nevertheless, as previously noted, impact assessment is highly problematic in the Congo River Basin due to the limited availability of data both temporally and spatially in this vast region, as well as its complex hydroclimatic conditions. This study aims to assess the climate change impacts on streamflow conditions and its hydropower potential on one of the main sub-watersheds of the Congo River Basin using a multi-model framework to represent catchment based on multiple hydrological models as well as climate data in the historical and future periods. Such analysis has not been done in Central African case studies to the best of the author's knowledge. The case study is the Kasai River Basin which plays a strategic role in the economic growth of the region in terms of agriculture, river navigation and hydroelectricity generation, as described in Chapter 4.

In Chapter 4, two conceptual hydrological models, HBV-MTL and GR4J, are used for streamflow simulation during historical and future periods. First, these models are calibrated using temperature and precipitation outputs of four reanalysis products during the historical period. In each hydrological model, both optimal and acceptable calibration parameter sets are found using the Generalized Likelihood Estimation method. The ensemble of calibrated models is then used to simulate the flow at the basin's outlet. The performance of these models is evaluated on daily and annual scales, and unfalsified models are used for impact assessment. According to the downscaled and bias-corrected projections of 19 GCMs under two RCPs, emission scenarios are used to simulate future flow and hydropower production conditions during the 2021-2099 period. This chapter is submitted to the *Journal of hydrology* (impact factor:5.72) on April 10th, 2022.

Discussion and conclusions over the findings of this chapter are described in Chapters 5 and 6, respectively.

CHAPTER 4 ARTICLE 1: MULTI-MODEL ASSESSMENT OF CLIMATE CHANGE IMPACTS ON THE STREAMFLOW CONDITIONS IN THE KASAI RIVER BASIN, CENTRAL AFRICA

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This chapter is submitted to the Journal of Hydrology with an impact factor of 5.72 on April 10th, 2022. Also, this project was presented at the Canadian Water Resource Association (CWRA) conference on August 4th, 2021.

Contribution of authors

The MSc student applied a multi-model climate change impact assessment in a case study. She collected and analyzed the climate outputs of observed, four reanalysis, as well as projections of 19 GCMs, calibrated two hydrological models, and conducted the simulations for impact assessment, drafted the original manuscript and revisions. Elmira Hassanzadeh and Musandji Fuamba supervised the project. Ali Sharifinejad provided support for Matlab codes of hydrological models. Salomon Salumu Zahera provided support in the collection of the historical hydroclimatic data.

Abstract

The Congo River Basin is the second-largest watershed globally, flowing through nine countries before reaching the Atlantic Ocean. The Kasai River Basin (KARB), containing about one-fourth of Congo's freshwater resources, plays a strategic role in sustaining navigation, food production, and hydroelectricity generation in Central Africa. A multi-model framework suited for data-scarce regions is applied for climate change impacts on water availability in the KARB to propose effective development plans in the future. This includes consideration of two conceptual hydrological models calibrated using four reanalysis datasets and fed with bias-corrected outputs of 19 climate models under two future Representative Climate Pathways (RCPs). Changes in mean annual discharge in the KARB from -18% to +3% are projected depending on the considered modeling configuration. This shows the sensitivity of impact assessment to the choice of models as well as input data. Moreover, about 9%, 18%, and 13% decline in streamflow signatures (Q10, Q50 and Q90) are projected based on the ensemble of models under RCP 8.5. A decrease of 14% and 5% in annual hydropower potential of the mainstream is estimated under RCPs 4.5 and 8.5, respectively. These changes in flow conditions should be considered in decision-making around constructing reservoirs and hydroelectricity generation.

Keywords: Climate change; Hydrological modeling; Streamflow regime; Reanalysis datasets; Kasai River Basin; Congo

4.1 Introduction

Central Africa is a strategic region globally (Aloysius et al., 2016; Laraque et al., 2020; Runge, 2008), containing large tropical rainforests that are significant carbon sinks and play a critical role in mediating the effects of global warming (Aloysius et al., 2016). The Congo River Basin in this region encompasses various countries and is the second largest watershed in the world, including about one-third of Africa's freshwater resources. Despite the abundant water budget, high potential for power production, and rich natural resources, the countries herein are the least economically developed and face various food and water security challenges (IPCC, 2021; UNEP, 2011). On top of the existing problems, the hydroclimatic conditions of the region have been altered due to the warming climate, which makes sustainable development highly challenging. Alterations in numbers and periods of dry and wet days, reduction of water content in rainforests, multidecadal drying trends in streamflow, increase of temperature by 0.5 °C with a stronger increasing trend in minimum than maximum temperature and decline of rainfall by 9% during the 20th century are few examples of changes in the past few decades (CSC, 2013; Diem et al., 2014; IPCC, 2014; Moukandi et al., 2020; Nicholson et al., 2018b; Sidibe et al., 2018). Continuation of changes in climate can cause severe socio-economic vulnerability in the region due to the lack of adequate infrastructure, industrialization, mismanagement, and political issues (Boko et al., 2007; CSC, 2013; Niang et al., 2014; Schneider et al., 2007). Therefore, understanding the impact of climate change on water availability in the Congo River Basin is essential to proposing adaptive water and energy management policies (Aloysius et al., 2016).

The impact of climate change can be assessed using the so-called "top-down" approach (Bhave et al., 2014) based on the projections of General Circulation Models (GCMs), which are downscaled to the spatial resolution of interest, and fed into impact assessment models (Sorland et al., 2018). The GCMs simulate the Earth's physical processes using various mathematical equations, representing mass and energy transfer through the climate system (Hannah, 2015). Due to the inconsistency of GCMs projections and the complexity of the Congo River Basin's climate system, using an ensemble of climate models is recommended for impact assessment (Aloysius & Saiers, 2017; Aloysius et al., 2016; Chen et al., 2011). Nevertheless, modeling the impact of climate change on water availability is highly challenging in the Congo River Basin. One of the main problems is the availability of sparse or low-quality hydroclimatic data in the watersheds (Sidibe et al., 2020; Zhou et al., 2014). Even if such data exist, they might be erroneous due to maintenance and operational issues, human errors, and environmental conditions (Diem et al., 2014; Samba et al., 2008). Indeed, the number of active stations in the Congo Basin region has been significantly reduced since the independence of the countries in 1960 (Laraque et al., 2020). Escalating political issues, lack of infrastructure such as limited transportation networks, and a limited budget for operation and maintenance are other contributing factors to scarce hydroclimatic stations (Hua et al., 2019; Washington et al., 2013; Zhou et al., 2014). This makes hydrological representation of catchment physical processes difficult even under the historical conditions in these regions. Hence, some approaches such as regionalization (Beck et al., 2016), use of satellite-derived data (Huang et al., 2020) or reanalysis datasets (Ghebrehiwot & Kozlov, 2021) have been commonly utilized. Reanalysis is a systematic approach to generating grid-based climate data using data assimilation schemes and models that are fed by available observational data, which are provided from various sources such as satellites, buoys, aircraft, and ship reports (Bosilovich et al., 2008; Parker, 2016). The improved quality and homogeneity of the reanalysis data make them a desirable choice for climate monitoring and research, as well as in commercial applications, particularly in data-scarce regions (Ghebrehiwot & Kozlov, 2021; Parker, 2016). The hydrological models using reanalysis can estimate river discharge as good as or even better than the ones using the station data (Essou et al., 2016; Fuka et al., 2014). Given the differences among reanalysis datasets attributed to the inter-model variability, assimilation approach, and available observations (Hamududu, 2012; Lin et al., 2014; Nicholson et al., 2018b; Washington et al., 2013), using an ensemble of reanalysis datasets in hydrological modeling is suggested to reduce the related uncertainty.

In addition to limited data, the complexity of catchments, including their size and remoteness, can affect the choice of hydrological models for process representations, too (Asante et al., 2008; Munzimi et al., 2019; Tshimanga & Hughes, 2014). The conceptual models have shown acceptable performance and have been suggested to be used in climate change impact studies, specifically in data scares regions of the Congo River Basin, due to their simplicity and lower number of variables compared to the other types (Chen et al., 2013; dos Santos Franciane et al., 2018; Hamududu, 2012; Her & Chaubey, 2015; Nonki et al., 2019; Singh & Marcy, 2017; Tshimanga & Hughes, 2012). For instance, using GW-PITMAN, it is found that the streamflow characteristics will change in the future, but the magnitude and sign of change are not consistent over the basin (Aloysius & Saiers, 2017; CSC, 2013; Tshimanga, 2012; Tshimanga & Hughes, 2012). Since the simulation of flow is sensitive to the structure of hydrological models, and different models may provide varying flow estimations, it is recommended to use more than one conceptual model for impact assessment (Ludwig et al., 2009; Seiller et al., 2012; Sharifinejad et al., 2021; Viney et al., 2009; Yaghoubi & Massah Bavani, 2014).

This study aims to assess the impact of climate change on water availability in the Kasai River Basin (KARB; 897,500 km^2), one of the key watersheds in the Congo River Basin, using an ensemble of state-of-the-art reanalysis data, two conceptual hydrological models, as well as multi-model climate projections under different future scenarios. Containing more than 25% of Congo's freshwater resources with an average annual discharge of 11500 m^3/s at the reaching point to the Congo River (Becker et al., 2018), the KARB plays a strategic role in Central Africa’s economic growth, with great potential in agriculture, hydropower, mining and navigation (GEIDCO, 2020).

The almost unexploited hydropower resource (~ 68 GW) of the KARB, due to the financial, political, and infrastructural issues, is considered one of the prioritized components of the sustainable development plan in Africa (GEIDCO, 2020). However, the high sensitivity of this energy resource to alterations in the streamflow regime makes hydropower production vulnerable to changing climatic conditions. Few studies have analyzed the performance of the water resources system in the KARB in the future (Devroey, 1939; Kisangala & Ntombi, 2012; Ntombi & Kisangala, 2002). While the existing studies over the Congo River Basin use a single hydrological model (e.g., Aloysius & Saiers, 2017; Hamududu, 2012; Tshimanga & Hughes, 2012), to the best of our knowledge a multi-model projection framework has been hindered for impact assessment over the KARB. The structure of the paper is as follows. In Section 4.2, the KARB and its major challenges in terms of water resources are described. Section 4.3 includes the framework of impact assessment, dataset and hydrological models used in this study. Section 4.4 presents the performance of hydrological models in the historical period and estimated flow conditions by the end of the century. The conclusions of the paper are highlighted in Section 4.5.

4.2 Case study

The Congo River Basin has an average annual discharge of 40,600 m^3/s and covers an area of about 3.7×10^6 km^2 (Laraque et al., 2001, see Figure 1). It encompasses five sub-watersheds, among which the Kasai River Basin is one of the largest watersheds (Moukandi et al., 2020). Around 72.4% of the KARB is located in Congo, and the remaining part (southwest) is in Angola (Jean Marie et al., 2016). The long-term average annual temperature of the basin is about 24°C (Jean Marie et al., 2016), and rainfall varies from 1431 to 1515 mm per year (Moukandi et al., 2020). The Kasai River (KAR), with a length of 2153 km, is the mainstream (Devroey, 1939), originating from the Munyango headwaters in Angola (Tshimanga, 2012). The Kwango, Kwilu, and Loange on the left bank of the KAR and Sankuru and Lulua on the right bank are other key rivers in the KARB with an average flow of 2092, 1207, 427, 2500, and 502 m^3/s, respectively (GEIDCO, 2020). These rivers confluence in Kutu Moke and have an average annual discharge of 8246 m^3/s at the outlet (Laraque et al., 2020, see Figure 1). The main hydrometric station in the KARB is the Kutu-Moke covering a drainage area of 750,000 km^2, about 20% of the Congo River Basin (Tshimanga, 2012). The basin's mean annual rainfall, temperature, streamflow discharge, and drainage area are presented in Table 4.1.

Containing 360 million cubic meters of the Congo River Basin's water budget per year, the KARB plays a key role in the water resource management of the region (Becker et al., 2018; Bultot, 1971). Currently, around 25% of the Democratic Republic of Congo's population resides with unequal distribution in the KARB. While most of the population still lives in rural areas, urbanization has been considerable in recent decades (Mbimbi Mayi Munene et al., 2021). Significant mining resources such as gold, diamonds, and other minerals exist in this region. Nevertheless, shifting agriculture is the primary source of income for most households, which highly depends on water availability in the area. In particular, food production is mostly based on rain-fed agriculture; therefore, any crisis in the basin's water availability might threaten food security at the regional scale (Brown et al., 2014). The basin is rich in flora and fauna and is home to various animal and fish species, including endangered habitats (Mbimbi Mayi Munene et al., 2021).

Despite the KARB's potential for power production, agriculture and rich natural resources, many households have limited access to electricity, safe drinking water, and health services due to the poorly developed infrastructures and political issues (World Bank, 2021). Several rapids and waterfalls flowing into the deep valleys make the KAR and its tributaries strategic for not only navigation purposes but also for hydropower generation, which can promote the region's energy supply. However, the only hydropower plant project in the advanced planning stage is the Katende hydroelectric dam, with a 64 Megawatts (MW) planned capacity (Mbimbi Mayi Munene et al., 2021).

As previously noted, changes in climate have already affected Central Africa, including the KARB. The Congo River has faced flow instability during the second half of the 20th century following a remarkable change by a sharp decline in the last decade (Diem et al., 2014; Laraque et al., 2001; Mahe et al., 2013; Nguimalet & Orange, 2019). In the KARB, rainfall intensity has dropped by around 9% from 1940 to 1999, with the change of annual rainfall from 1525 mm in 1920-1969 to 1388 mm during 1970-1990 (Laraque et al., 2020). Such alterations in precipitation have affected groundwater storage of the basin and have led to reductions in streamflow discharge (Mahe et al., 2013), e.g., from 8606 m^3/s in 1948-1991 to 6943 m^3/s in 1992-2012 at Kutu-Moke (Moukandi et al., 2020).

