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affiliée à l'Université de Montréal

**Développement d'une approche d'ensemble multi modèle pour une meilleure
évaluation des impacts des changements climatiques des bassins non jaugés**

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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**Développement d'une approche d'ensemble multi modèle pour une meilleure
évaluation des impacts des changements climatiques des bassins non jaugés**

présentée par **Salomon SALUMU**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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IN MEMORIAM

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RÉSUMÉ

La conception des ouvrages hydrauliques et autres types d'aménagements dans les cours d'eau est profondément influencée par le régime hydrologique, en supposant que le climat reste stationnaire. Toutefois, les preuves scientifiques incontestables démontrent une augmentation globale de la température et une transformation de la répartition temporelle et spatiale des précipitations, résultant des changements climatiques d'origine anthropique.

L'objectif global de cette thèse était d'approfondir la compréhension des études d'impact des changements climatiques sur les débits fluviaux et la production hydroélectrique induite, en particulier dans de vastes bassins non jaugés. Pour ce faire, le bassin du fleuve Congo en Afrique centrale a été choisi comme cas d'étude. Ce projet de recherche se compose de trois parties distinctes, chacune ayant contribué à la réalisation d'au moins un des sept articles scientifiques regroupés dans cette thèse, dont six constituent le corps principal de l'œuvre, et le septième figure en annexe.

Dans la première partie, les réanalyses atmosphériques ainsi que les données NEX-GDDP ont été considérées comme des sources alternatives de données météorologiques. Dans un premier temps, quatre réanalyses globales de nouvelle génération (CFSR, ERA-Interim, ERA5-Land et JRA-55), et ensuite, 13 ensembles de données NEX-GDDP-CMIP6 (BCC-CSM2-MR, CanESM5, CNRM-CM6-1, GFDL-CM4-gr2, GFDL-ESM4, INM-CM5-0, IPSL-CM6A-LR, MIROC6, MIROC-ES2L, MPI-ESM-1-2-HR, MPI-ESM-1-2-LR, MRI-ESM2-0, NorESM2-LM) ainsi que leurs prédécesseurs NEX-GDDP-CMIP5 (tels que BNU-ESM, CanESM2, CNRM-CM5, GFDL-ESM2G, GFDL-ESM2M, INM-CM4, IPSL-CM5A-LR, MIROC-ESM, MIROC-ESM-CHEM, MPI-ESM-MR, MPI-ESM-LR, MRI-CGCM3, NorESM1-M) ont été comparés aux données météorologiques d'observation. Par la suite, ces données ont été utilisées pour forcer deux modèles hydrologiques en vue de simuler les débits moyens au pas de temps journalier dans le bassin du fleuve Congo. Les résultats ont révélé que tous les ensembles de données étaient capables de reproduire de manière satisfaisante les cycles annuels de précipitations et de températures, et se sont avérés globalement adéquats pour la modélisation hydrologique.

Afin de garantir la fiabilité de la courbe de tarage utilisée pour le calcul des débits, une campagne de mesure des débits a été entreprise de juin à août 2019 à la station de Kinshasa, sur le fleuve Congo. En parallèle, un modèle de régression semi-paramétrique a été développé pour saisir la

relation complexe existant entre divers facteurs (tels que le niveau de l'eau et la vitesse d'écoulement) et les débits des rivières. Les résultats ont souligné l'existence d'une dépendance non linéaire entre ces facteurs et les débits fluviaux.

La deuxième partie de la thèse s'est penchée sur la modélisation multi-modèle, mettant en évidence que la moyenne pondérée des hydrogrammes simulés par plusieurs modèles améliore considérablement les performances par rapport aux modèles individuels les plus performants. Cette approche multi-modèle offre ainsi une opportunité significative de réduire l'incertitude dans les études d'impact liées aux changements climatiques.

La dernière partie du projet a été directement consacrée à l'évaluation des impacts des changements climatiques sur les débits fluviaux et sur la production hydroélectrique. Dans cette optique, des ensembles de données multi-modèles CMIP6 et CMIP5 de simulations climatiques ont été utilisés pour évaluer ces impacts. Les scénarios SSP2 4.5 et SSP5 8.5 ont été examinés pour CMIP6, couvrant les périodes futures 2041-2060 et 2071-2090. De plus, les scénarios RCP 4.5 et RCP 8.5 ont été analysés pour CMIP5, également pour les mêmes périodes. La période de référence retenue correspondait à la période 1981-2000. Les résultats ont permis de calculer la production hydroélectrique à partir des débits quotidiens observés pour les années 1981-2000, ainsi qu'à partir des débits quotidiens simulés par différents modèles climatiques et différents scénarios d'émissions.

Dans l'ensemble, cette thèse a apporté une contribution significative à l'amélioration de la modélisation hydrologique et à une meilleure compréhension des impacts des changements climatiques dans les bassins non jaugés. Elle ouvre la voie à une gestion plus éclairée et durable des ressources en eau, en particulier dans les régions où les données d'observation sont rares, tout en renforçant la confiance dans les analyses des impacts climatiques sur les infrastructures hydrauliques.

Mots clés : Bassins non jaugés, Réanalyses atmosphériques, Changements climatiques, Bassin du fleuve Congo, NEX-GDDP, Modélisation multi-modèle, Production hydroélectrique.

ABSTRACT

The design of hydraulic structures and other river developments is profoundly influenced by the hydrological regime, assuming climate stationarity. However, indisputable scientific evidence points to a global increase in temperature and alterations in the temporal and spatial distribution of precipitation due to anthropogenic climate change.

The overall objective of this thesis was to enhance the understanding of climate change impacts on river flows, especially in extensive ungauged basins. The Congo River basin in Central Africa was chosen as the case study. This research project is divided into three distinct parts, each contributing to at least one of the seven scientific articles included in this thesis, with six forming the main body of work and the seventh presented in an appendix.

In the first part, atmospheric reanalyses and NEX-GDDP data were considered as alternative sources of meteorological information. Initially, four state-of-the-art global reanalyses (CFSR, ERA-Interim, ERA5-Land, and JRA-55) and subsequently, 13 NEX-GDDP-CMIP6 datasets (BCC-CSM2-MR, CanESM5, CNRM-CM6-1, GFDL-CM4-gr2, GFDL-ESM4, INM-CM5-0, IPSL-CM6A-LR, MIROC6, MIROC-ES2L, MPI-ESM-1-2-HR, MPI-ESM-1-2-LR, MRI-ESM2-0, NorESM2-LM), along with their predecessors NEX-GDDP-CMIP5 (such as BNU-ESM, CanESM2, CNRM-CM5, GFDL-ESM2G, GFDL-ESM2M, INM-CM4, IPSL-CM5A-LR, MIROC-ESM, MIROC-ESM-CHEM, MPI-ESM-MR, MPI-ESM-LR, MRI-CGCM3, NorESM1-M) were compared to observed meteorological data. Subsequently, these data were used to force two hydrological models to simulate daily mean discharge in the Congo River basin. The results showed that all datasets were capable of satisfactorily replicating annual cycles of precipitation and temperature and were generally adequate for hydrological modeling.

To ensure the reliability of the rating curve used for discharge calculations, a discharge measurement campaign was conducted from June to August 2019 at the Kinshasa station on the Congo River. Simultaneously, a semi-parametric regression model was developed to capture the complex relationship between various factors (such as water level and flow velocity) and river discharge. The results highlighted the existence of a non-linear dependence between these factors and river discharge.

The second part of the thesis focused on multi-model modeling, demonstrating that the weighted average of hydrographs simulated by multiple models significantly improves performance

compared to the best-performing individual models. This multi-model approach offers a significant opportunity to reduce uncertainty in climate change impact studies.

The final part of the project was directly dedicated to assessing the impacts of climate change on river flows and hydroelectric production. To this end, multi-model CMIP6 and CMIP5 climate simulation datasets were used to evaluate these impacts. SSP2 4.5 and SSP5 8.5 scenarios were examined for CMIP6, covering future periods 2041-2060 and 2071-2090. Additionally, RCP 4.5 and RCP 8.5 scenarios were analyzed for CMIP5, also for the same periods. The reference period chosen was 1981-2000. The results enabled the calculation of hydroelectric production based on daily discharge observed for the years 1981-2000, as well as daily discharge simulated by different climate models and various emission scenarios.

Overall, this thesis has made a significant contribution to improving hydrological modeling and enhancing the understanding of climate change impacts in ungauged basins. It paves the way for more informed and sustainable water resource management, particularly in regions with limited observational data, while bolstering confidence in climate impact assessments on hydraulic infrastructure.

Keywords: Ungauged basins, Atmospheric reanalyses, Climate change, Congo River basin, NEX-GDDP, Multi-model modeling, Hydroelectric production.

TABLE DES MATIÈRES

IN MEMORIAM.....	III
REMERCIEMENTS	IV
RÉSUMÉ.....	V
ABSTRACT	VII
TABLE DES MATIÈRES	IX
LISTE DES TABLEAUX.....	XVII
LISTE DES FIGURES.....	XIX
LISTE DES SIGLES ET ABRÉVIATIONS	XXIV
LISTE DES ANNEXES.....	XXVIII
CHAPITRE 1 INTRODUCTION	1
1.1 Problématique	1
1.2 Contexte d'application	5
1.3 Objectifs de l'étude.....	6
1.3.1 Objectif général	6
1.3.2 Objectifs spécifiques	6
1.4 Méthodologie et Organisation de la thèse	7
1.4.1 Méthodologie de la recherche	7
1.4.2 Organisation de la thèse	8
CHAPITRE 2 REVUE DE LA LITTÉRATURE	11
2.1 Modélisation hydrologique dans les bassins versants non jaugés	11
2.1.1 Les Bassins non jaugés.....	11
2.1.2 Classification des modèles hydrologiques	12
2.1.2.1 Classification selon le degré de spatialisation	12
2.1.2.2 Classification selon la structure du modèle	12

2.1.3	Choix du modèle hydrologique	14
2.1.4	Calibration et validation du modèle hydrologique	14
2.1.5	Approches multi-modèles en modélisation hydrologique.....	15
2.2	Données utilisées en modélisation hydrologiques dans les bassins versants non jaugés	17
2.2.1	Données météorologiques	17
2.2.1.1	Utilisation des réanalyses atmosphériques	17
2.2.1.2	Utilisation des sorties des modèles climatiques	19
2.2.2	Données hydrométriques	20
2.3	Évaluation des impacts futurs des changements climatiques	21
2.3.1	Les modèles climatiques	21
2.3.2	Les ensembles multimodèles de simulations climatiques	23
2.3.3	NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).....	24
2.3.4	Les scénarios d'émission de GES	25
2.4	Impacts des changements climatiques sur les infrastructures	26
2.4.1	Changement climatique et le secteur de l'électricité	27
2.4.2	Impacts des changements climatiques sur la production hydroélectrique	27
CHAPITRE 3 ARTICLE 1: EVALUATING THE ACCURACY OF NEW GENERATION REANALYSIS OVER CONGO RIVER BASIN		29
Abstract		29
3.1	Introduction	31
3.2	Study area and objectives.	34
3.2.1	Study area.....	34
3.2.2	Study objectives	36
3.3	Data, and methods	37
3.3.1	Reanalysis data	37

3.3.2	Observed weather data	40
3.3.3	Method	41
3.3.3.1	Root mean squared error (RMSE) and normalized root mean squared error (NRMSE). ..	42
3.3.3.2	Coefficient of determination (R^2)	43
3.3.3.3	Bias and relative bias (BIAS and RBIAS)	43
3.3.3.4	Spatial analysis for multidimensional data	43
3.4	Results	44
3.4.1	Analysis of precipitation and temperature	44
3.4.2	Annual cycle of reanalysis rainfall (1981–2008)	46
3.4.3	Annual cycle of reanalysis extreme temperatures (1981–2008)	49
3.4.4	Comparison of reanalysis and observed rainfall products.	53
3.4.5	Comparison of reanalysis and observed extreme temperatures.	55
3.5	Discussions	60
3.5.1	Spatial and temporal Performance of Reanalysis precipitation products.....	60
3.5.2	Spatial and temporal Performance of Reanalysis temperature products.....	63
3.6	Conclusions	66
CHAPITRE 4 ARTICLE 2: A BAYESIAN APPROACH TO RIVER DISCHARGE PREDICTION UNDER UNCERTAINTY IN LARGE RIVERS: APPLICATION TO THE CONGO RIVER		68
	Abstract	68
4.1	Introduction	69
4.2	Study area and data	72
4.2.1	Congo River Basin (CRB).....	72
4.2.2	Data description.....	72
4.3	Methodology.....	77
4.4	Results and Discussions.....	80

4.5	Conclusion	86
CHAPITRE 5 ARTICLE 3: IMPROVING HYDROLOGICAL MODELING IN LARGE		
UNGAUGED BASINS: APPLICATION TO THE CONGO RIVER BASIN		
	Abstract	88
5.1	Introduction	89
5.2	Study area	93
5.3	Data and methods	96
5.3.1	Reanalysis data	96
5.3.1.1	CFSR	97
5.3.1.2	ERA-Interim	97
5.3.1.3	ERA5-Land	97
5.3.1.4	JRA-55	98
5.3.1.5	Observed streamflow data	98
5.3.1.6	Land use data	99
5.3.1.7	Soil type data	99
5.3.1.8	Curve Number map	100
5.3.2	Hydrological models	100
5.3.2.1	GR4J	100
5.3.2.2	HEC-HMS	100
5.3.3	Model calibration, and validation	102
5.3.4	Multi-model averaging methods	104
5.4	Results	105
5.4.1	Performance of Mono-model and mono-input	105
5.4.2	Performance of the multi-model averaging methods	112
5.4.2.1	Performance of mono-model multi-input	113
5.4.2.2	Performance of multi-model mono-input	115
5.4.2.3	Performance of multi-model multi-input	117
5.5	Discussions	120

5.5.1	Performance of global reanalysis products for hydrological modelling in CRB ...	120
5.5.2	Differences between the HEC-HMS and GR4J hydrological models	121
5.5.3	Performance of the multi-model averaging methods	122
5.6	Conclusions	123
CHAPITRE 6 : ENHANCING HYDROLOGICAL MODELING IN DATA-SCARCE REGIONS: ASSESSING NEX-GDDP DATASET FOR THE NORTHERN SUB-BASINS OF THE CONGO RIVER BASIN		125
ABSTRACT		125
6.1	Introduction	127
6.2	Study area and datasets	129
6.2.1	Study area	129
6.2.2	Datasets	131
6.3	Methodology	132
6.3.1	Comparison of 28 climatic datasets	132
6.3.2	Hydrological modelling	134
6.3.2.1	HEC-HMS model	134
6.3.2.2	GR4J	136
6.3.2.3	Model calibration, and validation	137
6.4	Results and discussions	138
6.4.1	Comparison of ERA5-Land, CMIP5 and CMIP6 NEX-GDDP	138
6.4.1.1	Annual cycle of monthly precipitation	138
6.4.1.2	Mean Bias Error (MBE)	141
6.4.1.3	Root mean squared error (RMSE)	142
6.4.1.4	Kling-Gupta efficiency (KGE)	143
6.4.1.5	Taylor Diagram (TD)	144
6.4.2	Performance evaluation of NEX-GDDP in hydrological modelling	145
6.4.2.1	Calibration and validation of hydrological models using CMIP6 datasets.	146

6.4.2.2	Calibration and validation of hydrological models using CMIP5 datasets.	147
6.4.2.3	Performance statistics of hydrological simulations	149
6.5	Conclusions and recommendations	153
CHAPITRE 7 : INVESTIGATING HYDROLOGICAL RESPONSES TO CLIMATE		
CHANGE OF THE CONGO RIVER BASIN USING MULTI-MODEL		
ENSEMBLE PROJECTIONS		
Abstract		155
7.1	Introduction	156
7.2	The Congo River basin (CRB)	159
7.3	Data and methods	160
7.3.1	Data	160
7.3.1.1	NEX-GDDP Datasets	160
7.3.1.2	Hydrometric and spatial data	161
7.3.2	Hydrological models	163
7.3.2.1	GR4J	163
7.3.2.2	HEC-HMS	163
7.3.2.3	Model calibration	164
7.3.3	Multi-model averaging approach	166
7.4	Results and Discussion	167
7.4.1	Performances of the hydrological models during the historical period	167
7.4.2	Performances of Multi-model averaging approach	168
7.4.3	Projected flow under changing climate	171
7.4.4	Projected changes in flow discharge at Bangui and Inga	176
7.5	Conclusions and recommendations	180
CHAPITRE 8 ARTICLE 4: CLIMATE CHANGE IMPACT ASSESSMENT ON GRAND		
INGA HYDROPOWER GENERATION USING MULTI-INPUT MODELLING		
Abstract		182

8.1	Introduction	183
8.2	Grand Inga - overview and project planning	185
8.2.1	Overview on Inga falls	185
8.2.2	Development prospects of Grand Inga.....	186
8.3	Data and methods	187
8.3.1	Modelling procedure	187
8.3.2	Data	187
8.3.2.1	System data for Inga Falls hydropower development.	187
8.3.2.2	Flow data	190
8.3.2.3	Data for future climate projection	191
8.3.3	Hydrological model.....	193
8.3.4	Model calibration	193
8.3.5	Multi-Input Ensemble Modelling.....	194
8.3.6	Hydropower generation simulations	195
8.3.6.1	Hydropower model application	196
8.3.6.2	Steps of the Hydropower Generation Simulation Project.....	197
8.4	Results and discussion	198
8.4.1	Hydrological Modelling	198
8.4.2	Projected Hydrologic scenario.	199
8.4.3	Hydropower generation simulations	201
8.4.3.1	Flow Duration Curve.....	201
8.4.3.2	Water utilization duration curve	202
8.4.3.3	Hydropower generation from observed flow 1981-2000	204
8.4.3.4	Hydropower generation from each future simulation.....	207
8.4.3.4.1	Hydropower generation from CMIP5 scenarios.....	213
8.4.3.4.2	Hydropower generation from CMIP6 scenarios.....	214
8.5	Conclusions	217

CHAPITRE 9	DISCUSSION GÉNÉRALE	220
9.1	Choix d'utilisation des réanalyses ou de NEX-GDDP en étude d'évaluation des impacts des changements climatiques	220
9.2	Approches multi-modèle dans un contexte des changements climatiques.....	221
9.3	Impacts des changements climatiques sur l'hydroélectricité	222
9.4	Recommandations pour les travaux futurs	223
CHAPITRE 10	CONCLUSION ET CONTRIBUTIONS.....	226
RÉFÉRENCES.....		229
ANNEXES		252

LISTE DES TABLEAUX

Table 3.1 Summary of the reanalysis dataset used in this study	40
Table 3.2 Description of 13 Observed weather stations used in this study	41
Table 3.3 Summary of statistical metrics for ERAI, CFSR, MERRA, ERA5-Land and JRA55 precipitation at the monthly resolution.....	62
Table 3.4 Summary of statistical metrics for ERAI, CFSR, MERRA, ERA5-Land and JRA55 mean temperature at the monthly resolution.....	65
Table 5.1 summarizes general information on all the databases detailed above.....	96
Table 6.1 Description of 13 CMIP6 global climate models and their CMIP5 predecessors using in this study	132
Table 6.2 Caption of x- axis for figures 5,6, and 7	141
Table 6.3 : Models calibration and validation estimated Nash values	149
Table 7.1 Model names, and modelling agency of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study	162
Table 7.2 : Caption of x- axis for figure 2.....	167
Table 7.3 Weights of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study calculated by GRC at Bangui outlet.....	169
Table 7.4 Weights of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study calculated by GRC at Inga outlet	170
Table 7.5 Change in flow due to Climate change for Bangui	177
Table 7.6 Change in flow due to Climate change for Inga	177
Table 8.1 Main technical data for the Inga Falls hydropower system (Source: Nzakimuena <i>et al.</i> ,2013)	188
Table 8.2 Cumulative values of flow ($Q_{\max}$) and capacity ($P_{\max}$) for each phase	189
Table 8.3 Overview of 13 NEX-GDDP CMIP6 models and their predecessors CMIP5 using in this study	192

Table 8.4 Inga Falls – Main results for simulated hydropower generation (1981-2000).....	207
Table 8.5 Main Results of CMIP5	211
Table 8.6 Main Results of CMIP6	211
Table 8.7 Main Results of change in hydropower generation due to Climate Change.....	212
Table 8. Hydro-climatic characteristics of the KARB	338
Table 9. Utilized reanalysis datasets, their temporal coverage, as well as spatial and temporal resolutions	339

LISTE DES FIGURES

Figure 1.1 Méthodologie de la recherche.....	7
Figure 1.2 Structure de la thèse.....	10
Figure 3.1 Orography of Congo River basin and the spatial distribution of the observation stations	36
Figure 3.2 The long-term patterns of ERA5-Land Monthly Averaged Rainfall for the period 1981– 2008.....	45
Figure 3.3 ERA5-Land Monthly Averaged Temperature patterns for the period 1981–2008.....	46
Figure 3.4 Annual cycle of precipitation over thirteen meteorological stations chosen within the Congo River Basin	48
Figure 3.5 Altitudes of observed stations.....	49
Figure 3.6 As in Figure 3.4, but for maximum temperature	50
Figure 3.7 As in Figure 3.6, but for minimum temperature	52
Figure 3.8 RBIAIS of monthly rainfall between reanalyses and observed dataset	54
Figure 3.9 RMSE of monthly rainfall between reanalyses and observed dataset	54
Figure 3.10 R^2 of monthly rainfall between reanalyses and observed dataset.....	55
Figure 3.11 BIAIS of monthly minimum temperature between reanalyses and observed dataset	56
Figure 3.12 BIAIS of monthly maximum temperature between reanalyses and observed dataset	56
Figure 3.13 BIAIS of monthly average temperature between reanalyses and observed dataset ..	57
Figure 3.14 RMSE of monthly minimum temperature between reanalyses and observed dataset	58
Figure 3.15 RMSE of monthly maximum temperature between reanalyses and observed dataset	58
Figure 3.16 R^2 of monthly minimum temperature between reanalyses and observed dataset.....	59
Figure 3.17 R^2 of monthly maximum temperature between reanalyses and observed dataset	60
Figure 4.1 Study area	72
Figure 4.2 Data description	75

Figure 4.3 Measured discharge	76
Figure 4.4 Proposed framework	78
Figure 4.5 Nonlinear partial effect of the water stage on the water discharge.....	81
Figure 4.6 Nonlinear partial effect of the water velocity on the water discharge	82
Figure 4.7 Nonlinear partial effect of the section area on the water discharge	83
Figure 4.8 Nonlinear partial effect of the section width on the water discharge	84
Figure 4.9 Coefficient of Determination in the training step	85
Figure 4.10 Coefficient of Determination in the testing step	86
Figure 5.1 (a) DTM, (b) land use/land cover map of the Congo River Basin.....	95
Figure 5.2 Observed daily time-series flows at (a) Ouesso (b) Kindu (c) Essaka and (d) Bangui gauged station (1981-2000).....	99
Figure 5.3 NSE values in calibration & validation for the GR4J model at Bangui outlet	106
Figure 5.4 NSE values in calibration & validation for the HEC-HMS model at Bangui outlet .	107
Figure 5.5 Observed and simulated streamflow hydrograph at Bangui outlets for the calibration period.....	107
Figure 5.6 Observed and simulated streamflow hydrograph at Bangui outlets for the validation period.....	108
Figure 5.7 NSE values in calibration & validation for the GR4J model at Ouesso outlet.....	108
Figure 5.8 NSE values in calibration & validation for the HEC-HMS model at Ouesso outlet .	109
Figure 5.9 NSE values in calibration & validation for the GR4J model at Essaka outlet.....	109
Figure 5.10 NSE values in calibration & validation for the HEC-HMS model at Essaka outlet	110
Figure 5.11 NSE values in calibration & validation for the GR4J model at Kindu outlet.....	110
Figure 5.12 NSE values in calibration & validation for the HEC-HMS model at Kindu outlet.	111
Figure 5.13 Observed and simulated streamflow hydrograph at Essaka outlets for the calibration period.....	111

Figure 5.14 Observed and simulated streamflow hydrograph at Essaka outlets for the validation period.....	112
Figure 5.15 Hydrographs of 4 members from GR4J model and the GRC average compared to the observations for the Bangui catchment with the most improvement	113
Figure 5.16 Mono-model (GR4J) multi-input averaging results.....	114
Figure 5.17 Hydrographs of 4 members from HEC-HMS and the GRC average compared to the observations for the Bangui catchment with the most improvement	114
Figure 5.18 Mono-model (HEC-HMS) multi-input averaging results.....	115
Figure 5.19 Combine HEC-HMS & GR4J hydrographs of 4 members compared to the observations for the Bangui catchment with the most improvement	116
Figure 5.20 Multi-model (HEC-HMS&GR4J) mono-input results	116
Figure 5.21 Hydrographs of 8 members and the GRCs average compared to the observations for the Bangui catchment with the most improvement.....	118
Figure 5.22 Multi-model, multi-input averaging results	119
Figure 5.23 GRC Average Returns higher NSE Values than the best member in the group.....	119
Figure 6.1 Location of the Bangui catchment used in this study.	130
Figure 6.2 Mean monthly precipitation during 1981 year for the CMIP5 models, ERA5-Land, and observations over Bangui watershed.....	139
Figure 6.3 As Figure 2 but for CMIP6 models	140
Figure 6.4 As Figure 3 but for Mean of CMIP5 & CMIP6 models	140
Figure 6.5 MBE of CMIP5, CMIP6, and Reanalysis.....	142
Figure 6.6 As Figure 5 but for RMSE.....	143
Figure 6.7 As Figure 6 but for KGE.....	144
Figure 6.8 Taylor diagram of average monthly precipitation for Bangui watershed for ERA5-Land (black), CMIP5 (Blue) and CMIP6 (red)	145

Figure 6.9 NSE values in calibration & validation for (a) the GR4J-CMIP5 model, (b) GR4J-CMIP6 model, (c) HEC-HMS-CMIP5 model and (d) HEC-HMS-CMIP6 model at BW outlet.	148
Figure 6.10 Hydrographs simulated using all 13 datasets for (a) the HEC-HMS model calibration and (b) HEC-HMS model validation.	149
Figure 6.11 Distribution of the discharge values of the different NEX-GDDP datasets for GR4J model at Bangui outlet. Results are based on daily discharges simulated in the calibration and validation periods. The lower and upper limits of each boxplot represent the 25th and 75th percentiles, respectively. The middle line represents the median (50th percentile)	151
Figure 6.12 As figure 11 but for HEC-HMS model.....	153
Figure 7.1 The Congo River basin and sub-basins studied (Inga & Bangui).....	160
Figure 7.2 The Congo.....	168
Figure 7.3 HEC-HMS model calibration for years 1981- 2000 at Inga outlet; dashed lines indicate hydrographs of 13 CMIP5 members, solid line indicates observed flows(black) and GRC average(pink).....	172
Figure 7.4 Simulated GRC ensemble mean daily river flows for the SSP2 4.5 and SSP5 8.5 scenarios at Bangui (a, b) and the corresponding box plots for these simulations (c). Shaded bands represent the 5% uncertainty ranges of GRC-CMIP6.....	174
Figure 7.5 Simulated GRC ensemble mean daily river flows for the RCP 4.5 and RCP 8.5 scenarios at Inga (a, b) and the corresponding box plots for these simulations (c). Shaded bands represent the 5% uncertainty ranges of GRC-CMIP5.....	175
Figure 7.6 Boxplots comparing change in average daily discharge simulated at Bangui outlet by 13 CMIP5 models (a) and 13 CMIP6 models (b) for impact scenarios with respect to the reference scenario. Boxplots represent the model agreement of the predicted changes. The lower, middle and upper box lines represent respectively the 25, 50 and 75 percentiles. Minimum and maximum values are indicated by the whiskers, outliers are shown by the red symbol.....	178
Figure 7.7 Boxplots comparing change in average daily discharge simulated at Inga outlet by 13 CMIP5 models (a) and 13 CMIP6 models (b) for impact scenarios with respect to the reference	

scenario. Boxplots represent the model agreement of the predicted changes. The lower, middle and upper box lines represent respectively the 25, 50 and 75 percentiles. Minimum and maximum values are indicated by the whiskers, outliers are shown by the red symbol..... 179

Figure 8.1 Drainage area of Congo River upstream of Grand Inga Hydroelectric project 186

Figure 8.2 (a) Daily water flow, (b) Flow duration curve at Inga Falls and (c) Water utilization duration curve for Inga Falls with full development (Inga 1-8)..... 191

Figure 8.3 HEC-HMS model calibration for years 1981- 2000; dashed lines indicate hydrographs of 13 CMIP5 members, solid line indicates observed flows(blue) and GRC average(red) 199

Figure 8.4 Annual GRC average flow in Congo River at Inga Falls gauging station for the reference period 1981–2000 and for projected future periods for different emission scenarios (a), (b). The figure (c) represents the relative change in %..... 200

Figure 8.5 Flow duration curve of Inga Falls for GRC CMIP5 scenarios 201

Figure 8.6 Flow duration curve of Inga Falls for GRC CMIP6 scenarios 202

Figure 8.7 Water utilization duration curve of Inga Falls for GRC CMIP5 scenarios 203

Figure 8.8 Water utilization duration curve of Inga Falls for GRC CMIP6 scenarios 204

Figure 8.9 Hydropower generation for Inga 1 to Inga 8 – Based on data for 1981-2000 205

Figure 8.10 Power duration curves for Inga 6, 7 and 8. Historical period 1981-2000..... 206

Figure 8.11 Simulated change in hydropower generation for CMIP5 (a) & (b) and CMIP6 (c) & (d) 208

Figure 8.12 Hydropower generation at Inga Falls for GRC CMIP5 scenarios 214

Figure 8.13 Hydropower generation at Inga Falls for GRC CMIP6 scenarios 215

Figure 8.14 Possible hydropower generation at Inga Falls beyond Inga 8 for GRC CMIP5 scenarios 216

Figure 8.15 Possible hydropower generation at Inga Falls beyond Inga 8 for GRC CMIP6 scenarios 216

LISTE DES SIGLES ET ABRÉVIATIONS

20CR	Twentieth Century Reanalysis
ACDP	Acoustic Doppler current profilers
	Architecture, Engineering, Construction, Operations, and
AECOM	Management
AEJ	African easterly jet
AGCM	Atmospheric Global Circulation Model
AH	Ampere-Hour
AOGCM	Atmosphere/Ocean General Circulation Model
ARMAX	AutoRegressive Moving Average model with eXogenous inputs
BCSD	Bias-Correction Spatial Disaggregation
BFC	Bassin du Fleuve Congo
BMA	Bayesian model averaging
BW	Bangui watersheds
Cf	Capacity Factor
CFSR	Climate Forecast System Reanalysis
CICOS	Commission Internationale du Bassin Congo-Oubangui-Sangha
CMAES	Covariance matrix adaptation evolution strategy
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CN	Curve Number
CORDEX	Coordinated Regional Downscaling Experiment
CRB	Congo River Basin
DEM	Digital Elevation Model
DJF	December – February
DRC	Democratic Republic of Congo
DSMW	Digital Soil Map of the World
DTM	Digital terrain model
ECA	Equatorial Central Africa
ECMWF	European Centre for Medium-Range Weather Forecasts
EDF	Électricité de France

EEQV	Energy equivalent of water
ERA5	Fifth generation ECMWF atmospheric reanalysis
ERA-Interim	ECMWF Reanalysis Interim
ESM	Earth System Model
FAO	Food and Agriculture Organization of the United Nations
FDC	Flow-duration curve
FLH	Full Load Hours
GCM	Global Climate Models
GES	Gaz à effet de serre
GHGES	Greenhouse gas emission scenarios
GIEC	Groupe d'experts intergouvernemental sur l'évolution du climat
GIHP	Grand Inga hydropower project
GMFD	Global Meteorological Forcing Dataset
GMFD	Global Meteorological Forcing Dataset
GR	Granger-Ramanathan
GR4J	Modèle du Génie rural à 4 paramètres journalier
GRA	Granger-Ramanathan averaging
GRC	Granger–Ramanathan averaging type C
HEC-HMS	Hydrologic Engineering Center-Hydrologic Modeling System
HRUs	Hydrologic response units
INERA	Institut de l'Environnement et de Recherches Agricoles
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Intertropical Convergence Zone
JJA	June to August
JRA-55	Japanese 55-year Reanalysis
<i>KGE</i>	Kling-Gupta efficiency
LLWs	Low-level westerlies
MAF	Mean annual flow
MAM	March to May
MBE	Mean Bias Error
MCG	Modèles de circulation générale

MCMC	Markov Chain Monte Carlo
MCR	Modèles climatiques régionaux
MERRA	Modern-Era Retrospective analysis for Research and Applications
METTELSAT	Agence Nationale de Météorologie et de Télédétection par Sattelit
MMA	Multi-model averaging
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NETCDF	Network Common Data Form
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NRCan	Natural Resources Canada
NSE	Nash-Sutcliffe efficiency
OGCM	Oceanic General Circulation Model
OLS	Ordinary least squares
PET	Potential evapotranspiration
PUB	Predictions in Ungauged Basins
QGIS	Quantum Geographic Information System
R^2	Determination coefficient
RCP	Representative Concentration Pathway
RDC	République Démocratique du Congo
<i>RMSD</i>	Root Mean Square Deviation
RMSE	Root Mean Square Error
RVF	Régie des voies fluviales
SCN	Standard curve number
SMA	Soil Moisture Accounting
SON	September to November
SRTM DEM	Shuttle Radar Topography Mission digital elevation model
SSPs	Shared Socioeconomic Pathways
SWAT	Soil and Water Assessment Tool
TD	Tailor Diagram
TWh	Terawatt hour

UBN	Upper Blue Nile
USDA	United States Department of Agriculture

LISTE DES ANNEXES

ANNEXE A - Forecasting the congo River Discharge and Water-level using an Artificial Neural Network Approach	252
ANNEXE B - Grand Inga as One of the Solutions for Africa Energy Deficit	263
ANNEXE C - Utilisation de données de réanalyses atmosphériques comme source alternative pour la modélisation hydrologique des bassins versants partiellement jaugés.....	290
ANNEXE D - A multi-criteria decision-making approach to select potential hydropower sites in the Democratic Republic of Congo	303
ANNEXE E - Modelling spatio-temporal flood inundation dynamics of riverine wetlands using time series flow and near real time satellite data	313
ANNEXE F- Rainwater Harvesting for Sustainable Agriculture for African Dry Regions.....	319
ANNEXE G - Multi-model assessment of climate change impacts on the streamflow conditions in the Kasai River Basin,Central Africa.....	329

CHAPITRE 1 INTRODUCTION

1.1 Problématique

Les changements climatiques, induit par les émissions de gaz à effet de serre (GES), accélèrent le cycle global de l'eau en augmentant les taux d'évaporation et de précipitations (Huntington, T. G. *et al.*, 2018; Qin *et al.*, 2020). Cela entraîne une redistribution des ressources en eau et une intensification des événements hydrologiques extrêmes, accentuant ainsi leur gravité (Qin *et al.*, 2020). Ces changements ont des implications profondes pour les infrastructures vitales liées aux ressources en eau, notamment la conception des barrages et la production d'hydroélectricité (Cui *et al.*, 2020; Ehsani *et al.*, 2017; Fluixá-Sanmartín *et al.*, 2018; Qin *et al.*, 2020; van Oorschot *et al.*, 2018).

Simultanément, la demande croissante en énergie pour soutenir le développement socio-économique entraînera une augmentation continue des émissions et des concentrations atmosphériques de GES, ce qui entraînera des changements climatiques et hydrologiques plus marqués au cours du XXI^e siècle (IPCC, 2014).

Cependant, d'un autre côté, l'hydroélectricité, en tant que source d'énergie renouvelable dominante et économique, joue un rôle essentiel dans la réduction des émissions de GES et l'atténuation des changements climatiques, et connaît une expansion vigoureuse dans de nombreuses régions du monde (Berga, 2016; Hamududu & Killingtveit, 2017; Lu *et al.*, 2020; Wasti *et al.*, 2022).

De nombreuses études (Chilkoti, V. *et al.*, 2017; Nohara *et al.*, 2006; Turner *et al.*, 2017; van Vliet *et al.*, 2016; Zhou, Y. *et al.*, 2015) ont examiné en détail les conséquences des changements climatiques sur les ressources en eau et la génération d'hydroélectricité. La plupart de ces études adoptent une approche de modélisation ascendante, couplant les projections des modèles de circulation générale (MCG) à un ou plusieurs modèles hydrologiques, ainsi qu'à des modèles

d'exploitation de réservoirs et d'hydroélectricité. À l'échelle mondiale, les résultats suggèrent de manière cohérente que le débit moyen annuel augmentera dans les régions à haute-latitude et les régions tropicales humides, tandis qu'il diminuera dans la plupart des régions tropicales arides, et que les événements hydrologiques extrêmes deviendront plus fréquents (IPCC, 2014; Qin *et al.*, 2020).

À mesure que le climat évolue, les variations dans les modèles de précipitations et de températures peuvent influencer le régime d'écoulement des cours d'eau, modifiant potentiellement le potentiel des ressources d'un bassin donné (Liu, L.-L. & Du, 2017; Liu, L. *et al.*, 2017; Schaefli, B., 2015). Étant donné que les entrées hydrologiques sont essentielles pour évaluer le potentiel exploitable d'un système hydroélectrique, les évaluations des impacts des changements climatiques doivent également intégrer des modèles hydrologiques représentant correctement le bassin versant qui alimente le système.

Cependant, le problème principal des bassins non jaugés réside dans la disponibilité de données hydroclimatiques rares ou de qualité médiocre dans les bassins versants (Sidibe *et al.*, 2020; Zhou, L. *et al.*, 2014). Même si de telles données existent, elles peuvent être erronées en raison de problèmes de maintenance et d'exploitation, d'erreurs humaines et de conditions environnementales (Diem *et al.*, 2014; Samba *et al.*, 2008).

Cela rend difficile la représentation hydrologique des processus physiques du bassin même dans des conditions historiques dans les bassins non jaugés. Par conséquent, certaines approches telles que la régionalisation (Beck, H. E. *et al.*, 2016), l'utilisation de données dérivées de satellites (Huang *et al.*, 2020) ou de jeux de données de réanalyses atmosphériques (Ghebrehiwot & Kozlov, 2021) ont été couramment utilisées. La réanalyse est une approche systématique visant à générer des données climatiques en grille à l'aide de schémas d'assimilation de données et de modèles

alimentés par des données d'observation disponibles, provenant de diverses sources telles que les satellites, les bouées, les avions et les rapports de navires (Bosilovich *et al.*, 2008; Parker, 2016). La qualité améliorée et l'homogénéité des données de réanalyse en font un choix souhaitable pour la surveillance et la recherche climatiques, ainsi que pour les applications commerciales, en particulier dans les bassins non jaugés (Ghebrehiwot & Kozlov, 2021; Parker, 2016). Les modèles hydrologiques utilisant des réanalyses peuvent estimer le débit des rivières aussi bien, voire mieux, que ceux utilisant les données des stations (Essou, G. R. C. *et al.*, 2016; Fuka *et al.*, 2014). Compte tenu des différences entre les jeux de données de réanalyse attribuées à la variabilité intermodèle, à l'approche d'assimilation et aux observations disponibles (Hamududu, B., 2012; Lin, R. *et al.*, 2014; Nicholson, S. E. *et al.*, 2018; Washington, Richard *et al.*, 2013), proposent l'utilisation d'un ensemble de jeux de données de réanalyse dans la modélisation hydrologique pour réduire l'incertitude associée.

L'intégration de la modélisation hydrologique introduit inévitablement des incertitudes dans les résultats des études (Chen, J. *et al.*, 2011; Ludwig *et al.*, 2009; Poulin *et al.*, 2011; Wilby, Robert L., 2005). Poulin *et al.* (2011) identifient plusieurs sources d'incertitude dans la modélisation des changements climatiques, parmi lesquelles les modèles climatiques et les scénarios d'émissions constituent des facteurs majeurs pour quantifier les impacts des changements climatiques (Blöschl & Montanari, 2010; Chen, J. *et al.*, 2011; Prudhomme *et al.*, 2003). Pour améliorer l'évaluation des impacts futurs et bien gérer les incertitudes, il est souvent recommandé de réaliser des études basées sur des ensembles de modèles (Minville *et al.*, 2010; Schaepli, Bettina, 2015). Ainsi, certaines études axées sur les effets des changements climatiques sur l'hydroélectricité, utilisant des approches basées sur les modèles hydrologiques, ont adopté des ensembles de modèles climatiques (Christensen & Lettenmaier, 2007; Kopytkovskiy *et al.*, 2015).

Les études sur les changements climatiques reposent sur une variété de modèles climatiques pour simuler des scénarios climatiques futurs correspondant à différentes trajectoires d'émissions de gaz à effet de serre (Metz *et al.*, 2007). L'extraction des données projetées pour différentes variables climatiques nécessite l'analyse des résultats de diverses simulations de catégories différentes de modèles climatiques, les modèles de circulation générale (MCG) étant les plus courants. Opérant généralement sur des échelles de grille grossières d'environ 2,5 degrés (~250 km), les MCG offrent une vue d'ensemble de la simulation climatique. Cependant, pour les études sur les impacts climatiques, des informations climatiques à plus petite échelle sont indispensables pour obtenir des estimations plus robustes. Cela souligne la nécessité d'une représentation détaillée des variables climatiques régionales, réalisable à travers des simulations climatiques à des résolutions supérieures. Les modèles climatiques régionaux (MCR) offrent une solution efficace en fournissant des informations climatiques à des échelles spatiales beaucoup plus fines que celles des grilles des MCG. Les MCR sont pilotés par des conditions aux limites latérales fournies par les MCG (Buontempo *et al.*, 2015; Dosio *et al.*, 2015). Bien que les MCR réduisent l'incertitude, les incertitudes inhérentes aux MCG demeurent (Dosio *et al.*, 2015). Plusieurs projets internationaux ont été initiés pour obtenir des données climatiques à l'échelle régionale, notamment le projet Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi *et al.*, 2009).

Récemment, la NASA (Administration nationale de l'aéronautique et de l'espace) a lancé le jeu de données Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), qui fournit des données à haute résolution (0,25°) à l'échelle mondiale. Ce jeu de données NEX-GDDP peut être utilisé pour étudier les changements climatiques futurs à l'échelle des bassins versants et peut être appliqué aux bassins fluviaux présentant une topographie complexe et une sensibilité climatique (Chen *et al.*, 2017; Jain, S. *et al.*, 2019).

Plusieurs études ont rapporté que les projections NEXGDDP de la température et des précipitations sont détaillées avec une résolution spatiale élevée et, lorsqu'elles sont utilisées dans des modèles hydrologiques, peuvent améliorer la compréhension de la disponibilité future des ressources en eau à court et à long termes sous les changements climatiques (Bao & Wen, 2017; Bokhari *et al.*, 2018; Chen *et al.*, 2017). La simulation réaliste des extrêmes à l'aide de l'ensemble de données NEX-GDDP a suggéré son applicabilité aux études sur les changements climatiques.

1.2 Contexte d'application

Le domaine d'application de ce projet de thèse est le bassin du Fleuve Congo (BFC).

Le BFC est situé en Afrique centrale et s'étend de la latitude 09°15'N en République centrafricaine à 13°28'S en Angola et en Zambie, et de la longitude 31°10'E à travers les Grands Lacs africains dans le rift Est-Africain jusqu'à 11°18 'E sur l'océan Atlantique. Le BFC est partagé entre neuf pays africains avec une superficie totale de 3 691 000 km². Il comprend une population d'environ 139 millions d'habitants en 2020 (Banque mondiale, 2020). La ressource en eau du bassin est vitale pour les moyens de subsistance des communautés locales, l'approvisionnement en eau potable, la sécurité alimentaire et la production d'énergie électrique. Le BFC regorge le plus grand site hydroélectrique au monde qui est le site d'Inga. Le site se trouve à 172 km de l'estuaire du fleuve Congo et à 282 km en aval de Kinshasa en RDC. Les chutes d'Inga sont situées à une latitude de 05°40' sud et une longitude de 13°39' est. Ce site draine environ 98 % de la superficie totale du bassin versant du fleuve Congo. Les chutes d'Inga s'étendent sur une longueur de 32 km avec une dénivellation de 97 mètres, correspondant à une pente moyenne de 3 m/km (Nzakimuena *et al.*, 2013). Le site offre la possibilité de développer des structures de production hydroélectrique avec une hauteur brute de chute de 150 mètres. Avec un débit moyen de 40 800 m³/s, le potentiel de puissance pouvant y être développée avec ces caractéristiques est estimé à environ 42 900 MW. Ce

site a fait l'objet de plusieurs projets de développement, mais à ce jour aucun n'a abordé, dans une perspective de développement durable, sa résilience aux impacts potentiels des changements climatiques.

1.3 Objectifs de l'étude

1.3.1 Objectif général

L'objectif général de cette thèse est d'améliorer la compréhension des études d'impacts des changements climatiques sur les débits et le potentiel hydroélectrique des bassins fluviaux non jaugés. Cet objectif général se décline en trois objectifs spécifiques.

1.3.2 Objectifs spécifiques

Objectif spécifique 1 : Évaluer la précision des données de précipitation et température des réanalyses atmosphériques par rapport aux observations météorologiques. Cet objectif a été atteint à travers l'article 1 (chapitre 3).

Objectif spécifique 2 : Développer, à partir de débits mesurés sur terrain, un modèle de régression semi-paramétrique capturant la relation complexe entre plusieurs facteurs et le débit de réponse et évaluer l'erreur par rapport aux débits calculés par la courbe de tarage. L'article 2 (chapitre 4).

Objectif spécifique 3 : Évaluer la précision des débits moyens journaliers simulés en utilisant des données de précipitation et température des réanalyses comme forçages météorologiques d'un modèle hydrologique global dans un contexte multi-modèle. Cet objectif a été atteint à travers l'article 3 (chapitre 5).

Objectif spécifique 4 : Évaluer la précision des débits moyens journaliers simulés en utilisant des données de précipitation et température des données haute résolution NEX-GDDP CMIP5&6

comme forçages météorologiques d'un modèle hydrologique global. Cet objectif a été atteint à travers le chapitre 6.

Objectif spécifique 5 : Évaluer les impacts des changements climatiques sur les débits moyens journaliers et le potentiel hydroélectrique en utilisant un cadre de modélisation multi-modèle et multi-input alimenté par les jeux de données NEX-GDDP CMIP5&6. Cet objectif a été atteint à travers le chapitre 7 et l'article 6 dans le chapitre 8).

1.4 Méthodologie et Organisation de la thèse

1.4.1 Méthodologie de la recherche

Pour la matérialisation des objectifs énumérés ci-dessus, la méthodologie développée dans cette thèse est basée sur la simulation. Le processus d'évaluation des impacts des changements climatiques adoptés dans le cadre de ce travail implique une chaîne de modélisation présentée à la Figure 1.1.

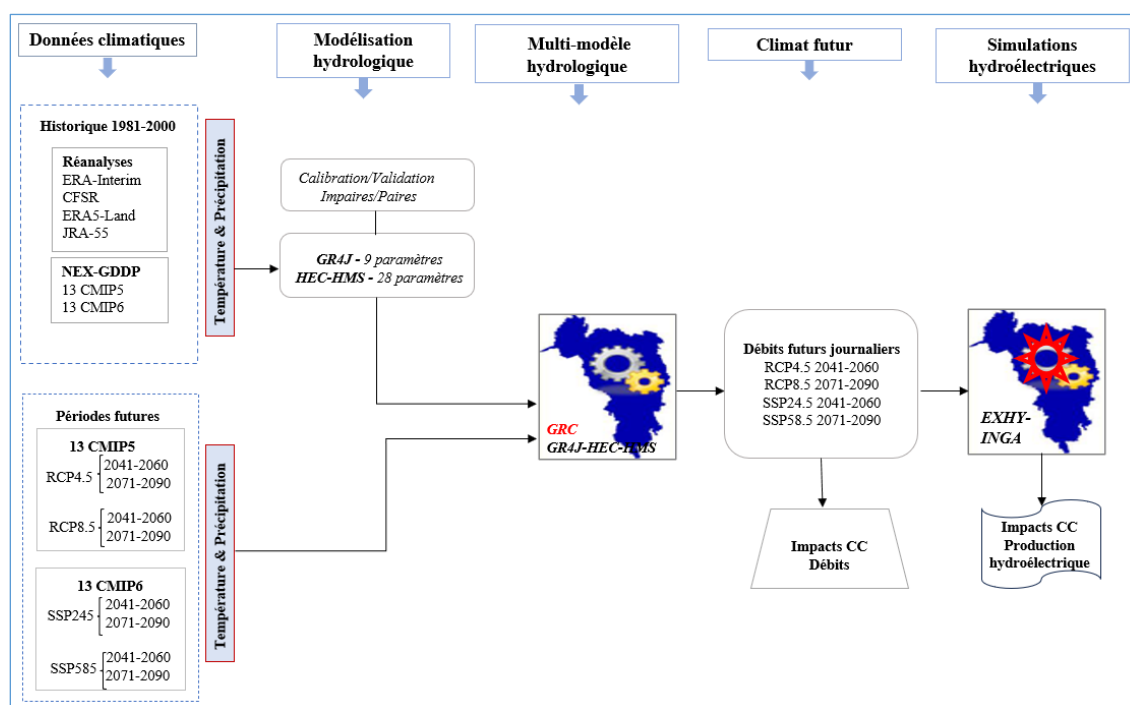


Figure 1.1 Méthodologie de la recherche

1.4.2 Organisation de la thèse

La thèse comporte 10 chapitres (figure 1.2). L'introduction et la conclusion et recommandations sont des chapitres à part entière.

La dissertation se compose de 10 chapitres distincts. Cette présente introduction est suivie d'une synthèse concise de la littérature générale. Ensuite, chacun des six chapitres consécutifs constitue un article publié, soumis, ou en préparation pour soumission à un journal scientifique. En dernière instance, sont présentées une analyse et une conclusion globale ainsi que des suggestions.

Le chapitre 3 constitue l'article 1 intitulé « Evaluating the Accuracy of New Generation Reanalysis Over Congo River Basin. » Cet article est soumis pour publication dans le *Journal of Applied Meteorology and Climatology*, il analyse les performances de plusieurs nouveaux produits de réanalyse pour déterminer ceux qui représentent le mieux les cycles annuels de précipitations et de températures. Ces travaux ont permis de déterminer si ces jeux de données pourraient être utilisés comme proxy en modélisation hydrologique, dans la suite des travaux.

Le chapitre 4 constitue l'article 2 ayant pour titre « A Bayesian approach to river discharge prediction under uncertainty in large rivers: Application to the Congo River ». Cet article est soumis pour publication dans le *Journal of hydrology*, il vise à développer, à partir de débits mesurés sur terrain, un modèle de régression semi-paramétrique capturant la relation complexe entre plusieurs facteurs (p. ex., le niveau, la vitesse d'écoulement) et le débit de réponse. Les conclusions de cet article, ont servi à valider les données des débits calculés par la courbe de tarage qui sont utilisées en modélisation hydrologique et hydroélectrique pour les quatre articles suivants.

Le chapitre 5 constitue l'article 3 intitulé « Improving hydrological modeling in large ungauged basins: Application to the Congo River Basin ». Cet article est soumis au *Water Resources Research journal* il propose une méthode pour moyenner les hydrogrammes provenant de deux

modèles auxquels on a fourni plusieurs sources de données. Les résultats de la combinaison ont été sensiblement améliorés par rapport aux membres individuels.

Le chapitre 6 intitulé « Enhancing hydrological modeling in data-scarce regions: Assessing NEX-GDDP dataset for the northern sub-basins of the Congo River Basin » Cet article en préparation pour soumission au *Hydrological Sciences Journal*, compare les données de température et précipitation de NEX-GDDP CMIP5&6 et aussi leurs performances comme forçages météorologiques d'un modèle hydrologique global, pour la simulation des débits moyens journaliers. Les résultats mettent la table pour de nouvelles utilisations de données alternatives, telles que les données issues de modèles globaux du climat.

Le chapitre 7 intitulé « Investigating hydrological responses to climate change of the Congo River Basin using multi-model ensemble projections » Cet article, en préparation pour soumission à *Earth's Future Journal*, utilise les méthodes de pondération multi-modèle afin d'améliorer les études d'impacts des changements climatiques. Le modèle a été appliqué dans le bassin du Fleuve Congo.

Le chapitre 8 constitue le quatrième et dernier article de la thèse. L'article est intitulé « Climate change impact assessment on Grand Inga hydropower generation using multi-input modelling ». Ces travaux ont été soumis pour publication au *Journal Renewable Energy*. Ils utilisent l'approche multi-modèle et multi-input pour évaluer les impacts des changements climatiques sur le potentiel hydroélectrique de Grand Inga en République Démocratique du Congo.

Le chapitre 9 présente la discussion générale de la thèse et le chapitre 10 présente la conclusion et les recommandations.

Un autre article et un chapitre du livre sont présentés en annexe. Il s'agit aussi de travaux auxquels je suis l'auteur principal. L'article intitulé « Forecasting the Congo River Discharge and Water-

level using an Artificial Neural Network Approach » est présenté à l'annexe II. Il développe un modèle de prévision de débit utilisant un réseau de neurones artificiels au barrage d'Inga. C'est un outil qui aidera l'équipe de gestion à disposer d'informations plusieurs jours à l'avance. Il a été publié au *Nile Water science & Engineering Journal*. Le chapitre trouvé à l'annexe I et intitulé « Grand Inga as One of the Solutions for Africa Energy Deficit » a été publié dans *Comprehensive Renewable Energy, 2e édition publiée par Elsevier*. Ce chapitre donne plus de détail sur les potentialités de Grand Inga. Ces deux contributions sont donc directement liées aux travaux de cette thèse. Finalement, plusieurs conférences, et présentations orales ont permis de disséminer les résultats et les conclusions des travaux effectués.

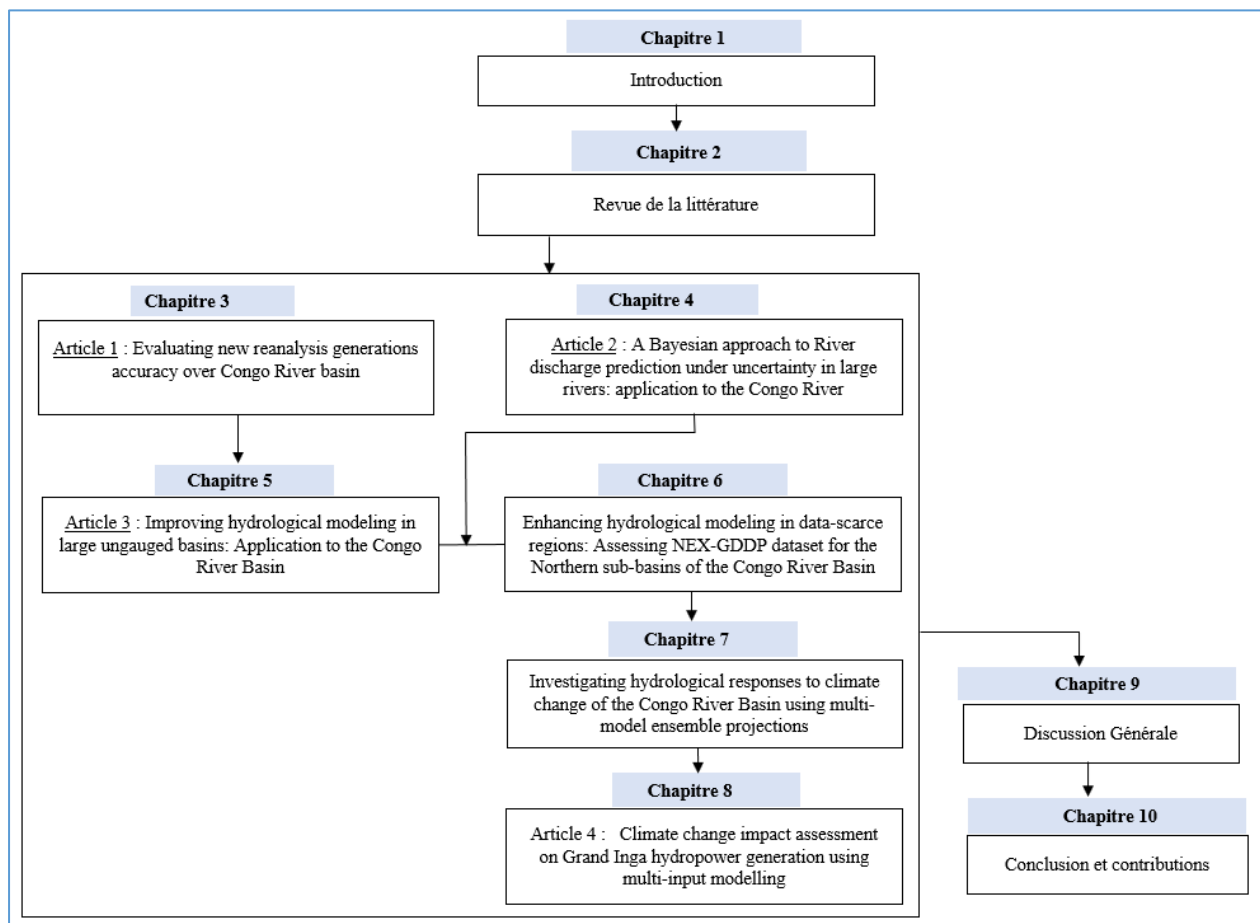


Figure 1.2 Structure de la thèse

CHAPITRE 2 REVUE DE LA LITTÉRATURE

2.1 Modélisation hydrologique dans les bassins versants non jaugés

2.1.1 Les Bassins non jaugés

En 2003 une décennie de recherche avait été lancée à l'initiative de l'International Association of Hydrological Sciences : la décennie 2003-2012 Predictions in Ungauged Basins (PUB). L'objectif de cette décennie était de faire progresser la communauté scientifique sur la compréhension des processus hydrologiques sous-jacents à la relation pluie-débit afin de passer du diktat du calage à la prééminence de la compréhension et d'ainsi améliorer les simulations en contexte non jaugé (Hrachowitz *et al.*, 2013; Rouhier, 2018; Sivapalan *et al.*, 2003).

Il est à noter que, beaucoup de bassins versants dans le monde ne sont pas équipés des stations d'observation hydrométéorologiques, ou du moins des stations de mesure pérenne et fiable (Rouhier, 2018). Par conséquent, le développement et le calage des modèles hydrologiques sont impossibles en raison du manque d'observations des variables hydrométéorologiques en termes de quantité ou qualité.

Par définition, les bassins versants non jaugés sont ceux qui ne disposent pas suffisamment de données pour diverses observations hydrologiques en termes de quantité et de qualité aux fins d'analyse aux échelles spatiales et temporelles appropriées avec un bon niveau de précision acceptable pour les applications pratiques (Sivapalan, 2003; Sivapalan *et al.*, 2003). Si la variable d'intérêt n'a pas été mesurée à la résolution requise, ou pendant la durée requise pour les prédictions ou pour la calibration du modèle, le bassin est considéré comme non jaugé par rapport à cette variable. Vu le nombre élevé des variables hydrologiques, chaque bassin versant est 'non jaugé' à certains égards.

2.1.2 Classification des modèles hydrologiques

2.1.2.1 Classification selon le degré de spatialisation

Selon le degré de spatialisation, le modèle peut être **global**, **semi-distribué** ou **distribué**. Dans un modèle global, le bassin est considéré comme une entité unique. Des relations empiriques relient les entrées et les sorties sans chercher à se rapprocher d'une loi physique (Gnouma, 2006). Dans de nombreux modèles globaux, les processus sont décrits sous forme d'équation simplifiées ou d'équations issues de raisonnements empiriques (Singh, S. K., 2010). Le modèle distribué, quant à lui, prend explicitement en compte la variabilité spatiale des processus et/ou les variables d'entrée et/ou des conditions aux limites et/ou des caractéristiques du bassin versant (Gnouma, 2006).

Les modèles globaux, malgré leurs limites, sont largement utilisés pour l'évaluation des impacts du changement climatique et pour la planification des ressources en eau (Hamududu, 2012). Ceci est principalement dû à leur simplicité de mise en œuvre et une exigence réduite des paramètres d'entrée (informations physiographiques) par rapport à d'autres types de modèles.

Les modèles distribués ont l'avantage de capturer la variabilité spatio-temporelle des composantes du cycle de l'eau et permet d'étudier le changement d'échelle. Cela est vrai pour les grands bassins où les paramètres d'entrée varient à travers le bassin; dans ce cas, ces changements peuvent être mis en œuvre dans leur contexte spatial par le modèle. Le manque de données d'entrée rend l'application de ces modèles difficile.

2.1.2.2 Classification selon la structure du modèle

Selon la structure du modèle, le modèle peut être conceptuel, à base physique ou dits 'boîtes noires'. Selon (Wheater, 2002), les modèles **conceptuels** sont basés sur deux critères: d'une part, la structure du modèle est spécifiée avant toute modélisation, et d'autre part tous les paramètres du modèle ont une interprétation physique directe (ils ne sont pas indépendamment mesurables). Par

conséquent, certains paramètres du modèle conceptuel doivent être estimés par étalonnage par rapport aux données observées. Les modèles conceptuels représentent généralement tous les composants des processus hydrologiques perçus comme étant d'importance dans la relation entrées-sorties à l'échelle du bassin versant (Wheater, 2002). À titre d'exemple on a le modèle HEC_HMS(Feldman, 2000), le modèle GR4J (Perrin *et al.*, 2003).

En théorie, les modèles à **base physique** sont définis par des paramètres entièrement mesurables et peuvent fournir une simulation continue de la réponse hydrologique sans calage (Pechlivanidis *et al.*, 2011). Ces modèles sont une compilation puissante des processus pertinents idéalisés mais soulèvent un certain nombre de questions importantes. La physique et la structure du modèle sont généralement basées sur le laboratoire ou l'expérience à petite échelle in situ sur le terrain, et sont donc affectées par la nature des expériences elles-mêmes. L'extrapolation à une plus grande (par exemple bassin versant) échelle implique souvent l'hypothèse que les processus physiques et les propriétés sont indépendantes de l'échelle, suscitant des inquiétudes quant à leur applicabilité (Beven, 2004). Nous pouvons citer, entre autres, les modèles SHE (Abbott *et al.*, 1986) et SWAT(Arnold & Fohrer, 2005).

Les modèles hydrologiques sont dits 'boîtes noires' s'ils établissent une relation purement mathématique entre les données d'entrée et de sortie. La relation est décrite par une ou plusieurs équations sans pour autant être décomposée en processus physiques. Avec l'avancée des nouvelles technologies en termes d'intelligence artificielle ou de machine learning, nous pouvons observer depuis quelques années un regain d'intérêt particulier pour ce type de méthodes (Rouhier, 2018; See *et al.*, 2007). Nous pouvons citer, entre autres, les modèles ARMAX (Jakeman & Whitehead, 1996) et les réseaux de neurones artificiels (Coulibaly *et al.*, 2000; Daliakopoulos & Tsanis, 2016; Li, B. *et al.*, 2016). Pour plus des détails, une littérature abondante est disponible.

2.1.3 Choix du modèle hydrologique

Selon la classification faite à la section 2.1.2, les deux principales catégories de modèles hydrologiques sont les modèles globaux et distribués. Dans les modèles de type global le bassin versant est considéré comme étant une entité unique, et les différentes variables d'états et météorologiques sont moyennées sur l'ensemble du bassin (Martel, 2019). Les études comparatives de deux types de modèles réalisées dans la littérature ont montré que les deux performant bien pour simuler les débits à l'exutoire (Smith et al., 2012). Le choix du modèle à utiliser dépend des objectifs fixés et des données d'entrées disponibles.

2.1.4 Calibration et validation du modèle hydrologique

À ce jour, de nombreux aspects des processus physiques qui régissent le cycle hydrologique demeurent partiellement énigmatiques. De plus, il subsiste une lacune significative en termes de données nécessaires pour appliquer pleinement les équations les plus complexes (Martel, 2019). Pour pallier cette problématique, les modèles hydrologiques recourent à une simplification des processus en utilisant diverses approximations et en ajustant un ensemble de paramètres (Martel, 2019). Ainsi, il devient impératif d'effectuer une calibration minutieuse du modèle hydrologique afin de déterminer les paramètres optimaux adaptés au bassin versant étudié.

La calibration d'un modèle hydrologique implique l'utilisation d'une fonction objectif visant à générer un hydrogramme simulé qui se rapproche au maximum des données observées (Arsenault et al., 2014; Gupta et al., 2014). Parmi les fonctions objectif couramment utilisées en hydrologie, on trouve la fonction de Nash et Sutcliffe (Nash & Sutcliffe, 1970), qui jouit d'une grande popularité (Jain, S. K. & Sudheer, 2008). Une autre fonction objectif de plus en plus adoptée en hydrologie est celle développée par Kling et Gupta (Gupta et al., 2009).

Dans la littérature scientifique, plusieurs stratégies sont utilisées pour calibrer les modèles hydrologiques. La stratégie la plus couramment employée consiste à diviser l'ensemble des données observationnelles en deux parties, l'une pour la calibration et l'autre pour la validation du modèle. Cette stratégie peut prendre plusieurs variantes, notamment la division des séries en deux ou trois parties. Dans le premier cas, le modèle est calibré sur une partie des données et validé sur l'autre, tandis que dans le second cas, le modèle est calibré sur une partie et validé sur les deux autres (Arsenault *et al.*, 2018; Klemeš, 1986). Une autre variante consiste à considérer les années impaires et paires. Dans ce cas, le modèle sera calibré sur les séries des années impaires et validé sur les années paires, ou vice versa (Arsenault *et al.*, 2018; Arsenault *et al.*, 2017b; Gowda *et al.*, 2012).

La stratégie moins couramment utilisée consiste à calibrer le modèle sur l'ensemble des données disponibles, sans passer par l'étape habituelle de validation du modèle. Cette approche garantit que le maximum d'informations provenant des données climatiques soit intégré dans l'ensemble des paramètres, réduisant ainsi toute incertitude supplémentaire liée au choix des années de calibration et de validation (Tarek, M. *et al.*, 2020). De plus, la performance du modèle s'améliore statistiquement lorsque davantage d'années sont incluses dans l'ensemble de données, et les compétences en calibration et validation ne sont pas nécessairement corrélées (Arsenault *et al.*, 2018).

2.1.5 Approches multi-modèles en modélisation hydrologique

Le concept de la modélisation multi-modèle repose sur l'idée que les modèles hydrologiques génèrent des erreurs liées à leur structure lors des simulations. En utilisant plusieurs modèles, il devient possible de produire des simulations qui présentent des surestimations de la réalité, ainsi que d'autres qui la sous-estiment. En combinant les résultats de ces modèles, il est envisageable de réduire l'erreur attribuable à la structure des modèles. Les méthodes de pondération multi-modèle

permettent d'agréger de manière plus efficace les résultats des différents modèles en fonction de leur performance pendant la phase de calage.

L'algorithme d'agrégation multi-modèles est une méthode statistique utilisée pour combiner les résultats de plusieurs modèles hydrologiques afin d'améliorer la précision et la fiabilité des prédictions. Il s'agit d'une forme d'agrégation de modèles qui fait intervenir plusieurs modèles ayant des structures et des hypothèses différentes pour capturer la complexité des systèmes hydrologiques. Des études d'inter comparaison récentes de telles méthodes ont identifié les schémas de pondération Granger-Ramanathan (GR) comme une classe robuste d'algorithmes pour les applications de modélisation hydrologique (Arsenault *et al.*, 2017a; Arsenault *et al.*, 2015; Diks, C. G. H. & Vrugt, J. A., 2010; Granger & Ramanathan, 1984; Wan, Y. J. *et al.*, 2021). L'approche GR comporte trois variantes, A, B et C (GRA, GRB et GRC). La variante GRA définit les poids en fonction de l'algorithme des moindres carrés ordinaires (OLS). L'objectif est de minimiser l'erreur quadratique moyenne (RMSE), mais le biais n'est pas corrigé. GRB est similaire à GRA, mais l'algorithme (OLS) est contraint de sorte que les poids se somment à l'unité. Enfin, GRC est sans contrainte, mais les valeurs moyennes du débit sont corrigées du biais grâce à l'utilisation d'un terme constant (Arsenault *et al.*, 2015 ; Granger & Ramanathan, 1984). Dans cette étude, nous avons utilisé la variante GRC car elle est robuste et facile à mettre en œuvre. Sa performance a été démontrée dans plusieurs études (Arsenault *et al.*, 2017 ; Arsenault *et al.*, 2015).

2.2 Données utilisées en modélisation hydrologiques dans les bassins versants non jaugés

2.2.1 Données météorologiques

2.2.1.1 Utilisation des réanalyses atmosphériques

Avec les avancées technologiques des dernières décennies, de nouvelles sources de données météorologiques appelées réanalyses atmosphériques ont été développées. Elles présentent l'avantage de fournir une couverture mondiale pour plusieurs centaines de variables climatiques, et leurs données sont cohérentes spatialement et temporellement (Dee *et al.*, 2011; Mesinger, F *et al.*, 2006; Saha *et al.*, 2010). Ainsi, les données provenant des réanalyses atmosphériques pourraient constituer une alternative intéressante aux données traditionnelles des stations météorologiques pour les études hydrologiques dans les régions où les données des stations météorologiques sont insuffisantes ou inexistantes. Les réanalyses font usage d'une grande variété de bases de données d'observation assimilées de manière complexe dans un modèle de prévision numérique du temps pour produire une synthèse spatialement et temporellement cohérente de différentes variables météorologiques sur la période historique récente. Le modèle de prévision des réanalyses demeure inchangé pour assurer la cohérence des données météorologiques simulées (Essou, 2016).

Plusieurs études ont rapporté les avantages de l'utilisation des produits de réanalyses pour la modélisation hydrologique et l'analyse des ressources en eau en Afrique en général, et particulièrement en Afrique centrale.

Pour identifier les "meilleurs" produits de réanalyses disponibles en Afrique équatoriale centrale, Hua *et al.* (2019) ont évalué sept produits de réanalyses (à savoir 20CR, CFSR, ERA-Interim, JRA-55, MERRA, NCEP-1 et NCEP-2) en se basant sur des observations de radiosondage de qualité et

un ensemble de données de pluie basé sur les mesures des pluviomètres. Ils ont constaté que MERRA2 se rapprochait le plus des données observées.

Siam, M. S. *et al.* (2013) ont examiné les produits de modèles climatiques mondiaux (GCMs) et de réanalyses qui offrent une représentation réaliste du cycle hydrologique dans les bassins du Congo et du Haut-Nil bleu. Selon leurs résultats, la réanalyse NCEP-NCAR, la Réanalyse du 40e anniversaire de l'ECWMF (ERA-40) et ERA-Interim présentaient les meilleures performances. La réanalyse ERA-Interim (ERA-I) a été utilisée pour surveiller et prévoir les conditions de sécheresse dans la corne de l'Afrique (Sahlu *et al.*, 2017). Les résultats ont montré un déficit de précipitations lors des deux saisons des pluies (octobre-décembre 2010 et mars-mai 2011), malgré ses limites pour représenter la variabilité interannuelle de mars à mai (Dutra, E. *et al.*, 2013).

Pokam, W. M. *et al.* (2012) ont analysé les caractéristiques des principaux composants du cycle de l'eau en Afrique centrale équatoriale (ECA) sur une période de 32 ans, allant de 1968 à 2000, en utilisant la base de données du projet de réanalyse NCEP/NCAR, tandis que Ceccherini *et al.* (2017) ont utilisé ERA-Interim pour étudier le régime de température extrême des vagues de chaleur en Afrique sur la période 1981-2015.

De nombreux produits de réanalyses sont couramment utilisés en Afrique comme substitut aux observations en raison de leur haute résolution spatiale et temporelle, de leur couverture globale, et ils ont été largement utilisés dans les domaines hydrologiques et agricoles (Bastola & François, 2012; Dembélé, Ceperley, *et al.*, 2020; Koutsouris, A. J. *et al.*, 2016; Lakew, H. B. *et al.*, 2020; Maharana *et al.*, 2018; Nkiaka *et al.*, 2017a; Poméon *et al.*, 2017; Tarek *et al.*, 2020; Zhan, W. *et al.*, 2016). Cependant, d'autres chercheurs ont évalué la performance des produits de réanalyses en les comparant à d'autres ensembles de données (Lakew, Haileyesus Belay *et al.*, 2017; Le Coz &

Van De Giesen, 2020; Nicholson, S. E. & Klotter, D. A., 2021; Quagraine *et al.*, 2020; Zhang, Q. *et al.*, 2013a).

2.2.1.2 Utilisation des sorties des modèles climatiques

Un avantage notable de modèles climatiques réside dans la cohérence physique des données, qui respectent les lois fondamentales de la conservation de l'énergie et de la masse. Ces modèles englobent une gamme complète de variables hydrologiques, de précipitations et de température pertinentes, couvrant à la fois les composantes atmosphériques et de surface de l'hydrologie, nécessaires pour établir un bilan hydrique complet dans un bassin versant (Essou *et al.*, 2016). Néanmoins, la résolution spatiale grossière et les limitations temporelles des sorties des modèles de circulation générale (GCM) entravent leur efficacité dans la fourniture d'informations significatives à l'échelle régionale (Kour *et al.*, 2016; Wilby, R. L. & Wigley, 1997). Ainsi, la nécessité se fait sentir de convertir les sorties des GCM en données météorologiques localisées à haute résolution, essentielles pour une modélisation hydrologique fiable, souvent désignée sous le nom de 'downscaling' (Hewitson & Crane, 1992; Kour *et al.*, 2016).

De nombreuses études dans la littérature ont utilisé la modélisation hydrologique basée sur les Modèles de Circulation Générale (GCM) (Ardoin-Bardin *et al.*, 2009; Faiz *et al.*, 2018; Giuntoli *et al.*, 2015; Ismail *et al.*, 2020; Kusangaya *et al.*, 2017; Nan *et al.*, 2021; Remesan *et al.*, 2014; Wanders & Van Lanen, 2015; Zheng *et al.*, 2018). Comme la résolution spatiale des sorties des GCM n'est pas adaptée pour représenter les scénarios de changement climatique à l'échelle d'un bassin versant ciblé en raison de sa plus grande échelle, le downscaling devient nécessaire pour capturer l'impact du changement climatique sur un bassin versant (Chiphang *et al.*, 2022; Mahmood *et al.*, 2018; Shin & Yi, 2019).

Actuellement, la National Aeronautics and Space Administration (NASA) a lancé le jeu de données Earth Exchange Global Daily Downscaled Projections (NEXGDDP), fournissant des données à haute résolution à l'échelle mondiale avec des intervalles de $0,25^\circ$. Ce jeu de données offre des perspectives prometteuses pour évaluer les impacts futurs du changement climatique au niveau des bassins versants, en particulier dans les bassins fluviaux caractérisés par une topographie complexe et une sensibilité au climat (Chen *et al.*, 2017; Chiphang *et al.*, 2022; Jain, S. *et al.*, 2019). Plusieurs études indiquent que les projections NEXGDDP de la température et des précipitations, avec leur haute résolution spatiale, améliorent la compréhension de la disponibilité des ressources en eau dans le contexte d'un climat changeant à court et à long terme, en opérant à des échelles régionales et locales (Bao & Wen, 2017; Bokhari *et al.*, 2018; Chen *et al.*, 2017; Chiphang *et al.*, 2022; Jain, S. *et al.*, 2019). Plusieurs études ont été menées pour évaluer les séries de données climatiques historiques et futures (Bokhari *et al.*, 2018; Musie *et al.*, 2020; Raghavan *et al.*, 2018; Zhang, Zhang, *et al.*, 2018). Ces ensembles de données se présentent comme une source prometteuse pour les évaluations des impacts des changements climatiques dans des régions dépourvues de données d'observation adéquates.

2.2.2 Données hydrométriques

Les modèles hydrologiques sont calés en comparant les débits simulés avec les données observées recueillies à partir de stations hydrométriques, généralement fournies par les agences compétentes. Souvent, les séries de données hydrométriques présentent de nombreuses lacunes, pouvant s'étendre sur plusieurs années sans observations. Contrairement aux données météorologiques, les lacunes dans la série de débits observés ne posent généralement pas de problème. En effet, ces débits observés servent uniquement de base de comparaison pour évaluer la performance des débits simulés par le modèle hydrologique et pour ajuster les paramètres du modèle. Par conséquent, le

modèle ignore simplement les périodes sans observations lors du calcul des métriques de performance (Martel & Arsenault, 2020).

La méthode traditionnelle de mesure des débits en rivière implique la création d'une courbe de tarage. Cette courbe est établie en effectuant des mesures ponctuelles simultanées de la profondeur de l'eau et du débit, couvrant toute la gamme de valeurs prévues avec autant de précision que possible. Cette approche repose sur l'hypothèse que la relation entre la hauteur de l'eau et le débit est univoque et constante au fil du temps, y compris pendant les périodes de crue. Cependant, il est important de reconnaître les limites de cette hypothèse, car la relation entre la hauteur de l'eau et le débit peut évoluer progressivement ou brusquement en raison de modifications des caractéristiques physiques et hydrauliques de la section de mesure (Mballa, 2016).

Pour surmonter cette difficulté, il est recommandé de réaliser des mesures ponctuelles sur une période donnée en utilisant d'autres appareils appropriés, afin de prendre en compte les éventuelles erreurs entre les mesures effectuées et les valeurs calculées à partir de la courbe de tarage.

2.3 Évaluation des impacts futurs des changements climatiques

2.3.1 Les modèles climatiques

L'utilisation de séries chronologiques d'observations historiques pour évaluer les changements projetés des extrêmes hydrométéorologiques est souvent problématique. Une approche plus adaptée est l'utilisation du concept de monde virtuel, où un modèle climatique est employé comme une représentation substitutive du monde réel. Ce modèle permet de créer une version virtuelle du monde réel, riche en données climatiques. La création de ce monde virtuel nécessite une quantité significative de temps de calcul, généralement réalisée grâce à l'utilisation de superordinateurs, afin de produire des simulations climatiques dans un laps de temps raisonnable. Ces simulations servent ensuite à générer des séries chronologiques avec une résolution spatiale et temporelle bien

supérieure à celles des séries observées dans le monde réel, qui se limitent aux données recueillies par les stations météorologiques(Martel, 2019).

Un avantage essentiel de ce monde virtuel réside dans son fondement sur les lois fondamentales de conservation de la masse, de l'énergie et du moment, garantissant ainsi la cohérence physique des données(Caya & Laprise, 1999; Martel, 2019; Music & Caya, 2007). Grâce à l'utilisation de différents scénarios d'émissions de gaz à effet de serre, il devient possible de projeter l'évolution du climat à l'horizon, que ce soit à court ou à long terme, afin d'évaluer les impacts des activités humaines sur celui-ci.

Parmi les types de modèles climatiques les plus répandus, on retrouve les modèles de circulation générale (MCG), également connus sous l'acronyme GCM (Global Circulation Model) ou modèle climatique global. Ces MCG se déclinent en trois formes principales :

Modèle de circulation générale atmosphérique (AGCM)

Modèle de circulation générale océanique (OGCM)

Modèle de circulation générale océan-atmosphère couplés (AOGCM)

De nos jours, le terme "GCMs" fait souvent référence aux modèles océan-atmosphère couplés, intégrant également des modèles continentaux pour la glace et la surface terrestre. Les GCMs permettent ainsi de simuler l'ensemble des processus physiques liés au climat, incluant la température, les précipitations, le vent, les nuages, etc., ainsi que leurs interactions(Martel, 2019).

Avec la complexité croissante de ces modèles, le concept de modèle de système terrestre, également désigné sous l'acronyme ESM (Earth System Model), représente la nouvelle génération de modèles couplés, incorporant en plus des modèles de biogéochimie marine et de chimie atmosphérique. L'avantage principal d'un ESM réside dans sa capacité à simuler l'évolution des gaz

à effet de serre, au lieu d'utiliser une composition prédéterminée, comme c'était le cas pour les GCM (Martel, 2019).

2.3.2 Les ensembles multimodèles de simulations climatiques

Les projections des changements climatiques futurs jouent un rôle fondamental dans l'amélioration de la compréhension du système climatique ainsi que dans la caractérisation des risques sociétaux et des options de réponse (O'Neill *et al.*, 2016). Avec l'utilisation croissante des modèles climatiques au sein de la communauté scientifique, il existe désormais d'importants ensembles de modèles climatiques couplés (GCM ou ESM) couvrant l'ensemble de la planète, tels que le CMIP3 (Coupled Model Intercomparison Project ; (Meehl *et al.*, 2007)), le CMIP5 (Taylor, K. E. *et al.*, 2012) et le CMIP6 (O'Neill *et al.*, 2016). Ces ensembles permettent d'accéder aux simulations de près de quarante modèles. Une grande partie des récents travaux de l'IPCC repose, entre autres, sur ces trois ensembles.

Malgré les nombreux avantages des modèles climatiques, leur résolution spatiale est souvent insuffisante pour analyser certaines variables climatiques, notamment les précipitations, notamment en ce qui concerne les phénomènes extrêmes. Pour pallier cette limitation, diverses techniques de descente d'échelle peuvent être employées pour transférer les données obtenues à partir des GCMs/ESMs, qui présentent une résolution spatiale grossière, vers une résolution spatiale plus fine. Ces méthodes de descente d'échelle se regroupent en deux catégories distinctes : les approches de descente d'échelle statistique et dynamique. Ces méthodes ne seront pas abordées dans ce travail.

2.3.3 NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)

La première version du jeu de données NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections) a été initialement publiée en 2015 dans le but d'améliorer la compréhension du public et d'aider la communauté scientifique à étudier les impacts des changements climatiques à des échelles allant du régional au local (Thrasher, B. *et al.*, 2012).

Cet ensemble de données est constitué de scénarios climatiques mondiaux à échelle réduite dérivés des exécutions du modèle de circulation générale (GCM) réalisées dans le cadre de la phase 5 du projet d'intercomparaison des modèles couplés (CMIP5), ainsi que de deux des quatre scénarios d'émissions de gaz à effet de serre connus sous le nom de Representative Concentration Pathways (RCPs). L'ensemble de données NEX-GDDP inclut des projections à échelle réduite pour les RCP 4.5 et RCP 8.5 à partir de 21 modèles et scénarios pour lesquels des données quotidiennes ont été produites et distribuées dans le cadre du CMIP5. Depuis lors, ces données ont été largement utilisées par divers groupes de scientifiques.

Récemment, les résultats de nouvelles expériences plus avancées ont conduit à une version plus précise. Cette nouvelle version de NEX-GDDP est composée de scénarios climatiques mondiaux à échelle réduite dérivés des exécutions du modèle de circulation générale (GCM) menées dans le cadre de la phase 6 du projet d'intercomparaison des modèles couplés (CMIP6) et de quatre scénarios d'émissions de gaz à effet de serre connus sous le nom de Shared Socioeconomic Pathways (SSPs). Non seulement ces projections mises à jour sont basées sur les résultats les plus récents du CMIP6, mais elles incluent également un ensemble élargi de variables (Thrasher, B. *et al.*, 2022).

Les ensembles NEX-GDDP-CMIP5/6 facilitent l'étude de la variabilité climatique et de son impact sur le climat passé et futur à l'échelle régionale et locale. NEX-GDDP-CMIP5/6 utilisent un algorithme de réduction d'échelle statistique appelé Bias-Correction Spatial Disaggregation (BCSD) pour surmonter les limites des projections des GCM.

La méthode BCSD comporte deux composantes. La première composante corrige les biais des GCMs en utilisant des mesures statistiques simples telles que la moyenne, la variance, la pente, par rapport aux ensembles de données observées du Global Meteorological Forcing Dataset (GMFD) disponibles auprès du groupe de recherche en hydrologie terrestre de l'Université de Princeton (Sheffield *et al.*, 2006). La deuxième composante implique une désagrégation spatiale, qui interpole la résolution grossière des données GCM en une résolution plus fine ($0,25 \times 0,25$) à travers les ensembles de données observées. Le NEX-GDDP fournit un ensemble de trois variables climatiques, notamment la température maximale quotidienne, la température minimale et les précipitations.

2.3.4 Les scénarios d'émission de GES

On élabore des scénarios de changement climatique en raison de l'incertitude élevée entourant les prévisions des changements climatiques à l'échelle régionale et locale. Ces scénarios décrivent les évolutions possibles à venir des émissions de gaz à effet de serre (GES), d'aérosols et d'autres gaz d'origine humaine dans l'atmosphère (Charron, 2016). Plusieurs scénarios d'émissions de GES ont été utilisés dans diverses études sur les impacts des changements climatiques, tels que le RCP4.5 et le RCP8.5 du CMIP5 (Martel, 2019; Meinshausen *et al.*, 2011), ainsi que le SSP 245 et le SSP585 pour le CMIP6 (Arunrat *et al.*, 2022; Li, S. Y. *et al.*, 2020; Wang, Z. Y. *et al.*, 2022), ce dernier étant le scénario le plus pessimiste dans les deux cas. La plupart des recherches sur les changements climatiques, qui ont utilisé plusieurs scénarios, indiquent que les conclusions générales restent

cohérentes, avec des variations plus prononcées associées aux scénarios caractérisés par des émissions plus élevées de gaz à effet de serre.

Il est important de noter que la majorité des recherches menées sur les changements climatiques, en utilisant plusieurs scénarios, indiquent que les conclusions générales restent cohérentes. Cela signifie que, quelle que soit la diversité des scénarios pris en compte, on observe une constance dans les tendances générales. Néanmoins, il est également évident que les scénarios caractérisés par des émissions plus élevées de gaz à effet de serre sont associés à des changements plus marqués. Plusieurs études antérieures (Kharin *et al.*, 2013; Martel, 2019; Rajczak & Schär, 2017) ont corroboré cette observation en démontrant que les scénarios de fortes émissions ont un impact plus significatif sur le climat et ses conséquences.

2.4 Impacts des changements climatiques sur les infrastructures

Les impacts des changements climatiques sur les infrastructures sont inévitables et pour la plupart, défavorables. Les infrastructures hydrauliques, essentielles au développement humain, sont particulièrement vulnérables, avec des preuves solides d'une augmentation significative des risques liés à l'eau douce en raison des changements climatiques (Ipcc, 2014). Les variations dans la qualité et la quantité de l'eau joueront un rôle clé dans les impacts sur les établissements humains et les infrastructures. Les événements météorologiques extrêmes, tels que les tempêtes et les ouragans, devraient s'intensifier, ce qui pourrait entraîner des inondations et menacer les réseaux de transport ainsi que les bâtiments. Ces changements projetés suscitent des inquiétudes parmi les ingénieurs, les planificateurs et les décideurs, car de bonnes infrastructures sont essentielles pour maintenir le niveau de vie. Il est donc impératif d'évaluer les impacts et de s'adapter de manière appropriée aux conditions climatiques changeantes pour assurer la durabilité des infrastructures et le bien-être de la société (Chilkoti, Vinod, 2019).

2.4.1 Changement climatique et le secteur de l'électricité

L'approvisionnement en électricité est essentiel pour garantir un niveau de vie de base et favoriser la croissance sociale et économique globale. À l'échelle mondiale, la production totale d'électricité à la fin de 2022 s'élevait à environ 29 165 TWh (Statistica, 2023). Les sources de production d'électricité peuvent être largement catégorisées en deux types : les sources renouvelables et les sources non renouvelables. Le secteur non renouvelable repose sur la combustion de combustibles fossiles, ce qui entraîne l'émission de gaz à effet de serre dans l'atmosphère, tandis que les sources renouvelables sont considérées comme respectueuses de l'environnement (Chilkoti, Vinod, 2019).

Actuellement, seulement 15 % de la production totale d'électricité provient de sources renouvelables (International hydropower association, 2023), le reste étant généré à partir de combustibles fossiles. Étant donné que la production d'électricité est responsable de plus de 25 % des émissions totales de gaz à effet de serre (Pachauri & Mayer, 2015) et que les sources d'énergie renouvelable émettent considérablement moins de gaz à effet de serre que les sources conventionnelles, les gouvernements sont résolus à prendre des mesures pour éliminer progressivement les sources de production d'électricité responsables de ces émissions et les remplacer par des options plus propres. Cette transition est inévitable dans le cadre de la stratégie d'action contre les changements climatiques.

2.4.2 Impacts des changements climatiques sur la production hydroélectrique

Les aménagements hydroélectriques représentent une composante essentielle des infrastructures énergétiques. Actuellement, cette source respectueuse de l'environnement répond à 15 % de la demande mondiale en électricité (International hydropower association, 2023). Le GIEC est d'avis qu'il existe une probabilité d'influences d'origine humaine sur le cycle global de l'eau (Pachauri & Mayer, 2015). Diverses études ont également révélé des niveaux variables d'impact des

changements climatiques sur la disponibilité de l'eau (Hamududu & Killingtveit, 2017; Hamududu, B. H. & Killingtveit, 2016; Lobanova *et al.*, 2016), qui constitue le principal intrant pour la production hydroélectrique. La modification du régime d'écoulement résultant des changements climatiques, qui affecte l'hydrologie régionale, a un impact sur le fonctionnement des infrastructures hydrauliques existantes, y compris les centrales hydroélectriques (Chilkoti, Vinod, 2019). Cela rend ces installations vulnérables aux futurs scénarios climatiques, mettant en péril la production d'énergie et les revenus qui en découlent.

Étant donné que les centrales hydroélectriques nécessitent des investissements en capital considérables et sont conçues pour fonctionner sur plusieurs décennies, il est impératif d'évaluer les conséquences des scénarios climatiques changeants sur la production hydroélectrique (Chilkoti, Vinod, 2019).

CHAPITRE 3 ARTICLE 1: EVALUATING THE ACCURACY OF NEW GENERATION REANALYSIS OVER CONGO RIVER BASIN

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Abstract

The meteorological data of precipitation and temperature constitute a very important component in hydrological modeling. The poor spatial coverage of meteorological stations in several regions of the world limits the ability of hydrological models to simulate river flows. To overcome this difficulty reanalysis products are widely considered as a valid proxy for observations at global scale. However, the accuracy of these reanalysis precipitation and temperature differs significantly at regional and local scales, especially over regions of high spatiotemporal heterogeneity such as Congo River basin. Therefore, it is essential to evaluate the ability of these reanalyses in hydrological related research.