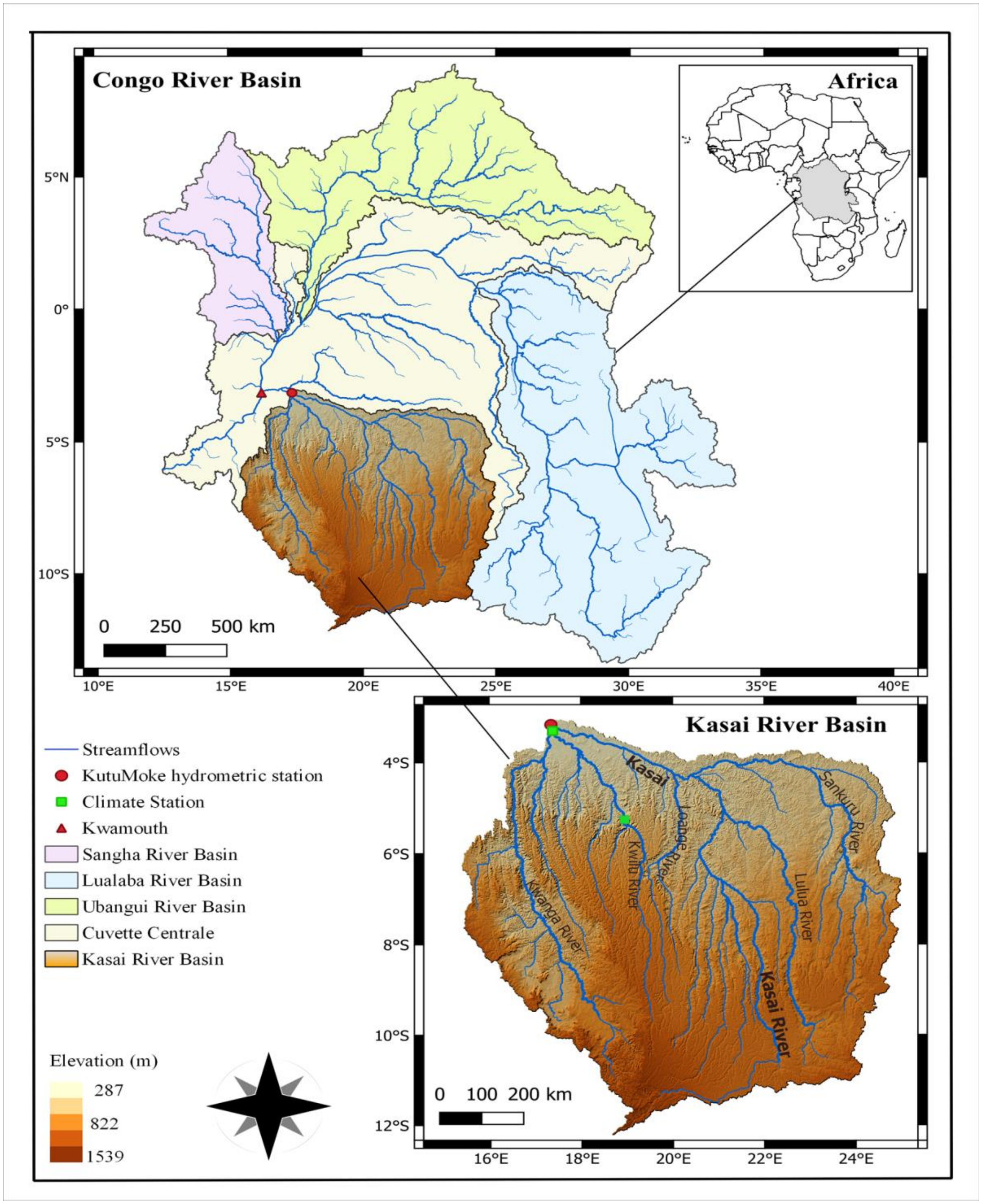

Figure 4.1 The Kasai River Basin, sub-watershed of the Congo River Basin in Central Africa, and its main tributaries. River networks and sub-basins are retrieved from Linke et al. (2019).

Using the outputs of GCMs, an increase of between 2-6°C in temperature is projected in Central Africa in the 21st century (Aloysius et al., 2016; Haensler et al., 2013; Niang et al., 2014). Regarding the precipitation, the projections diverge considerably (Niang et al., 2014; Orlowsky & Seneviratne, 2012; Rowell, 2012), and the changes are not homogenous over the basin. For instance, a decrease in precipitation in the south and a slight increase in the north are estimated (Aloysius & Saiers, 2017). As a result, no changes in annual average precipitation over the whole of Central Africa are projected (Haensler et al., 2013). However, for the KARB, the median of changes in annual total precipitation is projected to increase by around 10% in the late 21st century (2071-2100) under a high emission scenario. Reductions in precipitation during the dry seasons, i.e., June-July-August and September-October-November, are estimated (Haensler et al., 2013). The projected rise in temperature and the decrease or no change in the region's precipitation may lead to prolonged and more frequent dry periods in the future (Haensler et al., 2013). Moreover, drought-prone areas in the KARB, including savanna parts of the Katanga and the Kasai plateau, are expected to experience seasonal water shortages in the near future (UNEP, 2011).

Diverging changes in the streamflow regime in the KARB are estimated depending on the rainfall projections and utilized hydrological models (Orlowsky & Seneviratne, 2012; Rowell, 2012). For instance, using a global hydrological model with a spatial resolution of 0.5°, more than half of the GCMs in CMIP3 show a decrease in the average annual runoff by 2080 over the basin (Arnell, 2003). In another study, a marginal decrease in average annual runoff in the south and a slight increase (less than 10%) in other regions is projected using a macro-scale VIC hydrological model, forced with bias-corrected outputs of three GCMs in CMIP3 (Beyene et al., 2013). Such changes in flow make different sectors, including energy, food security, agriculture, environment and natural resources, vulnerable due to their low adaptive capacity (Boko et al., 2007). In these studies, the streamflow is simulated without considering routing through catchments, which may not properly represent flow series at a daily scale. Using a SWAT model for the Congo River Basin and considering an ensemble of GCMs, an increase in the mean seasonal runoff in wet seasons (from December to May) and a reduction in runoff during the dry period in the KARB (from Jun to November) but an overall increase in annual runoff of whole Congo River Basin is projected

(Aloysius and Saiers (2017). Nevertheless, there are some limitations in the noted study, such as the calibration of the model using monthly data due to the lack of observed daily streamflow. While in our study, the climate change impacts are assessed utilizing the high-resolution GCMs projections, the focus is also on understanding the importance of using different hydrological model structures and calibration, which have not been done before for this case study to the best of our knowledge.

4.3 Materials and methods

4.3.1 Framework for climate change impact assessment

Here, we applied a framework suited to the Central African Basins to assess the impact of climate change on the KARB, see Figure 4.2. As previously noted, for these scarce data regions, most studies suggest using an ensemble of reanalysis data for the calibration of hydrologic models (Bosilovich et al., 2008; Hua et al., 2019; Zhou et al., 2014). Therefore, in this study, a set of state-of-the-art reanalysis along with recorded climate data are used as input to hydrologic models. Moreover, HBV and GR4J hydrologic models are used to simulate natural streamflow, with the aim of addressing the inherent uncertainty of the hydrological models and avoiding divergence that may occur using a single model. The calibrated models using these data are forced with the outputs of an ensemble of GCMs under different future scenarios to project water availability by the end of the century. Accordingly, the changes in streamflow characteristics affecting hydropower production are investigated. The historical and future climatic data used in this study are described in Sections 4.3.2 and 4.3.3, respectively. Section 4.3.4 represents the employed hydrological models and their calibration and validation procedures.

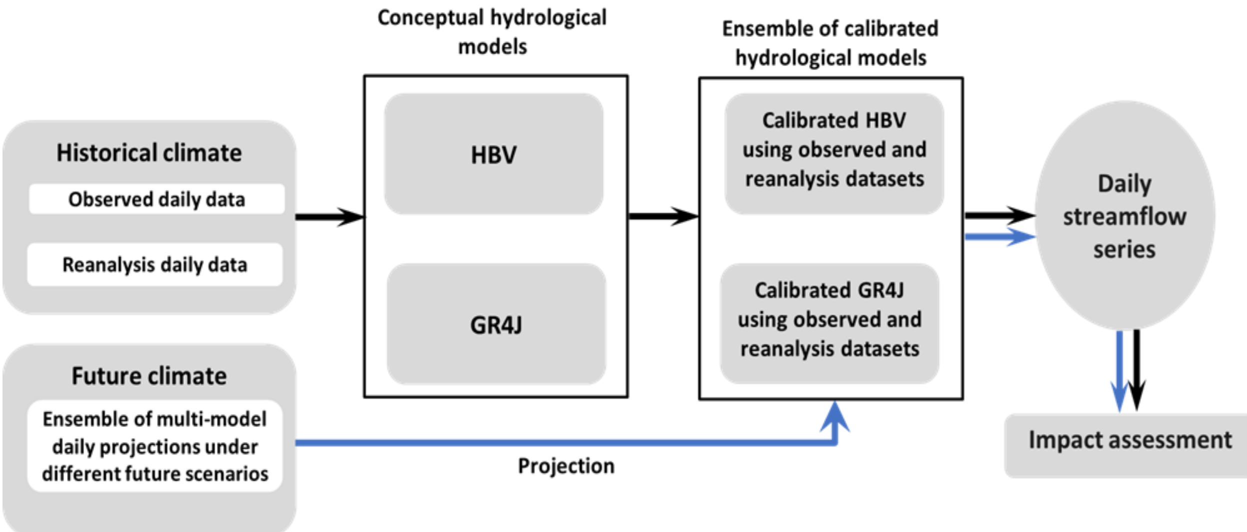

Figure 4.2 Framework to assess the climate change impacts on water availability in the KARB.

4.3.2 Station-based and reanalysis datasets

The streamflow data in the outlet, Kutu-Moke station, is obtained from the International Commission for the Congo-Ubangi-Sangha Basin (Laraque et al., 2020). Regarding the climate data, the recorded daily precipitation, as well as minimum and maximum temperature for the KARB, are obtained from the National Meteorological Agency of the Democratic Republic of Congo. Table 4.1 shows the characteristics of these data. Moreover, the temperature and precipitation data of 4 reanalysis, namely, ERA5-Land, CFSR, JRA55, and MERRA (Chen et al., 2021; Hua et al., 2019), are considered in this study, see Table 4.2.

The temporal variation of daily mean precipitation and temperature averaged over the KARB, as well as seasonal cycles of climatic data for each reanalysis product and observed data, are presented in Figure 4.3. Boxplots and lines respectively contain daily and expected daily temperature and precipitation values over a 30-year period (1981-2010), respectively. Overall, it is evident that the range of reanalysis datasets is different from each other and observed values, in particular considering precipitation. This can be due to divergence in the assimilation schemes, ground data used in assimilation, and/or utilized forecast climate models (e.g., Lin et al., 2014). Considering the right panel, it is clear that over the Kasai watershed, there are two high precipitation periods during March-April-May (MAM) and September-October-November (SON). However, the magnitude of rainfall in these wet seasons varies among reanalysis; MERRA is the most inconsistent dataset, which shows higher differences relative to other datasets. CFSR presents the wettest rainy season, while the JRA-55 data shows the driest season among reanalysis. Considering the dry season from June to August (JJA), all reanalysis capture similar distribution rather than the wet season. Figure 4.3 shows that all datasets are more consistent in seasonal temperature variation than precipitation, yet the temperature variability in the MERRA is more than in others. Overall, reanalysis provides reliable precipitation and temperature data for the river flow simulation.

Table 4.1 Hydro-climatic characteristics of the KARB.

Climate					**Streamflow**		
Station	Mean annual precipitation (mm)	Average minimum temperature (°C)	Average maximum temperature (°C)	Basin average precipitation (mm)	Station	Average annual flow (m^3/s)	Drainage area (km^2)
Bandundu	1554	21.4	30.8	1456	Kutu Moke	8070	750,000
Kiyaka	1649	20.0	29.3				

Table 4.2 Utilized reanalysis datasets, their temporal coverage, as well as spatial and temporal resolutions.

Dataset	**Source**	**Available temporal coverage**	**Spatial resolution**	**Temporal resolution**	**Reference**
ERA5-Land	ECMWF	1981-present	0.1°× 0.1°	Daily	(Muñoz-Sabater et al., 2021)
Climate Forecast System Reanalysis (CFSR)	NCEP	1979-present	0.5° × 0.5°	Daily	Saha et al. (2014)
Japanese 55-year Reanalysis (JRA-55)	Japan Meteorological Agency	1958-present	1.25°×1.25°	Daily	Kobayashi et al. (2015)
Modern-Era Retrospective analysis for Research and Applications (MERRA)	NASA GMAO	1979-2016	0.5° × 0.66°	Daily	Rienecker et al. (2011)

4.3.3 Climate model projections

The NASA Earth Exchange Global Daily Downscaled Projections dataset for 19 GCMs is used in this study (NCCS, 2020). The data include the maximum and minimum air temperature and precipitation with the spatial resolution of 0.25° from 1950 to 2100 for the historical and future periods. The projections are available under two Representative Concentration Pathways (RCPs), 4.5 and 8.5, corresponding to the intermediate mitigation and high emission scenarios, respectively (Thrasher et al., 2013). The near-term (2021-2040), mid-term (2041-2070), and long-term (2071-2099) horizons are considered to better discuss the results of impact assessment in the future.