In this study, we perform the most comprehensive evaluation of the ERA5-Land, JRA-55, ERA-Interim, CFSR, and MERRA reanalysis monthly precipitation and temperature products, to capture temperature and rainfall pattern of the Congo River basin. The reanalysis data have compared with observed climate data of thirteen ground stations, for 1981–2008. The overall results showed that all reanalyses products capture the major features of the rainfall and temperature annual cycle in the reference data but demonstrate an evident dispersion of spatiotemporal characteristics. ERA5-Land remarkably overestimates the precipitation in Goma. All reanalysis precipitation data are

worse in terms of RMSE (Root Mean Square Error) at Inga observation station and at Bandundu and Yangambi stations in terms of R^2 (Determination coefficient). Besides, mean temperature data for all reanalysis products have a good agreement with observed data. All data are better in terms of bias and RMSE and not so bad for R^2 .

This research finding stands that, all reanalysis precipitation datasets studied need further investigation for the use in hydrological modelling.

Keywords: Reanalysis, hydrological modelling, temperature, precipitation, Congo Basin

Author contributions.

Competing interests. The authors declare that they have no conflict of interest.

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3.1 Introduction

The Congo River is the largest river in western central Africa and the most powerful on the continent. It also has the second largest flow in the world trailing only the Amazon. The Congo River is very rich with opportunities for hydrologic research, yet poor in data and scientific knowledge (Alsdorf *et al.*, 2016; Salumu Zahera *et al.*, 2011).

The Congo climate regime is the most understudied climate regime in Africa and the most under researched large-scale convective region in the global tropics(Washington, Richard *et al.*, 2013).

A key reason for the paucity of work on the Congo, notwithstanding its global importance, is the dearth of available climate observations from the region. Only three meteorological stations from the Democratic Republic of Congo, for example, reported to the Global Telecommunication System in 2010 (Washington, Richard *et al.*, 2013). There was a dramatic decline in the number of rain gauges from more than 50 gauges between 1950 and 1980, following the work on collating the available record, to fewer than 10 over the 20 year period to 2010(Nicholson, Sharon E *et al.*, 1988; Washington, Richard *et al.*, 2013)

Although the Congo River plays a vital role for the populations and economy of the 10 countries on which its watershed extends, there are very few meteorological data concerning it.

Several studies have used hydrological models to characterize the behavior of the river and to facilitate decision-making regarding the rational planning and sustainable management of water resources(Aloysius & Sainers, 2017; Tshimanga, R. M. & Hughes, 2012, 2014; Tshimanga, R. M. *et al.*, 2011). The inputs for those hydrological models for the most case was based either on historical data, remote sensing data, or Global Climate Model (GCMs) output(Fatras *et al.*, 2021; Jung *et al.*, 2010; Lee *et al.*, 2011; Munzimi *et al.*, 2019; Shamseddin & Chaibi, 2020).

Although these data constitute major sources of information for hydrological models, they have serious limitations, mainly due to low spatial coverage and missing data in historical datasets, and the high sensitivity of remote sensing techniques to clouds obstruction and forest cover, and significant biases in global climate model output(Essou, G. R. *et al.*, 2016). This results in a deficit of meteorological information required by hydrological models. Hence the need to find other alternative sources of meteorological data that can help to overcome this deficit (Salumu & Fuamba, 2019).

Due to the technological advances in recent decades, new sources of meteorological data called atmospheric reanalyses have been developed. They have the advantage of providing global coverage for several hundred climate variables, and their data is spatially and temporally consistent (Dee *et al.*, 2011; Mesinger, F *et al.*, 2006; Saha *et al.*, 2010). Thus, data from atmospheric reanalyses could be an interesting alternative to traditional data from meteorological stations, for hydrological studies in regions where data from meteorological stations are insufficient or non-existent. They make use of a wide variety of observation databases assimilated in a complex fashion into a numerical weather prediction model to produce a spatially and temporally coherent synthesis of various meteorological variables over the recent historical period. The reanalysis forecast model remains unchanged for consistency of simulated weather data(Essou, G. R. *et al.*, 2016).

Several studies have reported the advantage of using reanalysis products for Hydrological modeling and water resources studies analysis in Africa in general and particularly in Central Africa.

For identifying the “best” reanalysis products available over Central Equatorial Africa, (Hua *et al.*, 2019) assessed seven reanalysis products (i.e., 20CR, CFSR, ERA-Interim, JRA-55, MERRA2, NCEP-1 and NCEP-2) based on quality-controlled radiosonde observations and a gauge-based rainfall data set. They found MERRA2 closest to observed data set.

Siam, Mohamed S *et al.* (2013) investigated GCMs and reanalyses' products that provide a realistic representation of the hydrological cycle over the Congo and upper Blue Nile (UBN) basins. According to their results NCEP–NCAR reanalysis, 40-yr ECWMF Re-Analysis (ERA-40), and ERA-Interim gave the best performance. The ERA-Interim reanalysis (ERA-I) was used to monitor and forecast drought conditions in the Horn of Africa (Sahlu *et al.*, 2017). The results show a precipitation deficit in both rains seasons (Oct.-Dec. 2010 and Mar.-May 2011), despite its limitations in representing the March–May interannual variability (Dutra, Emanuel *et al.*, 2013).

Pokam, Wilfried M *et al.* (2012) analysed the characteristics of the main components of the water cycle over Equatorial Central Africa (ECA) using the 32-year period, spanning from 1968 to 2000 of the NCEP/NCAR reanalysis project database, while (Ceccherini *et al.*, 2017) used ERA-Interim to investigate the extreme temperature regime of heat waves across Africa over 1981–2015.

Numbers of reanalysis products are routinely used in Africa, as a surrogate for observations due to its high spatial and temporal resolution and global coverage, and they have been widely used in hydrologic and agricultural applications (Bastola & François, 2012; Dembélé, Ceperley, *et al.*, 2020; Dembélé, Schaeffli, *et al.*, 2020; Koutsouris, Alexander J *et al.*, 2016; Lakew, H. B. *et al.*, 2020; Maharana *et al.*, 2018; Nkiaka *et al.*, 2017b; Poméon *et al.*, 2017; Tarek, Mostafa *et al.*, 2020; Zhan, Wang *et al.*, 2016). However, other researchers have instead evaluated the reanalysis products performance by comparing them to other datasets (Lakew, Haileyesus Belay *et al.*, 2017; Le Coz & Van De Giesen, 2020; Nicholson, Sharon E & Klotter, Douglas A, 2021; Quagraine *et al.*, 2020; Zhang, Q. *et al.*, 2013b).

This research aims to assess the performance of precipitation and temperature of five reanalysis products for water resource application in the Congo River basin, using observed data from 1981

to 2008. Thirteen observed gauges station are used to quantitatively evaluate reanalysis products accuracy in terms of consistency and discrepancy using statistical metrics.

3.2 Study area and objectives.

3.2.1 Study area

The Congo River Basin(CRB) is located in central Africa and spans over a drainage area of 3.7 million km² between 9°N, 12°E to 13.30°S, 34°E, and encompasses nine countries boundaries (Tshimanga, Raphael Muamba, 2012). It is one of three key areas of tropical convection and contains the planet's second largest rainforest(Creese *et al.*, 2019). The basin is also the region of highest lightning strike frequency on the planet(Washington, R. *et al.*, 2013). The Congo River Basin is a vast peneplain (with altitudes of less than 400 m), surrounded by moderate elevations to the north and south, and by the mountain range of the East African Valley to the East.

With the average annual flow of 40,000 m³/s, it is the second largest basin in the world trailing only the Amazon, contributing roughly 3.5 mm yr⁻¹ to global sea level(Beighley *et al.*, 2011). The sources of the Congo River are in the highlands of the East African Rift, in Lake Tanganyika, which feed the Lukuga and Lualaba rivers; these become the Congo River at Kisangani, below Boyoma Falls.

The Congo Basin precipitation is influenced by regional atmospheric circulation patterns(Dyer *et al.*, 2017). Mean annual precipitation ranges from ~1900 mm/yr along an east-west trend across the basin, decreasing northward and southward to ~1100 mm/yr(Alsdorf *et al.*, 2016). The basic seasonality of the rainy seasons follows the passage of the Intertropical Convergence Zone (ITCZ)(Pokam *et al.*, 2014). The southern African easterly jet (AEJ), low-level westerlies (LLWs), easterly waves and the surrounding ocean basins are among of dynamic features which modulate

Congo Basin precipitation(Dyer *et al.*, 2017; Farnsworth *et al.*, 2011; Nicholson, S. E. & Grist, 2003; Pokam, W. M. *et al.*, 2012)

The Congo Basin has a warm temperature throughout the year. However, some seasonality, can be detected in the western sector of the region, confined between the Congo Basin and the Atlantic Ocean(Dezfuli, 2017). The mean temperature in this area during July is several degrees cooler than in April.

Characterized by a complex hydrological system made up of the Congo River, its numerous tributaries and vast swamps, the Congo River Basin is very rich with opportunities for hydro-meteorological research, but yet poor in data and scientific knowledge(Salumu Zahera *et al.*, 2011).

Many people are undoubtedly excited for doing research on it, but they are always confronted to field data issues. The Basin is poorly gauged, and in most cases existing measurement networks are declining. Figure 3.1 shows the study area and the spatial distribution of selected stations. Therefore, the Congo climate regime, is the most understudied climate regime in Africa (Washington *et al.*, 2006; Washington, R. *et al.*, 2013) and the most under researched large-scale convective region in the global tropics.

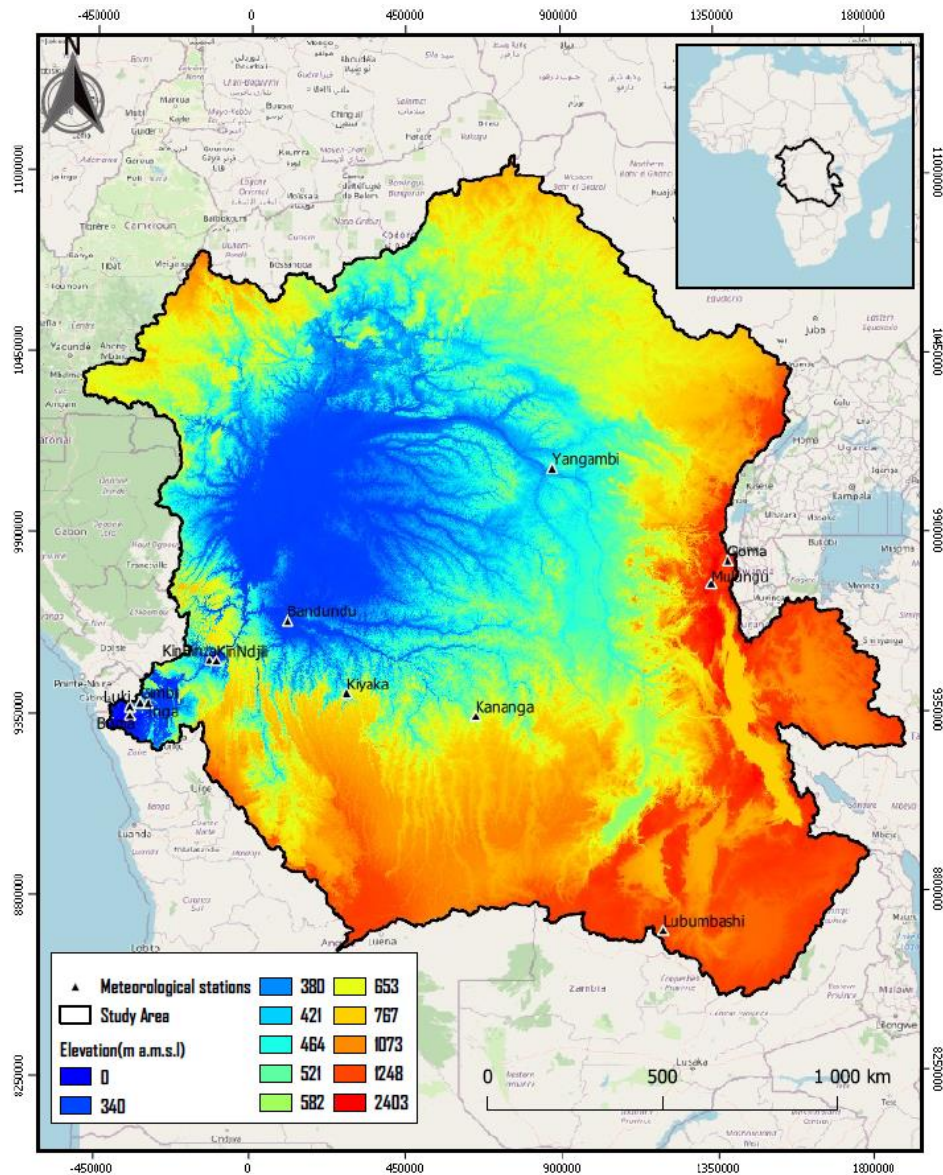


Figure 3.1 Orography of Congo River basin and the spatial distribution of the observation stations

3.2.2 Study objectives

This study aims to evaluate the potential of five new generation reanalysis data with reference to the observational data. The 1981–2008 period, which is the longest common period of all the databases was investigated at monthly scale. The monthly scale allows for a comparison against observed datasets available at the same temporal resolution, as well as against results from previous studies.

Also, the monthly scale was investigated because of validation at the daily scale over Congo Basin presents more difficulties, due to the absence of datasets at this resolution and to the absence of recorded daily data for many weather stations. The stations which record daily data, contain a large ratio of missing data, thus complicating the validation of data. Therefore, the specific objectives of this study are to:

1. compare modeled climate data (ERA5-Land, ERAI, CFSR, JRA-55, MERRA) with observed climate data from 13 meteorological stations in the Congo basin, to determine their uniformity and disparity.
2. provide an assessment of the capacity of ERA5-Land, ERAI, CFSR, JRA-55 and MERRA to reproduce an accurate representation of precipitation and temperature fields in Congo River basin at the monthly temporal scale.
3. understand the ability of the five-reanalysis data as an alternative of observation and their capacity to reproduce spatio-temporal rainfall patterns of the Congo River basin.

3.3 Data, and methods

3.3.1 Reanalysis data

Since the 1980s and 1990s, considerable improvements in weather forecasting and numerous improvements in models and assimilation methods have contributed to the idea of reanalyzing the recent past (Bengtsson & Shukla, 1988). A new analysis aims to provide the best estimate of the state of the atmosphere, ocean, and land surface for the recent past. The term reanalysis is synonymous with retroactive analysis because the analysis is performed over a period from the past to the present.

Reanalysis refers to a systematic approach for reproducing systematic and consistent meteorological data by accommodating 7–9 million observation data acquired through various

sources (e.g., radiosonde, buoy, airplanes, ships, etc.) every 6–12 h in the invariant data assimilation structure and meteorological model in an integrated manner (Kim *et al.*, 2018).

This wide array of observations provides information such as: radiative fluxes, winds, temperature, humidity, precipitation, albedo, snow, vegetation, and land cover, to name a few. The global coverage and the wide range of variables available with consistent resolution in time and space over the simulated period represent some of the main advantages of reanalyses for climate studies, including lower bias and finer resolution from one analysis to another (Wang, W. *et al.*, 2011). Despite this, reanalyses also have some limitations. Indeed, the reliability of some variables can vary considerably over time and space. In addition, changes in the number and quality of assimilated observations can introduce false variability and tendency (Saha *et al.*, 2010). In addition, the water balance is rarely preserved and reanalyses sometimes show substantial biases between variables that are not directly constrained by assimilation, such as precipitation (Sabarwal, Essou, Lucas-Picher, Poulin, *et al.*, 2016).

The first-generation reanalysis data refers to the global reanalysis data produced at the National Center for Atmospheric Research/National Centers for Environmental Prediction (NCAR/NCEP) and Europe Center for Medium-Range Weather Forecast (ECMWF) in the 1990s (Kalnay *et al.*, 1996; Kim *et al.*, 2018). ERA-15 was produced by ECMWF (Gibson *et al.*, 1997) and "Atmospheric Research Reanalysis" (NCEP-NCAR), also known as R-1 by NCEP (Kalnay *et al.*, 1996).

Due to the limitations of these first two datasets, the second-generation reanalysis data were then produced in the early 2000s by resolving several problems and adding the parametrization of physical processes in the same grid network: the "Department Of Energy reanalysis" (NCEP-DOE), also known under the name of R-2 (Kanamitsu *et al.*, 2002) and the North American

Regional Reanalysis (NARR), both developed by NCEP (Mesinger, Fedor *et al.*, 2004), ECMWF's ERA-40 reanalysis (Uppala, Sakari M *et al.*, 2005) and Japanese 25-year reanalysis JRA-25 (Onogi *et al.*, 2007) developed by the Japan Meteorological Agency (JMA). In 2010s, a third-generation reanalysis data which are significantly improved spatio-temporal resolution has been developed, comprising “Climate Forecast System Reanalysis” (CFSR) from NCEP (Saha *et al.*, 2010), (for “Japanese 55-year Reanalysis” (JRA-55) from Meteorological Research Institute of the Japan Meteorological Agency (Kobayashi *et al.*, 2015), ERA-Interim from ECMWF (Dee *et al.*, 2011) and “Modern-Era Retrospective analysis for Research and Applications ”(MERRA) produced by NASA (Rienecker *et al.*, 2011). The fourth generation reanalysis data refers to the global reanalysis data set of atmospheric composition (AC) developed in the earlier Monitoring Atmospheric Composition and Climate (MACC) projects between 2009 and 2014 and has been running fully operationally in the Copernicus Atmosphere Monitoring Service (CAMS), operated by the European Centre for Medium-Range Weather Forecasts (ECMWF) since January 2015 (Inness *et al.*, 2019). As part of implementing the EU-funded Copernicus Climate Change Service (C3S), ECMWF had produced during 2017-2018, the fifth-generation reanalysis data: ERA5 reanalysis (Raoult *et al.*, 2017). A major strength of ERA5 is the much higher temporal and spatial resolutions than those of previous global reanalyses (Hersbach, 2016; Olauson, 2018). Finally, the land component of the ERA5 climate reanalysis was improved for all types of land applications and produced ERA5-Land. Table 3.1 summarizes general information on all the databases detailed above.

Table 3.1 Summary of the reanalysis dataset used in this study

Product	Source	Assimilation scheme	Horizontal resolution	Period	Reference
CFSR	Global (National Centers for Environmental Information (NCEI; www.ncdc.noaa.gov/data-access/model-data/model-datasets/climate-forecast-system-versions2-cfsv2))	3D-VAR	0.313 (lon) x 0.312 (lat)	1979-2009	Saha et al. (2010)
ERA-Interim	Global (ECMWF as part of Copernicus Climate Change Services) (https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/)	4D-VAR	0.75 x 0.75	1979-present	Dee et al. (2011)
MERRA	Global (NASA Modeling and Assimilation Data and Information Services Center (MDISC) (https://disc.sci.gsfc.nasa.gov/mdisc))	3D-VAR, with incremental update	2/3 (lon) x 1/2 (lat)	1979-present	Rienecker et al. (2011)
JRA-55	Global (NCAR Computational Information Systems Laboratory (CISL) Research Data Archive (RDA; https://rda.ucar.edu))	4D-VAR	1.25 x 1.25	1958–2012	Kobayashi et al. (2015)
ERA5-Land	Global (ECMWF as part of Copernicus Climate Change Services) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=form)	4D-VAR	0.1 x 0.1	1950-present	Copernicus Climate Change Service (C3S) (2019)

3.3.2 Observed weather data

Thirteen observed weather data stations (Table 3.2) used in this study come from two main observed meteorological sources of data in DRC, the DRC National Meteorological agency (METTELSAT) and the National Institute for Agronomic Study and Research (INERA). Air temperature and precipitation data were acquired from eight METTELSAT observed stations and five INERA observed stations for the 1979-2010 period.

Those stations are selected because the data has undergone strict data quality controls, such as examining the consistency and homogeneity of data. Monthly rainfall and temperature data of those station were used in the evaluation of reanalysis products quality.

Table 3.2 Description of 13 Observed weather stations used in this study

Station	Source	Latitude(°N)	Longitude(°E)	Altitude(m)	Period
Bandundu	METTELSAT	-3.3	17.35	324	1979-2010
Boma	METTELSAT	-5.89	13.1	8	1979-2010
Gimbi	INERA	-5.52	13.37	480	1979-2010
Goma	METTELSAT	-1.68	29.23	1552	1979-2010
Inga	METTELSAT	-5.52	13.58	277	1979-2010
Kananga	METTELSAT	-5.88	22.42	654	1979-2010
KinBinza	METTELSAT	-4.37	15.25	445	1979-2010
KinNdjili	METTELSAT	-4.38	15.43	311	1979-2010
Kiyaka	INERA	-5.27	18.95	735	1979-2010
Lubumbashi	METTELSAT	-11.67	27.48	1276	1979-2010
Luki	INERA	-5.62	13.1	350	1979-2010
Mulungu	INERA	-2.3	28.78	1731	1979-2010
Yangambi	INERA	0.82	24.48	470	1979-2010

3.3.3 Method

This section discusses the analysis methods employed in the study. The methods are implemented in Matlab software.

A set of statistics metrics are usually used to quantitatively evaluate dataset accuracy in terms of consistency and discrepancy(Guo & Liu, 2016). To compare reanalyses products and rain gauge measurements, the below-mentioned statistical metrics have carried out as following:

- All the gridded reanalysis data, in NETCDF (Network Common Data Form) format has processed in Matlab platform and the dataset for each station has extracted according to latitude and longitude in excel for a specific period.
- Point to pixel comparison has done for reanalyses and observed data. The evaluation of temperature and precipitation data has carried out at monthly and annual scale using various statistical metrics.
- The mean annual cycles and monthly climate data are calculated and compared for individual chosen stations of the Congo River basin.
- For each meteorological station Root Mean Square Error (RMSE) and normalized root mean squared error (NRMSE), Coefficient of determination (R^2), and bias are calculated between reanalysis and observed data.

Note that all the statistics are calculated based on time series of gauge observed data.

The equations of these statistics are shown below.

3.3.3.1 Root mean squared error (RMSE) and normalized root mean squared error (NRMSE)

The Root mean squared error (RMSE) is a common accuracy performance measure that is frequently used as a measure of magnitude of errors (Eq. (1)) (Bostan *et al.*, 2012; Chai & Draxler, 2014; Spadavecchia & Williams, 2009).

NRMSE is computed as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (S_i - O_i)^2} \quad (1)$$

Where S_i and O_i represent data values for day i from reanalysis S and observation O datasets, and

N is the length of the time series.

3.3.3.2 Coefficient of determination (R^2)

The coefficient of determination (R^2 or r-squared) is a statistical measure who tells one how well the observed data fits the reanalysis (the goodness of fit) (Eq. (3)). R^2 is computed as:

$$R^2 = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (2)$$

3.3.3.3 Bias and relative bias (BIAS and RBIAS)

The bias is the difference between reanalyses and observed data for a given period. It indicates how much a reanalysis overestimates or underestimates relative to observed data. Bias can be expressed as absolute (BIAS) (Eq. (4)) or relative bias (RBIAS) (Eq. (5))(Essou, G. R. *et al.*, 2017; Liu, Z. J. *et al.*, 2018). Observed data is considered as the reference data in bias calculations.

Bias and RBIAS are computed as follows:

$$\text{BIAS} = \frac{1}{N} \sum_{i=1}^N (S_i - O_i) \quad (3)$$

$$\text{RBIAS (\%)} = \frac{\text{bias}}{\frac{1}{N} \sum_{i=1}^N O_i} 100 \quad (4)$$

Where S_i and O_i represent data values for day i from reanalysis S and observation O datasets, and N is the length of the time series.

3.3.3.4 Spatial analysis for multidimensional data

The Multidimension toolbox of ArcGIS 10.7.1 is used to spatial analysis of precipitation and temperature.

3.4 Results

3.4.1 Analysis of precipitation and temperature

The general pattern of Congo Basin precipitation consists of two rainy seasons: March to May (MAM) and September to November (SON), which has higher rain rates (Dyer *et al.*, 2017; Pokam, W. M. *et al.*, 2012; Washington, R. *et al.*, 2013). The driest season is June to August (JJA). The basic seasonality of the rainy seasons follows the passage of the Intertropical Convergence Zone (ITCZ)(Dezfuli, 2017).

In this section, we mapped the spatial and temporal distribution of reanalysis rainfall over the Congo Basin on monthly timescales. We examined then the evolution of the spatial distribution of monthly precipitation patterns through the annual cycle. All five new reanalysis generations investigated in this research capture the leading mode of Congo Basin-wide rainfall. We presented solely the ERA5-Land data due to its higher spatial resolution.

We saw in figure 3.2, that elevated rainfall totals were often recorded over high ground, Lake Tanganyika, and its shoreline, mainly southeast of the basin. The rainfall gradient known in the annual climatology was present throughout the year. Two rainy seasons identified from March to May, and October to November. The driest season from June to August.

However, the Congo River Basin is straddling the equator when it rains in the north it does not rain in the south and vice versa. It is clearly seen that from April to September, the north received more rainfall than the south. From November to February, the entire southern part of the basin from the equator received greater precipitation than the northern part. In March and October almost, the whole basin is watered.

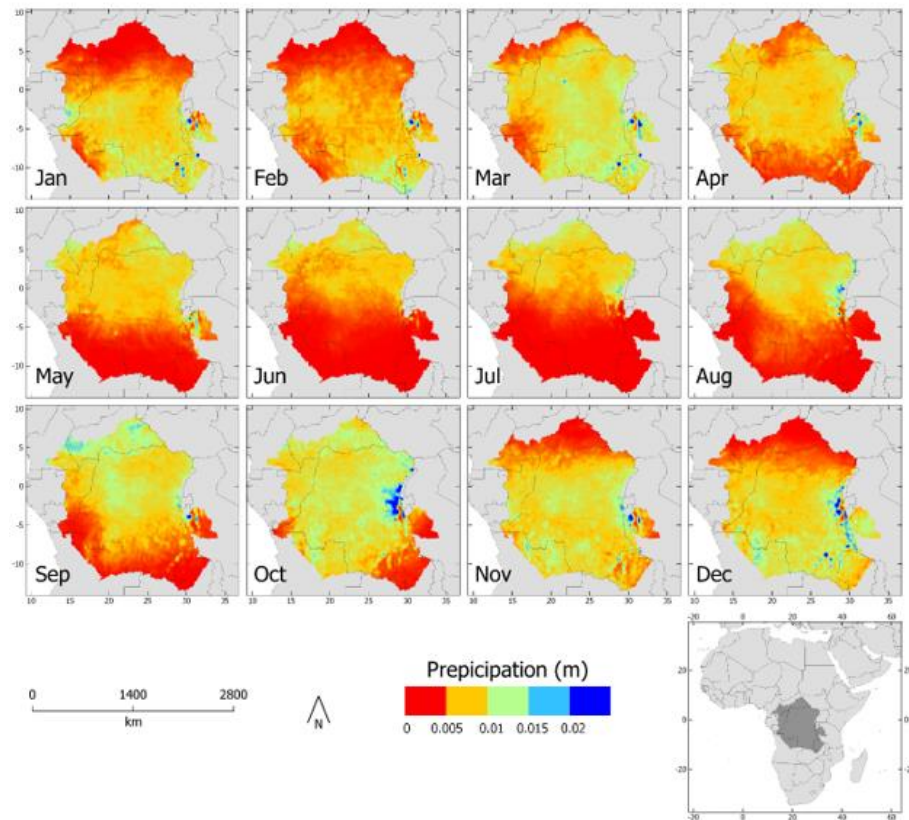


Figure 3.2 The long-term patterns of ERA5-Land Monthly Averaged Rainfall for the period 1981–2008.

The general pattern of Congo Basin temperature from reanalysis datasets in this study were examined in a similar manner to the precipitation data, with Figure 3.3 showing the mean monthly temperature for the ERA5-Land reanalysis products for the Congo River basin.

From figure 3.3, there is a good representation of mean seasonal and annual temperature values across the study area. For the rainy seasons, it clear seems that the temperature is predominantly higher than during the dry season. One exception is the eastern- central and southern-east, where the temperature is low within the year round because of a mountain's climate.

Still in Figure 3.3 we can see that the temperature is always high during the year on both sides of the equator.

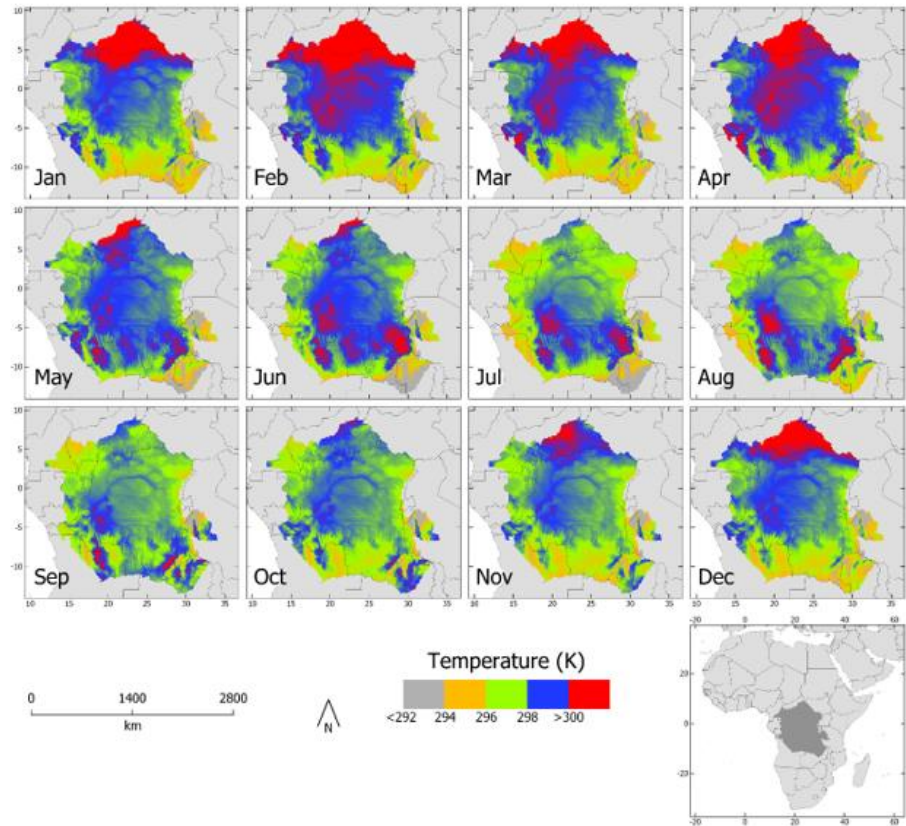


Figure 3.3 ERA5-Land Monthly Averaged Temperature patterns for the period 1981–2008.

3.4.2 Annual cycle of reanalysis rainfall (1981–2008)

We have examined the annual cycle behavior of five new reanalysis generation datasets, ERA5-Land, CFSR, MERRA, JRA-55, and ERAI from 1981-2008 which represents longest common period of all the databases investigated at monthly scale, over the Congo River Basin. Due to the monthly changes of the rainfall spatial distribution, the annual cycles would be distinctly different across the basin. We therefore compared, five new reanalysis generation products with thirteen observed stations whose data have been previously validated (Figure 3.4).

The results show that the means of all reanalysis datasets capture the leading mode of observed stations datasets. An overview of observed data reveals a dry season from May to August, and a wet season from September to April, this wet season had two rainfall peaks.

However, when examining the reanalysis annual cycles variation of individual locations for the chosen station, these peaks vary from station to station depending on its geographical position.

The stations investigated in this research can be classified into four groups according to their geographic locations. Further west we have the stations KinBinza, KinNdjili, Inga, Boma and Luki, in the central basin (Cuvette centrale) we have the stations of Bandundu and Yangambi. In the center we have Kananga and Kiyaka and in the east we have Goma, Mulungu and Lubumbashi. In each group the reanalyses show similar behavior at specific location. The figure 3 shows that the annual precipitation cycle has not closed properly for the stations located in the central basin (i.e., Bandundu and Yangambi). For example, the annual precipitation cycle has not closed properly at Bandundu station and the dry season has not emerged. Besides, all reanalyses at that station are very close to the peak of September / October and that of February / March. ERA5-Land remarkably overestimates the precipitation in Goma. The exact reason for this overestimation is not precisely identified. It is maybe caused by the altitude. According to (Jiao *et al.*, 2021), ERA5 precipitation data provides poor estimates of precipitation at high altitudes. The Goma observation station is not only at high altitude Fig.3.5 but also near an active volcano.

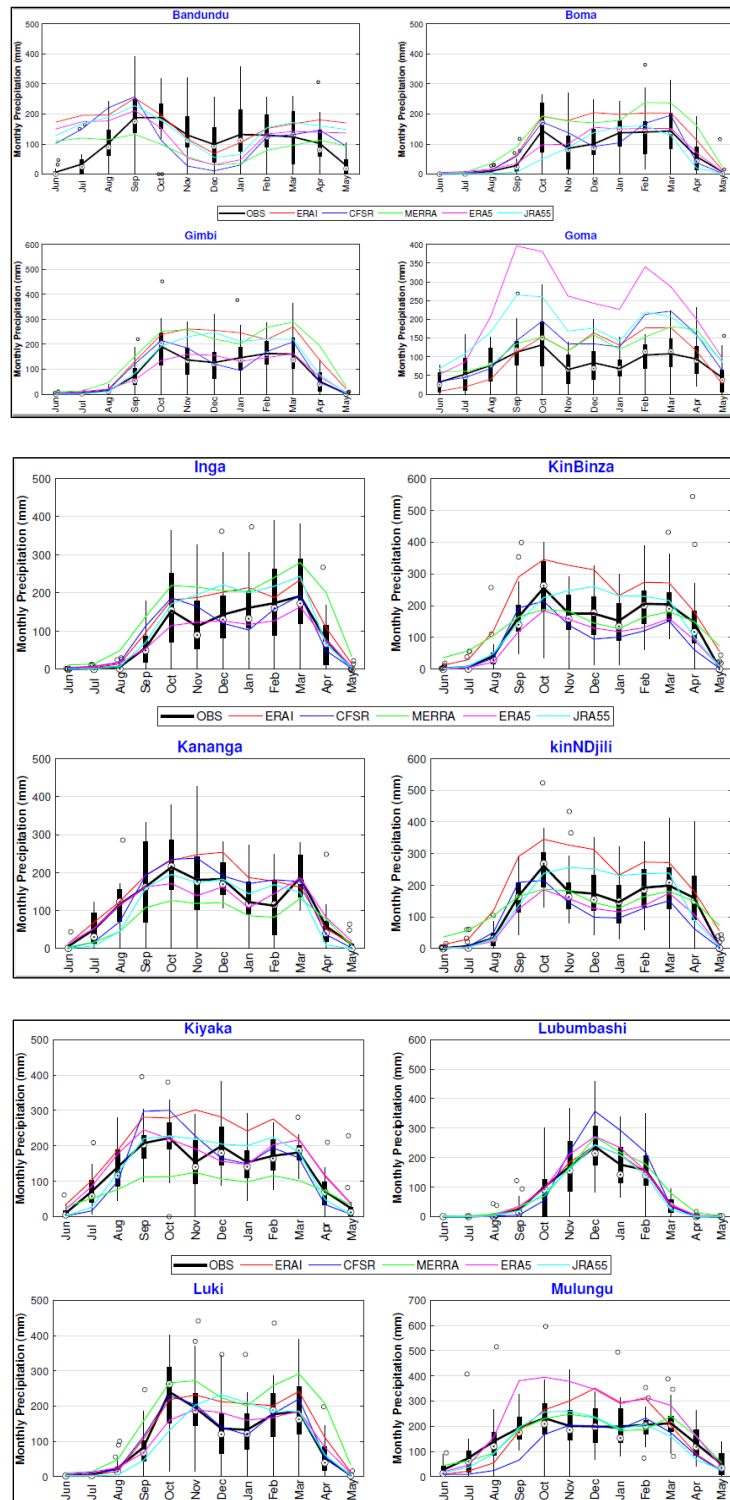


Figure 3.4 Annual cycle of precipitation over thirteen meteorological stations chosen within the Congo River Basin

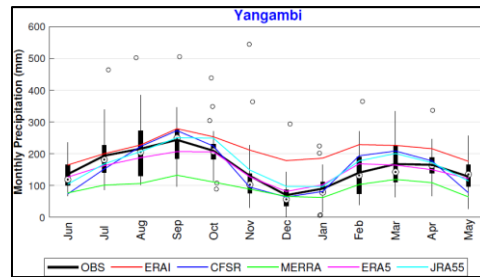


Figure 3.4 Annual cycle of precipitation over thirteen meteorological stations chosen within the Congo River Basin (Continued)

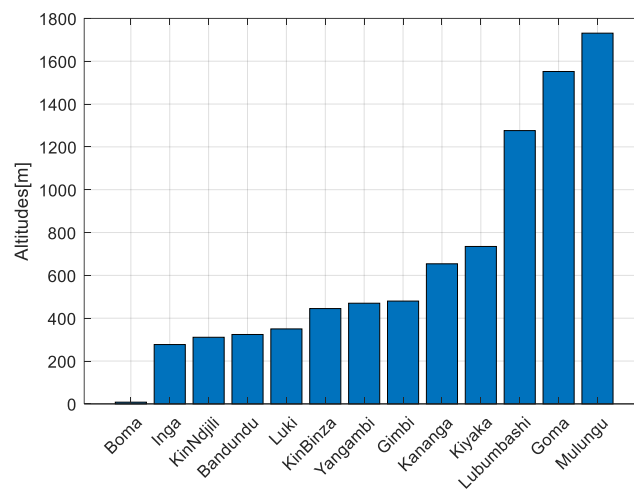


Figure 3.5 Altitudes of observed stations

3.4.3 Annual cycle of reanalysis extreme temperatures (1981–2008)

The ability of the reanalysis dataset to capture a realistic annual cycle of temperature is an important measure of its performance. Here, we present the 2-m average maximum and minimum temperatures for thirteen gauged observed station in Congo River basin. To validate the reliability of the reanalysis dataset performance, ERA5-Land, CFSR, ERA-Interim, MERRA, and JRA-55 are compared with the observed dataset (Figures 3.6 & 3.7).

The maximum and minimum peaks depend on the geographic location of the station on the basin. For the Bandundu station for example, the month of June is the hottest and the month of August

the coldest, For Boma and Gimbi it is March, which is colder and July the coldest, Goma is hotter in January and colder in August, Inga is hotter in February and colder in July. The two Kinshasa stations (KinBinza and KinNDjili) are warmer in March and colder in July. However, KinBinza station is cooler than KinNDjili this can be explained by the fact that the altitude of KinBinza is higher, and the station is covered with vegetation, while KinNDjili station is at the airport where there is no no vegetation, and the altitude is lower.

Overall, it is clearly visible that all reanalyses reproduce the annual cycle well. However, CFSR overestimates the maximum temperature values sometimes in an unexplained way such as the KinBinza, KinNDjili, Inga, Kiyaka and Luki stations. On the other hand, it underestimates the minimum values of temperatures.

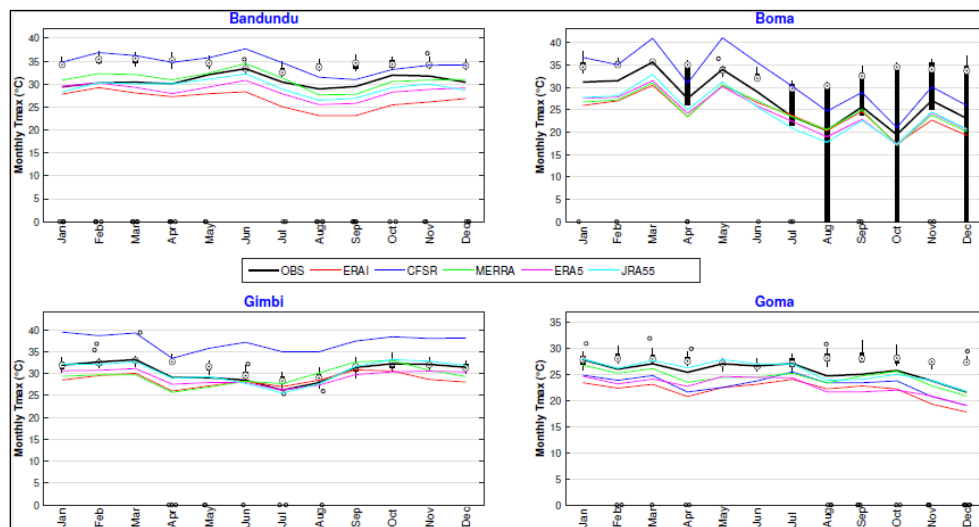


Figure 3.6 As in Figure 3.4, but for maximum temperature

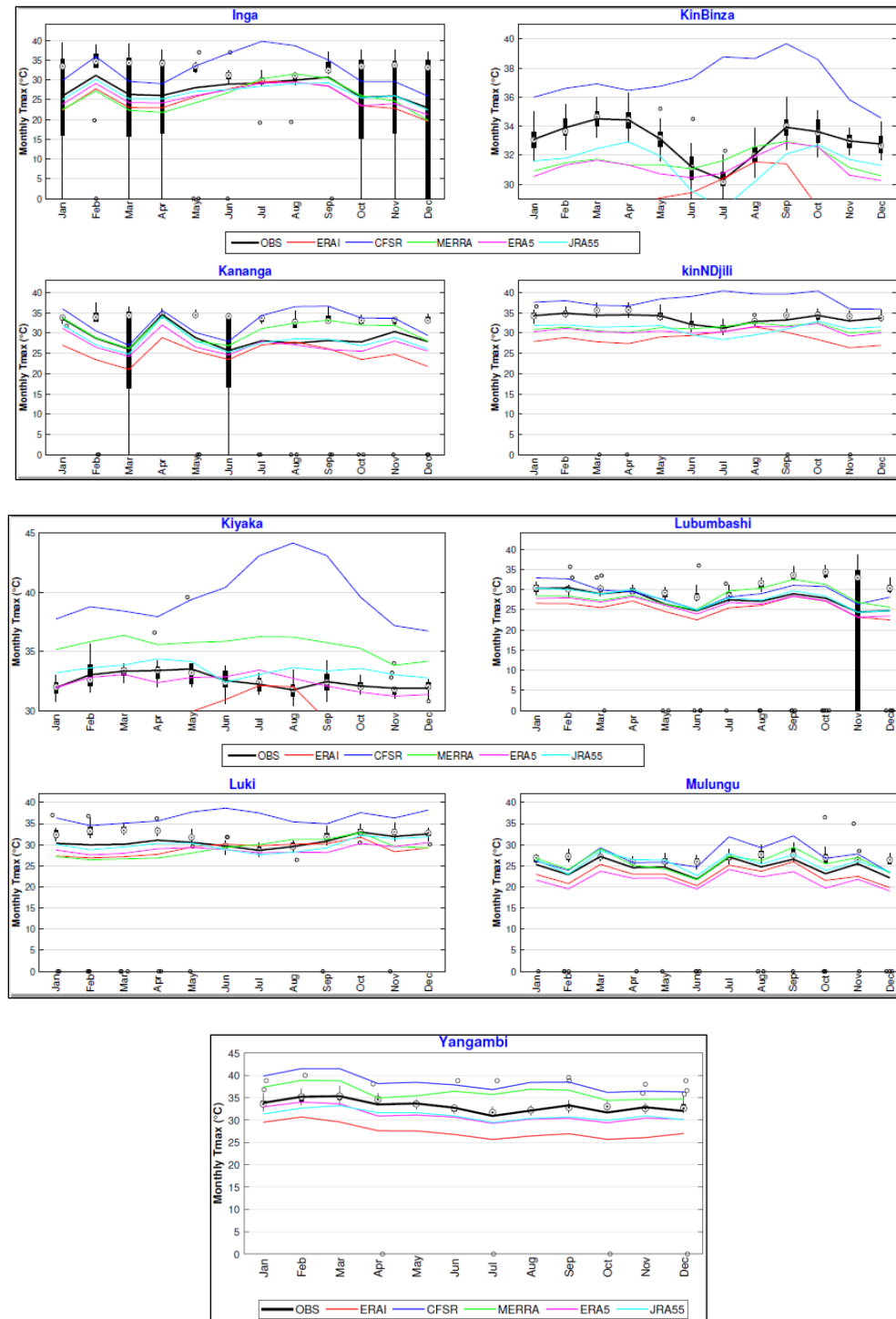


Figure 3.6 As in Figure 3.4, but for maximum temperature (Continued)

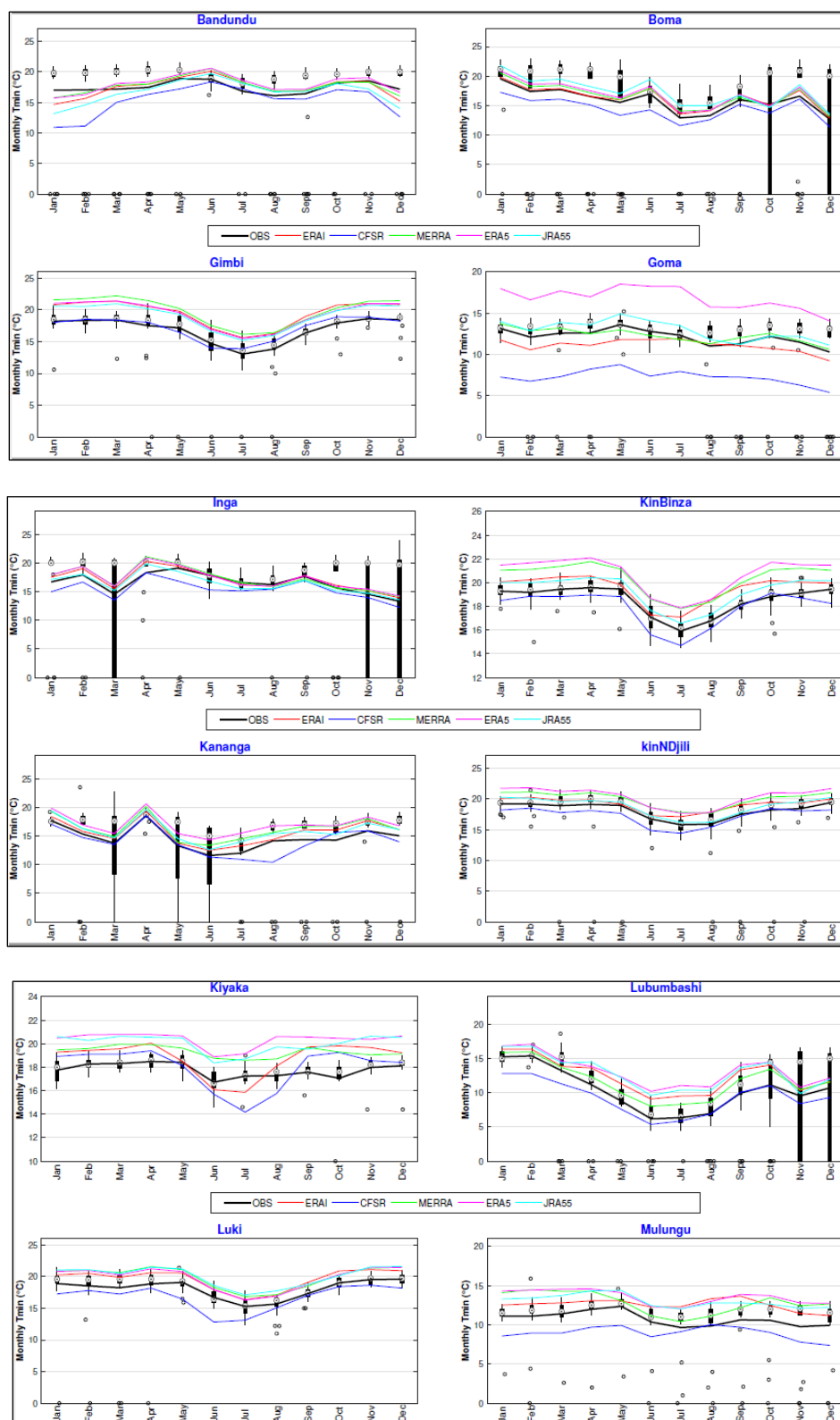


Figure 3.7 As in Figure 3.6, but for minimum temperature

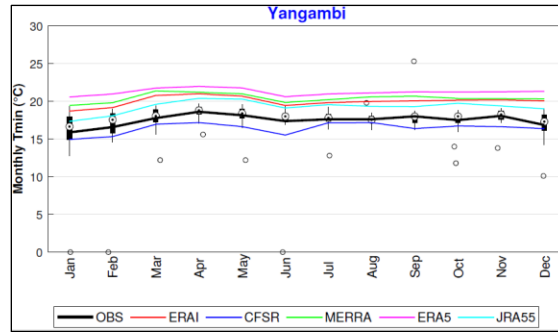


Figure 3.7 As in Figure 3.6, but for minimum temperature (Continued)

3.4.4 Comparison of reanalysis and observed rainfall products.

Differences between the mean monthly rainfall of reanalysis and observations (Figure 3.8&3.9) show that ERA5-Land data are much closer to the observations compared to the other reanalysis datasets investigated in this study. ERA5-Land has smaller value in both RBIAS and RMSE, probably because ERA5-Land has much higher spatial and temporal resolution than other reanalysis products, providing higher quality precipitation data in both space and time (Jiao *et al.*, 2021; Liu, Z. J. *et al.*, 2018). Figure 3.10 show that monthly rainfall series from reanalysis generally correlate well with the observations over the basin except Bandundu and Yangambi stations where the lowest correlations are observed. However, no reanalysis seems to stand out. This may be because their performance is comparable in representing the annual cycle of precipitation (see figure 3.4).

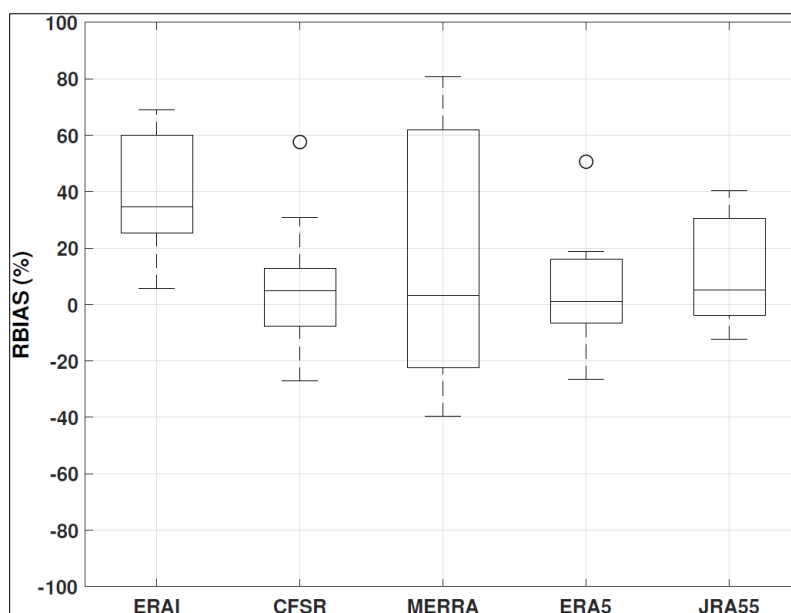


Figure 3.8 RBIAIS of monthly rainfall between reanalyses and observed dataset

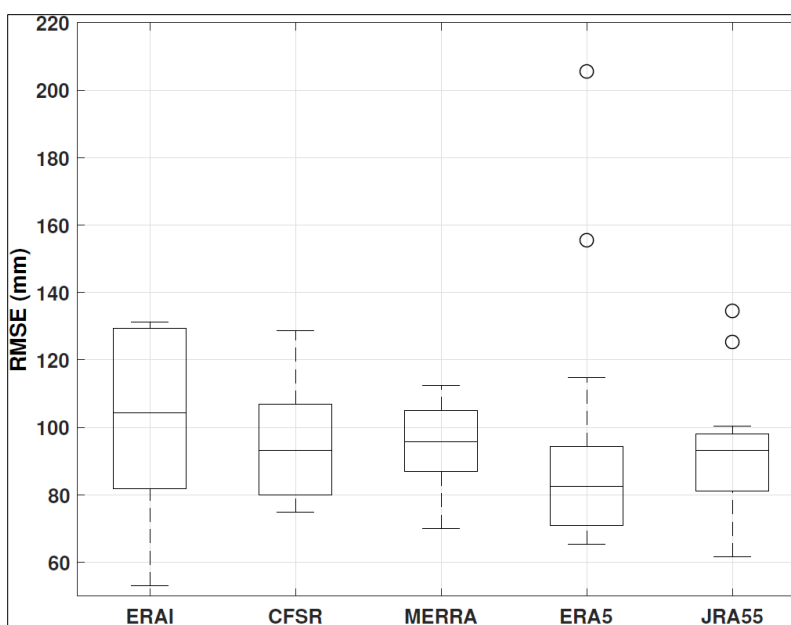


Figure 3.9 RMSE of monthly rainfall between reanalyses and observed dataset

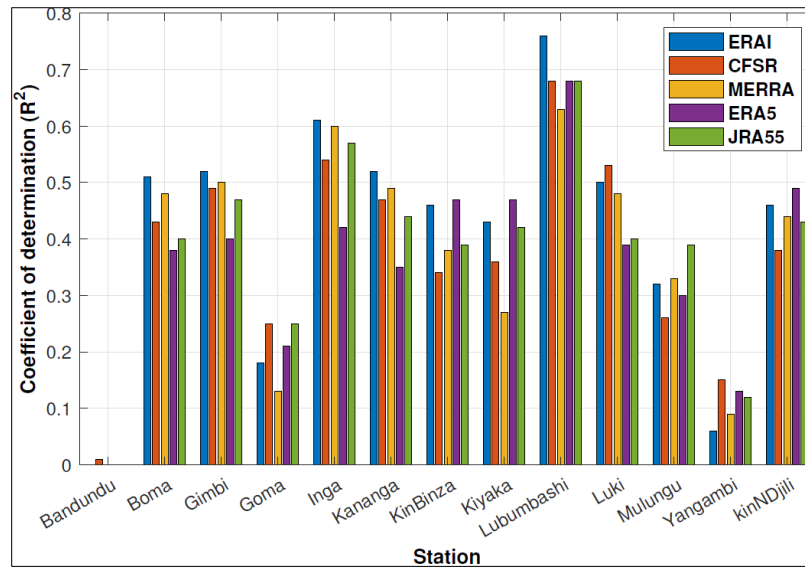


Figure 3.10 R^2 of monthly rainfall between reanalyses and observed dataset

3.4.5 Comparison of reanalysis and observed extreme temperatures.

The 2-m average maximum and minimum temperatures for thirteen stations of the Congo River basin are compared to ERA-Interim, JRA-55, MERRA, CFSR and ERA5-Land. As presented in section 3.4.3, all reanalysis dataset underestimated the maximum temperature and overestimated the minimum temperature, except of CFSR. CFSR has a cold bias for Tmin and a warm bias for Tmax. This is consistent with the results presented for the annual temperature cycle. The other reanalyses also present biases, but these are oriented in the opposite direction to that observed for CFSR (warm bias for Tmin, and cold bias for Tmax).

Among the reanalyses, ERA-Interim has the lowest mean bias over all dataset used for minimum temperature. The reanalyses performances are presented (Figure 3.11) and ERA-I has the best ranking (1.17 °C) for minimum temperature mean bias over all reanalyses. ERA-I is followed by CFSR (-1.41°C); JRA-55(1.41°C); MERRA(1.61°C) and ERA5-Land(2.44°C). However, the maximum temperature did not have the same behavior. As presented in Figure 3.12, MERRA has

the best ranking(-0.23°C) followed by JRA-55(-0.89°C) then by ERA5-Land(-2.16°C); ERA-I(-3.53°C) and CFSR(4.36°C).

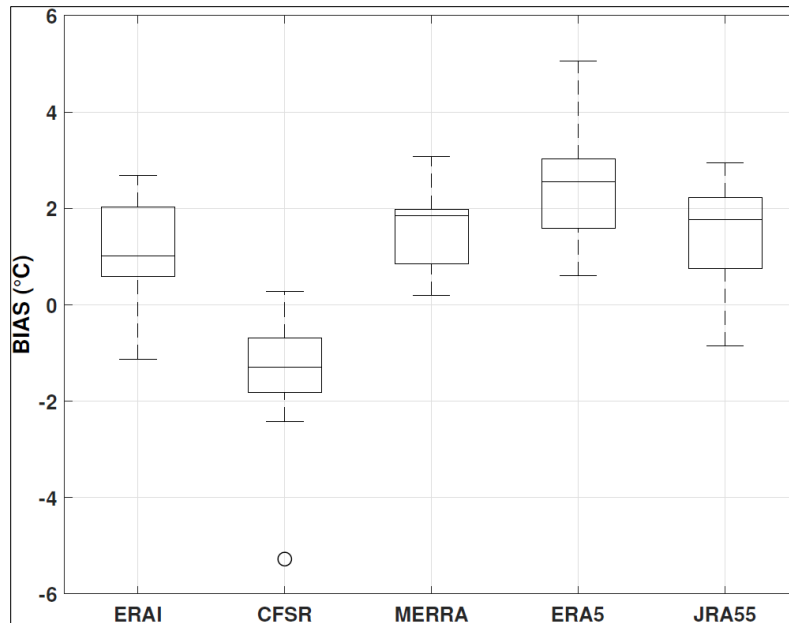


Figure 3.11 BIAIS of monthly minimum temperature between reanalyses and observed dataset

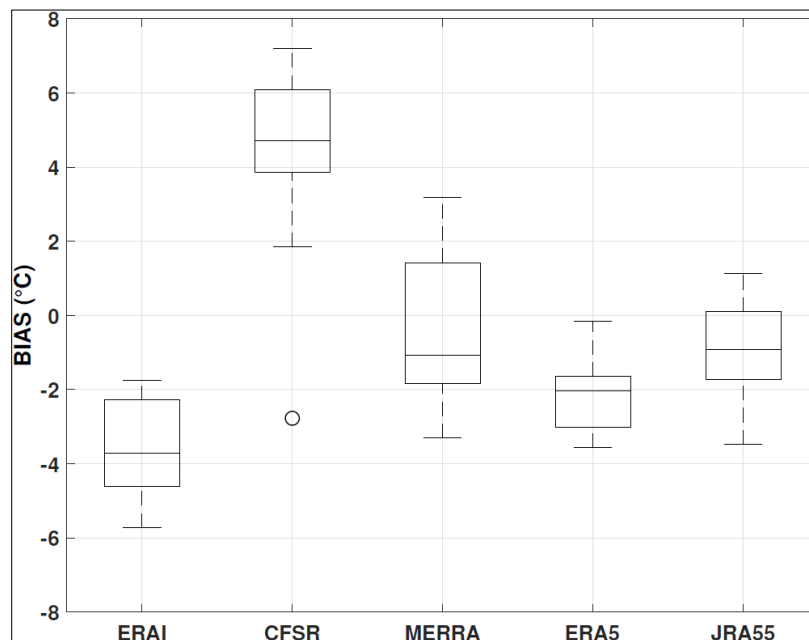


Figure 3.12 BIAIS of monthly maximum temperature between reanalyses and observed dataset

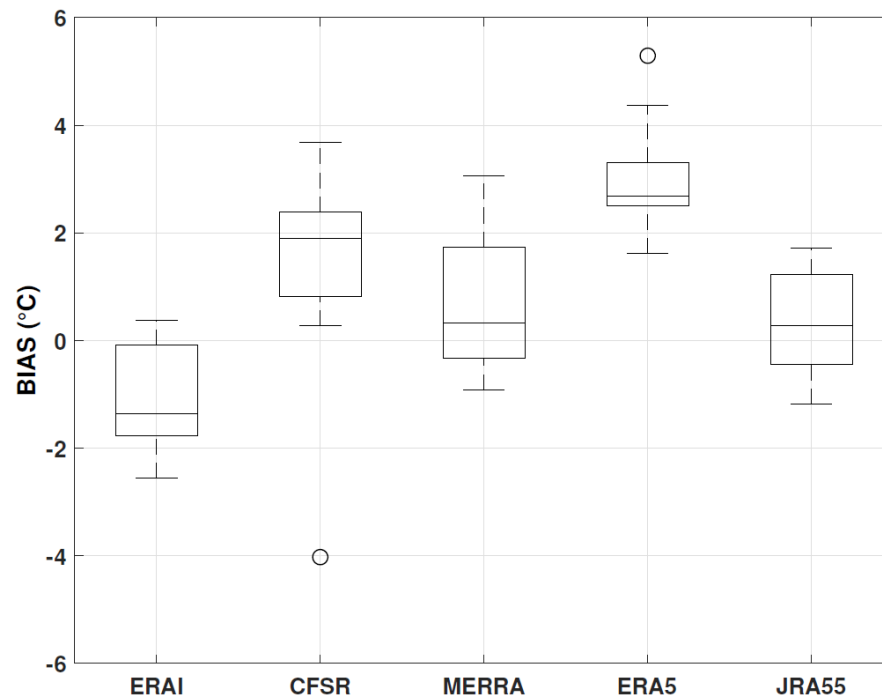


Figure 3.13 BIAIS of monthly average temperature between reanalyses and observed dataset

The RMSE values of minimum temperature for all reanalysis datasets are comprised between 2.1°C and 2.95°C (Figure 3.14). ERA-Interim performs better than other reanalysis dataset because of its lowest RMSE mean value of 2.16 °C. JRA-55 comes just after ERA-Interim with the RMSE value of 2.29, then MERRA with the RMSE of 2.34 CFSR with the RMSE value of 2.57 and finally ERA5-Land which is the least efficient reanalysis with the highest RMSE value of 2.94 °C.

Moreover, as noted above for the bias cases, things are different for the maximum temperature. Moreover, contrary to what is noted above for the cases of minimum temperature, things are different for the maximum temperature. It is rather JRA which has the lowest RMSE value of 2.11°C, after comes ERA5 with 2.68 °C, then MERRA with 3.42 °C and ERAI 4.23 °C, finally CFSR which has the highest value of 5.59 °C (Figure 3.15).

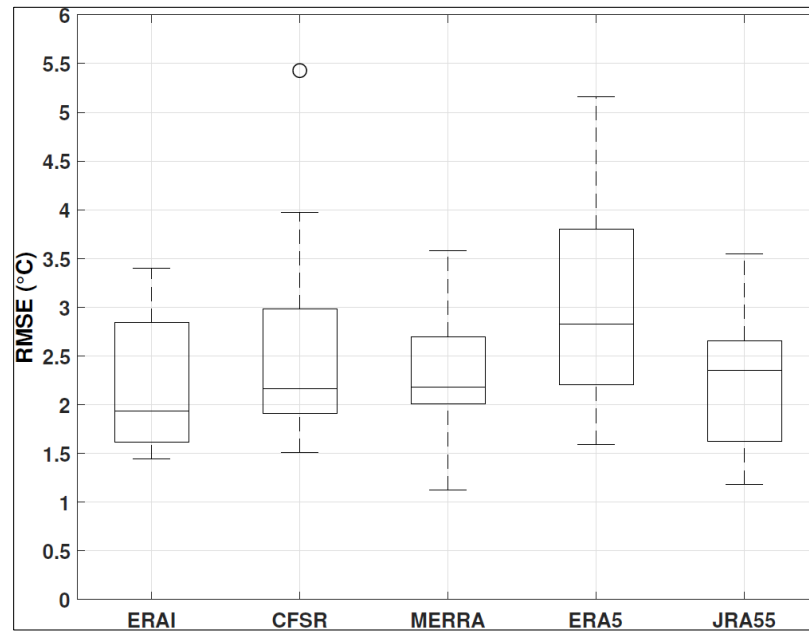


Figure 3.14 RMSE of monthly minimum temperature between reanalyses and observed dataset

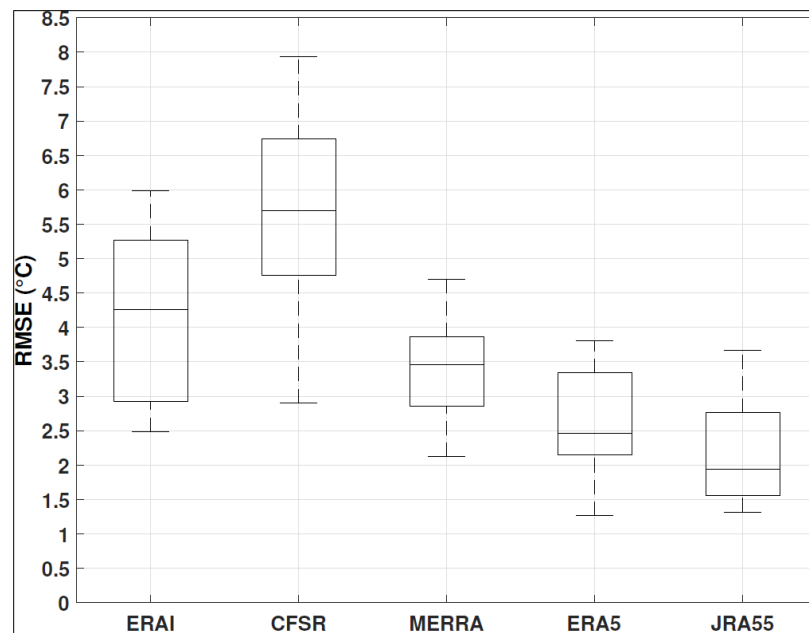


Figure 3.15 RMSE of monthly maximum temperature between reanalyses and observed dataset

Fig.15 &16 demonstrate how the correlation between five reanalyses: ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55, and observed extreme temperature data varies across thirteen

chosen stations. All reanalysis minimum temperature presented relatively better agreements with observed temperature for Boma, Gimbi, Inga, Kananga, KinBinza, Lubumbashi, Luki, and KinNDjili stations. However, Bandundu, Kiyaka, Yangambi in Cuvette centrale and Goma, Mulungu in eastern mountains of DR. Congo are not correlated to the observed minimum temperatures.

For the maximum temperature in Fig.16, there are only the stations of Bandundu, Lubumbashi, Goma and that of Mulungu which presented a relatively good correlation for the set of five reanalyses. At the stations of Boma, Gimbi, Inga, Kananga, KinBinza, Luki, KinNDjili we noted a good performance of JRA-55 and ERA5-Land. In general, ERA-Interim, CFSR and MERRA did not reproduce the maximum temperature.

As in precipitation, Figures 3.16&3.17 show that monthly temperature series from reanalysis overall, correlate well with the observations over the basin except Bandundu, Goma, Kiyaka, Mulungu and Yangambi stations where the lowest correlations are observed. However, no reanalysis stands out from the others, probably for the same reasons that precipitation.

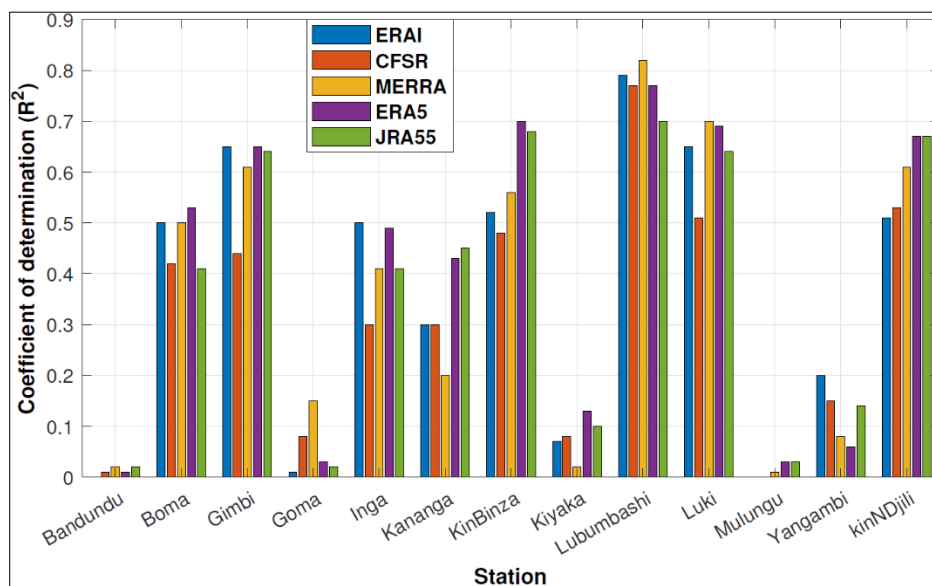


Figure 3.16 R^2 of monthly minimum temperature between reanalyses and observed dataset

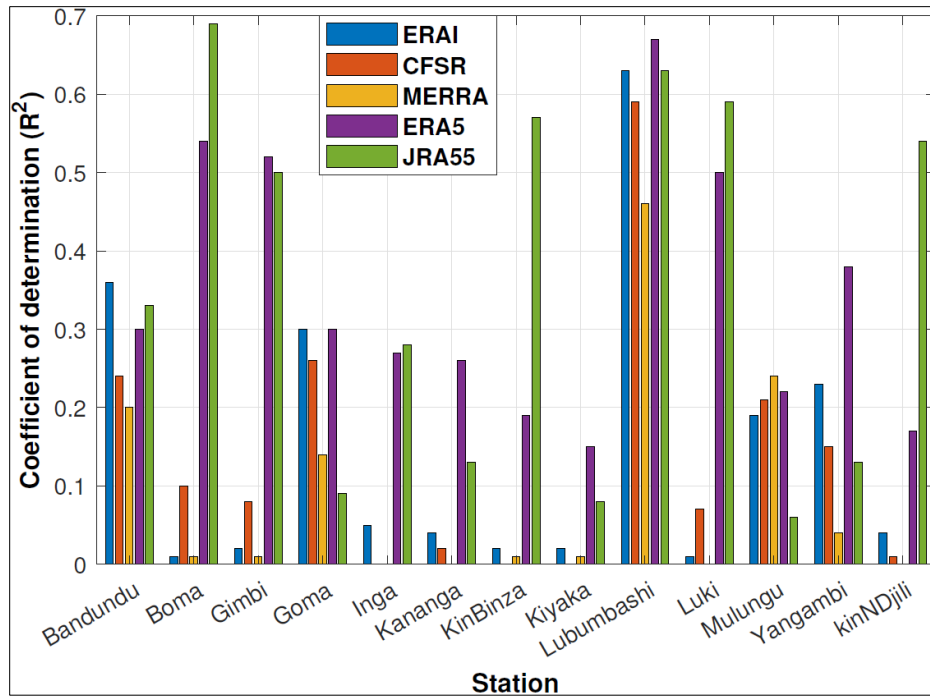


Figure 3.17 R^2 of monthly maximum temperature between reanalyses and observed dataset

3.5 Discussions

3.5.1 Spatial and temporal Performance of Reanalysis precipitation products

It is obvious that each reanalysis products have its own performance across the basin, in terms of spatio-temporal resolutions. Among the five datasets studied in this research, ERA5-Land and MERRA exhibit the finest temporal resolution of 1 h, ERA-Interim and JRA-55 share the same temporal resolution of 3 h and CFSR has 6h as temporal resolution.

Besides, ERA5-Land has finer spatial resolution of 0.1° compared to CFSR, MERRA, ERA-Interim, and JRA-55 with spatial resolution respectively of 0.313° , 0.5° , 0.75° and 1.25° . In terms of spatial coverage, CFSR, MERRA, ERA-Interim, and JRA-55 fully cover global regions ($-180^\circ\text{W} - 180^\circ\text{E}$, $90^\circ\text{S} - 90^\circ\text{N}$), whereas the spatial coverage of ERA5-Land is limited to the land regions with a considerable number of no-data grids in coastal regions(Xu *et al.*, 2022). It is not

easy to quantitatively estimate the performance of reanalysis precipitation dataset due to their complex variability at spatial and temporal scales.

At first glance, all reanalysis rainfall patterns averaged over the 1981–2008 period are similar (see Figure 3.4), with the main wet seasons and dry seasons standing out for the thirteen stations studied. However, a detailed analysis revealed significant differences amongst the five datasets (Table 3.3). Bandundu and Yangambi stations have very poor coefficient of determination values varying between 0 and 0.15 for all reanalysis compared to observed data. May be because these two stations are located in the central basin dominated by a very wide wetland and low altitude. However, Lubumbashi has good coefficient of determination values between 0.63 and 0.76 for all reanalysis compared to observed data.

Other stations can be grouped by geographical locations. Further west, Boma, Gimbi, Inga, KinBinza and KinNdjili stations have R^2 values between 0.34 and 0.59. In the center-east, the Goma and Mulungu stations with R^2 values between 0.13 and 0.39 and in the center, Kiyaka and Kananga with R^2 values between 0.13 and 0.39.

Contrary to the results of R^2 , the RMSE values of Bandundu and Yangambi are not drastically different to all other stations investigated. This also applies to stations in other geographical locations highlighted for R^2 . Except a significant increase in the RMSE values at the Inga station which gives systematically high values for all reanalyses between 1132.15 and 1207.01 mm.

The RBIAS analysis revealed significant differences amongst the five reanalysis datasets even at the same station. Bandundu and Kiyaka showed systematic overestimation for ERAI, CFSR, ERA5-Land, JRA55 and underestimation for MERRA. Boma and Lubumbashi showed systematic overestimation for ERAI, CFSR, ERA5-Land, MERRA, and underestimation for JRA55. Gimbi showed systematic overestimation for ERAI, CFSR, MERRA, JRA55 and underestimation for

ERA5-Land. KinBinza and KinNdjili showed systematic overestimation for ERAI, MERRA, JRA55 and underestimation for CFSR, ERA5-Land. Kananga showed systematic overestimation for ERAI, CFSR and underestimation for MERRA, JRA55, ERA5-Land. Mulungu showed systematic overestimation for ERAI, MERRA, ERA5-Land, and underestimation for CFSR, JRA55. Yangambi showed systematic overestimation for ERAI, JRA55 and underestimation for CFSR, MERRA, ERA5-Land. However, Luki showed systematic overestimation for the five reanalysis datasets studied and Inga showed systematic underestimation for the five reanalysis datasets studied.

In general, the RBIAS, RMSE, and R^2 over the five reanalysis datasets studied did not show clear performance trends for one specific reanalysis or another one. Overall, neither the altitudes and geographical locations of the stations nor the spatial and temporal resolutions of the reanalyses did not show a direct influence on the values of the statistical metrics (Table 3).

Table 3.3 Summary of statistical metrics for ERAI, CFSR, MERRA, ERA5-Land and JRA55 precipitation at the monthly resolution

Station	Metrics	ERAI	CFSR	MERRA	ERA5-Land	JRA-55
Bandundu	RBIAS (%)	56.31	11.27	-14.35	22.60	39.46
	RMSE (mm)	133.65	130.19	103.36	116.04	137.71
	R^2	0.01	0.02	0.00	0.00	0.00
Boma	RBIAS (%)	61.78	15.95	76.86	10.89	-11.60
	RMSE (mm)	89.29	76.73	97.39	69.71	74.84
	R^2	0.51	0.43	0.48	0.38	0.40
Gimbi	RBIAS (%)	68.98	11.86	80.74	-0.71	40.24
	RMSE (mm)	108.87	74.87	112.56	71.22	95.23
	R^2	0.52	0.49	0.50	0.40	0.47
Goma	RBIAS (%)	27.19	57.58	50.82	184.69	107.77
	RMSE (mm)	82.24	98.13	88.35	205.54	125.34
	R^2	0.18	0.25	0.13	0.21	0.25
Inga	RBIAS (%)	-84.90	-88.69	-81.04	-90.02	-85.72
	RMSE (mm)	1159.89	1192.05	1132.15	1207.01	1158.89
	R^2	0.57	0.49	0.59	0.47	0.55

Table 3.3 Summary of statistical metrics for ERAI, CFSR, MERRA, ERA5-Land and JRA55 precipitation at the monthly resolution (Continued)

Station	Metrics	ERAI	CFSR	MERRA	ERA5-Land	JRA-55
KinBinza	RBIAS (%)	59.79	-27.12	2.63	-26.51	12.62
	RMSE (mm)	129.27	98.00	87.84	87.65	100.38
	R ²	0.46	0.34	0.38	0.47	0.39
Kananga	RBIAS (%)	22.55	7.64	-34.01	-3.50	-12.33
	RMSE (mm)	80.42	90.83	84.06	79.42	80.13
	R ²	0.52	0.47	0.49	0.35	0.44
kinNDjili	RBIAS (%)	60.39	-23.50	2.93	-23.46	12.66
	RMSE (mm)	131.36	93.12	81.59	82.49	97.32
	R ²	0.46	0.38	0.44	0.49	0.43
Kiyaka	RBIAS (%)	46.57	3.19	-35.65	13.28	4.95
	RMSE (mm)	104.44	105.22	88.92	69.54	81.51
	R ²	0.43	0.36	0.27	0.47	0.42
Lubumbashi	RBIAS (%)	5.63	30.74	15.28	15.01	-3.07
	RMSE (mm)	53.05	90.08	70.10	65.37	61.62
	R ²	0.76	0.68	0.63	0.68	0.68
Luki	RBIAS (%)	26.32	4.87	60.05	1.08	2.49
	RMSE (mm)	90.16	80.96	109.29	86.54	94.58
	R ²	0.50	0.53	0.48	0.39	0.40
Mulungu	RBIAS (%)	12.75	-25.85	3.20	50.61	-6.61
	RMSE (mm)	129.47	111.77	95.75	155.51	90.36
	R ²	0.32	0.26	0.33	0.30	0.39
Yangambi	RBIAS (%)	34.70	-2.54	-39.60	-4.49	5.07
	RMSE (mm)	110.04	116.77	105.47	83.98	93.22
	R ²	0.06	0.15	0.09	0.13	0.12

3.5.2 Spatial and temporal Performance of Reanalysis temperature products

As for precipitation, the RBIAS analysis of the mean temperature revealed significant differences from one reanalysis to another even at the same station (Table 3.4). ERA-Interim underestimates the observed temperature, which results in a cool bias over all stations studied while CFSR overestimates the observed temperature, which results in a warm bias over all stations studied. MERRA is warmer than observations over Bandundu, Gimbi, KinBinza, Kananga, Kiyaka,

Lubumbashi, Luki, Mulungu and Yangambi, but cooler over KinNdjili, Inga and Boma observation stations. ERA5-Land underestimates the observed temperature over Bandundu, Boma, Inga, KinNdjili, Luki and Mulungu, but overestimates the observed temperature over Yangambi, Lubumbashi, Kiyaka, KinBinza, Kananga, Goma and Gimbi. JRA-55 is warmer than observations over Kananga, Goma, Lubumbashi, Kiyaka, Luki, Mulungu, Gimbi and cooler over Yangambi, KinBinza, KinNdjili, Inga, Boma and Bandundu.

In general, RMSE values of ERA5-Land indicate less gaps between reanalysis mean temperatures and observations than the other reanalysis data regardless of the geographical location of the stations except Boma, Goma, Kananga, Lubumbashi and Yangambi stations.

The RMSE values of the stations located at further west of the basin, Boma, Gimbi, Inga, KinBinza, KinNdjili and Luki are between 0.82 and 1.59 °C. In the center-east, the Goma and Mulungu stations are RMSE values between 1.20 and 1.38 °C, in the center, Kiyaka and Kananga are RMSE values between 1.01 and 1.46 °C and in the southern-east, the RMSE of Lubumbashi station is 1.64 °C.

Compared to precipitation (shown above), temperature RMSE is generally lower and is more easily simulated by the reanalyses.

As for precipitation, the coefficient of determination varies by reanalyses and by geographical location of the stations. Bandundu, Goma, Kananga, Kiyaka, Mulungu and Yangambi stations have poor coefficient of determination values varying between 0 and 0.39 for all reanalysis compared to observed data.

In general, all other stations have overall good coefficient of determination for all reanalyses with observations.

Indeed, the coefficients of determination for Boma are 0.42, 0.58, 0.70, 0.81 and 0.82 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55. Gimbi coefficients of determination are 0.53, 0.47, 0.43, 0.76, 0.74 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55. Inga coefficients of determination are 0.50, 0.22, 0.31, 0.55, 0.52 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55. KinBinza coefficients of determination are 0.07, 0.13, 0.33, 0.66, 0.73 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55. KinNdjili coefficients of determination are 0.05, 0.10, 0.27, 0.67, 0.74 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55. Lubumbashi coefficients of determination are 0.65, 0.74, 0.46, 0.69, 0.69 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55. Luki coefficients of determination are 0.48, 0.54, 0.38, 0.73, 0.72 respectively for ERA-Interim, CFSR, MERRA, ERA5-Land and JRA-55.

In summary, the reanalysis performs quite well with respect to temperature, probably because the atmospheric temperatures from radiosondes and satellites are regularly assimilated in the reanalysis systems (Essou, G. R. *et al.*, 2016).

Table 3.4 Summary of statistical metrics for ERAI, CFSR, MERRA, ERA5-Land and JRA55 mean temperature at the monthly resolution

Station	Metrics	ERAI	CFSR	MERRA	ERA5-Land	JRA-55
Bandundu	RBIAS (%)	-2.37	0.94	0.33	-0.92	-1.19
	RMSE (°C)	2.66	1.80	2.27	1.26	1.73
	R2	0.38	0.12	0.17	0.39	0.14
Boma	RBIAS (%)	-1.36	2.24	-0.92	-1.05	-0.52
	RMSE (°C)	2.11	2.60	1.63	1.39	1.03
	R2	0.42	0.58	0.70	0.81	0.82
Gimbi	RBIAS (%)	0.37	3.57	1.00	0.62	1.11
	RMSE (°C)	1.29	3.83	1.67	1.09	1.47
	R2	0.53	0.47	0.43	0.76	0.74
Goma	RBIAS (%)	-2.56	-4.03	-0.58	0.97	0.47
	RMSE (°C)	2.75	4.17	1.31	1.20	1.13
	R2	0.11	0.16	0.14	0.18	0.05

Table 3.4 Summary of statistical metrics for ERAI, CFSR, MERRA, ERA5-Land and JRA55 mean temperature at the monthly resolution (Continued)

Station	Metrics	ERAI	CFSR	MERRA	ERA5-Land	JRA-55
Inga	RBIAS (%)	-0.93	2.56	-0.61	-0.44	-0.39
	RMSE (°C)	1.81	3.22	1.95	1.54	1.66
	R2	0.50	0.22	0.31	0.55	0.52
KinBinza	RBIAS (%)	-1.48	1.77	0.23	0.23	-0.42
	RMSE (°C)	2.00	2.34	1.13	0.82	0.85
	R2	0.07	0.13	0.33	0.66	0.73
Kananga	RBIAS (%)	-1.70	1.82	1.89	0.28	0.27
	RMSE (°C)	2.25	2.62	2.87	1.01	0.99
	R2	0.01	0.02	0.00	0.21	0.30
kinNDjili	RBIAS (%)	-1.97	1.90	-0.25	-0.34	-0.92
	RMSE (°C)	2.49	2.57	1.32	0.95	1.24
	R2	0.05	0.10	0.27	0.67	0.74
Kiyaka	RBIAS (%)	-1.31	3.69	2.12	1.18	1.59
	RMSE (°C)	1.75	4.04	2.57	1.46	1.86
	R2	0.02	0.00	0.00	0.16	0.14
Lubumbashi	RBIAS (%)	-0.01	0.27	1.19	0.95	1.61
	RMSE (°C)	1.45	1.44	2.48	1.64	2.09
	R2	0.65	0.74	0.46	0.69	0.69
Luki	RBIAS (%)	-0.10	2.32	0.11	-0.10	0.59
	RMSE (°C)	1.28	2.66	1.39	0.93	1.16
	R2	0.48	0.54	0.38	0.73	0.72
Mulungu	RBIAS (%)	-0.07	0.44	1.68	-0.24	1.72
	RMSE (°C)	1.55	1.98	2.35	1.38	2.28
	R2	0.03	0.05	0.05	0.07	0.02
Yangambi	RBIAS (%)	-1.60	2.09	3.05	0.86	-0.15
	RMSE (°C)	1.97	2.47	3.64	1.37	1.22
	R2	0.16	0.13	0.05	0.22	0.10

3.6 Conclusions

This research aims to evaluate the performance of ERA5-Land, ERA-Interim, CFSR, JRA-55, and MERRA temperature and precipitation data from 1981 to 2008 based on observed data over Congo River basin. The comparisons were done between temperature and precipitation data from 13

meteorological observation stations against those from five reanalysis products. However, it is not easy to generalize the results of five reanalyses on the 13 stations. Each reanalysis has its own limitations likely related to assimilated observations, physical parameterizations, and model boundary conditions (Hua *et al.*, 2019; Lin, R. P. *et al.*, 2014). The relevant results were as follow:

- It has been observed that the reanalysis temperature and precipitation products can capture the temporal-spatial patterns comparing in-situ observed data in Congo River basin.
- In general, the RBIAS, RMSE, and R^2 over the five reanalysis datasets studied did not show clear performance trends for one specific reanalysis or another one.
- Overall, neither the altitudes and geographical locations of the stations nor the spatial and temporal resolutions of the reanalyses did not show a direct influence on the values of the statistical metrics.
- The reanalysis performs quite well with respect to temperature, probably because the atmospheric temperatures from radiosondes and satellites are regularly assimilated in the reanalysis systems.

These findings may improve an understanding of the error characteristics of the precipitation and temperature of newly reanalysis generation, compared to the observed data, as well as the similarities and differences between them over Congo River basin. It is important to highlight that the results are particular to the current analysis and study area over the 13 meteorological stations investigated. Considering the limited number of stations explored, other datasets might show better results. Lastly, we recommend the methodology shown in this study as the foundation for an analysis of further investigation for the use in the future works.

CHAPITRE 4 ARTICLE 2: A BAYESIAN APPROACH TO RIVER DISCHARGE PREDICTION UNDER UNCERTAINTY IN LARGE RIVERS: APPLICATION TO THE CONGO RIVER

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Abstract

Knowing the flow discharge in a river is important for the analysis of hydrological processes and planning for water infrastructure. Climate change increases the need for accurate prediction of river flow discharge to support better management of water infrastructure and to make comparisons with other climate observations.

A semiparametric regression model capturing the complex relationship between multiple factors (e.g., the stage, the flow velocity) and the response discharge is proposed. A fully Bayesian variable selection is applied to identify the most influential factors in the river flow equation and capture the uncertainty due to morphological, occurring in the river and measurements. The proposed approach is applied to data measures taken from June to August 2019 at the port of Kinshasa in the Congo River. The results show the inclusion of nonlinear dependencies between different covariates (e.g., water stage, river width) and the flow discharge response led to accurate prediction of the response although the reduced amount of data collected. This model is a valuable tool in the assessment of the flow in a large river where measured data are not usually available.

Keywords: Bayesian, semiparametric, uncertainty, discharge, stage, rating

4.1 Introduction

Accurate river flow prediction is important in the hydrological modeling and affects the design of water infrastructure in climate change context (Chen *et al.*, 2018; Feng *et al.*, 2019; Liu *et al.*, 2018; Shao *et al.*, 2018; Vrugt *et al.*, 2008). Traditional river discharge monitoring records river water stage that is converted into flow discharge using a predefined rating curve (Vougioukas *et al.*, 2011). This indirect calculation is source of uncertainties, particularly during high flows for which existing rating curves are not precise because few discharge measurements exist (Westerberg *et al.*, 2011).

The number of discharge measurements available for a particular cross-section greatly affect the calibration process of rating curves (Manfreda, 2018). Moreover, complex flow conditions (e.g., variable backwater, tidal flow, rapid changes in flow), reduce the performance of defined rating curves (Morlock *et al.*, 2002).

Uncertainty in flow discharge data measurement must be critically assessed before their use in water resource management (e.g., water resources estimation, hydrological modelling).

The Congo River basin is the second lung of the planet, the objective of extracting its accurate discharge in m^3/sec , is in the interest of the various studies of climate change mitigation and adaptation strategies. Measuring the accurate discharge in one of the least gauged river basins in the world interests many researchers in water and hydrological studies. Several previous works have been carried out on that concern. Łempicka (1972) published a synthesis of all the work prior to 1970 on flow measurements and calibration of the rating curve for the entire Congo River watershed. The main authors quoted for this work used the float method and the reel (Devroey, 1951, 1959). The rating curves equations obtained based on this work are used up to day to compute the Congo River discharge. Other campaigns of the same magnitude with more modern

devices are necessary to check and correct the old equations if necessary. Peters (1978) used these equations to conduct several studies on the morphology of the Congo River in the maritime reach. Oberg, Shelton, Gardiner, and Jackson (2009) used acoustic Doppler current profilers (ACDP), differential GPS, and echo sounders to measure discharge in the Lower Congo River for understanding the distribution of fish species. Other approaches have been used to assess the discharge of the Congo River. Santini, and Caporaso (2018) considered the simulated Congo River discharge in the Atlantic Ocean from 20 models of the Climate Model Intercomparison Project (CMIP5). But their results still require much progress in global modeling to be able to reproduce the observed discharge.

McMillan et al., 2017; Pedersen et al., 2019; Westerberg et al., 2011 investigated the importance of hydraulic scale modelling in the development of reliable rating curves for large discharges and evaluated new or existing gauging stations located at sites with challenging measurement conditions. Birgand *et al.* (2013) used random sampling of reference flow and stage data obtained with doppler flowmeters. Juston *et al.* (2014) calibrated the rating curve model using Bayesian methods to quantify uncertainty intervals in model parameters and predictions. Other approaches include the analysis of deviation from the rating curves (Tomkins, 2014), in situ collaborative interlaboratory experiments (Le Coz *et al.*, 2016), hydraulic model simulations (Di Baldassarre *et al.*, 2009).

Natural water flow, at a given cross-section of a river, is complex and depends on several factors that should be accurately measured to allow better discharge predictions. Continuous measurements rely on costly equipment such as doppler current profilers, which can only be used in a limited range of conditions (e.g. deep river channels), and therefore regular intensive measurements are rare except at some important locations (Shao *et al.*, 2018). Reduced

availability of reliable data does not allow building robust models that can predict flow discharge in large rivers with significant discharge ranges. Accurate prediction of the river flow discharge, in the context of climate change, for water infrastructure design, management and planning requires the use of river geometry attributes and flow characteristics in the prediction model.