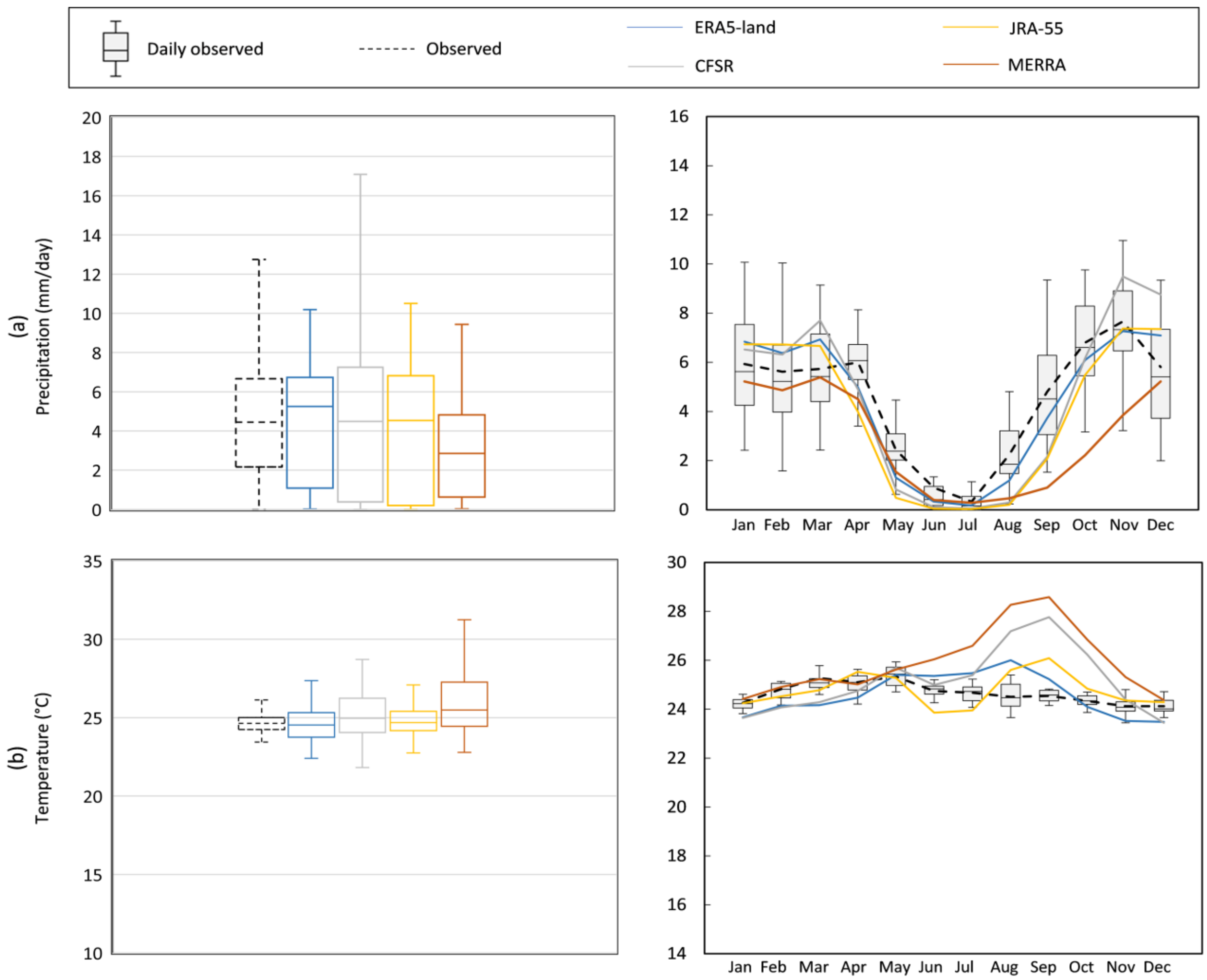

Figure 4.3 Daily precipitation and temperature values over a 30-year period based on the observed and four reanalysis datasets (Left panel), averaged over the KARB. The right panel shows the observed daily (boxplots) as well as expected values (lines) in each month based on observed and reanalysis datasets, which are averaged over the basin.

Here, the 19 GCMs simulations during the historical and future periods are compared with each other and reanalysis datasets in Figure 4.4. Overall, GCMs have a smaller variability than the reanalysis datasets, except MERRA, in the historical period, and GCMs have a closer median to ERA5-Land. Regarding the temperature, historical GCMs are similar to ERA5-Land and JRA-55 in terms of variability, with an almost identical median (around 24.5 °C). In general, our analysis reveals that there is a definite increase in temperature in the future ranging between 1.05-2.1°C and 1.3-4.0 °C under RCPs 4.5 and 8.5, respectively. These results are consistent with the findings of the previous studies (Aloysius et al., 2016; Haensler et al., 2013; Niang et al., 2014). Regarding the precipitation, a slight increase is expected in the long-term future. The median of projections during the future horizons ranges between 4.33-4.42 mm/day and 4.33-4.53 mm/day under low and high emission scenarios, respectively. These quantiles present around a 1% to 6% increase in the median of daily precipitation with respect to the historical values.

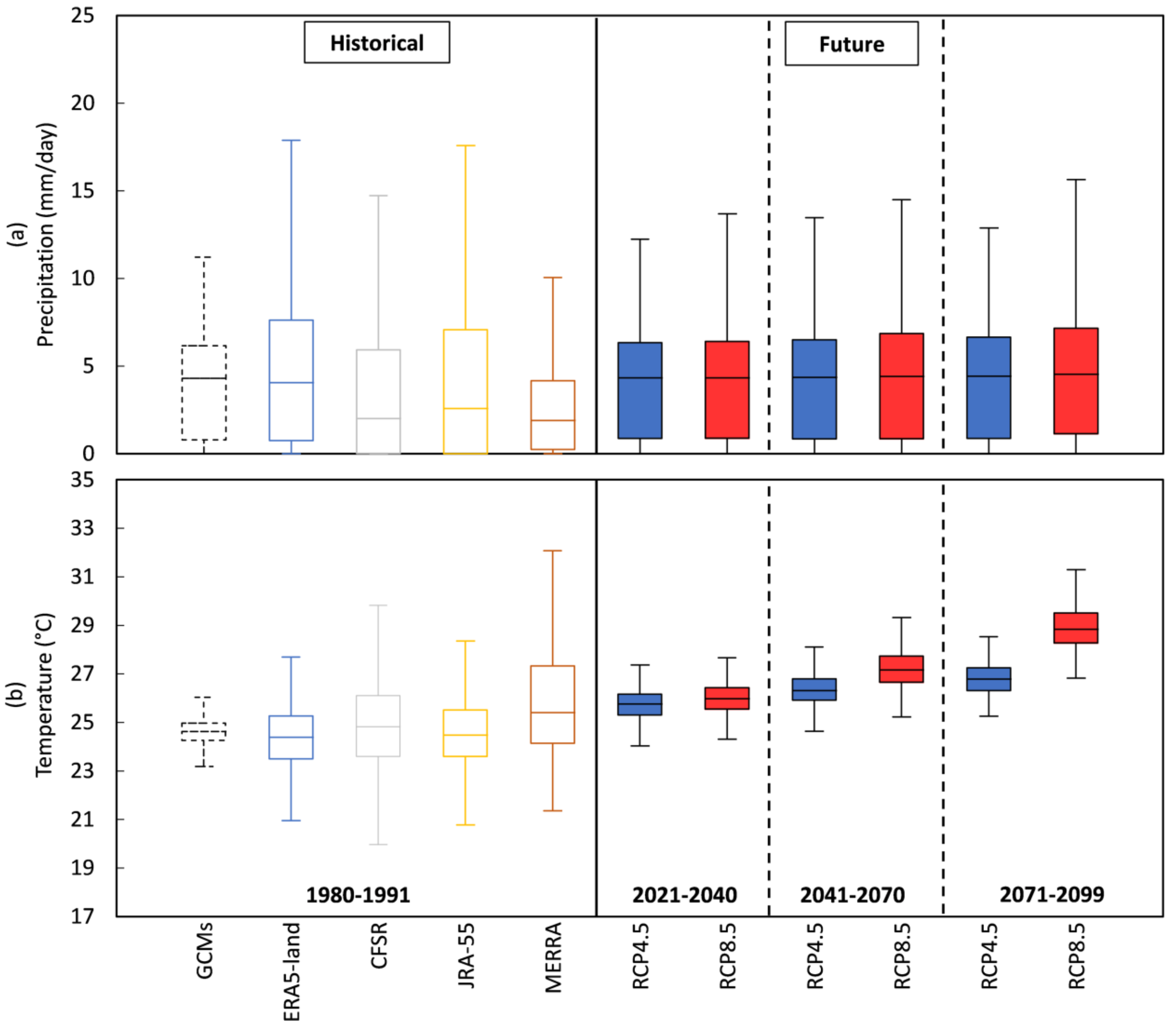

Figure 4.4 Comparison of (a) precipitation and (b) temperature in the future based on 19 climate models under RCPs 4.5 and 8.5 with respect to the historical values of (GCMs and reanalysis in the KARB.

4.3.4 Hydrological models

As noted earlier, HBV-MTL and GR4J models are used to simulate daily streamflow in the KARB due to their simplicity and accuracy (Kwakye & Bárdossy, 2020). HBV is widely used (Lindström et al., 1997; Seibert & Vis, 2012) in climate change impact studies (Hamududu, 2012; Nonki et al., 2019). In particular, the model has shown considerable potential for streamflow estimation in ungauged basins (Samuel et al., 2012; Seibert & Beven, 2009). HBV-MTL, a recently modified HBV model by (Sharifinejad et al., 2021), is used here. The main inputs to this model are daily precipitation, as well as maximum and minimum air temperature. The model consists of four main modules: soil moisture, surface runoff, interflow, and baseflow reservoirs. The precipitation, either rainfall or snowmelt, enters the soil moisture module. This module evaluates effective rainfall contributing to surface runoff, or the water infiltrates the soil used by vegetation through evapotranspiration. The evapotranspiration is estimated using the Hargreaves method (Hargreaves & Samani, 1985) because of its simplicity and minimum data requirements compared to other methods, especially in such a data-scarce region (Hargreaves & Allen, 2003). The remaining water in the soil is stored in two conceptual reservoirs, the so-called intermediate and deep soil layer, which gradually releases and forms the intermediate and base flow. Finally, the flow at the watershed outlet is stimulated by the accumulation of direct runoff, intermediate flow, and base flow routed through a triangle delay function. For more information about model structure and equations, see Sharifinejad et al. (2021).

The GR4J is a lumped model which estimates runoff based on daily temperature, precipitation, and potential evapotranspiration data. Unlike HBV, in GR4J, the net precipitation obtained by subtracting potential evapotranspiration from precipitation is divided into two portions. The model consists of three modules, namely production storage, routing storage, and two unit-hydrograph functions. First, a portion of net precipitation is stored in the production storage, from which the water percolates gradually, dependent on the soil moisture capacity. Meanwhile, some of the stored water used by vegetation lead to evapotranspiration. The other portion of the net precipitation integrates with the percolated water from production storage and contributes to the routing storage through unit hydrographs. Indeed, the unit hydrographs in the model address the lag time between precipitation and streamflow generation. In this stage, 10% of the existing water (runoff) is directly routed to the outlet using a two-sided unit hydrograph, while the remaining 90% is routed indirectly through the groundwater exchange using a one-sided unit hydrograph. More details about the model structure and equations can be found in Perrin et al. (2003).

The model parameterization includes a few steps. In brief, the data during the historical period is divided into three parts for model warm-up, calibration, and validation. The first year of data is used for warm-up to allow model states to tune out based on the initial conditions of the watershed (Sadegh et al., 2019; Seibert & Vis, 2012). The 66% and 34% of the remaining data are used for model calibration and validation, respectively, based on the split-sample test (KlemeŠ, 1986; Sharifinejad et al., 2021). The two hydrological models are calibrated against observed streamflow using an ensemble of climate datasets during the historical period, including station-based data as well as four reanalysis, ERA5-Land, CFSR, JRA55 and MERRA. Accordingly, the models' performance is evaluated based on the Kling-Gupta Efficiency (KGE) measure (Gupta et al., 2009), and the value of parameters are obtained for each model. The KGE presents a more comprehensive comparison between the estimated and observed values using different statistical criteria, namely standard deviation, mean and Pearson correlation coefficient, which are shown as α, β and r in the following equations (Eqs. 4.1, 4.2, and 4.3). As shown in Eq. 4.4, these criteria are combined in the KGE in a more balanced way using the Euclidean distance measure compared to other measures such as Nash-Sutcliffe Efficiency (Nash & Sutcliffe, 1970). The calibration and evaluation of the models are done considering this measure on daily and annual scales (Eq. 4.5). In Equation 4.1 to 4.3, σ_s and σ_0 are the standard deviation of simulated and observed flow, $\overline{S}$ and $\overline{O}$ are the mean simulated and observed flow, S_t and O_t are simulated and observed flow, respectively.

$$\alpha = \frac{\sigma_s}{\sigma_o} \qquad \text{(Eq. 4.1)}$$

$$\beta = \frac{\overline{S}}{\overline{O}} \qquad \text{(Eq. 4.2)}$$

$$r = \frac{\sum_t (O_t - \overline{O})(S_t - \overline{S})}{\sqrt{(\sum_t (O_t - \overline{O})^2)(\sum_t (S_t - \overline{S})^2)}} \qquad \text{(Eq. 4.3)}$$

$$KGE = 1 - \sqrt{(1-\alpha)^2 + (1-\beta)^2 + (1-r)^2} \qquad \text{(Eq. 4.4)}$$

$$Obj = Min\sqrt{(1-KGE_{daily})^2 + (1-KGE_{annual})^2} \qquad \text{(Eq. 4.5)}$$

The Shuffled Complex Evolution algorithm (SCE-UA) is used to calibrate the hydrological models (Duan et al., 1993; Yarpiz, 2020). In this method, the optimized parameter set is found based on a combination of random (Price, 1983) and deterministic approaches (Dixon et al., 1978), clustering (Törn, 1986) and competitive evolution (Holland, 1992). The optimized parameter sets are found in a natural evolution process through a global search. A population (parameter sets) is randomly sampled from the feasible space and then partitioned into several complexes that will evolve independently through the complex, competitive evolution technique. To avoid reaching local optima, the entire population is shuffled, and the information of complexes is shared. These processes are repeated since the convergence criteria are satisfied. In this study, 50 populations are selected randomly from the feasible space based on the parameter sets' range and are divided into five complexes. The evolution and shuffling of the independent complexes are repeated until the maximum iteration of 100. As a result, the best parameter sets with the smallest value for the considered objective function (Eq. 4.5) are obtained. This ensemble of parameter set is called "optimal parameter set" leading into "optimal flow simulation". Beside the use of global optimization in calibration of the models, to avoid the probable underestimation of the parametric uncertainty (Wu & Chen, 2015; Yang et al., 2007), the Generalized Likelihood Uncertainty Estimation (GLUE) is used (Beven & Binley, 1992, 2014; Mirzaei et al., 2015). GLUE is a statistical method employed in hydrological modeling for quantification of uncertainty attributed to the model parameters. Hence, instead of having one optimal parameter sets, there will be a range of acceptable parameter sets based on considered objective function. For this purpose, the initial parameter sets are selected randomly from the feasible range of parameters using a uniform probability distribution. The KGE is used as the statistical criteria to quantify the closeness of simulated and observed flow and find the acceptable parameter sets. Considering both daily and annual scale the value of KGE should be larger than 0.5 to select the "acceptable parameter sets". 10000 iterations are considered to generate the parameter sets. Using these "acceptable parameter sets", an ensemble of "acceptable streamflow" for each model are estimated.