Complex relationships among several variables and one response variable to describe natural processes can be captured using Bayesian approaches methods (Balekelayi *et al.*, 2019). The principal drawback of the probabilistic approaches is the necessary definition of the conditional response distribution that is not an easy task. Some processes (e.g., river water flow) do not follow frequently used distributions (e.g. exponential distribution family) and require more data to determine the empirical distribution of the response variable. In addition, if water infrastructures (e.g. dam) are planned to be built on the river, the interest in higher moments of the response is increased. Bayesian approaches are more attractive in this case since they allow a flexible representation of the output response with reduced number of instances in the dataset. Their advantage resides also in the ability to update the acquired knowledge using reduced dataset whenever new data are collected.

In this paper, a Bayesian additive model is proposed to predict large river flow discharge from river's attributes and flow characteristics measured with accurate tools. All continuous covariates are allowed to have linear and nonlinear effect on the response. The nonlinear effects are captured using smoothed penalized splines that better fit complex relationships. Categorical variables are only allowed to have linear response and are.

4.2 Study area and data

4.2.1 Congo River Basin (CRB)

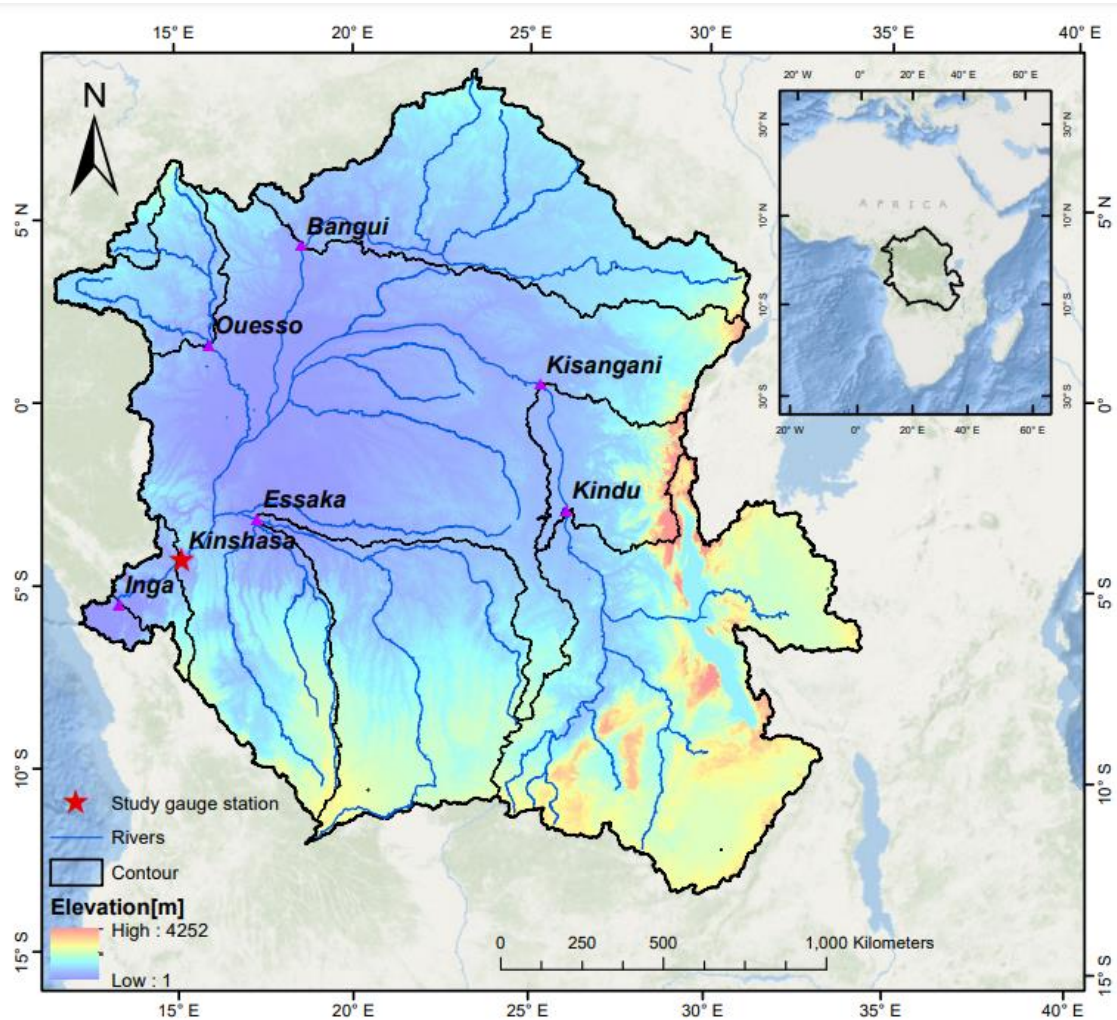


Figure 4.1 Study area

4.2.2 Data description

The study is based on measurements taken in a 3000 m wide cross section in the Congo River between the port of Kinshasa located on the geographical coordinates: $4^{\circ}17'48.66''$ south latitude and $15^{\circ}19'02.57''$ east longitude; and Brazzaville Beach located on coordinates: $4^{\circ}16'22.20''$ south latitude and $15^{\circ}17'36.59''$ east longitude. The data were collected in two stages, in morning and in afternoon of each working day from June to August 2019. Discharges were measured

using Acoustic Doppler Current Profiler (ADCP) designed for use on moving boats. Both bottom-track and GPS referenced boat velocities are considered for the 66 measurements carried out due to two measurements per day, one before noon and the other after noon.

The total of the used materials consisted of:

1. a boat for the crew and equipment;
2. a complete ADCP Kit;
3. a differential GPS which gives with an accuracy of 3mm the geographical coordinates of the region scanned by the ADCP;
4. a Getrac brand computer, equipped with the WinRiver II software, is the one that helps to manipulate the ADCP;
5. a Panasonic brand computer for fixing within an acceptable margin of the profile traced by the boat in order to remain in the correct position.
6. a 12V/180 Ampere-Hour (AH) battery.

The measurement operation consisted of following a cross-section in a previously chosen cross-section in order to measure the volume of water that passes through this section of the river.

The advantage of this device is that we are not necessarily obliged to follow a profile perpendicular to the flows, but to choose a section whose banks are straight and stable, because this would lead to a change in one of the parameters (width, depth, etc.). Indeed, during flow measurements, the disturbances recorded are integrated into the calculations carried out by the device automatically.

Figure 1 shows the distribution of the data used for this study. The water stage represents the water

level at the cross-section where the discharge was measured. Traditionally, the water stage-discharge curve was used to characterize the relationship between the cross-section geometry and the discharge flowing through the cross section. Water velocity is known to have direct impact on the discharge and is used to calculate steady state discharge over a river cross-section. Water stage and velocity are the flow characteristics whereas the section area and width represent the geometry of the cross-section where the flow is measured. These last two variables were also measured and included in the model to predict the river flow discharge. The reason of including these parameters is the irregular shape of the river cross section that cannot be idealized to regular shapes without losing singularities is the cross-section shape changes due to the bedload in the Congo River.

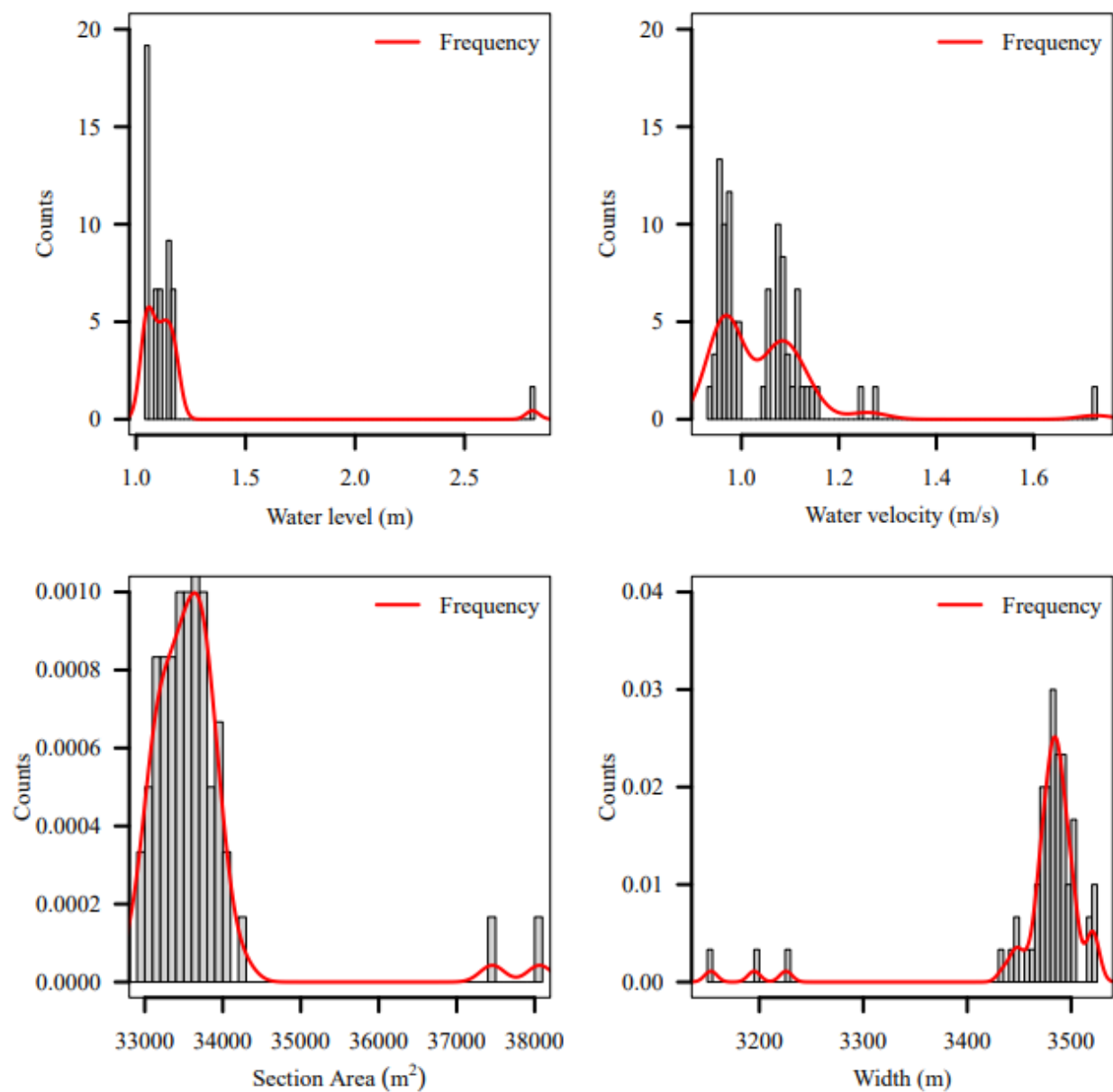


Figure 4.2 Data description

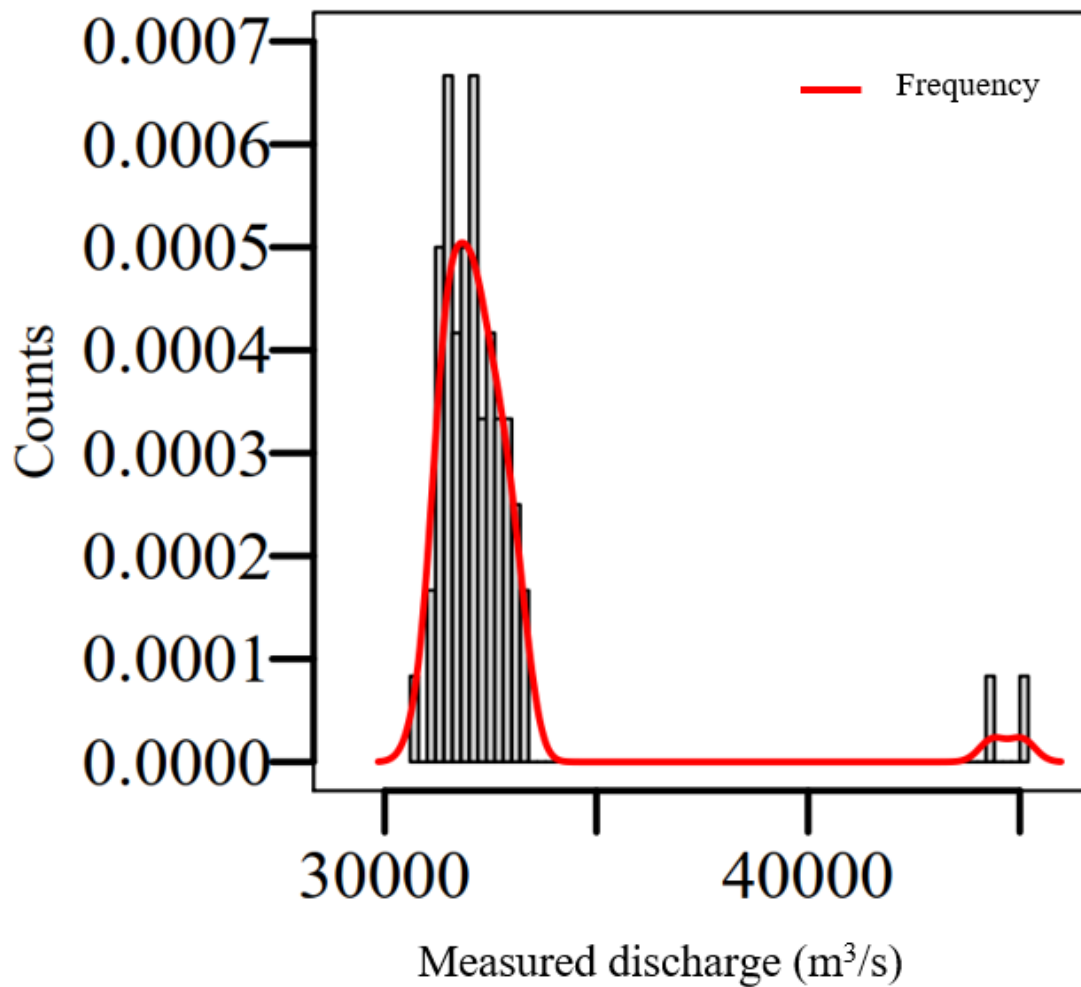


Figure 4.3 Measured discharge

Figure 4.3 shows the discharge considered in this study as the response of the model. It can be observed that some outliers are in the data. These outliers are not removed from the data because they lay in the range of possible range of discharges in the Congo River. In the Congo River, discharge fluctuates from 30,000 m³/s during low water flow (dry season) to 65,000 m³/s (high water flows). Seasonality across the Congo River basin is the major factor that is responsible of the changes in the Congo River. No major water intakes are observed in the region upstream from the port of Kinshasa.

4.3 Methodology

The proposed framework for this study is given in Figure 4.4. Discharge data measured were analyzed and the missing data were removed from the dataset. Outliers were identified using the Mahalanobis distance (Xiang et al. 2008) and were removed from the analysis. Distributions of the data remained after the processing are presented in Figure 4.2. Remaining data were classified into categorical and continuous groups. In this study, all the considered variables were classified as continuous (see Figure 4.2), and their smoothing splines functions are defined in Equation 1. The reduced amount of data led to the select a Bayesian approach with smooth splines that allows flexibility in the modeling process and updating prior knowledge once additional data are made available. The response flow discharge outcome does not usually follow exponential distributions. Quantification of uncertainties related to data and their propagation through the model is important in the management of water infrastructure. Thus, the definition of the location, the scale and the shape of the response variable and establishing its relationship with the covariates are desired.

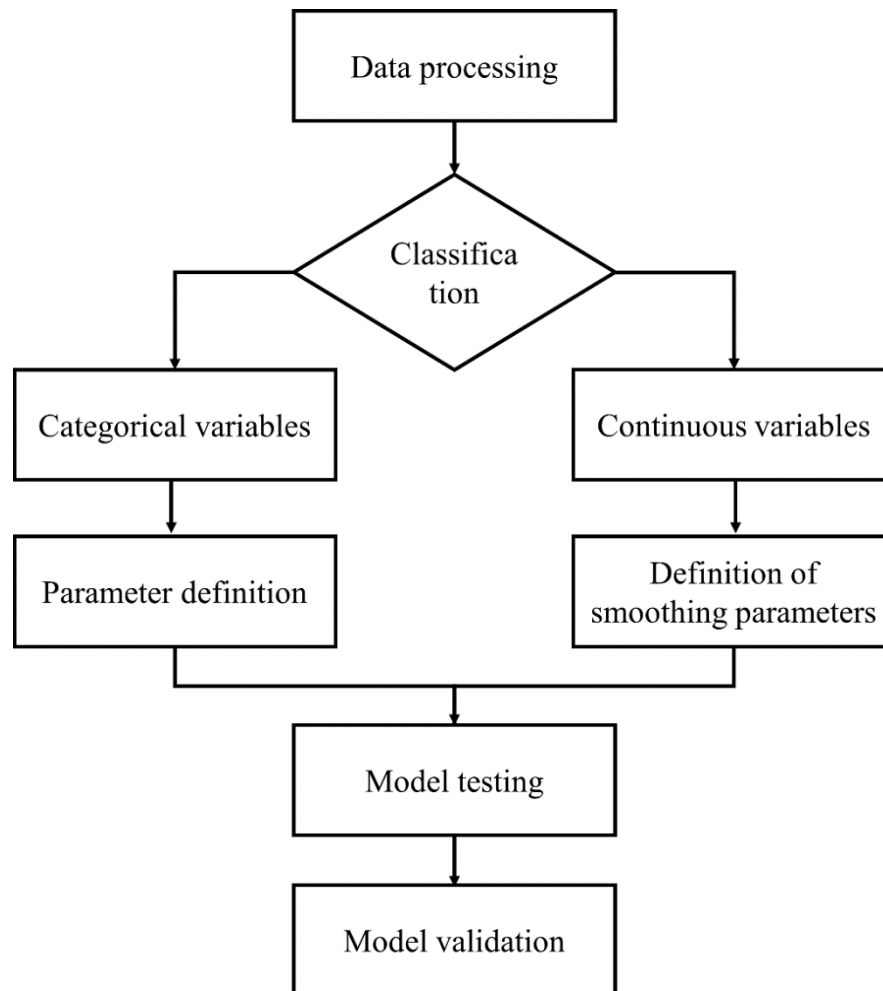


Figure 4.4 Proposed framework

Modeling the mean (location) as well as higher moments (scale and shape) of physical processes, such as water flow in rivers, in terms of covariates is well captured by generalized additive models that relax the distributional assumptions of a response variable. This approach is especially useful in the case of this study where the amount of available data is reduced.

The nonparametric part of the model is defined by penalized splines that represent the partial effect of the continuous variables on the response variable (Brezger, et al. 2005). Each spline is specified at between knots where penalization functions are defined to smooth the partial effect of the considered variable. The first step in the fitting procedure is the definition of a stopping

criterion and the number of iterations ($n = 20000$ for this study). The next step is the initialization of the parameters. Random values are affected to the parameters. Then, each parameter is updated using Markov Chain Monte Carlo (MCMC). In this study, a Bayesian inference algorithm is applied in two steps including a first estimation of parameters using Newton Raphson technique of solving equations (see Ben-Israel 1996 for details on the method) then, these estimates are used as starting points (priors) in the MCMC for estimating the posteriors. The optimization of the parameters' posteriors using the adaptive search interval algorithm is done sequentially for each parameter.

The final model considered in this study is:

Location

$$Q = h + f(h) + v + f(v) + Area + f(Area) + L + f(L) \quad (1)$$

Scale

$$\sigma = h + f(h) + v + f(v) + Area + f(Area) + L + f(L) \quad (2)$$

where h is the water stage, v is the water velocity, $Area$ is the cross-section area and L is the cross-section width. $f(.)$ is a spline function that allows to capture the partial effect of the covariates. Each of the selected factors were classified as continuous variables. These variables were allowed to have linear and nonlinear effect on the response mean. The nonlinear form of the variable is

captured through its modeling as a smooth spline function $f(\cdot)$. Q is the predicted discharge and σ is the second order moment of the discharge (Equation 2).

4.4 Results and Discussions

The application of the selected methodology to predict the Congo River flow discharge using the defined Bayesian additive model led to the results presented in this section. The developed model also allows the selection of the most influential factors on the flow discharge response. Only nonlinear relationships between the selected variables and the response discharge were found to be impactful on the discharge.

Water stage

Figure 3 shows the nonlinear relationship between the water stage and the discharge in the Congo River. At lower values, the impact of water stage on the water discharge is negative until a value of 1.7 m that correspond to the minimum impact of the water stage on the discharge. Above this value, the partial effect of water stage increases as water stage increase. The credibility band of the partial effect of the water stage is larger at its minimum that correspond to the water stage range between 1.5 and 2.0 m.

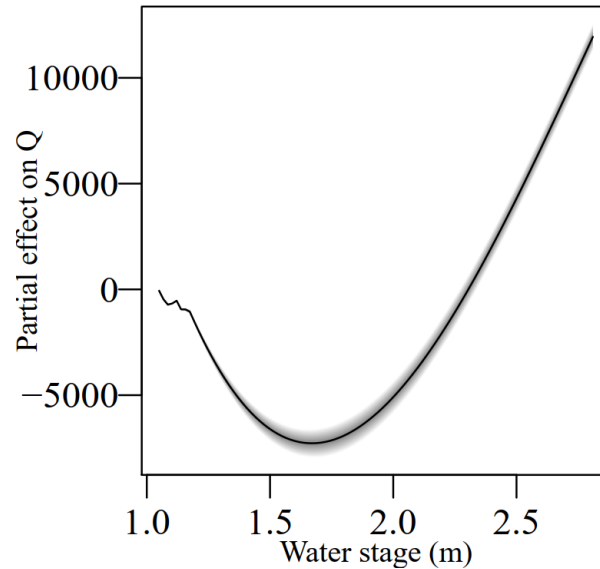


Figure 4.5 Nonlinear partial effect of the water stage on the water discharge

Water velocity

Water velocity is among the important factors that contribute to the water discharge response. The results obtained in this study show that the linear effect of the velocity does not have impact the water discharge. The nonlinear effect (Figure 4.5) shows a bell shape with a maximum partial effect occurring at the velocity of 1.45 m/s. The uncertainty band at this value is higher compared to uncertainty observed in the water stage nonlinear effect. The analysis of this nonlinear impact shows that at low velocity values (1 - 1.2 m/s), the partial effect of the velocity on the discharge is fluctuating around zero. However, when the flow velocity is between 1.2 – 1.45 m/s, the relationship between the velocity and the discharge is defined by an ascending curve showing that increasing the velocity will increase the discharge. Above 1.45 m/s, the partial nonlinear effect shows that the velocity is no longer contributing to the increase of the discharge. Further investigations are required to determine if the velocity of 1.45 m/s initiates morphological changes in the river geometry that might affect the relationship between the velocity and the

discharge.

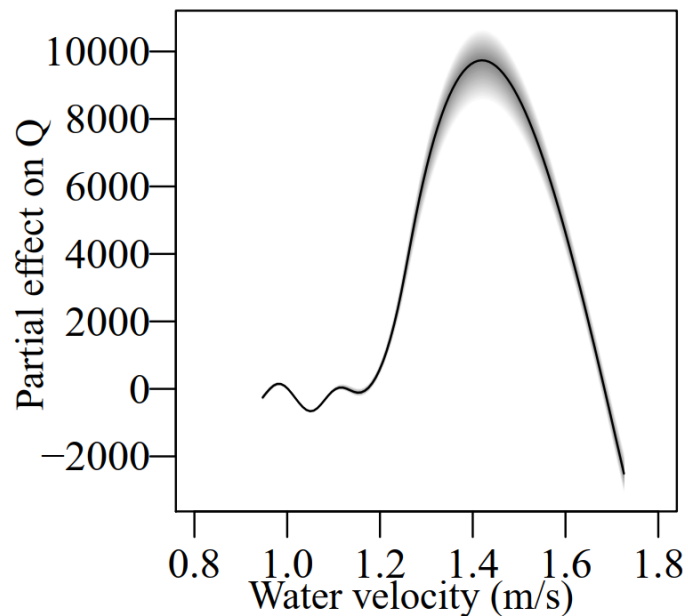


Figure 4.6 Nonlinear partial effect of the water velocity on the water discharge

Section area

It is known that the discharge and the cross-section area are directly proportional. However, the results obtained in this study show that the relationship between the cross-section area and the discharge is a nonlinear function that is represented in Figure 4.6. Small areas have high partial effect on the water discharge than larger areas. This study identified that the area of the river is a nonlinear function of the discharge. Figure 6 shows that when the cross-section area is getting large the discharge is not increasing.

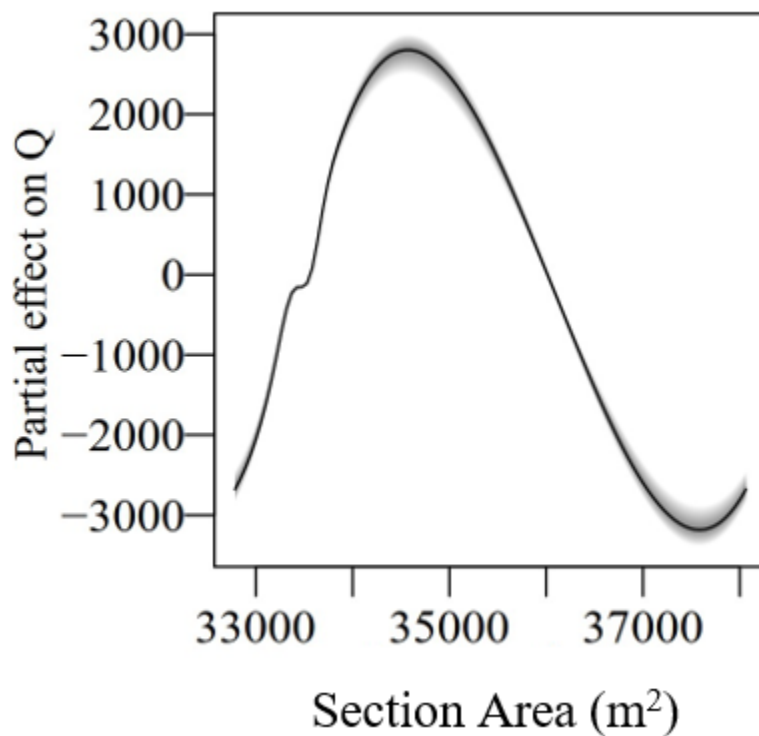


Figure 4.7 Nonlinear partial effect of the section area on the water discharge

Section width

The width of the cross-section has an observed effect on the discharge. Its partial effect represented in Figure 4.7 shows that at small width, the partial effect is high and decreases when the section width gets larger. The credible interval is large in the section width ranging from 3000 to 3350 m. This is due to the reduced amount of data collected in the range (see Figure 4. 8). Above this value, the uncertainty is reduced and the partial effect on the discharge starts increasing but will not get to the level it was at lower values of the section width.

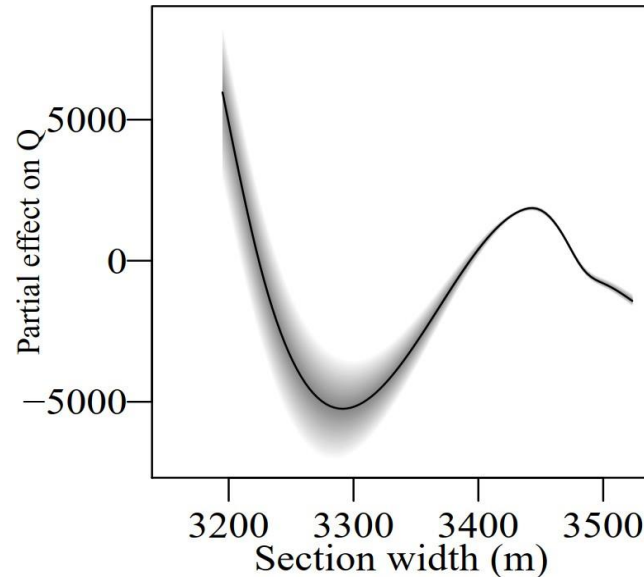


Figure 4.8 Nonlinear partial effect of the section width on the water discharge

Model performance

The advantage of building the nonparametric model in the assessment of physical processes is its ability to capture singularities that could have been missed even using high degree polynomial models. The performance obtained in the training and testing data confirms the superiority of the selected Bayesian approach. Data collected on the Congo River were split into training set (80% of the data) and testing set (20 % of the data). The calculated coefficient of determination between the observed and the predicted discharge during the training step is 0.99 (see Figure 4.9) and it is equal to 0.53 (see Figure 4.10) during the testing set. The reduced performance obtained using the testing set is due to the relatively small size of the testing set. In addition, the selected modeling approach allows the updating of the accumulated knowledge through the Bayesian process that underlies the technique. The performance of the proposed approach can also be seen in Figure 8 where most of the clustered response data points (between 30,000 m³/s to 34,000 m³/s) were well predicted as well as the outliers (above 45,000 m³/s).

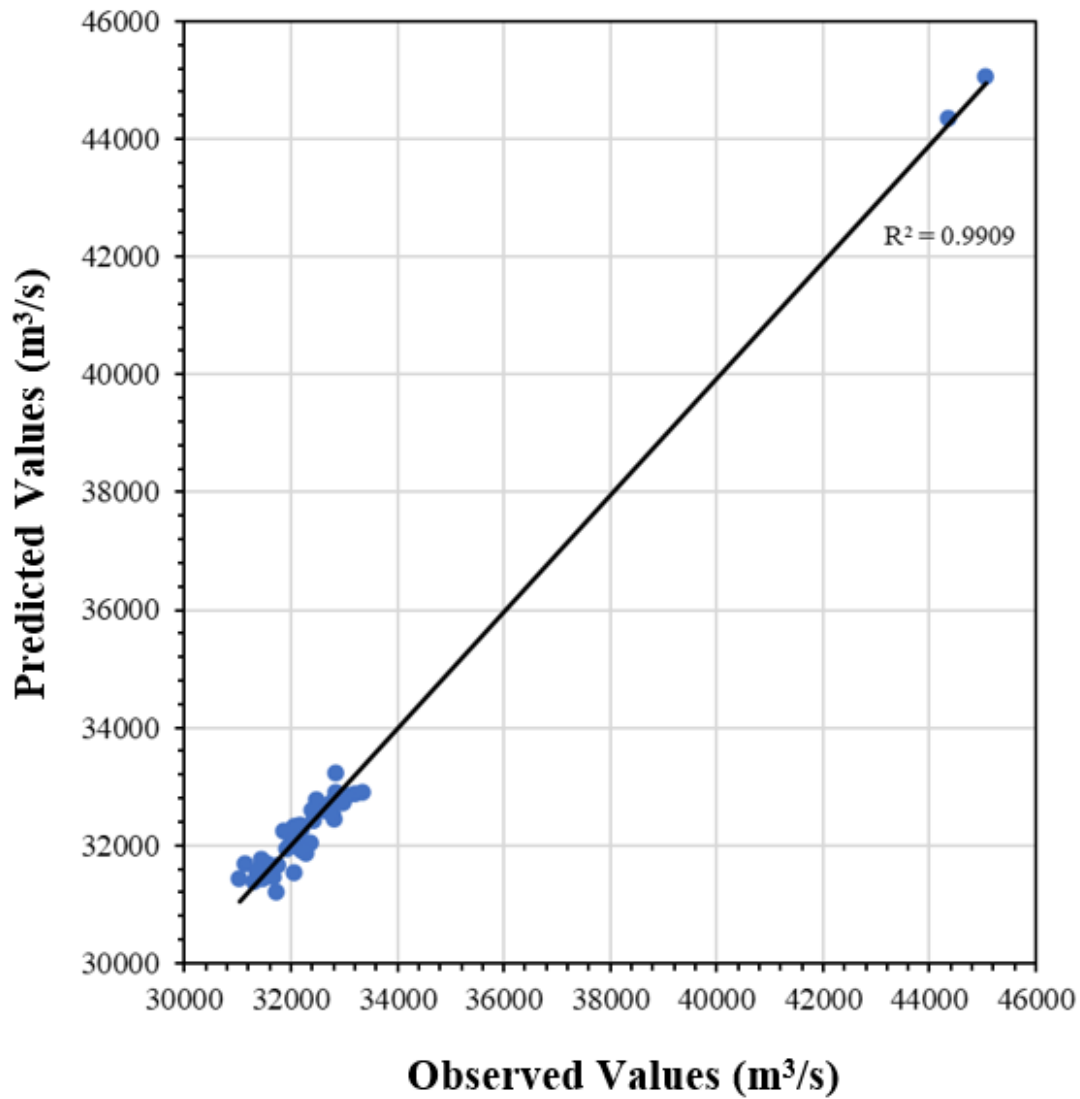


Figure 4.9 Coefficient of Determination in the training step

When more data become available, the obtained posteriors will be considered as priors and updated to capture the new information contained in the data. This is advantageous on traditional modeling of physical processes such as water flow in a river where data collection is an ongoing process and will be available in near future.

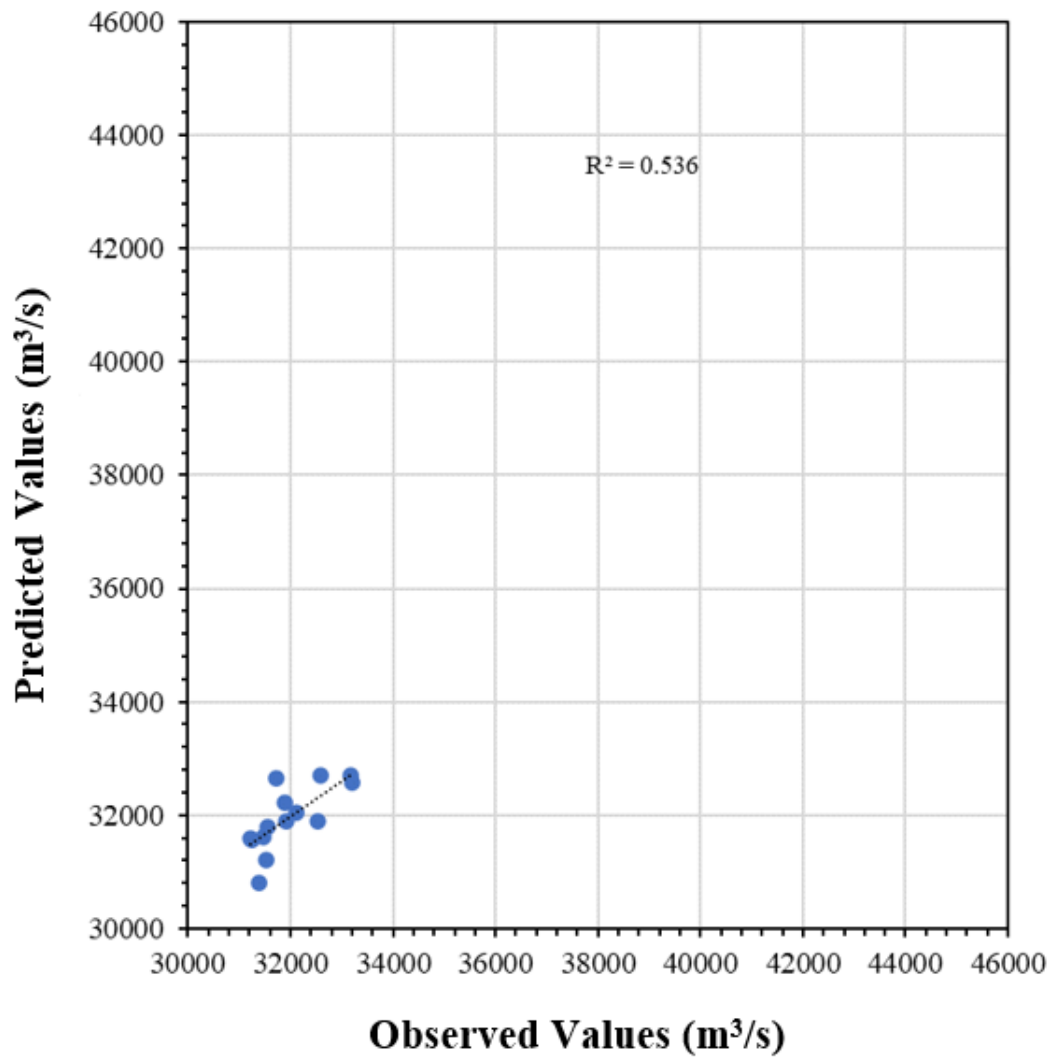


Figure 4.10 Coefficient of Determination in the testing step

4.5 Conclusion

Accurate prediction of river discharge allows better management of water resources and infrastructures. Complex changes in the river morphology and discharge fluctuations due to climate change led to the need for updating the relationship between the water stage and the discharge. A large data collection has taken place in the Congo River basin, and will, soon, allow better understanding of the process occurring in the basin and support the update of predictive model development for infrastructure management and flood control. There is a need for a flexible tool that can be built

from the available data and accurately predict future discharge while allowing parameter updating as more data becomes available.

A Bayesian inference model has been developed to predict the discharge at the port of Kinshasa on the Congo River. The technique is adequate in the context of a reduced amount of data and allows future updating. In addition, the proposed approach does not require the user to define priors since an automatic two-step procedure is used to first identify the priors using Newton-Raphson and then the selected priors are used in the MCMC procedure for parameter updating.

Multiple factors (water stage, water velocity, section width, section area) were used in the model where they are allowed to have both linear and nonlinear effects on the discharge response. Their nonlinear partial effects demonstrate the complexity of the relationship between these covariates and the response discharge. In addition, it should be highlighted that the relationship between the water stage and the discharge has two components (linear and nonlinear) that should be considered when predicting the discharge from water stage. The obtained results show a high coefficient of determination (0.99) that is reduced to 0.53 when applied to new unknown data (testing set). The low performance on the testing set is due to the reduced instances in the testing set. The advantage of the proposed model is its ability to accurately predict water discharge from reduced amount of data and its flexibility that allows the updating of model parameters as new data become available. The model will gradually allow the knowledge of processes occurring in the Congo River and better planning of infrastructure management and flow control as Kinshasa is set to become the largest city on the world by 2075 (Hoornweg & Pope, 2017).

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CHAPITRE 5 ARTICLE 3: IMPROVING HYDROLOGICAL MODELING IN LARGE UNGAUGED BASINS: APPLICATION TO THE CONGO RIVER BASIN

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Abstract

Accurate hydrological model simulations in large ungauged basins are crucial for sustainable water resources management. However, hydrological modeling in these basins is challenging due to the lack of data and the high spatial variability of hydrological processes. It has been shown in the literature that multi-model averaging can significantly improve hydrological model simulation skills. In this research it has been proposed, the classic multimodel averaging approach by feeding models with different climate datasets and treating each version as a unique model in the ensemble. The methodology was applied to the Congo River basin, which is one of the largest basins in the world and is poorly gauged. This new methodology used in this study combined two hydrological models, HEC-HMS and GR4J with four reanalysis datasets, Era-Interim, CFSR, JRA-55 and ERA5-Land to produce multi-model/multi-input, multi-model/mono-input, and mono-model/multi-input combined flows using a weighting scheme that minimizes the root mean square error (RMSE) between the combined and observed hydrographs. The performance of the combined models was evaluated using the Nash-Sutcliffe efficiency. The results show that the combined models outperform individual models in simulating the hydrological processes in the Congo River

basin. The multimodel averaging approach helps to reduce model uncertainty, and the multi-input method improves the accuracy of model outputs by incorporating additional data sources. The proposed methodology can be applied to other large basins with limited data availability, contributing to better water resources management and more informed decision-making.

Keywords: Multi-input; Multi-model averaging; Reanalysis; Ungauged basins; Congo River Basin.

5.1 Introduction

An accurate estimation of streamflow is a critical concern in surface hydrology, essential for sustainable water resources planning and management. This task is relatively straightforward for gauged basins, where extensive historical records of hydrological observations are available (Athira *et al.*, 2016). However, assessing water availability in ungauged basins is highly challenging due to the absence of measured data. As pointed out by Sivapalan *et al.* (2003), ungauged basins lack sufficient records, both in terms of data quantity and quality, of hydro-meteorological observations. An ungauged or poorly gauged catchment refers to a basin that lacks comprehensive data for a specific variable of interest (Razavi & Coulibaly, 2013). A substantial portion of river basins, stream reaches, and tributaries around the world are either ungauged or poorly gauged (Mishra & Coulibaly, 2009; Razavi & Coulibaly, 2013; Sivapalan *et al.*, 2003; Young, 2006). Consequently, predicting behavior in ungauged basins poses a significant challenge for hydrologists globally. This challenge arises not only due to the inherent complexity and difficulty of the task but also because of the considerable uncertainties associated (Zamoum & Souag-Gamane, 2019). Consequently, a multitude of studies have endeavored to develop suitable techniques for generating watershed responses in ungauged basins using hydrological models.

Hydrological models are useful tools to provide hydrological information for water resources management. They are used to transform liquid and solid precipitation into flows, using meteorological data to increase their predictive capacity (Singh, V. P. & Woolhiser, 2002; Tarek, M. *et al.*, 2020). Their use in large river basins requires a significant amount of meteorological data to drive them. The performance of the model depends on the quality of the input data used (Lauri *et al.*, 2014).

In various regions across the globe available surface observations may be sparse or non-existent, and often the quality of the historical measurement data can also be questioned, resulting in a lack of meteorological information required by hydrological models. In addition, a marked decrease in the number of weather observation stations has been observed since the beginning of the 21st century throughout the world (Menne *et al.*, 2018; Tarek *et al.*, 2020). To deal with this problem, reanalyses datasets are often used (Beck *et al.*, 2020; Beck *et al.*, 2017; Essou, 2016; Tarek *et al.*, 2020).

Reanalysis datasets are not directly dependent on the density of surface observational networks and have the potential to provide surface variables in areas with little to no surface coverage (Essou *et al.*, 2016; Essou *et al.*, 2017; Essou, G. R. *et al.*, 2016; Tarek *et al.*, 2020). Essou *et al.* (2017) demonstrated that reanalysis products provide good proxies to observations and even superior to interpolated datasets in regions with sparse data.

The advantage of using reanalyses in hydrological modeling lies in their spatial and temporal resolutions which are continually improving (Dembélé, Ceperley, *et al.*, 2020; Essou *et al.*, 2017; Gleixner *et al.*, 2020; Salumu & Fuamba, 2019; Tarek *et al.*, 2020). Despite the quality of the data used as input, studies have shown that the models that performed the best were not consistently the same when applied to different types of basins with varying characteristics and climatic conditions

(Diks & Vrugt, 2010; Qi *et al.*, 2021). This suggests that there isn't a one-size-fits-all model that can be determined in advance as the best choice for every situation involving diverse catchment attributes.

The reason behind this variability is that catchments can differ significantly in terms of their physical features, hydrological behaviors, and the climatic conditions they experience. Because of these variations, a single model might excel in one scenario but perform poorly in another. Even the most advanced model cannot maintain a consistent superiority across all the diverse catchment characteristics and the range of climatic conditions they are subject to (Wan, Y. J. *et al.*, 2021).

This lack of model consistency highlights the need for using multiple models when dealing with a wide array of catchment characteristics and climatic variations. By employing a suite of models, each designed to capture different aspects of hydrological processes and suitable for different contexts, we can increase the chances of obtaining accurate predictions and a better understanding of uncertainty. The choice of which model to use for a specific application should be based on a careful consideration of the particular characteristics of the catchment and the prevailing climatic conditions to ensure more reliable results. Multi-model averaging methods, defined as using the outputs from multiple models to obtain one output, are proved to be more efficient in hydrological modeling than their individual members, by numerous studies (Arsenault *et al.*, 2017b; Arsenault *et al.*, 2015; Wan *et al.*, 2021).

A wide range of methods including arithmetic mean (AM) and weighted averaging (WA) have been used to integrate multiple models (Huo *et al.*, 2019). More sophisticated techniques employ weighted schemes, with differential weightings applied to each input model reflecting their relative advantages or limitations (Wan *et al.*, 2021). Recently,

Granger-Ramanathan averaging (GRA) has been gaining popularity as it outperforms other multi-model combination methods (Diks, C. G. H. & Vrugt, J. A., 2010). Arsenault *et al.* (2015) compared 9 averaging methods over 429 catchments in the United States and concluded that the Granger-Ramanathan averaging type C (GRC) methods perform better than any individual member. Diks, C. G. H., and Vrugt, J. A. (2010) compared seven averaging methods by using eight conceptual watershed models and found that the Granger-Ramanathan averaging method is superior to other methods. Other techniques have been developed to find the best average scheme. Clark *et al.* (2011) concluded that the outputs from one model, calibrated with different objective functions, could be considered as different models, and be used to improve the performance of averaging methods. Arsenault *et al.* (2017b) found that promising model averaging results could be achieved by using the outputs from one model, driven by different climate datasets.

Compared to the use of a single input, the use of hydrological model outputs, driven by multi-inputs as ensemble members, may create a more precise combination for data-sparse regions.

Overall, multi-model averaging technique can significantly improve the accuracy of the streamflow simulations, indicating the importance of weighting the models based on their performance.

Two objectives are defined for the present study. The first objective is to evaluate the hydrological modelling potential of ERA5-Land, CFSR, ERA-Interim and JRA-55 precipitation and temperature datasets over four watersheds hydrologically heterogeneous of the Congo River Basin using two hydrological models.

The second objective is to explore if reanalysis datasets may be used as constructive sources of information for hydrologic modeling in a multi-model and multi-input averaging framework. Specifically, which one of the following combinations may provide the best simulated hydrographs:

- (1) one reanalysis data set and several models; (2) one model and several reanalyses data sets; or
- (3) several models and several reanalyses data sets?

5.2 Study area

This study was carried out in the Congo River basin (CRB). Located in western central Africa, the CRB stands as the continent's mightiest river basin (as illustrated in Figure 5.1a). With a staggering area of 3.7 million km², it is second in size and discharge worldwide, only surpassed by the Amazon. It also claims the title of the world's premier carbon sink (Runge, 2022). Although the Congo River presents a wealth of research opportunities, it has been understudied due to data limitations. Many are keen to explore it but encounter challenges with field data. Spanning from 9°N to 14°S, and longitudinally from 11°E to 35°E, the basin is shared among nine countries: Angola, Burundi, DR. Congo, Republic of Congo, Cameroon, Central African Republic, Rwanda, Tanzania, and Zambia (Aloysius & Sainers, 2017). As of 2020, it hosts roughly 139 million residents, a number projected to surge, particularly in Central Africa. By 2035, a 60% increase is expected, doubling by 2050. This growth will inevitably encroach upon forested regions, intensifying demands on agriculture and accelerating deforestation. The CRB's water is essential for sustaining local communities, offering drinking water, food, and power generation. A significant portion of the CRB lies above the Equator. Its equatorial positioning exposes it to varied climatic conditions. While its extremities experience marked dry and wet periods, the equatorial middle enjoys two rainy seasons (Bultot & Griffiths, 1971). The northern and southern CRB experience their peak rainfalls in June-July-August and December-January-February, respectively. In the central region, the primary rainy period falls between September-October-November, with a secondary one from March-April-May. On average, the basin receives about 1500 mm of rain annually. Covering 45% of the CRB, the rainforests here remain relatively untouched compared to

their counterparts in the Amazon and Southeast Asia (Aloysius & Siers, 2017; Gibbs et al., 2010; Nilsson et al., 2005). Grasslands and savannahs, marked by tall grasses, dense woodlands, and low-lying shrubs, also occupy 45% of the area (Adams *et al.*, 1996; Bartholome & Belward, 2005; Hansen, M. C. *et al.*, 2008; Laporte *et al.*, 1998). Meanwhile, water bodies, mainly lakes and wetlands, make up about 2% and are primarily found in the basin's southeastern and western equatorial sections (Figure 1b). The soil profiles of the CRB, depicted in Figure 1c, range from various clay types to sandy loams (Matungulu, 1993; Van Velthuisen & Verelst, 2009). Although these soils are generally deep and offer good drainage, they're acidic, nutrient-deficient, and show low potassium supply and cation exchange capacities (Matungulu, 1993). For easier analysis of rainfall and runoff patterns, the CRB was sectioned into four: northern (NC), equatorial (EQ), southwestern (SW), and southeastern (SE). The EQ hosts the majority of rainforests, while the SE boasts an intricate network of lakes and wetlands. The bulk of the CRB's populace resides in the NC, SE, and SW regions (Warszawski et al., 2017).

Industrial endeavors, both large-scale and informal like artisanal mining and logging, are proliferating in the Congo (Koenig, 2008). Notable is the Kibali gold mine and its associated 20 MW hydropower plant. There's also significant untapped hydroelectric potential in the Republic of the Congo, with grand plans like the "Grand Inga Dam" poised to dwarf even China's Three Gorges Dam in generation capacity.

Additionally, the river networks span thousands of kilometers suitable for navigation, promoting interbasin water transfer. Given the region's infrastructure challenges, waterways are more viable for trade and transportation (Alsdorf et al., 2016). There are proposals in place, such as the Palambo dam project, aimed at addressing water scarcity issues in places like Lake Chad (Salman & Momha, 2009).

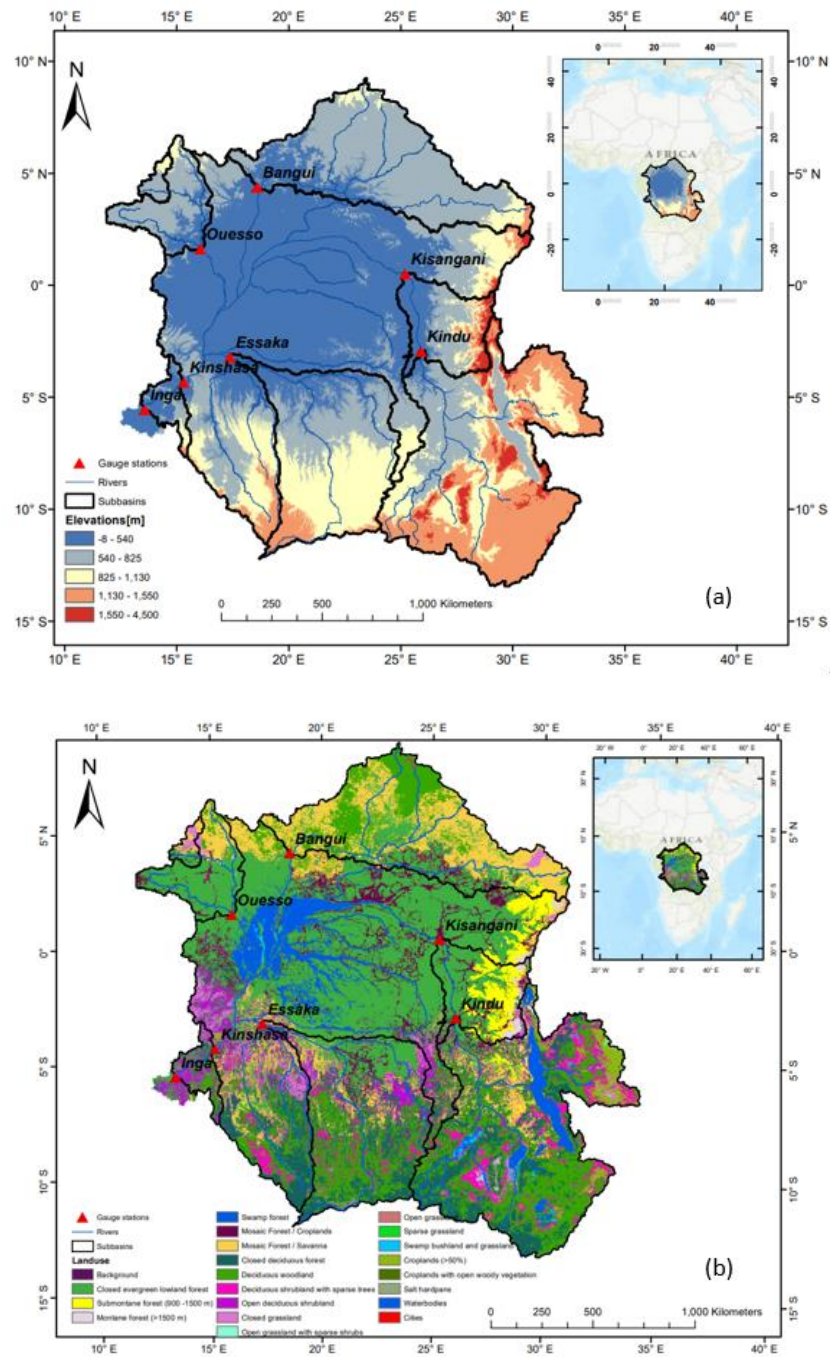


Figure 5.1 (a) DTM, (b) land use/land cover map of the Congo River Basin.

5.3 Data and methods

5.3.1 Reanalysis data

Considering the common period and the availability of datasets used in this study, the analysis period is selected as 1981 – 2000, and the extent is from 15°S to 10°N latitudes and 10°W to 34°E longitudes. The variables chosen for comparison are daily precipitation and temperature at 2 m height above ground surface. These datasets were subbasin-averaged over the Congo River basin. As the hydrological models used in this study required daily precipitations and temperatures, all the precipitation and temperature datasets are converted from sub-daily to daily time scales (mm/day and °C units respectively for daily precipitation and temperature). The spatial resolution for example for ERA5-Land (9 km) and temporal (1h) are better than several observation networks today except for certain parts of Europe and the United States (See table 5.1).

Table 5.1 summarizes general information on all the databases detailed above

Product	Source	Assimilation scheme	Horizontal resolution	Period	Reference
CFSR	Global (National Centers for Environmental Information (NCEI; (www.ncdc.noaa.gov/data-access/model-data/model-datasets/climate-forecast-system-versions2-cfsv2))	3D-VAR	0.313 (lon) x 0.312 (lat)	1979-2009	Saha et al. (2010)
ERA-Interim	Global (ECMWF as part of Copernicus Climate Change Services) (https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/)	4D-VAR	0.75 x 0.75	1979-present	Dee et al. (2011)
MERRA	Global (NASA Modeling and Assimilation Data and Information Services Center (MDISC) (https://disc.sci.gsfc.nasa.gov/mdisc))	3D-VAR, with incremental update	2/3 (lon) x 1/2 (lat)	1979-present	Rienecker et al. (2011)
JRA-55	Global (NCAR Computational Information Systems Laboratory (CISL) Research Data Archive (RDA; https://rda.ucar.edu))	4D-VAR	1.25 x 1.25	1958–2012	Kobayashi et al. (2015)
ERA5-Land	Global (ECMWF as part of Copernicus Climate Change Services) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=form)	4D-VAR	0.1 x 0.1	1950-present	Copernicus Climate Change Service (C3S) (2019)

5.3.1.1 CFSR

The third-generation product called Climate Forecast System Reanalysis (CFSR) was released by the National Centers for Environmental Prediction (NCEP) from a coupled atmosphere-ocean-land surface climate system with an interactive sea ice component. It covers the period from 1979 to the present day and uses a three-dimensional variational data assimilation approach (Saha *et al.*, 2010). CFSR assimilates satellite radiation rather than estimated temperature and humidity values (Wang, W. *et al.*, 2011). Estimates of greenhouse gas concentration changes, aerosols, and solar variations are used as forcings in the CFSR; CFSR also assimilates hydrologic quantities from a parallel land surface model forced by NOAA/Climate Prediction Center (CPC) Merged Precipitation Analysis (CMAP) (Xie & Arkin, 1997) and daily measurement analysis unified CPC (Wang, W. *et al.*, 2011). The horizontal resolution of CFSR is 0.313° (longitude) X 0.312° (latitude), and the CFSR dataset is freely available online (CFSR, 2023)

5.3.1.2 ERA-Interim

ERA-Interim is the third generation product reanalysis released by ECMWF in 2006 (Dee *et al.*, 2011), which replaced its previous generation, ERA-40 (Uppala, S. M. *et al.*, 2005) and incorporates four dimensional variational (4-D VAR) data assimilation, variational bias correction for satellite radiances and other enhancements in data handling. The horizontal resolution of ERA-Interim is T255 (~80 km) with 60 vertical hybrid levels reaching to 0.1 hPa from surface. ERA-Interim data is available at 6-hourly time step from 1 January 1979 to 31 August 2019. It has been superseded by the ERA5 reanalysis.

5.3.1.3 ERA5-Land

ERA5-Land is the fifth-generation reanalysis from ECMWF. ERA5-Land provides hourly high resolution information of surface variables using a significantly more advanced 4D- var

assimilation scheme. The data is a replay of the land component of the ERA5 climate reanalysis with a finer spatial resolution: ~9 km grid spacing. ERA5-Land includes information about uncertainties for all variables at reduced spatial and temporal resolutions. The ERA5-Land is available for public use for the period from 1950 to 2-3 months before the present.

5.3.1.4 JRA-55

JRA-55 is the second reanalysis project (known as the Japanese 55-year Reanalysis) using 4D-VAR data assimilation method and variation bias correction for satellite data, and is an improved version of Japanese 25 yr reanalysis (JRA-25)(Onogi *et al.*, 2007). The horizontal resolution of JRA-55 is reduced Gaussian TL319 (~55 km) with 60 horizontal levels up to 0.1 hPa, and is available at 6-hourly timestep for a period of 55 yr starting from 1958 (Ebita *et al.*, 2011) from NCAR's Research Data Archive.

5.3.1.5 Observed streamflow data.

Streamflows records at each watershed outlet are provided by the R.V.F (Régie des voies fluviales). Figure 5.2 present the plot of observed daily time-series flows at four sub-basins stream gage stations. These data were used to calibrate the hydrological models at each of the 4 catchments and evaluate the hydrological modelling performance. The 4 outlets of the selected catchments are Kindu (25°55'45" lon E; 2°57'10" lat S), Essaka (17°56'30" lon E; 3°24'00" lat S), Bangui (18°35'45" lon E; 3°21'30" lat N), Ouesso (16°05'00" lon E; 1°39' 00" lat N). The availability of streamflow data was the main indicator for watershed delineation and the limiting factor for the simulation length. Missing data were left as they were simply not included in the computation of the evaluation metrics.

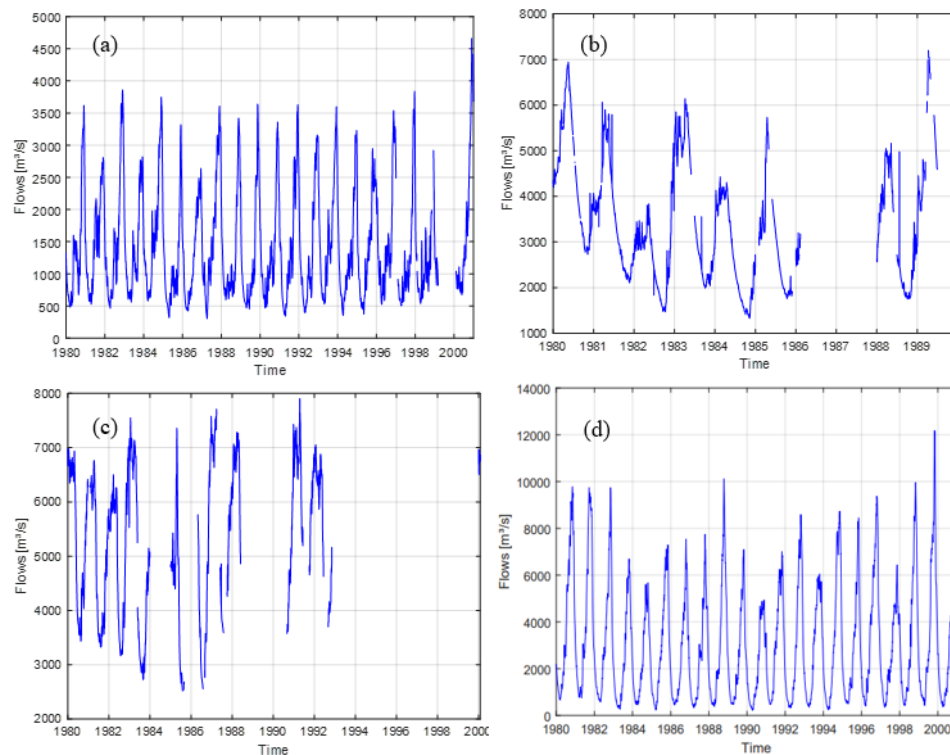


Figure 5.2 Observed daily time-series flows at (a) Ouessou (b) Kindu (c) Essaka and (d) Bangui gauged station (1981-2000).

5.3.1.6 Land use data

The Glob land Cover map (2008–2012) with 300 m spatial resolution was obtained from the European Space Agency, Climate Change Initiative (CCI-LC-PUG, 2016) since land cover is the major factor that affects runoff, evapotranspiration, and soil erosion characteristics of the basin. The Congo River basin is currently dominated by forest as the primary land cover (Figure 5.1b).

5.3.1.7 Soil type data

The other major factor of the basin property is the soil type (Figure 5.1c). The global soil dataset, the Digital Soil Map of the World (DSMW) v3.6 amended by the Food and Agriculture Organization of the United Nations (FAO) in 2007, was used in this study (Zeng et al., 2017).

5.3.1.8 Curve Number map

The Curve Number (CN) is a land-cover index for a given land and soil type to determine the amount of rainfall that infiltrates into the ground and the amount that becomes runoff for a specific storm event (USDA, 1986). In this study, a spatial analysis technique using ArcGIS was implemented for developing a geo-database of the standard curve number (SCN) for the whole Congo River basin (Figure 5.1d).

5.3.2 Hydrological models

5.3.2.1 GR4J

GR4J is a deterministic, conceptual, hydrologic model based on a cascading reservoir production and routing scheme (Perrin et al., 2003). Water is routed from these reservoirs to the outlet in parameterized unit hydrographs (Tarek, M. *et al.*, 2020). The original GR4J model includes four parameters namely the production storage capacity X1, the groundwater exchange coefficient X2, the one day ahead maximum capacity of the routing storage X3 and the time base of unit hydrograph X4, but the version used in this study had nine parameters in order to include a snow-accounting and snowmelt routine, namely CEMANEIGE (Poissant et al., 2017). As HEC-HMS Model, GR4J requires also daily precipitation, temperature, and potential evapotranspiration (PET) as inputs. The PET was computed using the Oudin formulation (Oudin et al., 2005). The model can be calibrated quickly, therefore, various versions of the model have already been successfully applied in different regions (Hublart et al., 2015; Le Lay et al., 2007; Mostafaie et al., 2018).

5.3.2.2 HEC-HMS

HEC-HMS is a deterministic, conceptual, and semi-distributed hydrologic model developed by the US Army Corps of Engineers to simulate the hydrologic response of a watershed subject to a given hydrometeorological input (Scharffenberg et al., 2010). It is designed to simulate the complete

hydrological processes and can be used for both continuous and event-based modelling (Bhuiyan *et al.*, 2017). HEC-HMS has several Loss Method. However, several of them, for example the SCS Curve Number, are not suitable for performing a continuous simulation with dry and wet periods that follow one another over a long period. Therefore, since our objective is to carry out a simulation over several years, the Soil Moisture Accounting Loss Model (SMA) is suitable (Ouédraogo *et al.*, 2018; Singh & Jain, 2015). This conceptual method makes it possible to simulate the movement of water vertically through five surface (Canopy and Surface) and underground (Tension/Upper zone storage, Groundwater layer 1 and 2) reservoirs, making it possible to obtain excellent results. The structure of SMA is described in detail in the HEC-HMS Technical Reference Manual (Feldman, 2000).

HEC-HMS is an integrated physically based simulation tool for all hydrologic processes of dendritic watershed systems and parameters can be directly measured from watershed. Importantly it provides reasonable results, beyond the measurement of the parameters since the model maintains the physical laws of the process.

HEC-HMS model has been used in many studies to analyze urban flooding, flood damage reduction, flood warning system planning, floodplain regulation, flood frequency, reservoir and system operation, environmental flows and river restoration, water supply planning, etc (Hussain *et al.*, 2021). The HEC-HMS is a powerful commonly used physical tool to simulate hydrologic processes. Generally, in ungauged catchments, the choice of physically based hydrologic models is considered better and acceptable (Hussain *et al.*, 2021).

The continuous and event based hydrological modeling of gauged and ungauged dendritic watershed systems has been performed using HEC-HMS model in different regions, example Mona Lake watershed Michigan(Chu & Steinman, 2009); Tonle Sap Lake Basin in Cambodia(Chea &

Oeurng, 2017); Simly dam watershed, Pakistan(Abbas *et al.*, 2015); Abnama Watershed, Iran(Majidi & Vagharfard, 2013); various catchments in African regions (Chakraborty & Biswas, 2021; Gebre, 2015; Singh & Jain, 2015; Verma *et al.*, 2022; Wallner *et al.*, 2012; Zelelew & Melesse, 2018).

However, the initial estimation of model parameters is very important because, if this is not done correctly, it is very likely that the hydrological model will be not able to converge during calibration, resulting in a model that is impossible to calibrate. It requires daily precipitation, temperature, and potential evapotranspiration (PET) as inputs. The PET was computed using the Oudin formulation(Oudin *et al.*, 2005).

5.3.3 Model calibration, and validation

The first step in this study was to calibrate and validate all the sub-catchments with the four reanalysis datasets and the observed hydrometric data. The direct runoff at the four gauged locations, Bangui, Ouesso, Kindu and Essaka was calibrated and validated on daily time scale from 1981 to 2000. Therefore, there were a total of 32 model calibration and validation (4 basins $\times$ 2 hydrological models $\times$ 4 reanalysis datasets). In the scientific literature, there are several strategies for calibrating hydrological models. The most used strategy is to divide the observational data set into two parts, one part for calibration and another one for model validation. This strategy can have several variants, the series can be split into two or three. In the first case, the model is calibrated on one part and validated on the other and in the second case the model is calibrated on one part and validated on the other two (Arsenault *et al.*, 2018; Klemeš, 1986). Another variant consists in considering the years even and odd. In this case, the model will be calibrated on the series of odd years and validated on even years or vice versa (Arsenault *et al.*, 2018; Arsenault *et al.*, 2017a; H. Gowda *et al.*, 2012).

The least used strategy consists in calibrating the model on the entire available record of data, without going through the usual stage of validation of the model. This strategy ensures that the maximum amount of information from the climate data is present in the parameter set and therefore that there is no additional uncertainty related to the choice of calibration and validation years (Tarek *et al.*, 2020). And model performance is statistically better when more years are added to the dataset and validation and calibration skills are not necessarily correlated (Arsenault *et al.*, 2018).

In this study, Both HEC-HMS and GR4J models were calibrated on the odd years in the dataset and the even years were used as the validation period from 1981 to 2000. HEC-HMS has a lot of parameters which makes it difficult to calibrate. We made a first estimate of the parameter set using information from the HEC-GeoHMS Extension, alongside the ArcHydro extension in ArcMap 10.7.1. HEC-GeoHMS returned erroneous values for some physical parameters (reach length, slope...). We have manually corrected these values on QGIS 3.14.

The initial step in HEC-HMS model calibration is a manual adjustment of model parameters using the trial-and-error method, which enables the modeler to make a subjective adjustment of parameters that gives an appropriate fit between observed and simulated hydrographs (Zhang *et al.*, 2013). Then, the simplex optimization method with peak weighted RMS objective function incorporated in HEC-HMS was used for automatic calibration to refine the parameter values. However, GR4J model was calibrated using the Covariance Matrix Adaptation Evolution Strategy (CMAES) algorithm (Hansen, N. *et al.*, 2003; Tarek *et al.*, 2020). CMAES performs well for small and large parameter spaces. It was also shown to be robust and is one of the best auto-calibration algorithms for hydrological modelling (Arsenault *et al.*, 2014; Tarek *et al.*, 2020).

5.3.4 Multi-model averaging methods

Multi-model averaging (MMA) algorithm is a statistical method used to combine the results of multiple hydrological models. Its aim is to improve the accuracy and reliability of predictions. MMA is a type of model averaging that leverages multiple models with distinct structures and assumptions, hoping to capture the intricacy of hydrological systems.

Recent intercomparison studies of such methods have identified the Granger-Ramanathan (GR) weighting schemes as a robust class of algorithms for hydrological modeling applications (Arsenault *et al.*, 2017b; Arsenault *et al.*, 2015; Diks, C. G. H. & Vrugt, J. A., 2010; Granger & Ramanathan, 1984; Wan, Y. J. *et al.*, 2021). The GR approach has three variants, A, B and C (GRA, GRB and GRC). The GRA variant defines the weights based on the ordinary least squares (OLS) algorithm. The RMSE is minimized but the bias is not corrected. GRB is similar to GRA, but the OLS algorithm is constrained so that the weights sum to unity. Finally, GRC is unconstrained, but the mean values of throughput are bias corrected through the use of a constant term (Arsenault *et al.*, 2015; Granger & Ramanathan, 1984). In this study we used the GRC variant because it is robust and easy to implement. Its performance has been demonstrated in several studies (Arsenault *et al.*, 2017b; Arsenault *et al.*, 2015). The GRC combined flows are computed as follows:

$$\begin{aligned}
 W_{GRC} &= (Q_{sim}^T Q_{sim})^{-1} Q_{sim}^T Q_{obs} - W_0 (Q_{sim}^T Q_{sim})^{-1} Q_{sim}^T l \\
 W_0 &= \frac{l^T \{ Q_{obs} - Q_{sim} \times [(Q_{sim}^T Q_{sim})^{-1} Q_{sim}^T Q_{obs}] \}}{n - Q_{sim} (Q_{sim}^T Q_{sim})^{-1} Q_{sim}^T l} \\
 Q_{GRC} &= Q_{sim} W_{GRC} + W_0
 \end{aligned} \tag{1}$$

Where W_{GRC} = GRC weights; Q_{sim} = $n \times m$ matrix of n daily simulated streamflow values and m ensemble members; Q_{obs} = $m \times 1$ vector of observed streamflow; l = unit vector of length

m; W_0 = bias correction term; Q_{GRC} = combined streamflow; and superscript T = matrix is transposed.

3.5. Application of Multi-model and Multi-Input averaging approach

The Multi-model and multi-input averaging approach was applied only on Bangui sub-basin considered as our benchmark because it is the only one sub-basin without missing data in observed discharge stage. The hydrological models were run for Bangui sub-basin using their optimal parameter set and the corresponding reanalysis data on the calibration period for a total of 8 simulated hydrographs (2 hydrological models $\times$ 4 datasets). Different combinations of models were generated for each of the trials. For the calibration period, the GRC weighting approach was applied to generate the weights according to the simulated and the observed hydrographs. Once the weights were computed the hydrological models were run once again, this time for the validation period. The same weights were applied to the 8 members to generate a single weighted hydrograph which was assessed using the Nash-Sutcliffe Efficiency metric.

5.4 Results

5.4.1 Performance of Mono-model and mono-input

The first step in this work was to calibrate and validate HEC-HMS and GR4J models for four sub-catchments of the CRB (Bangui, Essaka, Kindu and Ouesso) using four reanalysis data set (CFSR, ERA-Interim, ERA5-Land, JRA-55). In doing so, it was generally found that the JRA-55 reanalysis did not yield acceptable results. The bad set of parameters and the inability of the models to adapt to the reanalysis were the main causes of this poor performance.

As mentioned above, the model performance was assessed using the Nash-Sutcliffe Efficiency metric (NSE). The NSE values obtained over the calibration and validation period at Bangui gauging station, using different reanalysis data are shown in figure 5.3 for GR4J model and figure

5.4 for HEC-HMS. From figure 5.3 & 5.4, it is seen clear that ERA5-Land is by far the best reanalysis dataset for hydrological modelling, the CFSR dataset is ranking second, ERAI occupies the third position, and JRA55 is the last. The calibrated model performance evaluation in simulating streamflow at the Bangui gauging station using ERA5-Land reasonably reproduces the observed streamflow. The observed versus simulated streamflow hydrograph analysis (Figure 5.5 & 5.6) reveals a good agreement between the two. It is also interesting to note that HEC-HMS model responds similarly to different reanalysis data at the Essaka, Kindu, and Ouesso gauging stations. ERA5-Land is the most efficient followed by CFSR then ERAI, and finally JRA55 (Figure 5.8, 5.10 & 5.12). This order was respected both for the model calibration and for the model validation. However, GR4J model does not perform well at the Kindu and Essaka gauging stations (see Figure 5.9 & 5.11). This could be well explained by the high missing data rates at these two gauging stations.

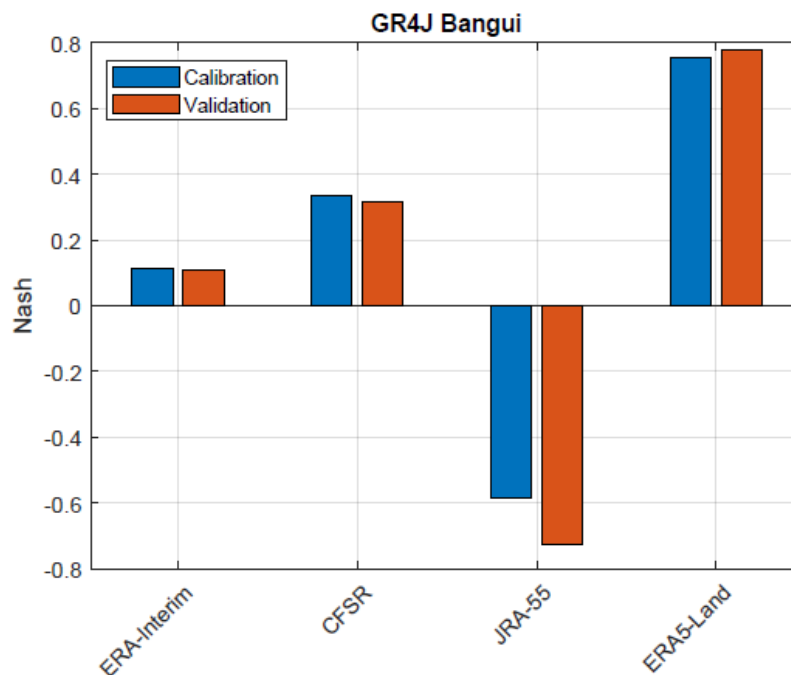


Figure 5.3 NSE values in calibration & validation for the GR4J model at Bangui outlet

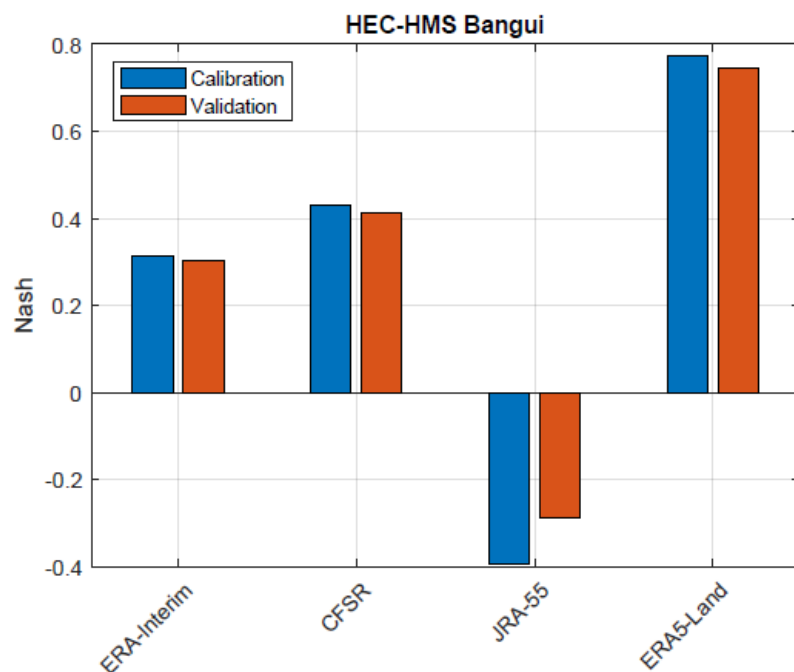


Figure 5.4 NSE values in calibration & validation for the HEC-HMS model at Bangui outlet

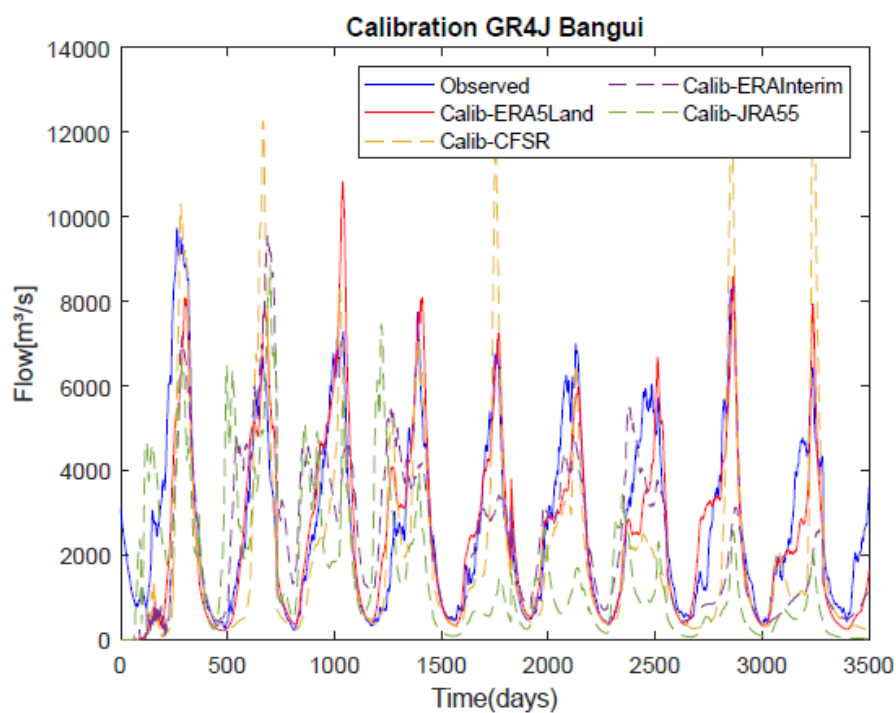


Figure 5.5 Observed and simulated streamflow hydrograph at Bangui outlets for the calibration period

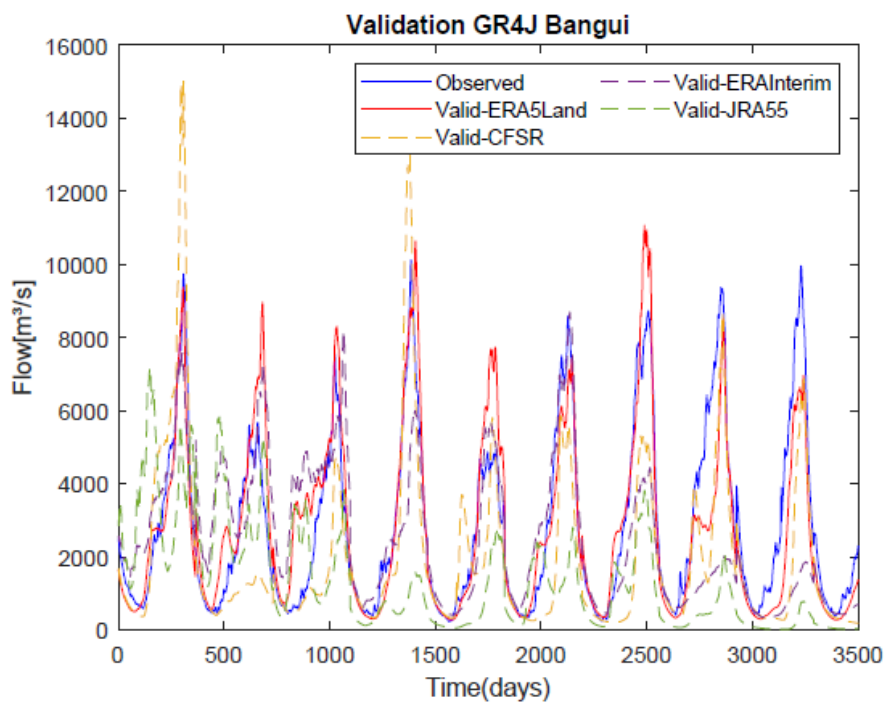


Figure 5.6 Observed and simulated streamflow hydrograph at Bangui outlets for the validation period

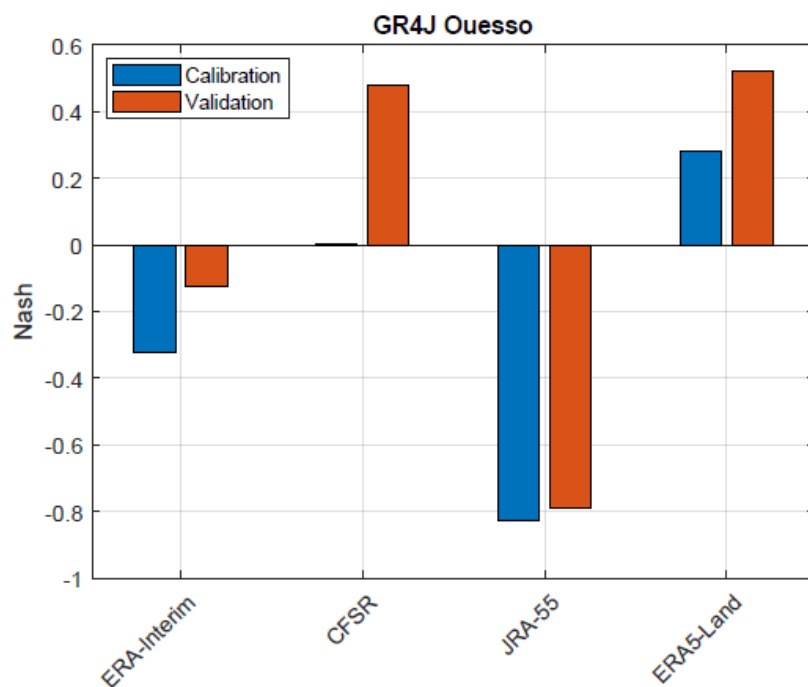


Figure 5.7 NSE values in calibration & validation for the GR4J model at Ouesso outlet

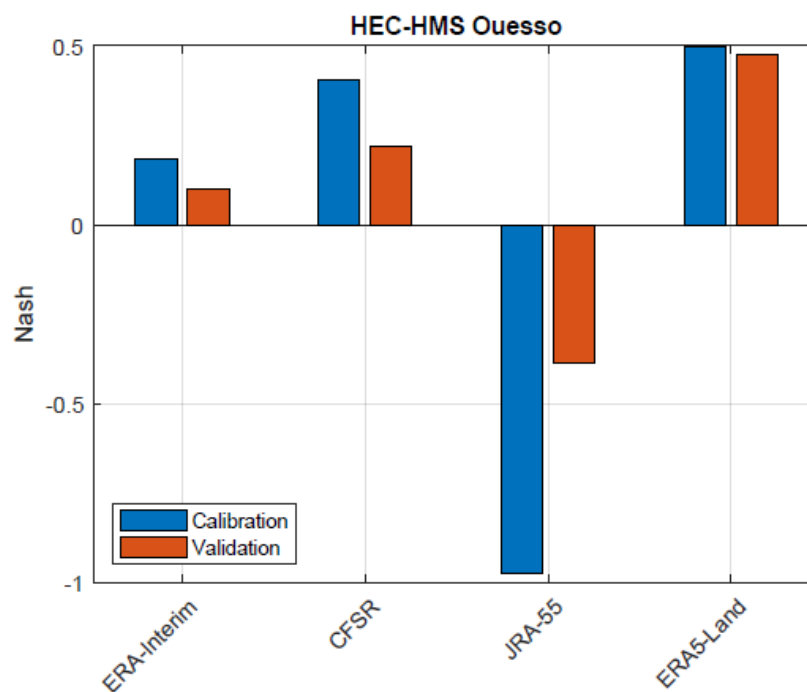


Figure 5.8 NSE values in calibration & validation for the HEC-HMS model at Ouesso outlet

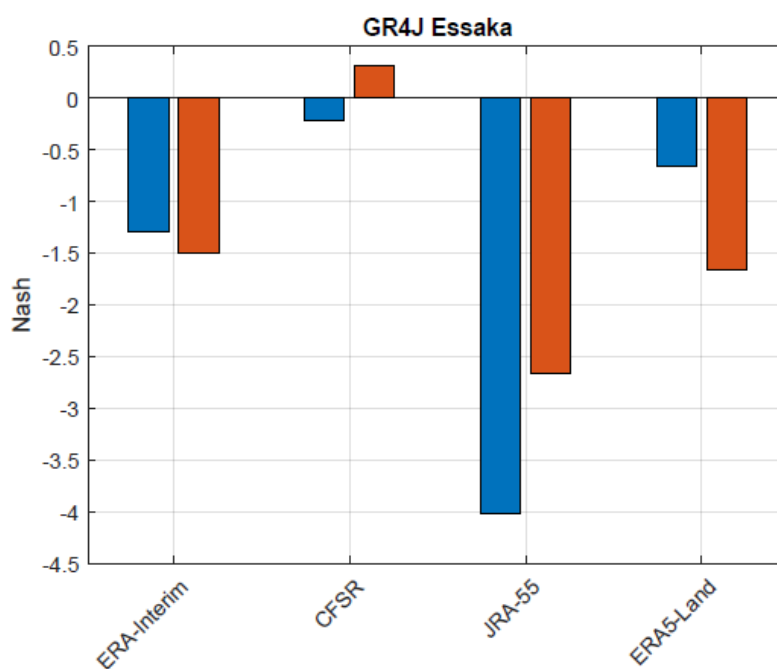


Figure 5.9 NSE values in calibration & validation for the GR4J model at Essaka outlet

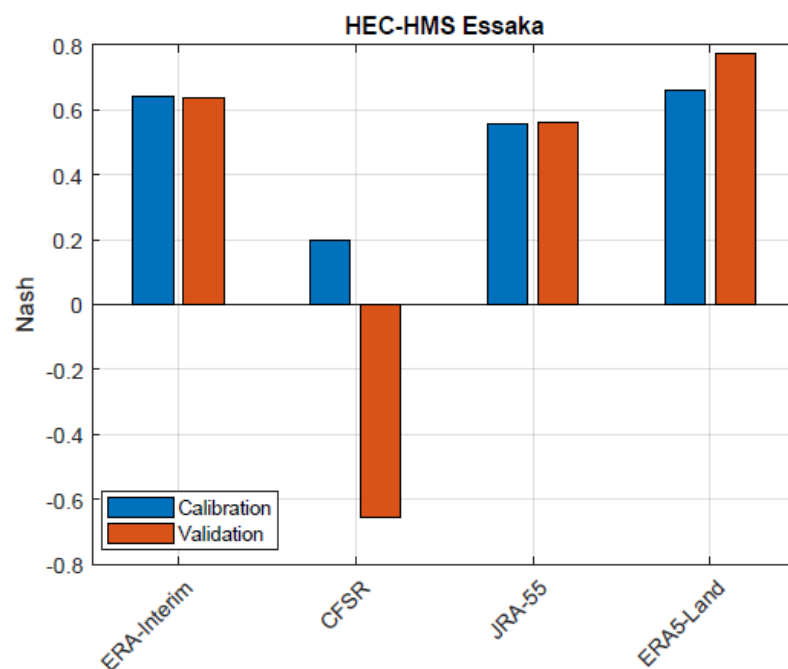


Figure 5.10 NSE values in calibration & validation for the HEC-HMS model at Essaka outlet

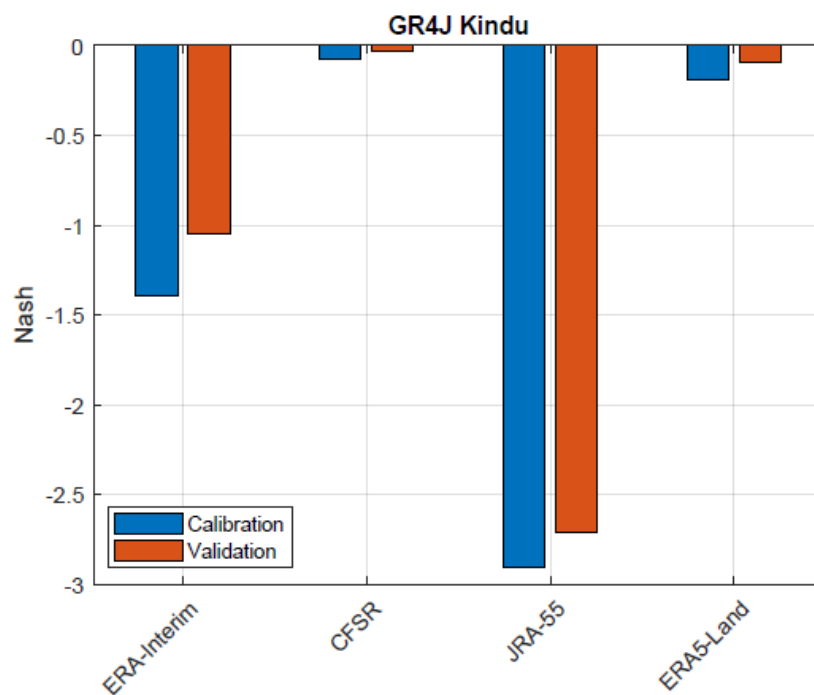


Figure 5.11 NSE values in calibration & validation for the GR4J model at Kindu outlet

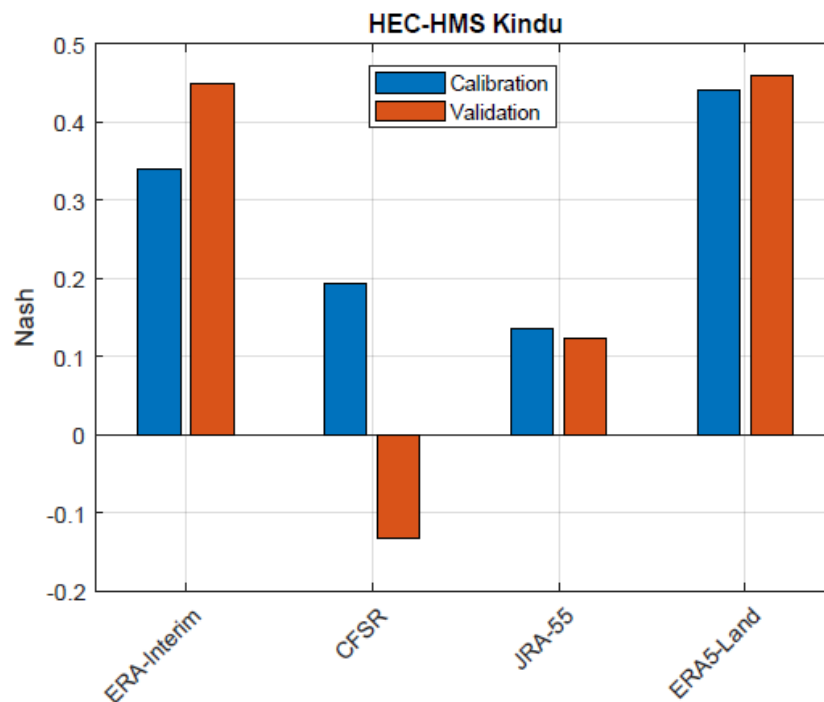


Figure 5.12 NSE values in calibration & validation for the HEC-HMS model at Kindu outlet

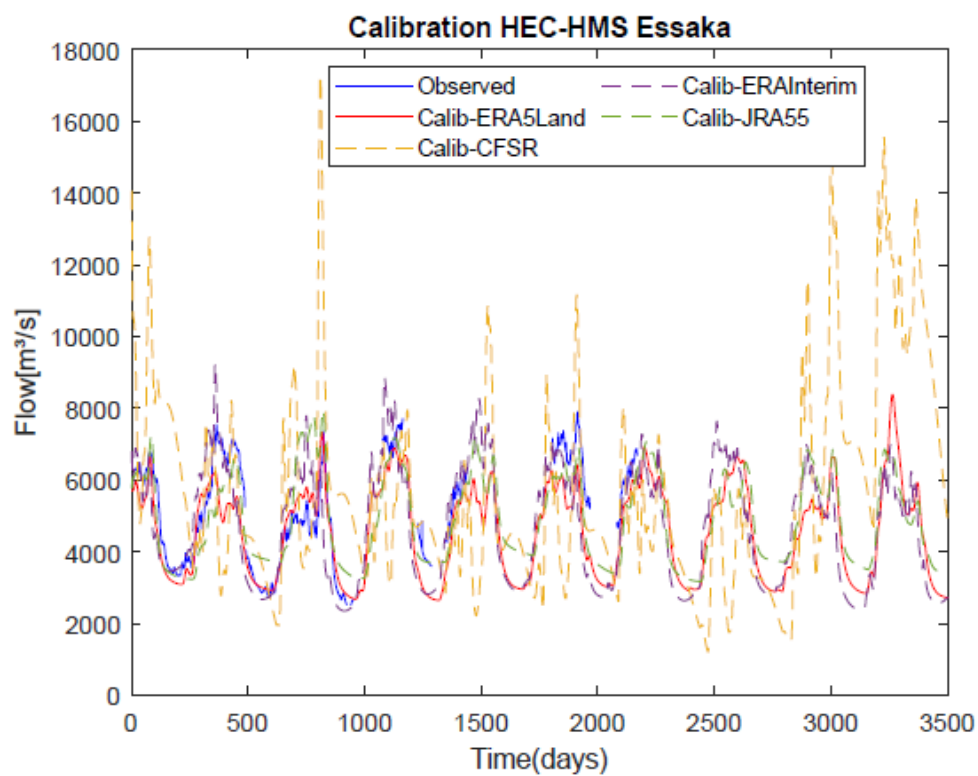


Figure 5.13 Observed and simulated streamflow hydrograph at Essaka outlets for the calibration period

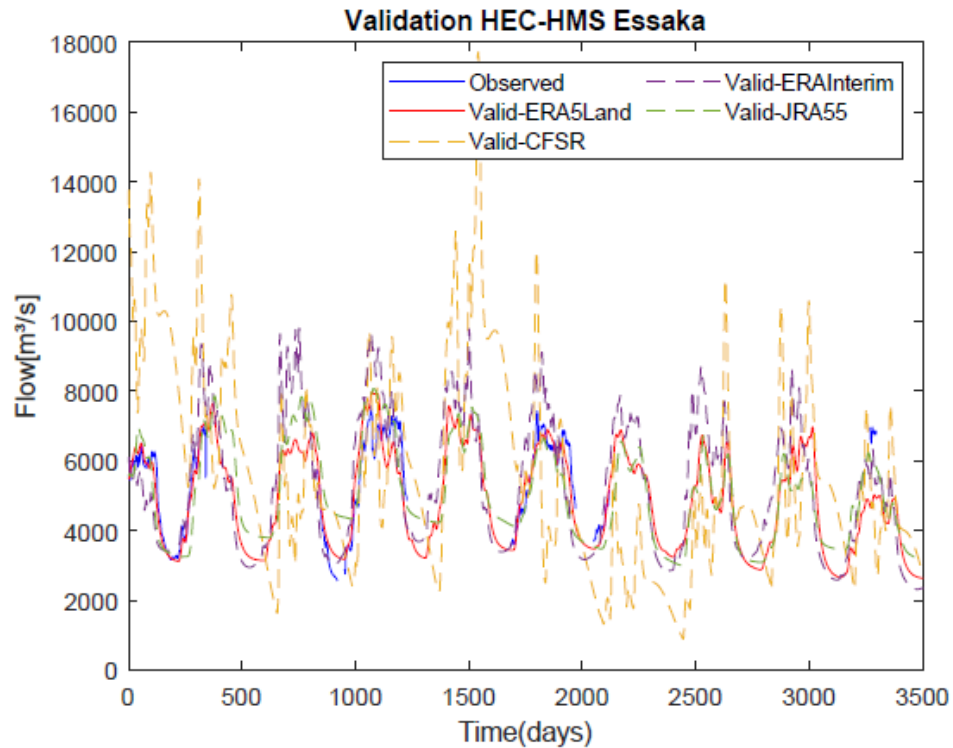


Figure 5.14 Observed and simulated streamflow hydrograph at Essaka outlets for the validation period

5.4.2 Performance of the multi-model averaging methods

Current literature suggests that multi-model averaging can improve simulation accuracy over the best individual model in the ensemble (Arsenault *et al.*, 2017a). As mentioned above, we will verify that this is the case in the Bangui sub-basin (Our benchmark) in this article. The classic multi-model averaging approach will be tested on all scenarios.