4.4 Results

4.4.1 Performance of the hydrological models during the historical period

Based on the availability of daily streamflow and climate datasets, 1980-1991 is considered as the historical period for streamflow simulation. The HBV and GR4J models are calibrated using the observed as well as four reanalysis datasets. The performance of these models in reproducing the observed streamflow is assessed using the KGE measure, see Table S1 in the Supplementary Materials. The low KGE values, i.e., less than 0.4 and 0.2 for HBV and GR4J models, are not acceptable, which can be attributed to the low quality of the observed station-based data, demystified in various studies (Aloysius & Saiers, 2017; Tshimanga & Hughes, 2014). Hence, these models are not considered for impact assessment. However, the calibrated models using the reanalysis datasets provide reasonable results. Figure 4.5 shows the daily and annual time series of the observed and simulated flow using HBV (left) and GR4J (right) models fed with the four reanalysis datasets during the calibration and validation periods, respectively. Considering the simulations, both the optimal and an ensemble of acceptable flow series, corresponding to their parameter conditions, noted in Section 4.3.4, are presented. Both seasonality in discharge and overall distribution of discharge (monthly hydrograph) are simulated well. Moreover, the KGE values above 0.5 for all 8 configurations indicate that these models perform better than the calibrated models using the observed data, which is concluded by other researchers as well (Essou et al., 2016; Fuka et al., 2014).

However, the performance of the models varies depending on the applied reanalysis datasets for calibration as well as the considered hydrological model (Dakhlaoui et al., 2017; Osuch et al., 2015). Considering both daily and annual time series, it seems that the calibrated models with ERA5-Land datasets perform better, in particular, in representing the peak flow timing and magnitude and low flows. Conversely, the models calibrated with MERRA show a larger discrepancy in estimating flow discharge. The impact of input data on flow simulation is more evident at the annual scale. For instance, both HBV and GR4J models using the CFSR dataset continuously underestimate the annual flow during the historical period, while the calibrated models using JRA-55 estimate streamflow more accurately than with the CFSR dataset. It is noteworthy to mention that the ERA5-based models more precisely simulate annual flow by around half relative error than other datasets. Besides the input data, it is clear that the structure of the hydrological models is critical in simulating streamflow. For instance, using the MERRA dataset, the HBV model during the validation period (1989-1991) underestimates annual flow while the GR4J model overestimates it. In addition, the GR4J model better reproduces the daily flow with a lower relative bias (0.05) than HBV (0.1) and a higher Correlation Coefficient by a 0.05 difference, given the ERA5-Land dataset. Considering the long-term annual hydrograph of simulated and observed flow (Figure 4.6), in the wet season (March-April-May), the HBV model calibrated with ERA5 simulates high flows more accurately than other models (with 2% bias respecting the observed ones) while GR4J with the same dataset (ERA5-Land) show a larger difference in the simulated peak flow with observations by around 7% bias. Meanwhile, the largest bias in estimated flow in the wet season is related to the GR4J model calibrated using the CFSR.

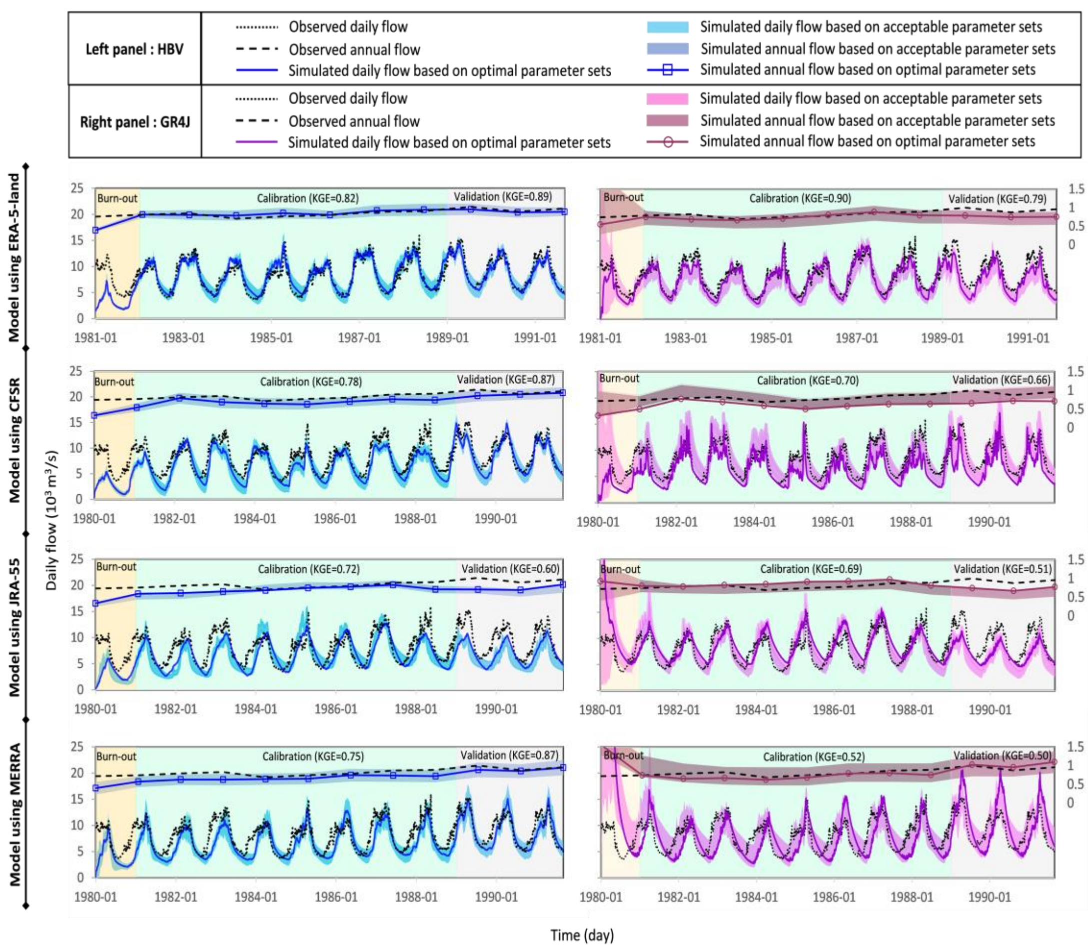

Figure 4.5 Observed and simulated daily and annual flow during the historical period at the outlet using four reanalysis datasets forced to HBV (left) and GR4J (right) models.

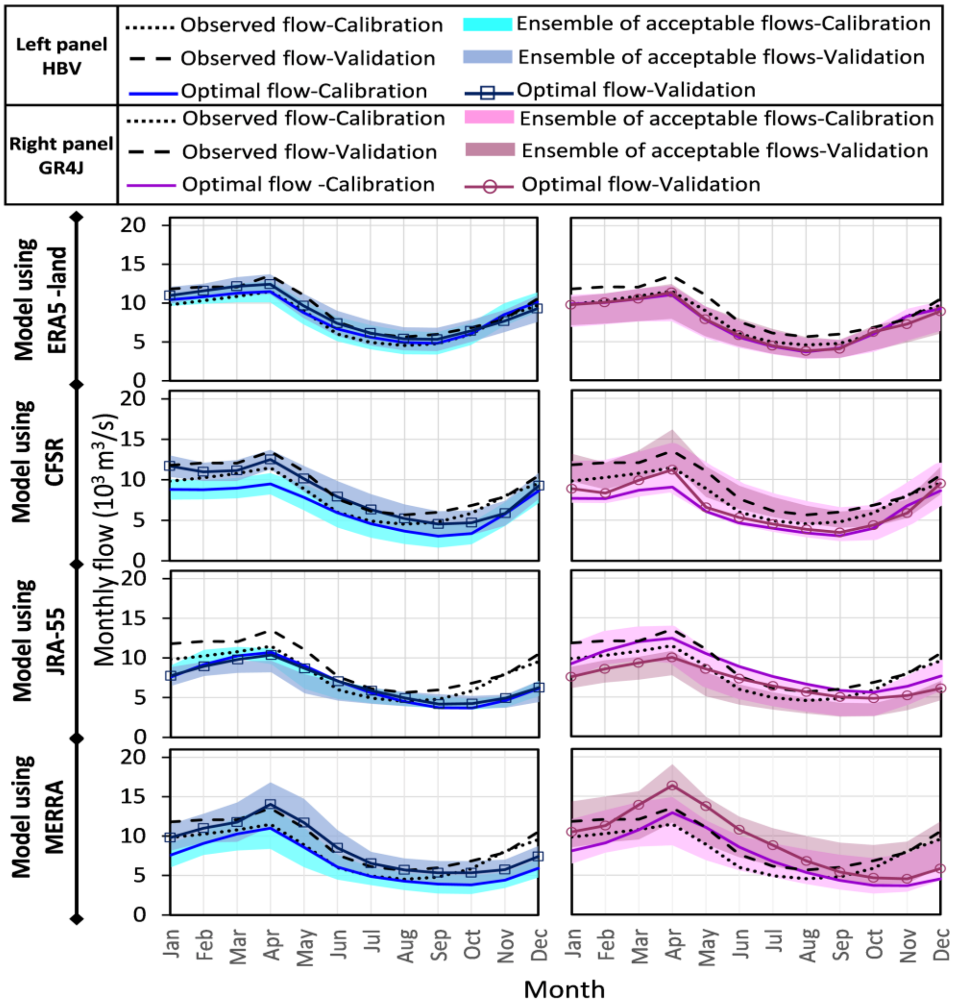

Figure 4.6 Observed (dashed line) and simulated long-term annual hydrographs (solid line and shaded areas) during the historical period at the outlet using different reanalysis datasets forced to HBV (left) and GR4J (right) Models.

To better understand the differences between the models, the envelopes of simulated flow considering all reanalysis using HBV and GR4J are shown in Figure 4.7 in the top and bottom rows, respectively. Considering the ensemble of acceptable flow, the GR4J model presents a wider range of values and overestimates daily flows than the HBV model. During the wet season, GR4J estimates higher values for annual peak flow, e.g., greater than 15000 m^3/s, while the low flows are approximately the same for both models. It is evident that the shape of the annual hydrograph obtained from the HBV model is more consistent with the observed one, in particular in the first quarter of the year. However, the difference between the two models, HBV and GR4J, is negligible (less than a 5% difference considering the mean annual hydrographs). Since the differences in the performance of these 8 configurations are not significant, all of them are used for impact assessment.

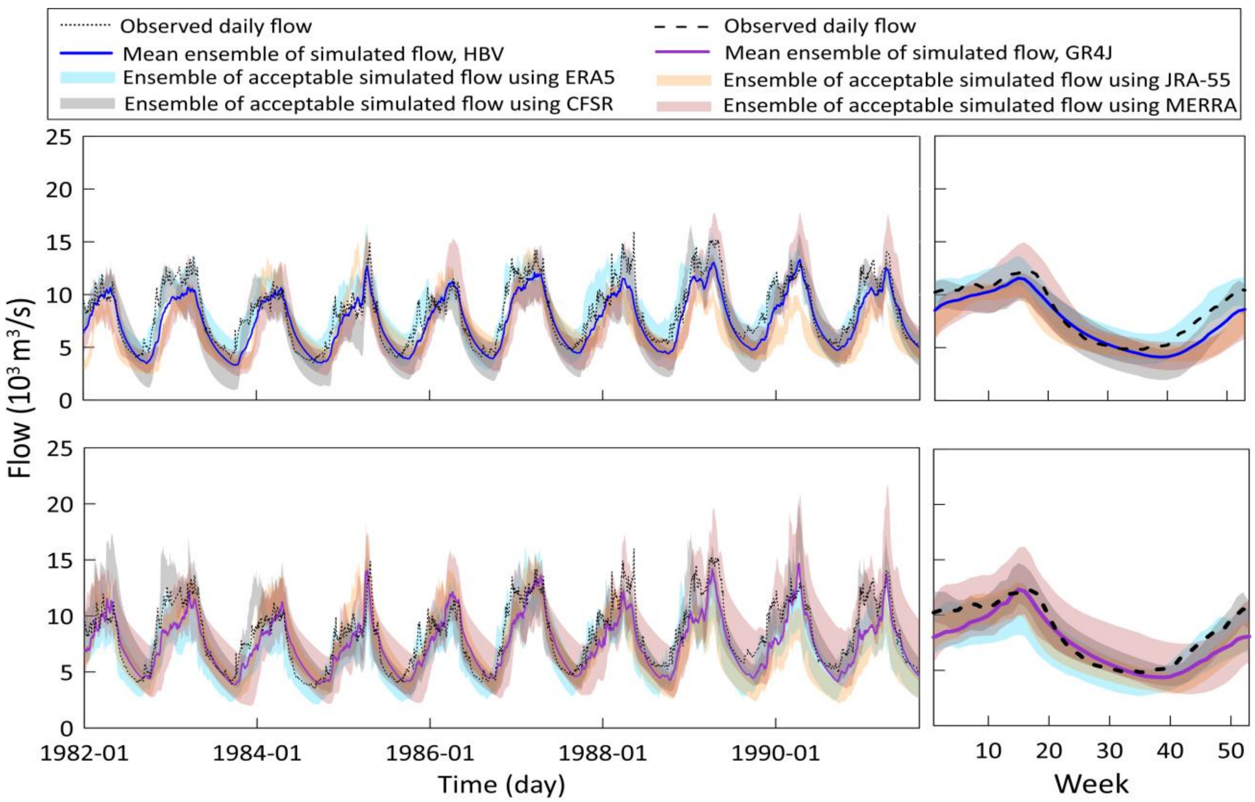

Figure 4.7 Comparison between the simulated (solid line and shaded areas) and observed (dashed line) expected daily (left) and annual (right) hydrographs at the outlet during the historical period using four reanalysis datasets in the calibration of hydrological models HBV (top) and GR4J (bottom).

4.4.2 Projected streamflow conditions under changing climate

The outputs of 19 climate models under RCPs 4.5 and 8.5 are fed to these eight hydrological models to estimate the flow in the KARB during the future horizons. The observed and projected mean annual streamflow hydrographs at the basin's outlet under RCP8.5 using HBV and GR4J models calibrated with four reanalysis are presented in Figure 4.8. The right panel in this figure shows all projected flows under these 8 configurations. The results for RCP4.5 are depicted in Figure S1 in the Supplementary Materials. Overall, the models show changes in flow conditions; however, the estimated rate of change depends on the considered modeling configuration. For instance, the rate of decrease is more considerable based on the HBV than the GR4J model. Indeed, the projected flow using GR4J, an ensemble of 4 configurations, presents no change in the near term and midterm future and a slight increase in the long term under a high emission scenario. Such divergence between the results of these two models can be logical due to the noted differences in the structure and performance of these models during the historical period.