First, a model will be tested with the four reanalyses (mono-model/multi-input) then two combined models will be tested on one reanalysis at a time (multi-model/mono-input) and finally the two models will be tested on the four reanalyses (multi-model/multi-input).

5.4.2.1 Performance of mono-model multi-input

The purpose of this section was to measure the effects of mono-model/multi-input averaging. To this end, we ran the HEC-HMS and GR4J models with the four reanalysis datasets, producing four members each. Figure 5.15 shows the hydrographs of all members including that of the mono-model/multi-input averaging, while Figure 5.16 shows the NSE results. This type of mono-model/multi-input averaging increases model performance.

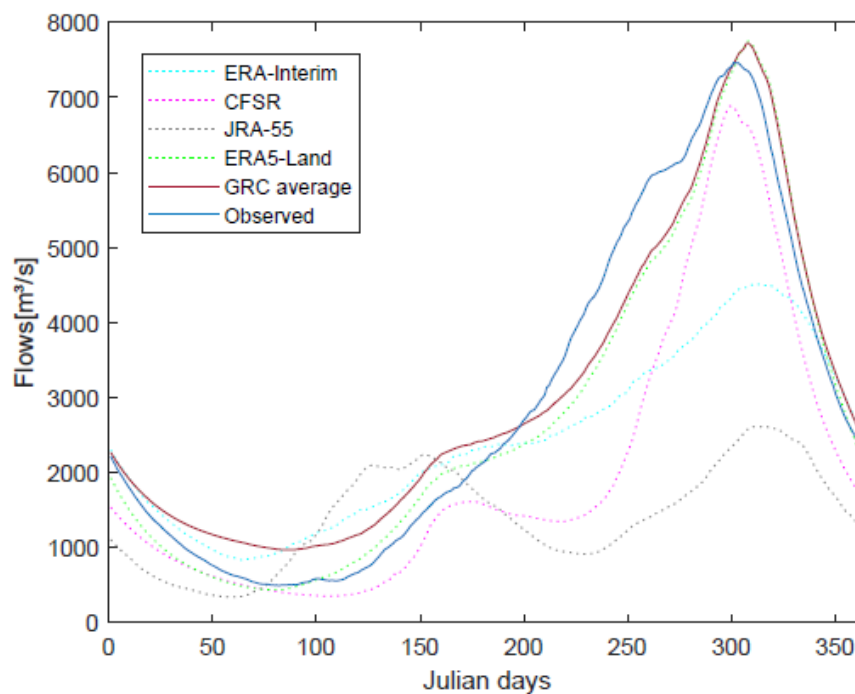


Figure 5.15 Hydrographs of 4 members from GR4J model and the GRC average compared to the observations for the Bangui catchment with the most improvement

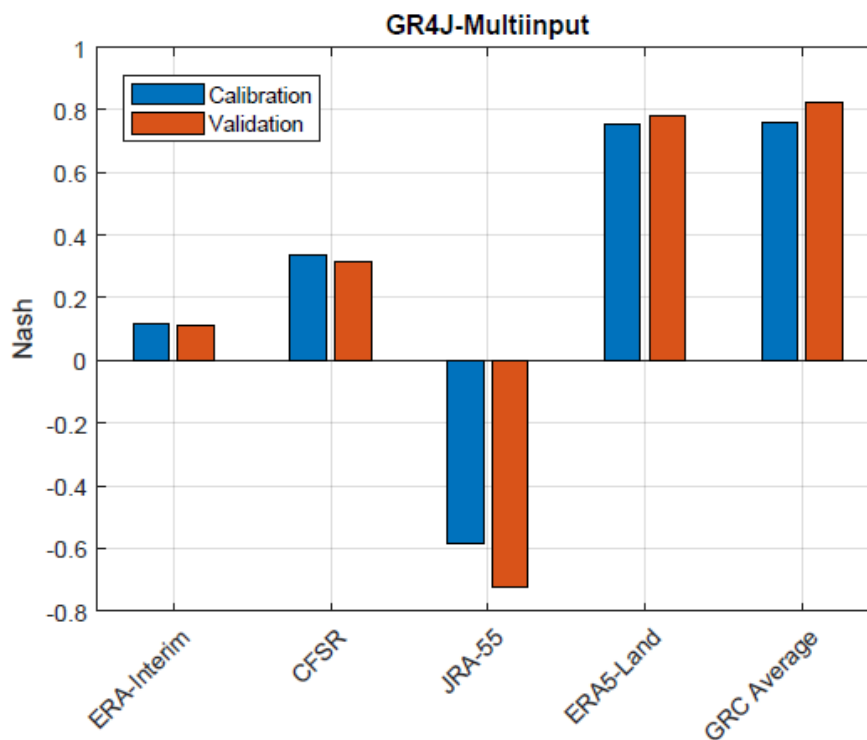


Figure 5.16 Mono-model (GR4J) multi-input averaging results

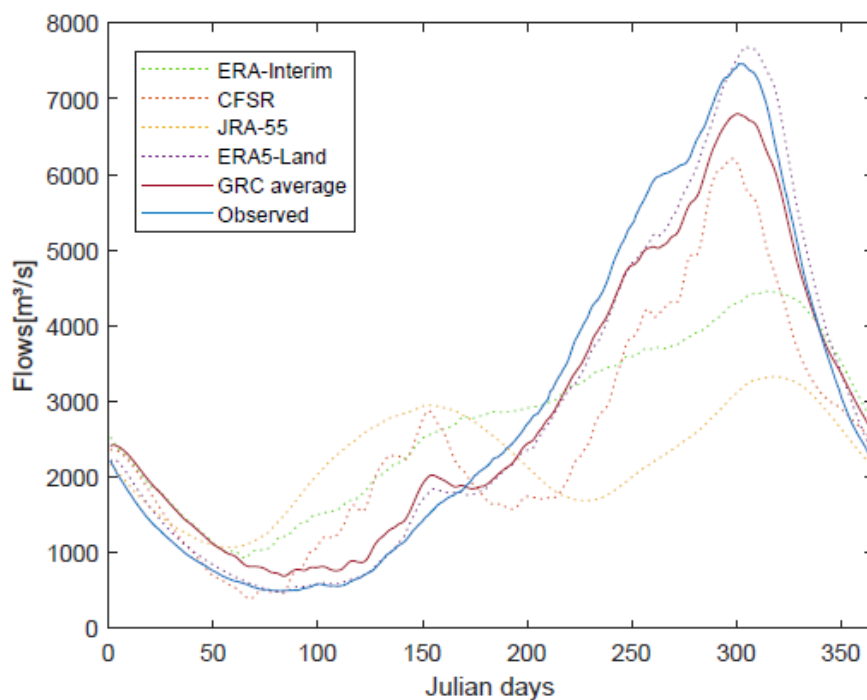


Figure 5.17 Hydrographs of 4 members from HEC-HMS and the GRC average compared to the observations for the Bangui catchment with the most improvement

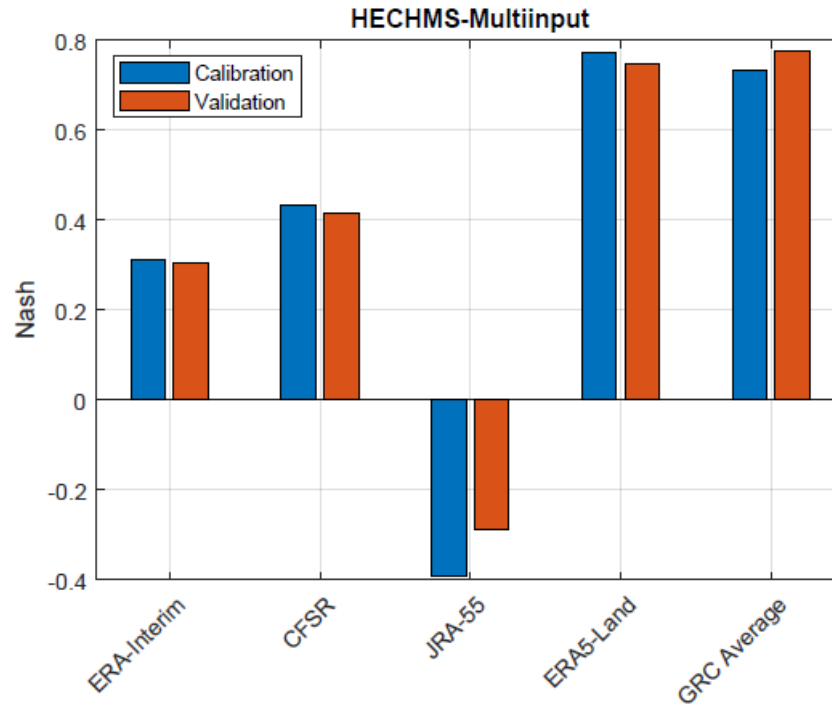


Figure 5.18 Mono-model (HEC-HMS) multi-input averaging results

5.4.2.2 Performance of multi-model mono-input

In this section, the multi-model averaging was conducted on the four climate datasets independently. Figure 5.20 shows the NSE values in calibration and validation for the four-reanalysis data set. The GRC averaging improved the Nash Sutcliffe Efficiency of the generated hydrograph compared to the other individual models in all cases (Figure 5.19). It is clear that this type of multi-model averaging increases performance.

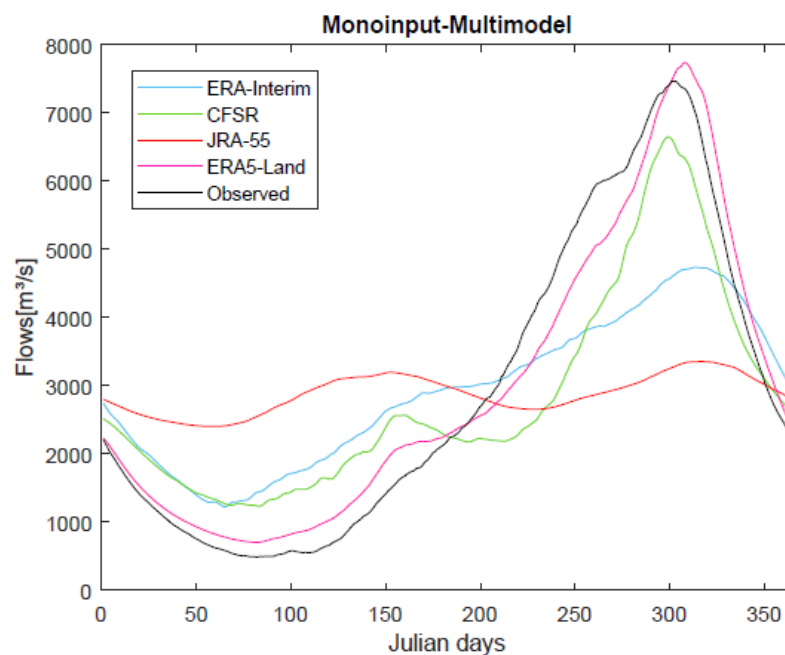


Figure 5.19 Combine HEC-HMS & GR4J hydrographs of 4 members compared to the observations for the Bangui catchment with the most improvement

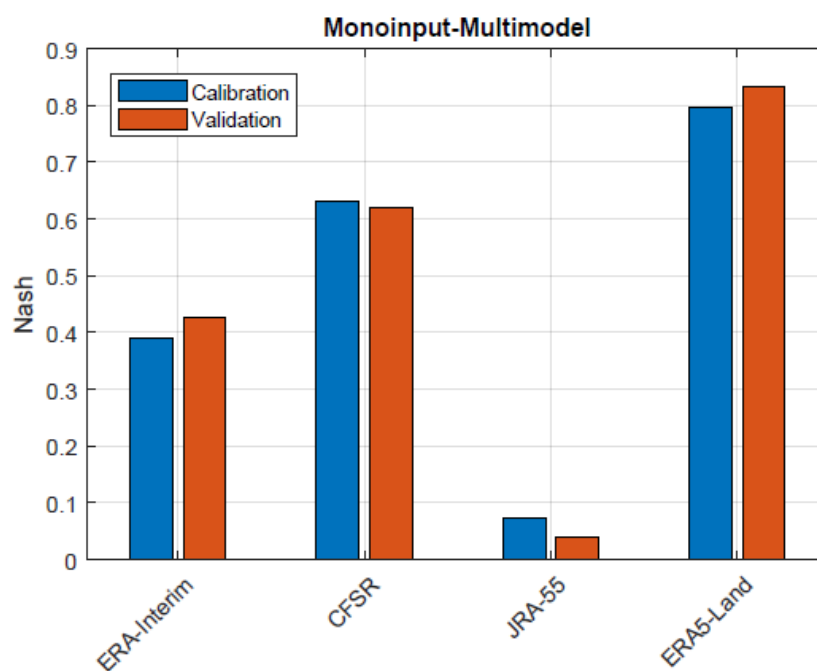


Figure 5.20 Multi-model (HEC-HMS&GR4J) mono-input results

5.4.2.3 Performance of multi-model multi-input

Finally, an 8-member multi-input, multi-model averaging approach was tested, and the results are presented in Figures 5.21&5.22. It is quite clear from Figure 28 that the multi-model/multi-input approach improved performance by a good margin. The NSE value increased by 0.092 in the calibration period and by 0.076 in the validation period using multi-model/multi-input averaging when compared to the best performing single member of the ensemble.

Overall, it can be seen that the GRC average outperformed the individual members. The individual catchment gains in performance for each model/reanalysis data pair despite the worst performance of JRA-55 in all the catchment studied. The GRC average has an NSE of 0.824 in the calibration period and 0.853 in the validation period, whereas the best individual model has an NSE of 0.773 in the calibration period and 0.777 in the validation period. Figure 5.21 show how the averaged hydrograph outperforms the individual members.

The increase in performance was analyzed further to determine possible number of times the multi-model and multi-input averaging had a higher NSE than the best individual member in the ensemble.

First, we compared the averaged flow to the best member within each group; secondly, we compared the 8-member ensemble average to the best member from each other groups; the results are presented in Figure 5.23.

From Figure 5.23, the 8-member average outperformed the best member from each of the groups than the GRC average from within the same groups. This means that the information provided by the 8 members was actively used to improve performance. For example, the four-member GR4J GRC average scored higher NSE values than the best individual member and the four-member HEC-HMS GRC average scored higher NSE values than the best individual member, whereas the

8-member GRC average showed similar improvements over the both GR4J GRC average and HEC-HMS GRC average. It is also interesting to note that the improvements using the GRC average were proportional to the overall model performance. The GR4J model, which offered the least stellar performance, benefitted the most when the 8-member GRC average is compared to the best member of that group.

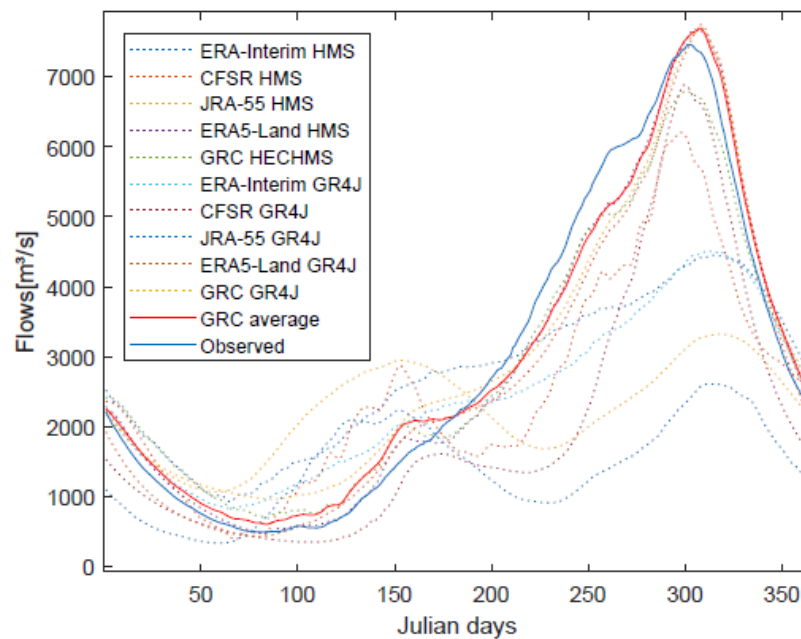


Figure 5.21 Hydrographs of 8 members and the GRCs average compared to the observations for the Bangui catchment with the most improvement

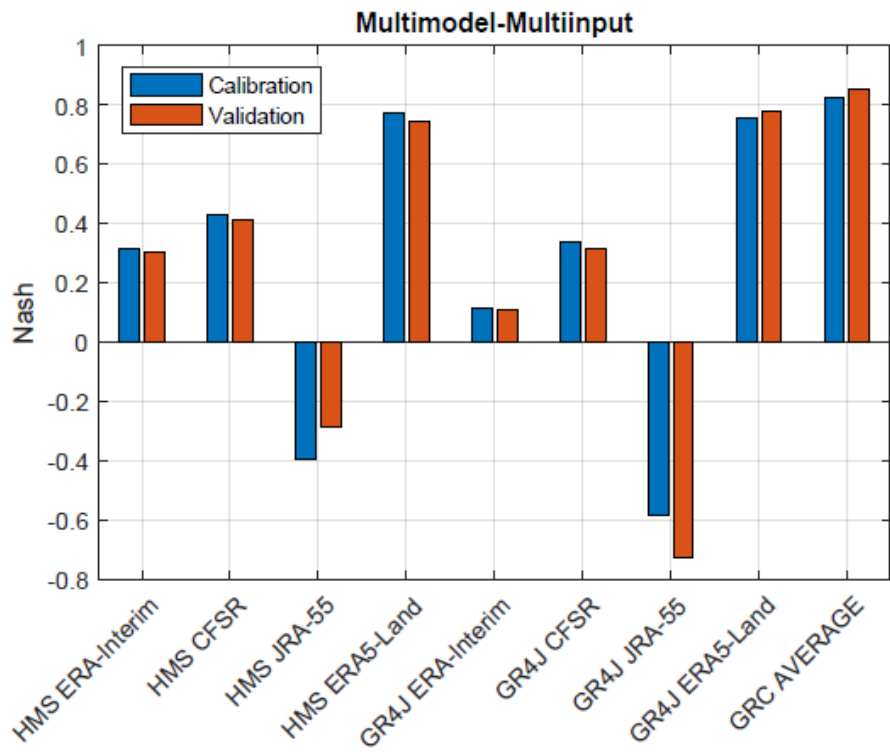


Figure 5.22 Multi-model, multi-input averaging results

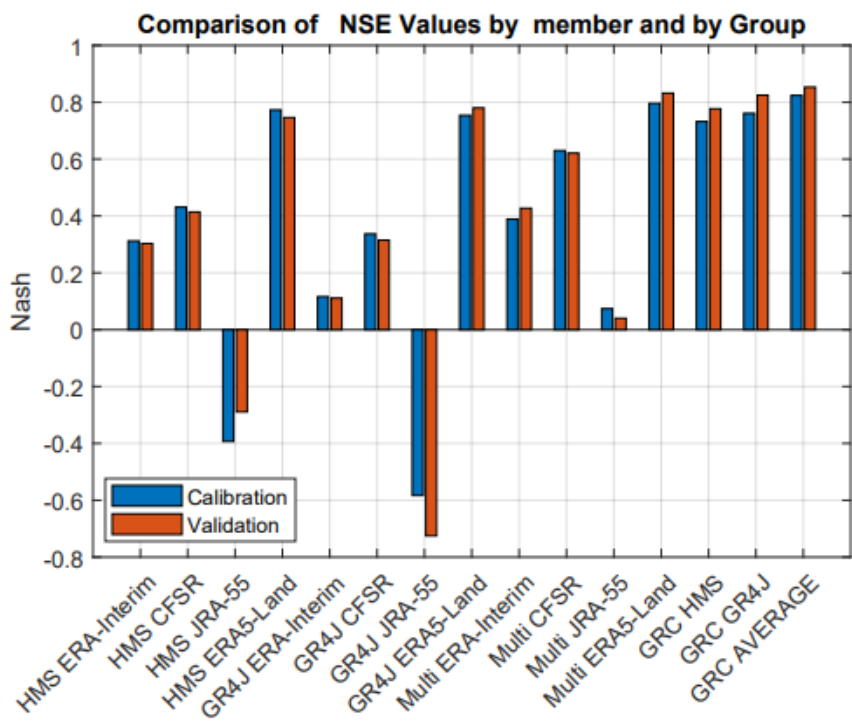


Figure 5.23 GRC Average Returns higher NSE Values than the best member in the group

5.5 Discussions

5.5.1 Performance of global reanalysis products for hydrological modelling in CRB

In the first part of this study, we have investigated how well global reanalysis products can simulate river flows when used in hydrological modelling in the CRB. Two hydrological models, HEC-HMS and GR4J were run in four catchments with distinct geographical and climatic environments in the Congo River basin.

The models Performance were evaluated by means of the NSE metrics. For each of the catchments, the overall results show that the ERA5-Land reanalysis outperforms the other reanalysis datasets, while CFSR comes second followed by ERAI, and finally JRA-55. This hierarchy of reanalysis data in the hydrological simulation results is respected for both considered models. The best performing model is the one that has been forced by the reanalysis of a better spatial resolution. This means that the spatial resolution of the reanalysis data is of paramount importance in hydrological modelling. These results are consistent with those of previous research undertaken in different regions around the world, at different spatio-temporal resolutions and used in other types of hydrological models (Tarek, M. *et al.*, 2020; Wanzala *et al.*, 2022; Xu *et al.*, 2022). They contradict the results of (Gascon *et al.*, 2015; Nkiaka *et al.*, 2017a) who estimated in their studies that the spatial resolution of the reanalyses had no impact on the hydrological simulation. Our results also contradict the finding of (Fu *et al.*, 2011) who demonstrated that, the impact of spatial resolution of rainfall was insignificant for catchment sizes above 250 km² and negligible for catchments larger than 1000 km².

Several studies have shown that the accuracy of a simulation based on atmospheric reanalysis data was equivalent or superior to that of meteorological observation stations for certain scenarios.

Auerbach *et al.* (2016) spatially interpolated the CFSR, the results were consistently equivalent to or better than individual weather stations located 25 to 50 km from the center of the basins. Essou *et al.* (2017) investigated three reanalyses, ERA-Interim, CFSR, and MERRA and one gridded observations database over Canada, Natural Resources Canada (NRCan) The results indicate that for hydrological modeling in regions with high spatial variability of precipitation, reanalyses data perform better than gridded observations when the weather station density is low. Also, studies have shown that the differences between the reanalysis data and the observed data were small enough to allow the direct use of the reanalysis data directly in a hydrological model, without the need for bias correction (Sabarly, Essou, Lucas-Picher, Brissette, *et al.*, 2016). We conclude that, in the absence of gauged meteorological data, reanalysis data could constitute a good surrogate product as input for hydrological modelling in data-scarce areas such as the Congo River basin.

5.5.2 Differences between the HEC-HMS and GR4J hydrological models

In this study, two hydrological models were selected to perform the hydrological evaluation of the reanalysis datasets. In normal conditions i.e., no missing data in discharge series, both models were shown to perform generally well over the catchments used in this study, as can be seen in Figures 9&10. Interestingly, both GR4J and HEC-HMS return similar results for any reanalysis dataset in Bangui catchment. However, HEC-HMS performs better than GR4J everywhere data missing in discharge series, that can be attributed to its more flexible model structure and parameterizations that can better adapt to various hydrological conditions. Since the main objective of this study was to evaluate the reanalysis dataset for hydrological modelling, the interest is not to compare the hydrological model performances, but to compare the reanalysis-driven simulations to the others for each model. In both cases, as can be seen in Figure 5.23, ERA5Land-driven hydrological models clearly outperform all other reanalysis-driven models, which shows that the precipitation

and temperature scheme in ERA5-Land is superior to that in ERA-Interim, CFSR, and JRA-55 for hydrological modelling purposes. The main finding to this point is that when the observation station network is of poor quality or too sparse, then ERA5-Land can be used as proxy and get an acceptable hydrological response.

5.5.3 Performance of the multi-model averaging methods

The second part of this paper show that the model averaging approach increases the performance in multi-model averaging, multi-input averaging, and in a combination of both. The results are consistently superior (in terms of NSE) with GRC averaging than with the individual models, with only a few cases where the averaging fares worse than the individual members.

Figures 24 and 26 demonstrate that both hydrological models perform quite differently for catchments whose streamflow series have missing data. The HEC-HMS model performed well in Essaka and Kindu even for the JRA-55 reanalysis which posed many problems for the other catchments but GR4J did not perform for these two catchments. However, despite the fact that the variability due to the climate inputs (reanalysis) is much greater for a given model, the combination of the two hydrological models perform equally well with the different climate inputs. This suggests that the multi-input approach can be a powerful tool given a few different sets of climate data, and that the addition of a model, even if it is generally weaker than others used by hydrologists, can still increase the performance by bringing more information to the averaging scheme.

The results of this study obtained from in combining two hydrological models are excellent despite the fact that there were underperforming models in the group. In addition, the fact that the results are also striking in validation shows that although the way the hydrologic processes are handled inside the combination are not well known, it does not suffer from overfitting (Arsenault, R., 2015).

This further proves the effectiveness of this approach, because (Najafi *et al.*, 2011) have proven for example that the use of Bayesian model averaging (BMA) has a net effect to drag down the overall performance of the averaged hydrograph when a model hydrology was working significantly worse than the others in the group. This effect was not found in our study by the fact that the GRC averaging method is much less affected by poor models than BMA (Arsenault *et al.*, 2015). However, other studies have shown that combining multiple models and multiple gridded climate datasets contributes to increased performance (Arsenault *et al.*, 2017a).

5.6 Conclusions

This study was based first on evaluating the reanalysis data as a potential reference dataset for hydrological modelling over the CRB, by performing a large-scale hydrological modelling study using ERA5-Land, ERA-Interim, CFSR and JRA-55 as forcing data to two hydrological models. The results showed that ERA5-Land precipitation and temperature data were greatly improved compared to ERA-Interim, CFSR, and JRA-55. These improvements were then shown to translate well to the hydrological modelling results, where both hydrological models showed significant increases in skill with ERA5-Land as opposed to ERA-Interim, CFSR, and JRA-55. In all cases, ERA5-Land was consistently better than ERA-Interim, CFSR, and JRA-55 for hydrological modelling over CRB. While some limitations could be applied to ERA5-Land, it seems that this reanalysis should be considered a high-potential dataset for hydrological modelling in regions where observations are lacking either in number or in quality.

The second part of the research was based on the multi-model averaging framework with two hydrological models fed climate data from four different reanalysis data set to act as independent models. This allowed reducing the simulated streamflow errors stemming from the model structure as well as from the climate data. The results have shown that the gains in calibration and validation

are much larger than with individual model. It is also shown that the multi-input averaging produces almost equivalent accurate results than multi-model averaging while requiring only one hydrological model. This makes the multi-input approach appealing for operational applications. This study is part of an on-going research aimed at understanding the hydrological process of the Congo River basin with the aim of improving water resources management. The next step of the study will be the use of these results to assess the impacts of climate changes in the Congo River basin.

Acknowledgments.

The authors thank the contribution of the discharge data providers including the Régie des voies fluviales (RVF) and the Commission Internationale du Bassin du Congo-Oubangui-Sangha (CICOS), who facilitated the acquisition of discharge data for the project.

Data Availability Statement.

- Digital Elevation Model (DEM) 90 m of the city of Kinshasa downloaded from <https://earthexplorer.usgs.gov/> (last access: 20 April 2018).
- The Glob land Cover map (2008–2012) with 300 m spatial resolution was obtained from the European Space Agency, Climate Change Initiative (CCI-LC-PUG, 2016; <http://maps.elie.ucl.ac.be/CCI/viewer/download.php>).
- The USDA texture classes of the FAO Digital Soil Map of the World (FAO, 1997). And K-Factor for different soil types is available at <http://www.omafra.gov.on.ca/english/engineer/facts/12-051.htm> (last access: 20 April 2018).

CHAPITRE 6 : ENHANCING HYDROLOGICAL MODELING IN DATA-SCARCE REGIONS: ASSESSING NEX-GDDP DATASET FOR THE NORTHERN SUB-BASINS OF THE CONGO RIVER BASIN

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Ma contribution telle qu'elle sera soumise au journal: Conceptualization, Methodology, Software, Formal analysis, Writing-Original draft, Visualisation.

ABSTRACT

Hydrological modeling in regions with limited data availability presents a notable obstacle due to the paucity of observed data essential for model calibration and validation. Precipitation and temperature time series encounter a multitude of challenges, including short time spans, insufficient spatial coverage, data gaps, and biases originating from various sources. These issues are particularly pronounced in areas like the Congo River Basin. Consequently, the exploration of alternative datasets to serve as substitutes for inadequate or missing weather data emerges as a critical avenue of research. This study assesses the efficacy of a novel, bias-corrected, high-resolution daily downscaled dataset known as NEX-GDDP for hydrological modeling within the Congo River Basin. The datasets can be categorized into two distinct groups: rainfall and temperature projections derived from 13 NEX-GDDP-CMIP6 models and their CMIP5 predecessors. Hydrological simulations were conducted using a lumped conceptual hydrological model, calibrated using historical NEX-GDDP dataset records. Before engaging in hydrological

simulations, thorough evaluations of the NEX-GDDP datasets were performed to gauge their ability to replicate observed monthly precipitation patterns across the basin. The results demonstrate that both CMIP6 and CMIP5 model data effectively capture the spatial distribution of monthly precipitation within the basin. In the realm of hydrological modeling, the NEX-GDDP datasets provide accurate representations of observed discharge patterns. These findings underscore the NEX-GDDP dataset's value as a reliable proxy for gauged precipitation and temperature in the context of hydrological modeling for ungauged basins. Despite the absence of direct observational data, the dataset's high-resolution nature contributes to an enhanced depiction of spatial and temporal climate variations, consequently yielding more precise simulations of hydrological processes. The NEX-GDDP dataset emerges as a dependable alternative when observed data are lacking, enabling the estimation of streamflow, water balance components, and other pertinent hydrological variables within ungauged basins. By bridging data gaps and leveraging its refined resolution, the NEX-GDDP dataset facilitates a more comprehensive understanding of hydrological dynamics in regions where conventional observational data are scarce.

Keywords: Congo basin, hydrological modelling, precipitation and temperature proxies, ungauged basins, CMIP5, CMIP6, NEX-GDDP.

6.1 Introduction

Hydrological models serve as valuable tools for investigating hydrological processes within watersheds where direct measurements are limited (Abbaspour *et al.*, 2015; Ajaaj *et al.*, 2019; Li, H. X. *et al.*, 2009). These models have the capacity to convert climate-related time series data for a watershed, typically consisting of precipitation and temperature records, into simulated flow data. These simulated flows enable the utilization of hydrological models for research, forecasting, and extrapolation purposes. In all instances, the effectiveness of these models is contingent upon the accuracy of the input data utilized. Traditionally, meteorological stations provided the primary observational data for hydrological studies (Essou, 2016). Although these observations offer valuable insights, they are constrained by limitations in temporal and spatial coverage, often featuring low resolutions and short time spans. Furthermore, these data may suffer from gaps, errors, and biases due to measurement instruments (Goodison *et al.*, 1981).

In regions with sparse meteorological station networks or limited historical records, researchers sought alternative sources of meteorological data. These sources encompass historical documents, interpolated gridded data, remote sensing data, atmospheric reanalysis, and outputs from General Circulation Models (GCMs) (Essou, 2016). Each of these data categories presents its own advantages and drawbacks. In this study, we focus on investigating GCM outputs.

All of these data sources have strengths and weaknesses. In this study the GCMs output will be investigated.

One notable advantage of these simulated environments lies in the physical consistency of the data, which adheres to fundamental laws of energy and mass conservation. These models encompass a comprehensive range of relevant hydrological, precipitation, and temperature variables, encompassing both atmospheric and surface hydrology components, necessary for establishing a

comprehensive water balance within a catchment (Essou *et al.*, 2016). Nonetheless, the coarse spatial resolution and temporal limitations of GCM outputs hinder their effectiveness in providing meaningful information at a regional scale (Kour *et al.*, 2016; Wilby, R. L. & Wigley, 1997). Thus, the need arises to convert GCM outputs into localized, high-resolution meteorological data, essential for dependable hydrological modeling, often referred to as 'downscaling' (Hewitson & Crane, 1992; Kour *et al.*, 2016).

Numerous studies in the literature have employed hydrological modeling driven by General Circulation Models (GCMs) (Ardoin-Bardin *et al.*, 2009; Faiz *et al.*, 2018; Giuntoli *et al.*, 2015; Ismail *et al.*, 2020; Kusangaya *et al.*, 2017; Nan *et al.*, 2021; Remesan *et al.*, 2014; Wanders & Van Lanen, 2015; Zheng *et al.*, 2018). As GCM output spatial resolution isn't suitable for representing climate change scenarios at a targeted watershed level due to its larger scale, downscaling becomes necessary to capture the impact of climate change on a catchment (Chiphang *et al.*, 2022; Mahmood *et al.*, 2018; Shin & Yi, 2019).

Presently, the National Aeronautics and Space Administration (NASA) has launched the Earth Exchange Global Daily Downscaled Projections (NEXGDDP) dataset, providing high-resolution global-scale data at 0.25° intervals. This dataset holds promise for assessing future climate change impacts at a watershed level, particularly in river basins characterized by complex topography and climate sensitivity (Chen *et al.*, 2017; Chiphang *et al.*, 2022; Jain, S. *et al.*, 2019). Multiple studies indicate that the NEXGDDP projections of temperature and precipitation, with their high spatial resolution, enhance the understanding of water resource availability under changing climate conditions in both the short and long term, operating at regional and local scales (Bao & Wen, 2017; Bokhari *et al.*, 2018; Chen *et al.*, 2017; Chiphang *et al.*, 2022; Jain, S. *et al.*, 2019). Several studies have been conducted to evaluate historical and future projections of climate datasets

(Bokhari *et al.*, 2018; Musie *et al.*, 2020; Raghavan *et al.*, 2018; Zhang, You, *et al.*, 2018). These datasets emerge as a promising input for climate change impact assessments in areas lacking adequate observational data, like the Congo River Basin.

This study is part of a larger research project examining climate change impacts within the Congo River Basin, aiming to uncover historical and future influences on hydrology and hydropower potential. The current paper aims to explore the viability of employing a newly developed statistically downscaled dataset, NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections), as substitutes for measured precipitation and temperature in hydrological modeling. Specifically, we assess 13 historical CMIP6 datasets and equal number for their predecessors CMIP5 for hydrological simulations within the Bangui watersheds of the Congo River Basin. Prior to hydrological modeling, we evaluate NEX-GDDP and reanalysis datasets' representation of precipitation characteristics across the watershed, utilizing data from 45 weather stations as a baseline.

6.2 Study area and datasets

6.2.1 Study area

The Oubangui river (Fig. 6.1) is the second largest tributary of the Congo River, with a length of 2400 km from the source (Uele River) to its confluence with the Congo River, and a drainage basin of 644 000 km² (Bouillon *et al.*, 2012; Coynel *et al.*, 2005) of which 489 600 km² (76 %) is located upstream of Bangui. . However, the methods used to derive the Oubangui drainage basin area are often not described. For deriving the upstream area of Bangui, we used the 90 m SRTM DEM (Shuttle Radar Topography Mission digital elevation model) (Farr *et al.*, 2007) and an equal-area projection with the WGS84 ellipsoid to derive topographic downslope directions and to link together flow directions and hence the river network (Lehner *et al.*, 2008).

The mean annual precipitation in the catchment is $\sim 1400 - 1540$ mm/yr (Laraque *et al.*, 2001). The hydrology of the Oubangui is characterized by a single main flood peak and maximum discharge typically in October–November. Mean annual discharge has fluctuated between $2120 \text{ m}^3/\text{s}$ (1990) and $6110 \text{ m}^3/\text{s}$ (1969) (Bouillon *et al.*, 2012). The Oubangui is navigable up to Bangui for freight ships coming from Kinshasa and Brazzaville. Further upstream rapids, with shallow water do not allow any navigation by larger vessels (Runge & Nguimalet, 2005). The main hydraulics structure in the Oubangui course is a dam constructed in 1989 at Mobaye.

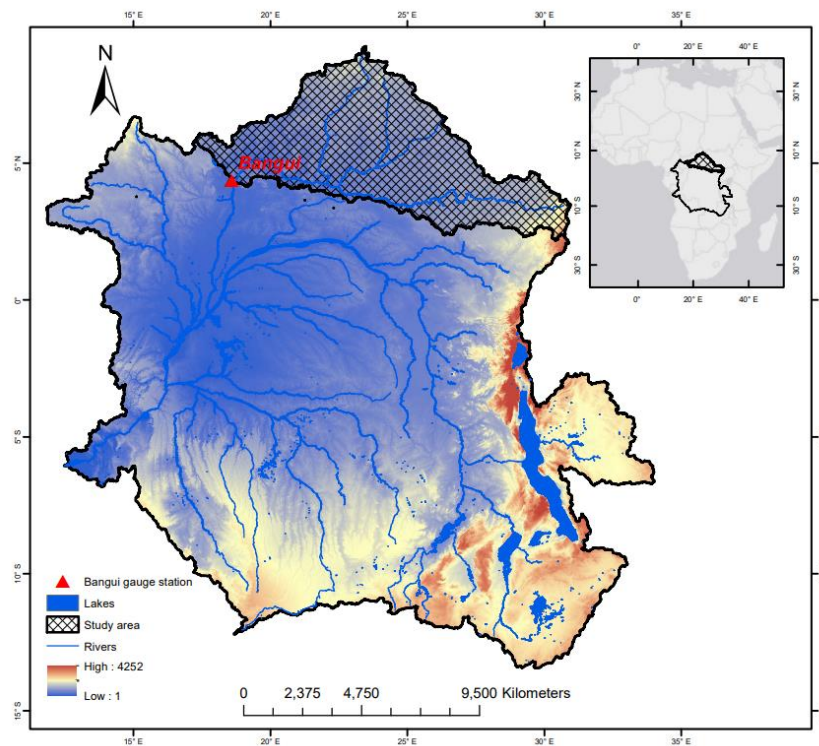


Figure 6.1 Location of the Bangui catchment used in this study.

6.2.2 Datasets

This study made use of 28 different climatic datasets. These datasets can be classified into three categories: (1) observed datasets, (2) reanalysis datasets, and (3) NEX-GDDP datasets.

1. The monthly precipitation of observed and ERA5-Land dataset was used only for comparison of the datasets over Bangui watersheds (BW), and not for hydrological simulation. The observed dataset was used as a baseline for the dataset comparison. The monthly precipitation datasets for 45 weather stations for 1981 year were obtained from CICOS (Commission Internationale du Bassin Congo-Oubangui-Sangha).

2. The ERA5-Land reanalysis data for 1981 year were averaged over the watershed.

3. The NEX-GDDP dataset is a high resolution ($0.25^\circ \times 0.25^\circ$), bias-corrected, and statistically downscaled daily data available for the entire globe. Datasets were generated by downscaling coarser-resolution GCMs. Bias-corrected Spatial Disaggregation (BCSD) method was applied to correct the bias using the gridded Global Meteorological Forcing Dataset (GMFD) of the Terrestrial Hydrology Research Group at the Princeton University (Sheffield *et al.*, 2006). The BCSD method compares the historical period GCM simulations with the GMFD data based on quantile mapping. The obtained correlations are then used to bias correct future projections. Bilinear interpolation technique and scaling factors are used to further disaggregate the bias-corrected coarse resolution GCMs to a $0.25^\circ \times 0.25^\circ$ resolution (Mandapaka & Lo, 2018).

This study uses 13 historical simulations of CMIP6 (Thrasher, B *et al.*, 2021) and equal number for their predecessor CMIP5 (Thrasher, Bridget *et al.*, 2012) for hydrological modelling. The datasets were obtained from an open-source platform, NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) available at <https://www.nccs.nasa.gov/services/data-collections>. The list of GCMs and their developing organization is given in Table 6.1.

Table 6.1 Description of 13 CMIP6 global climate models and their CMIP5 predecessors using in this study

Model Name		Modeling Agency	Resolution Lon. x Lat.
CMIP6	CMIP5		
BCC-CSM2-MR	BNU-ESM	Beijing Climate Center, China Meteorological Administration (China)	0.25° x 0.25°
CanESM5	CanESM2	Canadian Centre for Climate Modelling and Analysis (Canada)	0.25° x 0.25°
CNRM-CM6-1	CNRM-CM5	Centre National de Recherches Météorologiques, France	0.25° x 0.25°
GFDL-CM4-gr2	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, USA	0.25° x 0.25°
GFDL- ESM4	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, USA	0.25° x 0.25°
INM-CM5-0	INM-CM4	Institute for Numerical Mathematics, Russian Academy of Science /Russia	0.25° x 0.25°
IPSL-CM6A-LR	IPSL-CM5A-LR	L'Institut Pierre-Simon Laplace (France)	0.25° x 0.25°
MIROC6	MIROC-ESM	National Institute for Environmental Studies, The University of Tokyo (Japan)	0.25° x 0.25°
MIROC-ES2L	MIROC-ESM-CHEM	National Institute for Environmental Studies, The University of Tokyo (Japan)	0.25° x 0.25°
MPI-ESM-1-2-HR	MPI-ESM-MR	Max Planck Institute for Meteorology (Germany)	0.25° x 0.25°
MPI-ESM-1-2-LR	MPI-ESM-LR	Max Planck Institute for Meteorology (Germany)	0.25° x 0.25°
MRI-ESM2-0	MRI-CGCM3	Meteorological Research Institute (Japan)	0.25° x 0.25°
NorESM2-LM	NorESM1-M	Norwegian Climate Centre (Norway)	0.25° x 0.25°

6.3 Methodology

6.3.1 Comparison of 28 climatic datasets

The monthly observed dataset is used as a baseline in evaluating the performance of the other datasets. The performance of each dataset was evaluated using mean, Mean Bias Error (MBE), Root Mean Square Error (RMSE), Kling-Gupta efficiency (KGE), and Taylor diagrams.

The formulas of MBE, RMSE, KGE and Taylor diagrams are defined as follows:

$$MBE = \frac{1}{N} \sum_{i=1}^N (S_i - O_i) \quad (1)$$

where O_i is the observation value and S_i is the simulation value, and N is the length of the time series.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (S_i - O_i)^2} \quad (2)$$

Where S_i and O_i represent data values for day i from simulation S and observation O datasets, and N is the length of the time series.

$$KGE = 1 - \sqrt{(r - 1)^2 + (\gamma - 1)^2 + (\beta - 1)^2} \quad (3)$$

$$\gamma = \frac{\mu_s}{\mu_o} \quad (4)$$

$$\beta = \frac{\alpha_s / \mu_{os}}{\alpha_o / \mu_o} \quad (5)$$

where r is Pearson's correlation between simulation (s) and observed data (o) and β represents the bias normalized by the standard deviation of the observed data. γ is a fraction of the variation coefficient reflecting spatial variability, and μ and σ represent the mean and standard deviation of the simulation (s) and observed data (o), respectively. The values of KGE vary between 1 and $-\infty$, where 1 indicates a perfect agreement. The KGE is a robust metric and is also commonly used as a metric for spatial assessment (Nashwan & Shahid, 2020).

Taylor diagram (Taylor, Karl E, 2001) quantifies the pattern similarity between two variables (i.e., monthly precipitation from observations and simulation). The standard deviations of the simulation (σ_p) and observation (σ_o), the correlation coefficient (r), and the statistical indicator of root mean

square difference (RMSD) to quantify the difference between the two discrete variables p and o are determined as follows:

$$\sigma_p = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - \bar{p})^2} \quad (6)$$

$$\sigma_o = \sqrt{\frac{1}{N} \sum_{i=1}^N (o_i - \bar{o})^2} \quad (7)$$

$$RMSD = \sqrt{\frac{1}{N} \sum_{i=1}^N [(p_i - \bar{p})(o_i - \bar{o})]^2} \quad (8)$$

where p and o are the mean values, N is the number of datasets that are both temporal and spatial patterns in this study.

The Taylor diagram provides a concise statistical summary of how well the pattern distribution of the two variables matches. The diagram visualizes their correlation, root mean square difference, and variances of data (i.e., standard deviation). In this study, the

Taylor diagram was used to visualize and evaluate the precipitation performance of NEX-GDDP and ERA5-Land over the BW.

6.3.2 Hydrological modelling

6.3.2.1 HEC-HMS model

HEC-HMS (Hydrologic Engineering Center's Hydrologic Modeling System) is a computer-based hydrologic modeling software developed by the US Army Corps of Engineers (Feldman, 2000). It is widely used for simulating the hydrologic processes of rainfall-runoff in a watershed.

HEC-HMS allows engineers, hydrologists, and water resource professionals to analyze and predict the response of a watershed to various precipitation events. The model utilizes both empirical and physical-based methods to simulate the rainfall-runoff process, incorporating various hydrologic

components such as precipitation, evaporation, infiltration, snowmelt, and routing of runoff through the watershed.

The basic principle behind HEC-HMS is to divide a watershed into sub-basins and further divide them into hydrologic response units (HRUs) based on the land use, soil type, and other relevant characteristics. These HRUs represent homogeneous areas within the sub-basins with similar hydrologic properties. HEC-HMS allows users to define the parameters for each HRU, including the soil properties, vegetation characteristics, and routing methods.

HEC-HMS provides a user-friendly graphical interface that enables users to input data, define watershed characteristics, and set up simulation scenarios. It offers a wide range of tools for analyzing and visualizing the simulation results, including hydrographs, time series plots, and maps.

HEC-HMS has several Loss Method. However, several of them, for example the SCS Curve Number, are not suitable for performing a continuous simulation with dry and wet periods that follow one another over a long period. Therefore, since our objective is to carry out a simulation over several years, the Soil Moisture Accounting Loss Model (SMA) is suitable (Ouédraogo et al., 2018; Singh & Jain, 2015).

The SMA simulates the movement and storage of water on vegetation, in soil layers, at the soil surface, and in the soil profile (Bennett & Peters, 2000). The different storage layers in the SMA model include Canopy-interception storage, Surface-interception storage, Soil profile storage, and Groundwater storage. The model calculates the flow into, out of, and between the storage volumes. Precipitation, infiltration, percolation, surface runoff, groundwater flow, and evapotranspiration are all examples of this flow. The amount of water that can infiltrate during a period depends on the amount of water available, the condition of the soil profile, and the maximum infiltration rate

that the model user specifies. For each interval in the analysis, the SMA model computes the Potential infiltration volume.

The outputs generated by HEC-HMS are valuable for a variety of applications, including flood forecasting, water resources management, reservoir operation, and design of hydraulic structures. The model helps in understanding the hydrologic behavior of a watershed, evaluating the impact of land use changes or infrastructure projects, and assessing the effectiveness of different flood mitigation measures(Jiang *et al.*, 2016; Kabeja *et al.*, 2020; Kazezyılmaz-Alhan *et al.*, 2021; Sahu *et al.*, 2023).

HEC-HMS model has been used by several researcher and has shown excellent results worldwide including in African regions(Chakraborty & Biswas, 2021; Gebre, 2015; Singh & Jain, 2015; Verma *et al.*, 2022; Wallner *et al.*, 2012; Zelelew & Melesse, 2018). It requires daily precipitation, temperature, and potential evapotranspiration (PET) as inputs. The PET was computed using the Oudin formulation (Oudin *et al.*, 2005).

6.3.2.2 GR4J

The GR4J (Génie Rural à 4 paramètres Journalier) model is a lumped conceptual hydrological model that is commonly used for simulating daily streamflow in ungauged or poorly gauged catchments. It was developed by the French Institute of Agricultural Research (INRA) to capture the dominant hydrological processes in a simple and efficient manner(Perrin *et al.*, 2003).

The original GR4J model represents the watershed as a single conceptual unit and is based on four parameters that characterize the hydrological behavior of the catchment. These parameters are:

X1: Production store parameter: It represents the storage capacity of the watershed to hold water and release it slowly over time.

X2: Routing store parameter: It represents the time it takes for water to flow through the watershed and reach the outlet.

X3: Maximum potential evapotranspiration parameter: It represents the maximum rate at which water can be evaporated or transpired from the catchment.

X4: Shape parameter: It represents the shape of the unit hydrograph, which describes the response of the catchment to a unit input of rainfall. However, the version used in this study had nine parameters in order to include a snow-accounting and snowmelt routine, namely CEMANEIGE (Poissant et al., 2017). As for HEC-HMS Model, GR4J requires also daily precipitation, temperature, and potential evapotranspiration (PET) as inputs. The PET was computed using the Oudin formulation (Oudin et al., 2005).

The GR4J model has been widely used in various hydrological applications, including flood forecasting, water resources management, and climate change impact assessment. It is particularly useful in situations where limited data are available, as it requires only a small number of parameters and daily precipitation and evapotranspiration data. Although the GR4J model provides a simplified representation of the hydrological processes, it has shown good performance in many catchments worldwide and has been widely applied in practice. Its simplicity and efficiency make it an attractive choice for hydrological modeling in data-scarce regions or when quick assessments are required (Hublart et al., 2015; Le Lay et al., 2007; Mostafaie et al., 2018).

6.3.2.3 Model calibration, and validation

One of the main challenges in large-scale hydrological modelling is the proper estimation of model parameters in model calibration step (Mazzoleni *et al.*, 2019). In this study we calibrated the catchment with the historical period of 26 NEX-GDDP datasets and the Bangui hydrometric data. The calibration period was the odd years from 1981–2000, whereas the validation was only

calculated based on the even years. This allows sampling years in the entire period, thus decreasing the odds of missing a change of hydrological regime between the calibration and validation period. For example, a traditional calibration on the first half of the dataset and validation on the second half could be biased because of a change from a series of humid years to dry years on the threshold date. The proposed method on odd-even years samples the historical records uniformly (Arsenault *et al.*, 2017a). The calibration for GR4J model were performed using the Covariance Matrix Adaptation Evolution Strategy (CMAES) algorithm (Hansen, Nikolaus & Ostermeier, 1996). However, initial step in HEC-HMS model calibration was a manual adjustment of model parameters using the trial-and-error method, which enables the modeler to make a subjective adjustment of parameters that gives an appropriate fit between observed and simulated hydrographs (Zhang *et al.*, 2013). Then, we used the Optimization Trials tool incorporated in HEC-HMS for automatic calibration to refine the parameter values. The objective function used was the Nash-Sutcliffe Efficiency (NSE) metric (Nash & Sutcliffe, 1970) as it is the most well-known continuous streamflow performance measure and is adequate in most cases over long time series. It does have drawbacks, such as heavily weighting peak flows, but it is still regarded as an adequate metric for overall goodness-of-fit evaluation (Arsenault *et al.*, 2017b).

6.4 Results and discussions

6.4.1 Comparison of ERA5-Land, CMIP5 and CMIP6 NEX-GDDP

6.4.1.1 Annual cycle of monthly precipitation

As a first step, this study compared the monthly precipitation rate over Bangui watershed as simulated by CMIP6, CMIP5, and ERA5-Land against the observed data. The annual cycle of ERA5-Land, individual member of CMIP6/5 and their multimodel ensemble mean in comparison with observed data is presented in Figures 6.2, 6.3, and 6.4. Over the watershed, observed data demonstrate a modal pattern characterized by a single peak during July – September (JAS). The

months of December – February (DJF) are relatively dry seasons, with December being the driest, reflecting < 9 mm/month precipitation rate over the BW. Interestingly, both the CMIP5 and the CMIP6 models reproduced the annual precipitation cycle over BW. However, ERA5-Land demonstrates a bimodal pattern with peaks during FMA and SON. Moreover, improvement is further noted in the reproducibility of JAS peak (229.48 mm/month) in CMIP6 with notable models such as BCC-CSM2-MR (223.53 mm/month), GFDL-ESM4 (233.69 mm/month), MIROC-ES2L (233.95 mm/month), MPI-ESM1-2-HR (220.91 mm/month), and NorESM2-LM (239.31 mm/month) able to simulate the peak satisfactorily. Comparative analysis of model performance in the simulation of the peak for CMIP6, CMIP5, and ERA5-Land reveal varying features. Interestingly, the CMIP6 ensemble mean and CMIP5 ensemble mean robustly reproduced the modal climatology of JAS, unlike ERA5-Land. This shows better reproducibility of annual rainfall over the Bangui watershed by NEX-GDDP.

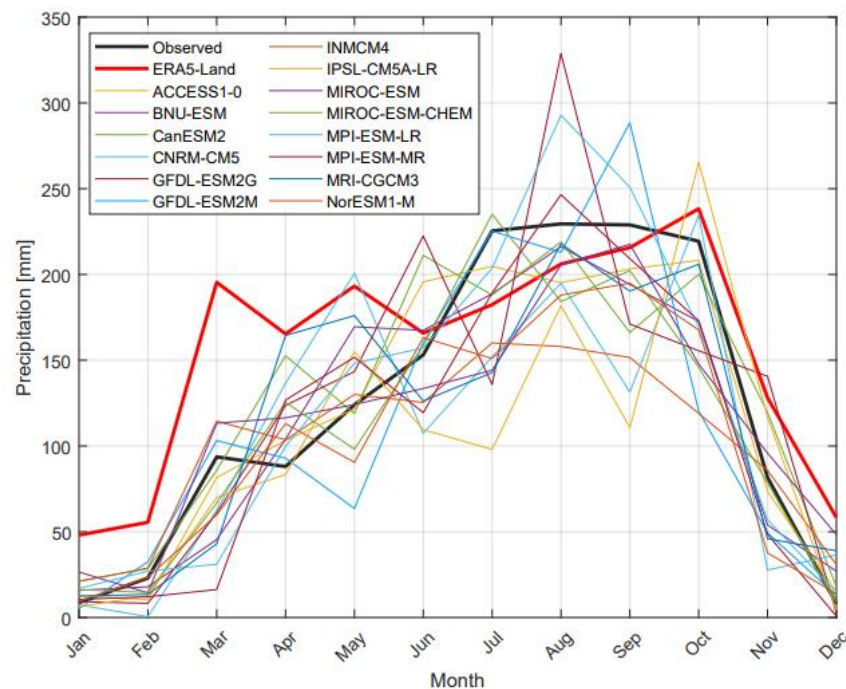


Figure 6.2 Mean monthly precipitation during 1981 year for the CMIP5 models, ERA5-Land, and observations over Bangui watershed

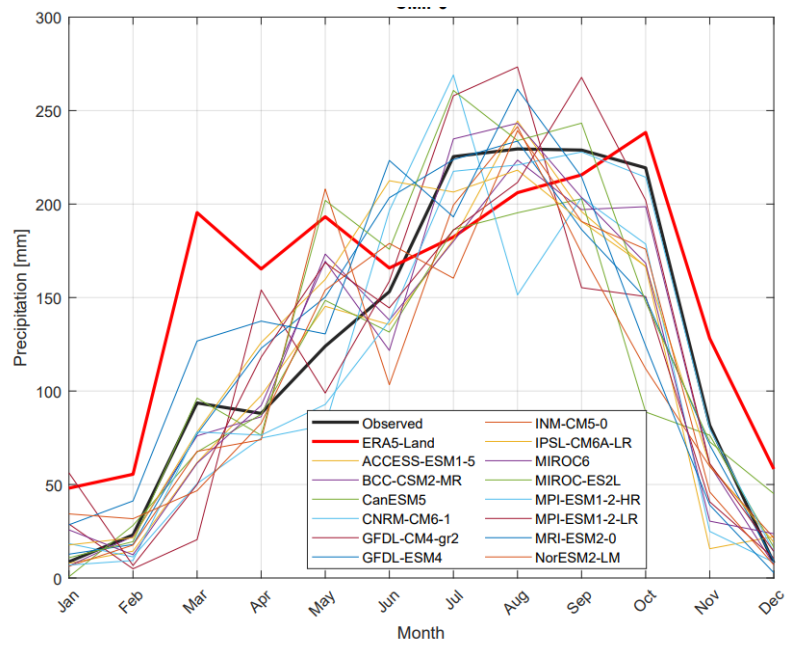


Figure 6.3 As Figure 2 but for CMIP6 models

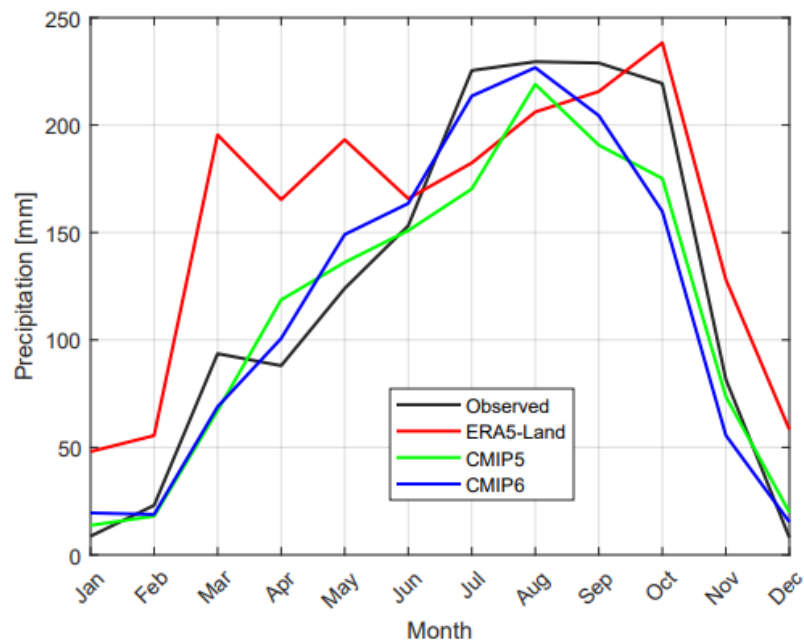


Figure 6.4 As Figure 3 but for Mean of CMIP5 & CMIP6 models

6.4.1.2 Mean Bias Error (MBE)

The MBE is one of widely used statistical metric for assessing the performance and accuracy of simulated data. It represents the arithmetic mean of the differences between the observed, ERA5-Land, and NEX-GDDP data, providing a measure of the overall bias of simulated in reproducing the observed data. The MBE of ERA5-Land, and NEX-GDDP rainfall over BW is shown in figure 6.5. It can be seen from the figure 6.5 that the estimated MBE for CMIP6 and CMIP5 were very nearby unlike ERA5-Land. Positive and negative MBE values indicate overestimation or underestimation, respectively, and help identify potential biases in the model. Highest positive bias was observed for ERA5-Land.

Table 6.2 Caption of x- axis for figures 5,6, and 7

N0	CMIP6	CMIP5	Reanalysis
1	BCC-CSM2-MR	BNU-ESM	ERA5-Land
2	CanESM5	CanESM2	ERA5-Land
3	CNRM-CM6-1	CNRM-CM5	ERA5-Land
4	GFDL-CM4-gr2	GFDL-ESM2G	ERA5-Land
5	GFDL- ESM4	GFDL-ESM2M	ERA5-Land
6	INM-CM5-0	INM-CM4	ERA5-Land
7	IPSL-CM6A-LR	IPSL-CM5A-LR	ERA5-Land
8	MIROC6	MIROC-ESM	ERA5-Land
9	MIROC-ES2L	MIROC-ESM-CHEM	ERA5-Land
10	MPI-ESM-1-2-HR	MPI-ESM-MR	ERA5-Land
11	MPI-ESM-1-2-LR	MPI-ESM-LR	ERA5-Land
12	MRI-ESM2-0	MRI-CGCM3	ERA5-Land
13	NorESM2-LM	NorESM1-M	ERA5-Land

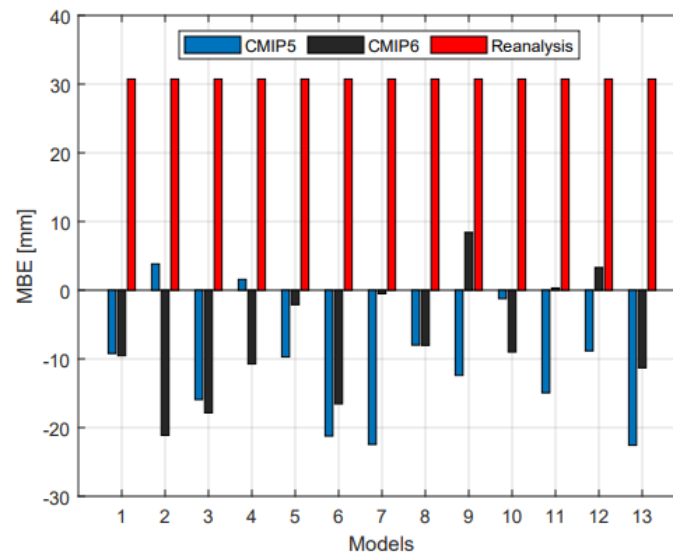


Figure 6.5 MBE of CMIP5, CMIP6, and Reanalysis

6.4.1.3 Root mean squared error (RMSE)

The RMSE is a fundamental statistical measure used in hydrology to assess the accuracy of models by comparing their simulations to observed data. Lower RMSE values indicate better agreement between observed and simulated data, while higher values suggest larger discrepancies. The RMSE explains the difference between observed and simulated precipitation, and, therefore, it provides the spread of error or the performance of the model. The RMSE allows modelers to identify which model performs better in capturing the observed data. It can be seen from the figure 6.6 that the estimated RMSE values for CMIP6 and CMIP5 were low comparing to ERA5-Land excepted CNRM-CM5, GFDL-ESM2G, and IPSL-CM5A-LR models which produced highest RMSE of 51.52, 55.18 and 57.29.

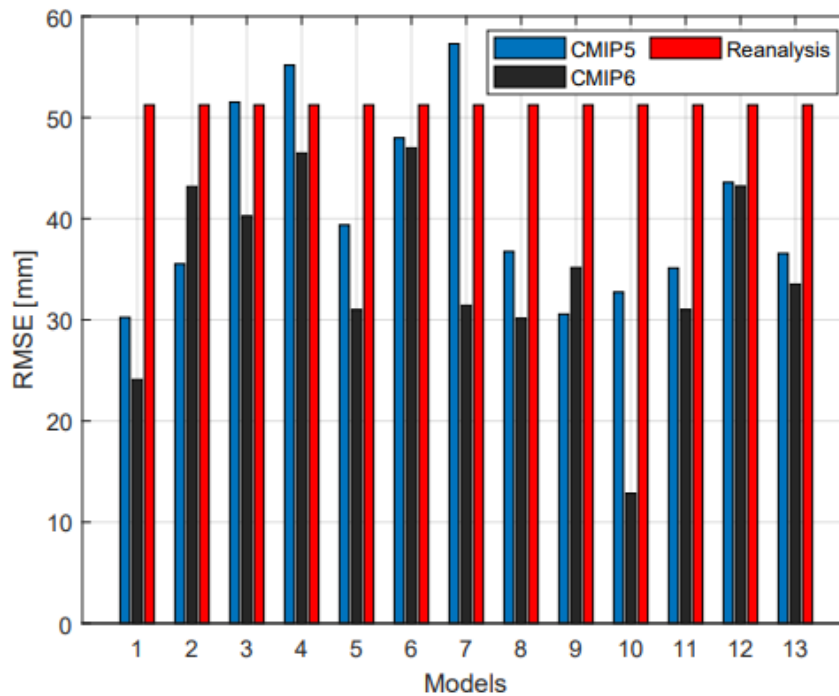


Figure 6.6 As Figure 5 but for RMSE

6.4.1.4 Kling-Gupta efficiency (KGE)

The KGE is a powerful and comprehensive metric for evaluating the accuracy and reliability of models by comparing their simulations to observed data. By incorporating correlation, bias, and variability aspects, KGE offers a robust and informative assessment of model performance. As a versatile performance metric, KGE provides a comprehensive assessment of model performance, particularly in capturing multiple aspects of observed data. High KGE values indicate good model accuracy, while low or negative values highlight areas for model improvement. It can be seen from the figure 6.7 that the KGE values were found above 0.5 in all datasets investigated. However, the estimated values of CMIP6 were highest than CMIP5 and ERA5-Land.

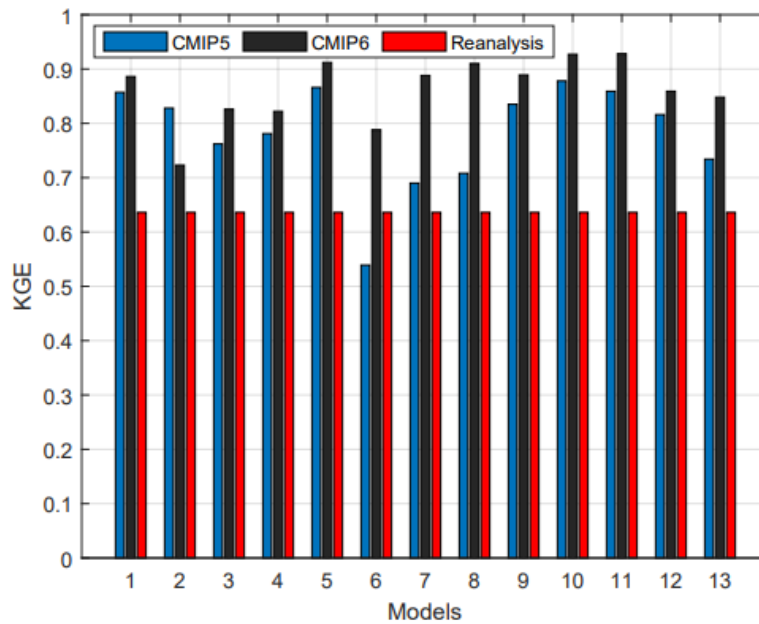


Figure 6.7 As Figure 6 but for KGE

6.4.1.5 Tailor Diagram (TD)

By plotting multiple performance metrics, such as correlation, root mean squared deviation (RMSD), and standard deviation ratio, in a single graph, the TD offers a holistic view of how well each model configuration reproduces the observed data. Figure 6.8 presents the Taylor diagram of the monthly average runoff between NEX-GDDP models, and ERA5-Land over BW. Note that 13 CMIP6 models and 13 CMIP5 models in the paper are represented by red and blue symbols in Fig. 8., and ERA5-Land by black symbol. The simulation result is assumed close to the reference value, when there would be relatively high correlation, low RMS errors, and minimum difference of standard deviation with respect to the reference value. All CMIP6 models had the CC between 0.85 and 1, the RMSD between 10 and 45, and the SD between 65 and 90. The CMIP5 models had almost the same behavior that CMIP6 but a little less efficient. The CC were between 0.75 and 0.95, the RMSD between 20 and 60, and the SD between 45 and 90. However, ERA5-Land had

less SD than all CMIP models except INMCM4 and MIROC-ESM which indicates that ERA5-Land have lower variability in the basin.

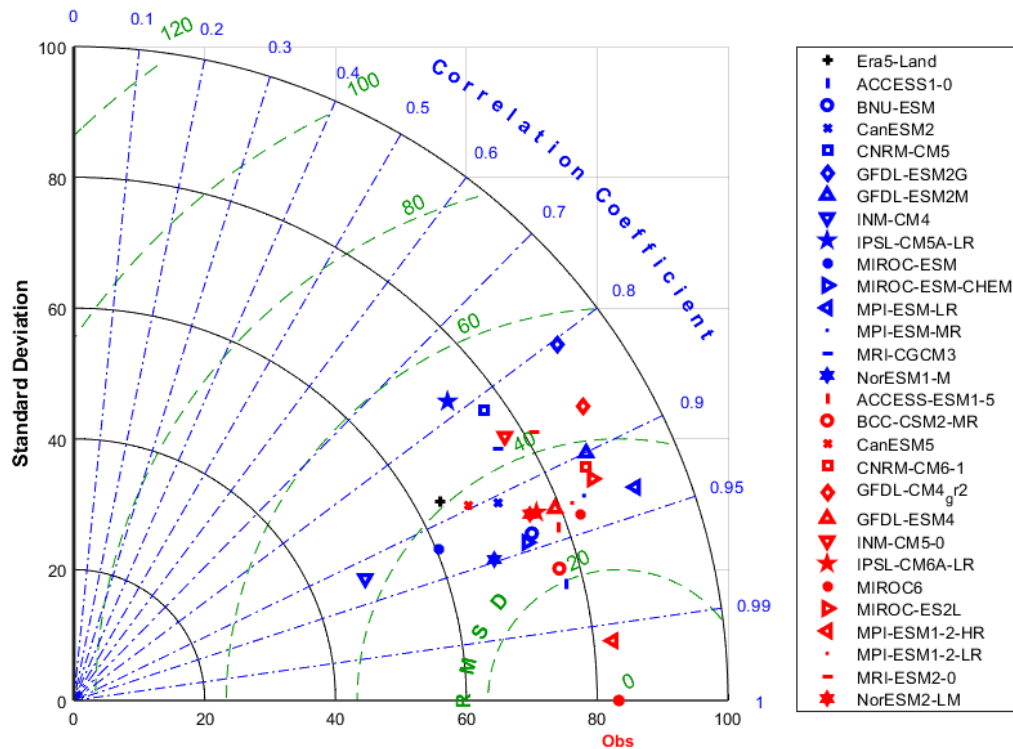


Figure 6.8 Taylor diagram of average monthly precipitation for Bangui watershed for ERA5-Land (black), CMIP5 (Blue) and CMIP6 (red)

6.4.2 Performance evaluation of NEX-GDDP in hydrological modelling

The NEX-GDDP datasets provide valuable information on climate projections from various global climate models (GCMs) under different emission scenarios, making them a valuable resource for studying the potential impacts of climate change on hydrological systems. The purpose of this research was to investigate the possibility of using a new statistically downscaled dataset, NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections) as proxies for gauged precipitation and temperature for hydrological modelling. The performance of NEX-GDDP datasets in hydrological modelling was evaluated on the basis of the specific calibration of GR4J and HEC-HMS models. In the specific calibration, GR4J and HEC-HMS models are specifically

calibrated to each specific member of 13 historical CMIP6 datasets and equal number for their predecessor CMIP5 for Bangui watersheds in the Congo River basin.

6.4.2.1 Calibration and validation of hydrological models using CMIP6 datasets.

In this section the flows of Bangui catchment were simulated using each of the 13 historical NEX-GDDP CMIP6 datasets in GR4J and HEC-HMS model. As mentioned above, the model performance was assessed using the Nash-Sutcliffe Efficiency metric (NSE). The NSE is a widely used indicator in hydrological modelling due to its flexibility to be applied to various types of mathematical models (Gupta & Kling, 2011; McCuen *et al.*, 2006; Ritter & Muñoz-Carpena, 2013). The NSE values obtained over the calibration and validation period at Bangui gauging station, using the 13 NEX-GDDP CMIP6 datasets are shown in figures 6.9 (b) for the GR4J and figure 6.9 (d) for HEC-HMS model. Table 6.3 gives the details of the statistical performance in terms of NSE for both hydrological models GR4J and HEC-HMS under both CMIP5 and CMIP6 NEX-GDDP datasets.

The performance of the CMIP6 datasets in hydrological modelling regarding the statistical evaluation metrics NSE shows differences across 13 NEX-GDDP CMIP6 data set chosen in this study. For the GR4J model calibration period, NSE varies between -0.18 to 0.475 and for model validation period between -0.23 to 0.449. Furthermore, the NSE for HEC-HMS model varies between 0.327 to 0.573 for calibration period and between 0.324 to 0.625 for validation period. The INM-CM5-0 model shows the best performance for HEC-HMS model calibration period with the NSE value of 0.573. The NorESM2-LM had a lowest NSE value equal to 0.327. All NSE values for HEC-HMS model were higher than those for GR4J. Also, all these values are greater or equal

to 0.5 except for the CNRM-CM6-1, GFDL-CM4-gr2, MPI-ESM-1-2-HR, and NorESM2-LM models with the NSE values respectively equal to 0.396 ,0.384,0.375 and 0.327.

Overall, it can be seen that HEC-HMS model performs better than GR4J model when using the 13 NEX-GDDP CMIP6 datasets in the CRB at Bangui outlet.

6.4.2.2 Calibration and validation of hydrological models using CMIP5 datasets.

As for CMIP6 in section 6.4.2.1, the flows of Bangui catchment were also simulated using each of the 13 historical NEX-GDDP CMIP5 datasets in GR4J and HEC-HMS model and the model performance was assessed using the Nash-Sutcliffe Efficiency metric (NSE). The NSE values obtained over the calibration and validation period at Bangui gauging station, using the 13 NEX-GDDP CMIP5 datasets are shown in figures 6.9 (a) for the GR4J and figure 6.9 (c) for HEC-HMS model. From table 3 it has been seen that the NSE values for the GR4J model calibration period, varies between -0.13 to 0.751 and for the GR4J model validation period between -0.32 to 0.707. Furthermore, the NSE for HEC-HMS model varies between 0.352 to 0.765 for calibration period and between 0.230 to 0.707 for validation period. In contrary to CMIP6 were INM-CM5-0 model shown the best performance for HEC-HMS model calibration period with the NSE value of 0.573, MPI-ESM-MR was more efficient for HEC-HMS model calibration period with the NSE value of 0.765. The INM-CM4 had a lowest NSE value equal to 0.352. All NSE values for HEC-HMS model were higher than those for GR4J except CanESM2, BNU-ESM, and CNRM-CM5 with the NSE values respectively equal to 0.751, 0.684, and 0.567. As for CMIP6, HEC-HMS performs better than GR4J for CMIP5. Figure 10 represents the 13 hydrographs simulated using all 13 CMIP5 datasets at Bangui outlet.

From table 6.3, it seems clear that in general, HEC-HMS performs better than GR4J when using the 13 NEX-GDDP CMIP5 and CMIP6 datasets in CRB at Bangui outlet. It seems clear also that CMIP5 datasets performs better than CMIP6 datasets when used as input data in hydrological modelling in CRB at Bangui outlet.

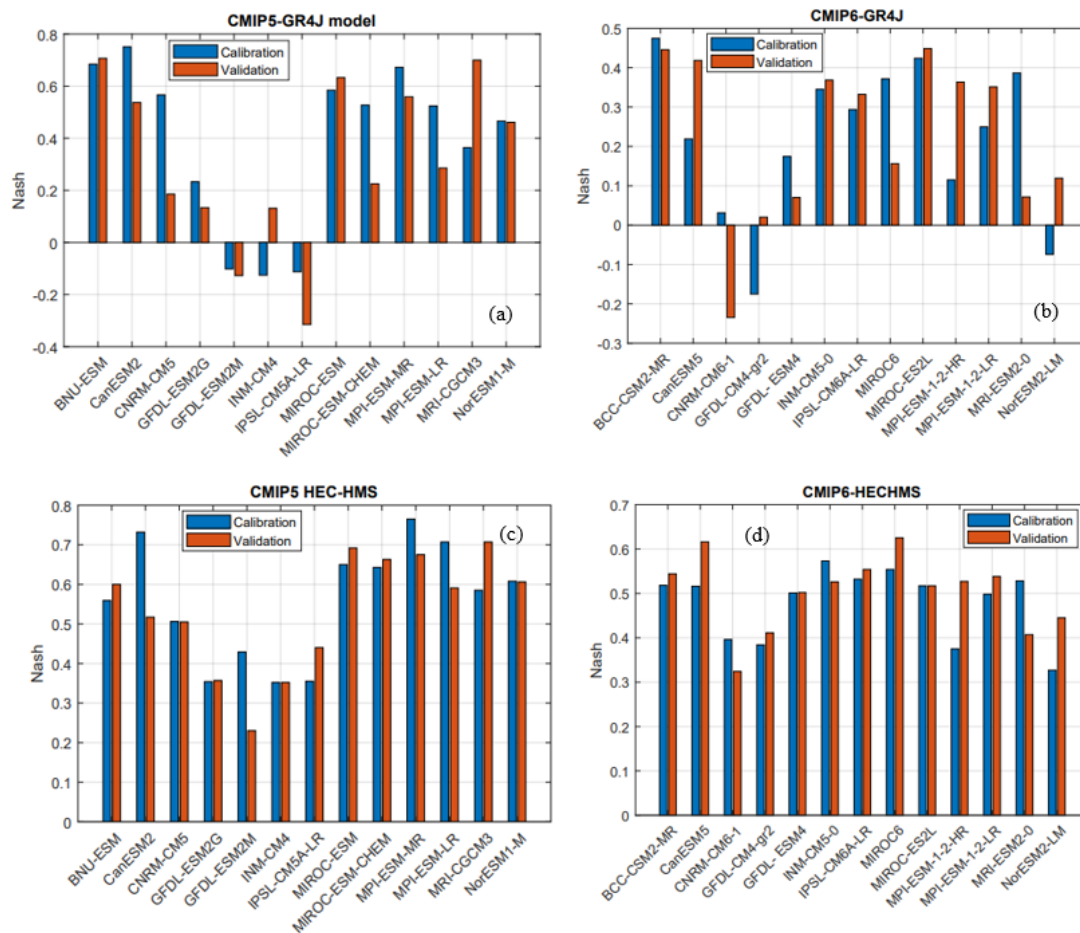


Figure 6.9 NSE values in calibration & validation for (a) the GR4J-CMIP5 model, (b) GR4J-CMIP6 model, (c) HEC-HMS-CMIP5 model and (d) HEC-HMS-CMIP6 model at BW outlet.

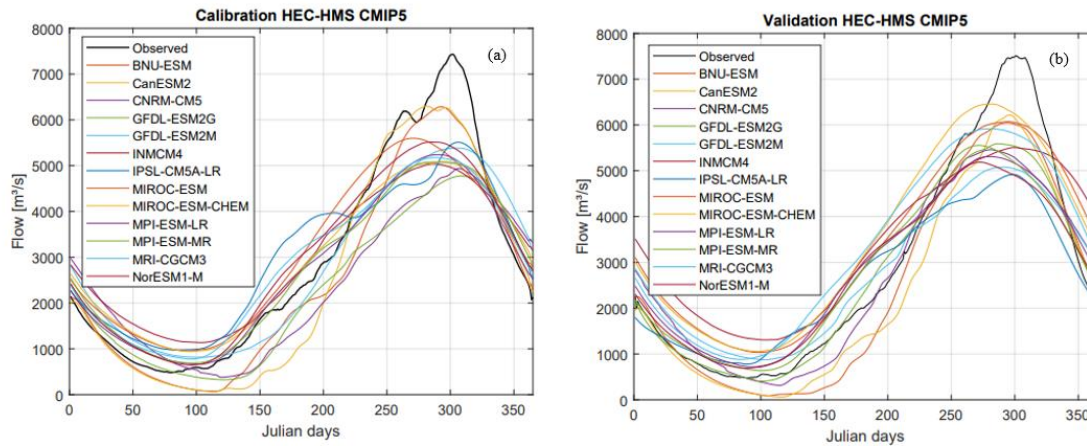


Figure 6.10 Hydrographs simulated using all 13 datasets for (a) the HEC-HMS model calibration and (b) HEC-HMS model validation.

Table 6.3 : Models calibration and validation estimated Nash values

NEX-GDDP Models		GR4J Model				HEC-HMS Model			
CMIP6 (a)	CMIP5 (b)	Nash (a)		Nash (b)		Nash (a)		Nash (b)	
		Cal.	Val.	Cal.	Val.	Cal.	Val.	Cal.	Val.
BCC-CSM2-MR	BNU-ESM	0.475	0.446	0.684	0.707	0.518	0.544	0.559	0.600
CanESM5	CanESM2	0.219	0.418	0.751	0.537	0.516	0.616	0.732	0.517
CNRM-CM6-1	CNRM-CM5	0.031	- 0.23	0.567	0.186	0.396	0.324	0.506	0.505
GFDL-CM4-gr2	GFDL-ESM2G	- 0.18	0.02	0.233	0.134	0.384	0.411	0.354	0.357
GFDL- ESM4	GFDL-ESM2M	0.175	0.070	- 0.10	- 0.13	0.501	0.502	0.429	0.230
INM-CM5-0	INM-CM4	0.345	0.368	- 0.13	0.131	0.573	0.526	0.352	0.352
IPSL-CM6A-LR	IPSL-CM5A-LR	0.294	0.332	-0.11	- 0.32	0.532	0.554	0.355	0.44
MIROC6	MIROC-ESM	0.371	0.156	0.584	0.633	0.554	0.625	0.650	0.692
MIROC-ES2L	MIROC-ESM-CHEM	0.424	0.449	0.527	0.225	0.517	0.517	0.643	0.663
MPI-ESM-1-2-HR	MPI-ESM-MR	0.115	0.363	0.672	0.559	0.375	0.527	0.765	0.675
MPI-ESM-1-2-LR	MPI-ESM-LR	0.250	0.351	0.524	0.286	0.498	0.538	0.707	0.591
MRI-ESM2-0	MRI-CGCM3	0.387	0.072	0.364	0.700	0.528	0.407	0.585	0.707
NorESM2-LM	NorESM1-M	-0.074	0.119	0.466	0.461	0.327	0.445	0.608	0.606

6.4.2.3 Performance statistics of hydrological simulations

Upon analyzing the simulation results, a box plot has been constructed to visualize the distribution of simulated discharges as shown in figure 6.11 and 6.12. The box plot provides an insightful representation of the statistical characteristics of the data and facilitates the identification of key patterns and outliers in the river's flow behavior. The box plot in figure 11 exhibited a pronounced asymmetrical distribution of simulated discharges by GR4J, with a notable clustering of data points

around the higher end of the range. The median discharges for calibration period were 2285 cubic meters per second (m^3/s) and 2020 cubic meters per second (m^3/s) for validation period, which indicates the central tendency of the river's flow during the 20-year period. However, the box plot's whiskers were considerably elongated, extending to higher values of discharge, suggesting a substantial spread of the data.

Figure 6.11 shows a considerable number of outlier values in the box plot, represented as individual data points beyond the whiskers. These outlier values are significantly higher than the majority of the simulated discharges and indicate extreme flow events in the river basin. The presence of numerous outliers implies that the river experienced sporadic, intense discharge events during the simulation period. Such events might be associated with heavy rainfall, or other extreme hydrological conditions that were captured by the model.

The interquartile range (IQR) was relatively narrow compared to the range covered by the whiskers, highlighting the concentration of most of the simulated discharges within a limited range. This indicates that the river basin generally experienced moderate flow conditions, with occasional periods of intense flooding.

The presence of numerous outliers underscores the importance of considering extreme events in the design and management of water resources, flood protection measures, and infrastructure planning. The hydrological model used in this study demonstrated the ability to capture the variability and the occurrence of extreme discharge events. However, it is essential to exercise caution when interpreting the results, as the model's performance might be influenced by uncertainties in input data, parameterization, or limitations in the representation of certain hydrological processes. In conclusion, the box plot of the simulated discharges presented a clear depiction of the river's flow distribution, highlighting the median, quartiles, and an abundance of

outlier values. The presence of many outlier discharges indicated the occurrence of significant extreme events during the simulation period, warranting further investigation and consideration in water resource management and planning. Further sensitivity analysis and validation against observed data would be necessary to improve the model's accuracy and reliability in representing extreme hydrological events.

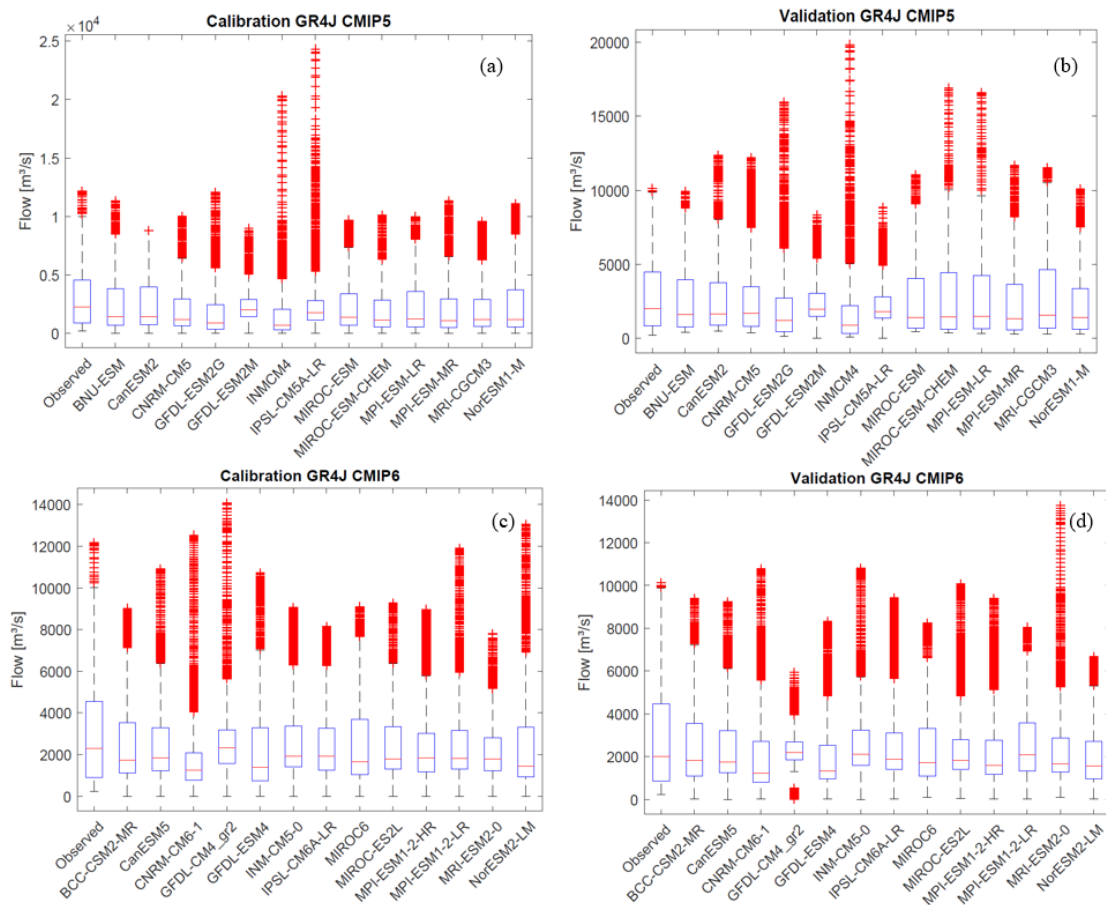


Figure 6.11 Distribution of the discharge values of the different NEX-GDDP datasets for GR4J model at Bangui outlet. Results are based on daily discharges simulated in the calibration and validation periods. The lower and upper limits of each boxplot represent the 25th and 75th percentiles, respectively. The middle line represents the median (50th percentile)

The box plot in figure 6.12 was generated to visually represent the distribution of simulated discharges by HEC-HMS model. The absence of outlier values in the box plot indicates a relatively consistent pattern of flow within the river over the 20-year period. The central tendency of the distribution is characterized by the median discharges, which are 2285 cubic meters per second (m^3/s) for the calibration period and 2020 cubic meters per second (m^3/s) for validation period. These values serve as a representative measure of the river's typical flow rate during the study period.

The symmetry of the box plot, with the median positioned near the center of the box, indicates a balanced distribution of data points on either side. This symmetry, coupled with the absence of outliers, suggests that the hydrological model was successful in capturing the primary hydrological processes within the river basin and that the simulation aligns well with the observed flow behavior. In summary, the box plot of the simulated discharges illustrates a distribution characterized by its central tendency and narrow interquartile range. The lack of outlier values suggests a stable and consistent flow pattern within the river basin over the 20-year simulation period. This information is essential for establishing a baseline understanding of the river's hydrology under current climate conditions, which can serve as a reference for future studies that assess the impact of changing climate scenarios on the river's flow behavior.

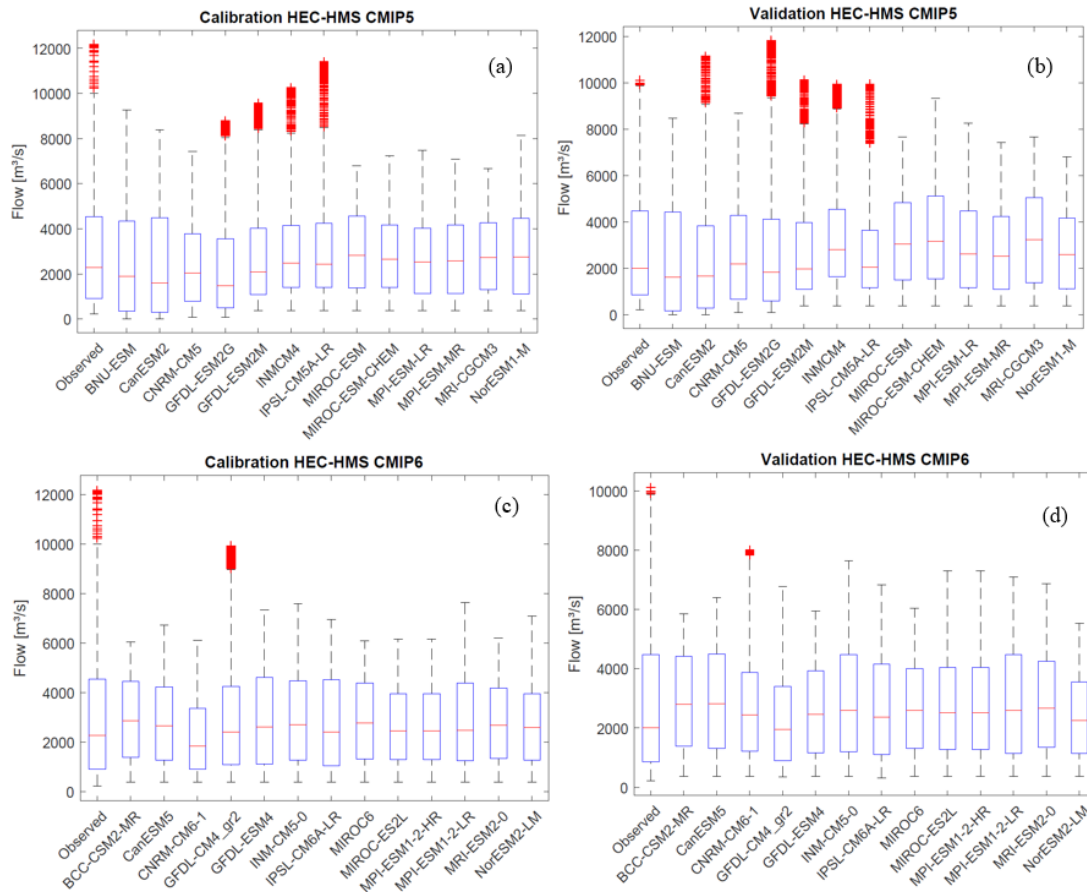


Figure 6.12 As figure 11 but for HEC-HMS model

6.5 Conclusions and recommendations

In this study, the monthly precipitation rate over Bangui watershed as simulated by CMIP6, CMIP5, and ERA5-Land were compared first to observed data. It has been seen a better reproducibility of annual rainfall over the Bangui watershed by CMIP6 and CMIP5 unlike ERA5-Land. Then four other metrics, MBE, RMSE, KGE and TD were evaluated. All metrics values indicated that CMIP6 and CMIP5 were nearest the observed than ERA5-land.

The potential use of precipitation and temperature data from CMIP6 and CMIP5 as direct inputs for hydrological modeling was investigated. Precipitation and temperature series were used to calibrate two lumped hydrological models and to simulate river flows over Congo River Basin at

Bangui outlet. The Nash-Sutcliffe values of simulated river flows using CMIP6 forcings were compared against simulated streamflow using CMIP5 for the two hydrological models GR4J and HEC-HMS.

Results showed that NSE values of CMIP6 are generally comparable to those of CMIP5 over the case study for both GR4J and HEC-HMS. Furthermore, it should be noted that the models from CMIP5 give better results than those from CMIP6. In addition, the HEC-HMS model performed much better than GR4J.

This study shows that CMIP6 and CMIP5 have a strong potential for use as proxies to weather station data, that ERA5-Land. This potential is particularly promising in regions where weather station coverage is limited.

However, the quality and reliability of future climate projections from GCMs can vary, affecting the robustness of model results and also the representation of hydrological processes and the model structure itself can introduce uncertainties in the simulation of future hydrological responses. Additionally, the selection of emission scenarios and the spatial resolution of GCM outputs may influence the results of hydrological model simulation.

To address the challenges associated with calibration and validation using NEX-GDDP datasets, it is strongly recommended to perform an ensemble calibration and validation approach, using multiple GCMs and emission scenarios to capture the range of uncertainties in future climate projections.

CHAPITRE 7 : INVESTIGATING HYDROLOGICAL RESPONSES TO CLIMATE CHANGE OF THE CONGO RIVER BASIN USING MULTI-MODEL ENSEMBLE PROJECTIONS

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Abstract

The Congo River holds exceptional significance within Africa and the global landscape due to its substantial size and crucial role in the regional ecosystem and economy. Ranking as the second longest river on the continent, after the Nile, and the world's second largest river by discharge volume, following the Amazon, the river's complex features, including rapids, waterfalls, and an intricate network of tributaries, have garnered scholarly interest. However, its hydrological response to impending climate change remains relatively unexplored. This study aims to bridge this knowledge gap by utilizing the newly refined, bias-corrected, high-resolution daily downscaled dataset NEX-GDDP to drive two hydrological models, HEC-HMS and GR4J. Addressing the uncertainty arising from General Circulation Model (GCM) outputs, the research employs the Granger-Ramanathan (GRC) technique to develop multi-model ensemble projections. With these tools, the study investigates alterations in runoff patterns within the Congo River Basin's Bangui and Inga outlets under projected climate scenarios, employing both CMIP6 and CMIP5 multi-model ensembles. Examining CMIP5 findings, indications emerge that discharge at Bangui may decrease by 12.80% under RCP 4.5 during 2041-2060, followed by a steeper reduction of 24.60% in 2071-2090. For RCP 8.5, projections suggest reductions of 7.10% and 11.90% during the same

intervals. Conversely, CMIP6 projections anticipate discharge increases of 50.71% (SSP2 4.5, 2041-2060), 37.38% (SSP2 4.5, 2071-2090), alongside modest increases of 2.83% (SSP5 8.5, 2041-2060), followed by a reduction of 3.54% (SSP5 8.5, 2071-2090). Notably, all CMIP5 and CMIP6 scenarios foresee increased discharge at the Inga outlet, ranging from 7.08% to 25.18% under distinct climate projections. This research sheds light on the expected hydrological responses to forthcoming climate changes, offering valuable insights for effective water resource management within the Congo River Basin.

Keywords: Multi-model and multi-input, NEX-GDDP, CMIP5, CMIP6, Congo River Basin, Climate change.

7.1 Introduction

The focus on changing climatic patterns and their repercussions on water resources has gained significant attention due to their substantial environmental and socioeconomic implications (Ahsan *et al.*, 2023; Karsten *et al.*, 2004; Luo *et al.*, 2019; Reshmidevi *et al.*, 2018). The rise in global mean temperatures is already affecting regional water budgets, accompanied by changing precipitation and evapotranspiration patterns projected under climate change scenarios. These alterations are anticipated to impact hydrological systems profoundly (Huntington, Thomas G., 2006). Consequently, assessing riverine systems' sensitivity and hydrological responses to these climate shifts is crucial for devising effective water management policies and adaptation strategies (Ahsan *et al.*, 2023; Bhatta *et al.*, 2019; Reshmidevi *et al.*, 2018; Rodrigues *et al.*, 2020). Several studies have delved into the hydrological impacts of changing climates across diverse river basins worldwide (Aloysius & Saiers, 2017; CSC, 2013; Karam, S. *et al.*, 2022; Karam, Sara *et al.*, 2023; Liu, L. *et al.*, 2011; Tan *et al.*, 2017; Tshimanga, R. M. & Hughes, 2012; Vetter *et al.*, 2017; Yu *et al.*, 2018). Global circulation models (GCMs) are widely employed tools for projecting climate

change outcomes under varying emission scenarios. Nevertheless, GCMs offer insights at a coarse scale with sizeable grid dimensions, falling short in capturing the regional diversity that profoundly influences hydrological processes on a basin level (Hakala *et al.*, 2019). To address this limitation, regional climate models (RCMs) with finer grid resolutions have been developed to enhance GCM outputs having higher resolution with reduced errors and biases, and at the same time, improving the future projections of climate factors at finer scale (Mahmood *et al.*, 2018; Shin & Yi, 2019). While RCMs exhibit improved performance in simulating local climates, they still inherit significant errors and biases from GCMs (Chen, Jie *et al.*, 2013). Consequently, direct utilization of RCM outputs in hydrological models can lead to notable disparities between model outputs and observed data (de Oliveira *et al.*, 2017). Thus, it is imperative to undertake bias adjustment of the raw RCM results prior to engaging in any hydrological simulations (Luo *et al.*, 2019).

A significant contribution to the field comes from the National Aeronautics and Space Administration (NASA), which has introduced the Earth Exchange Global Daily Downscaled Projections (NEXGDDP) dataset. This dataset offers a global-scale, high-resolution (0.25°) dataset and stands as a substantial advancement. The NEX-GDDP dataset's utility extends to the study of future climate change at the watershed level, proving valuable for river basins characterized by intricate topography and climate sensitivity, without necessitating any additional processing (Chen *et al.*, 2017; Chiphang *et al.*, 2022; Jain, S. *et al.*, 2019). Numerous studies underscore the NEXGDDP dataset's merits, particularly its detailed projections of temperature and precipitation at a high spatial resolution. Incorporating these projections into hydrological models has the potential to enhance comprehension of future water resource availability across various timescales, be it in the short-term or the long-term, amid changing climatic conditions (Bao & Wen, 2017; Bokhari *et al.*, 2018; Chen *et al.*, 2017; Chiphang *et al.*, 2022). Jain, S. *et al.* (2019) emphasize the

superiority of NEX-GDDP data in comparison to CMIP5 and Coordinated Regional Climate Downscaling Experiment (CORDEX) data, especially concerning the Indian monsoon. Jain, S. *et al.* (2019) observed marked improvements in the simulation of seasonal and daily mean temperature and precipitation, highlighting NEX-GDDP's capability for climate change investigations, including the faithful representation of extremes.

The escalating concern among policy makers and water management planners revolves around the repercussions of climate change on water resources within the Congo River Basin. This issue hinges on alterations in precipitation patterns and temperature across Central Africa, consequently influencing streamflow magnitudes and hydrologic processes. However, the existing predictive framework for the hydrology of the CRB faces challenges due to sparse data and limited model evaluations against available information (Aloysius & Saiers, 2017; Beighley *et al.*, 2011; Wohl *et al.*, 2012). Therefore, there is a pressing need to explore and comprehend the manner in which regional hydrologic processes respond to climate change.

This study pursued several objectives: (i) projecting forthcoming climate changes in the CRB through the utilization of downscaled NEX-GDDP datasets for temperature and precipitation, (ii) evaluating the impacts of climate changes on streamflow at the Bangui outlet under RCP 4.5 and RCP 8.5 for CMIP5, as well as under SSP2 4.5 and SSP5 8.5 for CMIP6 emission scenarios, using a combination of the GR4J and HEC-HMS models, and (iii) examining the influence of climate changes on streamflow at the Inga outlet under similar scenarios, albeit employing the HEC-HMS model.

The findings of this study possess paramount importance for water resource management and the development of hydropower plants. Furthermore, they offer essential guidance to decision makers

and water policy experts, equipping them with insights necessary to devise strategic interventions aligned with the projected climate change scenarios.

7.2 The Congo River basin (CRB)

The Congo River originates in the highlands and mountains of the East African Rift system. It is located in Central Africa extending from latitude 09°15'N in the Central African Republic to 13°28'S in Angola and Zambia, and from longitude 31° 10'E through the Great African Lakes in the East African Rift to 11° 18'E on the Atlantic Ocean (Figure 7.1). The CRB is shared between nine African countries with a total surface of 3,691,000 km². The basin comprises a population of approximately 139 million inhabitants in 2020 (World Bank). The basins water resource is vital for local livelihoods, drinking water supply, food security and energy generation. The Congo River is the only major river to cross the Equator twice. In doing so, the basin lies in both the Northern and Southern Hemispheres causing it to receive year-round rainfall from the migration of the Inter-tropical Convergence Zone (ITCZ) (Beyene *et al.*, 2012; Kundzewicz *et al.*, 2007). After the north has its wet season in the spring and summer, the ITCZ moves south, and the southern part of the basin receives large amounts of rain. This results in little seasonal variability in the Congo mainstream water flow. The heart of Congo River basin enjoys an equatorial climate with no dry season whereas the far north and south benefit from a tropical climate. The annual average rainfall in the Congo River basin varies between 1,500 and 2,000 mm per year depending on the location of the sub-basins. As the singular river basin flows mainly in this equatorial part of Africa, the main stem exhibits a more constant flow compared to other African major rivers with an average of 45,000m³/s. It does show some inter-annual variability with July and August being the months of low flow whereas December is the month of high flow. The tributaries from the South, such as the Kasai, have two periods of low water and two of high in the year, but the tributaries from the north,

such as the Ubangi, have a single maximum. Consequently, the regime of the main river does vary from place to place (Shahin, 2002).

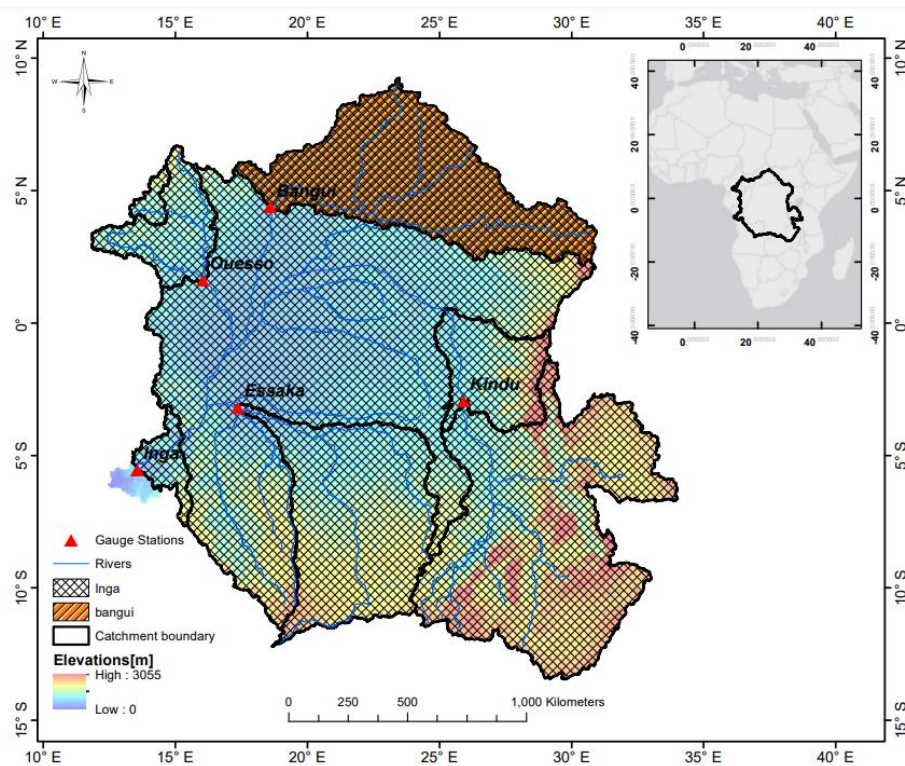


Figure 7.1 The Congo River basin and sub-basins studied (Inga & Bangui)

7.3 Data and methods

7.3.1 Data

7.3.1.1 NEX-GDDP Datasets

This study utilizes a high-resolution dataset derived from NEX-GDDP-CMIP6 and CMIP5 datasets. This dataset proves instrumental in examining climate variability and its repercussions on both historical and future regional climates. The NEX-GDDP employs a Bias-Correction Spatial Disaggregation (BCSD) algorithm to enhance the accuracy of General Circulation Models (GCMs) projections. This algorithm is divided into two phases for CMIP5 (1950–2005) and CMIP6 (1950–2014) historical runs. The first phase rectifies GCM biases through statistical measures such as

mean, variance, and slope, aligning them with observed data from the Global Meteorological Forcing Datasets (GMFD) provided by Princeton University's Terrestrial Hydrology Research Group. The second phase focuses on spatial disaggregation, refining coarse GCM data to a finer resolution (0.250×0.250) using observed datasets.

The NEX-GDDP dataset delivers three key climate variables: daily maximum temperature, minimum temperature, and precipitation. It covers Retrospective Runs for CMIP5 (1950–2005) and CMIP6 (1950–2014), as well as Prospective Runs for CMIP5 (2006–2100) and CMIP6 (2015–2100), under projections RCP 4.5 and RCP 8.5 from 21 CMIP5 GCMs, and SSP245 and SSP585 from 35 CMIP6 models. This comprehensive dataset is archived at <https://cds.nccs.nasa.gov/nex-gddp/>. The study mainly concentrates on three CMIP5 experiments: historical, RCP 4.5, and RCP 8.5, as well as three CMIP6 experiments: historical, SSP245, and SSP585.

The projected streamflow analysis in this study spans the time periods 2041–2060 and 2071–2090. A total of 13 NEX-GDDP-CMIP6 models, along with their corresponding 13 CMIP5 predecessors (refer to table 1), are employed for the analysis.

7.3.1.2 Hydrometric and spatial data

Streamflow records from each measurement station are provided by the R.V.F (Régie des voies fluviales). Specifically, the dataset encompassed the daily flow rates at Bangui ($18^{\circ}35'45''$ longitude E; $3^{\circ}21'30''$ latitude N) and Inga ($13^{\circ}39'$ longitude E; $05^{\circ}40'$ latitude S) outlets over a span of 20 years, ranging from January 1, 1981, to December 31, 2000. These data were employed to calibrate and validate the hydrological models at these two specific outlets.

Obtaining the Glob Land Cover map (2008–2012) with a spatial resolution of 300 meters was facilitated through the European Space Agency, Climate Change Initiative (CCI-LC-PUG, 2016; <http://maps.elie.ucl.ac.be/CCI/viewer/download.php>). The focus on land cover is due to its

significant impact on basin characteristics such as runoff, evapotranspiration, and soil erosion. Notably, the Congo River basin currently exhibits a prevailing forest land cover.

Another pivotal determinant of basin attributes is soil type. In this study, the global soil dataset, specifically the Digital Soil Map of the World (DSMW) v3.6 amended by the Food and Agriculture Organization of the United Nations (FAO) in 2007, was utilized (Zeng *et al.*, 2017). The dataset can be accessed at: <https://data.apps.fao.org/map/catalog/srv/eng/catalog.search#/metadata/446ed430-8383-11db-b9b2-000d939bc5d8>.

Table 7.1 Model names, and modelling agency of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study

Model Name	Modelling Agency	Resolution Lon. x Lat.
BCC-CSM2-MR BNU-ESM	Beijing Climate Center, China Meteorological Administration (China)	0.25° x 0.25°
CanESM5 CanESM2	Canadian Centre for Climate Modelling and Analysis (Canada)	0.25° x 0.25°
CNRM-CM6-1 CNRM-CM5	Centre National de Recherches Météorologiques, France	0.25° x 0.25°
GFDL-CM4-gr2 GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, USA	0.25° x 0.25°
GFDL-ESM4 GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, USA	0.25° x 0.25°
INM-CM5-0 INM-CM4	Institute for Numerical Mathematics, Russian Academy of Science /Russia	0.25° x 0.25°
IPSL-CM6A-LR IPSL-CM5A-LR	L'Institut Pierre-Simon Laplace (France)	0.25° x 0.25°
MIROC6 MIROC-ESM	National Institute for Environmental Studies, The University of Tokyo (Japan)	0.25° x 0.25°
MIROC-ES2L MIROC-ESM-CHEM	National Institute for Environmental Studies, The University of Tokyo (Japan)	0.25° x 0.25°
MPI-ESM-1-2-HR MPI-ESM-MR	Max Planck Institute for Meteorology (Germany)	0.25° x 0.25°
MPI-ESM-1-2-LR MPI-ESM-LR	Max Planck Institute for Meteorology (Germany)	0.25° x 0.25°
MRI-ESM2-0 MRI-CGCM3	Meteorological Research Institute (Japan)	0.25° x 0.25°
NorESM2-LM NorESM1-M	Norwegian Climate Centre (Norway)	0.25° x 0.25°

7.3.2 Hydrological models

7.3.2.1 GR4J

GR4J stands as a deterministic, conceptual, and lumped hydrologic model founded on a cascading reservoir production and routing mechanism (Perrin et al., 2003). Within this framework, water movement progresses through these reservoirs, ultimately reaching the outlet via parameterized unit hydrographs (Tarek, M. *et al.*, 2020). Initially, the GR4J model encompassed four primary parameters: the production storage capacity (X1), the groundwater exchange coefficient (X2), the one-day-ahead maximum capacity of routing storage (X3), and the time base of the unit hydrograph (X4). However, the version employed in this study was expanded to include nine parameters, enabling the integration of a snow-accounting and snowmelt routine referred to as CEMANEIGE (Poissant et al., 2017).

Similar to the HEC-HMS Model, GR4J necessitates daily records of precipitation, temperature, and potential evapotranspiration (PET) as input data. The computation of PET was executed using the Oudin formulation (Oudin et al., 2005). Notably, the model offers the advantage of rapid calibration, allowing its efficient application in various contexts. Multiple iterations of the model have already demonstrated successful utilization in diverse geographical regions (Hublart et al., 2015; Le Lay et al., 2007; Mostafaie et al., 2018).

7.3.2.2 HEC-HMS

HEC-HMS, developed by the US Army Corps of Engineers, stands as a deterministic, conceptual, and semi-distributed hydrologic model tailored for simulating the hydrological behavior of watersheds in response to given hydrometeorological inputs (Scharffenberg et al., 2010). This model comprehensively captures the entire spectrum of hydrological processes and accommodates both continuous and event-based modeling (Bhuiyan et al., 2017).

HEC-HMS encompasses various Loss Methods; however, certain approaches, such as the SCS Curve Number, are unsuitable for continuous simulation across prolonged periods marked by alternating dry and wet periods. Given our goal of performing long-term simulations over multiple years, the Soil Moisture Accounting Loss Model (SMA) proves more fitting (Ouédraogo *et al.*, 2018; Singh & Jain, 2015). This conceptual approach effectively emulates water movement through five surface (Canopy and Surface) and subsurface (Tension/Upper zone storage, Groundwater layers 1 and 2) reservoirs, yielding highly accurate outcomes. Detailed insight into the SMA's structure is available in the HEC-HMS Technical Reference Manual (<https://www.hec.usace.army.mil/confluence/hmsdocs/hmsum/latest>).

The efficacy of the HEC-HMS model is evident through its extensive use by researchers worldwide, demonstrating exceptional performance, including within African regions (Chakraborty & Biswas, 2021; Gebre, 2015; Singh & Jain, 2015; Verma *et al.*, 2022; Wallner *et al.*, 2012; Zelelew & Melesse, 2018). Accurate initial parameter estimation holds immense significance for this model, as incorrect estimation can hinder calibration convergence, rendering the model uncalibratable. The model necessitates daily inputs of precipitation, temperature, and potential evapotranspiration (PET), with PET computed using the Oudin formulation (Oudin *et al.*, 2005).

7.3.2.3 Model calibration

The initial phase of this study involved the calibration of both the HEC-HMS and GR4J models at the Bangui outlet, as well as the HEC-HMS model at the Inga outlet. This was accomplished by utilizing 13 CMIP6 and 13 CMIP5 datasets, in conjunction with observed hydrometric data. As a result, a total of 78 model calibrations were performed. This encompassed [(Bangui $\times$ 2 hydrological models $\times$ 13 datasets $\times$ 2) + (Inga $\times$ 1 hydrological model $\times$ 13 datasets $\times$ 2)].

Among the calibration strategies employed, one approach involved calibrating the model using the complete available dataset without following the traditional validation stage. This strategy capitalizes on maximizing the information embedded in climate data within the parameter set, thereby minimizing additional uncertainty associated with the selection of calibration and validation years (Tarek *et al.*, 2020). Notably, the statistical improvement of model performance often results from the inclusion of more years in the dataset, and the skills in validation and calibration aren't necessarily interdependent (Arsenault *et al.*, 2018).

In this research, both the HEC-HMS and GR4J models were calibrated based on the full dataset without the standard validation phase. The complexity of HEC-HMS, due to its numerous parameters, posed challenges in calibration. Initial parameter estimates were derived using information from the HEC-GeoHMS Extension, coupled with the ArcHydro extension in ArcMap 10.7.1. Corrective adjustments were made manually using QGIS 3.14 to rectify erroneous values returned by HEC-GeoHMS for certain physical parameters (such as reach length and slope).

The calibration of the HEC-HMS model commenced with a manual fine-tuning of model parameters, employing the trial-and-error method. This subjective approach allowed the modeler to iteratively adjust parameters to achieve a suitable alignment between observed and simulated hydrographs (Zhang *et al.*, 2013). Subsequently, the Optimization Trials tool within HEC-HMS was utilized for automated calibration, refining parameter values. Conversely, the calibration of the GR4J model employed the Covariance Matrix Adaptation Evolution Strategy (CMAES) algorithm (Hansen, N. *et al.*, 2003; Tarek *et al.*, 2020). CMAES has demonstrated proficiency across both small and large parameter spaces, known for its robustness and recognized as one of the foremost auto-calibration algorithms in hydrological modeling (Arsenault *et al.*, 2014; Tarek *et al.*, 2020).

7.3.3 Multi-model averaging approach

The Multi-model averaging (MMA) algorithm is a statistical technique utilized to enhance the accuracy and reliability of predictions by amalgamating outcomes from multiple hydrological models. This method of model averaging employs diverse models with distinct structures and assumptions to effectively capture the intricate nature of hydrological systems. Recent comparative investigations of such methodologies have pinpointed the Granger-Ramanathan (GR) weighting schemes as a robust category of algorithms for hydrological modeling applications (*Arsenault et al., 2017b; Arsenault et al., 2015; Diks, C. G. H. & Vrugt, J. A., 2010; Granger & Ramanathan, 1984; Wan, Y. J. et al., 2021*)

The GR approach encompasses three variations: A, B, and C (GRA, GRB, and GRC). GRA establishes weights using the ordinary least squares (OLS) algorithm, minimizing the root mean square error (RMSE) but without bias correction. GRB, akin to GRA, constrains the OLS algorithm to ensure weight summation to unity. GRC, on the other hand, is unconstrained, yet the mean values undergo bias correction through the incorporation of a constant term (*Arsenault et al., 2015; Granger & Ramanathan, 1984*). For this study, the GRC variant was adopted due to its robustness and ease of implementation, a performance showcased across multiple studies (*Arsenault et al., 2017b; Arsenault et al., 2015*).

In the context of this research, the multi-model and multi-input averaging approach was implemented for the Bangui sub-basin, while the Mono-model and multi-input approach were applied to Inga. Hydrological models were executed utilizing their optimal parameter configurations and corresponding CMIP6/5 data. Diverse model combinations were generated for each trial. During the calibration phase, the GRC weighting technique was employed to determine weights based on simulated and observed hydrographs. Subsequently, once weights were

computed, the hydrological models underwent another run, specifically during the validation period. The same weights were then applied to individual members, resulting in a singular weighted hydrograph. The evaluation of this weighted hydrograph was carried out employing the Nash-Sutcliffe Efficiency metric.

7.4 Results and Discussion

7.4.1 Performances of the hydrological models during the historical period

Based on the availability of daily streamflow and climate datasets, 1981-2000 is considered as the historical period for streamflow simulation. The HEC-HMS and GR4J models are calibrated using the 13 NEX-GDDP-CMIP6 and 13 NEX-GDDP-CMIP5 datasets. The performance of these models in reproducing the observed streamflow is assessed using the Nash–Sutcliffe model efficiency coefficient (NSE), see Bangui results in figure 2. It is clear that, the calibrated models using the NEX-GDDP datasets provide reasonable results.

Table 7.2 : Caption of x- axis for figure 2

N0	CMIP5	CMIP6
1	BNU-ESM	BCC-CSM2-MR
2	CanESM2	CanESM5
3	CNRM-CM5	CNRM-CM6-1
4	GFDL-ESM2G	GFDL-CM4-gr2
5	GFDL-ESM2M	GFDL- ESM4
6	INM-CM4	INM-CM5-0
7	IPSL-CM5A-LR	IPSL-CM6A-LR
8	MIROC-ESM	MIROC6
9	MIROC-ESM-CHEM	MIROC-ES2L
10	MPI-ESM-MR	MPI-ESM-1-2-HR
11	MPI-ESM-LR	MPI-ESM-1-2-LR
12	MRI-CGCM3	MRI-ESM2-0
13	NorESM1-M	NorESM2-LM

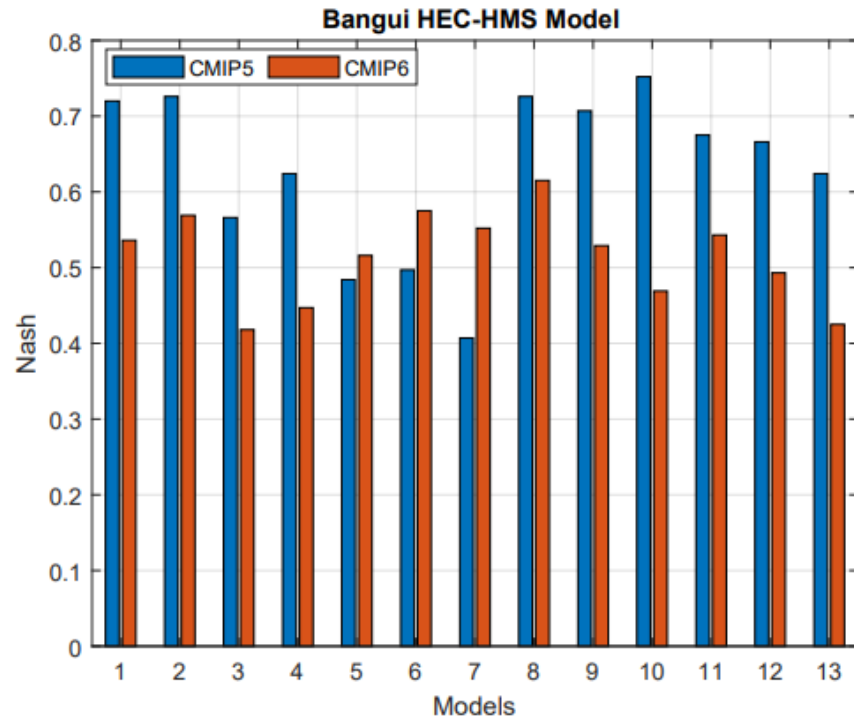


Figure 7.2 The Congo

7.4.2 Performances of Multi-model averaging approach

The weights assigned to each NEX-GDDP dataset with the GRC are presented in Table 7.3 and Table 7.4. The proposed approach assigned varying weights to different NEX-GDDP datasets. For HEC-HMS-NEX-GDDP-CMIP5 at the Bangui outlet, the highest weights were given to BNU-ESM (0.24), CanESM2 (0.16), MIROC-ESM-CHEM (0.47), MPI-ESM-MR (0.37), MPI-ESM-LR (0.23), and MRI-CGCM3 (0.11). In contrast, for HEC-HMS-NEX-GDDP-CMIP6 at the Bangui outlet, the highest weights were assigned to CanESM5 (0.15), GFDL-CM4-gr2 (0.10), INM-CM5-0 (0.37), IPSL-CM6A-LR (0.36), and MIROC6 (0.45).

For GR4J-NEX-GDDP-CMIP5 at the Bangui outlet, the highest weights were allocated to BNU-ESM (0.10), CanESM2 (0.12), IPSL-CM5A-LR (0.15), MPI-ESM-MR (0.14), and NorESM1-M (0.22). Meanwhile, for GR4J-NEX-GDDP-CMIP6 at the Bangui outlet, the highest weights went

to BCC-CSM2-MR (0.23), CanESM5 (0.15), MIROC-ES2L (0.15), and MPI-ESM-1-2-HR (0.32).

In all cases, weights assigned to the remaining NEX-GDDP datasets were less than 0.1.

For the Inga outlet, significant weights were assigned to certain NEX-GDDP datasets, such as BNU-ESM (0.68), CanESM2 (0.19), GFDL-ESM2G (0.26), IPSL-CM5A-LR (0.33), and MPI-ESM-LR (0.22) for HEC-HMS-NEX-GDDP-CMIP5. In the case of HEC-HMS-NEX-GDDP-CMIP6, substantial weights were given to CanESM5 (0.60), CNRM-CM6-1 (0.60), GFDL-ESM4 (0.36), MIROC-ES2L (0.17), and MPI-ESM-1-2-HR (0.45). Weights assigned to the remaining NEX-GDDP datasets were below 0.1. The performance of this weighting technique was evaluated using the Nash metric.

Table 7.3 Weights of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study calculated by GRC at Bangui outlet

Model Name	HEC-HMS	GR4J
BCC-CSM2-MR	-0.1249	0.2360
BNU-ESM	0.2426	0.1034
CanESM5	0.1504	0.1454
CanESM2	0.1592	0.1237
CNRM-CM6-1	-0.1006	-0.0786
CNRM-CM5	0.0341	-0.0465
GFDL-CM4-gr2	0.1064	0.0140
GFDL-ESM2G	0.0840	0.0115
GFDL- ESM4	-0.0186	-0.0485
GFDL-ESM2M	-0.1625	-0.0341
INM-CM5-0	0.3698	0.0690
INM-CM4	-0.1362	0.0930
IPSL-CM6A-LR	0.3561	0.0915
IPSL-CM5A-LR	-0.1856	0.1488
MIROC6	0.4523	0.0104
MIROC-ESM	-0.0627	0.0356
MIROC-ES2L	-0.2514	0.1505
MIROC-ESM-CHEM	0.4655	-0.1269

Table 7.3 Weights of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study calculated by GRC at Bangui outlet (Continued)

Model Name	HEC-HMS	GR4J
MPI-ESM-1-2-HR	-0.1884	0.3249
MPI-ESM-MR	0.3747	0.1420
MPI-ESM-1-2-LR	-0.0954	-0.1010
MPI-ESM-LR	0.2335	-0.2233
MRI-ESM2-0	0.0417	-0.0752
MRI-CGCM3	0.1131	-0.0439
NorESM2-LM	-0.3207	-0.0493
NorESM1-M	-0.3660	0.2175

Table 7.4 Weights of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study calculated by GRC at Inga outlet

Model Name	HEC-HMS	
	CMIP6	CMIP5
BCC-CSM2-MR	-0.3972	
BNU-ESM		0.6824
CanESM5	0.5968	
CanESM2		0.1943
CNRM-CM6-1	0.6009	
CNRM-CM5		-0.1004
GFDL-CM4-gr2	-0.0644	
GFDL-ESM2G		0.2596
GFDL-ESM4	0.3594	
GFDL-ESM2M		0.0784
INM-CM5-0	-0.3295	
INM-CM4		-0.0879
IPSL-CM6A-LR	0.0655	

Table 7.4 Weights of 13 CMIP6 (in bold) global climate models and their CMIP5 predecessors using in this study calculated by GRC at Inga outlet (Continued)

Model Name	HEC-HMS	
	CMIP6	CMIP5
IPSL-CM5A-LR		0.3325
MIROC6	0.0808	
MIROC-ESM		0.0283
MIROC-ES2L	0.1732	
MIROC-ESM-CHEM		-0.1326
MPI-ESM-1-2-HR	0.4455	
MPI-ESM-MR		-0.0044
MPI-ESM-1-2-LR	-0.0658	
MPI-ESM-LR		0.2153
MRI-ESM2-0	0.0324	
MRI-CGCM3		-0.0071
NorESM2-LM	0.0642	
NorESM1-M		0.0913

7.4.3 Projected flow under changing climate

As outlined in the methodology section, the initial phase of this study encompassed the calibration of both the HEC-HMS and GR4J models at the Bangui outlet, as well as the calibration of the HEC-HMS model at the Inga outlet.

The calibration of the HEC-HMS and GR4J models was carried out utilizing data from the Bangui and Inga outlets. Historical datasets spanning the period from 1981 to 2000, derived from 13 NEX-GDDP-CMIP6 and their precursor CMIP5 datasets, were employed in the model development process. To determine the model weights, the GRC weighting approach was applied, which involved a comparison between simulated and observed hydrographs. The weights obtained during

this calibration phase were subsequently applied to all 13 model members to generate a unified, weighted hydrograph. This composite hydrograph was then evaluated using the Nash-Sutcliffe Efficiency metric for both CMIP6 and CMIP5 scenarios.

For hydrological modeling, daily precipitation and temperature data were utilized, while daily streamflow data was employed for model calibration. Figure 3 provides a summary of the daily streamflow patterns simulated during the calibration period at Inga outlet.

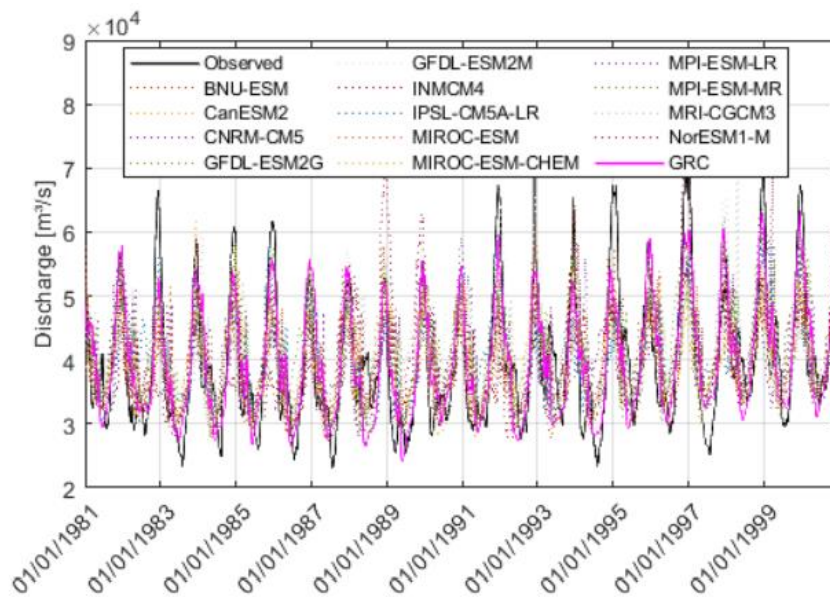


Figure 7.3 HEC-HMS model calibration for years 1981- 2000 at Inga outlet; dashed lines indicate hydrographs of 13 CMIP5 members, solid line indicates observed flows(black) and GRC average(pink)

As outlined in Section 3.1.1, our study leverages future climate scenarios, specifically RCP 4.5 and RCP 8.5 for NEX-GDDP-CMIP5, as well as SSP2 4.5 and SSP5 8.5 for CMIP6. These scenarios serve as the foundation for generating input data for our calibrated hydrological models.

With these future climate scenarios in place, our selected models have been equipped with the GRC method to optimize the amalgamation of objective functions. The results of this simulation are visually presented in Figures 7.4 and 7.5, offering insights into the model outcomes for the

specified target periods spanning from 2041 to 2060 and 2071 to 2090, respectively. These figures provide a detailed view of the anticipated hydrological changes under different climate scenarios.

Figures 4a, 4b for Bangui outlet and 5a, 5b at Inga outlet show an illustrative representation of the uncertainty range encompassing 5% of the projected flows for our selected climate scenarios. These scenarios encompass RCP 4.5 and RCP 8.5 from NEX-GDDP-CMIP5, as well as SSP2 4.5 and SSP5 8.5 from NEX-GDDP-CMIP6. This range of uncertainty is critical to understanding the variability and potential deviations in the anticipated hydrological changes within our study.

The 5% uncertainty range indicates a spectrum of possible outcomes within which the projected flows may vary. It serves as a crucial tool for assessing the reliability and robustness of our predictions, particularly in the face of changing climatic conditions. By providing this range, we acknowledge that while we have quantified our projections, there is inherent variability and potential deviations that need to be considered for sound decision-making and planning.

This level of detail allows stakeholders, researchers, and decision-makers to gain a more comprehensive understanding of the potential fluctuations in hydrological patterns and the level of confidence that can be attributed to our projections. In essence, these figures provide a critical visual aid for evaluating and interpreting the significance and implications of the projected flow changes within our selected climate scenarios. Figure 7.4c and 7.5c show the boxplot of future flows projections.

In conclusion, Figures 5 and 6 offer a valuable representation of the uncertainty range, which plays a pivotal role in enhancing the reliability and applicability of our study's findings. They serve as a means to communicate the intricacies and potential variations in the projected flows, ultimately contributing to more informed and resilient decision-making in the context of changing climate conditions.

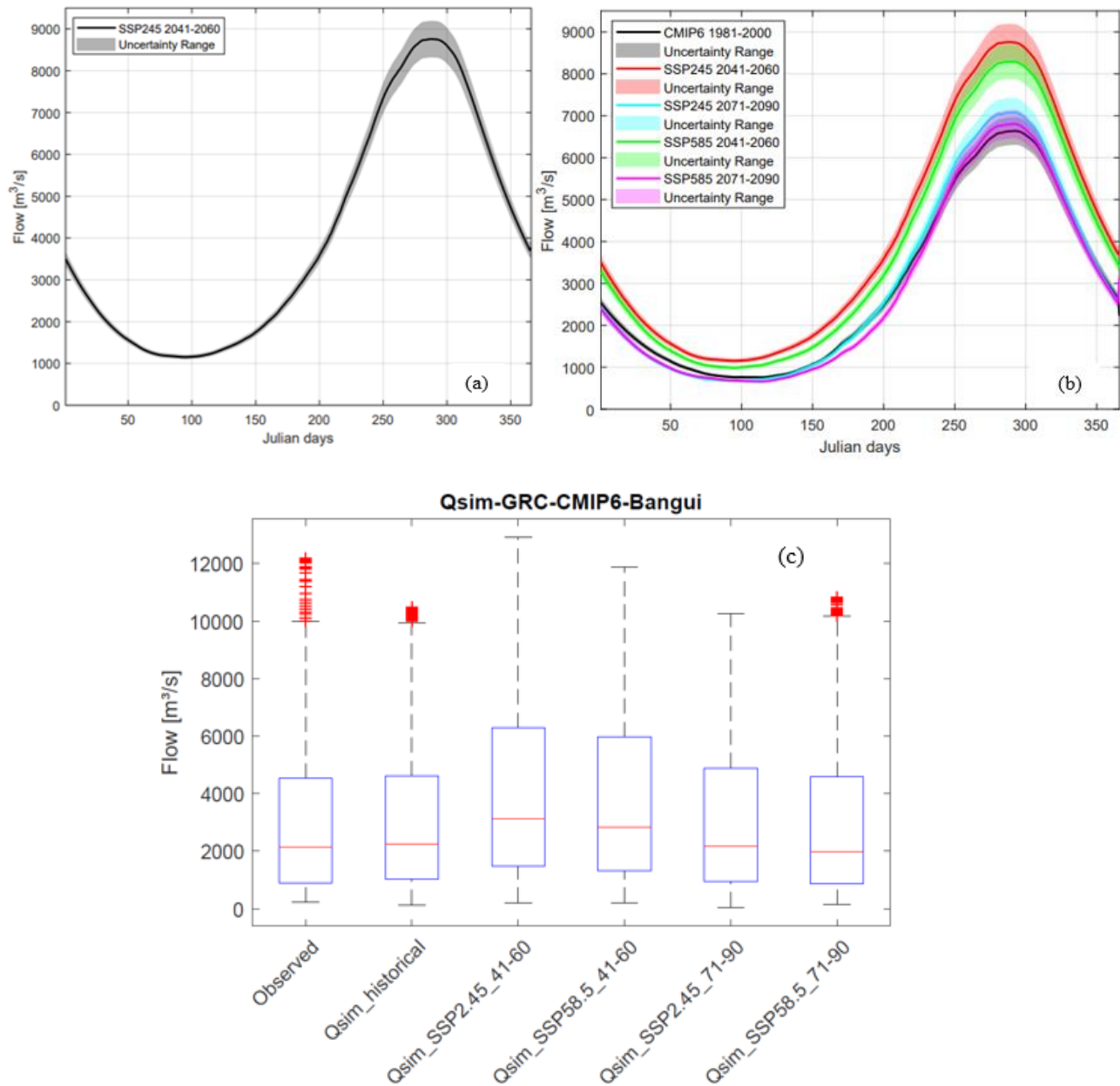


Figure 7.4 Simulated GRC ensemble mean daily river flows for the SSP2 4.5 and SSP5 8.5 scenarios at Bangui (a, b) and the corresponding box plots for these simulations (c). Shaded bands represent the 5% uncertainty ranges of GRC-CMIP6

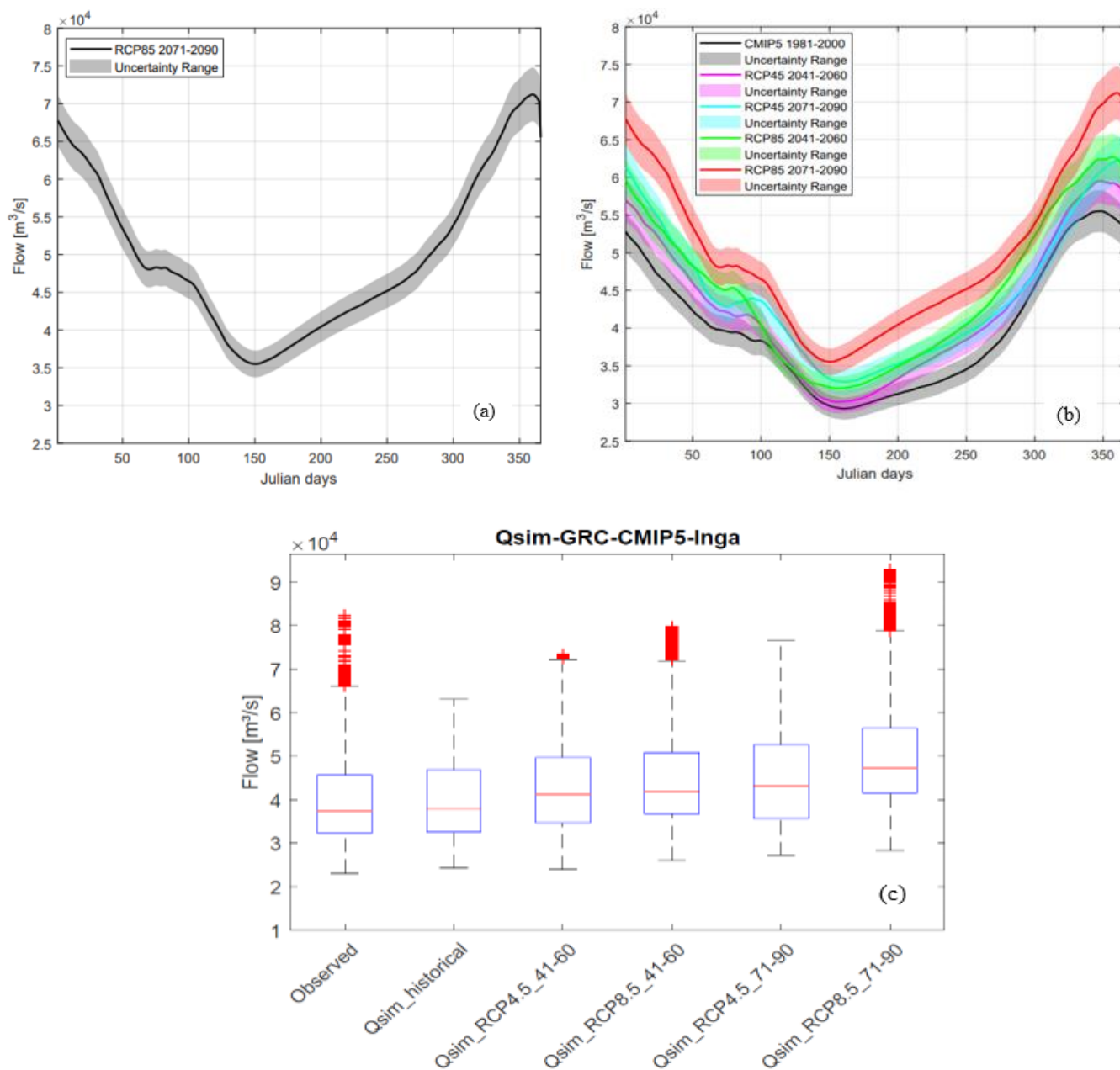


Figure 7.5 Simulated GRC ensemble mean daily river flows for the RCP 4.5 and RCP 8.5 scenarios at Inga (a, b) and the corresponding box plots for these simulations (c). Shaded bands represent the 5% uncertainty ranges of GRC-CMIP5

7.4.4 Projected changes in flow discharge at Bangui and Inga

Based on the predictions for the two target periods, 2041-2060 and 2071-2090, of CMIP5, when compared to the baseline period of 1981-2000, the average river flow at the Bangui outlet will decrease by 12.80% in Scenario RCP 4.5 and by 7.10% in Scenario RCP 8.5 during the 2041–2060 time span. For the 2071–2090 period, it is projected to decrease by 24.60% in Scenario RCP 4.5 and by 11.90% in Scenario RCP 8.5 (see Table 7.5). This significant decrease raises concerns about water security in the Bangui sub-basin.

In contrast to CMIP5, the predictions for the same two target periods, 2041-2060 and 2071-2090, of CMIP6, relative to the baseline period of 1981-2000, show that the average river flow at the Bangui outlet will increase by 50.71% in Scenario SSP2 4.5 and by 2.83% in Scenario SSP5 8.5 for the 2041–2060 time span. For the 2071–2090 period, it is projected to increase by 37.38% in Scenario SSP2 4.5 and decrease by 3.54% in Scenario SSP5 8.5.

However, similar to Bangui, for the same target periods, all CMIP5 and CMIP6 scenarios anticipate increased discharge at the Inga outlet (refer to Table 7.6). The predictions for CMIP5, in comparison to the 1981-2000 baseline, suggest an increase in average river flow by 7.08% in Scenario RCP 4.5 and by 12.22% in Scenario RCP 8.5 for the 2041–2060 time span, and an increase by 11.82% in Scenario RCP 4.5 and by 25.18% in Scenario RCP 8.5 for the 2071–2090 time span.

For the Inga outlet, the CMIP6 predictions follow a similar trend to CMIP5. The average river flow is projected to increase by 7.54% in Scenario SSP2 4.5 and by 3.94% in Scenario SSP5 8.5 for the 2041–2060 period and increase by 10.02% in Scenario SSP2 4.5 and by 4.09% in Scenario SSP5 8.5 for the 2071–2090 period. Inga outlet is expected to remain secure, with no significant negative impact. However, the designers of hydraulic structures at Inga should consider this increase in flow when planning their projects.

Table 7.5 Change in flow due to Climate change for Bangui

	NEX - GDDP	EMISSION SCENARIO	TIME PERIOD	CHANGE IN FLOW [%]
Relative change- CMIP5	CMIP5	RCP 4.5	2041-2060	-12.80
	CMIP5	RCP 4.5	2071-2090	-24.60
	CMIP5	RCP 8.5	2041-2060	-7.10
	CMIP5	RCP 8.5	2071-2090	-11.90
Relative change- CMIP6	CMIP6	SSP2 4.5	2041-2060	+50.71
	CMIP6	SSP2 4.5	2071-2090	+37.38
	CMIP6	SSP5 8.5	2041-2060	+2.83
	CMIP6	SSP5 8.5	2071-2090	-3.54

Table 7.6 Change in flow due to Climate change for Inga

	NEX - GDDP	EMISSION SCENARIO	TIME PERIOD	CHANGE IN FLOW [%]
Relative change- CMIP5	CMIP5	RCP 4.5	2041-2060	+7.08
	CMIP5	RCP 4.5	2071-2090	+11.82
	CMIP5	RCP 8.5	2041-2060	+12.22
	CMIP5	RCP 8.5	2071-2090	+25.18
Relative change- CMIP6	CMIP6	SSP2 4.5	2041-2060	+7.54
	CMIP6	SSP2 4.5	2071-2090	+10.02
	CMIP6	SSP5 8.5	2041-2060	+3.94
	CMIP6	SSP5 8.5	2071-2090	+4.09

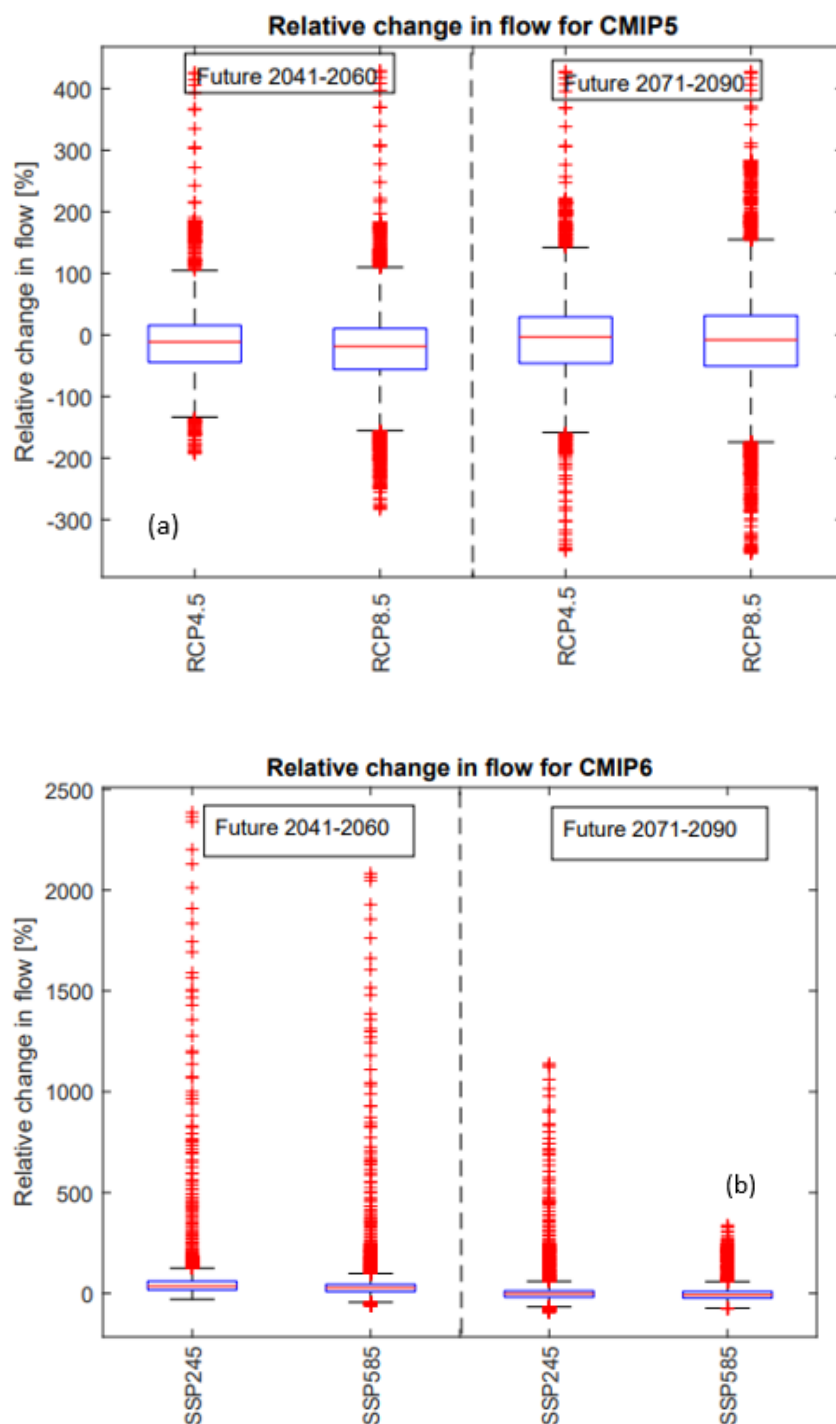


Figure 7.6 Boxplots comparing change in average daily discharge simulated at Bangui outlet by 13 CMIP5 models (a) and 13 CMIP6 models (b) for impact scenarios with respect to the reference scenario. Boxplots represent the model agreement of the predicted changes. The lower, middle and upper box lines represent respectively the 25, 50 and 75 percentiles. Minimum and maximum values are indicated by the whiskers, outliers are shown by the red symbol.

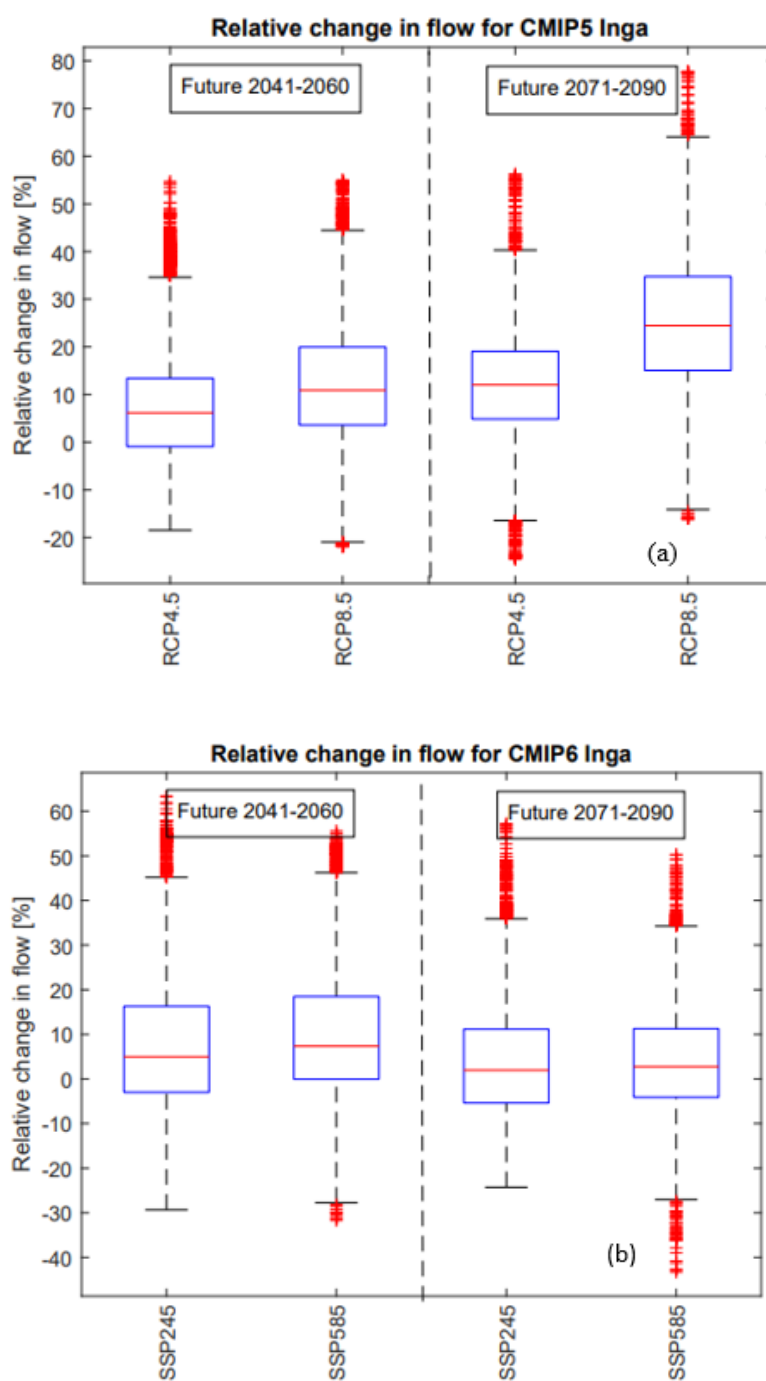


Figure 7.7 Boxplots comparing change in average daily discharge simulated at Inga outlet by 13 CMIP5 models (a) and 13 CMIP6 models (b) for impact scenarios with respect to the reference scenario. Boxplots represent the model agreement of the predicted changes. The lower, middle and upper box lines represent respectively the 25, 50 and 75 percentiles. Minimum and maximum values are indicated by the whiskers, outliers are shown by the red symbol.

7.5 Conclusions and recommendations

13 NEX-GDDP-CMIP6 and 13 NEX-GDDP-CMIP5 datasets were employed to project future hydrological scenarios for the Congo River Basin under different climate scenarios: SSP2 4.5 and SSP5 8.5 for CMIP6, and RCP4.5 and RCP8.5 for CMIP5.

These NEX-GDDP outputs were used to drive two hydrological models, HEC-HMS and GR4J, at the Bangui outlet, as well as one hydrological model, HEC-HMS, at the Inga outlet. The flows simulated by these models were then combined using a multi-model ensemble (MME), which, when compared to individual models, offers improved accuracy and reliability.

At the Bangui outlet, the performance of HEC-HMS, as compared to GR4J, was superior. This can be attributed to the detailed distributed parameter inputs in both space and time domains. Whether at the Bangui or Inga outlet, it was evident that the GRC approach significantly improved the performance of flow simulations compared to individual models and the simple average method (SAM).

These results demonstrate the potential for applying MME approaches in various other regions. Based on the combined predictions for the two target periods, compared to the baseline, the average annual flow of the Congo River Basin at the Bangui outlet is projected to decrease by 12.80% under RCP 4.5 during 2041-2060, followed by a steeper reduction of 24.60% in 2071-2090. For RCP 8.5, projections suggest reductions of 7.10% and 11.90% during the same intervals. In contrast, CMIP6 projections anticipate discharge increases of 50.71% (SSP2 4.5, 2041-2060) and 37.38% (SSP2 4.5, 2071-2090), alongside modest increases of 2.83% (SSP5 8.5, 2041-2060), followed by a reduction of 3.54% (SSP5 8.5, 2071-2090).

Notably, all CMIP5 and CMIP6 scenarios foresee increased discharge at the Inga outlet, ranging from 7.08% to 25.18% under distinct climate projections.

In summary, the use of a multi-model ensemble (MME) with a GRC averaging method is concluded to enhance flow predictions by providing a combined, better-weighted parameter set compared to individual models. These results indicate that it is possible to reduce uncertainty and improve the accuracy of future projections using MME-weighted models, as the MME approach helps mitigate bias and leverage the best performance of individual models.

Future work should consider applying the same methodology to other river basins (e.g., the Nile River Basin) to confirm its utility. Additionally, exploring the use of other hydrological models is warranted.

CHAPITRE 8 ARTICLE 4: CLIMATE CHANGE IMPACT ASSESSMENT ON GRAND INGA HYDROPOWER GENERATION USING MULTI-INPUT MODELLING

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Ma contribution telle que soumise au journal : Conceptualization, Methodology, Software, Formal analysis, Writing-Original draft, Visualisation.

Abstract

Climate change is expected to alter hydrological regimes, affecting the operation and performance of hydropower generation and facilities. The aim of the present study is to carry out a multi-input based study to assess the impacts of climate change on hydropower generation by using the new bias-corrected high-resolution daily downscaled dataset NEX-GDDP available through the NASA Center for Climate Simulation, and subsequently to analyze the effect of using model ensemble in projecting the future hydrology and energy generation scenario. The Grand Inga hydropower project, located on Congo River in the Democratic Republic of Congo, is the largest proposed hydropower scheme in the world. A hydrologic model of the basin, draining into the dam, is developed using a conceptual HEC-HMS model driven by an ensemble of 13 new bias-corrected high-resolution daily downscaled dataset NEX-GDDP CMIP6 and their predecessor CMIP5 under two Shared Socio-economic Pathway (SSP2-4.5 and SSP5-8.5) and two Representative Concentration Pathways (RCP 4.5 and RCP 8.5). The hydropower generation in the Inga Falls complex has been simulated by a hydropower simulation model. Hydropower generation has been computed from observed daily flow in the years 1981-2000, and from simulated daily flows for

different climate models and different emission scenarios. The transformation from flow to power is based on technical data for the existing (Inga 1 and 2) and planned (Inga 3-8) hydropower system at Inga Falls. The results indicate that Grand Inga will be very secure against negative climate impacts, and not at all sensitive for possible negative changes. This is valid not only for the existing system (Phase 1-2) but also for Phase 3,4 and 5. It is only during Phase 6, 7 and 8 that climate change will have an impact. And this seems mostly to be positive, increasing the generation potential.

Keywords: Grand Inga; GRC averaging; NEX-GDDP datasets; Congo basin.

8.1 Introduction

The acceleration of the global water cycle through increased evaporation and precipitation rates caused by greenhouse gas (GHG) emissions is a direct consequence of climate change (Huntington, T. G. *et al.*, 2018; Qin *et al.*, 2020; Syed *et al.*, 2010). This alteration redistributes water resources and intensifies the frequency and severity of extreme hydrological events (Loaiciga *et al.*, 1996; Qin *et al.*, 2020; Syed *et al.*, 2010), thereby impacting the operation of water infrastructure such as dam design and hydropower production (Cui *et al.*, 2020; Ehsani *et al.*, 2017; Fluixá-Sanmartín *et al.*, 2018; Qin *et al.*, 2020; van Oorschot *et al.*, 2018). The growing energy demand to support socioeconomic advancement is anticipated to drive further GHG emissions, amplifying atmospheric concentrations and resulting in a more pronounced climate and hydrological shift in the 21st century (IPCC, 2014). Against this backdrop, hydropower emerges as a dominant and cost-effective renewable energy source that plays a pivotal role in curbing GHG emissions and mitigating climate change. It's experiencing robust expansion across various global regions (Berga, 2016; Hamududu & Killingtveit, 2017; Lu *et al.*, 2020; Wasti *et al.*, 2022). Previous studies have

predominantly explored climate change's impact on water resources and hydropower generation using a top-down modeling approach. These studies integrated projections from general circulation models (GCMs) with hydrological models, reservoir operation models, and hydropower models (Chilkoti, V. *et al.*, 2017; Nohara *et al.*, 2006; Turner *et al.*, 2017; van Vliet *et al.*, 2016; Zhou, Y. *et al.*, 2015). It was generally observed that globally, projected annual mean streamflow would rise in high-latitude and wet tropical areas, while it would decrease in most dry tropical regions, alongside increased frequency of hydrological extremes (IPCC, 2014; Qin *et al.*, 2020).

Climate change introduces variability in precipitation and temperature patterns, impacting the streamflow regime and consequently affecting the resource potential of a basin (Liu, L.-L. & Du, 2017; Liu, L. *et al.*, 2017; Schaepli, B., 2015). Given that hydrological inputs are pivotal in assessing hydropower system potential, climate change impact assessments (CCIA) should integrate hydrologic models that accurately represent the contributing catchment (Chen, J. *et al.*, 2011; Ludwig *et al.*, 2009; Poulin *et al.*, 2011; Wilby, Robert L., 2005). These studies inherently carry uncertainties (Poulin *et al.*, 2011), primarily stemming from climate model and emission scenario uncertainties. To mitigate this, ensemble-based studies are recommended (Blöschl & Montanari, 2010; Minville *et al.*, 2010; Schaepli, Bettina, 2015), with hydrologic-model-based climate change assessments incorporating climate model ensembles (Christensen & Lettenmaier, 2007; Kopytkovskiy *et al.*, 2015).

Climate change studies rely on diverse climate models simulating future climate scenarios for different greenhouse gas emission scenarios (GHGES). Projected climate variable data can be derived from various simulation runs of climate models, with general circulation models (GCMs) being common. Regional climate models (RCMs) offer a solution by providing high-resolution climate information based on GCM data (Buontempo *et al.*, 2015; Dosio *et al.*, 2015). The National

Aeronautics and Space Administration (NASA) recently launched the Earth Exchange Global Daily Downscaled Projections (NEXGDDP) dataset, which facilitates future climate change studies at the watershed scale, as demonstrated by (Chen *et al.*, 2017) and (Jain, S. *et al.*, 2019).

The Grand Inga hydropower project (GIHP) on the Congo River in the Democratic Republic of Congo (DRC) is a notable initiative, comprising the world's largest proposed hydropower scheme. Positioned at the Inga Falls site, it holds enormous potential for energy production. As climate change poses a significant threat to such projects, evaluating its impact on hydropower generation becomes imperative. Thus, this study aims to systematically assess climate change's effect on GIHP performance using a hydrological-electricity modeling framework fueled by NEX-GDDP datasets. It further analyzes the influence of model ensembles in projecting future hydrology and energy generation scenarios, offering insights into the potential adaptation strategies required for managing the GIHP under evolving climate conditions.

8.2 Grand Inga - overview and project planning

8.2.1 Overview on Inga falls

The hydropower potential of the Congo River at the Inga site has been known since the beginning of the 20th century. The Inga site is a 32-km stretch of the Congo River, located approximately 280 km downstream of the Capital city of Kinshasa in the Democratic Republic of the Congo (DRC) (Figure 1). This stretch of river has a natural river profile that drops 97 m in elevation. With a mean annual flow (MAF) of around 40 000 m³/s at this site and a gross head that may be raised to 150 m, The hydroelectric potential in Inga falls is huge, the installed capacity could be developed to exceed 47 000 MW with an annual generation exceeding 360 TWh. This can be compared to the present (2021) hydropower fleet in whole Africa of 38 000 MW and 146 TWh. The two first phases of the development of the Inga site, Inga 1 (350 MW) and Inga 2 (1,400 MW), were completed in

1971 and 1982, respectively. Since then, no major new power plants have been constructed in the Country.

8.2.2 Development prospects of Grand Inga

Many studies on further development of Grand Inga have been performed, a good summary of possible future development is given by Nzakimuena *et al.* (2013) and Zahera, and Fuamba (2022). The hydropower simulation models developed in this study was based on the final proposed scheme elaborated by AECOM-RSW/EDF consortium and submits to the Congolese government in 2012 as provisional feasibility report for the development study of the Inga hydroelectric site and associated interconnections. In this scheme further development has been planned in several phases, from Phase 3 to Phase 8. Each phase will consist of several turbine/generator sets, from 8-12 in each Nzakimuena *et al.* (2013).

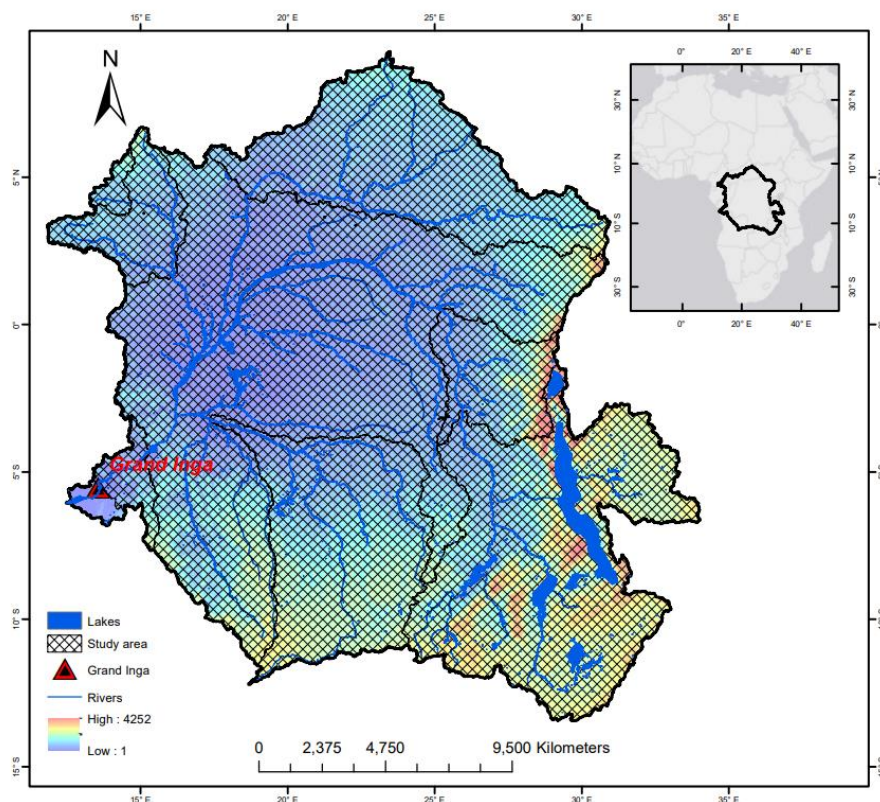


Figure 8.1 Drainage area of Congo River upstream of Grand Inga Hydroelectric project

8.3 Data and methods

8.3.1 Modelling procedure

This study was carried out by first developing a conceptual hydrological model which is calibrated based on historical climate dataset and the observed streamflow. The hydrological model is subsequently forced with the projected future high- resolution NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset. The hydropower generation model was used to compute the future energy production.

8.3.2 Data

8.3.2.1 System data for Inga Falls hydropower development.

Data for existing (Inga 1 and 2) and planned (Inga 3-8) is summarized in Table 8.1. It should be noted that further development is also possible, given that a residual flow still exists after the installation of eight projected phases. Some calculations are done here for two additional phases (Inga 9 and 10).

Table 8.1 Main technical data for the Inga Falls hydropower system (Source: Nzakimuena *et al.*, 2013)

Main steps (Phases) in Inga's development		Data per generating unit (turbine/generator)				
Phase	# of units	Q _{max} [m ³ /s]	Head [m]	EEQV1 [kWh/m ³]	EEQV2 [MW/m ³ /s]	P _{max} [MW]
Inga 1	6	130	50	0.125	0.450	58.5
Inga 2	8	252.5	58	0.157	0.566	143
Inga 3	11	600	150	0.376	1.354	813
Inga 4	8	685	150	0.376	1.354	928
Inga 5	8	685	150	0.376	1.354	928
Inga 6	8	685	150	0.376	1.354	928
Inga 7	8	685	150	0.376	1.354	928
Inga 8	8	685	150	0.376	1.354	928
Inga 9	8	685	150	0.376	1.354	928
Inga 10	8	685	150	0.376	1.354	928

Table 8.2 Cumulative values of flow ($Q_{\max}$) and capacity ($P_{\max}$) for each phase

Cumulative values		
Phase	$Q_{\max}$	$P_{\max}$
	m ³ /s	MW
Inga 1	780	351
Inga 2	2800	1495
Inga 3	9400	10434
Inga 4	14880	17856
Inga 5	20360	25278
Inga 6	25840	32700
Inga 7	31320	40122
Inga 8	36800	47544
Inga 9	42280	54966
Inga 10	47760	62388

$Q_{\max}$: Max turbine flow

Head: Gross head Intake to Tailwater

EEQV1: Energy equivalent of water, kWh/m³

EEQV2: Power equivalent of water, MW per m³/s

$P_{\max}$: Power capacity at full turbine flow, MW

The three columns EEQV1, EEQV2 and $P_{\max}$ have been compute based on $Q_{\max}$ and Head, with some additional assumptions regarding turbine and generator efficiency, and head losses.

Phase 9 and 10 have been added here, to show the possibility of further expansion of the project and compute utilization. Same type of turbines as in Inga 4-8 were assumed.

8.3.2.2 Flow data

The streamflow data for the Inga outlet was sourced through the R.V.F (Régie des voies fluviales). These data played a crucial role in both the calibration process and the assessment of the hydrological modeling's performance. Specifically, the dataset encompassed the daily flow rates at Inga Falls over a span of 20 years, ranging from January 1, 1981, to December 31, 2000 (as depicted in Figure 8.2a). The flow duration curve is visualized in Figure 8.2b.

Key statistics extracted from the dataset are as follows:

Average flow: 39,912 m³/s

Median flow: 37,393 m³/s

Maximum flow: 82,428 m³/s (occurred on December 28, 1996)

Minimum flow: 23,063 m³/s (recorded on July 26, 1987).

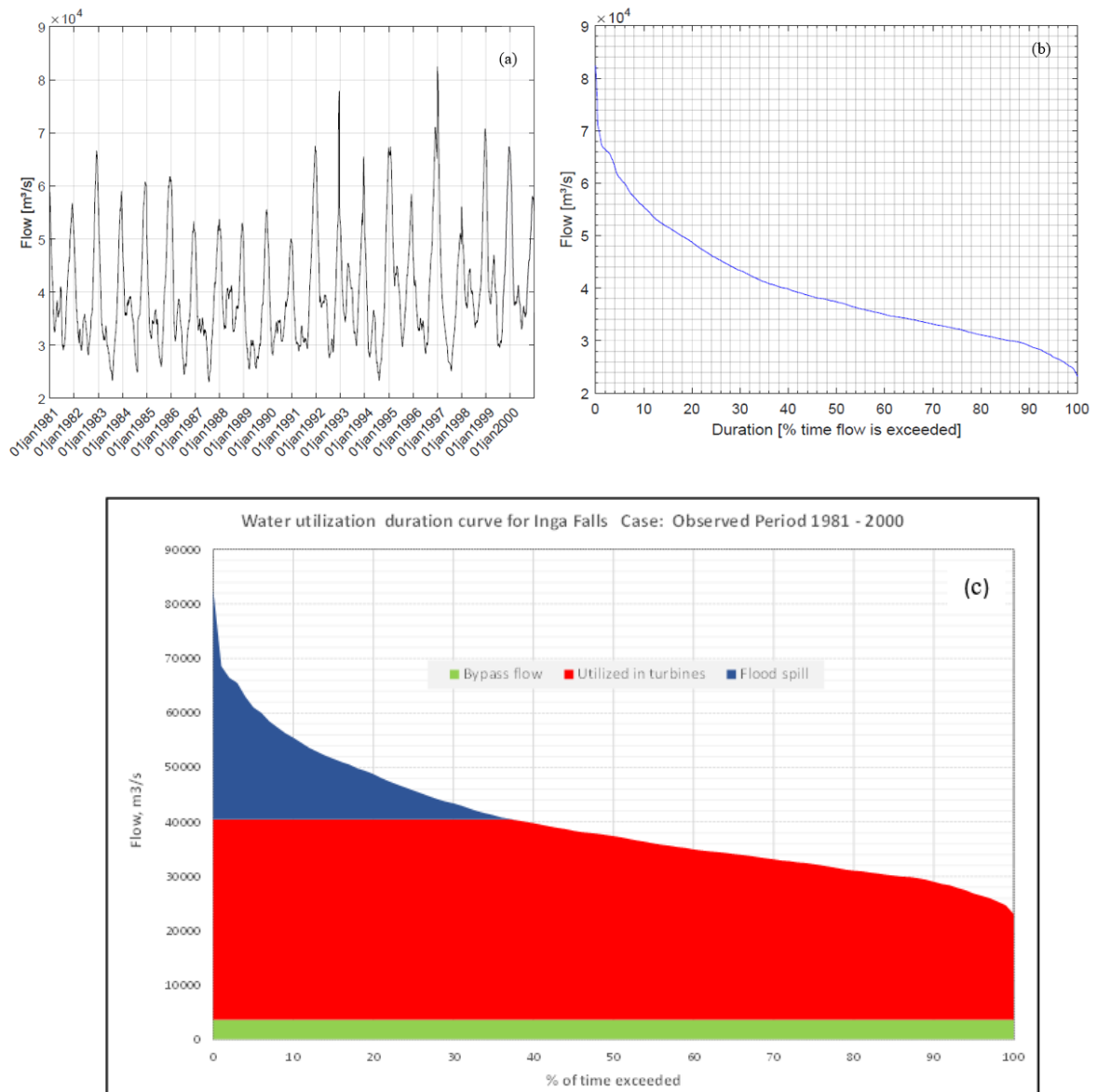


Figure 8.2 (a) Daily water flow, (b) Flow duration curve at Inga Falls and (c) Water utilization duration curve for Inga Falls with full development (Inga 1-8)

8.3.2.3 Data for future climate projection

To assess the hydrological response to climate change in the Congo River basin, a high-resolution NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset was used in this study. The NEX-GDDP-CMIP5 (Thrasher, Bridget *et al.*, 2012) and NEX-GDDP-CMIP6

(Thrasher, B. *et al.*, 2022) dataset can be used in conducting studies of climate change impacts at the spatial scale of individual towns, cities, and watersheds. NEX-GDDP is the output of Coupled Model Inter-Comparison Project Phase 5 (CMIP5) and Phase 6 (CMIP6) GCMs downscaled at high spatial resolution ($0.25^\circ \times 0.25^\circ$) and available as daily data projections from 1950–2100. The bias correction and spatial disaggregation (BCSD) regression-based statistical downscaling method was applied in the development of this dataset to improve the efficiency of low-resolution GCMs for removing local biases (Thrasher, Bridget *et al.*, 2012; Thrasher, B. *et al.*, 2022; Wood *et al.*, 2004). A subset of 13 CMIP6 models and their predecessor CMIP5 was selected in this research (Table 3).

Table 8.3 Overview of 13 NEX-GDDP CMIP6 models and their predecessors CMIP5 using in this study

Model Name		Modeling Agency	Resolution Lon. x Lat.
CMIP6	CMIP5		
BCC-CSM2-MR	BNU-ESM	Beijing Climate Center, China Meteorological Administration (China)	$0.25^\circ \times 0.25^\circ$
CanESM5	CanESM2	Canadian Centre for Climate Modelling and Analysis (Canada)	$0.25^\circ \times 0.25^\circ$
CNRM-CM6-1	CNRM-CM5	Centre National de Recherches Météorologiques, France	$0.25^\circ \times 0.25^\circ$
GFDL-CM4-gr2	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory, USA	$0.25^\circ \times 0.25^\circ$
GFDL- ESM4	GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, USA	$0.25^\circ \times 0.25^\circ$
INM-CM5-0	INM-CM4	Institute for Numerical Mathematics, Russian Academy of Science /Russia	$0.25^\circ \times 0.25^\circ$
IPSL-CM6A-LR	IPSL-CM5A-LR	L'Institut Pierre-Simon Laplace (France)	$0.25^\circ \times 0.25^\circ$
MIROC6	MIROC-ESM	National Institute for Environmental Studies, The University of Tokyo (Japan)	$0.25^\circ \times 0.25^\circ$
MIROC-ES2L	MIROC-ESM-CHEM	National Institute for Environmental Studies, The University of Tokyo (Japan)	$0.25^\circ \times 0.25^\circ$
MPI-ESM-1-2-HR	MPI-ESM-MR	Max Planck Institute for Meteorology (Germany)	$0.25^\circ \times 0.25^\circ$
MPI-ESM-1-2-LR	MPI-ESM-LR	Max Planck Institute for Meteorology (Germany)	$0.25^\circ \times 0.25^\circ$
MRI-ESM2-0	MRI-CGCM3	Meteorological Research Institute (Japan)	$0.25^\circ \times 0.25^\circ$
NorESM2-LM	NorESM1-M	Norwegian Climate Centre (Norway)	$0.25^\circ \times 0.25^\circ$

8.3.3 Hydrological model

Temperature and precipitation from the new high- resolution NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset was used as input to a hydrological model to predict water inflows along the complete watercourse of the Congo River. Hydrological modelling was performed by the HEC-HMS model. The HEC-HMS model is designed to simulate the complete hydrological processes and can be used for both continuous and event-based modelling (Bhuiyan *et al.*, 2017). HEC-HMS has several Loss Method. However, with soil moisture accounting (SMA) algorithm, it accounts for watershed's soil moisture balance over a long-term period and is suitable for simulating daily, monthly, and seasonal stream flow (Ouédraogo *et al.*, 2018; Singh & Jain, 2015). The SMA algorithm takes explicit account of all runoff components including direct runoff (surface flow) and indirect runoff (interflow and groundwater flow) (Roy *et al.*, 2013). The model requires inputs of daily rainfall, soil condition and other hydro meteorological data. Besides precipitation and temperature, the only other input to the SMA algorithm is the potential evapotranspiration rate. The potential evapotranspiration was computed using the Oudin formulation (Oudin *et al.*, 2005). HEC-HMS model has been used by several researcher and has shown excellent results (Singh & Jain, 2015; Yuan *et al.*, 2019; Zelelew & Melesse, 2018). The structure of SMA is described in detail in the HEC-HMS Technical Reference Manual (Feldman, 2000).

8.3.4 Model calibration

The first phase of this methodology involved calibrating the HEC-HMS model at the Inga outlet. This calibration process utilized 13 CMIP6 and 13 CMIP5 historical datasets, coupled with observed hydrometric data. Consequently, a total of 26 model calibrations were undertaken, representing (Inga x 1 hydrological model x 13 datasets x 2).

One of the calibration strategies applied encompassed calibrating the model using the entire available dataset, bypassing the conventional validation phase. This strategy capitalizes on extracting maximum information from climate data to shape the parameter set, thereby reducing additional uncertainty linked to selecting calibration and validation periods (Tarek *et al.*, 2020). Importantly, the statistical enhancement of model performance often arises from expanding the dataset with more years, and the skills required for validation and calibration are not inherently intertwined (Arsenault *et al.*, 2018).

Within this study, the HEC-HMS model underwent calibration across the complete available dataset (1981-2000), without following the customary validation step. Due to the model's intricate parameter landscape, a preliminary parameter estimation was derived using insights from the HEC-GeoHMS Extension in tandem with the ArcHydro extension within ArcMap 10.7.1. However, discrepancies in certain physical parameters (such as reach length and slope) emerged from HEC-GeoHMS, necessitating manual rectification through QGIS 3.14.

The primary step in the calibration of the HEC-HMS model involved a manual fine-tuning of model parameters, employing the trial-and-error approach. This methodology empowered the modeler to subjectively adjust parameters, facilitating an appropriate alignment between observed and simulated hydrographs (Zhang, J. *et al.*, 2013). Subsequently, the Optimization Trials tool integrated within HEC-HMS was employed for automated calibration, serving to refine parameter values.

8.3.5 Multi-Input Ensemble Modelling

The concept of combining the output obtained from different models or methods was discussed and used in the pioneering works of (Bates & Granger, 1969; Dickinson, 1973, 1975; Newbold & Granger, 1974) and others (Arsenault *et al.*, 2017b; Zhang & Yang, 2018). The essence of the

concept of these methods is that each model output captures certain important aspects of the information available about the process being modeled, thereby providing a source of information that may be different from that of other models (Shamseldin *et al.*, 1997; Zhang & Yang, 2018). Combining these various sources of information may enable the user to gain a merged, all-inclusive picture for a given study area (Zhang & Yang, 2018). Several methods of combining model outputs have been reported: the simple average method, the weighted average method (Shamseldin *et al.*, 1997; Zhang & Yang, 2018), the neural network method (Araghinejad *et al.*, 2011; Zhang & Yang, 2018), Bayesian model averaging method (BMA) (Duan *et al.*, 2007), Shuffle complex averaging (SCA) (Duan *et al.*, 1992), and Granger Ramanathan A, B and C (GRA, GRB and GRC) (Granger & Ramanathan, 1984). Compared with more traditional averaging methods, GRA is becoming popular due to its ability to optimize weights based on performance and thus providing a superior choice in modeling. In this study, the GRC variant (Arsenault *et al.*, 2017a) was implemented because it is robust, easy to implement, and fast, which were key selection criteria for this study.