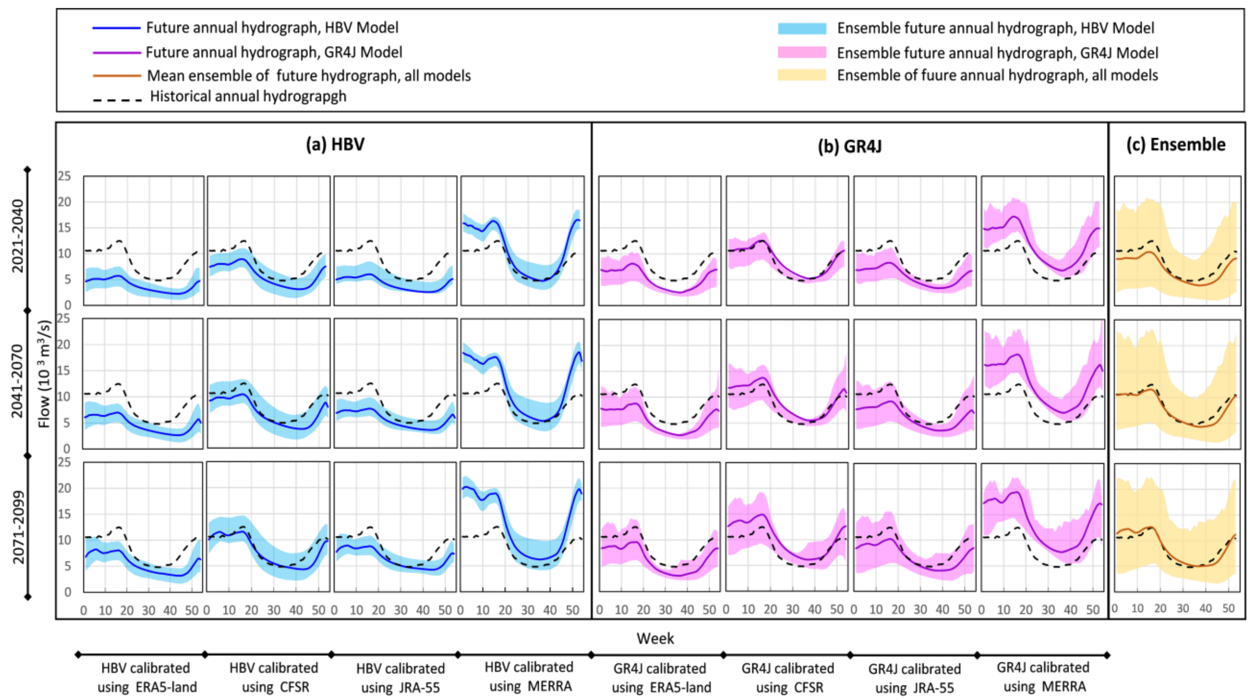

Figure 4.8 Observed (dashed line) versus projected ensemble (shaded area) and expected (solid line) mean annual streamflow hydrograph at the basin's outlet under RCP8.5 using HBV (left) and GR4J (middle) models calibrated with four reanalysis, and all configurations (right) using the outputs of 19 GCMs.

Considering the impact of reanalysis, the models calibrated using ERA5-Land, CFSR, and JRA-55 show almost similar hydrographs. In contrast, MERRA-based models have considerably different hydrographs in shape and high flow magnitudes showing an increase in future high flows.

The mean of projections based on all 8 model configurations (right panel) reveals a slight decline in streamflow volume with no change in peak flow timing at the outlet of KARB under RCP 8.5. Regarding the RCP 4.5, one week earlier peak flow is projected for the mean annual flow during all future horizons. This reduction in flow might be due to a decrease in rainfall and an increase in the evapotranspiration caused by temperature rise. These findings are consistent with the previous studies on the Congo River Basin (Aloysius & Saiers, 2017; Arnell, 2003; Beyene et al., 2013; Haensler et al., 2013). For instance, Aloysius and Saiers (2017) estimated prolonged periods of low flow and runoff decline in the southern headwater areas due to rainfall decrease in comparison to their reference period of 1986-2005. They also found a runoff increase of 10.4% over the whole southwestern region under RCP8.5 during 2046-2065.

Such decreases in streamflow discharge can affect water resources management in the KARB. Here, the changes in 90th (Q90), 50th (Q50), and 10th (Q10) percentiles of flow are analyzed to have a better understanding of flow conditions in the future based on individual and all model configurations. For this purpose, the observed (recorded) and simulated annual flow duration curves (i.e., empirical cumulative probability distributions of flow in each year) are found during the historical and future horizons. The long-term mean annual quantiles for the observed flow are calculated by averaging these values over the historical period. Regarding the future period, the annual values are found under each and all 8 model configurations considering the optimal and acceptable parameter sets under RCPs 4.5 and 8.5 and 19 GCM outputs. The relative changes between these future annual quantiles under RCPs 8.5 and 4.5 and the long-term historical value are presented in Figures 4.9 and S2 in the Supplementary Materials, respectively. The results are shown per model configuration, as well as the ensemble of values per each hydrological model, followed by a boxplot containing values per all configurations.

While an overall decrease in all three flow signatures is projected considering the ensemble of all eight models, the magnitude and sign of change vary among configurations. Interestingly, considering the long-term horizon under RCP 8.5, the high flow is expected to decrease by 40% by HBV-ERA5 and 22% by GR4J-ERA5, whereas the MERRA-based models estimate an increase of 50% by HBV and 57% by GR4J for Q50. Indeed, the model calibrated with MERRA datasets shows completely different changes than the models calibrated with other reanalysis datasets. This model overestimates the high flows during the historical period too. Figure 4.9 also shows that the GR4J-based models estimate a larger range of change in quantile than HBV ones. Moreover, although both models project a decline in Q10, Q50 and Q90 in all future horizons, the percentage of reduction based on HBV models is more intense. For example, the Q50 is projected to decrease on average by -23% based on HBV and -1% by GR4J models under RCP 8.5 and in the late century. The results based on all model configurations (black boxplot) reveal a decline of 9%, 18%, and 13% for the low, median, and high flow, respectively, under RCP 8.5. These ranges of reduction are larger under RCP4.5, i.e., -24% for Q10, -28% for Q50 and -25% for Q90, respectively, see Figure S2 in the Supplementary Materials. This is mainly because of the higher rate of increase in mean precipitation relative to the historical period under RCP8.5 than RCP4.5, see Figure 4.4(a).

As previously noted, the values of high flows are particularly important for the estimation of potential hydropower production in this region. Therefore, here the trend in annual Q90 is analyzed over 2021-2100, which is estimated using the individual and all model configurations, given the acceptable and optimal parameter sets, fed by 19 GCM outputs under RCPs 4.5 and 8.5, see Figure 4.10. The long-term average annual Q90 equal to 12030 m^3/s during the historical period is shown as the benchmark (reference value). The projected trend in high flow by the ensemble of models reveals a slight decline in hydropower potential. It is apparent that the estimated values and trends of Q90 in the future significantly differ among the model configurations. In particular, the MERRA-based model notably shows a different trend than others. The calibrated models with ERA5-Land and JRA-55 estimate a decrease in high flow over the whole century under both scenarios. Besides, it is noteworthy to mention that the estimated Q90 values by the GR4J using CFSR show almost no change under RCP 4.5 and a slight increase under RCP 8.5 from the mid to the end of the century. In comparison, the trendline for Q90 based on the HBV-CFSR model remains below the reference level over the whole century under both emission scenarios. Indeed, the expected values of Q90 based on all models (right panels) remain below the reference level under RCP4.5, whereas it reaches the long-term historical quantile by 2058 and slightly increases by the end of the century under RCP8.5.

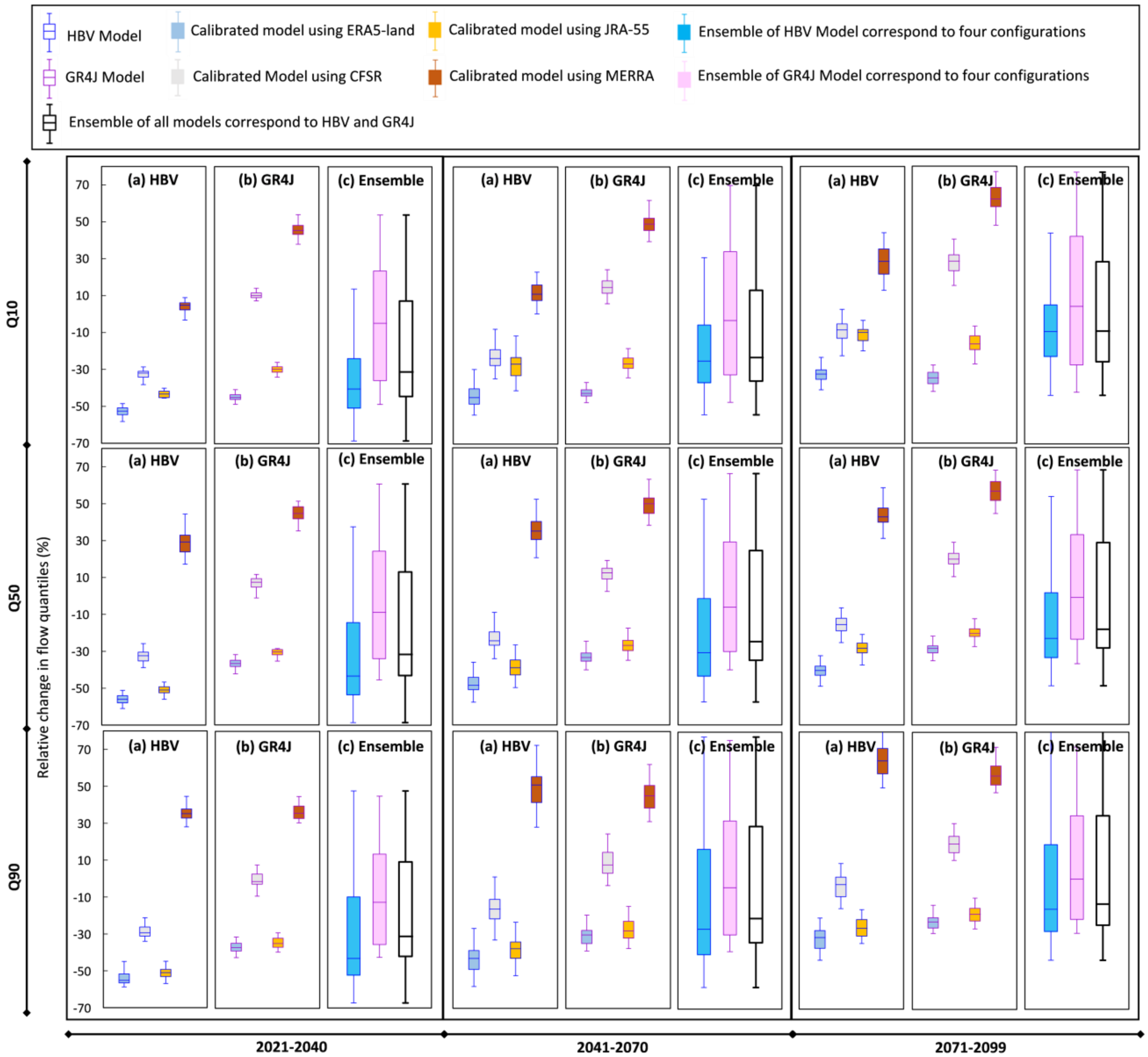

Figure 4.9 Relative changes between the estimated annual streamflow quantiles by individual and all model configurations fed by outputs of 19 GCMs under RCP8.5 with respect to the long-term average historical value.

Mann-Kendall trend test (Mann, 1945), a commonly-used nonparametric method in climate analysis (see Kaemo et al., 2022; Ojo & Ilunga, 2018), is employed to understand the trend and determine its significance. The p-values and trend slope of expected future annual Q90 calculated for individuals and all configurations are presented in Table S2 in the Supplementary Materials. The results of the significance test reveal an increasing trend in high flow based on the ensemble of all models under both RCPs 4.5 and 8.5 with the significance level of 0.05 and p-value of 4.5E-10 and 1.5E-18, respectively. Notably, the slope of the trend line under RCP8.5 is double compared to RCP4.5. These changes in streamflow conditions, particularly high flows, mean that the decisions around constructing reservoirs and hydroelectricity generation should take into account the impacts of climate change.