8.3.6 Hydropower generation simulations

The planning, design, operations, and financial evaluation of hydropower systems are based on hydrological time series. Normally periods ranging between 20 to 50 years are used for evaluations (Hamududu, 2012). To obtain the change in hydropower production that results from climate change, production calculations are necessary, and these are carried out using hydropower simulation models. The simulation model reflects the main features of the existing hydropower system and is thus run over several years to get stable average estimates, first in the current period and then in the future. There are not so many hydropower simulation models when compared to hydrological models. The simplest and statistical way of computing power production is correlation between historical records of flow and production (Hamududu, 2012). However, this does not work

in all cases. The best approach is to use a process-based hydropower simulation in which most of the important components of the hydropower system are defined. In this study, the hydropower generation was simulated using an Excel-based program system to convert from flow to power (kW) and electrical energy (kWh), for both existing and planned hydropower generating units (turbine+generator). The simulation model is operating on a daily time step, each day simulating sum generation for all generating units, In the presentation of results, these are summed up for all generating unit in each phase.

8.3.6.1 Hydropower model application

Hydropower generation calculations are based on observed daily flows from 1981 to 2000 and simulated daily flows derived from various climate models and emission scenarios. The conversion from flow to power relies on technical data from both existing (Inga 1+2) and planned (Inga 3-10) phases of the hydropower system at Inga Falls. (Table 1 and 2).

For each of the up to 81 generating units in the full development (Inga 1-Inga10) the power and energy generation is computed as:

$$P = 9.81 * \eta * Q * H_n$$

$$E = P * 24$$

where:

P is power in kW

E is electrical energy in kWh/day

η is total efficiency in turbine, generator and transformer

Q is flow in m³/s

H_n is net head (gross head – head loss) in m

For Inga 1 and 2, efficiency parameters were derived from operational data, whereas Inga 3-10 assumes Francis turbines with a 96% efficiency, a combined generator + transformer efficiency of 98%, and 2.1 % head loss.

For practical reasons, the terms MW and TWh are used in presentations for P and E, where:

1 MW = 1000 kW

1 TWh = 1 000 000 000 kWh

The comprehensive (Grand Inga) project is scheduled to unfold in eight phases, with Phase 1 and 2 being existing power plants and Phase 3 to 8 being in the planning stages. The various phases encompass different numbers of units, utilizing the full 150 m head, except for Phase 1 and 2, which utilize only a limited part of it (Table 8.1). The augmentation of head is accomplished by constructing a substantial dam across the river, elevating the intake level to 150 m. A minimum bypass flow of 10% of average flow (3700 m³/s) is stipulated for all simulations. In this study, two additional Phases (9 and 10) were introduced to analyze the remaining potential, beyond Inga 8.

8.3.6.2 Steps of the Hydropower Generation Simulation Project

1. Define the hydropower model for existing and prospective developments in Inga Falls.
2. Generate power from observed flow from 1981-2000 (Baseline, 1 Run).
3. Generate power from flow data acquired from 13 Climate models for 1981-2000 (13 runs).
4. Produce generation from future flow data under two main climate modeling scenarios: CMIP5 and CMIP6, each involving different models, RCP/SSP scenarios, and time frames, leading to 65 different runs per scenario.

5. Compile summary results for all models and emission scenarios.

8.4 Results and discussion

The findings related to hydrological modeling, climate scenario forecasts, simulations of upcoming hydrological predictions, and future energy production are outlined in this section.

8.4.1 Hydrological Modelling

As started in the methodological section, HEC-HMS model has been calibrated based on the data available at the Inga outlet. The historical datasets of 13 NEX-GDDP-CMIP6 and their predecessors CMIP5 for the period 1981-2000 have been used for the model development. The GRC weighting approach was applied to generate the weights according to the simulated and the observed hydrographs. The same weights were applied to the 13 members to generate a single weighted hydrograph which was assessed using the Nash-Sutcliffe Efficiency metric for CMIP6 and CMIP5. The weights generated during the calibration of each hydrograph are then employed for model run in future climate scenario. The detailed results of calibration are not presented here for brevity. Daily precipitation and temperature data is used for hydrologic modeling while the

daily streamflow data is used for model calibration. Figure 8.3 presents the summary of simulation of the daily streamflow patterns during the calibration period.

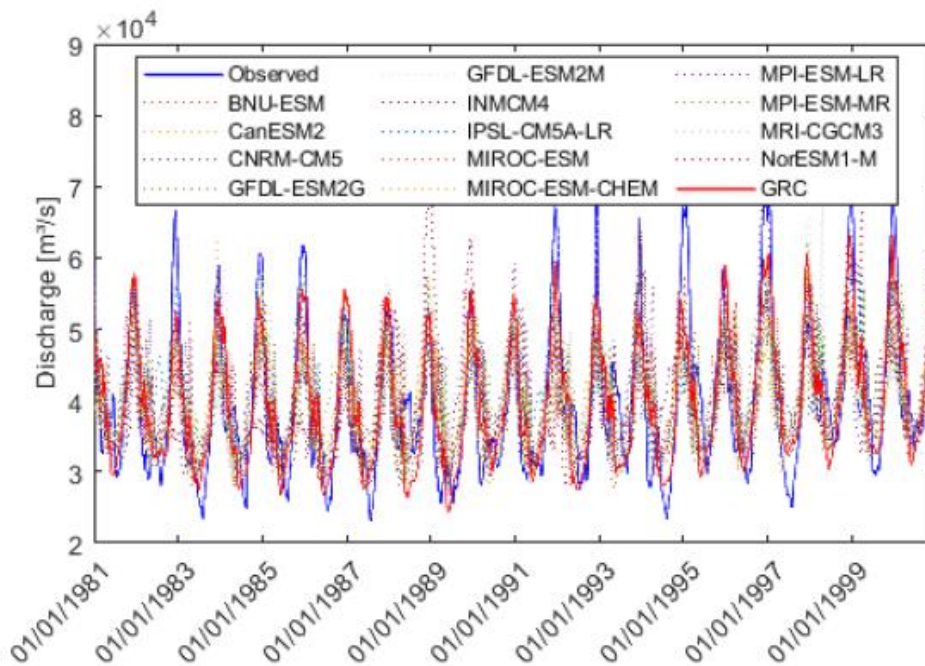


Figure 8.3 HEC-HMS model calibration for years 1981- 2000; dashed lines indicate hydrographs of 13 CMIP5 members, solid line indicates observed flows(blue) and GRC average(red)

8.4.2 Projected Hydrologic scenario.

After interpreting the projections in climate variables, the projection in hydrologic scenario is assessed. Streamflow of the basin is generated by forcing the projected climate data into the earlier calibrated hydrological model. The runoff generation for the future scenario shall be the combined

effect of precipitation and temperature projections. Future streamflow pattern by each of the model scenarios is presented in Figure 8.4 and compared with the historical flows.

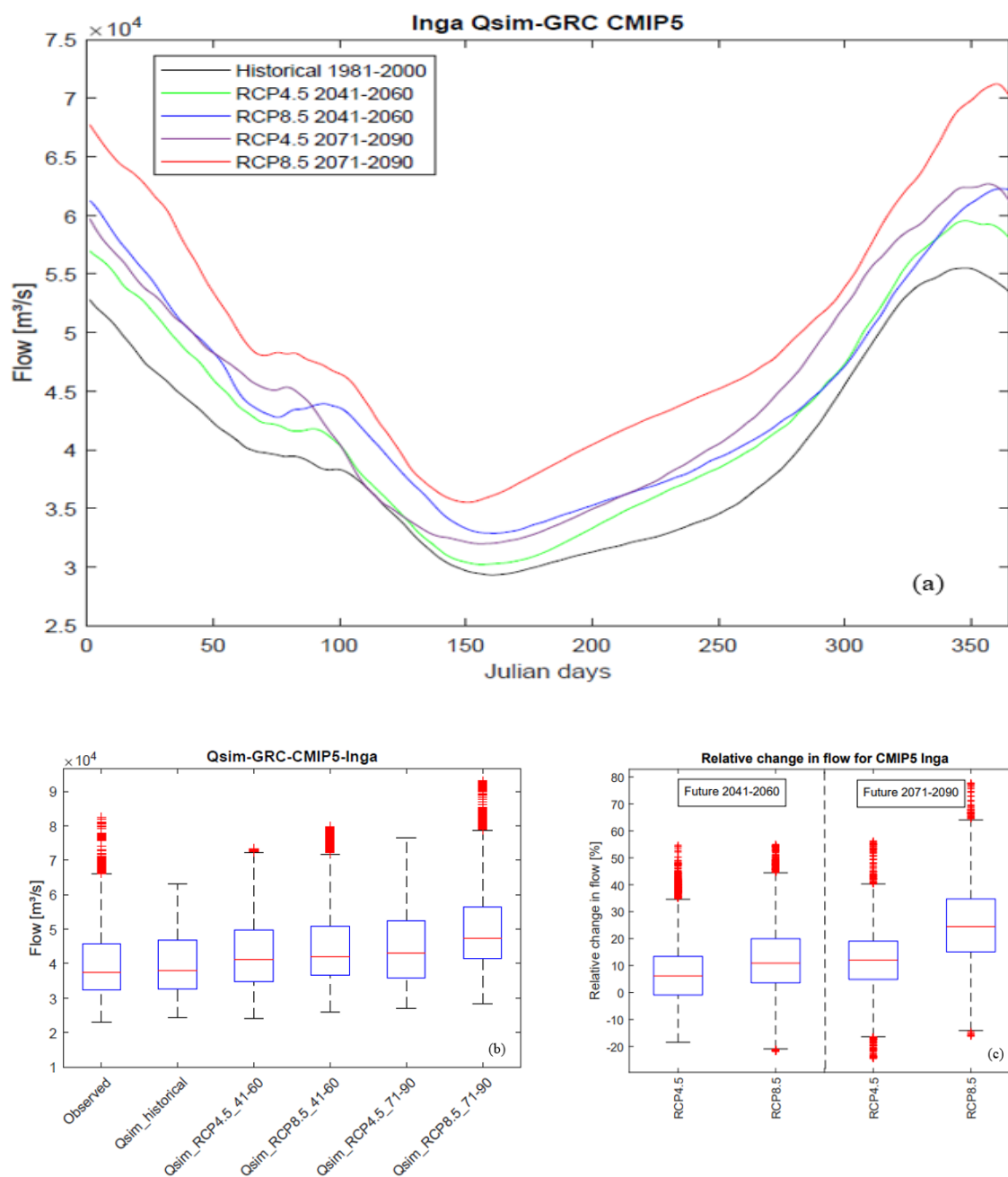


Figure 8.4 Annual GRC average flow in Congo River at Inga Falls gauging station for the reference period 1981–2000 and for projected future periods for different emission scenarios (a), (b). The figure (c) represents the relative change in %.

8.4.3 Hydropower generation simulations

8.4.3.1 Flow Duration Curve

The flow-duration curve (FDC) was prepared with the GRC daily discharge simulated from HEC-HMS model averaged over 20 years for the baseline period and future time periods for both CMIP5 and CMIP6 scenarios (Figures 8.5&8.6).

This FDC presents for Inga Falls the duration during which a certain flow value is reached or exceeded for both CMIP5 and CMIP6 scenarios. It allows you to select the nominal flow rate of the projected installation by taking into account the reserved flow rate and the technical minimum flow rate of the equipment. It also makes it possible to estimate the power of the plant and its average annual production.

Its distribution throughout the year is necessary for economic reasons since the sales prices applied to independent producers vary with the seasons of the year and the hours of the day.

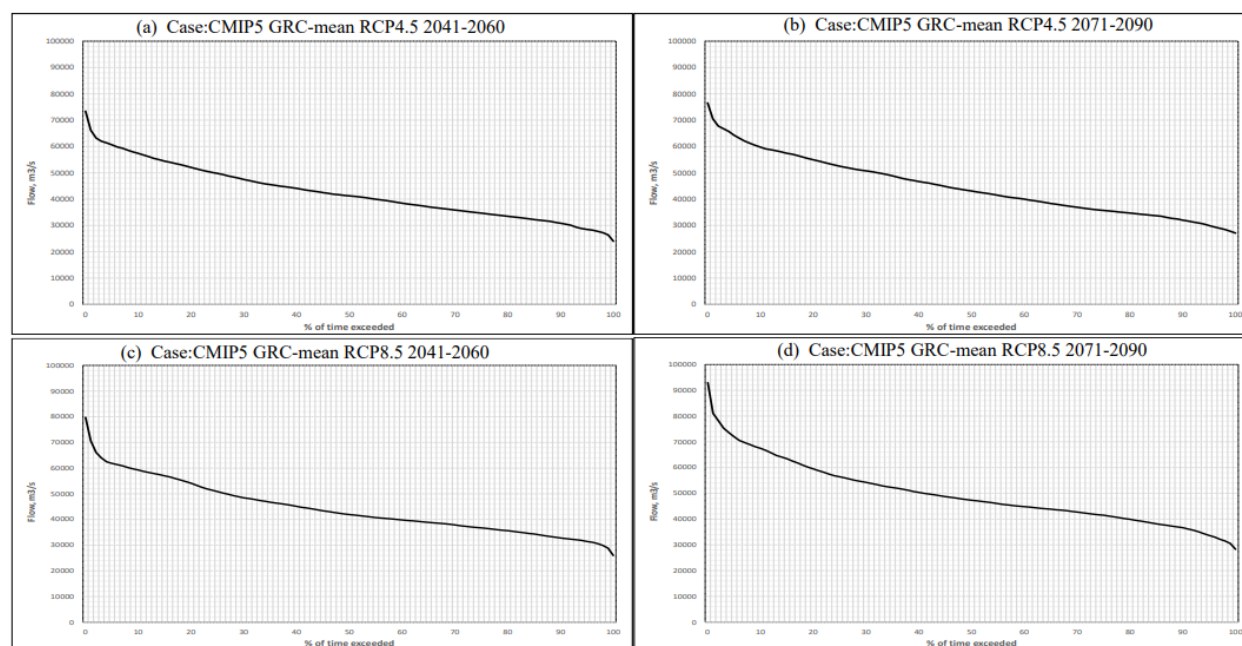


Figure 8.5 Flow duration curve of Inga Falls for GRC CMIP5 scenarios

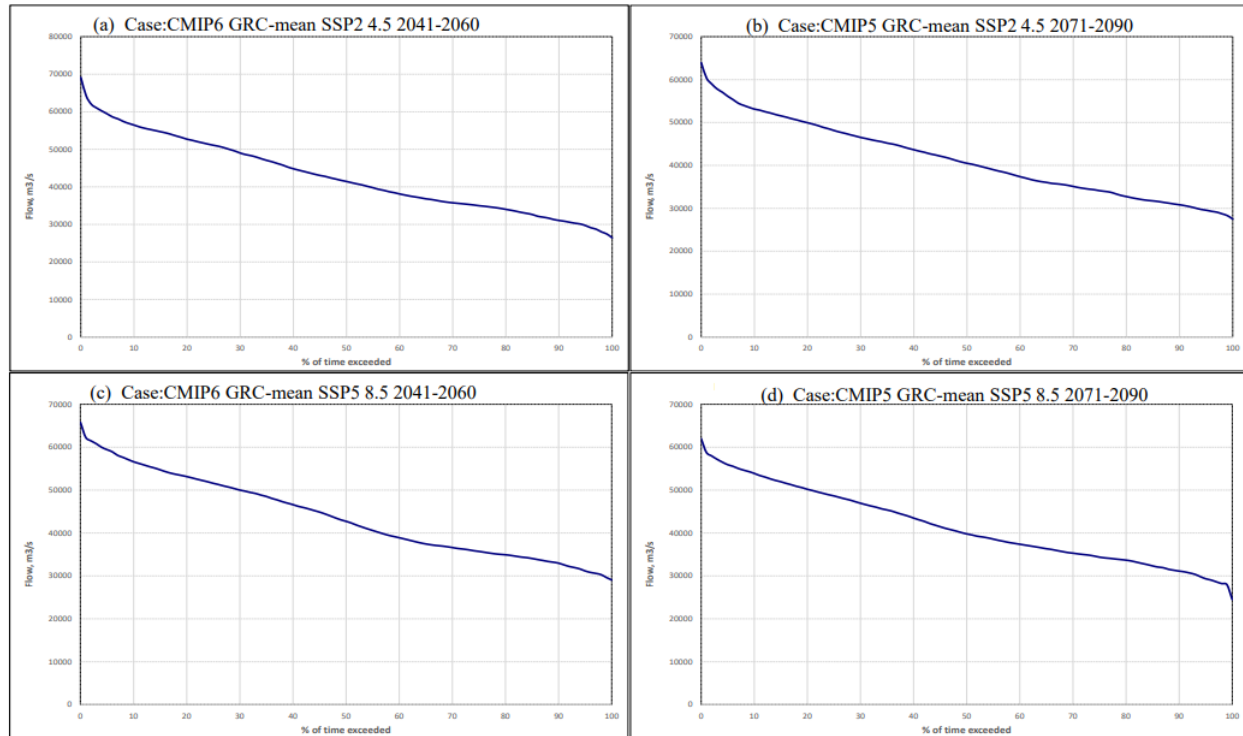


Figure 8.6 Flow duration curve of Inga Falls for GRC CMIP6 scenarios

8.4.3.2 Water utilization duration curve

The minimum bypass (environmental) flow of $3700 \text{ m}^3/\text{s}$ requires water. At full development up to and including Inga 8, the maximum flow that can be utilized in power plants is $36800 \text{ m}^3/\text{s} + 3700 \text{ m}^3/\text{s}$ or $40500 \text{ m}^3/\text{s}$. Any flow larger than this will lead to flood spill at the dam. The maximum power capacity at this flow ($36800 \text{ m}^3/\text{s}$) is 47544 MW. This is equivalent to 1.14 TWh/day. Figures 8.7 and 8.8 visualize total water utilization for Inga Falls, for CMIP5 and CMIP6 respectively, based on simulated flow for all scenarios. It is observed that there is ample water to maintain full capacity in the turbines approximately 40% of the time, while Inga 6, 7, and 8 will experience intervals where full generation capacity is not attainable.

Power generation is simulated daily, prioritizing water use as follows:

1. Minimum flow (3700 m³/s) - Highest Priority.
2. Units in Phase 1 - Second Priority.
3. Units in Phase 2 - Third Priority.
4. Units in Phases 3 to 8 - Decreasing Order of Priority.

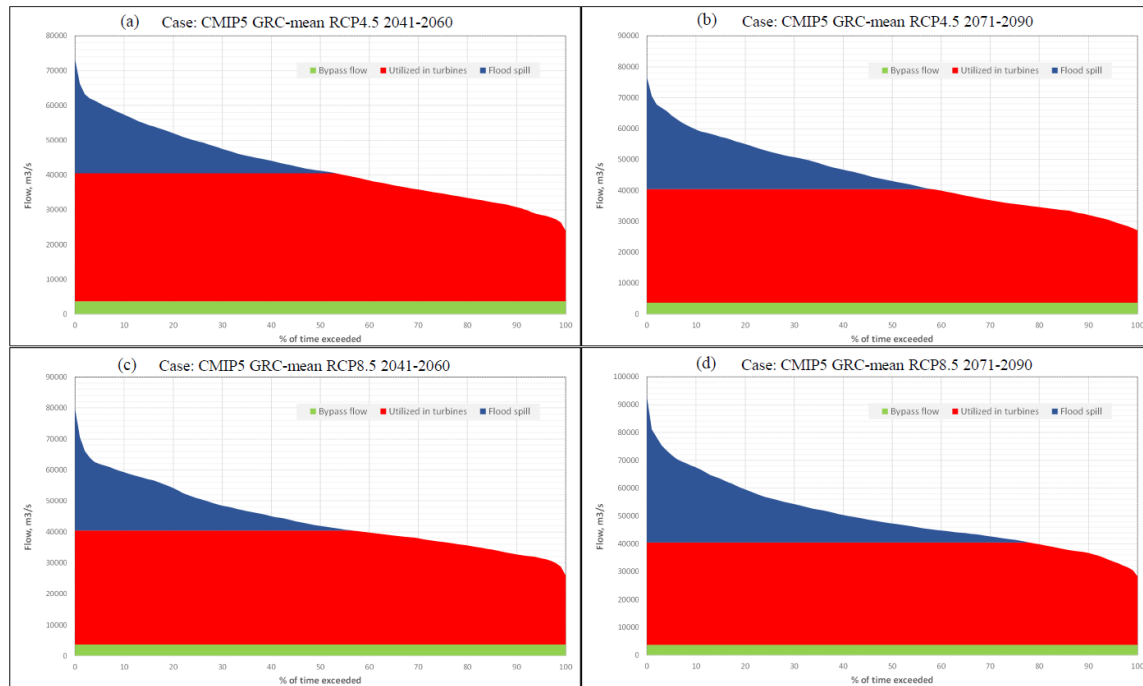


Figure 8.7 Water utilization duration curve of Inga Falls for GRC CMIP5 scenarios

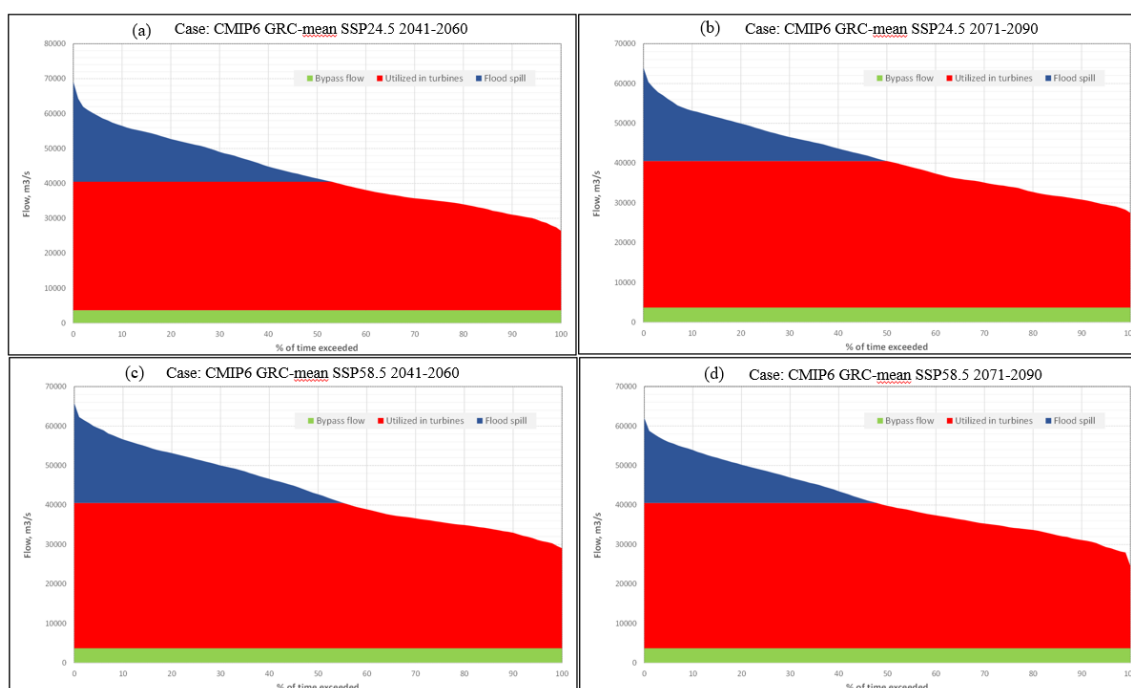


Figure 8.8 Water utilization duration curve of Inga Falls for GRC CMIP6 scenarios

8.4.3.3 Hydropower generation from observed flow 1981-2000

Historically (1981-2000), the minimum flow at Inga Falls has been 23063 m³/s. The total capacity for Phase 1 and Phase 2 power plants is only 3580 m³/s (6*130+8*252.5) so there will always be enough water to run Inga 1 and 2 at full capacity, and still supply the minimum flow of 3700 m³/s. In fact, there will nearly always be water enough to also meet the full capacity for Inga 3, Inga 4, and Inga 5. But with the introduction of Inga 6, there will be episodes where the available flow is not always enough to run at full capacity, and the number of such episodes will increase for each Phase. This is illustrated by Figure 8.9 below:

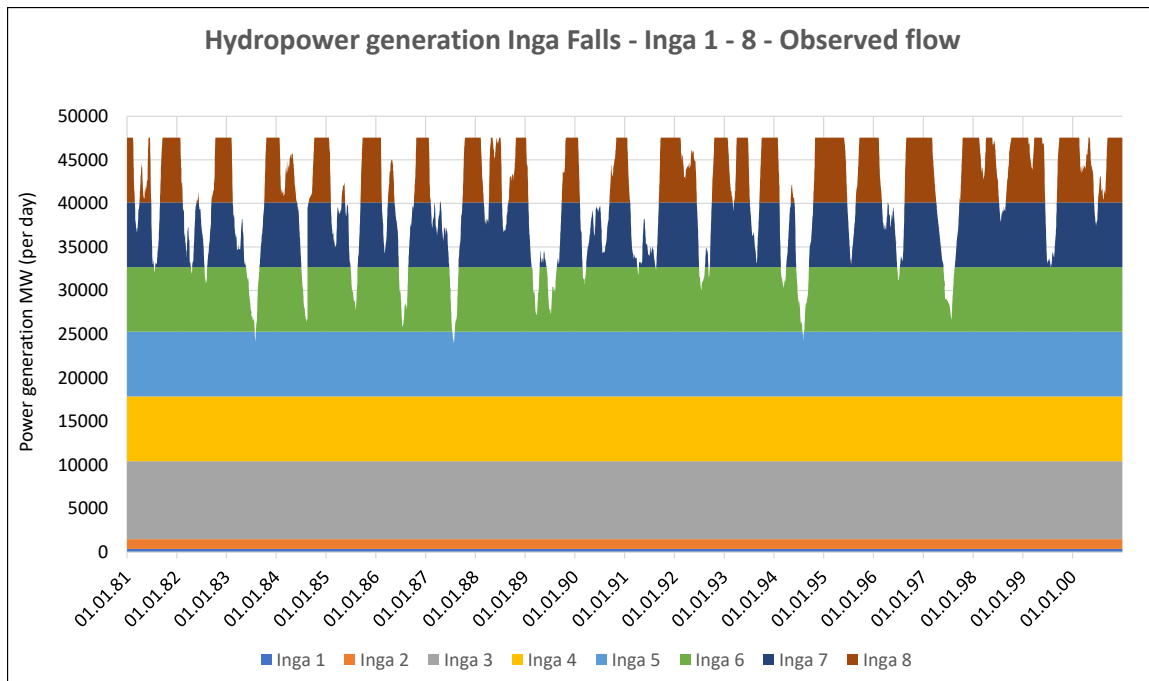


Figure 8.9 Hydropower generation for Inga 1 to Inga 8 – Based on data for 1981-2000

Figure 8.9 shows simulated generation (MW) each day during the historic period 1981-2000. The results are stacked so it is easy to see if there is a reduced generation due to limiting flow. We can see that power plants in Phase 1 to 5 almost always generate at full capacity, while those in Phases 6, 7 and 8 have increasing episodes of reduced or no generation, due to shortage of water. (Phase 5 has a few days with flow slightly below capacity). The average number of Full Load Hours (FLH) and Capacity Factor (C_f) is computed for each simulation and results are shown in Table 4, the two rightmost columns. The duration curves for Inga 6, 7 and 8 are shown in Figure 8.10. Increasing the installed capacity beyond Inga 8 is probably not economically viable, but we have still computed and presented the results in the Table 8.4.

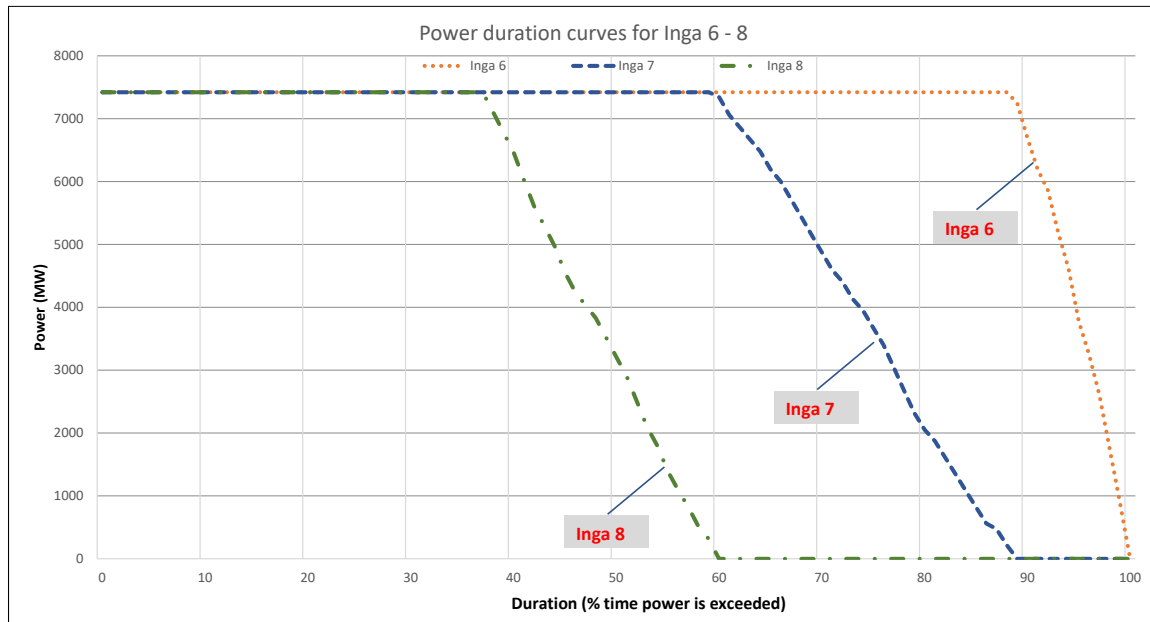


Figure 8.10 Power duration curves for Inga 6, 7 and 8. Historical period 1981-2000

It can be seen from Table 8.4 that the number of Full Load Hours (FLH) and Capacity Factor (C_f) decreases from 8760 hours and 100% for Inga 1 to Inga 5, to 4221 hours and 48% for Inga 8. Main generation results for each Phase are shown in Table 8.4. The results are computed cumulative, as flow ($Q_{\max}$), power ($P_{\max}$) and average annual Energy generation (Energy) for each Phase from Inga 1 up to and including this Phase. It can be seen that computed energy generation of a fully developed system (Inga 1 to Inga 8) would give an average annual generation of 360 TWh/year, practically 1 TWh/day.

Table 8.4 Inga Falls – Main results for simulated hydropower generation (1981-2000)

Cumulative values			Results for 1981-2000		
Phase	Q _{max}	P _{max}	Energy	FLH	C _f
	m ³ /s	MW	TWh/yr	hours	%
Inga 1	780	351	2.4	8760	100 %
Inga 2	2800	1495	10.4	8760	100 %
Inga 3	9400	10434	88.7	8760	100 %
Inga 4	14880	17856	153.7	8760	100 %
Inga 5	20360	25278	218.7	8756	100 %
Inga 6	25840	32700	280.5	8320	95 %
Inga 7	31320	40122	328.8	6510	74 %
Inga 8	36800	47544	360.1	4221	48 %
Inga 9	42280	54966	379.9	2663	30 %
Inga 10	47760	62388	392.8	1747	20 %

8.4.3.4 Hydropower generation from each future simulation

Each of the future simulations (Model run) is done with a timeseries of 20 years (like 1981-2000) flow data and the hydropower system as described above. This results in a time-series of hydropower generation (MW/day) for each of the 8 phases. The results are summarized into the following main statistics:

Average annual generation Inga 1-2

Average annual generation Inga 3-8

For this study, the generation in existing powerplants Inga 1 and 2 is not affected by climate change and is therefore not used further. There will always be enough water for full supply even after possible climate change. The main Results of change in hydropower generation due to Climate Change for CMIP5 and CMIP6 are summarized in table 8.5,8.6 and 8.7. Figure 8.11 shows simulated change in hydropower generation for all future scenarios of CMIP5 and CMIP6.

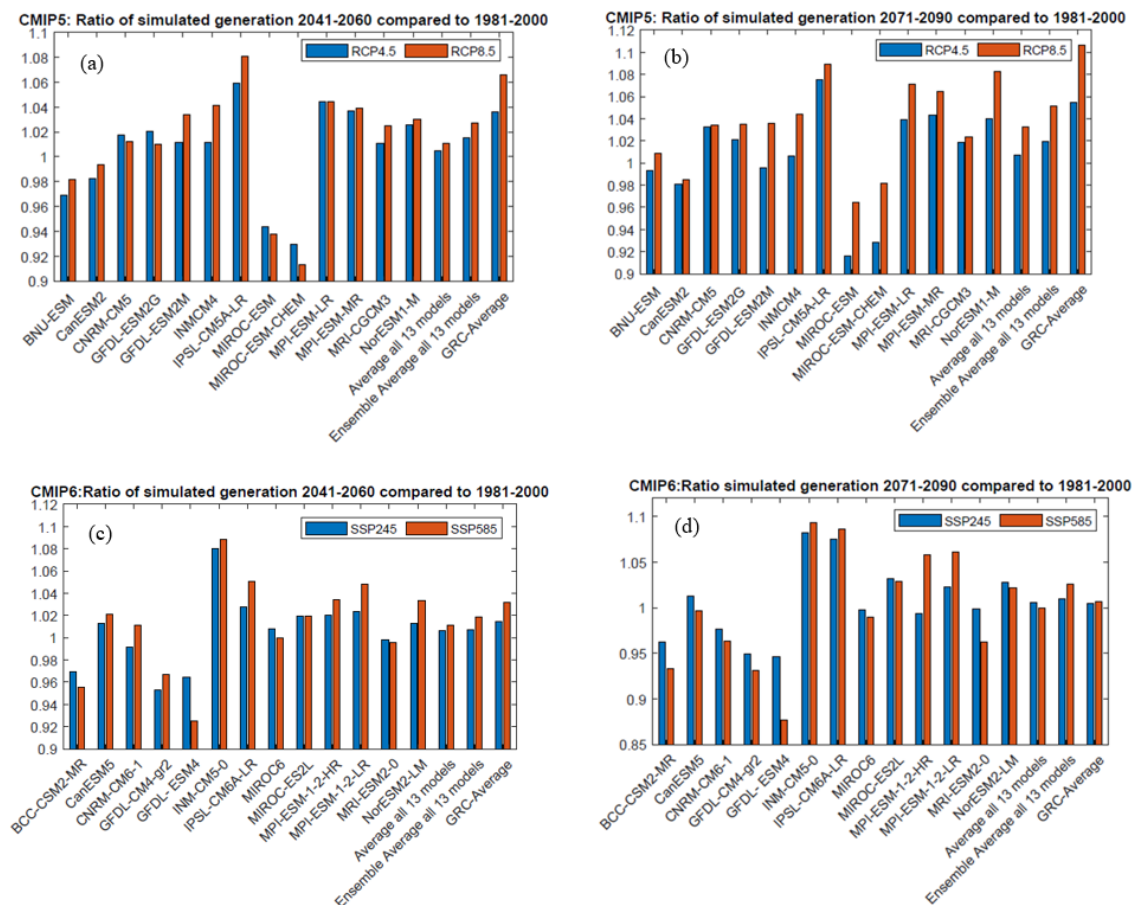


Figure 8.11 Simulated change in hydropower generation for CMIP5 (a) & (b) and CMIP6 (c) & (d)

Table 8.5 Main Results of CMIP5

				Simulated hydropower generation (TWh/year) for power plant units included in Inga Phase 3 to Phase 8													Average	Average	Average
	IPCC Assessment	Emission Scenario	Time period	BNU-ESM	CanESM2	CNRM-CM5	GFDL-ESM2G	GFDL-ESM2M	INMCM4	IPSL-CM5A-LR	MIROC-ESM	MIROC-ESM-CHEM	MPI-ESM-LR	MPI-ESM-MR	MRI-CGCM3	NorESM1-M	Average all 13 models	Ensemble Average all 13 models	GRC-Average
Simulated annual generation, CMIP5	CMIP5	-	1981-2000	363.8	370.8	367.7	365.2	367.9	358.7	368.0	366.8	361.9	369.7	371.6	372.3	365.9	366.9	371.5	355.0
	CMIP5	RCP4.5	2041-2060	352.6	364.3	374.3	372.7	372.2	362.9	389.7	346.1	336.5	385.9	385.2	376.3	375.3	368.8	377.2	367.8
	CMIP5	RCP4.5	2071-2090	361.2	363.7	379.6	372.9	366.4	360.9	395.8	336.0	335.9	384.2	387.7	379.2	380.6	369.5	378.9	374.6
	CMIP5	RCP8.5	2041-2060	357.1	368.5	372.2	368.8	380.5	373.4	397.8	343.9	330.4	386.1	386.0	381.7	376.8	371.0	381.6	378.5
	CMIP5	RCP8.5	2071-2090	366.8	365.2	380.2	378.0	380.9	374.4	400.9	353.9	355.1	396.0	395.6	381.0	396.0	378.8	390.8	392.7

Table 8.6 Main Results of CMIP6

				Simulated hydropower generation (TWh/year) for power plant units included in Inga Phase 3 to Phase 8													Average	Average	Average
	IPCC Assessment	Emission Scenario	Time period	BCC-CSM2-MR	CanESM5	CNRM-CM6-1	GFDL-CM4-gr2	GFDL-ESM4	INM-CM5-0	IPSL-CM6A-LR	MIROC6	MIROC-ES2L	MPI-ESM-1-2-HR	MPI-ESM-1-2-LR	MRI-ESM2-0	NorESM2-LM	Average all 13 models	Ensemble Average all 13 models	GRC-Average
Simulated annual generation, CMIP6	CMIP6	-	1981-2000	369.8	374.7	379.6	378.9	378.7	369.3	369.9	374.2	373.0	376.0	376.5	379.5	371.4	374.7	377.5	363.8
	CMIP6	SSP24.5	2041-2060	358.6	379.5	376.5	361.0	365.2	398.9	380.2	377.1	380.2	383.6	385.4	378.9	376.1	377.0	380.2	369.1
	CMIP6	SSP24.5	2071-2090	355.8	379.5	370.6	359.5	358.4	399.7	397.9	373.4	384.9	373.4	385.2	378.9	381.7	376.8	381.2	365.5
	CMIP6	SSP58.5	2041-2060	353.2	382.5	383.9	366.5	350.4	402.0	388.5	374.2	380.2	388.7	394.6	378.0	383.7	378.9	384.5	375.3
	CMIP6	SSP58.5	2071-2090	345.0	373.5	365.7	352.8	331.9	403.6	402.0	370.2	383.9	398.0	399.7	365.3	379.5	374.7	387.2	366.4

Table 8.7 Main Results of change in hydropower generation due to Climate Change

	IPCC Assessment	Emission Scenario	Time period	BNU-ESM / BCC-CSM2-MR	CanESM2 / CanESM5	CNRM-CM5 / CNRM-CM6-1	GFDL-ESM2G / GFDL-CM4-gr2	GFDL-ESM2M / GFDL-ESM4	INMCM4 / INM-CM5-0	IPSL-CM5A-LR / IPSL-CM6A-LR	MIROC-ESM / MIROC6	MIROC-ESM-CHEM / MIROC-ES2L	MPI-ESM-LR / MPI-ESM-1-2-HR	MPI-ESM-MR / MPI-ESM-1-2-LR	MRI-CGCM3 / MRI-ESM2-0	NorESM1-M / NorESM2-LM	Average all 13 models	Ensemble Average all 13 models	GRC-Average
Relative change - CMIP5	CMIP5	RCP4.5	2041-2060	0.97	0.98	1.02	1.02	1.01	1.01	1.06	0.94	0.93	1.04	1.04	1.01	1.03	1.00	1.02	1.04
	CMIP5	RCP4.5	2071-2090	0.99	0.98	1.03	1.02	1.00	1.01	1.08	0.92	0.93	1.04	1.04	1.02	1.04	1.01	1.02	1.05
	CMIP5	RCP8.5	2041-2060	0.98	0.99	1.01	1.01	1.03	1.04	1.08	0.94	0.91	1.04	1.04	1.03	1.03	1.01	1.03	1.07
	CMIP5	RCP8.5	2071-2090	1.01	0.98	1.03	1.03	1.04	1.04	1.09	0.96	0.98	1.07	1.06	1.02	1.08	1.03	1.05	1.11
Relative change - CMIP6	CMIP6	SSP24.5	2041-2060	0.97	1.01	0.99	0.95	0.96	1.08	1.03	1.01	1.02	1.02	1.02	1.00	1.01	1.01	1.01	1.01
	CMIP6	SSP24.5	2071-2090	0.96	1.01	0.98	0.95	0.95	1.08	1.08	1.00	1.03	0.99	1.02	1.00	1.03	1.01	1.01	1.00
	CMIP6	SSP58.5	2041-2060	0.96	1.02	1.01	0.97	0.93	1.09	1.05	1.00	1.02	1.03	1.05	1.00	1.03	1.01	1.02	1.03
	CMIP6	SSP58.5	2071-2090	0.93	1.00	0.96	0.93	0.88	1.09	1.09	0.99	1.03	1.06	1.06	0.96	1.02	1.00	1.03	1.01

Table 8.7 shows the ratio between simulated annual generation in Inga 3-8 and simulated generation during 1981-2000 for the same model.

8.4.3.4.1 Hydropower generation from CMIP5 scenarios

Table 8.7 shows the projected change in the ensemble mean and range of the hydropower potential relative to the reference period under different RCPs. The mean annual power (MAP) generally increases in the two future time horizons.

As for the historical period (1981-2000) (Figure 8.9), in all CMIP5 futures scenarios there will always be enough water to operate Inga 1, Inga 2, Inga 3, Inga 4, and Inga 5 at their maximum capacity while ensuring a minimum flow rate of 3700 m³/s. This historical stability underscores the reliability of the system during that time frame.

However, unlike the historical period, the number of episodes introduced from Inga 6 decreases significantly for RCP4.5 scenario and almost disappears for RCP8.5 scenario.

This positive change is a consequence of the increasing of river flow patterns anticipated in the future.

As we move further along to the Inga 7 and Inga 8 phases, the episodes of favorable conditions persist, but they exhibit a less pronounced presence compared to the historical period. This phenomenon can be attributed to the projected increase in river flow for these future periods, which necessitates a more nuanced assessment of water availability and utilization.

To visually encapsulate these findings, please refer to Figure 8.12, which graphically illustrates the evolving dynamics of water supply and its impact on the various Inga phases.

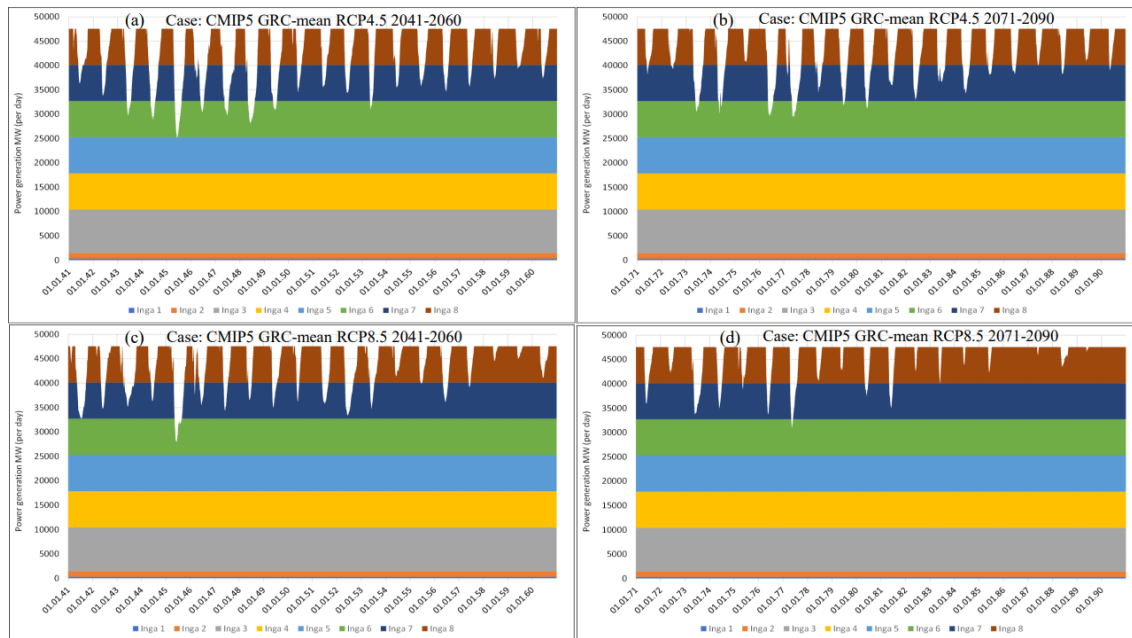


Figure 8.12 Hydropower generation at Inga Falls for GRC CMIP5 scenarios

8.4.3.4.2 Hydropower generation from CMIP6 scenarios

Hydroelectric production under the CMIP6 scenarios closely mirrors that of the CMIP5 scenarios. This consistency in outcomes is vividly depicted in Figure 8.13, where it becomes evident that all CMIP6 scenarios exhibit a strikingly similar pattern to that observed in CMIP5.

The data suggests that, despite the updated modeling and projections of CMIP6, the overall performance and behavior of hydroelectric production remain remarkably consistent with the previous CMIP5 findings. This alignment between the two sets of scenarios underscores the robustness and reliability of the observations, further reinforcing the implications for hydroelectric production in the context of climate change.

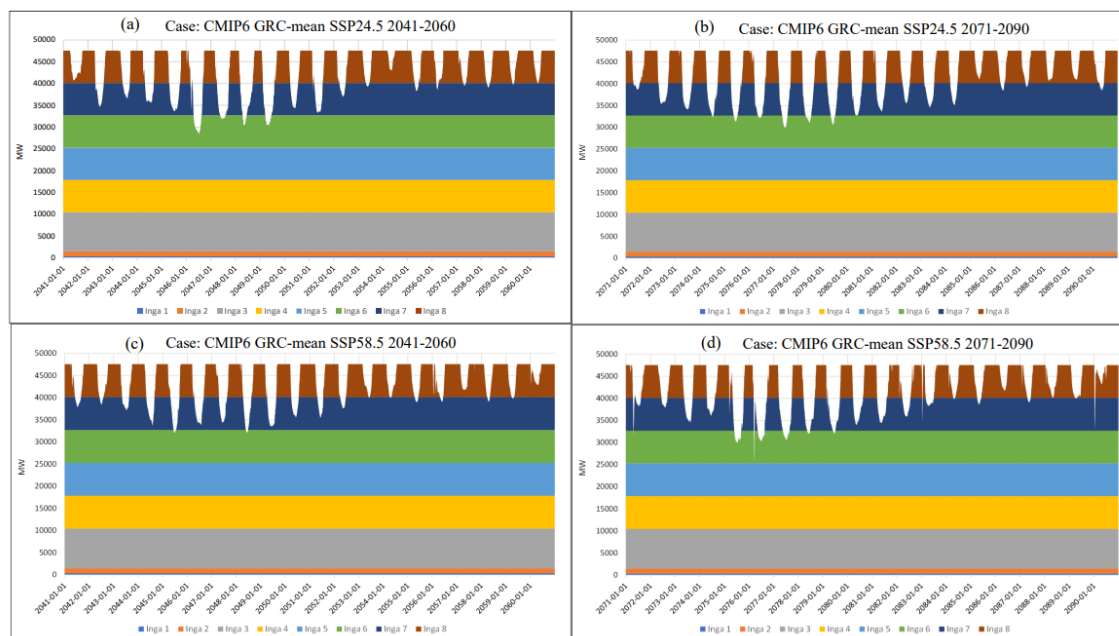


Figure 8.13 Hydropower generation at Inga Falls for GRC CMIP6 scenarios

8.4.3.4.3 Hydropower generation from CMIP5 and CMIP6 scenarios beyond Inga 8

Figures 8.14 and 8.15, as depicted in the graphs, shed light on a pertinent aspect. Under both today's climate and the CMIP5 and CMIP6 scenarios, there appears to be a substantial surplus of water that might otherwise go to waste if not harnessed for power generation purposes, particularly in the context of Inga 9 and 10. This will happen when the flow exceeds $40\,500\text{ m}^3/\text{s}$, where the total capacity of all generation units included in Inga 1 to 8 (Table 8.2) will be fully utilized and the environmental flow demand of $3700\text{ m}^3/\text{s}$ is met. The volume of water at flows $> 40\,500\text{ m}^3/\text{s}$ can be seen at Figure 8.2 (Observed flow) and Figure 8.7 and 8.8 (Future scenarios).

This surplus underscore the opportunity for further expansion and development, presenting a compelling case for considering the feasibility of such projects in the broader context of sustainable resource utilization and regional development.

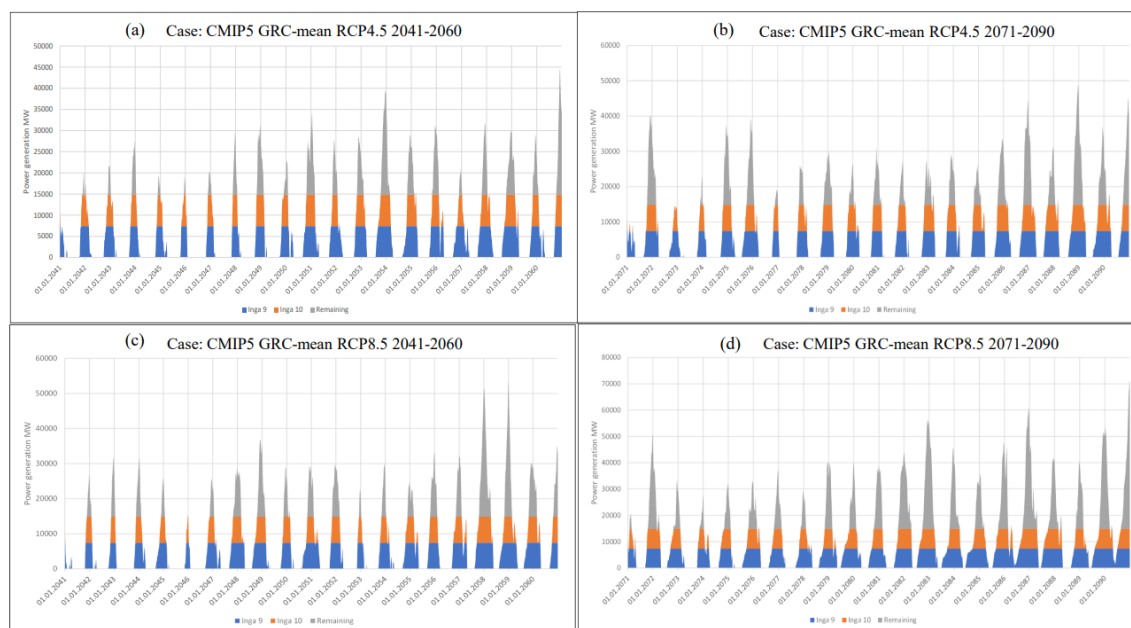


Figure 8.14 Possible hydropower generation at Inga Falls beyond Inga 8 for GRC CMIP5 scenarios

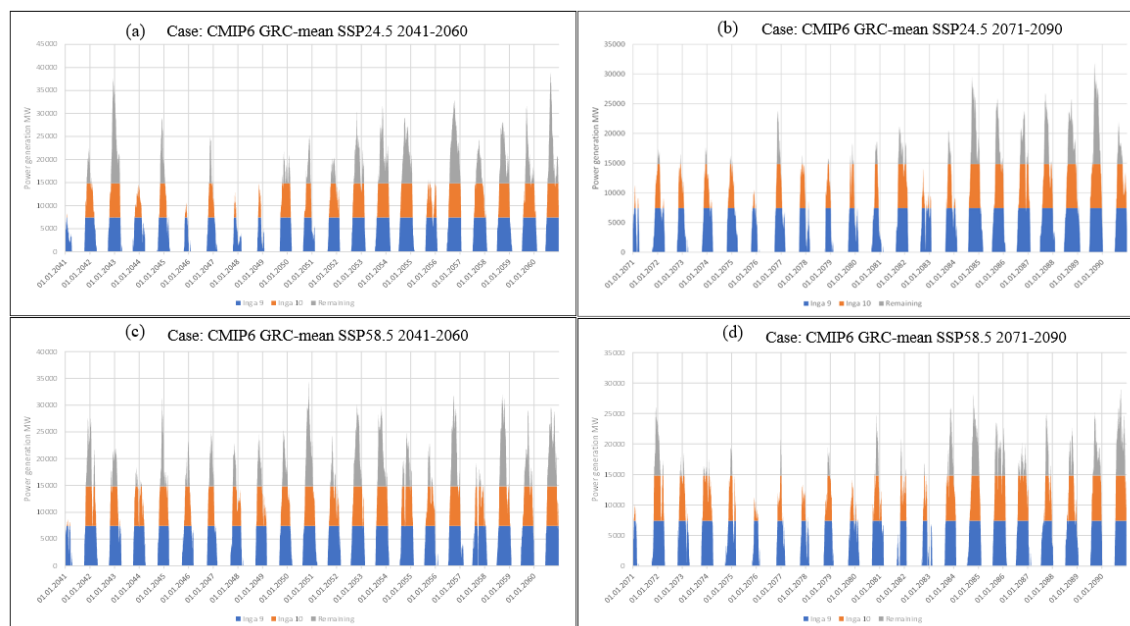


Figure 8.15 Possible hydropower generation at Inga Falls beyond Inga 8 for GRC CMIP6 scenarios

8.4.3.4.4 Hydropower generation downstream from Inga Falls

Downstream from Inga Falls, extending towards the town of Matadi, the river gracefully descends in altitude, covering approximately 38 kilometers with a natural drop ranging from 32 meters to 35 meters. This residual fall in elevation presents an intriguing prospect for the distant future, particularly when considering advancements in dam construction techniques. It holds the promise of a multifaceted development endeavor that could seamlessly combine the benefits of hydroelectric power generation and enhanced navigability of the river.

This dual-purpose initiative has the potential to not only harness clean energy but also facilitate more efficient transportation and navigation along the waterway. Such a synergy between energy production and navigation could pave the way for a financially viable project, offering a win-win solution for both energy needs and improved river transport.

This important issue has been not included in the present model; it will be addressed in our next study.

8.5 Conclusions

The present research was carried out to assess the changes in hydropower generation resulting from projected climate change conditions. The changing climate is posing a great threat to the future civilizations, due to the variations in precipitation and temperature patterns which indirectly is bound to alter hydrological cycle and consequently the streamflow pattern at a given place (Chilkoti, V. *et al.*, 2017). Rivers are very important for human live as various human activities are directly depended on example power generation. The entire infrastructure has been affected by the varying streamflow regime due to changing climate. Hydropower potential relies on the quantum of available water in the given stream and the extent of energy generation is hence allied with the streamflow pattern. It is vital to carry out an impact assessment for the existing hydropower

facilities as they are huge capital investment schemes and a realistic study shall incorporate a hydrologic model (Chilkoti, V. *et al.*, 2017; Schaefli, B., 2015). In this study, the Grand Inga Hydroelectric project located in Congo River in the DRC was considered as a case study. The Grand Inga is a well-known, large-scale hydropower project in the world that will provide comprehensive benefits of flood control, power generation, Hydrogen production, and navigation which will be affected by climate change. The hydrological model was driven by the climate change projections of 13 NEX-GDDP CMIP6 and their predecessors CMIP5 under two RCPs and two SSPs to simulate the change of natural streamflow in the Inga Falls basin under climate change. The streamflow data of the nearby Inga gage was used to calibrate the hydrological model of the project basin and also to validate the power generation model. The hydrology of the basin was simulated using the conceptual hydrological model HEC-HMS. Future horizon of study was periods from year 2041-2060 and 2071-2090 whereas year 1981-2000 was taken as control period for climate data. An ensemble approach was used to conduct the climate change impact assessment study wherein a 13 NASA NEX-GDDP-CMIP6 and 13 NASA NEX-GDDP-CMIP5 datasets were used.

The overall impact on the Inga Falls technical potential is expected to be positive. It is clear that Inga Falls will be very secure against negative climate impacts, and not at all sensitive for possible negative changes both CMIP5 and CMIP6 scenarios. This is valid not only for the existing system Inga 1 and Inga 2, but also for Inga 3,4 and 5. It is only during Inga 6, 7 and 8 that climate change will have an impact. And this seems mostly to be positive, increasing the generation potential. These findings indicate that the water resources management of the Inga Falls and upstream basin must take corresponding adaptive measures in the future, in order to make use of flood water and cope with the risk of increased inter-annual fluctuation of inflow for the impounding of Inga 6 to

Inga 8. Increasing the flood storage capacity and strengthening the joint operation of the upstream cascade reservoirs are important means to overcome these adverse effects and are expected to turn adverse effects into favorable ones. The next step is to strengthen the research on the integrated management strategy of water resources in the upstream of Inga Falls under climate change.

CHAPITRE 9 DISCUSSION GÉNÉRALE

9.1 Choix d'utilisation des réanalyses ou de NEX-GDDP en étude d'évaluation des impacts des changements climatiques

L'un des aspects cruciaux de cette thèse réside dans le choix de l'utilisation de données comme substitut aux observations, notamment dans les régions dépourvues de stations de mesure, pour mener des études d'évaluation des impacts des changements climatiques. Ainsi, le premier objectif de cette thèse consistait à évaluer le potentiel des données relatives aux précipitations et aux températures, provenant à la fois des réanalyses atmosphériques et du jeu de données NEX-GDDP, dans le contexte de la modélisation hydrologique en lien avec les changements climatiques.

Pour atteindre cet objectif, plusieurs réanalyses atmosphériques globales de nouvelle génération, caractérisées par leur résolution spatiale relativement fine, ont été prises en considération. Il s'agit notamment de ERA-Interim, CFSR, MERRA et ERA5-Land. De plus, treize modèles de données climatiques NEX-GDDP-CMIP6 (tels que BCC-CSM2-MR, CanESM5, CNRM-CM6-1, GFDL-CM4-gr2, GFDL-ESM4, INM-CM5-0, IPSL-CM6A-LR, MIROC6, MIROC-ES2L, MPI-ESM-1-2-HR, MPI-ESM-1-2-LR, MRI-ESM2-0 et NorESM2-LM) ainsi que treize NEX-GDDP-CMIP5 (comme BNU-ESM, CanESM2, CNRM-CM5, GFDL-ESM2G, GFDL-ESM2M, INM-CM4, IPSL-CM5A-LR, MIROC-ESM, MIROC-ESM-CHEM, MPI-ESM-MR, MPI-ESM-LR, MRI-CGCM3 et NorESM1-M) ont été pris en compte. Les simulations hydrologiques ont été menées sur l'ensemble du bassin versant du fleuve Congo, caractérisé par une diversité de sous-bassins représentant différentes zones climatiques de la région. Les modèles hydrologiques HEC-HMS et GR4J ont été utilisés pour ces simulations.

En général, la plupart des simulations hydrologiques ont produit des résultats satisfaisants, à quelques exceptions près. Les principaux défis ont émergé lors de l'application de ces modèles

hydrologiques à des projections climatiques futures. Deux scénarios distincts ont été observés. Le premier scénario, utilisant le modèle hydrologique forcé par les réanalyses, nécessite une correction des biais pour s'adapter aux conditions futures. En revanche, le deuxième scénario, impliquant le modèle hydrologique forcé par NEX-GDDP, n'a pas nécessité de correction des biais, étant donné que les biais étaient similaires. Une étude comparative a été réalisée pour évaluer les biais des réanalyses par rapport à ceux de NEX-GDDP, en les comparant aux observations disponibles, lorsqu'elles étaient disponibles. Cette analyse a révélé que les biais associés à NEX-GDDP étaient considérablement plus faibles que ceux des réanalyses. En conséquence, il est apparu plus judicieux d'utiliser le modèle hydrologique forcé par NEX-GDDP pour les projections climatiques futures, compte tenu de cette comparaison avantageuse des biais.

9.2 Approches multi-modèle dans un contexte des changements climatiques

Les résultats de la modélisation hydrologique dans le contexte multi-modèle, tels que présentés au chapitre 5, ont clairement révélé l'extraordinaire potentiel de cet outil dans le domaine de l'hydrologie. Cette approche a démontré sa capacité à significativement réduire, voire éliminer, les erreurs intrinsèques aux modèles hydrologiques, tout en maximisant leurs atouts, comme le soulignait déjà (Arsenault, R., 2015).

De manière tout aussi remarquable, le chapitre 8 a introduit une approche de modélisation multi-input qui a engendré des résultats aussi performants que ceux obtenus par le multi-modèle. Dans cette méthode, un seul modèle hydrologique a été sollicité par plusieurs jeux de données, aboutissant ainsi à des résultats prometteurs. Cependant, ce qui s'est avéré encore plus convaincant, c'est la combinaison synergique de ces deux approches, à savoir le multi-modèle et le multi-input, qui a permis d'améliorer considérablement les résultats. Cette nouvelle méthode novatrice corrige de manière significative les imperfections inhérentes aux modèles hydrologiques.

Ces avancées majeures ont été largement mises en œuvre dans les chapitres 7 et 8 de cette thèse, notamment dans le cadre de la réduction de l'incertitude des études d'impact des changements climatiques. Les modèles climatiques, tout comme les modèles hydrologiques, présentent des biais systémiques. L'application de cette nouvelle approche permet d'envisager la réduction de ces biais lors de l'évaluation des impacts des changements climatiques sur les systèmes hydriques, ouvrant ainsi la voie à des avancées significatives dans la compréhension et la gestion des ressources en eau dans un contexte de changement climatique, comme le suggérait déjà (Arsenault, R., 2015).

9.3 Impacts des changements climatiques sur l'hydroélectricité

Il est important de noter que dans la littérature scientifique, il existe une disparité notable entre le nombre de modèles hydrologiques disponibles et le nombre de modèles spécifiques à l'hydroélectricité. Alors que de nombreux modèles hydrologiques sont utilisés pour étudier les régimes hydrologiques des rivières, la production d'énergie hydroélectrique est souvent abordée de manière plus simpliste.

L'approche la plus élémentaire consiste à établir une corrélation entre les données historiques de débits des rivières et la production d'électricité correspondante. Cependant, cette méthode s'avère insuffisante pour capturer la complexité des processus hydroélectriques dans leur intégralité.

La meilleure approche pour étudier la production d'énergie hydroélectrique consiste à utiliser des modèles de simulation basés sur les processus. Ces modèles définissent les principaux composants du système hydroélectrique, y compris les turbines et les générateurs, et intègrent des paramètres tels que les caractéristiques de la centrale, les variations des débits d'eau et les contraintes opérationnelles. L'utilisation de ces modèles permet de représenter plus fidèlement la réalité en prenant en compte les mécanismes de conversion de l'énergie hydraulique en énergie électrique.

Dans le cadre de cette étude, la production hydroélectrique a été simulée en utilisant un système de programmation basé sur Excel. Ce modèle de simulation fonctionne avec une granularité temporelle quotidienne, ce qui signifie qu'il simule la production d'énergie pour chaque jour de l'année. Il prend en compte les caractéristiques de toutes les unités de production hydroélectrique existantes ainsi que celles prévues dans le cadre de futurs projets hydroélectriques. Les résultats de la simulation sont ensuite compilés et résumés pour chaque phase ou composante du système hydroélectrique, fournissant ainsi une vision globale de la production d'électricité sur l'ensemble de la période étudiée.

Cette approche basée sur la simulation des processus offre plusieurs avantages. Elle permet de mieux comprendre la dynamique de la production d'énergie hydroélectrique, de prédire les performances des centrales hydroélectriques sous différentes conditions hydrologiques et de tester divers scénarios opérationnels. En outre, elle offre une base solide pour évaluer les impacts potentiels des changements climatiques sur la production hydroélectrique et pour planifier des mesures d'adaptation appropriées. En fin de compte, cette méthode contribue à une gestion plus précise et efficace des ressources hydroélectriques, en garantissant une production d'électricité fiable et durable.

9.4 Recommandations pour les travaux futurs

Les travaux de cette thèse ont révélé le potentiel considérable des réanalyses atmosphériques et du jeu de données NEX-GDDP en matière de modélisation hydrologique. Cependant, il convient de souligner que l'étude ne s'est pas penchée sur la capacité de ces données à simuler les débits extrêmes, car cela dépassait le cadre des objectifs de la recherche. Il serait judicieux d'envisager des travaux ultérieurs visant spécifiquement à évaluer la pertinence de ces données pour la

modélisation des débits extrêmes, étant donné leur importance dans la gestion des ressources en eau.

De plus, il est important de noter que cette étude s'est principalement concentrée sur l'analyse des précipitations et des températures en relation avec la modélisation hydrologique. Cependant, d'autres variables climatiques, telles que l'évapotranspiration, le ruissellement et l'humidité relative, revêtent également une grande importance dans la compréhension des processus hydrologiques. Il serait donc recommandé d'inclure ces variables dans les futures études de modélisation hydrologique afin de prendre en compte de manière plus complète les interactions entre le climat et les systèmes hydriques.

Par ailleurs, il est à noter que les données NEX-GDDP utilisées n'ont pas fait l'objet d'un post-traitement supplémentaire en raison du manque d'observations adéquates dans la zone d'étude. Il serait intéressant d'explorer la possibilité d'appliquer un post-traitement supplémentaire à ces données pour voir si cela pourrait améliorer la qualité des résultats obtenus.

L'approche multi-modèle développée dans cette étude s'est limitée à la combinaison des modèles issus du même projet d'intercomparaison, que ce soit CMIP5 ou CMIP6. Il serait opportun d'envisager des recherches futures qui explorent la combinaison de modèles provenant de différents ensembles, ce qui pourrait apporter une perspective plus large et complète aux projections hydrologiques.

Enfin, il est impératif de reconnaître que le changement climatique est une réalité incontournable. Les concepteurs, planificateurs et gestionnaires des ressources en eau doivent intégrer ces changements potentiels dans leurs décisions futures. Lors de la conception d'ouvrages hydrauliques de grande envergure, il est recommandé de prendre en compte la non-stationnarité des conditions hydrologiques, ce qui contribuerait à réduire l'incertitude des projections et à assurer une meilleure

résilience face aux changements climatiques. De plus, il est essentiel d'intégrer des scénarios futurs d'utilisation des terres dans les études à venir, car ces scénarios auront un impact significatif sur les ressources en eau.

En ce qui concerne l'estimation de l'évapotranspiration, il demeure un défi pour les scénarios futurs. Dans l'analyse actuelle, l'évaporation est calculée en fonction de la température, mais il est recommandé de développer des méthodes plus sophistiquées pour estimer l'évapotranspiration dans le contexte des périodes futures, compte tenu de son rôle crucial dans le cycle hydrologique.

En somme, pour mieux anticiper et gérer les impacts des changements climatiques sur les ressources en eau, il est essentiel de continuer à explorer de nouvelles méthodes, de diversifier les données utilisées et d'ajuster les règles de conception pour prendre en compte ces changements fondamentaux dans notre environnement hydrologique.

Les futurs travaux de recherche devraient accorder une attention particulière aux impacts environnementaux des centrales hydroélectriques dans un contexte de changements climatiques. Il est crucial d'évaluer de manière approfondie comment ces changements affecteront la biodiversité et les écosystèmes aquatiques à proximité des installations hydroélectriques.

Les décisions relatives à l'hydroélectricité sont intrinsèquement liées à des facteurs économiques, politiques et sociaux. Les futures études sur les impacts des changements climatiques sur l'hydroélectricité devraient prendre en compte ces dimensions et les intégrer dans la recherche de solutions viables.

CHAPITRE 10 CONCLUSION ET CONTRIBUTIONS

L'évaluation des impacts des changements climatiques sur les infrastructures revêt aujourd'hui une importance capitale dans le domaine de l'ingénierie. Elle repose sur des fondements scientifiques solides, sans lesquels il serait impossible d'entreprendre une analyse de cette envergure en toute confiance. Plus précisément, les estimations de la production hydroélectrique dépendent directement de la disponibilité de données hydrologiques fiables. Par conséquent, une base de modélisation hydrologique solide constitue le socle essentiel pour des calculs hydroélectriques robustes, notamment en contexte de scénarios climatiques.

L'objectif global de cette thèse était d'approfondir notre compréhension des études d'impact des changements climatiques sur les débits et le potentiel hydroélectrique des bassins fluviaux caractérisés par la rareté, voire l'absence, de stations de mesure. Plus précisément, il s'agissait d'évaluer le potentiel des données de précipitation et de température issues des réanalyses atmosphériques et de NEX-GDDP dans le contexte de la modélisation hydrologique en contexte des changements climatiques. Au travers des articles présentés dans les chapitres 3 à 8, cette recherche a permis de mieux cerner le potentiel des réanalyses et du jeu de données NEX-GDDP dans le domaine de la modélisation hydrologique, ainsi que leur possible utilisation pour les projections climatiques. Les efforts déployés dans ce projet de recherche ont débouché sur des contributions originales dans l'étude des impacts des changements climatiques au sein de bassins non jaugés.

Tout d'abord, cette étude a analysé les performances de plusieurs produits de réanalyse plus récents afin de déterminer ceux qui offraient la meilleure représentation des cycles annuels de précipitations et de température. Cette démarche a été entreprise dans une région géographique cruciale, où les ensembles de données de réanalyse revêtent une importance particulière en raison

de la rareté des données de surface. Cette analyse originale s'est appuyée sur un ensemble de données d'observation récentes sans précédent, spécifiquement recueillies dans le bassin du Congo. Ensuite, un modèle de régression semi-paramétrique a été développée pour saisir la relation complexe entre divers facteurs (tels que le niveau de l'eau, la vitesse d'écoulement) et les débits des rivières. L'application d'une sélection de variables entièrement bayésienne a permis d'identifier les facteurs les plus influents dans l'équation des débits et de prendre en compte l'incertitude associée aux changements morphologiques dans les rivières et aux mesures effectuées. Ce modèle permet de vérifier la fiabilité de la série des débits calculés par la courbe de tarage.

Dans le cadre de l'aspect multi-modèle de ce projet, il a été démontré que certaines méthodes de pondération pouvaient considérablement améliorer la qualité des simulations par rapport aux résultats issus des membres individuels de l'ensemble. Les applications de ces méthodes, telles qu'elles ont été mises en œuvre au cours de cette recherche, ont abouti à des conclusions plus solides que ce qui avait précédemment été exposé dans la littérature. Il convient de souligner que cet aspect du concept multi-modèle n'avait jamais été exploré auparavant dans le contexte du bassin du Congo.

De plus, une contribution méthodologique significative a été apportée, portant sur l'utilisation de la moyenne GRC dans le cadre des projections climatiques futures. Cette dimension du concept multi-modèle représentait une innovation novatrice dans le domaine de la recherche.

Enfin, la dernière contribution majeure de cette thèse concerne le développement d'une nouvelle approche de la modélisation hydroélectrique, basée sur Excel. Cette initiative est née de la nécessité de disposer d'un modèle adapté aux particularités de l'étude, celles-ci étant insuffisamment couvertes par les modèles préexistants. Ainsi, cette nouvelle méthode s'est avérée essentielle pour répondre aux besoins spécifiques du cas d'étude.

En conclusion, cette thèse a apporté des éclaircissements significatifs dans le domaine de l'étude des impacts des changements climatiques sur les bassins non jaugés. Elle a amélioré la précision des modèles hydrologiques, introduit des méthodologies originales, et ouvert de nouvelles perspectives pour la modélisation hydrologique en contexte de changement climatique. Ces avancées sont essentielles pour garantir une planification et une gestion durables des ressources en eau, en particulier dans les régions où les données d'observation sont rares.

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- Normalement, les références insérées avec EndNote dans le texte et les annexes apparaîtront dans la zone ci-dessus.

ANNEXES

ANNEXE A - FORECASTING THE CONGO RIVER DISCHARGE AND WATER-LEVEL USING AN ARTIFICIAL NEURAL NETWORK APPROACH

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Abstract

Rating curves are used to estimate the discharge in rivers, especially in the Congo River. However, the rating curves used for the Congo River, established since 1959, are inadequate because of the changes recurrently occurring in the morphology of the river. The streamflow processes are complex and highly nonlinear and are a result of combination of different factors such as catchment, rainfall, geomorphologic and climatic characteristics. In fact, the sediment load, in the Congo River, is one of the highest load materials in rivers in the world. Furthermore, the changes in climate and morphology, create quasi permanent unsteady flows in the river. On the other side, accurate forecasting of streamflow is essential for efficient operations and optimal allocation of water resources. Flow forecast for hours, days, months in advance is vital for hydropower agencies. This research aims at developing a flow forecast tool using Artificial Neural Network at the Inga dam. The input data are the water stage measured at the port of Kinshasa situated 350 km upstream the dam. The tool showed a better prediction of flow at Inga dam and will support the management team to have information days in advance.

Keywords: Artificial Neural Network, Discharge, Congo River, Water-level, Flow forecast, Inga dam.

1 Introduction

Discharges and water levels are essential components of river hydrodynamics (Khan, Hasan, Panwar, & Chakrapani, 2016). Discharge measurement is time consuming, hazardous, and costly. A cheaper alternative is the so-called rating curve that embodies a functional relationship between the water level (called stage when measured from a datum) and discharge with the help of field measurements. Once a reliable rating curve is available discharge can be estimated from the rating curve using the observed water level (stage)(Bhattacharya & Solomatine, 2005).

The relationship existing between the water-surface stage (i.e. the water level) and the simultaneous flow discharge in rivers and open channels is known as stage-discharge relation or rating curve, or also just rating (Braca, 2008). The rating curve is a very important tool in surface hydrology because the reliability of discharge data values is highly dependent on a satisfactory stage-discharge relationship at the gauging station (Braca, 2008). Although the preparation of rating curves seems to be an essentially empiric task, a wide theoretical background is needed to create a reliable tool to switch from measured water height to discharge.

The rating curve is established by concurrent measurements of stage and discharge (through velocity measurements, dilution methods, or other techniques) and the results are fitted graphically or statistically to yield the rating curves (Schmidt & Yen, 2001). Reliable estimation of discharge in a river is the crucial component of efficient surface water management and planning. Once a relationship is established it can be used for forecasting discharge from future measurements of water level only. In the evolution of river science, a substantial amount of work has been done on predicting future discharges and water levels.

The rating curve can be constructed with the help of polynomial regression or auto-correlation-based statistical method. A number of models have been proposed to predict water discharges and water levels in a river (Abrahart & See, 2000; Atiya, El-Shoura, Shaheen, & El-Sherif, 1999). Birgand, Lellouche, and Appelboom (2013) calculated rating curves from random sampling of reference flow and stage data. Based on the Jones formula, Petersen-Øverleir (2006) proposed a methodology utilizing nonlinear regression as a solution for situations in which the stagedischarge relationship is affected by hysteresis due to unsteady flow; Clemmens, and Wahlin (2006) evaluated the accuracy of various methods for finding stage-discharge relationships. Guven, and

Aytek (2009) also reported that Liao, and Knight (2007) proposed three analytic stage-discharge formulas for prismatic open channels that are suitable for manual calculation. As mentioned by Guven, and Aytek (2009), the body of literature contains many applications of other soft computing techniques in stage-discharge modeling. Jain, and Chalisgaonkar (2000) established a stage-discharge relationship based on three layer feed forward ANNs, Sudheer, and Jain (2003) explored the effectiveness of a radial basis function (RBF), and Bhattacharya, and Solomatine (2005) observed that ANNs and M5 model trees predicted the stage-discharge relationship much more accurately than the traditional rating curves. Deka, and Chandramouli (2003) compared the performance of an ANN model, a modularized ANN model, a conventional curve-fitting approach, and a neuro-fuzzy model for deriving the rating curve using a case study.

Rating curve used to estimate the discharge in the Congo River at Kinshasa station, was established since 1959. It became inadequate for forecasting water level and discharge because of the changes recurrently occurring in the river morphology.

In this research water flow at Inga dam is forecasted from observed water levels at the Port of Kinshasa, situated 350 km upstream, using Artificial Neural Network. Data availability and the objective of protecting Inga dam from flooding through appropriate decision making are the reason why this port is selected.

2 Study site

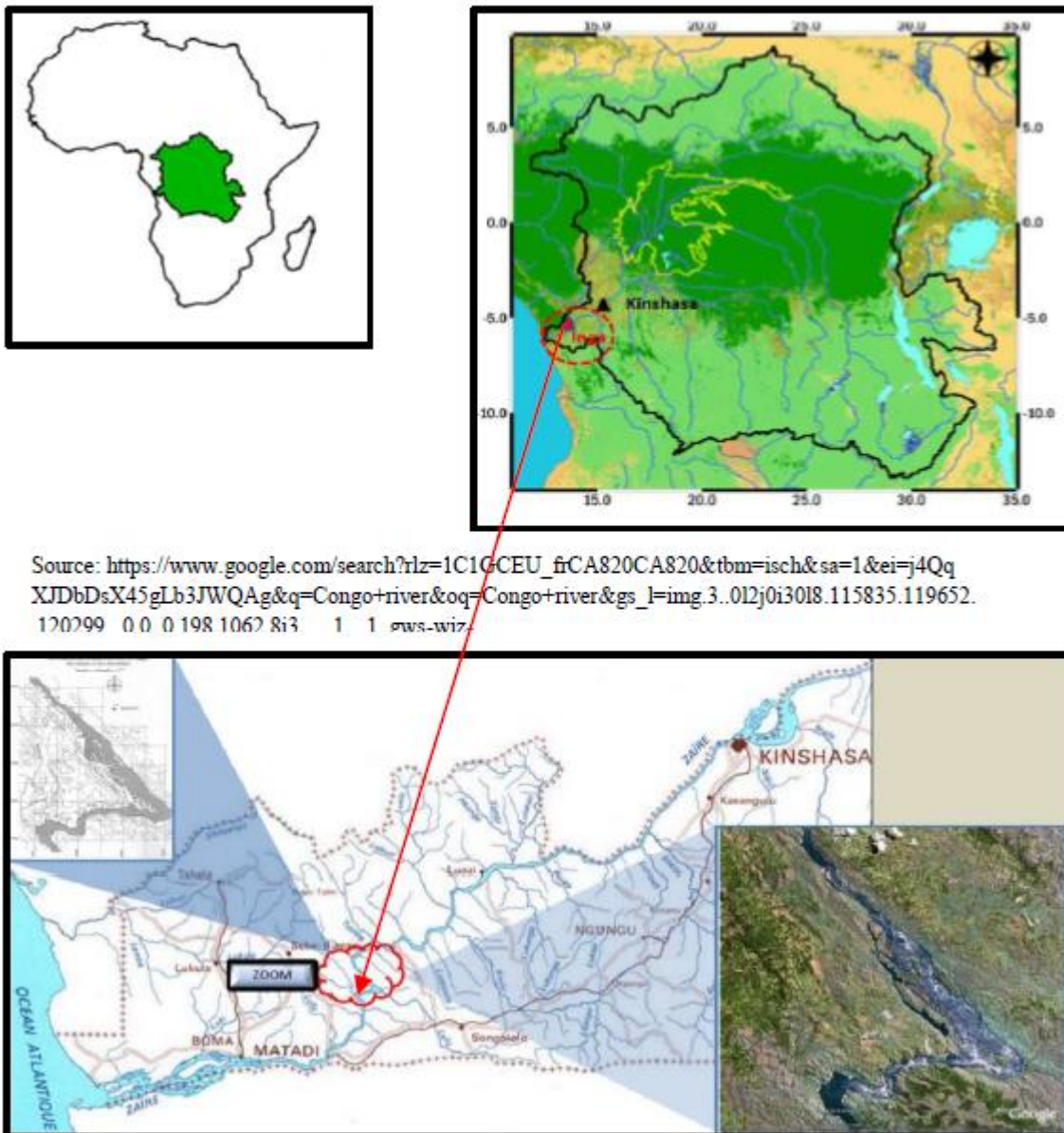
The Inga dams' site is located in western Democratic Republic of the Congo, 150 km upstream of the mouth of the Congo River, and 225 km southwest of Kinshasa on the Congo River (Fig. 1). The Congo River is the world's second largest in terms of flow (42,000 m³/s), after the Amazon, and the second longest river in Africa (4,700 km), after the Nile River. It empties into the equatorial Atlantic Ocean creating what is famously known as the Congo Plume. The plume is a high-productivity area arising from the rich nutrient flow from the river and is detected as far as 800 km offshore. The plume accounts for 40-80% of total carbon productivity and is one of the largest carbon sinks in the world.

The river is unique in that it has large rapids and waterfalls very close to the mouth while most rivers have these features upstream. The dam site is on the largest waterfall in the world by volume, the Inga Falls. Inga Falls is a series of falls and rapids that drop in elevation via small rapids. The

main falls are 4 km wide, dropping to about 21.37 metres near a bend and forming hundreds of channels and rivulets and many small islands.

3 Available data

The data set used in this study was obtained from the waterway agency of the Democratic Republic of Congo. The time series of daily stage and discharge data was taken from the port station of Kinshasa from 1903 to 2010 (Fig. 2).



Source:(Tonino-J., 2015)

Figure 1. Study site location

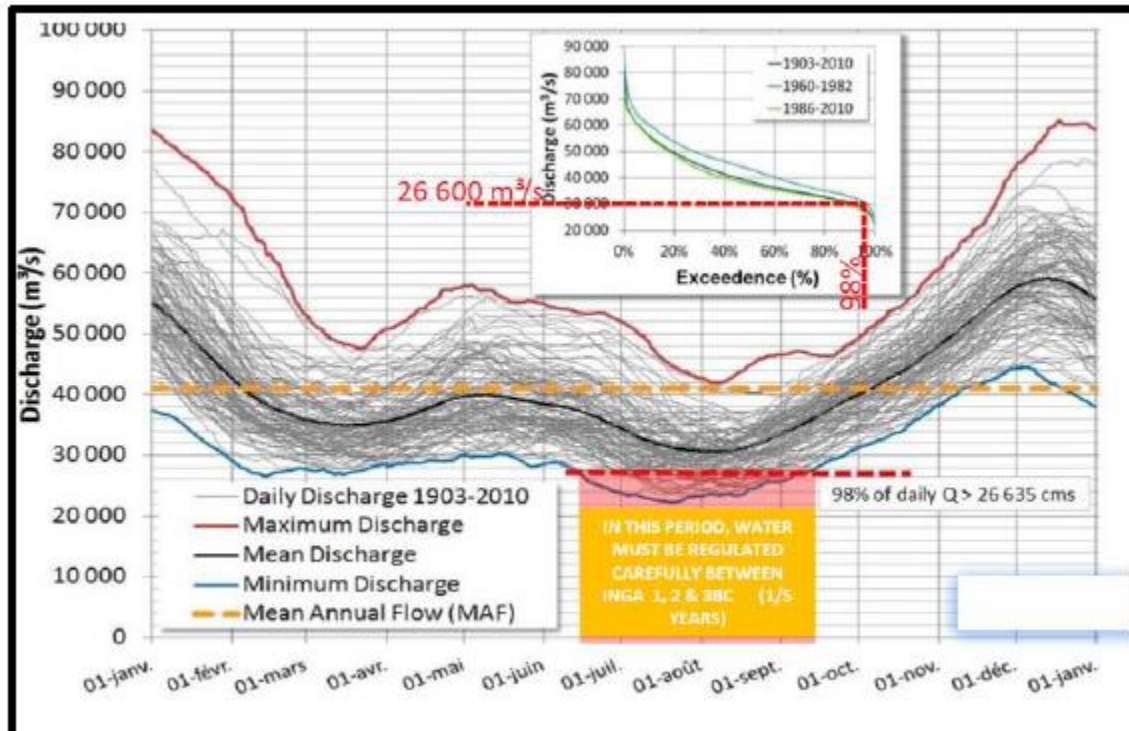


Figure 2. Daily discharge of the Congo River at Inga 1903-2010 (Société Nationale d'Électricité, 2012).

4 Methodology

From past and present observations of water level at the port of Kinshasa, the future water flow at Inga dam is predicted for the next day. To reduce the uncertainty and to account for the complexity of hydrological processes occurring between Inga and Kinshasa, only four previous days and the actual observation have been incorporated in the model. In addition, the two points define a blackbox with the input water levels at Kinshasa and output flows at Inga. ANN selection is justified.

4.1 Weka Interface

Weka (Waikato Environment for Knowledge Analysis) is a popular suite of machine learning software written in Java, developed at the University of Waikato, New Zealand (Arora, 2012). The Weka suite contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to this functionality.

The original non-Java version of Weka was TCL/TK frontend software used to model algorithms implemented in other programming languages, plus data preprocessing utilities in C, and a Make

file-based system for running machine learning experiments. This Java-based version (Weka 3) is used in many different application areas, in particular for educational purposes and research. There are various advantages of Weka:

- It is freely available under the GNU General Public License
- It is portable, since it is fully implemented in the Java programming language and thus runs on almost any architecture
- It is a huge collection of data preprocessing and modeling techniques
- It is easy to use due to its graphical user interface

Weka supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection. All techniques of Weka's software are predicated on the assumption that the data is available as a single flat file or relation, where each data point is described by a fixed number of attributes.

4.2 Classification Function Multilayer Perceptron

Multilayer Perceptron classifier is based upon backpropagation algorithm to classify instances. The network is created by an MLP algorithm. The network can also be monitored and modified during training time. The nodes in this network are all sigmoid (except for when the class is numeric in which case the output nodes become unthresholded linear units).

The backpropagation neural network is essentially a network of simple processing elements working together to produce a complex output. The backpropagation algorithm performs learning on a multilayer feed-forward neural network. It iteratively learns a set of weights for prediction of the class label of tuples. A multilayer feed-forward neural network consists of an input layer, one or more hidden layers, and an output layer. An example of a multilayer feed-forward network is shown in Fig.3(Khan et al., 2016).

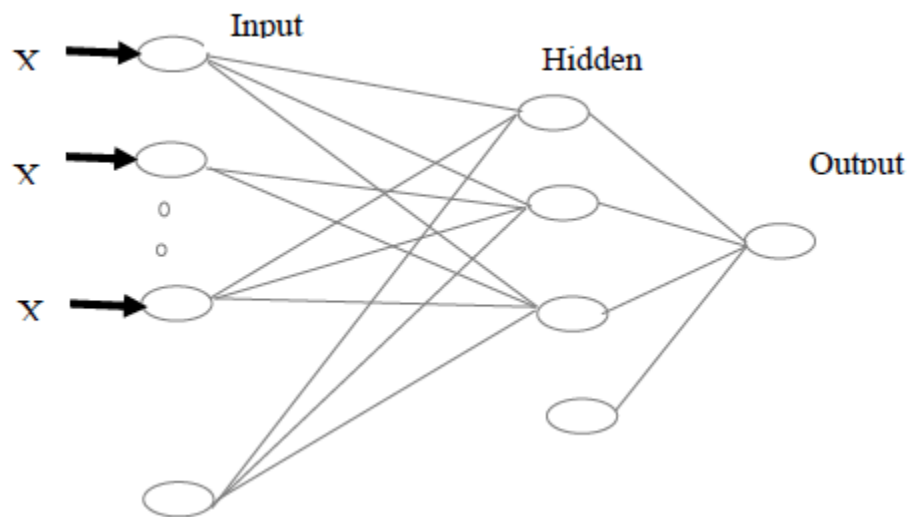


Figure 3. The structure of the artificial neural networks

Each layer is made up of units. The inputs to the network correspond to the attributes measured for each training tuple. The inputs are fed simultaneously into the units making up the input layer. These inputs pass through the input layer and are then weighted and fed simultaneously to a second layer of “neuronlike” units, known as a hidden layer.

The outputs of the hidden layer units can be input to another hidden layer, and so on. The number of hidden layers is arbitrary, although in practice, usually only one is used (Witten, Frank, Hall, & Pal, 2016). At the core, backpropagation is simply an efficient and exact method for calculating all the derivatives of a single target quantity (such as pattern classification error) with respect to a large set of input quantities (such as the parameters or weights in a classification rule) (Werbos, 1990). To improve the classification accuracy we should reduce the training time of neural network and reduce the number of input units of the network (Lu, Setiono, & Liu, 1996).

5 Results and discussion

Two models have been developed and tested against a testing set data that represent 25 % of initial data. Table 1 gives the results evaluation parameters. Model 1 uses only water levels at the port of Kinshasa as input parameters. From Fig. 4, it is seen that the ANN captured the pattern of water flow at the Inga dam but could not reproduce high flows. This can be explained in the fact that there are several incoming water flows between the two points (e.g. the Inkisi creek could at some point discharge high flows in the river that have great change in the flow at Inga and is not

predictable from Kinshasa). The model is well calibrated since there is not much changes between the Root Mean Squared Error (RMSE) of the training and the testing runs. The same observation occurs for the Mean Absolute Error (MAE) and the Relative Error (RE).

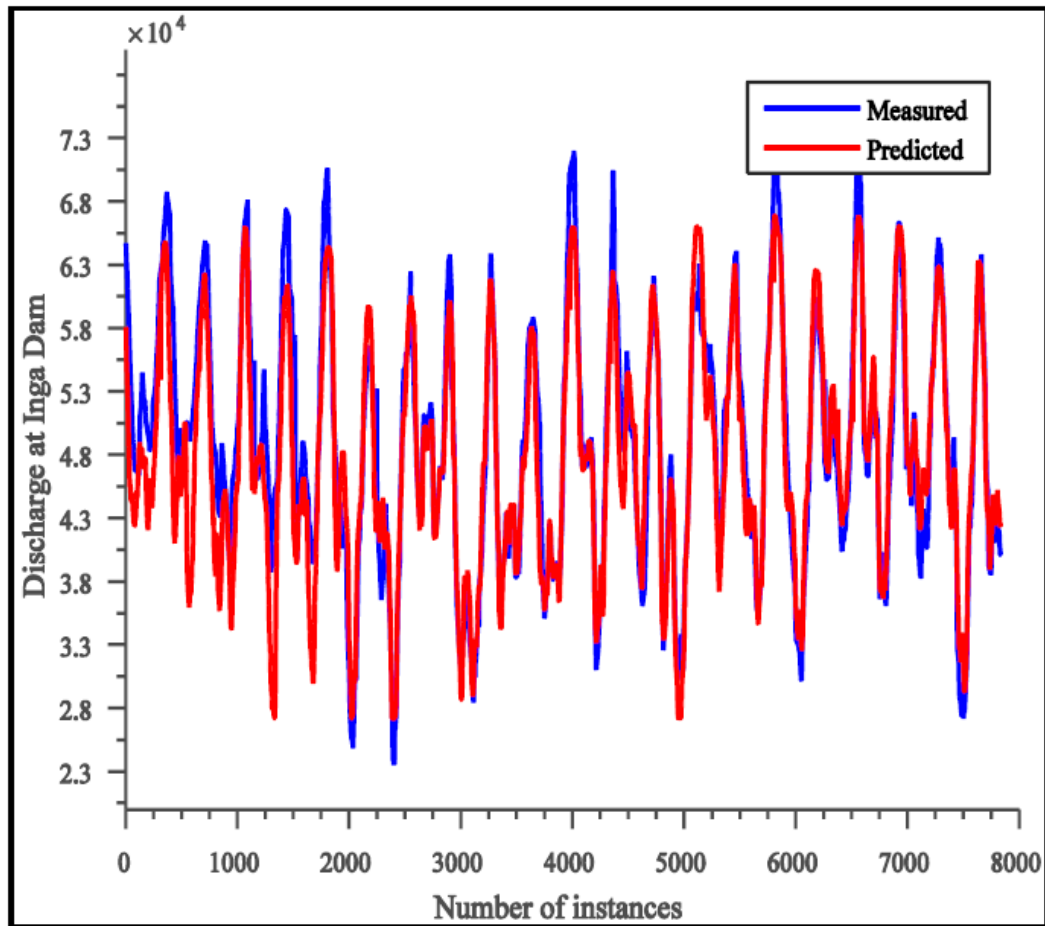


Figure 4: Model 1 training data

Table 1: Models results comparison

	Model 1		Model 2	
	Training	Testing	Training	Testing
Correlation Coefficient	0.93	0.92	0.99	0.98
MAE	2592.24	2770.38	195.48	197.33
RMSE	3480.38	3510.19	374.47	388.92
RE	33.27	35.79	2.51	2.53

The second model (Model 2) in Table 1 is built from the previous model with the inclusion of previous observed water flows at the Inga dam. The observed water flows are transmitted to Kinshasa each morning. Thus, the decision maker can use this model to forecast the coming water flows at the dam and orient team on field. Testing model 2 (Fig. 5) shows perfect match between the prediction and observations. The correaltion coefficient makes a good jump up to 0.98 for the testing data. Most important, the RMSE error dropped by 90 %. The reduction of RMSE and all the relative errors shows that the blackbox should at least have insigth of .

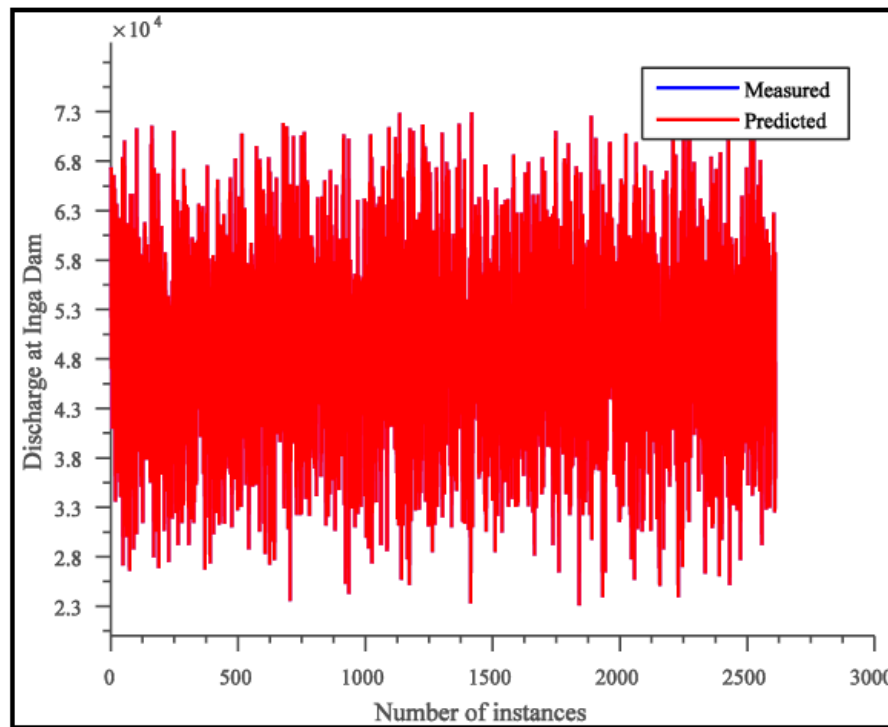


Figure 5: Model 2 testing data

The inclusion of previous water flows shows an enhancement of the model 1 that is based only on the water levels at the port of Kinshasa. From this study, it can be observed that the contribution of other creeks (e.g. Inkisi creek) between the port of Kinshasa and Inga dam is not negligible. However, for an early decision making, the use of water level at the port of Kinshasa gives an orientation on the attitude to adopt in the definition of operating policies especially in rainy seasons (9 months of the year in the region).

This study provides a tool to support decision making from water levels observed at the port of Kinshasa. It shows that the lack of incoming water flows between measurement stations (Port of Kinshasa and Inga dam) can be overcome through the application of well-developed models. ANN

is perfect for this time of application and is more flexible to include more data as they become available.

6 Conclusions and recommendations

In this paper, the potential use of ANN to predict the discharge in a river from stage recorded data is demonstrated. The discharge at time t at 350 km downstream the gauge station is first calculated using the recorded water stage for the 5 previous days. The increased number of variable is aims at the reduction of error in the predictions. The high RMSE obtained from this model will lead to overestimation of the discharge with high consequences on the operations of the dam. The reduction of the error is obtained by introducing in the prediction the discharge of the two previous days. ANN is a powerful tool and lead to accurate prediction if the model is well construct. Future work will investigate the optimal number of variable (H and Q) to include in the model for discharge prediction with a given level of error.

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ANNEXE B - Grand Inga as One of the Solutions for Africa Energy Deficit

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1 Introduction

The electricity deficit in Africa causes hundreds of thousands of deaths each year due to the use of wood-burning stoves for cooking; interferes with the functioning of hospitals and emergency services; compromises educational goals and increases the cost of doing business (African Development Bank Group, 2021).

According to African Development Bank Group (ADB), over 640 million Africans have no access to energy, corresponding to an electricity access rate for African countries at just over 40%, the lowest in the world (African Development Bank Group, 2021).

Access to electricity remains an essential driver of development for African communities in both urban and rural areas. Africa is endowed with immense hydroelectric potential, a large part of which is concentrated at the Inga Falls site in the Democratic Republic of Congo (DRC).

The Inga Falls site on the Congo River have an exceptional longitudinal profile. This profile is made up of an impressive series of rapids, where there is a drop of 98 m between the island of Sikila and the confluence of the Bundi, separated by a straight-line distance of only 15 km.

With an interannual modulus which is established at 40,000 m³/s, and a flow rate exceeded for 98% of the time which amounts to 26,400 m³/s, and the physical characteristics, this site conceals a hydroelectric potential estimated at more than 40,000 MW in guaranteed power (Société Nationale d'électricité, 2012). This power represents nearly 40% of the total guaranteed

hydroelectric potential of the DRC, estimated at nearly 100,000 MW.

The annual production of the fully equipped site would be 305 TWh (TWh ¼ Terawatt-hour, or billion kWh). It is undoubtedly the most important source of hydraulic power in the world, concentrated at the same location.

As having regional and continental dimensions, the Grand Inga project is one of the key priorities of the African Union (AU) agenda 2063 (Gnassou, 2019). The U.N. Environment Programme described the plan to build the Grand Inga, hydroelectric dam as the most important hydroelectric project in all of Africa (Yildiz et al., 2016).

In addition, the topographical configuration of the site lends itself remarkably to a gradual laying out (Amadou et al., 2006). Therefore, the various studies carried out provide for the project to be carried out by splitting according to the real electricity needs. The enhancement of the site is scheduled in different stages. These steps go from Inga 3 to Inga 8 since Inga 1 and Inga 2 already exist.

For the development of Grand Inga, which will have to start with Inga 3, the Congolese Government does not have the necessary financial means on its own. It will have to resort to external investments which constitute a crucial factor for a positive result as regards the development of the project.

The challenges of attracting investment are largely underpinned by the problem of credible engagement.

At present, the Government of the DRC has not yet reassured potential investors that the agreements reached regarding the financing of the project will be respected throughout the life of the project. This is particularly important given the nature of the electricity industry which is a sunk cost sector.

As proof, the World Bank withdrew from the project in 2016, declaring that the Kabila regime had taken a different strategic direction from that agreed in 2014.

The bank argued that unilateral changes were made to the terms of agreement for the technical assistance project, resulting in a breach of the contract (Eyita-Okon, 2020).

The present chapter highlight how the huge Democratic Republic of Congo's hydropower potential resources, at the Inga site can contribute significantly to reducing the energy deficit in Africa.

It is structured as follows. The next section deals with the energy supply deficit in Africa.

Then the abundant DRC's water resource and its hydropower potential. Following this, an overview on the Inga Falls Site history is presented. After that, the main studies, and realizations on Inga site

since 1960 will be discussed. Finally, the project planning, challenges and prospects will be provided.

2 Energy supply deficit in Africa

Despite the abundance of natural resources and an impressive amount of renewable energy resources, most of the African population lives in extreme poverty. This is because the extremely rich resource deposits are not being used. According to Omorogbe and Ordor (2018), 1,1 billion people lacks access to electricity and 1,9 billion without clean cooking fuels in Africa. This trend is expected to continue over the next 30 years (Chidebell-Emordi, 2015). This is particularly true of sub-Saharan Africa, who is the least electrified region of the world (Karekezi and Kithyoma, 2002). Therefore, efforts to narrow the gap in electricity access for these countries are particularly important for progress.

In 2019, the 20 countries with the largest populations lacking access to electricity made up 76% (580 million people) of the global access deficit (World Health Organization, 2019). Nigeria and Democratic Republic of Congo topped the list of the three countries in Sub-Saharan Africa with the largest deficits, with 90 million and 70 million people, respectively, lacking access (World Health Organization, 2019).

Although much effort is being made to reduce the electricity access deficit in Africa, the rate of progress in most countries remains below population growth, resulting in a net increase in the access deficit. This access deficit becomes more and more difficult to close over time. According to International Energy Agency (2021), electricity demand in the rest of sub-Saharan Africa is set to quadruple by 2040, driven by rising incomes and industrialization. To reduce this deficit significantly, several sources of clean renewable energy are available solar (solar photovoltaic, solar thermal), hydroelectricity, wind power, biomass, geothermal energy. However, compared with other renewable options and fossil fuels, developing new large-scale hydropower plants remains attractive in many developing and emerging economies in Asia, Africa and Latin America where there is still significant untapped hydropower potential to supply flexible electricity and meet increasing demand (International Energy Agency, 2021).

Grand Inga will be able to cover the electricity consumption needs of the DR Congo and all neighboring countries, as well as interregional areas, including West and South Africa (Song et al., 2020). After meeting the African electricity demand Grand Inga could still export a supplement to

southern Europe. Considering the potential electricity market in Africa and reasonable transmission options, from D. R. Congo to surrounding countries, the development of the Grand Inga hydropower is of great significance for the industrialization of Africa.

3 Hydropower resources in D.R. Congo

In this section, we portray the overall potential hydropower resources in the Democratic Republic of Congo.

3.1 Water resources in D.R. Congo

The Democratic Republic of Congo is the most water-rich country in Africa. It is watered by the Congo River whose a mean flow is $41,000 \text{ m}^3/\text{s}$. The Congo River boasts the largest discharge volume in Africa (1260 km^3), equivalent to 15 times the mean annual runoff of the Nile River and second in the world after the Amazon River (Partow, 2011).

The Congo Basin area is around $3,841,400 \text{ km}^2$ and is the largest in Africa. This vast Basin occupies the western part of the African continent. It extends between 9° of the North latitude and 13° of the South latitude. It lies longitudinally between the meridians of 12° and 34° east of the Greenwich. It is a large basin which, from an orographic point of view, can be subdivided into three main parts:

- The central basin, located between 300 and 500 m above sea level, which occupies approximately 25% of the entire surface of the Basin;
- The peripheral part reaching 1000 m of altitude which covers 50% of the Basin;
- The part exceeding 1000 m of altitude which occupies the last 25%.

The course of the Congo River is very characteristic:

- in its first part it flows in a south-north direction to Kisangani, located 2500 km from the source;
- downstream from Kisangani, the river changes direction and heads northwest;
- it reaches not far from the 22nd parallel, its northernmost part from where it branches off towards the West until the 20th parallel;
- then it changes direction again and heads southwest;

- after having crossed the equator for the second time and reached the regions of Bandundu and Bas-Congo, it joins the Atlantic Ocean at Banana.

The hydrological regime of the Congo River is conditioned by the location of its tributaries.

1/3 of these are in the northern hemisphere and the remaining 2/3 in the southern hemisphere.

When the tributaries of the southern tropical zone are in flood those of the northern tropical zone are in low water and vice versa. The areas of the hydrographic basins of the main tributaries of the Congo River are given in Table 1. While it drains nine countries, 62% of the river basin lies within the DRC (Partow, 2011). The DRC has one of the most extensively dense river networks in the world, totaling more than 20,000 km of riverbanks (Frenken, 2005). Covering approximately 86,080 km², lakes and rivers account for 3.5% of the country's land area. The DRC has an extensive system of lakes and wetlands, which are well described in the literature (Aveling et al., 2003). The DRC has an average annual precipitation of around 1543 mm/year, varying in space and time (800–1800 mm/year). Fig. 1 below shows the surface water resources map of the DRC.

3.2 Hydropower potential resources in D.R. Congo

The enormous extension as well as the exceptional hydrological and climatic characteristics of the Congo Basin have encouraged, since the colonial period, some researchers to study its hydroelectric potential. Cifarha (1994) investigated the studies carried out in 1972 and 1977 by the design offices SICAI (Italy) and TRACTEBEL (Belgium) which covered a large part of the national territory except the South and South-East areas.

Table 1 Areas of the hydrographic basins of the main tributaries of the Congo River.

<i>Directs tributaries</i>	<i>Confluence locality</i>	<i>Basins area (km²)</i>
Mongala	Mobeka	52,750
Lulonga	Lulonga	83,750
Ikelemba	Mbandaka	14,700
Ruki	Mbandaka	168,490
Kasai	Kwamouth	890,970
Inkisi	Zongo	14,420
Kwilu	Pelo	7150
Mpozo	Matadi	7700
Total area of tributaries		1,239,930
Tributaries of the Ubangi	(Lua & Ngiri)	43,870
Remaining basin of the Ubangi		728,960
Basin drained directly by the Congo between Bumba and the ocean		480,970
Total Congo basin downstream of Bumba		2,493,730
Total Congo basin upstream of Bumba		1,337,660
Total Congo basin		3,831,400

Source: Cifarha M (1994) *Les Ressources Hydro-électriques du Zaïre*.

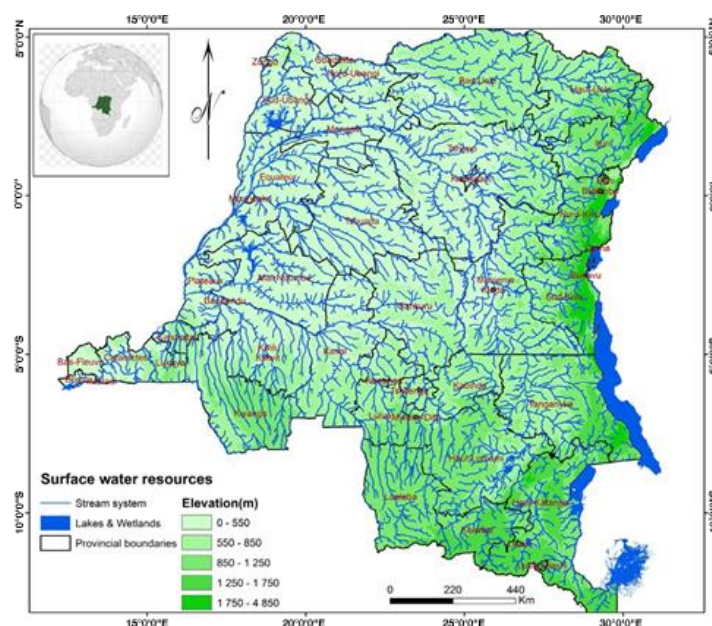


Fig. 1 Surface water resources in DRC. Derived from World Wildlife Fund HydroSHEDS; FAO Inland Water Bodies; and Référentiel Géographique Commun (RGC).

The first approach of these studies consisted of a systematic inventory of the large watercourses (tributaries of the first to the third order of the Congo River) to globally assess the hydroelectric potential of the DRC. In view of the objective pursued, these studies have made it possible to delimit certain sections of watercourses that are interesting for hydroelectric exploitation. In this same context, only a few sites offering the possibility of supplying a large quantity of electrical energy have been studied in sufficient detail or simply pointed out. Also, in the evaluation of the hydroelectric potential of the DRC, the inventory was not followed by field visits, nor generalized on small and medium-sized rivers whose knowledge of the characteristic elements would be essential for the study of the electrification of rural centers.

The second approach to the inventory of hydroelectric resources concerned the specific studies carried out and subordinated especially by specific projects for the electrification of certain urban centers, production units and social entities in rural areas.

These studies had led to the erection, under the aegis of public authorities or private organizations, of large, medium, and small hydroelectric power production units.

Besides, in this same context there are studies whose projects could not be carried out for the following reasons:

- the existence in the vicinity of another source of hydroelectric power in operation and offering the possibility of meeting the expressed demand.
- the existence of the possibilities of electrification of the centers concerned by means of power transmission lines drawn from distant sources for reasons of profitability of the latter.
- lack of funding.

In February 2016, the Ministry of Energy and Hydraulic Resources (MERH) of the DRC published the second edition of the Atlas of Renewable Energies, the first edition of which was released in August 2014. In this edition, the number of identified sites has now increased from 780 (shown in the first version of the atlas) to 890 identified and located sites (Chinamula et al., 2016). Compared to the 217 sites previously listed (but without locating them), this edition significantly advances the state of knowledge on the energy resources abounding in the DRC and the possible options to achieve access for all and all to renewable energies, in accordance with the ambitions set by the DRC.

This Atlas shows how the country's overall hydroelectric potential (100,000 MW) is distributed across the country (Chinamula et al., 2016). While it was known that the INGA hydroelectric site alone has an estimated potential of 44,000 MW, nothing was indicated on the breakdown of the rest of the national potential. With this Atlas, we realize that an estimated potential of around 10,000 MW is largely decentralized and offers to the country the possibility of developing medium-sized hydroelectric facilities (mini or small hydroelectric plants, that is to say of which the capacity varies between 1 and 10 MW) but also hydroelectric applications even better adapted to the structure of the local market (micro and pico hydroelectric which are below the megawatt) on all of its 145 territories (Chinamula et al., 2016).

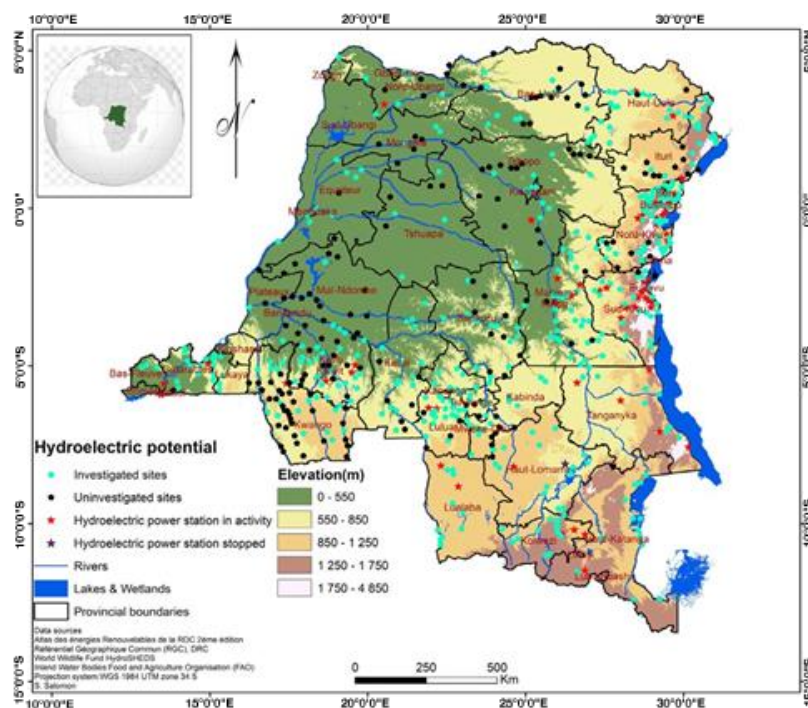


Fig. 2 Hydroelectric potential in DRC. Derived from World Wildlife Fund HydroSHEDS; FAO Inland Water Bodies; Référentiel Géographique Commun (RGC); and Atlas des énergies Renouvelables de la RDC 2ème édition.

This is a sizeable asset for ensuring the exploitation of such an economic resource (by making savings in transmission infrastructure, the costs of which generally represent between 30 and 50% of the investment cost in the field of hydropower). These sites are generally located in the most rural part of different territories which is also the area with the least electricity supply (with an access rate of 1% in 2012) and the most populated area (60–70% of the Congolese population). Most of these sites have been the subject of summary studies (which provide information, for each site, on the characteristics of the upstream watercourse, the socio-economic parameters of the immediate environment as well as the estimation of the potential and local energy needs). The Fig. 2 shows the hydroelectric potential of all the sites known to date.

4 Overview on Inga falls site

4.1 Location

The Inga Falls site stands on the Congo River 172 km from the estuary and 282 km downstream from Kinshasa in the Democratic Republic of Congo (DRC). It is located at 051400 south latitude and 131390 east longitude. The Inga site on the Congo River is drained by around 98% of the total

area of the Congo basin. Fig. 3 shows the Congo River watershed as well as the location of the Inga site.

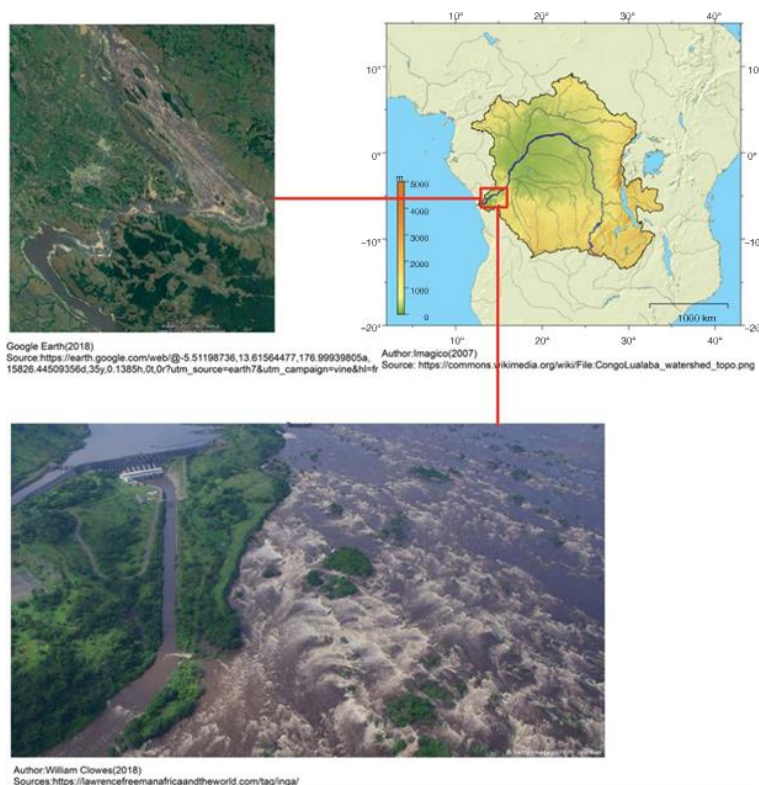


Fig. 3 Inga site location.

4.2 Physiographic characteristics

The Inga Falls extend over a length of 32 km with a drop of 97 m for an average slope of 3 m/km. The site allows the development of production structures with a gross head of 150 m (Nzakimuena et al., 2013a). The average flow of the Congo River is 40,800 m³/s. The potential power that can be developed with these characteristics is of the order of 42,900 MW for the Inga site. In addition to the main valley that the river flows through, there are two secondary valleys suitable for hydroelectric development. The first secondary valley, narrower and offering a smaller drop, the Nkokolo valley, has already been developed with the Inga 1 (gross drop varying from 45 to 48 m) and Inga 2 (gross drop varying from 51 to 59 m) power plants the second secondary valley, the valley of the Bundi river, is wider and allows a greater drop (up to 150 m). This valley has not yet been developed but

has been the subject of numerous studies to develop the Grand Inga hydroelectric complex there (Nzakimuena et al., 2013a).

4.2.1 Topography

The longitudinal profile of the Congo River is exceptional, the river rushes towards the ocean in a succession of rapids whose drop is from 255 m between Kinshasa and Matadi. The most impressive series of rapids constitutes the site of Inga, where there is a drop of 98 m between the island of Sikila and the confluence of the Bundi, separated by a straight-line distance of only 15 km (Francou, 1977). The topography of the Inga site shown in Fig. 4 (Nzakimuena et al., 2013b), is characterized by three major depressions:

- the low-water channel of the Congo River,
- the three valleys (Grande Valley, Sikila Valley and Nkokolo Valley) that form the flood plains of the Congo River, and
- the Bundi River Valley, which is a tributary on the west bank of Congo River.

4.2.2 Geology

The Inga region belongs to the Mayumbe system, series of the Duizi. The general direction of the layers is N.-N.-W. - S.-S.-E. with a strong inclination towards the West (Geulette, 1957). The bedrock at the Inga site area is composed primarily of five types of rock: granite, granitic gneiss, greenstone, rhyolite schist, and micaceous & sericite quartzite (see Fig. 5) (Nzakimuena et al., 2013b). These rock formations are found in bands, aligned in a N.E.-S.W. direction. The Congo River carved its bed in the least solid rock, thus remaining confined between two bands of granitic rock.

The rhyolite schist (shown in the photograph of Fig. 5) and greenstone in the SW are of particular importance, as the hydroelectric structures will be founded on these. The first geologic maps of the region were drafted in 1955 by the geologist A. Bertossa, which were later analyzed and commented on by geology experts such as M.I. de Magnée in 1957 (Nzakimuena et al., 2013b).

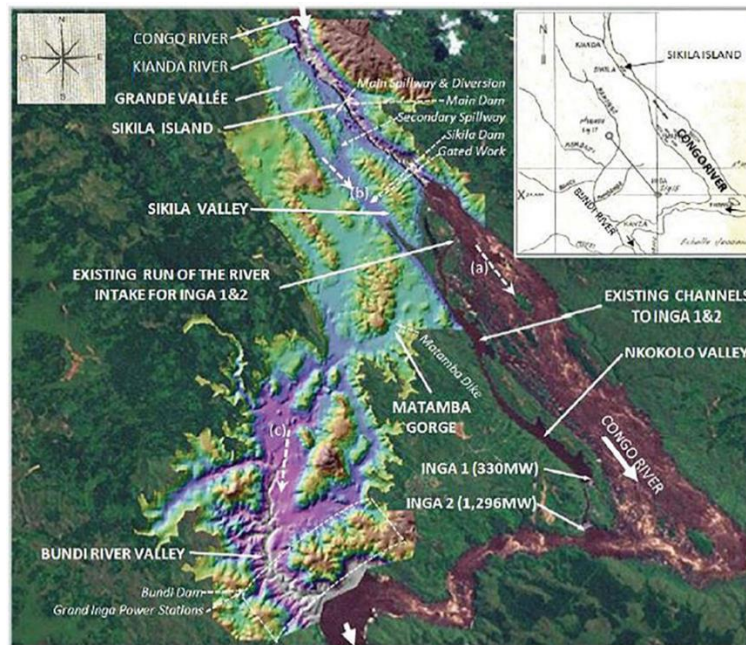


Fig. 4 Topography of the Inga Site. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

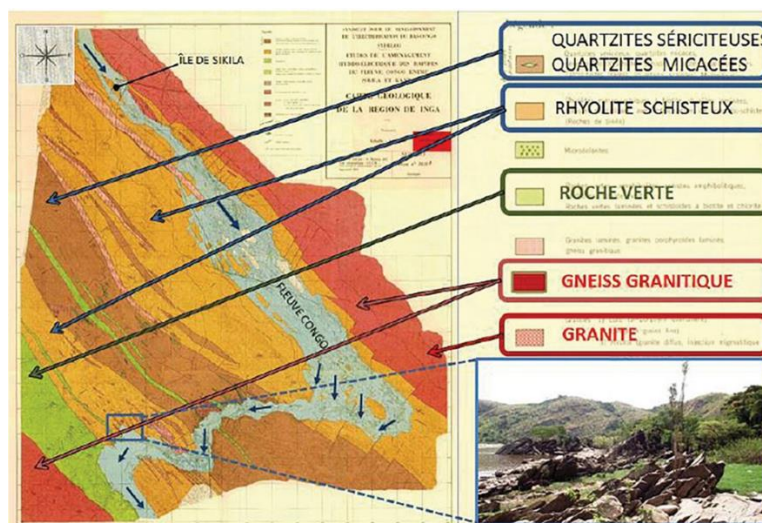


Fig. 5 Geology of Inga site. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

Even currently, there was apprehension regarding carrying out underground works in these types of rock. Furthermore, concerns were raised regarding the bearing capacity of the greenstone and the construction of concrete dams on this formation. The rhyolite schist is found in layers 0.5 to 1.0 m thick, oriented in a N.E.-S.W. direction, with a S.W. dip. The schistosity of the rock has always been a concern and should be carefully considered in the design. In the Bundi Valley, the

greenstone transitions from a schist formation near its interface with the rhyolite in the N.E. to a more solid formation near its interface with the granite in the S.W. Since 1971, due to these geological concerns and considerations, the construction of aboveground powerhouses and open headrace canals has been favored. To realize this, the normal operating water level (NWL) of the Grand Inga reservoir will have to be raised from 190.00 m (before 1970s) to 205.00 m (after 1971).

4.2.3 Hydroelectric potential of Inga Falls

The hydroelectric potential of the Congo River at the Inga site has been known since the beginning of the 20th century. Hydrometric monitoring of the river began in 1902, and numerous studies have been carried out over the years, progressively transforming the first development schemes proposed in 1955. The Inga site is a 32-km stretch of the Congo River, located approximately 280 km downstream of the Capital city of Kinshasa in the Democratic Republic of the Congo (DRC). This stretch of river has a natural river profile that drops 97 m in elevation.

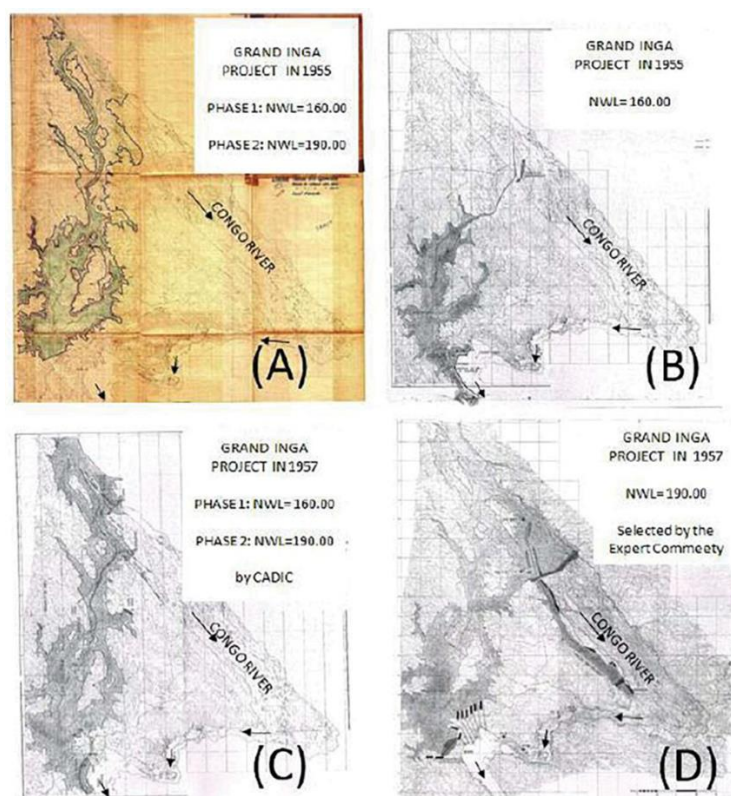


Fig. 6 Layout Schemes of the Inga Site (1955–1957). Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

With a mean annual flow (MAF) of 40,800 m³/s at this site and a gross head that may be raised to 150 m, the gross hydroelectric potential is very important. The Inga Falls on the Congo River have a hydroelectric potential estimated at over 40,000 MW in guaranteed power. This power represents nearly 40% of the total guaranteed hydroelectric potential of the Rep. Dem. of the Congo, estimated at nearly 100,000 MW. The configuration of the site, with the presence of two contiguous valleys to the major bed of the river, suggests that its development is based essentially on two development plans, namely the Nkokolo plan and that of the Bundi. The Nkokolo plan includes the existing power plants, Inga 1, and Inga 2, with a total installed capacity of 1750 MW. The Bundi plan would include the installation of the Grand Inga project power plants, the total guaranteed power of which is estimated at nearly 39,000 MW (Société Nationale d'électricité, 2012).

5 Grand Inga project description

5.1 Inga site pre-Congo independence history

Captain James TUCKEY was, in 1816, the first European explorer of the site of Inga, because before him, no European had ascended the river beyond the rapids of Yelala (Pirenne, 1957). He had been instructed by the British Admiralty to see whether the Congo River was not the mouth of the Niger, of which only part of the upper course was known at the time, near Tombouctou, or, on the contrary, whether the Congo River did not cross the African continent to the east and if, therefore, it could not become an access route to East Africa from the Atlantic Ocean (Pirenne, 1957).

The name INGA as transcribed in Captain Tuckey's travel documents, is an erroneous transcription of the term "YINGA." To the question asked to know what is the name of this site? The autochthons responded "YINGA" which means "yes" in the local language (Agence Pour Le Développement Et La Promotion Du Projet Grand Inga, 2019).

In September 1816 Captain Tuckey learned that several of his men had died of fever. His companions and himself also being affected to varying degrees, he no longer lingered at the Inga site and resumed, as quickly as possible, the route to the maritime reach where he only rejoined his ship to die with the members of his scientific expedition and several crew members.

In 1876, LÉOPOLD II invited the Brussels Geographical Conference to designate bases of operation near the mouth of the Congo River. The next year, an Englishman, Mr. ARTHINGTON, encouraged the Baptist Missionary Society in London to launch a steamer on the upper part of the

river. A few months later, STANLEY, at the end of his memorable crossing of the mysterious continent, reached, on the Manianga-Isangila reach, the extreme point reached by captain TUCKEY (Pirenne, 1957).

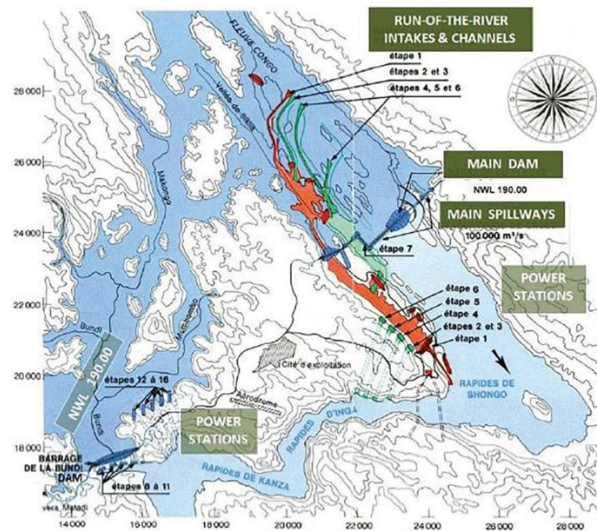


Fig. 7 Layout Scheme Proposed in 1960. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

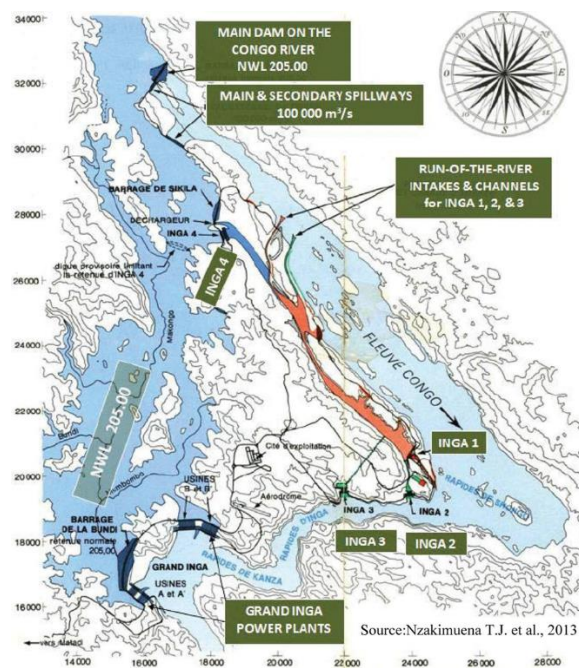


Fig. 8 Layout Scheme Proposed in 1971. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

The Inga site was the object, in 1885, of a first topographical study during the search for a route for the railway intended to bypass the region of the cataracts. The first geological survey of the river line at the Inga salient took place in 1887 (Campus, 1958).

In 1900 the Secretary of the Independent State of Congo (ÉIC), Hubert Droogmans, published the first detailed map of the Inga site, at 1: 100,000, drawn up by the surveyor Abrassart, of the cadastre service of the Independent State of Congo.

The Robert THYS mission, who studied the river downstream from Léopoldville and immediately upstream from Matadi, in 1910–1911 gathered the first scientific data on the hydrology of Congo River (Thys, 1912).

In 1952, the Syndicat Sydelco carried out numerous works in the region of Inga, in particular:



Source: <https://archive.internationalrivers.org/fr/campaigns/le-barrage-grand-inga-rd-congo>

Fig. 9 View of the Inga 1 hydro plant.

- the installation of permanent hydrographic study equipment on the river banks;
- the placement of spotting signals for aerial surveys used by the services of the Geographical Institute of Congo for the entire 200 km² of the Inga site;
- construction of a 20 km carriage road from Matadi to Boma;
- the construction of two final bridges of 22 m and 52 m respectively on the Mvunzi and Bundi rivers;

- the construction on the Inga plateau of houses for three European agents and about 60 native workers;
- construction of a landing strip for light aircraft, etc. (7SUR7.CD, 2021).

Several groups, future users of the energy that will be produced at Inga, were created with a view to associating Belgian interests in Inga's work. Among these groups, there was URANINGA (Electrobel, Overseas Company, Electr rail, Evence Coppée, Belgian- Nuclear, Brufina, Cominière, Sofina, Traction, Union Fin. Boël) created on the initiative of the Minister for the Colonies, to study the possibility of installing a uranium enrichment plant near Inga (7SUR7.CD, 2021).

The United States of America opposed this, clearly expressing its desire to prevent the production of enriched uranium abroad. Note that the atomic bombs dropped by the US military on Hiroshima and Nagasaki in Japan during World War II were made with enriched uranium from uranium ore mined from the Shinkolobwe mines in Katanga (DRC).

For the United States of America, setting up a uranium enrichment plant in a country that produced uranium meant paving the way for that country to manufacture an atomic weapon of mass destruction, and therefore a threat to the world (7SUR7.CD, 2021).

On November 13, 1957, the Belgian government officially announced the decision to develop the Inga site by building vast dams and hydroelectric power stations. During the same official meeting, King Baudouin underlined in his speech that: “the importance and the economic value of the energy available make it a duty for Belgium to ensure its implementation” (7SUR7.CD, 2021).

In December 1957, the National Institute of Studies for the Development of Bas-Congo, commonly known as the Inga Institute, was created by Royal Decree. The objective of this institute was to study all the hydroelectric equipment of the site, the infrastructure, the method of financing the equipment works of the site, the economic possibilities of using the electric current, the problems of transport, demographic, social and urbanization. In the same year, the International Committee of Experts was created to study the projects submitted by the consulting firms in purpose to making proposals to the Government. The Fig. 6 shows the first schemes proposed in 1955–1957 (Nzakimuena et al., 2013b).

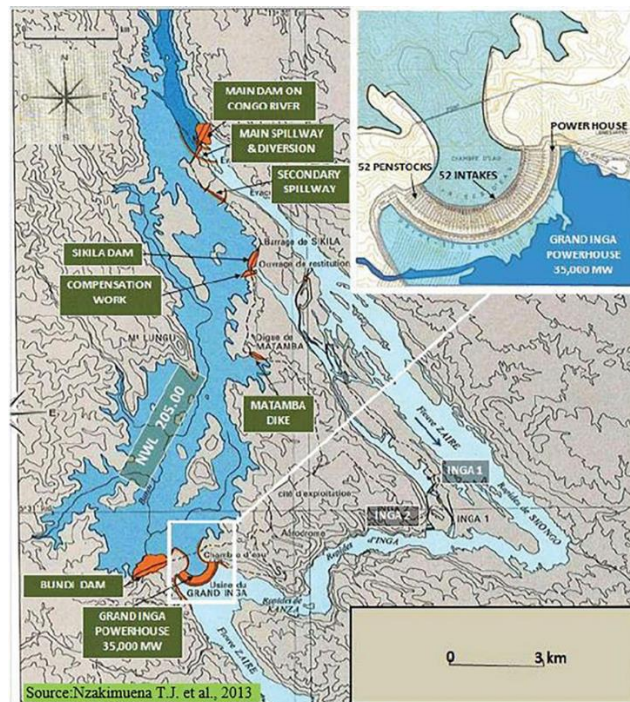


Fig. 10 Layout scheme proposed in 1974. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

In 1958, Fernand Campus, Pro-Rector of the University of Liège, President of the Committee of Experts for Inga, President of the National Institute of Studies for the Development of Bas-Congo and Member of the Royal Academy of Colonial Sciences, published an important study on the hydroelectric development of the Congo River in Inga (7SUR7.CD, 2021).

This study can be considered as the scientific basis of the Grand Inga project in the sense that it contains the detailed description of the Inga site, its geology, hydrology, bathymetry, calculations of power and energy measurements available in depending on the height of the falls and the flow, etc.

In February 1960, the Abelinga union gave Epinga all the results of its complementary study from which it emerged that the development of the Van Deuren valley (Nkokolo Valley) with a first stage of 200,000 KW was technically possible without compromising the further development of the site (Fig. 7).



Fig. 11 View of the Inga 2 hydro plant.

5.2 Main studies and realizations on Inga site since 1960

On June 30, 1960, the colony of the Belgian Congo acquired its independence. The new state, visionary, created at the end of 1960, a new body called “High Commission of Inga” whose aim was to direct on behalf of the new state the activities of Epinga. From 1816, the date of the discovery of the Inga Falls, to 1961, year 1 of the First Republic, the Inga project would finally come to fruition. The new government of Congo will be taken several actions and subsequently several development plans will be proposed over the years. Most of them included multi-stage development to accommodate changing energy demand.

In 1961, President J. Kasa-Vubu re-established contacts with the B.I.R.D. and the Union of Electricity Users. The B.I.R.D. made the financing of Inga's development conditional on the prior signing of a contract for the sale of electrical energy to American aluminum producers, particularly Kaiser Aluminum (7SUR7.CD, 2021).

In 1963, the Italians of the company Italo-Congolese for Industrial Activities (SICAI) took an interest in the Inga project, they resumed the studies of Abelinga and thought they could create an industrial development pole focused on the domestic market. November 24, 1965: This date marks the birth of the Second Republic by a military coup. President Kasa-Vubu is ousted from power by the army led by Colonel Mobutu, which he had just raised 6 days earlier to the rank of Lieutenant-General of the Congolese National Army (ANC) during an official ceremony at Camp Kokolo in

Kinshasa. The Congolese government promulgated a Decree-Law establishing the National Office for the Development of the Inga Zone of Influence, responsible for economic coordination.

In 1967, President J.D. Mobutu decided to start construction of the Inga 1 Power Plant. For this, he created the Inga Technical and Financial Control Committee. This committee was responsible for updating the technical file and overseeing construction work on the site. As of this date, the country still had no agreements with the users of the electricity that will be produced, in this case, a steel plant and a fertilizer plant.

In January 1968, President Mobutu dissolved Epinga, the Inga High Commission and the National Office for the Development of the Inga Zone of Influence. Their attributions were entrusted to the Technical and Financial Control Committee of Inga, the Contracting Authority being the Congolese State and the industrialization studies linked to Inga supervised by the Office of the Presidency of the Republic under the direction of the Rwandan electrical engineer Barthélémy Bisengimana Rwema. The procurement supplies and assembly of the equipment were entrusted to Italinga, a group made up of a public works company and two Italian builders. This date also marks the effective start of work on the Inga 1 dam.

In 1969, the European Economic Community (C.E.E.) supported the Inga dam project.

In May 1970, Inga's Technical and Financial Control Committee was dissolved and replaced by a new company, the National Electricity Company (SNEL).

In 1971, the site's layout was revised by eliminating underground power stations to reduce geological risks (Fig. 8).

In 1972, the Italian companies Ansaldo-Gie and Astaldi completed the construction of the dam and the hydroelectric plant and commissioned the Inga 1 plant with 6 groups of turbines-generators of 58.5 MW per unit, for a total power of 351 MW (Fig. 9).

At the end of 1973, construction of the Inga 2 dam and hydroelectric plant began.

The most recognizable layout scheme was proposed by EDF in 1974 and is shown in Fig. 10. Compared to the scheme proposed in 1971, Inga 3 was eliminated to maximize the production at the Grand Inga mega powerhouse, which took on a semi-circular form.

Inga 4 was also removed from the layout and was replaced by an outlet work.

In 1982: End of work on the dam and hydroelectric plant of Inga 2: Inga 2A with 4 groups assembled by the Acec-Westinghouse consortium and Inga 2B with 4 groups assembled by the Siemens-Neyrpic consortium. Each group has a power of 178 MW, for a total power of 1424 MW (Fig. 11).

In 1983: The HTCC Inga-Kolwezi line (commonly called Inga-Shaba) was put into service on November 24 by President Mobutu (Fig. 12).

In 2004, Signature of the Western Power Corridor and Telecommunication (Westcor) agreements between the governments and the electricity companies of five member countries: South Africa, Angola, Botswana, Namibia, and DRC.

In 2005, after Westcor's failure, BHP-Billiton proposed to carry out the project with a tunnel option based on the feasibility study carried out by the Canadian firm SNC-Lavalin. This option will not be retained either.

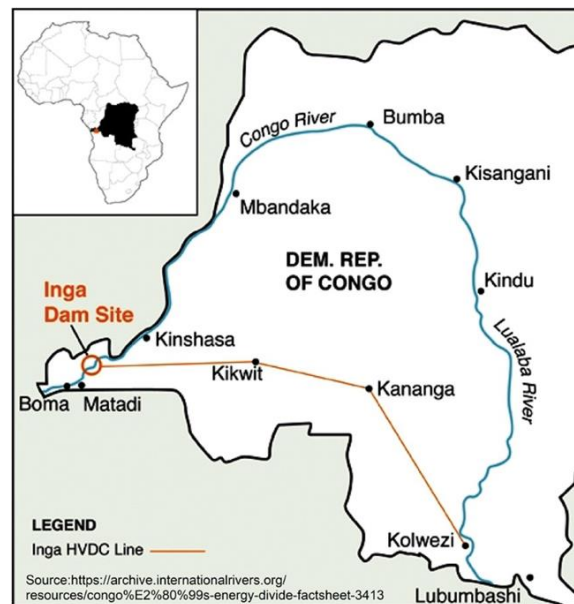


Fig. 12 HTCC Inga-Kolwezi line.

In 2010, at the initiative of the Central African Power Pool (PEAC), the African Development Bank (ADB) agrees to finance an optimal development study of the Inga site. The ADB and the AECOM-RSW/EDF consortium sign a contract for this purpose.

In 2011, organization at the Grand Hôtel in Kinshasa of a national preparatory workshop for the launch of the development study for the Inga site in successive phases according to the feasibility study carried out by AECOM-RSW/EDF. This is the third project named “Open sky option”. It

was this last option that was chosen. Following the difficulties in obtaining financing to commence work on the Grand Inga project, as proposed in 1974, designers returning to the idea of an intermediate phase, called Inga 3. AECOM-RSW/EDF reinvestigated and identified Inga 3 as a major strategic stepping-stone towards the realization of Grand Inga.

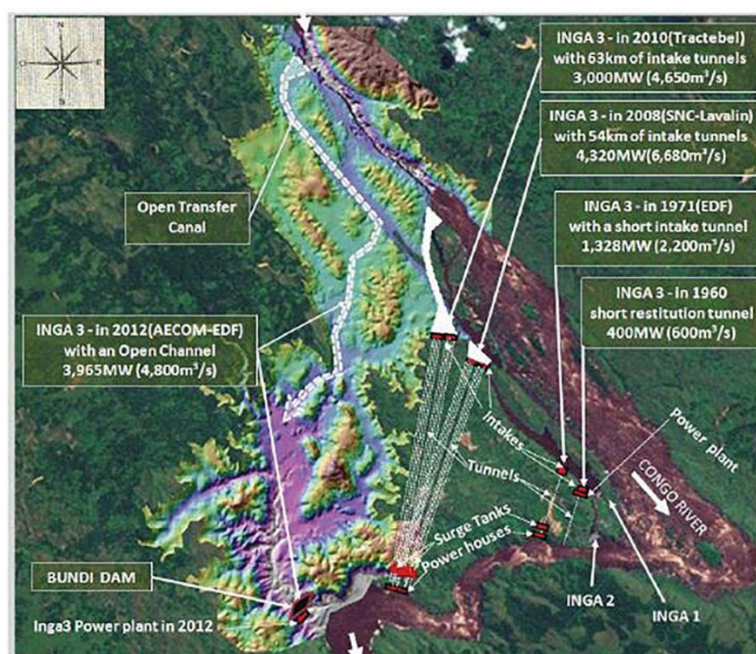


Fig. 13 Inga 3: A Crucial Step Towards the Development of Grand Inga. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

In 2012, the AECOM-RSW/EDF consortium submits to the Congolese government the provisional feasibility report for the development study of the Inga hydroelectric site and associated interconnections. The evolution of the Inga 3 layout over the years (1960, 1971, 2006, 2010 and 2012) is presented in Fig. 13 (Nzakimuena et al., 2013b).

This final proposal submitted, envisioned a phased development plan for Grand Inga, which included two or three stages: low head, medium head, and high head. In this plan, Inga 3 would be the first step. The cumulative installed capacity will be 44,396 MW or 46,562 MW depending on the number of units installed at Inga 3. Although the annual energy produced (335.9 TWh) would be almost similar to that of the 1974 scheme, the phasing and costs will be quite different. The final proposed scheme elaborated by AECOM-RSW/EDF, through a complete year of studies, is shown in Fig. 14.

5.3 Inga project planning, challenges, and prospects

The Grand Inga Project is the largest, most powerful and possibly most controversial prospective hydroelectric dam development project ever imagined (Warner et al., 2019). It is the flagship of the Democratic Republic of the Congo's (DRC) development strategy, a proposal of overwhelming prestige which has captured global imagination since the 1960s (Klemm, 2015; Warner et al., 2019). The Congolese government perceives Grand Inga as an important link for its economy. It is making considerable efforts to carry out this very ambitious project. However, the outlook for planning faces several challenges.

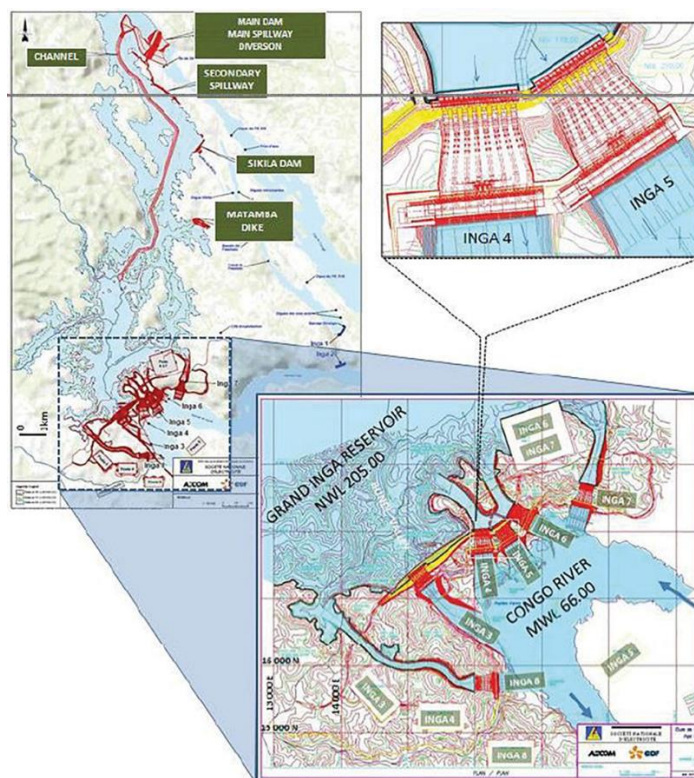


Fig. 14 Layout Scheme Proposed by AECOM-EDF in 2012. Nzakimuena T-J, St-Pierre S, Bossé Y, Lorillou P, Rousselin A, and Kitoko L (2013a) Hydroelectric development schemes of the Inga site (Democratic Republic of Congo). ICOLD International Symposium. Seattle, USA.

5.3.1 Development prospects for the Inga site

The development of the Inga site is placed in a perspective of finding a solution to the country's chronic deficit in electrical energy and of exporting electrical energy to other countries at the regional level.

The Democratic Republic of Congo (DRC) has been experiencing a chronic energy deficit for many years, especially during the low flow period of the Congo River. The strengthening of the country's high voltage network, associated with the realization of a major hydroelectric production project on the Inga site can alone make it possible to make up for this increasingly penalizing deficit for the economy.

The Government of the DRC is multiplying strategies to sustainably strengthen its electricity system. It undertakes to achieve two ambitious goals:

1. to achieve a population electrification rate of 50% by 2030 (less than 10% currently) for a population that will double, reaching 111 million inhabitants by that date (Société Nationale d'électricité, 2012).
2. provide electricity, because of a structuring network for the country, to High Voltage (HV) consumers, in particular the mining industries in the provinces of Katanga and Kasai.

At the same time as the rehabilitation of existing facilities, the Government has taken a series of measures aimed at strengthening the transport network associated with the Inga site and preparing studies relating to the continued development of the site. These measures aim to meet in the long term both national electricity needs, and the energy demand expressed by several other countries and the private sector (mining in particular).

The implementation of these measures comes in a favorable context marked by the return of peace in the country and in the Great Lakes region, in general, the favorable evolution of the controversy concerning the construction of dams, the creation of African power pools, the creation of the New Partnership for Africa's Development (NEPAD) and soaring oil prices (Société Nationale d'électricité, 2012).

Indeed, NEPAD's Short Term Action Plan (PACT) has made the Grand Inga Integrative Project Study (GIIS) one of its priorities.

This study is also one of the 20 priority infrastructure projects of NEPAD and is one of the 10 initiatives identified as flagship projects by the Committee of Heads of State and Government responsible for the implementation of NEPAD (Société Nationale d'électricité, 2012).

5.3.2 Challenges of the project

The Grand Inga project is a massive endeavor and as such, requires coordinating many stakeholders (including foreign investors, private investors, and domestic agencies) who have competing interests and priorities for the project. Without the coordination and buy-in from all these parties, the DRC government will be unlikely to move the project forward. Therefore, addressing challenges becomes a balancing act among many stakeholders. The biggest challenges for the project are ensuring safeguards, dealing with Africa's geopolitics, navigating the politics of United States agencies, and increasing the DRC's capacity for developing the Grand Inga project (Gasparro, 2017).

6 Conclusion

This chapter begins by briefly describing the water resources of the Democratic Republic of Congo. It then proceeded to the description of the hydroelectric resources generated by the abundant water resource and the appropriate topographical configuration. Finally, a deep description of the studies carried out on the Inga hydroelectric site was investigated.

These studies have proved the profitability of the development of the Grand Inga project, and especially of the role that this project must play on the African continent. According to NEPAD's vision, the challenges and security of electric power for the countries of sub-Saharan Africa could be met through the trading of the energy produced by the Inga project. An energy exchange between the West African Power Pool, the East African Power Pool; and the Southern Africa Power Pool was highly recommended for this purpose (Tshombe et al., 2007).

On environmental point of view, the development of the Inga project will not have a remarkable impact on global warming. However, although the present and future potential production capacities, proving the technical feasibility of the proposed schemes are demonstrated, the realization of the project depends largely on adequate financial resources to be mobilized through investments in public-private partnerships. In addition, other concerns are to be noted for this major project:

- Institutional capacities to manage and maintain existing energy infrastructure, including production and distribution systems. Civil society views Inga 1 and 2 dams as projects where lack of capacity and attention to detail has resulted in long delays and exorbitant cost over runs. The

Inga 2 dam was expected to produce the cheapest energy in the world. Yet, once commissioned, the energy production costs were among the highest.

- the fact that the energy produced can only go to industrial and urban centers and large mines in the DRC, bypassing rural areas

and small and medium-sized enterprises that need access to energy in the DRC.

- Foreign investors, private investors and national agencies have divergent interests and priorities for the project.

Ultimately, the advancement and completion of this ambitious project requires a lot of intelligence for the coordination and support of all these parties, otherwise it is unlikely that the DRC government will be able to move the project forward.

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ANNEXE C - UTILISATION DE DONNÉES DE RÉANALYSES ATMOSPHÉRIQUES COMME SOURCE ALTERNATIVE POUR LA MODÉLISATION HYDROLOGIQUE DES BASSINS VERSANTS PARTIELLEMENT JAUGÉS

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Résumé

Les modèles hydrologiques constituent des outils d'une importance capitale dans la gestion des ressources en eau. Ils permettent de transformer des séries décrivant le climat sur un bassin versant (typiquement des séries de précipitations et de températures) en séries de débits simulés. Cependant, la performance de ces modèles est grandement tributaire de la qualité des données d'entrée utilisées.

Le plus souvent, les données utilisées sont les observations enregistrées par les stations météorologiques. Mais elles sont généralement limitées dans l'espace et dans le temps, et par conséquent limitent la capacité des modèles hydrologiques à représenter adéquatement la variabilité spatio-temporelle des processus hydrologiques à l'échelle des bassins versants. À cela s'ajoutent d'autres problèmes qui les affectent tels que les lacunes, les erreurs et les biais liés aux instruments de mesure. Par ailleurs, elles ne permettent pas de déterminer convenablement les valeurs de retour des extrêmes. Le problème s'accroît dans des régions où on note une très faible densité spatiale des stations météorologiques, et une absence quasi-totale de stations ayant de longs relevés d'observations.

En revanche, les réanalyses sont générées de façon dynamique par des modèles de prévisions météorologiques couplés atmosphère-océan, avec assimilation des données d'observation qui servent à « guider » les simulations. Elles ont l'avantage d'avoir une meilleure résolution spatiale,

et de s'étendre sur des horizons temporels plus longs. Toutefois, elles présentent des biais par rapport aux données d'observation.

L'objectif de cet article était de montrer que malgré ces biais, les réanalyses peuvent être utilisées dans les études hydrologiques aux fins d'évaluation de la ressource en eau et plus précisément elles peuvent conduire les modèles hydrologiques à une description optimale des débits quotidiens.

Dans cette étude les données de précipitation et température de la réanalyse « Climate Forecast System Reanalysis » (CFSR) ont été utilisées comme intrants météorologiques dans le modèle hydrologique semi-distribué HEC-HMS pour simuler les débits moyens journaliers du bassin versant du fleuve Congo à Kindu.

Le modèle a été calé pour la période de six ans de 1980-1985 et validé pour une période de sept ans de 1998-2003. Les premiers résultats montrent une performance acceptable avec une erreur de 21% pour le calage, et une bonne performance pour la validation avec une erreur de 14%.

Mots clés: Modèle hydrologique, gestion des ressources en eau, performance, données alternatives, bassin versant, débit.

1. Introduction

L'eau est une ressource essentielle, précieuse, parfois rare et toujours fragile. Une gestion efficace de la disponibilité de cette ressource naturelle indispensable à la vie, constitue un des défis majeurs de la communauté scientifique. Son cycle et ses interactions avec les milieux terrestres et atmosphérique sont étudiés par l'hydrologie (Essou, 2016). L'hydrologie intervient dans plusieurs applications dont la planification et la gestion des ressources en eau (irrigation, production hydroélectrique, etc.) et la prévision des événements extrêmes (tels que les inondations et sécheresses) (Hingray, Picouet, & Musy, 2009; Singh & Woolhiser, 2002).

Les modèles hydrologiques sont utilisés dans ces cas pour simuler la réponse hydrologique des hydrosystèmes aux sollicitations météorologiques (Payraudeau, 2002; Pechlivanidis, Jackson, McIntyre, & Wheeler, 2011).

Ces modèles hydrologiques nécessitent certaines données dont les principales peuvent être groupées en trois groupes. Le premier groupe est constitué de données sur les caractéristiques physiques du bassin versant telles que son contour, sa superficie, sa topographie et l'occupation du

sol, et de données sur son réseau hydrographique telles que les profils en long et en travers des biefs principaux. Le deuxième groupe se compose de données sur les conditions initiales telles que l'humidité du sol, l'accumulation initiale de neige et le débit initial. Le troisième groupe se compose de données hydrométriques telles que les débits et les niveaux d'eau dans la rivière, et de données météorologiques telles que la précipitation et la température.

D'une manière générale les données météorologiques proviennent des stations météorologiques qui ne fournissent que les mesures ponctuelles. Cependant, dans plusieurs régions à travers le monde, les réseaux de stations météorologiques sont clairsemés, ce qui entraîne un déficit de l'information météorologique requise par les modèles hydrologiques. D'où la nécessité de trouver d'autres sources alternatives de données météorologiques pouvant contribuer à pallier ce déficit.

Une littérature abondante existe sur le sujet, exposant différentes approches d'estimation de données météorologiques à des sites où les stations météorologiques sont clairsemées ou inexistantes, pour des applications hydrologiques. Les principales approches rapportées dans la littérature sont l'estimation de données soit par interpolation spatiale de stations météorologiques (Herrera et al., 2012; Sun et al., 2014; Wibig, Jaczewski, Brzóska, Konca-Kędzińska, & Pianko-Kluczyńska, 2014), par télédétection au moyen de radar (Rango, 1994; Yilmaz et al., 2005) ou de Satellites (Gleason & Smith, 2014; Schmugge, Kustas, Ritchie, Jackson, & Rango, 2002; Tang, Gao, Lu, & Lettenmaier, 2009), ou encore, par combinaison du peu de données de stations disponibles et de données de télédétection (Xiaoyang, Jietai, Yuanjing, & Jiren, 2003; Yu, Chen, Li, Bao, & De la Paix, 2011).

Bien que ces différentes approches aient connu un certain succès, quelques défis majeurs demeurent. D'un autre côté, grâce aux progrès technologiques des dernières décennies, de nouvelles sources de données météorologiques appelées réanalyses atmosphériques ont été développées. Elles ont l'avantage d'offrir une couverture globale pour plusieurs centaines de variables climatiques, et leurs données sont spatialement et temporellement cohérentes (Dee et al., 2011; Mesinger et al., 2006; Saha et al., 2010b). Ainsi donc, les données provenant des réanalyses atmosphériques pourraient être une alternative intéressante aux traditionnelles données de stations météorologiques, pour des études hydrologiques dans des régions où les données de stations météorologiques sont insuffisantes ou inexistantes. À ce jour, le potentiel des réanalyses pour la modélisation hydrologique a été peu évalué dans la littérature de manière générale, très peu en

Afrique et absolument pas dans le bassin du fleuve Congo, comparativement à celui des données estimées par les approches énumérées précédemment. Dans ce contexte, la présente recherche vise à évaluer le potentiel des données de précipitation et température de la réanalyse de troisième génération « Climate Forecast System Reanalysis » (CFSR)(Saha et al., 2010b) dans le modèle hydrologique semi-distribué HEC-HMS. Afin de simuler les débits moyens journaliers du sous-bassin du bassin versant du fleuve Congo à Kindu.

2. Zone d'étude et données

2.1.Zone d'étude

Le bassin du fleuve Congo est le deuxième plus grand au monde et est situé au centre de l'Afrique. La zone de drainage est d'environ 3 800 000 km². Le débit moyen annuel, de l'ordre de 40 000 m³ / s, arrive juste après le fleuve Amazone.

Le bassin du Congo est caractérisé par un système hydrologique complexe composé du fleuve Congo, de ses nombreux affluents et de vastes marécages. Les sources du fleuve Congo se trouvent sur les hauts plateaux du Rift est-africain, dans le lac Tanganyika, qui alimentent les rivières Lukuga et Lualaba; ceux-ci deviennent le fleuve Congo à Kisangani, au-dessous des chutes Boyoma.

Le sous-bassin Kindu draine plus de 789 234 km² et génère un débit moyen de 3 400 m³ / s à la station de jaugeage de Kindu. Ses coordonnées géographiques sont; Long :25° 55'45'' Lat :2°57'10''. Le cours du fleuve Congo se caractérise par la présence de nombreux lacs et zones humides qui influencent grandement le régime d'écoulement des sous-bassins en aval. La capacité de stockage de ces masses d'eau est massive (par exemple, le lac Tanganyika) et modifie considérablement les régimes d'écoulement en aval.

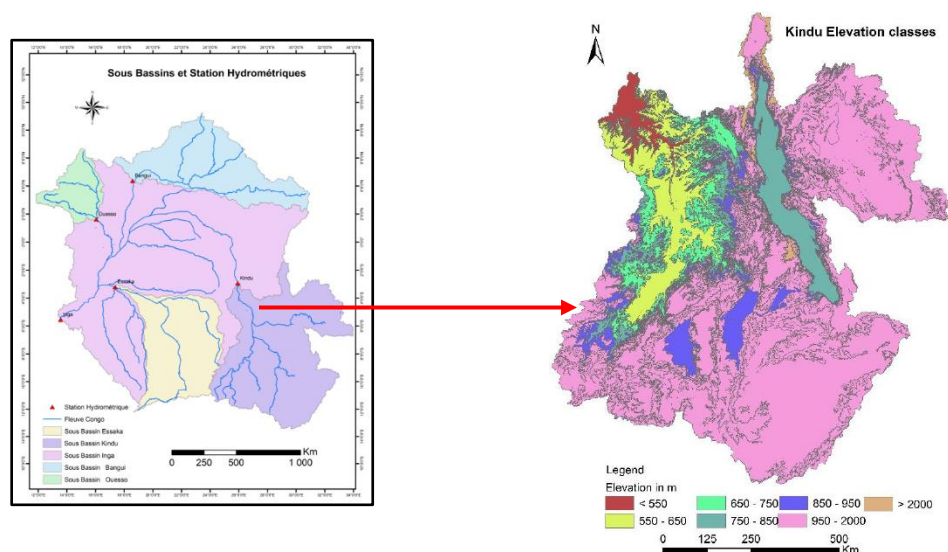


Figure 1 : Bassin du fleuve Congo(gauche), sous-bassin Kindu(droite)

2.2.Données utilisées

2.2.1. Réanalyses atmosphériques

2.2.1.1. Historique

Depuis les années 80 et 90, les améliorations considérables apportées aux prévisions météorologiques et les nombreuses améliorations apportées aux modèles et aux méthodes d'assimilation ont contribué à l'idée de réanalyser le passé récent (Bengtsson & Shukla, 1988). Une nouvelle analyse vise à fournir la meilleure estimation de l'état de l'atmosphère, de l'océan et de la surface des terres pour le passé récent. Le terme réanalyse est synonyme d'analyse rétroactive, car l'analyse est exécutée sur une période passée jusqu'au présent. Les réanalyses sont des ensembles de données maillées en trois dimensions produites par un modèle de prévision météorologique. Ces ensembles de données peuvent être caractérisés par deux caractéristiques principales: premièrement, un schéma d'assimilation intégrant les données observées provenant de différentes sources afin de fournir l'état de l'atmosphère le plus cohérent qui soit. Deuxièmement, le schéma d'assimilation et le modèle de prévision d'une réanalyse restent inchangés pendant toute la période simulée (Dee et al., 2011). De cette manière, les incohérences pouvant être induites par les mises

à jour continues du système de production de données sont évitées. De nombreuses observations mesurées à partir de différentes sources sont assimilées dans le processus de réanalyse, comme les sondages radio, les avions, les bateaux, les satellites, les capteurs de surface, les bouées, etc.

Ce large éventail d'observations fournit des informations telles que: flux radiatifs, vents, température, humidité, précipitations, albédo, neige, végétation et couverture terrestre, pour n'en nommer que quelques-uns. La couverture mondiale et la vaste gamme de variables disponibles avec une résolution cohérente dans le temps et dans l'espace au cours de la période simulée représentent certains des principaux avantages des réanalyses pour les études climatiques, notamment un biais plus faible et une résolution plus fine d'une analyse à l'autre (Wang et al., 2011). Malgré cela, les réanalyses présentent également certaines limites. En effet, la fiabilité de certaines variables peut varier considérablement dans le temps et dans l'espace. De plus, l'évolution du nombre et de la qualité des observations assimilées peut introduire une fausse variabilité et tendance (Saha et al., 2010a). De plus, le bilan hydrique est rarement conservé et les réanalyses montrent parfois des biais substantiels entre des variables qui ne sont pas directement contraintes par l'assimilation, comme les précipitations (Sabarly, Essou, Lucas-Picher, Poulin, & Brissette, 2016).

Dans les années 1990, le "European Centre for Medium-Range Weather Forecasts" (ECMWF) et le "National Centers for Environmental Prediction" (NCEP) ont commencé à produire les premières réanalyses globales : les ERA-15 pour ECMWF (Gibson et al., 1997) et « Atmospheric Research Reanalysis » (NCEP-NCAR), également connue sous le nom de R1 pour NCEP (Kalnay et al., 1996). Face aux limites de ces deux premiers jeux de données, une deuxième génération de réanalyses a été produite : le « Department Of Energy reanalysis » (NCEP-DOE), connue aussi sous le nom de R2 (Kanamitsu et al., 2002) et le « North American Regional Reanalysis » (NARR), toutes les deux développées par NCEP (Mesinger et al., 2004), la réanalyse ERA-40 de ECMWF (Uppala et al., 2005) et la réanalyse japonaise sur 25 ans JRA-25 (Onogi et al., 2007) développée par Agence météorologique du Japon (JMA). Récemment, une troisième génération a été développée, comprenant « Climate Forecast System Reanalysis » (CFSR) de NCEP (Saha et al., 2010a), ERA-Interim de ECMWF (Dee et al., 2011) et « Modern-Era Retrospective analysis for Research and Applications » (MERRA) produite par la NASA (Rienecker et al., 2011). Un nouveau produit ERA5 de la toute dernière génération de réanalyse vient d'être fourni par ECMWF

(Olauson, 2018). Cette réanalyse n'a pas fait l'objet de la présente étude, car n'étant pas encore suffisamment utilisée et documentée dans les régions partiellement jaugées.

Depuis leur apparition, les réanalyses météorologiques sont largement utilisées dans les universités et dans l'industrie pour des fins de modélisation (Olauson, 2018). Elles ont aussi été évaluées de manière cohérente.

2.2.1.2. Sélection de la réanalyse pour un site

Le choix d'une réanalyse pour un site donné dépend de critères de sélection que l'on s'impose selon les objectifs de la recherche. Les principaux critères sont : La résolution spatiale, la couverture temporelle, l'âge de la réanalyse. Il faudra ajouter à cela une bonne corrélation avec les séries observées in-situ.

Pour cette étude, le choix de la réanalyse a été opéré parmi les trois produits de la troisième génération définis ci-haut qui sont : CFSR, MERRA, ERA-Interim. Le tableau 1 présente la description de ces trois réanalyses.

Tableau 1. Description de réanalyses investiguées dans cette étude

Réanalyse	Acronyme	Résolution horizontale	Assimilation	Source	Référence
ECMWF interim reanalysis	ERA-Interim (ERA-I)	3/4°x3/4°	4DVAR	http://apps.ecmwf.int/datasets/	Dee et al. (2011)
Climate Forecast System Reanalysis	CFSR	0.313° (lon)x 0.312° (lat)	3DVAR	http://cfs.ncep.noaa.gov/cfsr/	Saha et al. (2010)
Modern-Era Retrospective Analysis for Research and Applications	MERRA	2/3°(lon)x1/2°(lat)	3DVAR	http://disc.sci.gsfc.nasa.gov/mdisc/overview/index.shtml	Rienecker et al. (2011)

Étant donné que l'unique station d'observation météorologique du sous-bassin étudié n'avait pas une couverture temporelle qui coïncide avec celles de réanalyses de 3ème génération (1979 à ce jour), il n'a pas été possible d'établir la comparaison entre les deux. Seul critère de sélection pris en compte était la résolution horizontale. C'est pour cette raison que le CFSR a été choisi.

2.2.1.3. Réanalyse CFSR

La réanalyse CFSR est produite par le « National Centers for Environmental Prediction » (NCEP) à partir d'un système climatique couplé atmosphère – océan – surface terrestre avec une composante de glace de mer interactive. Il couvre la période de 1979 à nos jours et utilise une approche d'assimilation de données variationnelles en trois dimensions (Saha et al., 2010b). Le CFSR assimile le rayonnement du satellite plutôt que les valeurs de température et d'humidité estimées (Wang et al., 2011).

Les estimations des changements de concentration de gaz à effet de serre, des aérosols et des variations solaires sont utilisées comme forçages dans le CFSR; Le CFSR assimile également les quantités hydrologiques d'un modèle parallèle de surface terrestre forcé par l'analyse fusionnée des précipitations (CMAP) de NOAA / Climate Prediction Center (CPC) (Xie & Arkin, 1997) et par l'analyse quotidienne de mesure unifiée du CPC (Wang et al. 2011). La résolution horizontale de CFSR est 0.313° (longitude) X 0.312° (latitude), et le jeu de données CFSR est disponible gratuitement en ligne (<http://cfs.ncep.noaa.gov/cfsr/>).

2.2.2. Série de débits

Les données quotidiennes sur le débit du fleuve enregistrées à la station hydrométrique de Kindu ont été obtenues auprès de la Régie des Voies Fluviales (RVF) de la République Démocratique du Congo. Ce débit au temps de temps journalier du fleuve a été utilisé pour le calage et la validation du modèle HEC-HMS. Le débit utilisé pour le calage et la validation a été limité respectivement aux années 1980 à 1985 et 1998 à 2003, car la disponibilité de données de qualité sur le débit a été limitée à ces années pour le sous-bassin de Kindu.

3. Modélisation hydrologique avec HEC-HMS 4.3

3.1. Configuration du modèle

Le modèle utilisé dans cette étude, HEC - HMS 4.3, mis au point par le Corps of Engineers de l'armée américaine, est conçu pour simuler les processus précipitation-ruissellement des systèmes de bassins versants dendritiques. La configuration du modèle HEC-HMS comprend un modèle de

bassin, un modèle météorologique, des spécifications de commande et des données d'entrée (données de série chronologique).

3.2. Calage et validation du modèle

La procédure d'échantillonnage fractionné est suivie dans le test du modèle. Six années (1980-1985) de données d'écoulement observées sont utilisées pour le calage du modèle hydrologique et les données restantes pour sept années (1998-2003) à des fins de validation. Les caractéristiques du bassin hydrographique, à savoir l'utilisation des sols, les propriétés du sol, etc., sont maintenues constantes pendant toute la période de simulation. Les paramètres de taux de perte constant et de déficit maximal, nécessaires pour la méthode du déficit et de la perte constante, ainsi que le paramètre de décalage de bassin dans la méthode de transformation hydrographique SCS, sont pris en compte dans la simulation.

4. Résultats et discussions

L'évaluation de la performance du modèle était obtenue par la méthode de déviation du volume total. La précision est considérée comme excellente si l'erreur est de plus ou moins 5%, bonne si elle est de 10% et acceptable pour 25%.

Le calage de HEC-HMS a été réalisé en optimisant les paramètres suivants: la conductivité du sol(mm/H), le coefficient de stockage H, la constante de récession et le rapport de récession. La figure 2 montre les résultats du calage de HEC-HMS qui sont acceptables avec l'erreur moyenne absolue sur le volume de 21%. Cela peut s'expliquer par des données de mauvaise qualité et une mauvaise modélisation des pertes.

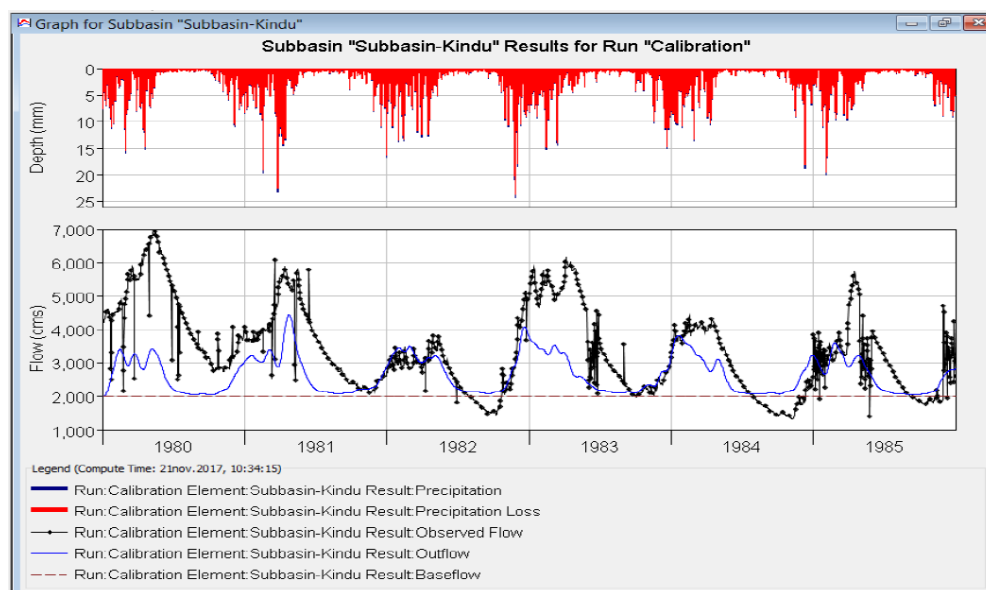


Figure 2 : Calage du modèle HEC-HMS à Kindu

Les résultats de la validation de HEC-HMS se sont mieux comportés que ceux du calage selon les méthodes et paramètres sélectionnés. Au vu des résultats, l'erreur obtenue ici est de 14%.

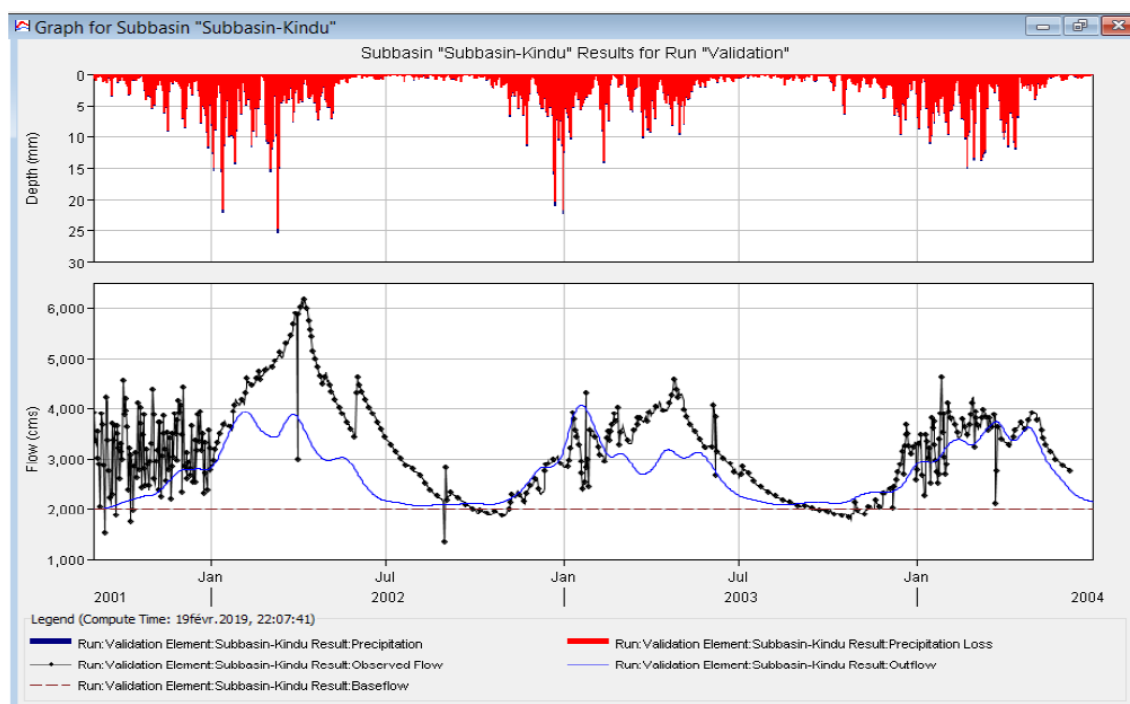


Figure 3 : Validation du modèle HEC-HMS à Kindu

5. Conclusions

Dans cette étude, nous avons évalué l'applicabilité de la réanalyse atmosphérique CFSR comme donnée d'entrée dans un modèle hydrologique semi-distribué HEC-HMS afin de simuler le débit dans le sous-bassin du fleuve Congo à Kindu. Les premiers résultats de l'étude sont acceptables pour le calage du modèle avec une erreur moyenne absolue sur le volume de 21% et ils sont plutôt bons pour la validation avec erreur moyenne absolue sur le volume de 14%.

Le modèle calé peut être utilisé pour une analyse plus poussée de la réaction du bassin aux changements d'utilisation du sol et du climat et à différents scénarios de gestion utilisant le modèle HEC-HMS.

D'une manière générale, l'utilisation des données météorologiques globales de la réanalyse CFSR pour la modélisation des bassins versants pourrait constituer une bonne alternative pour les zones du bassin où les données météorologiques fiables font défaut. En outre, l'évaluation de l'applicabilité d'autres réanalyses atmosphériques globales, telles que "Modern-Era Retrospective Analysis for Research and Applications" (MERRA), "ECMWF interim reanalysis" (ERA-Interim) ainsi que la dernière génération ERA5, et d'autres pour la modélisation hydrologique d'un bassin versant ou d'un bassin donné peut offrir des options alternatives pour les zones de données limitées.

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Conflits d'intérêts

Les auteurs déclarent qu'il n'y a aucun conflit d'intérêts pour cette étude.

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ANNEXE D - A MULTI-CRITERIA DECISION-MAKING APPROACH TO SELECT POTENTIAL HYDROPOWER SITES IN THE DEMOCRATIC REPUBLIC OF CONGO

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1. Introduction

Renewable energy is environmentally friendly and constitutes a sustainable alternative for power supply. The power sector in Democratic Republic of Congo (DRC) faces major challenges, including low generation capacity, inefficient institutions, and low electricity access. The DRC total hydropower potential over of 100 Gigawatts (GW) the third largest potential in the world after China and Russia could yield transformative returns for the country's economic development (Tonino-J., 2015).

The hydropower projects are complex, interdisciplinary integrated systems, because there are large numbers of civil, mechanical and electrical components with different characteristics. The success of the hydropower project is no longer dominated by only economic criteria. Several other criteria, such as environmental, social and technical aspects need to be taken into consideration. Therefore, hydropower project development can be analysed as a typical multi-criteria decision analysis or making (MCDA or MCDM) problem (Adhikary, Roy, & Mazumdar, 2015). Inaccurate design, improper selection of project or any parameter will have high negative impact on the overall cost and efficiency. Thus, it will result in producing less power at a higher cost-perwatt (Adhikary & Kundu, 2014).

The multi- criteria methods can provide better understanding of decision problem and promote the role of participants in decision making processes. The methods help to improve quality of decisions by making them more explicit, rational and efficient. Negotiating, quantifying, and communicating

the priorities are also facilitated with the use of these methods (Pohekar & Ramachandran, 2004; Supriyasilp, Pongput, & Boonyasirikul, 2009).

In the final analysis of any renewable energy research, it is the energy delivered versus the investment cost which has to be optimized for a feasible engineering solution.

Spatially distributed sites with sometimes conflicting factors make the decision making a complicated task that should be methodically addressed. The proposed study applies the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) developed by Yoon and Hwang (1995), to assess the potential hydropower sites and rank them in order to assist the actors involved in the development of hydropower in DRC. Furthermore, the study investigates the Inga site with definition of several alternatives to understand the basis of the selection of this site.

2. Methodological approach

Decision is an activity of choosing a strategy or action in problem solving. The act of choosing a strategy or action that the manager believes will provide the best solution (Saaty, 2004; Siregar, Arisandi, Usman, Irwan, & Rahim, 2017).

There are several methods involving multi-criteria decision making, such as the weighted sum method (WSM), the weighted product method (WPM), the preference ranking organization method for enrichment evaluation (PROMETHEE), the elimination and choice translating reality (ELECTRE), compromise programming (CP), multi-attribute utility theory (MAUT), the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is one of the most popular technique among the multi-criteria decision-making methods (Ozturk & Batuk, 2011). The TOPSIS method is chosen because it is easy to use and understand. The result can be explained and justified. The intent of MCDM methods is to improve the quality of decisions involving multiple criteria by making choices more explicit, rational, and efficient. This goal can be achieved by displaying trade-offs among criteria so stakeholders, decision makers can understand the advantages and disadvantages of the alternatives (Hobbs & Horn, 1997).

2.1. Multi-criteria decision making based on TOPSIS.

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is a simple ranking method in conception and application. The standard TOPSIS method attempts to choose

alternatives that simultaneously have the shortest distance from the positive ideal solution and the farthest distance from the negative-ideal solution (Opricovic & Tzeng, 2004; Rahim, Siahaan, et al., 2018; Rahim, Supiyandi, et al., 2018). The positive ideal solution maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria. TOPSIS makes full use of attribute information, provides a cardinal ranking of alternatives, and does not require attribute preferences to be independent (Adhikary, Kundu, Roy, & Mazumdar, 2013).

Let $A = \{A_i | i = 1, \dots, n\}$ and $C = \{C_j | j = 1, \dots, m\}$ denote the set of alternatives and the set of criteria, respectively. In our case, A is the set of hydropower site and C is the set of importance measures previously defined.

Let $Y = \{y_{ij} | i = 1, \dots, n; j = 1, \dots, m\}$ represents the set of performance ratings which includes the performance rating of each alternative with each criteria and $\omega = \{\omega_j | j = 1, \dots, m\}$ is the set of weights of the alternatives ($\omega_j \geq 0$ and $\sum_{j=1}^m \omega_j = 1$). As several no commensurate criteria with potentially different scales are combined with TOPSIS, a scaling equation is needed for the performance rating (Almoghathawi, Barker, Rocco, & Nicholson, 2017). One example is shown in Eq. (1)

$$r_{ij}(y) = \frac{y_{ij}}{\sqrt{\sum_{i=1}^n y_{ij}^2}}, \quad i=1, \dots, n; j=1, \dots, m \quad (1)$$

The weights are then applied to the scaled performance rating, shown in Eq. (2).

$$v_{ij}(y) = \omega_j r_{ij}(y), \quad i=1, \dots, n; j=1, \dots, m \quad (2)$$

The positive ideal solution (PIS), A^+ , is determined as the collection of the most preferred weighted and scaled performance ratings for each criterion. Likewise, the negative ideal solution (NIS), A^- , is the least preferred rating. The PIS and NIS is found with Eqs. (3) and (4), respectively, where J^+ and J^- are defined as the set of benefit criteria and the set of cost criteria, respectively.

$$A^+ = \{v_1^+(y), v_2^+(y), \dots, v_m^+(y)\} = \{(\max_{1 \leq i \leq n} v_{ij}(y) | j \in J^+), (\min_{1 \leq i \leq n} v_{ij}(y) | j \in J^-)\} \quad (3)$$

$$A^- = \{v_1^-(y), v_2^-(y), \dots, v_m^-(y)\} = \{(\min_{1 \leq i \leq n} v_{ij}(y) | j \in J^+), (\max_{1 \leq i \leq n} v_{ij}(y) | j \in J^-)\} \quad (4)$$

The separation of each alternative from the PIS and the NIS is found from Euclidean distance using Eqs. (5) and (6). D_i^+ and D_i^- are the distances between alternative A_i and the PIS and the distance between alternative A_i and the NIS, respectively.

$$D_i^+ = \sqrt{\sum_{j=1}^m [v_{ij}(y) - v_j^+(y)]^2}, \quad i=1, \dots, n \quad (5)$$

$$D_i^- = \sqrt{\sum_{j=1}^m [v_{ij}(y) - v_j^-(y)]^2}, \quad i=1, \dots, n \quad (6)$$

Finally, the similarity of alternative A_i to the PIS is calculated with Eq. (7), where the alternative with the largest S_i^+ value is the most preferred. The ranking of alternatives across the m criteria is found by ordering the S_i^+ from largest to smallest.

$$S_i^+ = \frac{D_i^-}{D_i^+ + D_i^-}, \quad i=1, \dots, n \quad (7)$$

2.2. The procedural steps for TOPSIS method

To apply the proposed approach, we follow the steps shown in Fig. 1. below:

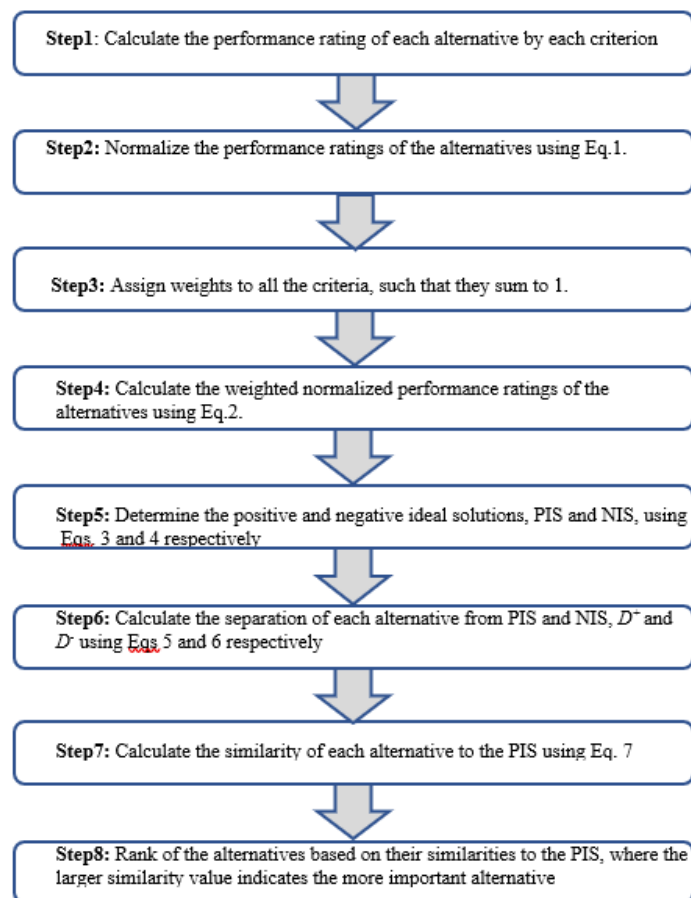


Fig. 1. The stepwise procedure of the proposed approach.