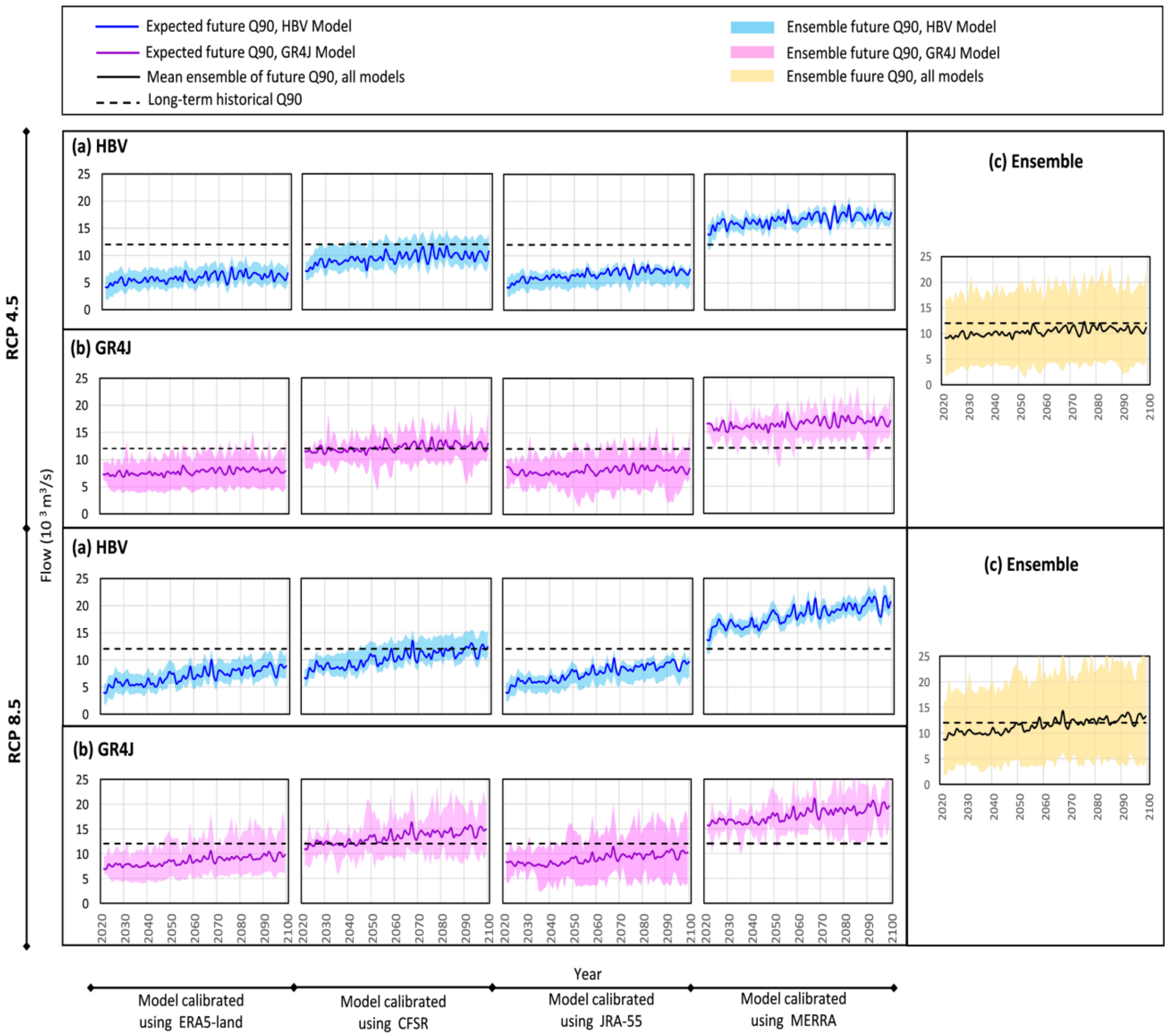

Figure 4.10 The ensemble (shaded area) and expected (solid line) values of annual Q90 in the future under RCPs 4.5 and 8.5 based on calibrated HBV (blue) and GR4J (pink) models using four reanalysis datasets (left) and all 8 model configurations (right). The dashed line shows the long-term annual Q90 values during the historical period.

Here, the gross hydropower potential for both present and future periods is estimated to provide an overall indication of the relative changes in the basin (Pandey et al., 2015; Yamba et al., 2011). The amount of hydropower generated from the flow with the discharge of Q and head difference of H can be estimated by $P = \rho g Q H \eta$, where P is the power, ρ is the density of water, g is the gravity acceleration, and η is the overall efficiency of the turbine. The theoretical hydropower production is estimated by considering the natural drop of the KARB mainstream for the head, which is 1120 m (GEIDCO, 2020). The mean of annual high flow (Q90) obtained from the ensemble of all of 8 model configurations in the future is used as Q, which is equal to 10332 and 11436 m^3/s under RCPs 4.5 and 8.5, respectively. Accordingly, the relative change in the theoretical hydroelectric generation between future and historical periods is calculated. Assuming that the efficiency coefficient of 0.7 is resealable, the result reveals that the theoretical potential of the basin will decrease by around 14% and 5% under RCP4.5 and RCP8.5, respectively, in the long-term future. Such changes in hydropower potential should be considered in energy supply and development plans.

4.5 Summary and conclusions

This study assesses the possible impacts of climate change on streamflow characteristics and hydropower potential using a multi-model framework over the KARB, an important watershed in the Congo River Basin, Central Africa. For this purpose, two conceptual hydrological models, HBV and GR4J, which are calibrated using four reanalysis products, are fed with 19 GCMs

bias-corrected outputs under two emission scenarios, RCPs 4.5 and 8.5. Results reveal that both hydrological models calibrated with different reanalysis datasets can simulate the observed flow in the KARB with acceptable performance. Considering both daily and annual time series, the calibrated models with ERA5-Land datasets perform better, particularly in representing the peak flow timing and magnitude and low flows. Our simulations under climate change scenarios show that flow discharge is likely to decrease with no change in peak timing and seasonality. However, the estimated magnitude of change depends on the considered configuration, i.e., the hydrological model and the reanalysis dataset used for calibration and the future scenario. Overall, changes in mean annual discharge ranging from −18% to +3% at the outlet of the basin in the future are estimated in comparison to observed values. Among model configurations, MERRA-based models and GR4J-CFSR-based models show an increase in annual hydrographs, while others are similar with a declining trend. Considering flow signatures, while an overall decrease in all three quantiles (Q10, Q50, and Q90) is projected based on the ensemble of all 8 modeling configurations, the magnitude and sign of change vary among configurations. Given the importance of high flow (Q90) in hydropower potential analysis, our analysis reveals that Q90 will be decreased by 25% and 13% under RCPs 4.5 and 8.5, respectively, with respect to the long-term average historical value. Consequently, the theoretical hydropower potential is expected to decline by 14% and 5% under low and high emission scenarios, respectively. In addition, trend analysis reveals that annual power potential follows a significant increasing trend between 2021-2100 based on the ensemble of all models with a p-value of 4.5E-10 and 1.5E-18. Although the mean annual flow's magnitude is below the reference line (long-term average historical value) during the future period, its trend is positive toward the end of the century. Moreover, although the projections show a decline in annual high flow, these decreased rates are not likely to make a major water supply issue for hydropower generation. Based on the ensemble of all models, the average decrease in low flow (Q10) is projected by 24% and 9% in the long-term future under RCP4.5 and RCP8.5, respectively. This decline in low flow might affect navigation, which has already been threatened by climate change over the KARB, as reported by CICOS (2016). The changes in low and high flow can also have implications for aquatic life, channel maintenance, and flooding. Hence, the water managers should consider these changes in policymaking and water allocations.

Our study is the first step toward a multi-model climate change impact assessment in the Congo River Basin and has some limitations. In future research with the ongoing field measurements that CICOS has planned within the KARB, one may apply hydrological models with different catchment representations (both lumped and semi-distributed models) or include more models to estimate flow. Furthermore, in this study, the GCMs outputs based on the CMIP5 project are used. It is recommended to use other climate model outputs that are recently released, i.e., CMIP6, to better highlight the probable future conditions of the basin. Such analysis in the context of the applied framework can also be extended to analyze the vulnerability of other catchments in the Congo River Basin to provide an integrated impact assessment within the whole basin conditions. This integration can provide policymakers with more comprehensive knowledge of water resources, energy, agriculture and ecosystem management. Notably, the flow projections of this study account for changing climate and can be considered a part of an investigation of multiple stressors on water resources. It is also suggested that other key aspects such as population growth and rising water demand be considered in the development of adaptation policies.

Acknowledgements

This project is partly funded by NSERC (RGPIN-06979-2020), held by the third author.

Supplementary Materials

Table S.1 Performance of HBV and GR4J hydrological models calibrated using observed and four reanalysis data sets during the historical periods.

Used datasets and models / Criteria	Observed data		ERA5-Land		CFSR		JRA-55		MERRA	
	HBV	GR4J	HBV	GR4J	HBV	GR4J	HBV	GR4J	HBV	GR4J
Kling-Gupta efficiency	0.37	0.18	0.82	0.9	0.78	0.7	0.72	0.69	0.75	0.52
Nash-Sutcliffe efficiency	-0.96	-2.82	0.66	0.82	0.5	0.4	0.4	0.42	0.41	0.2
Pearson correlation	0.26	0.22	0.8	0.85	0.75	0.64	0.57	0.52	0.65	0.41
Relative Bias	-0.38	-0.62	0.1	-0.05	-0.17	-0.22	-0.13	0.09	-0.16	-0.09

Table S.2 P-value and trend slope of expected future annual Q90 based on individual and all model configurations under scenario RCP4.5.

Model	**Test results** / **Datasets used In calibration**	**RCP 4.5**			**RCP 8.5**		
		P-value	Slope	Trend Significance	P-value	Slope	Trend Significance
HBV	ERA5-Land	7.9E-09	19.98	Yes	6.5E-18	50.96	Yes
	CFSR	7.7E-10	27.62	Yes	6.0E-18	57.19	Yes
	JRA-55	1.3E-14	28.92	Yes	7.6E-22	58.18	Yes
	MERRA	1.9E-09	28.65	Yes	4.2E-18	69.57	Yes
GR4J	ERA5-Land	1.7E-08	12.80	Yes	2.1E-17	32.22	Yes
	CFSR	3.2E-08	18.35	Yes	5.4E-17	45.34	Yes
	JRA-55	3.1E-05	11.95	Yes	4.4E-15	34.50	Yes
	MERRA	1.2E-06	19.35	Yes	6.9E-16	46.96	Yes
All models	Ensemble of 8 configurations	4.5E-10	21.54	Yes	1.5E-18	49.95	Yes

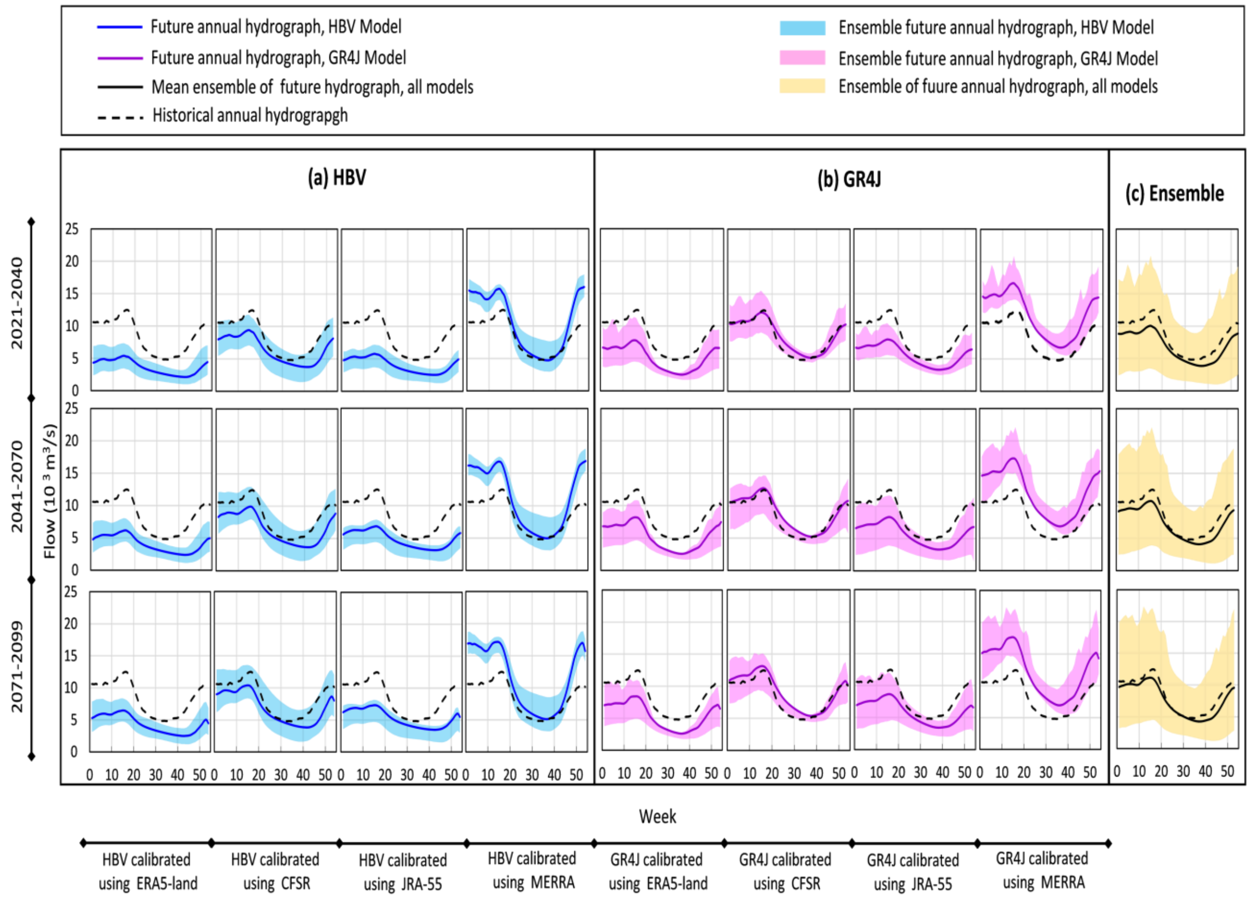

Figure S.1 Projected ensemble and expected mean annual streamflow hydrograph (shaded area and solid line) at basin's outlet under RCP4.5 using two hydrological models, HBV (left) and GR4J (middle), and the ensemble of all models (right) versus historical annual flow hydrograph (dashed line).