Based on proposed methodology, some criteria were selected as mentioned in Table-1.

Table 1: Definition of criteria and alternative

Hydropower site selection		
Notation	Criteria	Aspects
C1	Safety factor	Ecological safety, plant safety etc.
C2	Social factor	Job creation, Public Health etc.
C3	Hydrological factor	Flow-duration curve (FDC), ...
C4	Economic factor	Initial coast, maintenance coast etc.
C5	Technological factor	Topography, Geology, Efficiency, Reliability etc.
C6	Environmental factor	Ecology, GHG Emission reduction etc.
Notation	Alternative	
A1	Inga1	
A2	Inga2	
A3	Inga3	
A4	Inga4-Inga8	
A5	N'zilo	
A6	N'seke	
A7	Zongo1	
A8	Zongo2	
A9	Sanga	
A10	Mwadingusha	
A11	Koni	
A12	Kakobola	
A13	Katende	
A14	Matebe	
A15	Ruzizi1	
A16	Ruzizi2	
A17	Kilubi	
A18	Kyirbi	
A19	Mobayi	
A20	Tshopo	

3. Results

Evaluating or making decision of hydropower project or any of its parameter is a complex analysis as it is always unique and site specific.

To solve problems experienced by company so that the company does experience optimal benefit in the selection potential hydropower site, the system built is a support system for selecting hydropower site using the Technique for Order of Preference method by Similarity to Ideal Solution (TOPSIS). Then set several criteria including Safety factor, Social factor, Hydrological factor, Economic factor, Technological factor, Environmental factor.

The first step is to determine criteria as seen in table 1 and using 20 Alternatives.

Table2: Values matrix

Values matrix						
	Safety factor	Social factor	Hydrological factor	Economic factor	Technological factor	Environmental factor
Criteria	C1	C2	C3	C4	C5	C6
weighting factor	0.1	0.2	0.4	0.2	0.05	0.05
Alternatives						
Inga1	1	1	0.8	0.9	1	1
Inga2	1	1	0.8	0.9	1	1
Inga3	1	1	0.8	0.9	1	1
Inga4-Inga8	1	1	0.8	0.9	1	1
N'zilo	1	0.7	0.8	1	0.6	1
N'seke	1	0.6	0.6	1	0.6	1
Zongo1	1	0.8	0.8	1	1	1
Zongo2	1	0.8	0.8	1	1	1
Sanga	1	0.4	0.8	1	0.6	1
Mwadingusha	1	0.5	0.8	1	0.4	1
Koni	1	0.4	0.7	1	0.4	1
Kakobola	1	0.4	0.8	1	0.4	1
Katende	1	0.8	0.7	1	0.4	1
Matebe	1	0.4	0.8	1	0.4	1
Ruzizi1	1	0.8	0.8	1	0.4	1
Ruzizi2	1	0.8	0.8	1	0.4	1
Kilubi	1	0.6	0.8	1	0.4	1
Kyirbi	1	0.4	0.8	1	0.4	1
Mobayi	1	0.8	0.8	1	0.4	1
Tshopo	1	0.8	0.8	1	0.4	1

Table3: Normalized matrix

Normalized matrix						
	Safety factor	Social factor	Hydrological factor	Economic factor	Technological factor	Environmental factor
Criteria	C1	C2	C3	C4	C5	C6
weighting factor	0.1	0.2	0.4	0.2	0.05	0.05
Alternatives						
Inga1	0.05	0.09311	0.065466	0.046778	0.113122	0.05
Inga2	0.05	0.09311	0.065466	0.046778	0.113122	0.05
Inga3	0.05	0.09311	0.065466	0.046778	0.113122	0.05
Inga4-Inga8	0.05	0.09311	0.065466	0.046778	0.113122	0.05
N'zilo	0.05	0.065177	0.065466	0.051975	0.067873	0.05
N'seke	0.05	0.055866	0.0491	0.051975	0.067873	0.05
Zongo1	0.05	0.074488	0.065466	0.051975	0.113122	0.05
Zongo2	0.05	0.074488	0.065466	0.051975	0.113122	0.05
Sanga	0.05	0.037244	0.065466	0.051975	0.067873	0.05
Mwadingusha	0.05	0.046555	0.065466	0.051975	0.045249	0.05
Koni	0.05	0.037244	0.057283	0.051975	0.045249	0.05
Kakobola	0.05	0.037244	0.065466	0.051975	0.045249	0.05

Katende	0.05	0.074488	0.057283	0.051975	0.045249	0.05
Matebe	0.05	0.037244	0.065466	0.051975	0.045249	0.05
Ruzizi1	0.05	0.074488	0.065466	0.051975	0.045249	0.05
Ruzizi2	0.05	0.074488	0.065466	0.051975	0.045249	0.05
Kilubi	0.05	0.055866	0.065466	0.051975	0.045249	0.05
Kyirbi	0.05	0.037244	0.065466	0.051975	0.045249	0.05
Mobayi	0.05	0.074488	0.065466	0.051975	0.045249	0.05
Tshopo	0.05	0.074488	0.065466	0.051975	0.045249	0.05

Table4: Weighted Normalized matrix

Weighted Normalized matrix						
	Safety factor	Social factor	Hydrological factor	Economic factor	Technological factor	Environmental factor
Criteria	C1	C2	C3	C4	C5	C6
weighting factor	0.1	0.2	0.4	0.2	0.05	0.05
Alternatives						
Inga1	0.005	0.018622	0.026187	0.009356	0.005656	0.0025
Inga2	0.005	0.018622	0.026187	0.009356	0.005656	0.0025
Inga3	0.005	0.018622	0.026187	0.009356	0.005656	0.0025
Inga4-Inga8	0.005	0.018622	0.026187	0.009356	0.005656	0.0025
N'zilo	0.005	0.013035	0.026187	0.010395	0.003394	0.0025
N'seke	0.005	0.011173	0.01964	0.010395	0.003394	0.0025
Zongo1	0.005	0.014898	0.026187	0.010395	0.005656	0.0025
Zongo2	0.005	0.014898	0.026187	0.010395	0.005656	0.0025
Sanga	0.005	0.007449	0.026187	0.010395	0.003394	0.0025
Mwadingusha	0.005	0.009311	0.026187	0.010395	0.002262	0.0025
Koni	0.005	0.007449	0.022913	0.010395	0.002262	0.0025
Kakobola	0.005	0.007449	0.026187	0.010395	0.002262	0.0025
Katende	0.005	0.014898	0.022913	0.010395	0.002262	0.0025
Matebe	0.005	0.007449	0.026187	0.010395	0.002262	0.0025
Ruzizi1	0.005	0.014898	0.026187	0.010395	0.002262	0.0025
Ruzizi2	0.005	0.014898	0.026187	0.010395	0.002262	0.0025
Kilubi	0.005	0.011173	0.026187	0.010395	0.002262	0.0025
Kyirbi	0.005	0.007449	0.026187	0.010395	0.002262	0.0025
Mobayi	0.005	0.014898	0.026187	0.010395	0.002262	0.0025
Tshopo	0.005	0.014898	0.026187	0.010395	0.002262	0.0025

Table5: Positive and negative Ideal solution

Positive and negative Ideal solution						
	Safety factor	Social factor	Hydrological factor	Economic factor	Technological factor	Environmental factor
Criteria	C1	C2	C3	C4	C5	C6
Positive Ideal	0.005	0.018622	0.026187	0.010395	0.005656	0.0025
Negative Ideal	0.005	0.007449	0.01964	0.009356	0.002262	0.0025

Table6: Alternative to be recommended

Measure of separation of each alternative solution		
Alternatives	Aggregated	Rank
Inga1	0.927945743	1
Inga2	0.927945743	1
Inga3	0.927945743	1
Inga4-Inga8	0.927945743	1
N'zilo	0.591912269	11
N'seke	0.283710795	19
Zongo1	0.738771443	5
Zongo2	0.738771443	5
Sanga	0.371017999	15
Mwadingusha	0.409948697	14
Koni	0.220696258	20
Kakobola	0.362105862	16
Katende	0.577189109	12
Matebe	0.362105862	16
Ruzizi1	0.664308666	7
Ruzizi2	0.664308666	7
Kilubi	0.481564852	13
Kyirbi	0.362105862	16
Mobayi	0.664308666	7
Tshopo	0.664308666	7

4. Discussions

Assignment of weights

Criteria weights have been discussed and assigned by expert groups for each main criteria and sub-criteria. Because of weight assignment, the hydrological aspect is the most important aspect in the view of the experts. Then, the importance of the aspects ranking from the second most to the least are socio- economics, electricity generation, engineering and economics, and stakeholder involvement, respectively. The main criteria, sub- criteria, and their weights can be summarized in Table 2. Some sub-criteria can be measured quantitatively. The results of quantitative sub-criteria for the 20 hydropower sites are presented in Table1. Two scenarios have been studied to determine the priority for development of each project. In the first scenario the weight is equal for all aspects, which means all aspects are equally important. This scenario is called fair weight scenario. In the other scenario the weights assigned by an expert was used in the analysis. It was decided that the hydrological aspect is the most important aspect. Then, 20 sites have been sorted by their potential when considering for each criteria and all criteria.

Final rankings

The rankings from all aspects are presented in Table 6. The results from the Inga sites seem to be the most preferable when considering all aspects. Therefore, there is no need for large construction result in cost saving and less impact to environment and community nearby the site.

5. Conclusion

The development of hydropower depends on several conditions. Using the MCDM approach can help decision makers understand and compare the advantages and disadvantages of each site. Some factors, especially those involving stakeholder participation, may be modified in the future depending on the understanding and perception of hydropower by those living in the project area. Acceptance by the people is paramount. In the past, some sites could not be built if people in the area did not accept the project even though the results for electricity generation, engineering and economy were excellent. Therefore, including aspects other than technical conditions helps a lot in prioritizing the development of hydropower. For this study, sites with high hydrologic potential appear to be the most preferable considering all aspects, as it is not necessary to build large areas, thereby reducing costs and reducing costs. less impact the environment and community near the site.

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ANNEXE E - MODELLING SPATIO-TEMPORAL FLOOD INUNDATION DYNAMICS OF RIVERINE WETLANDS USING TIME SERIES FLOW AND NEAR REAL TIME SATELLITE DATA

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Abstract

Information regarding the spatial extent and timing of flooding in the world's major wetlands is important to a wide range of research questions including global methane models, water management, and biodiversity assessments. The Pool Malebo is one of the 33 wetlands Ramsar's priority areas in the DRC, and is subject to substantial development and pressures that require intensive hydrological modeling and monitoring. This research is focused on quantifying the wetland cover changes in the Pool Malebo, utilizing the near real time satellite data and hydraulic modelling approach. It integrated river flow time series and Moderate Resolution Imaging Spectroradiometer (MODIS) images with 10 days temporal and 250m spatial resolution to assess the wetland extent and dynamics over the study area on both temporal and spatial dimensions. The spatial and temporal dynamics of the wetland were performed by the analyses of change of the NDVI derived from MODIS and the different areas cover by different land cover types (bare soil, water, and vegetation). The NDVI product, acquired in the wet season from 2006 to 2015, are classified into three main land cover classes namely water, vegetation and soil by using the knowledge of the area in order to clearly separate bare soil and vegetation from water within the wetland. Flow data of the same period, acquired from the port station of Kinshasa, were analyzed to derive flow peaks by using the annual flood series method. The flood extent maps generated with HEC-RAS model were compared to water extent from the classification for validation purposes. The area of different land cover types were extracted from the maps and plotted as

histograms. The statistical analysis was done for each land cover type for the detection of trends in the areas that constitute the wetland. The results show that MODIS is useful remote sensing product for dynamic monitoring of flooding, particularly in wetlands.

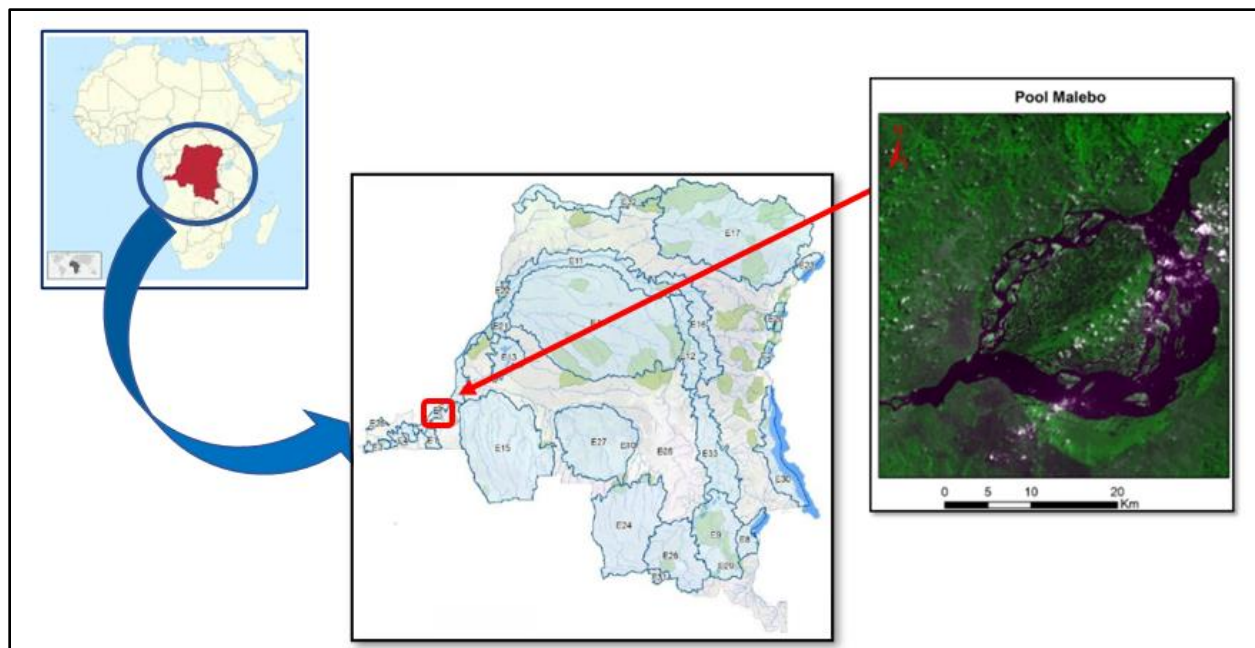


Figure D1:30 wetlands representatives zones selected by Ramsar

Source: Michèle, http://www.ramsar.org/pdf/wurc/wurc_dr-congo_inventaire2008.pdf/

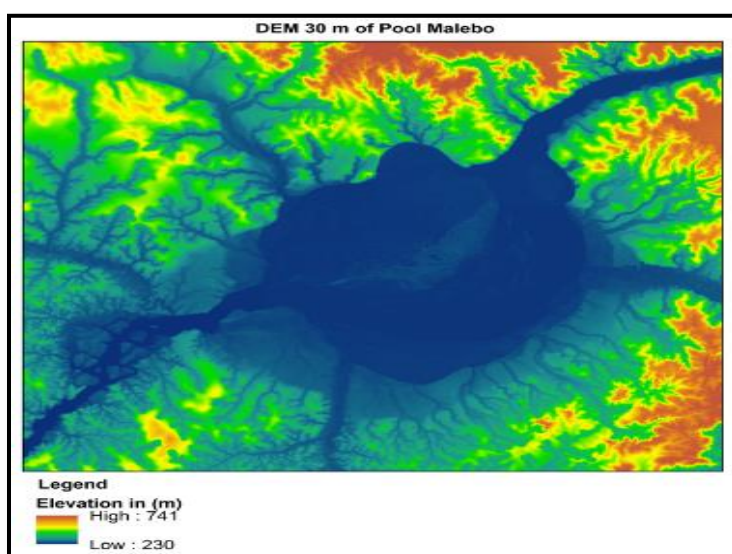


Figure D2: Digital Elevation Model of the Study area

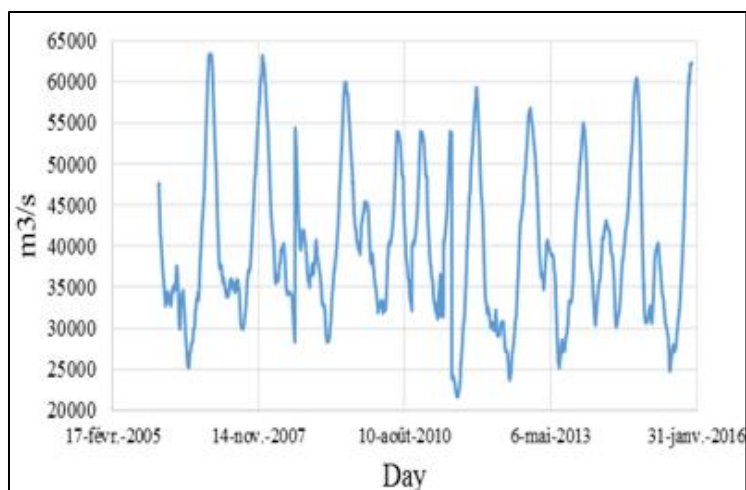


Figure D3: Daily discharge data at Kinshasa port station

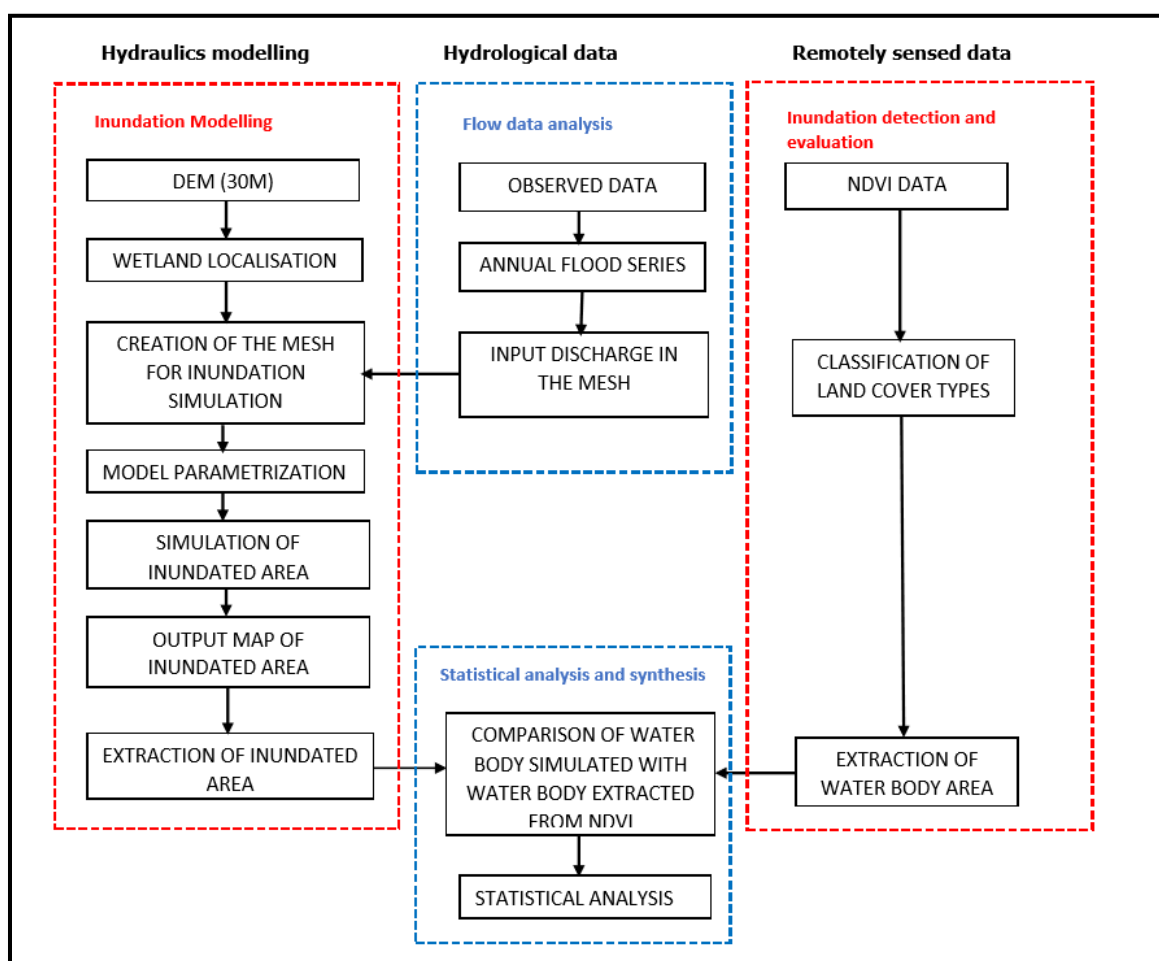


Figure D4: Flowchart of methodology showing its four components, adapted from (Huang, Chen, & Wu, 2014)

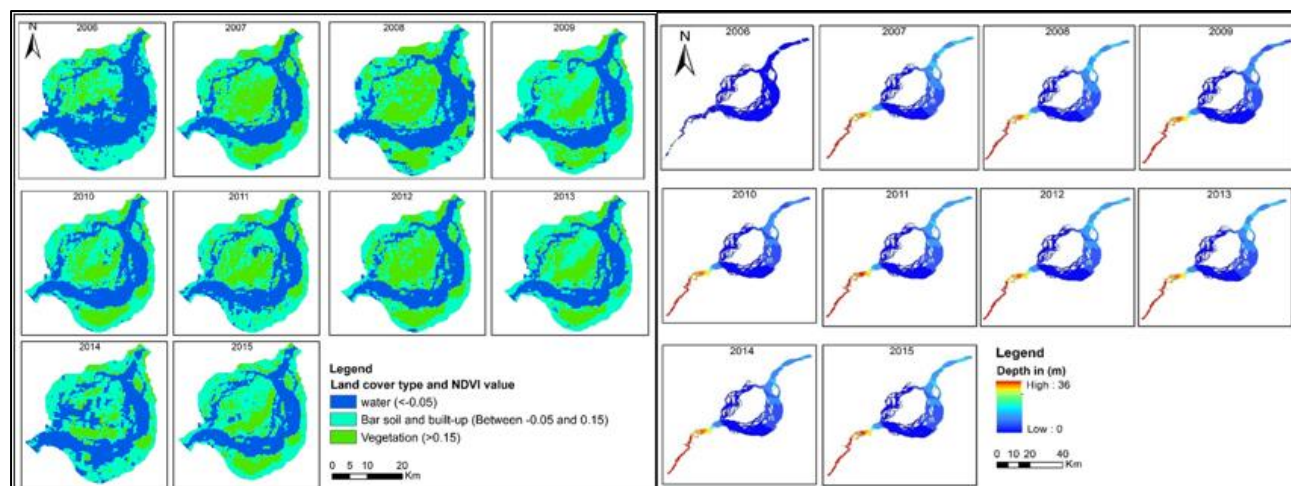


Figure D5: Comparison between MODIS (left panel) detected inundations and model simulated (right panel) from 2006 to 2015

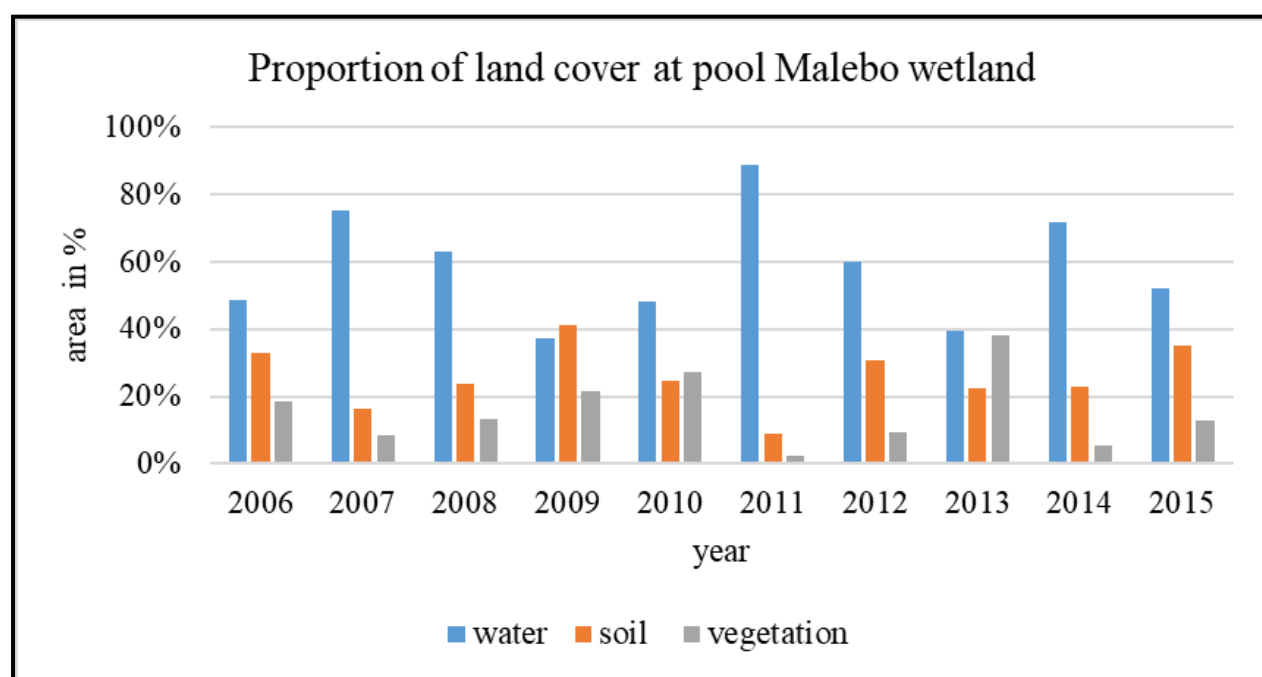


Figure D6: Proportion of land cover at pool Malebo wetland

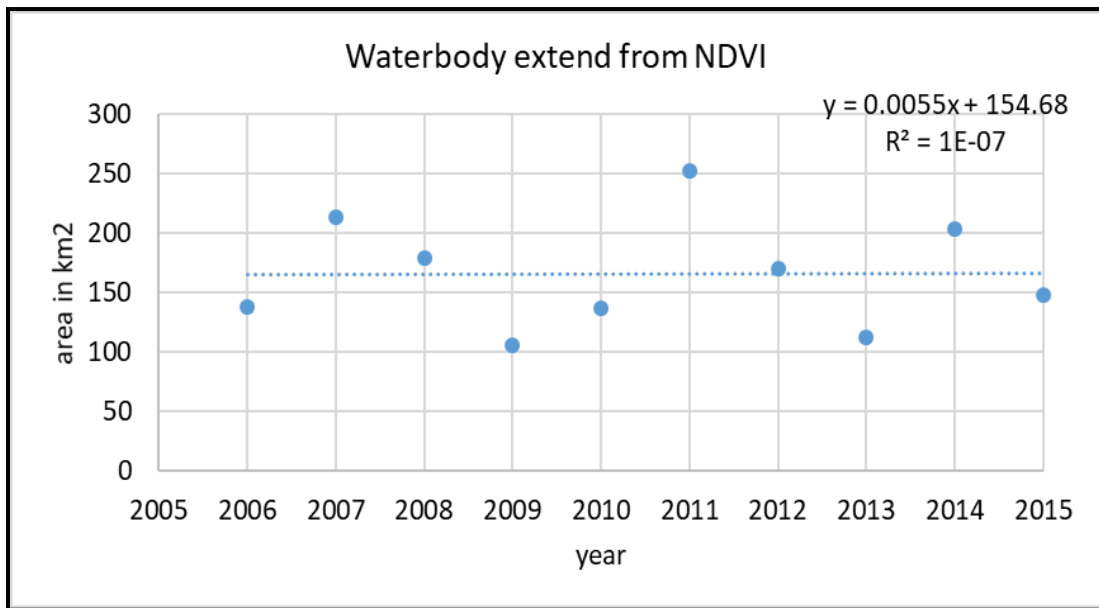


Figure D7:Water body extend from NDVI

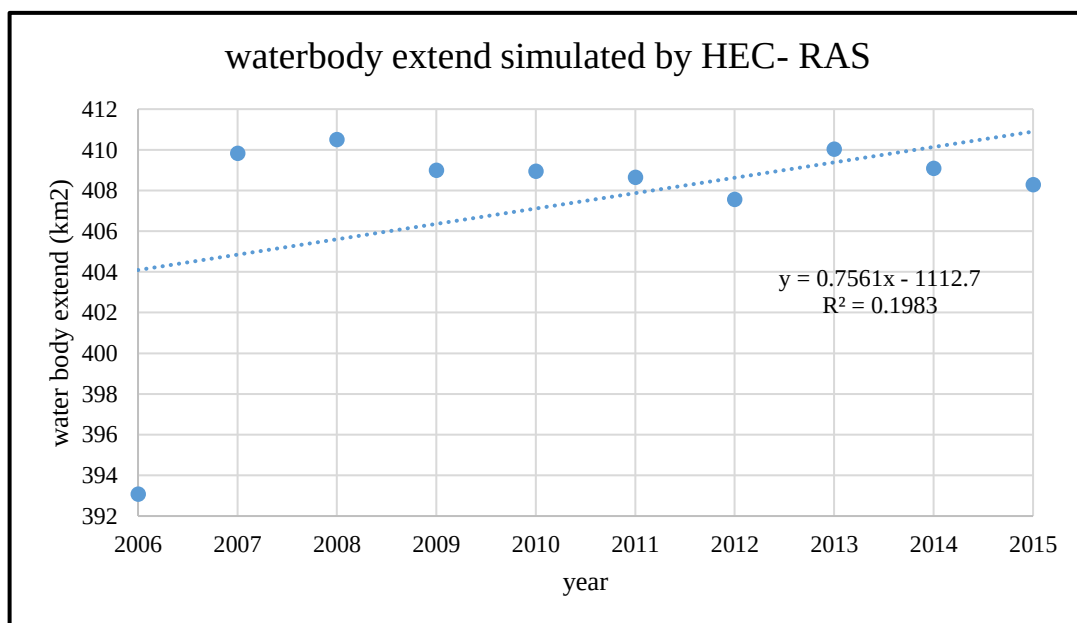


Figure D8:Water body extend simulated by HEC-RAS Model

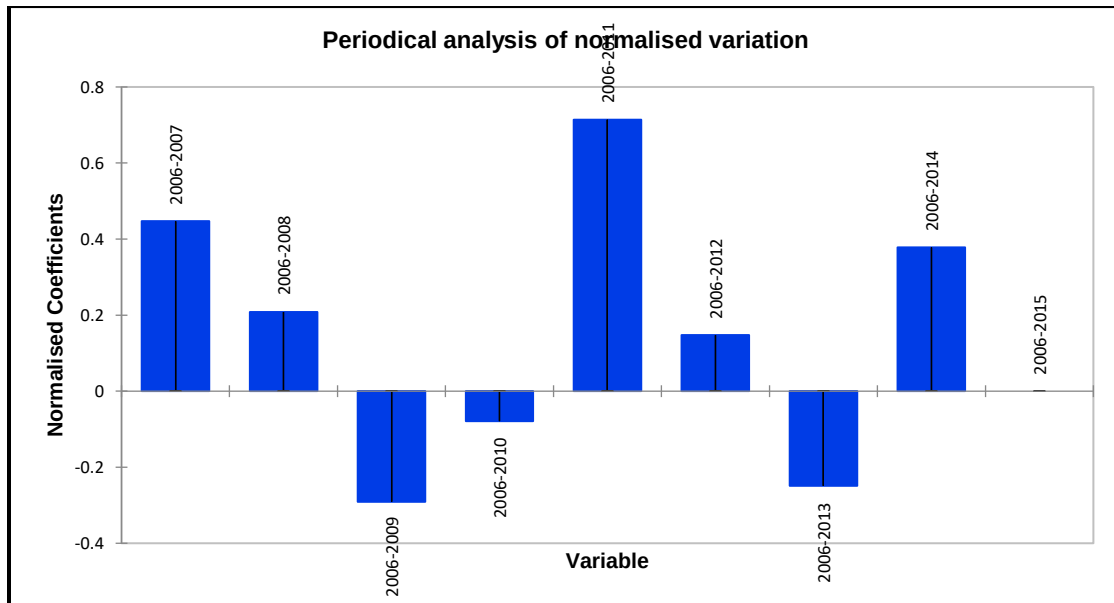


Figure D9:Normalised coefficients from NDVI

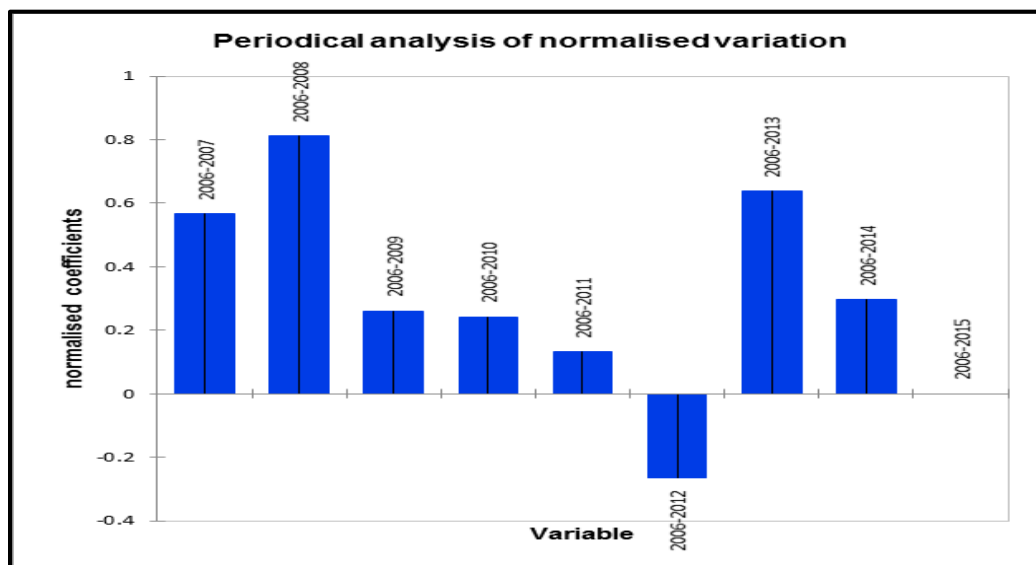


Figure D10:Normalised

ANNEXE F- RAINWATER HARVESTING FOR SUSTAINABLE AGRICULTURE FOR AFRICAN DRY REGIONS

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Article présenté à la Conférence on the global framework on water scarcity in agriculture, Praia, Cabo Verde, west
africa, 7-10 february 2023.

ABSTRACT

More than 80 percent of sub-Saharan agriculture depends on “green water”: moisture from rain held in the soil. In large parts of the continent, most rainfall evaporates before generating “blue water”, or runoff. Arid deserts and semi-arid savannahs make up 40% of the region's land area. These receive too little surface runoff (less than 100 millimeters per year) to grow maize (maize), rice, millet and sorghum (which requires at least 400 mm per year) using irrigation alone. 10 to 20 billion dollars per year for 10 to 15 years should be invested in Africa in the capacity building, planning and infrastructure development for small-scale water harvesting systems to achieve the goals of eradicating hunger and poverty and enabling long-term economic development.

Introduction

Water is considered as the most critical resource for sustainable agricultural development worldwide. Irrigated areas will increase in forthcoming years, while fresh water supplies will be diverted from agriculture to meet the increasing demand of domestic use and industry (Chartzoulakis & Bertaki, 2015). Agriculture production is highly dependent on water and increasingly subject to water risks. It is the world's largest water user, accounting for 70% of total consumption (El-Beltagi et al., 2022). According to Chen, Liu, Mei, Yan, and Garré (2018), rainfed agriculture accounts for 80% of global cultivated land and provides 60– 70% of the globe's food. Rainfed agriculture is becoming more popular in the world for helping in food production because of increasing drought conditions. Agriculture is also the major polluter of water.

Improving agriculture's water management is therefore essential to a sustainable and productive agro-food sector. More than 40% of global land is under arid or semi-arid climatic conditions (Boutraa, 2010). In the arid and semi-arid areas water is the most limiting factor in reducing agricultural production (Cattivelli et al., 2008). As a result, water management and conservation in the agriculture sector are now a challenge. Water availability for agricultural producers is steadily declining because urban populations' water needs are essentially increasing. Farmers are looking for novel approaches to enhance soil moisture to resolve both problems. Rainwater harvesting is one traditional practice that can aid in the solution to this issue.

Principles and practices of rainwater harvesting

In the arid and semi-arid regions, annual precipitation is generally low relative to potential evaporation and is poorly distributed over the crop-growing season. The non-uniform distribution of precipitation in these areas results in frequent drought periods during the crop-growing season.

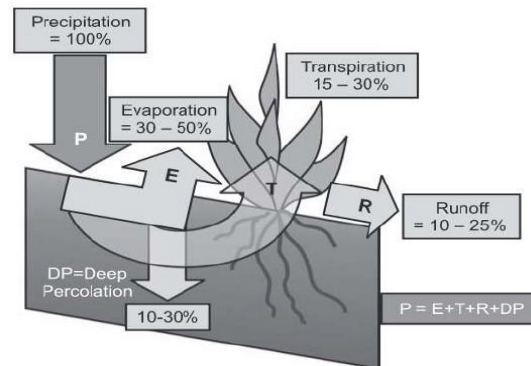


Figure 1: Average hydrological conditions in semi-arid environment (Oweis, Prinz, & Hachum, 2012)

Most rainstorms are of high intensity and often the intensity is greater than the soil infiltration rate, runoff occurs. Runoff greatly reduces the amount of water that infiltrates into the soil and hence less water becomes available to the crop (Oweis, Prinz, & Hachum, 2012). Figure 1 shows what happens to precipitation under semi-arid conditions. Rainwater harvesting means capturing rainwater where it falls or capturing the runoff in your own village or town. And taking measures to keep that water clean by not allowing polluting activities to take place in the catchment.

The basic principle of agricultural water harvesting is to capture precipitation falling on one part of the land and transfer it to another part, thereby increasing the amount of water available to the latter part. The objective is to provide enough water to crops on one part of the land to support economical agricultural production. Regardless of the purpose or the type, all water harvesting systems have the following components (Figure 2): a catchment area, a storage facility and a target.

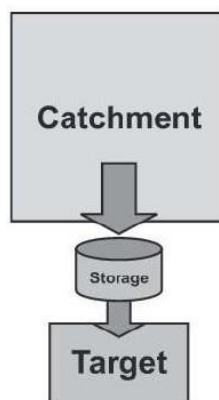


Figure 2: Major components of a typical water harvesting system (Oweis, Prinz, & Hachum, 2012).

Methods and techniques in rainwater harvesting

There are several classifications of water harvesting methods, but the most used system is based on the size of catchment, i.e., micro-catchment and macro-catchment. Micro-catchment systems can be subclassified into rooftop systems (Figure 3) and on-farm systems (Figure 4). Macro-catchment systems can be subclassified into long-slope systems (Figure 5) and floodwater systems (Figure 6).



Figure 3: Rooftop harvesting for a sloped building (Pala et al., 2021).

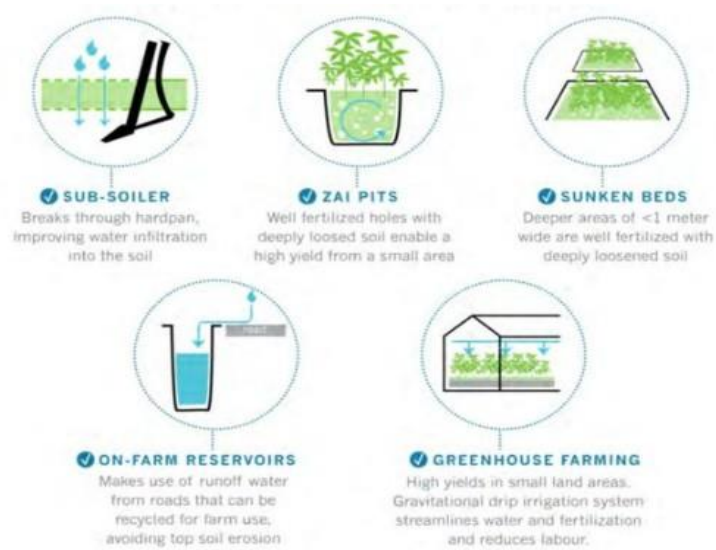


Figure 4: The on-farm rainwater harvesting technologies implemented in all 37 counties in Kenya (Chesterman & Neely, 2015).



Figure 5: Sloped rainwater harvesting



Figure 6: Floodwater harvesting pilot plant at Iipopo (Namibia)

Benefits of rainwater harvesting

Rainwater harvesting has many benefits but the main one is that it is a sustainable water management practice that can be implemented by anyone on many different levels, from a simple rain barrel to a comprehensive rainwater harvesting system that integrates with an irrigation system or household plumbing. Overall, rainwater harvesting is viewed as a practice that is socially acceptable and environmentally responsible all the while, promoting self-sufficiency.

The water conservation benefits of rainwater harvesting

- The rainwater that falls on your roof and property is essentially free. All it takes is a method to harvest it into a tank or cistern for later use.
- Rainwater harvesting can be a great educational tool to get people to recognize their individual or household water usage. This can get them to start conserving water in other areas around their home.
- For communities that rely on imported water to supply their needs, collecting rainwater that falls naturally in the community can reduce the need for imported water.
- Rainwater harvesting helps utilities reduce peak demands during summer months, saving treated water for more important and appropriate water uses.
- While rainwater can be a perfect primary water source for many uses and situations, it is also a great backup water supply for emergency situations.

The environmental benefits of rainwater harvesting

- Rainwater harvesting can reduce stormwater runoff from a property. The elimination of runoff can reduce contamination of surface water with pesticides, sediment, metals,

and fertilizers.

- By reducing stormwater runoff, rainwater harvesting can reduce a storm's peak flow volume and velocity in local creeks, streams, and rivers, thereby reducing the potential for streambank erosion.
- Rainwater harvesting systems can be employed as simple and effective methods to meet a municipality's stormwater management program requirements of individual properties.
- It is an excellent source of water for plants and landscape irrigation since it has no chemicals such as fluoride and chloramines (chlorine).

The water-energy nexus benefits of rainwater harvesting

While the logical use of rainwater harvesting is for water conservation purposes, it also reduces energy use within a community.

- Typically, the end use of the rainwater is located on the property where the rainwater is collected. Replacing municipal water use at a home and property with rainwater reduces the amount of water that a municipality must treat and then pump to your house. The treatment and pumping of municipally provided water require a lot of energy.
- The implementation of rainwater harvesting can help meet new standards of energy and water efficiency ratings and codes that are being developed in communities.

The economic benefits of rainwater harvesting

- Collecting and using rainwater to replace municipal water use reduces your water bill
- Reducing municipal water use for areas such as irrigation reduces the amount of water that a municipality must treat and pump. This, in turn, reduces water service cost to a municipality.
- The widespread implementation of rainwater harvesting within a municipality's service area can reduce the long-term water development needs of a city, allowing the city to use their existing water infrastructure investments more efficiently. The cost to the community to supply treated water is becoming more expensive every year. The cost to construct dams, pipes, and treatment plants, not to mention the cost of maintenance and infrastructure replacement is huge. As water users, the ratepayers in the community ultimately will foot this rising bill. Therefore, the practice of rainwater harvesting can reduce water demand and thus allow municipalities to provide potable water service at a lower cost.
- Designing and installing rainwater collection systems can provide sustainable jobs for the economy of the future. The rainwater harvesting industry can become a leading employer in the green infrastructure movement.
- Rainwater stored onsite in a rainwater harvesting system can be available for wildfires and help protect the house and property. Insurance companies can offer discounts for

storing water onsite for fire protection.

The ancillary benefits of rainwater harvesting

- Rainwater can be used for irrigation use, indoor non-potable water use, and/or potable water supply.
- Rainwater harvesting can provide an independent water source in areas where other water sources are unavailable, or the water quality is unacceptable, or they are too expensive to develop, or they are too difficult to obtain.
- If used as a potable water source, the zero hardness of rainwater provides many advantages. It eliminates the scale build-up in household appliances that could occur with the use of other water sources. This will extend the life of the appliances. In addition, it reduces the amount of detergent or soaps needed in laundry and dishwashing appliances, reducing money spent on these detergents and soaps.
- Rainwater from a potable rainwater harvesting system that has been properly filtered and disinfected is some of the best tasting water available. It doesn't have the many chemicals that municipally treated water has such as fluoride or chloramines (chlorine).

African Countries and Water Harvesting

As shown in Figure 7, African countries that experience reduced annual rainfall are those where efforts have been made and innovative technologies put in place to capture the most rainwater and subsequently use it for various needs, as well both domestic and agro-pastoral. These countries are located mainly in the northern, eastern and southern parts.

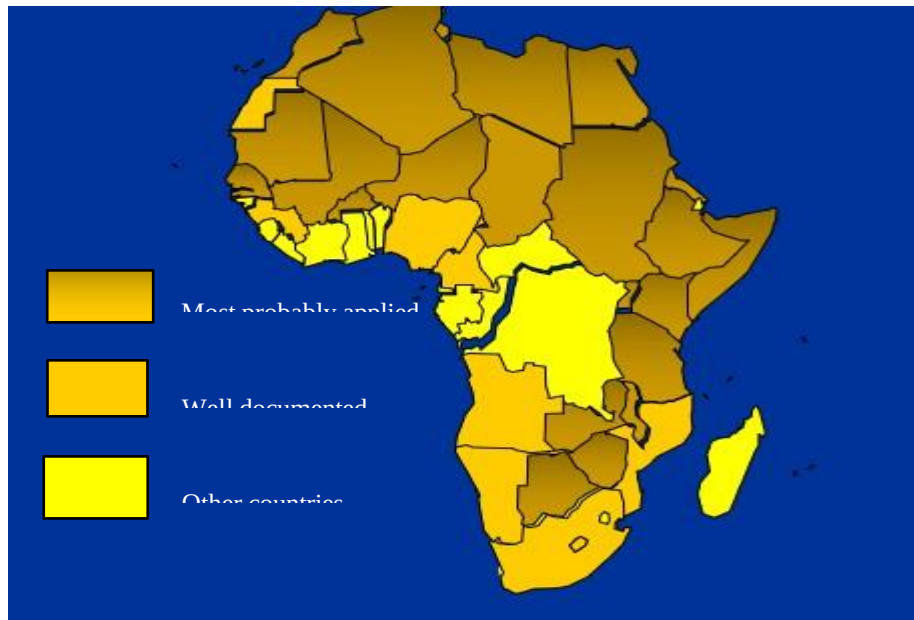


Figure 7: African Countries using Water Harvesting Techniques

More than 80 percent of sub-Saharan agriculture depends on “green water”: moisture from rain held in the soil. In large parts of the continent, most rainfall evaporates before generating “blue water”, or runoff. Arid deserts and semi-arid savannahs make up 40% of the region's land area. These receive too little surface runoff (less than 100 millimeters per year) to grow maize (maize), rice, millet and sorghum (which requires at least 400 mm per year) using irrigation alone. Projected precipitation in the near future will be more variable and could be 25% lower in many semi-arid regions if average global temperatures warm 2°C above pre-industrial levels (Rockström and Falkenmark, 2015).

Increase Water Harvesting for Agriculture in Africa

Agriculture experts agree that global food needs will continue to grow as the world's population grows. To meet them by 2050, global food production will need to double. The solution is to radically rethink global water management strategies and policies.

Sub-Saharan Africa is among the regions of the world where this challenge must be met. Indeed, the population of this region is expected to more than double by 2050 to nearly 2.5 billion, or 25% of the projected world population. While half of its current billion people live in extreme poverty, a quarter are undernourished and a fifth face severe water shortages. Nearly two-thirds of the population live in rural areas, and agriculture on much of the land is limited by water resources that are variable and unpredictable. Integrated water management is necessary to serve as a framework for achieving the United Nations SDG (Sustainable Development Goals) in food security. A specific goal on sustainable rainfall management for ecosystems and food production in water-scarce regions of the world is needed to achieve the goals of eradicating hunger and poverty and enabling long-term economic development. term.

Rockström and Falkenmark (2015) argue that major institutions and foundations investing in Africa's development, such as the African Development Bank, the World Bank and the Alliance for a Green Revolution in Africa initiative, should invest in the capacity building, planning and infrastructure development for small-scale water harvesting systems. The costs are significant: investments of around 10 to 20 billion dollars per year for 10 to 15 years would be necessary, comparable to those for basic sanitation, infrastructure, and water supply. But they offer a return on capital in terms of development and resilience.

Conclusion

Water harvesting is the collection and concentration of runoff water. It can be used to produce crops in areas with insufficient rain for rainfed agriculture, like in sub-Saharan African regions. It can improve pasture and crop yield and it is suited for arid, semi-arid and semi-humid regions. It has positive side effects on water and soil conservation. The water is stored in the soil, in cisterns, ponds or reservoirs. Traditionally used in many (semi-)arid areas of the world and specifically in Africa, its use is still far below its potential!

A specific goal on sustainable rainfall management for ecosystems and food production in water-scarce regions of the world is needed to achieve the goals of eradicating hunger and poverty and enabling long-term economic development. term.

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ANNEXE G - MULTI-MODEL ASSESSMENT OF CLIMATE CHANGE IMPACTS ON THE STREAMFLOW CONDITIONS IN THE KASAI RIVER BASIN, CENTRAL AFRICA

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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 flows 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

1. Introduction

Central Africa is a strategic region globally (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 that includes 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; 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 propose 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 & Sainers, 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 for 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 generate 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, aircrafts, 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 scarce 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 & Siers, 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 km²), 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 m³/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 as 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 the 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 2, the KARB and its major challenges in terms of water resources are described. Section 3 includes the framework of impact assessment, dataset and hydrological models used in this study. Section 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 5.

2. Case study

The Congo River Basin has an average annual discharge of 40,600 m³/s and covers an area of about 3.7×10^6 km² (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 m³/s, respectively (GEIDCO, 2020). These rivers confluence in Kutu Moke and have an average annual discharge of 8246 m³/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 km², 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 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 m³/s in 1948-1991 to 6943 m³/s in 1992-2012 at Kutu-Moke (Moukandi et al., 2020).

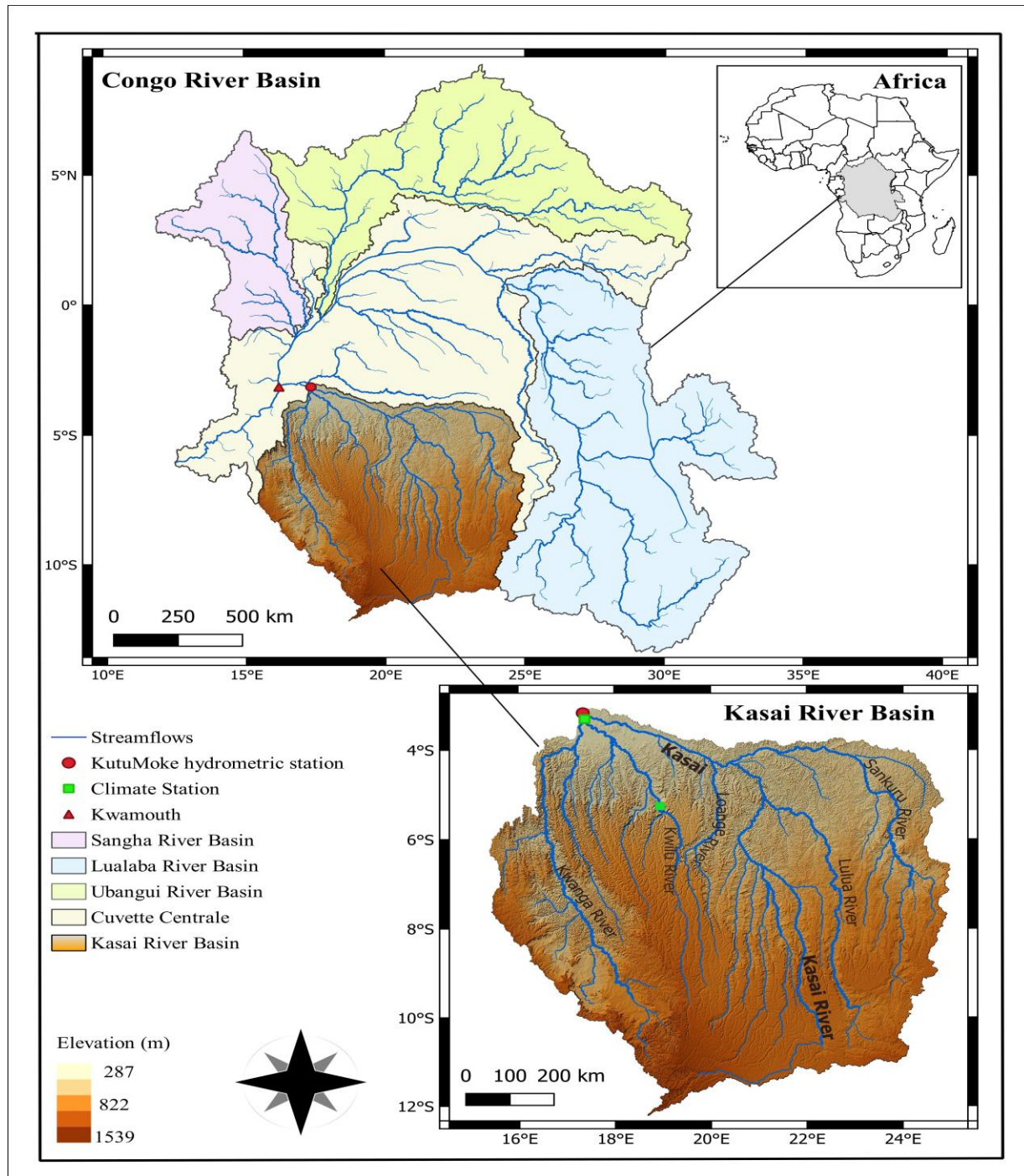


Figure 1. The Kasai River Basin, sub-watershed of the Congo River Basin, in Central Africa, and its main tributaries. River networks and sub-basins are retrieved from Linke et al. (2019).

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 shortage 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.

3. Materials and methods

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 2. As previously noted, for these scarce data regions, most studies suggest using an ensemble of reanalysis data for 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 3.2 and 3.3, respectively. Section 3.4 represents the employed hydrological models and their calibration and validation procedures.

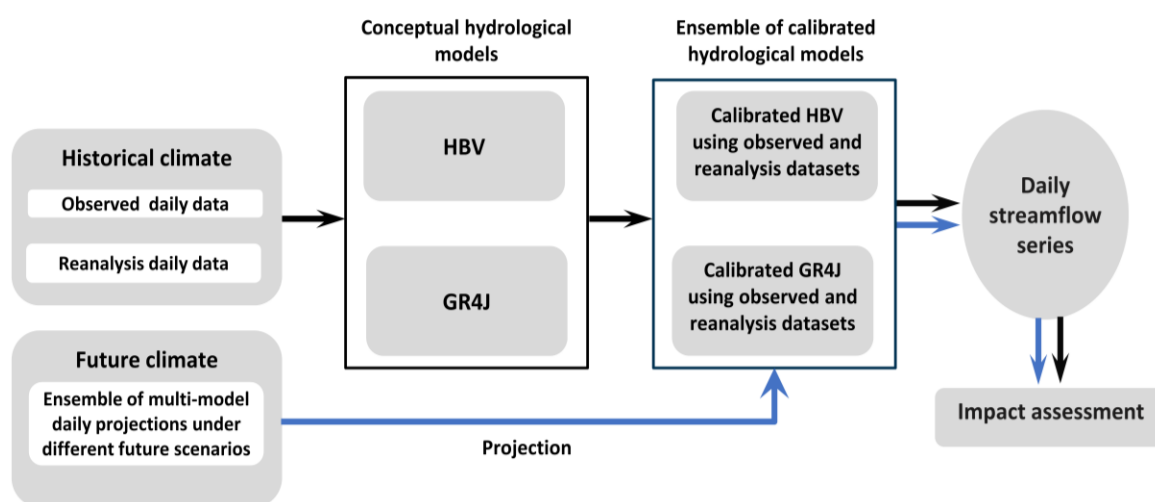


Figure 2. Framework to assess the climate change impacts on water availability in the KARB.

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 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 2.

Table 8. 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)	Drainag e area (km ²)
Bandundu	1554	21.4	30.8	1456	Kutu Moke	8070	750,000
Kiyaka	1649	20.0	29.3				

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 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 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 9. 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	$0.1^{\circ} \times 0.1^{\circ}$	Daily	(Muñoz-Sabater et al., 2021)
Climate Forecast System Reanalysis (CFSR)	NCEP	1979-present	$0.5^{\circ} \times 0.5^{\circ}$	Daily	Saha et al. (2014)
Japanese 55-year Reanalysis (JRA-55)	Japan Meteorological Agency	1958-present	$1.25^{\circ} \times 1.25^{\circ}$	Daily	Kobayashi et al. (2015)
Modern-Era Retrospective analysis for Research and Applications (MERRA)	NASA GMAO	1979-2016	$0.5^{\circ} \times 0.66^{\circ}$	Daily	Rienecker et al. (2011)

3.3. *Climate model projections*

The NASA Earth Exchange Global Daily Downscaled Projections dataset for 19 GCMs are 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.

Here, the 19 GCMs simulations during the historical and future periods are compared with each other and reanalysis datasets in Figure 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 1% to 6% increase in the median of daily precipitation with respect to the historical values.

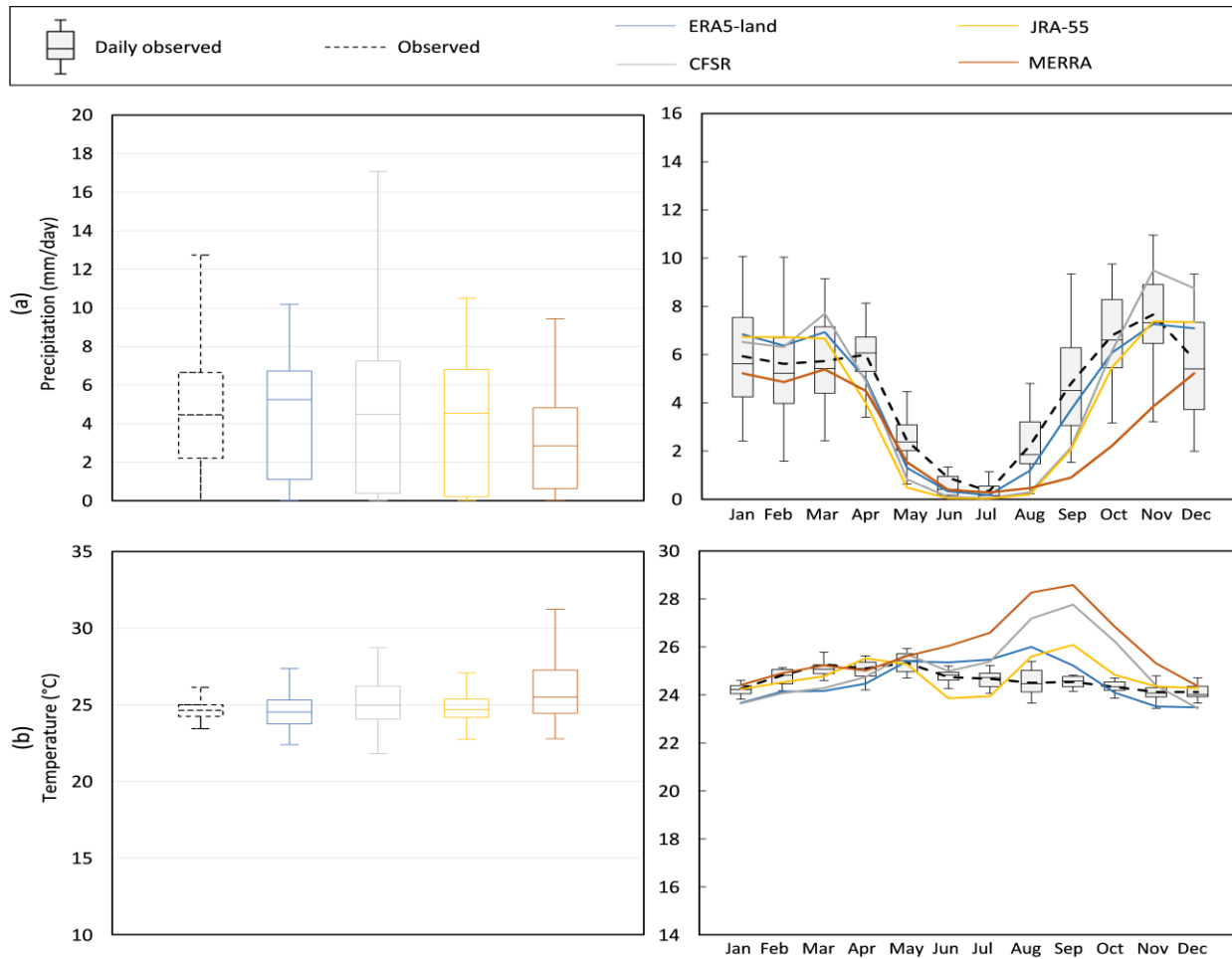


Figure 3. Daily precipitation and temperature values over a 30-year period based on the observed and four reanalysis datasets (Left panel), averaged over the KARB. The right panel shows the observed daily (boxplots) as well as expected values (lines) in each month based on observed and reanalysis datasets, which are averaged over the basin.

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).

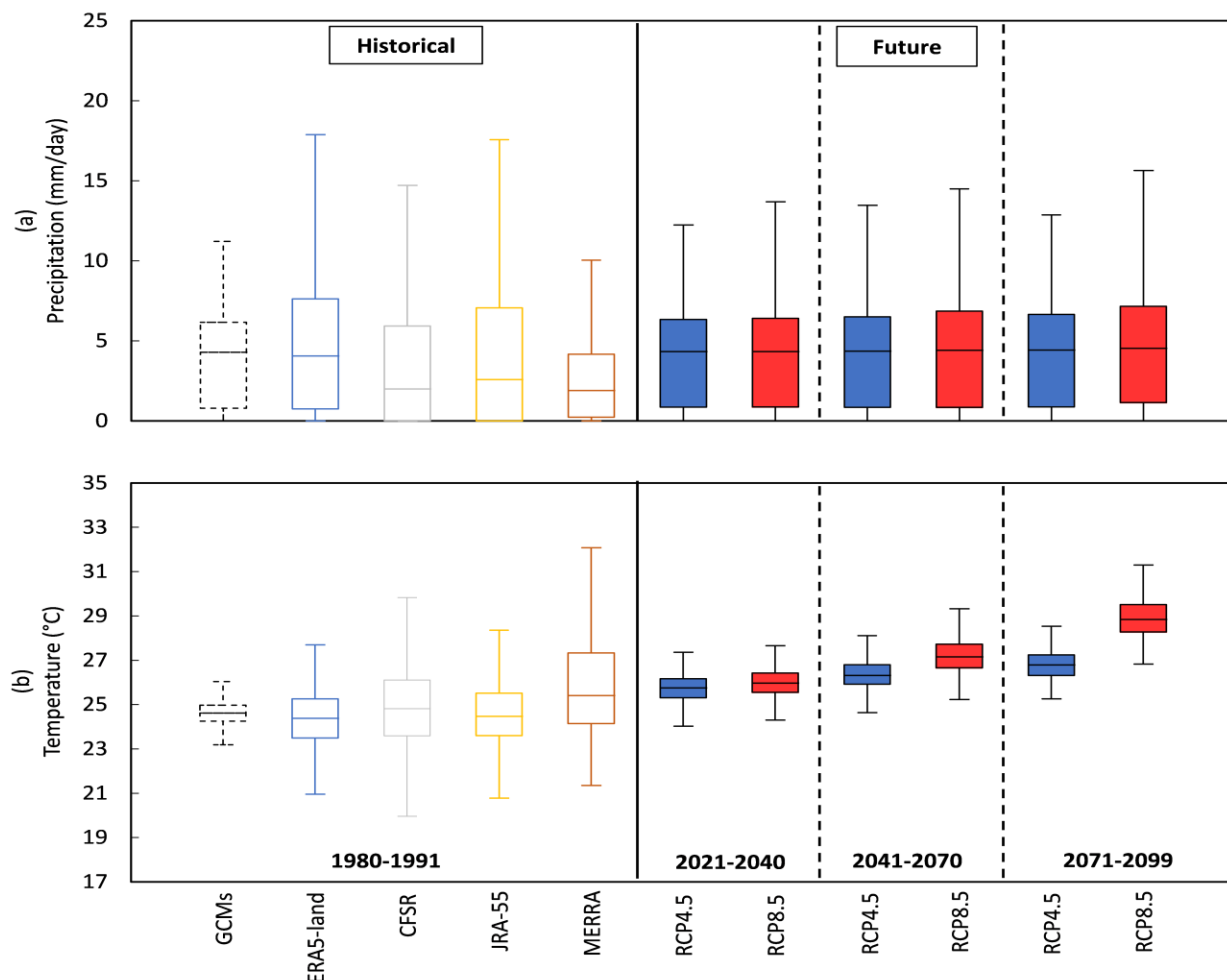


Figure 4. Comparison of (a) precipitation and (b) temperature in the future based on 19 climate models under RCPs 4.5 and 8.5 (right) with respect to the historical values of (GCMs and reanalysis (left) in the KARB.

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 (Eqs1, 2, and 3). As shown in Eq. 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 at daily and annual scales (Eq. 5). In Equation 1 to 3, σ_s and σ_o are the standard deviation of simulated and observed flow, $\bar{S}$ and $\bar{O}$ are the mean simulated and observed flow, S_t and O_t are simulated and observed flow, respectively.

$$\alpha = \frac{\sigma_s}{\sigma_o} \quad (\text{Eq. 1})$$

$$\beta = \frac{\bar{S}}{\bar{O}} \quad (\text{Eq. 2})$$

$$r = \frac{\sum_t (O_t - \bar{O})(S_t - \bar{S})}{\sqrt{(\sum_t (O_t - \bar{O})^2)(\sum_t (S_t - \bar{S})^2)}} \quad (\text{Eq. 3})$$

$$KGE = 1 - \sqrt{(1 - \alpha)^2 + (1 - \beta)^2 + (1 - r)^2} \quad (\text{Eq. 4})$$

$$Obj = \text{Min} \sqrt{(1 - KGE_{daily})^2 + (1 - KGE_{annual})^2} \quad (\text{Eq. 5})$$

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. 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. Results

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 & Sainers, 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 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 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 0.05 difference, given the ERA5-land dataset. Considering the long-term annual hydrograph of simulated and observed flow (Figure 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.

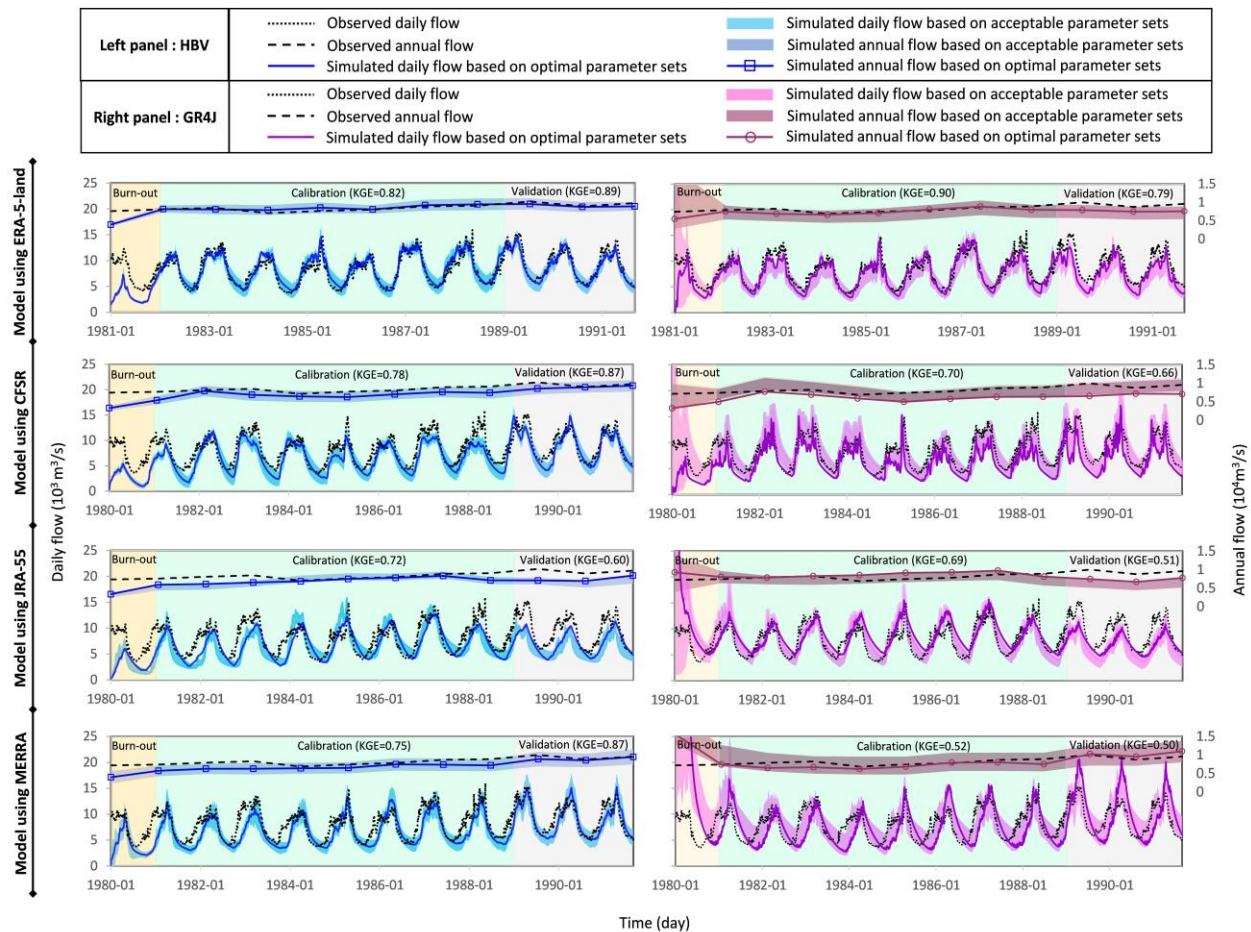


Figure 5. Observed and simulated daily and annual flow during the historical period at the outlet using four reanalysis datasets forced to HBV (left) and GR4J (right) models.

To better understand the differences between the models, the envelopes of simulated flow considering all reanalysis using HBV and GR4J are shown in Figure 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 $15000 \text{ m}^3/\text{s}$, 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 5% difference considering the mean annual hydrographs). Since the differences among the performance of these 8 configurations are not significant, all of them are used for impact assessment.

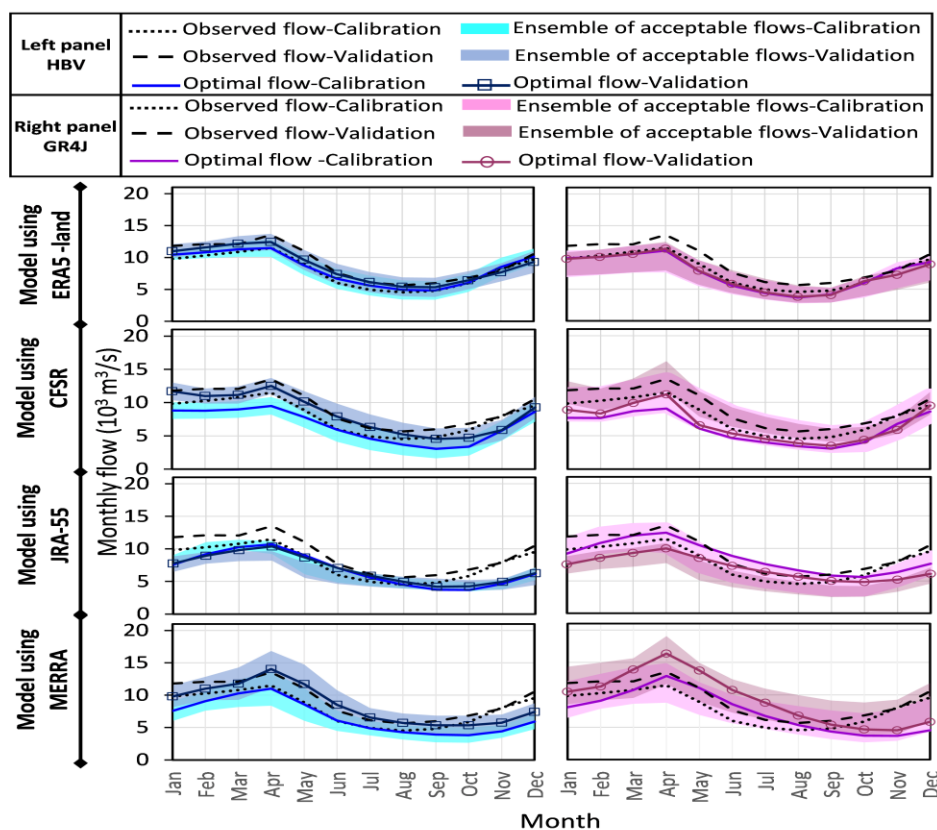


Figure 6. Observed (dashed line) and simulated long-term annual hydrographs (solid line and shaded areas) during the historical period at the outlet using different reanalysis datasets forced to HBV (left) and GR4J (right) Models.

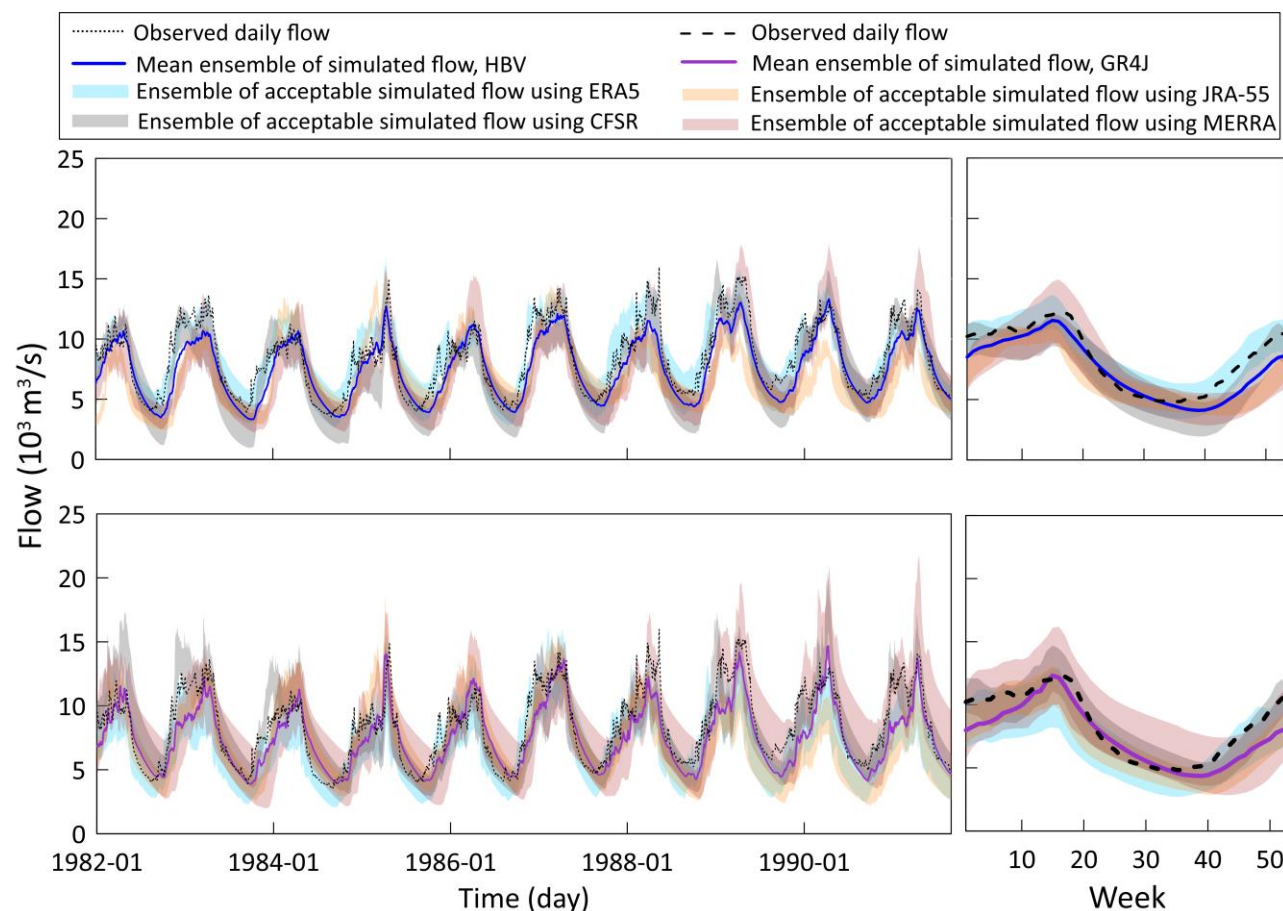


Figure 7. Comparison between the simulated (solid line and shaded areas) and observed (dashed line) expected daily (left) and annual (right) hydrographs at the outlet during the historical period using four reanalysis datasets in the calibration of hydrological models HBV (top) and GR4J (bottom).

4.2. 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 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 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.

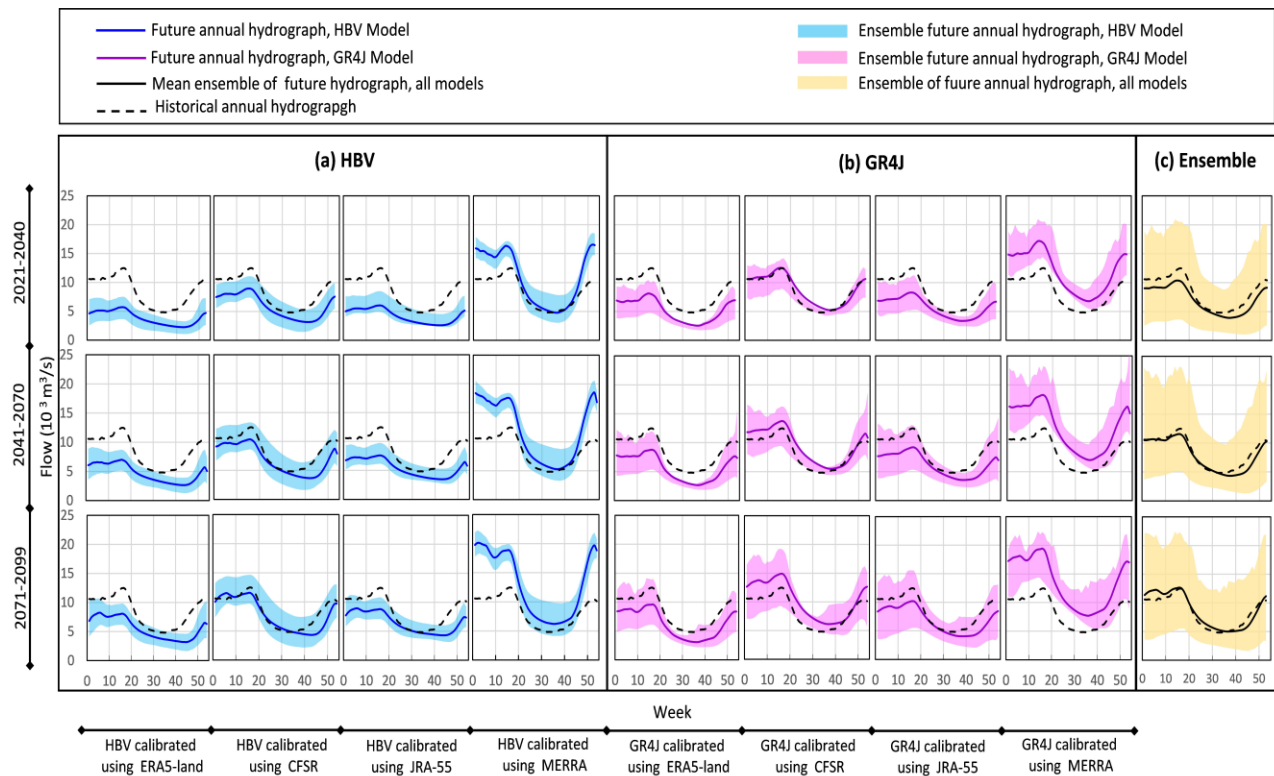


Figure 8. Observed (dashed line) versus projected ensemble (shaded area) and expected (solid line) mean annual flow hydrograph at the basin's outlet under RCP8.5 using HBV (left) and GR4J (middle) models calibrated with four reanalysis, and all configurations (right) using the outputs of 19 GCMs.

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 for 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 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 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(a).

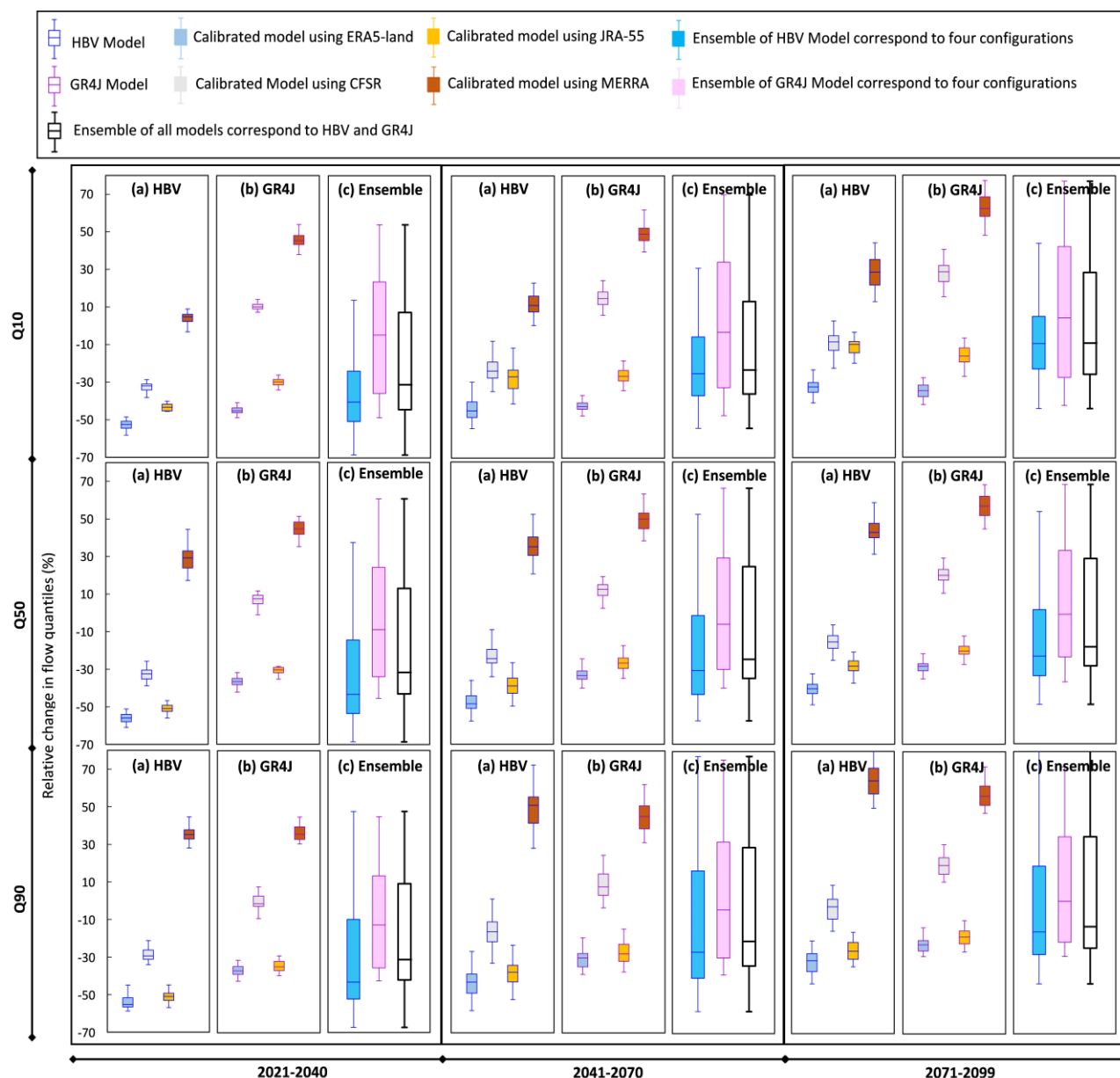


Figure 9. Relative changes between the estimated annual streamflow quantiles by individual and all model configurations fed by outputs of 19 GCMs under RCP8.5 with respect to the long-term average historical value.

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 10. The long-term average annual Q90 equal to 12030 m³/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 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) remains 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.

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 individual, 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 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.

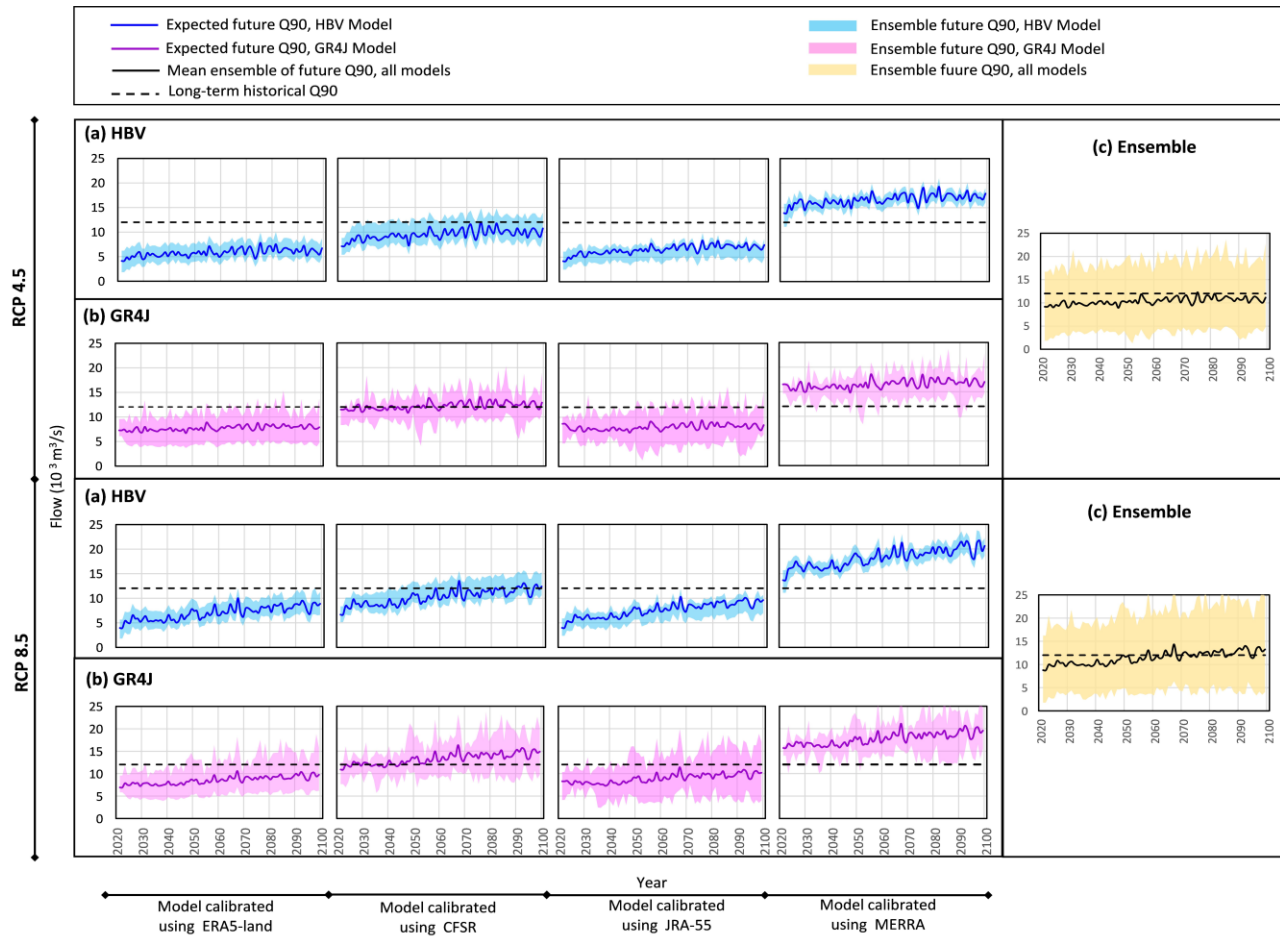


Figure 10 The ensemble (shaded area) and expected (solid line) values of annual Q90 in the future under RCPs 4.5 and 8.5 based on calibrated HBV (blue) and GR4J (pink) models using four reanalysis datasets (left) and all 8 model configurations (right). The dashed line shows the long-term annual Q90 values 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.

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., 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 is 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, 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 the 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 CMIP5 project is 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 for 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.

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