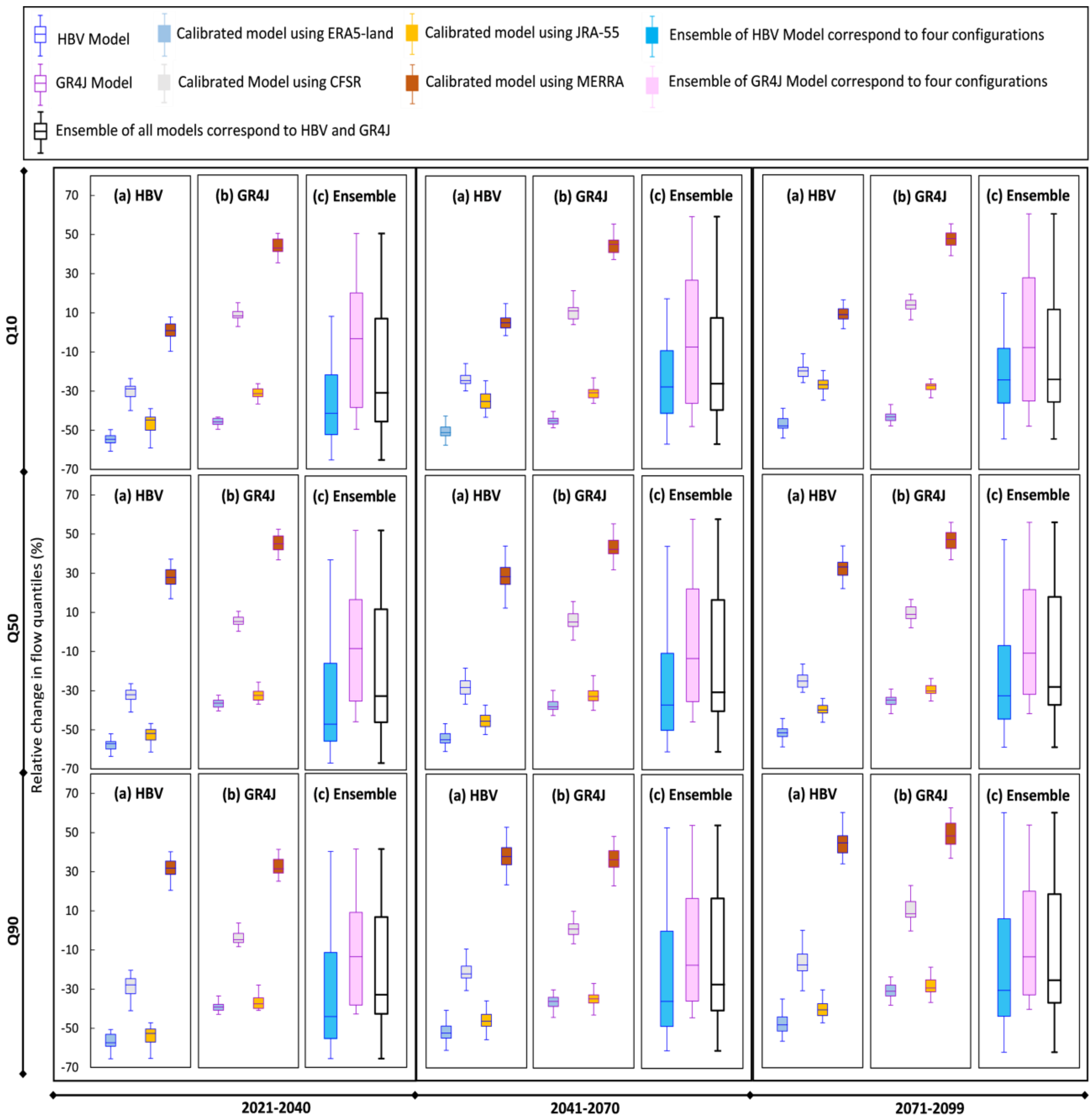

Figure S.2 Relative changes of annual future streamflow quantiles based on the different configurations using GR4J and HBV Models and the ensemble of all simulations under RCP4.5 with respect to the long-term historical values.

CHAPTER 5 GENERAL DISCUSSION

As discussed earlier in this study, a multi-model framework is used to assess the vulnerability of KARB's water availability and hydropower potential to changing climate. This model-based approach performance is sensitive to the hydrological models and climate model projections and historical climatic data used for calibration of hydrological models. This study shows the importance of the choice of models as well as input data and the use of a muti-models approach instead of a single-model-based analysis. Over the KARB, there are inconsistencies between GCMs projections to capture rainfall variation, which has been demonstrated by other studies over Central Africa as well (Aloysius et al., 2016; Ghebrehiwot & Kozlov, 2021; Niang et al., 2014; Washington et al., 2013). Also, the differences between the estimated flow conditions under two RCPs indicate the sensitivity of flow projection to the emission scenarios. Hence considering 19 GCMs under two emission scenarios can reduce the uncertainty because averaging tends to offset errors across models.

Besides, based on the results, we can argue that using multiple hydrological models calibrated with four reanalysis datasets instead of only one single model can potentially decrease the vulnerability of the assessment by representing more probable catchment conditions. Meanwhile, calibration of these models based on an ensemble of parameter sets along with optimal parameters is more rigorous than a deterministic approach. Compared to a deterministic calibration approach, it can reduce misleading projections by raising our knowledge about uncertainties in simulations. If we consider simulations of 2 hydrological models and 4 reanalysis but using optimal calibration parameters instead of an ensemble of parameter sets, it can affect the flow projections. For instance, in the long-term future (2071-2099) under RCP8.5, comparing the projected future hydrograph reveals that using optimal parameter sets will result in a higher rate of flow by an average of 20%. The multi-model framework provides us with all possible future flow conditions leading to less uncertain projections in impact studies.

CHAPTER 6 CONCLUSION (AND RECOMMENDATIONS)

The KARB is known for its immense water resources, which are already unexploited and can be used for the sustainable development of different sectors, including energy, navigation, fishing, irrigation, industry, and tourism in Central Africa. Climate change threatens this large freshwater and associated ecosystem. The major water-related challenges over the basin are water supply for drinking and sanitation, hydroelectricity production, irrigation development and river transport, and water pollution by the industrial, mining, and agricultural sectors. All these issues need to be studied using an integrated water resource management approach (IWRM; CICOS, 2016) under changing climate.

Moreover, as a substantial component of the development plan in the Congo River Basin, including the KARB, hydropower production is subject to changing patterns of river flow, extreme events, and seasonal variation. Among the lower and upstream of the Congo River mainstream, KAR is considered in hydropower development priorities. Therefore, having a better knowledge of streamflow conditions in the future is a key component of integrated water management that contributes to the region's sustainable development. Climate change impacts on the flow discharge can be investigated by applying a top-down approach using hydrological models and climate model projections (e.g., precipitation and temperature). Estimated flow by hydrological models that reliably represent the system's hydrology may vary due to differences in the model structure. Although the differences might be negligible in the historical period, they can cause divergence in simulated flow in the uncertain future. Hence to avoid the probable uncertainty attributed to the hydrological models and inter-model variability of GCMs projections, a multi-model framework is considered in this study to analyze the streamflow condition under changing climate. Moreover, the availability of adequate and quality observed data causes challenges in the hydrologic representation of catchments in data scares regions. In this regard, using an ensemble of reanalysis datasets can address data issues.

The applied multi-model framework consists of two hydrological models, i.e., HBV-MTL and GR4J, and 19 climate model projections. Each hydrological model is calibrated and validated during the historical period using four reanalysis products as climatic input data. Accordingly, the future streamflow is simulated by incorporating the GCMs climatic projections in calibrated hydrological models. Given the importance of parameter uncertainty in hydrological modeling, besides the optimization method through calibration, the uncertainty analysis is conducted to find an ensemble of acceptable parameter sets, and ultimately the models generate an ensemble of streamflow. Concerning the future, the bias-corrected outputs of GCMs under avoided greenhouse gas emission scenarios, and business-as-usual, i.e., RCP4.5 and RCP8.5, are fed into the calibrated impact models. Accordingly, the estimated flows for each model configuration, as well as the ensemble of all models, are used in impact analysis.

Results indicate that all models calibrated using different reanalysis datasets reliably represent the daily and annual flow conditions in the historical period and acceptably capture flow regime characteristics such as peak flow timing and seasonality. However, the models have dissimilar performances based on the input data used to reproduce the streamflow at the basin’s outlet. For instance, the HBV and GR4J model forced by ERA5-Land input data has better performance and more accurate flow estimation than other datasets. Considering the mean of four envelope simulations, the HBV model underestimates the high flow on the weekly scale. Analysis based on statistical measures shows that the hydrological model performance is relatively more sensitive to the input data than the model structure.

The multi-model ensemble approach reveals that overall, the changes in flow conditions are expected in future; however, the estimated rate of change depends on the considered modeling configuration. For instance, the rate of decrease is more considerable based on the HBV model than GR4J. Considering the ensemble of 4 configurations of GR4J, the projected flow presents almost no change in the near term and midterm future and a slight increase in the long term under a high emission scenario. In comparison, HBV simulations under 4 configurations show a decrease in streamflow rate. The flow signatures (90th, 50th and 10th) percentiles variation is investigated during the three future periods, given the importance of streamflow characteristics on hydropower potential. An overall decrease in all three flow signatures is projected considering the average (median) of the ensemble of all eight models. The future long-term high flow (Q90) as an indicator of high hydropower potential is projected to decrease by average (median) -25% and -13% under

RCPs 4.5 and 8.5. Although overall, the mean high flow over the whole century (2021-2099) declined with respect to the reference level (1977-1991), its trend during the future period is increasing. The trend analysis based on the Mann-Kendall test indicates that the high flow increasing trend based on the ensemble of all models under both future scenarios RCP4.5 and RCP8.5 is significant with the significance level of 0.05 and the p-value of 4.5E-10 and 1.5E-18, respectively. With these changes, the theoretical hydropower potential of the basin will decrease by about 14% and 5% under RCP4.5 and RCP8.5, respectively, in the long-term future. Policymakers should take into account such decreases in hydropower potential in the energy supply and future development plans.

This study shows how flow conditions depend on the utilized input datasets and the hydrological models, and consequently, this can affect the future flow projections in climate change impact assessment. While using a single hydrological model may be misleading for climate change impact studies, employing an ensemble of hydrological and climate models can decline the associated uncertainty in the top-down approach. It is suggested to apply other hydrological models and recently released climate model projections, CMIP6 instead of CMIP5, to analyze better the framework's sensitivity to the model structure and climatic variables. Besides, in this study, a set of four reanalysis is used for the calibration of models. In future works, other reanalysis products, i.e., the next generation of reanalysis can be used. In addition, the multi-model approach used in this study for the KARB is recommended to apply to other sub-watersheds within the Congo River Basin to provide policymakers and water managers with integrated knowledge of the region. Moreover, concerning integrated water resource management, it is suggested that along with climate change, other stressors on streamflow regime, i.e., water demand rising and population growth, are considered in future flow projections. Finally, given the lack of appropriate observed data, adding more ground-based hydroclimatic stations can address data issues in this region which data distribution centers should take into account. Hence with adequate hydrometric stations within the KARB, one may apply hydrological models with both lumped and semi-distributed models to evaluate catchment representation importance in impact studies.

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APPENDIX A DESCRIPTION OF THE HBV-MTL MODEL

The HBV-MTL, a recently modified version of the HBV model, is used in this study. The diagram of the model is presented in Figure A.1. The precipitation is considered to be either rainfall r snow, or a combination of them, which is determined by the air temperature threshold (Eq. A.1) (Turcotte et al., 2007). If the precipitation is in the form of snow, the depth of accumulated snow will be calculated based on Eq. A.2. in the case of snowfall, the water equivalent of it is calculated to enter the model as the available liquid water. Also, in the model, to do conversion of snow to liquid water, the snow density is assumed to be 10 percent of water density. Using the degree-day method (Seibert & Vis, 2012), the snowmelt is calculated. Briefly, the snowmelt is obtained based on the ambient temperature, the degree-day factor and the melting threshold (Eq.A.3). Many factors are contributed to the degree-day coefficient, such as the watershed's characteristics and typically, it is considered a constant value ranging from 1.6 to 6 mm/°C (U.S. Dept. of Agriculture, 2004).

However, in some studies, it is estimated as a function of air temperature and accumulated snow (Bergstroem, 1975). The melting threshold typically is assumed to be zero, and its spatial variation based on altitude and catchment characteristics is neglected. Another assumption in this model is that the melted snow leaves the snowpack while the pores are filled with water, as shown in Eq. A.4. If retained water in the pores of the snowpack will refreeze if the air temperature drops below the threshold, which is assumed to be the same as the snowmelt threshold (Eq. A.5). at the end of the precipitation module, the available liquid water is estimated based on rainfall, snowmelt, the refrozen water and the water which leaves the snowpack (Eq. A.6). Snowmelt and refreezing of snow is a common phenomenon in cold regions, while in our case study, as it is located in the tropical region with no snow, these snow processes do not happen, and the precipitation all is in the form of rainfall during a year.

In the next stage, the available liquid water can either directly flow over the surface or infiltrate into the soil, depending on the soil moisture and temperature. Soil temperature is dynamically estimated in each time step as a function of initial soil temperature and the eleven-day average of air temperature, and the available snowpack on the surface, if applicable (Eq. A.7). Concerning the infiltration, the modified SCS method is used in this model (Neitsch et al., 2011). Based on the comparison of soil moisture to the wilting point, the amount of infiltration and runoff in each time step will be determined, and the soil curve number (CN) will be revised (Eq. A.8). In the case of the existence of frozen soil in cold regions, the soil CN is revised based on the soil saturation level and other soil characteristics (Eq. A.9). Accordingly, using the revised soil CN, the retention and initial abstraction are calculated in Eq. A.10 and A.11, respectively. Then the runoff and the infiltration to the soil are estimated using Eq. A.12 and A.13, respectively.

In the soil medium, some parts of water that are absorbed by the soil particles can not move through the soil layer, and they just contribute to the soil moisture (Eq. A.15). While the free water in the soil infiltrates to the deep layer contributing to the intermediate and deep groundwater reservoirs (Eq. A.14). on the other hand, the water infiltrated into the soil can be used by vegetation through evapotranspiration and affect the soil moisture. In the model, actual evapotranspiration is estimated based on the potential evapotranspiration and existing soil moisture using Eq. A.16. different methods have been developed for the estimation of potential evapotranspiration. In this study, the method developed by Hargreaves and Samani (1985) is used mainly because of its lower data required to estimate potential evapotranspiration. The available water content in the near-surface soil layer is represented as the soil moisture and estimated dynamically based on evapotranspiration rate and soil moisture recharge (Eq. A.17).

Infiltrated water to the deeper soil layer is stored in two conceptual reservoirs, intermediate and deep soil layers, which are gradually released and form interflow and base flow (Eq. A.18, A.19 and A.20). the available water content in intermediate and deep soil layer is calculated using water balance Equations A.21 and A.22. then all three calculated flow namely interflow, baseflow and near-surface runoff contribute to generating streamflow at the watershed's outlet (Eq. A.23). The generated flow is routed based on the watershed's physical characteristics using a triangular weighting function to simulate flow at the outlet (Eq. A.24). Finally, the total flow of the watershed is estimated by multiplying the catchment's area by the generated flow in the previous step, which was for a unit of area (Eq. A.25). All equations are presented below, and the utilized abbreviations for variables are explained in Table A.1. Note that subscript 't' comes along with the variable's name and shows the time step.

Table A.1 Variables and calibration parameters used in the HBV model equations

Variables					
Variable	**Abbreviation**	**Variable**	**Abbreviation**	**Variable**	**Abbreviation**
Precipitation	P_t	Rainfall	$rain_t$	Snowfall	$snow_t$
Maximum temperature	$T_{\max}$	Minimum temperature	$T_{\min}$	Average temperature	$T_{ave,t}$
Accumulated snow	S_{P_t}	Refrozen water in the snowpack	R_{f_t}	Snowmelt	S_{m_t}
Retained water in the snow medium	S_{W_t}	Water output of snow medium	LW_t	Snow cover coefficient	M_t
Soil moisture	SM_t	Soil temperature	ST_t	Soil revised curve number	$CN_{soil,t}$
Initial abstraction	IA_t	Soil retention	SR_t	Infiltration	I_t
Direct runoff	DR_t	Soil moisture recharge	SMR_t	Groundwater recharge	GWR_t
Potential evapotranspiration	ETP_t	Actual evapotranspiration	ETA_t	Shallow groundwater storage	SS_t
Interflow	IF_t	Baseflow	BF_t	Percolation	$PERC_t$
Streamflow	F_t	Deep groundwater storage	DS_t	Routed flow	RF_t
Total flow	TF_t				

Table A.1 Variables and calibration parameters used in the HBV Model equations-*continued*

Calibration parameters					
Parameter	**Abbreviation**	**Parameter**	**Abbreviation**	**Parameter**	**Abbreviation**
Snow gauge correction factor	SCF	Snowfall temperature threshold	$T_{a,thres}$	Degree-day coefficient	DD
Snowmelt temperature threshold	$T_{m,thres}$	Snow's retaining capacity coefficient	$Snowcap$	Refreeze coefficient	F
Soil curve number	CN	Soil field capacity	FC	Moisture coefficient	β
Wilting point coefficient	WP	Frozen soil temperature threshold	ST_{thres}	Frozen soil coefficient	FSC
Wet-period interflow coefficient	K_0	Wet-period threshold	L	Normal interflow coefficient	K_1
Percolation coefficient	K_p	Baseflow coefficient	K_2	Delay length	N_{delay}

$$\begin{cases} rain_t = P_t; snow = 0 & T_{\min,t} \geq T_{a,thres} \\ rain_t = \dfrac{T_{\max,t} - T_{a,thres}}{T_{\max,t} - T_{\min,t}} \times P_t; snow_t = SCF \times (P_t - rain_t); & T_{\min,t} < T_{a,thres} AND T_{\max,t} > T_{a,thres} \\ rain_t = 0; snow_t = SCF \times P_t; & T_{\max,t} \leq T_{a,thres} \end{cases} \quad \text{(Eq. A.1)}$$

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

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

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

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

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

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

$$ST_t \leq T_{s,thres} : CN_{soil,t} \quad \text{(Eq. A.8)}$$

$$= \begin{cases} CN - \dfrac{20 \times (100 - CN)}{100 - CN + \exp(2.533 - 0.0636 \times (100 - CN))} & SM_t < WP \times FC \\ CN \times (0.00673 \times (100 - CN)) & SM_t > 0.95 \times FC \\ CN & WP \times FC \leq SM_t \leq 0.95 \times FC \end{cases}$$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

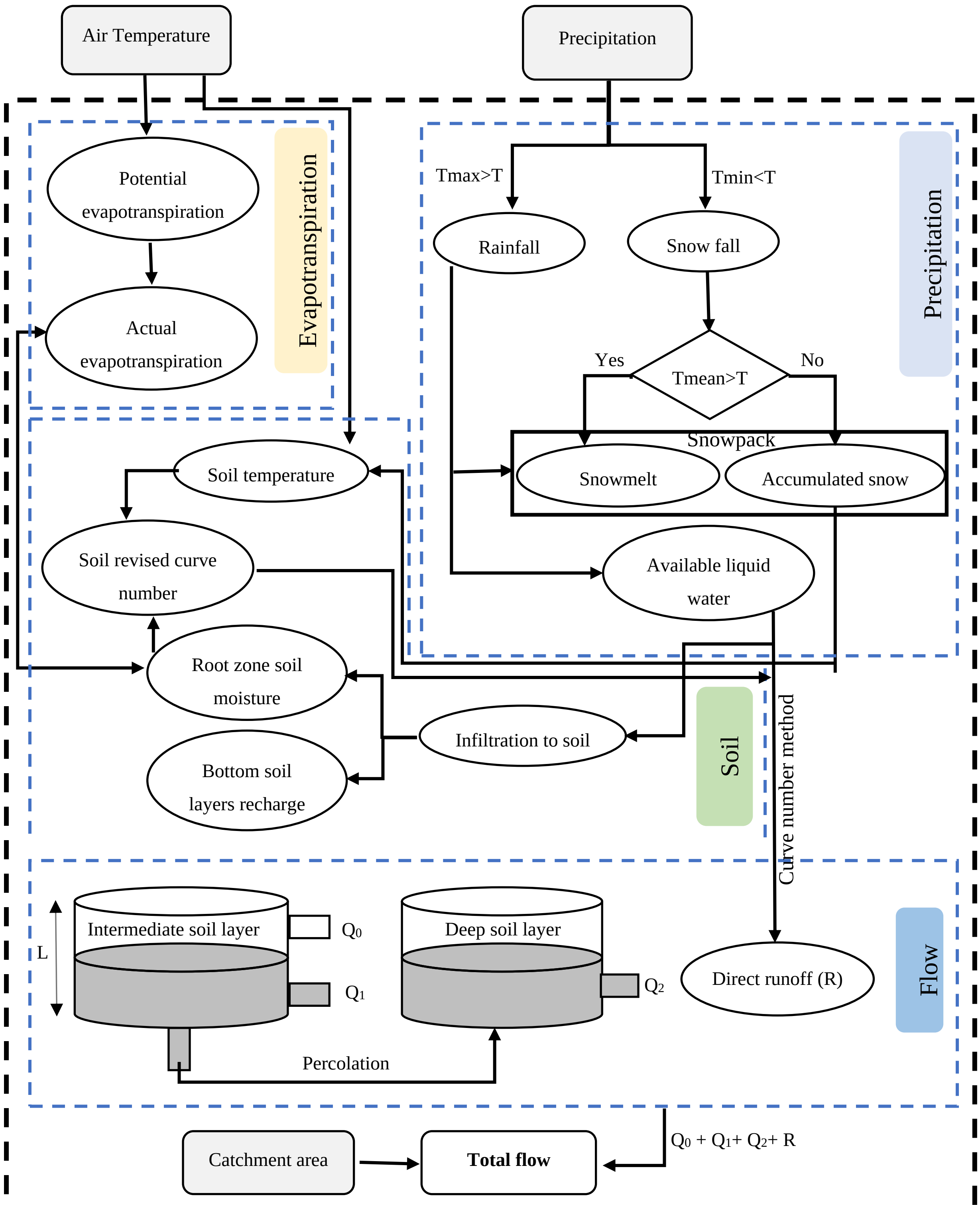

Figure A.1 Schematic of HBV hydrological model

APPENDIX B DESCRIPTION OF THE GR4J MODEL

GR4J is the improved version of the GR3J model (Michel, 1989), proposed by (Perrin et al., 2003). This model is a conceptual four-parameter rainfall-runoff model in a daily timescale. In Figure B.1, the schematic diagram of the model is shown. The main inputs of this model are precipitation and maximum and minimum air temperature. As mentioned in the previous section for the HBV model, in this study, the potential evapotranspiration is estimated using the Hargreaves method (Hargreaves & Samani, 1985). In the first step, the net precipitation and net evapotranspiration are calculated by subtracting potential evapotranspiration from precipitation (Eq. B.1 and B.2). if the net precipitation is not zero, a portion of it will contribute to filling the production storage, which represent the soil layer in this model. This portion is determined as a function of the water level in the production storage using a parabolic equation (Eq. B.3, Michel, 1989). The remained portion will directly contribute to the surface runoff. In the case of existing net evapotranspiration, the actual evapotranspiration is calculated based on the water level in production storage (Eq. B.4). in each time step, the available water content is dynamically calculated based on the amount of initial water level, actual evapotranspiration, and the portion of net precipitation entering the production storage (Eq. B.5). Note that the water level in production storage has a maximum capacity threshold, and the calculated water level can not exceed this threshold. Then the water remaining in the soil layer (production storage) is percolated to the deeper layer using a power function of the reservoir water content (Eq. B.6). Accordingly, the water content in production storage will be updated (Eq. B.7). The percolated water, along with the direct runoff, will enter the routing stage (Eq. B.8). In the GR4J model, the routing of flow is simulated in a linear function using two unit hydrographs which are used to simulate the time lag between the precipitation and streamflow generation. The water reached the routing storage is divided into two fixed components. 90% of it 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 the corresponding S-curves (Eq. B.9 to B.17). Meanwhile, the catchment water exchange with groundwater contributing to both flow components is estimated (Eq. B.18). The water level in the routing reservoir is dynamically calculated based on the initial water level in storage and outflow of the unit hydrograph (Eq. B.19). Accordingly, the outflow from the routing reservoir is estimated based on the updated water content in the reservoir in each time step (Eq. B.20), and the water level is updated (Eq. B.21). same as the flow discharge from the routing storage, the output of the two-sided hydrograph is subject to water exchange with groundwater (Eq. B.22). Finally, the total flow based on two calculated components is estimated (Eq. B.23). the variables, as well as parameters used in model calibration, are presented in Table B.1.

Table B.1 Variables and calibration parameters used in the GR4J Model equations

Variables					
Variable	**Abbreviation**	**Variable**	**Abbreviation**	**Variable**	**Abbreviation**
Precipitation	P	Evapotranspiration	E	Net precipitation	P_n
Maximum temperature	$T_{\max}$	Minimum temperature	$T_{\min}$	Net evapotranspiration	E_n
Portions of net precipitation enter into production store	P_s	The water level in the production store	S	Groundwater exchange term	F
Actual evapotranspiration	E_s	Percolation from the production store	$Perc$	Water enters into routing stage	P_r
One-sided unit hydrograph	UH_1	Two-sided unit hydrograph	UH_2	S-curve corresponds to UH1	SH_1
S-curve corresponds to UH2	SH_2	time	t	The water level in the routing store	R
Outflow from UH1	Q_9	Outflow from UH2	Q_1	Outflow from routing reservoir	Q_r
Total direct runoff	Q_d	Total streamflow	Q		

Table B.1 Variables and calibration parameters used in the GR4J Model equations-*continued*

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

$$P_n = P - E \quad \text{and} \quad E_n = 0 \quad \text{If } P \geq E \qquad \text{(Eq. B.1)}$$

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

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

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

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

$$Perc = S\left\{1-\left[1+\left(\frac{4}{9}\frac{S}{x_1}\right)^4\right]^{-1/4}\right\} \qquad \text{(Eq. B.6)}$$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

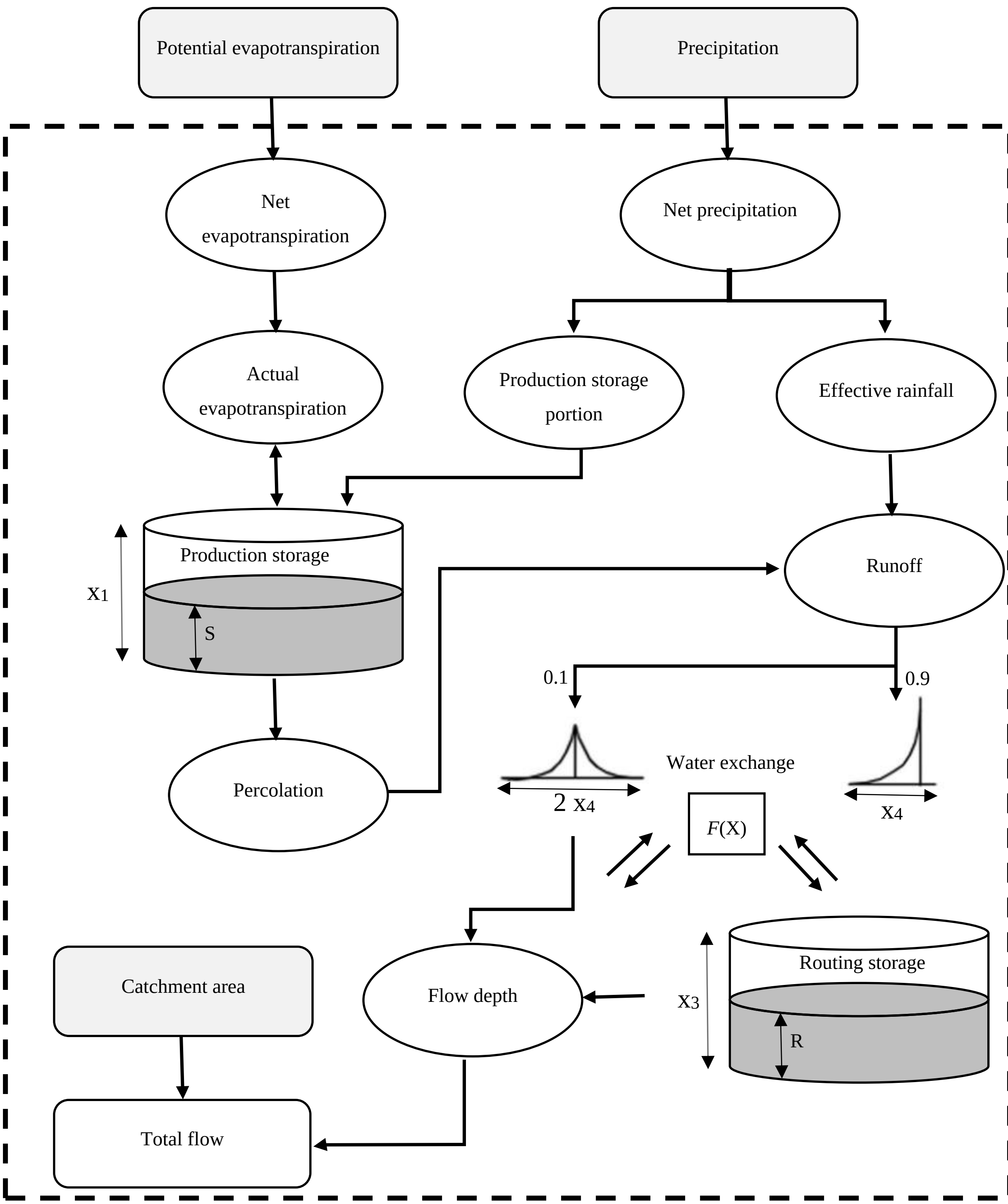

Figure B.1 Schematic of GR4J hydrological model