

CONSTRAINING SIMULATION
UNCERTAINTIES IN A HYDROLOGICAL
MODEL OF THE CONGO RIVER BASIN
INCLUDING A COMBINED MODELLING
APPROACH FOR CHANNEL-WETLAND
EXCHANGES

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HYDROLOGICAL MODEL OF THE CONGO RIVER BASIN
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CHANNEL-WETLAND EXCHANGES**

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ABSTRACT

Compared to other large river basins of the world, such as the Amazon, the Congo River Basin appears to be the most ungauged and less studied. This is partly because the basin lacks sufficient observational hydro-climatic monitoring stations and appropriate information on physiographic basin properties at a spatial scale deemed for hydrological applications, making it difficult to estimate water resources at the scale of sub-basins (Chapter 3). In the same time, the basin is facing the challenges related to rapid population growth, uncontrolled urbanisation as well as climate change. Adequate quantification of hydrological processes across different spatial and temporal scales in the basin, and the drivers of change, is essential for prediction and strategic planning to ensure sustainable management of water resources in the Congo River Basin. Hydrological models are particularly important to generate the required information. However, the shortness of the available streamflow records, lack of spatial representativeness of the available streamflow gauging stations and the lack of understanding of the processes in channel-wetland exchanges, are the main challenges that constrain the use of traditional approaches to models development. They also contribute to increased uncertainty in the estimation of water resources across the basin (Chapter 1 and 2). Given this ungauged nature of the Congo River Basin, it is important to resort to hydrological modelling approaches that can reasonably quantify and model the uncertainty associated with water resources estimation (Chapter 4) to make hydrological predictions reliable.

This study explores appropriate methods for hydrological predictions and water resources assessment in ungauged catchments of the Congo River Basin. In this context, the core modelling framework combines the quantification of uncertainty in constraint indices, hydrological modelling and hydrodynamic modelling. The latter accounts for channel-wetland exchanges in sub-basins where wetlands exert considerable influence on downstream flow regimes at the monthly time scale. The constraint indices are the characteristics of a sub-basin's long-term hydrological behaviour and may reflect the dynamics of the different components of the catchment water balance such as climate, water storage and different runoff processes. Currently, six constraint indices namely the mean monthly runoff volume (MMQ in $\text{m}^3 \cdot 10^6$), mean monthly groundwater recharge depth (MMR in mm), the 10th, 50th and 90th percentiles of the flow duration curve expressed as a fraction of MMQ (Q_{10}/MMQ , Q_{50}/MMQ , Q_{90}/MMQ) and the percentage of time that zero flows are expected (%Zero), are used in the

modelling approach. These were judged to be the minimum number of key indices that can discriminate between different hydrological responses. The constraint indices in the framework help to determine an uncertainty range within which behavioural model parameters of the expected hydrological response can be identified. Predictive equations of the constraint indices across all climate and physiographic regions of the Congo Basin were based only on the aridity index because it was the most influential sub-basin attribute (Chapter 5) for which quantitative information was available. The degree of uncertainty in the constraint Q10/MMQ and Q50/MMQ indices is less than 41%, while it is somewhat higher for the mean monthly runoff (MMQ) and Q90/MMQ constraint indices.

The established uncertainty ranges of the constraint indices were tested in some selected sub-basins of the Congo Basin, including the Lualaba (93 sub-basins), Sangha (24 sub-basins), Oubangui (19 sub-basins), Batéké plateaux (4 sub-basins), Kasai (4 sub-basins) and Inkisi (3 sub-basins). The results proved useful through the application of a 2-stage uncertainty approach of the PITMAN model. However, it comes out of this study that the application of the original constraint indices ranges (Chapter 5) generated satisfactory simulation results in some areas, while in others both small and large adjustments were required to fully capture some aspects of the observed hydrological responses (Chapter 6). Part of the reason is attributed to the availability and quality of streamflow data used to develop the constraint indices ranges (Chapter 5). The main issue identified in the modelling process was whether the changes made to the original constraints at headwater-gauged sub-basins can be applied to ungauged upstream sub-basins to match the observed flow at downstream gauging stations. Ideally, only gauged sub-basin's constraints can be easily revised based on the observed flow. However, the refinement made to gauged sub-basins alone may fail to substantially affect the results if ungauged upstream sub-basins exert a major impact on defining downstream hydrological response. The majority of gauging stations used in this analysis are located downstream of many upstream ungauged sub-basins and therefore adjustments were required in ungauged sub-basins. These adjustments consist of shifting the full range of a constraint index either towards higher or lower values, depending on the degree to which the simulated uncertainty bounds depart from the observed flow. While this modelling approach seems effective in capturing many aspects of the hydrological responses with a reduced level of uncertainty compared to a previous study, it is recommended that the approach be extended to the remaining parts of the

Congo Basin and assessed under current and future development conditions including environmental changes.

A 2D hydrodynamic river-wetland model (LISFLOOD-FP) has been used to explicitly represent the inundation process exchanges between river channels and wetland systems. The hydrodynamic modelling outputs are used to calibrate the PITMAN wetland sub-model parameters. The five hydrodynamic models constructed for Ankoro, Kamalondo, Kundelungu, Mweru and Tshiengalele wetland systems have been partially validated using independent estimates of inundation extents available from Landsat imagery. Other sources of data such as remote sensing of water level altimetry, SAR images and wetland storage estimates may be used to improve the validation results. However, the important objective in this study was to make sure that flow volume exchanges between river channels and their adjacent floodplains were being simulated realistically.

The wetland sub-model parameters are calibrated in a spreadsheet version of the PITMAN wetland routine to achieve visual correspondence between the LISFLOOD-FP and PITMAN wetland sub-model outputs (Storage volumes and channel outputs). The hysteretic patterns of the river-wetland processes were quantified using hysteresis indices and were associated with the spill and return flow parameters of the wetland sub-model and eventually with the wetland morphometric characteristics. One example is the scale parameter of the return flow function (AA), which shows a good relationship with the average surface slope of the wetland when the coefficient parameter (BB) of the same function is kept constant to a value of 1.25. The same parameter (AA) is a good indicator of the wetland emptying mechanism. A small AA indicates a wetland that slowly releases its flow, resulting in a highly delayed and attenuated hydrological response in downstream sub-basins. This understanding has a practical advantage for the estimation of the PITMAN wetland parameters in the many areas where it is not possible, or where the resources are not available, to run complex hydrodynamic models (Chapter 7). The inclusion of these LISFLOOD-FP informed wetland parameters in the basin-scale hydrological modelling results in acceptable simulations for the lower Lualaba drainage system. The small wetlands, like Ankoro and Tshiengalele, have a negligible impact on downstream flow regimes, whereas large wetlands, such as Kamalondo and Mweru, have very large impacts.

In general, the testing of the original constraint indices in the region of wetlands and further downstream of the Lualaba drainage system has shown acceptable results. However, there

remains an unresolved uncertainty issue related to the under and over-estimation of some aspects of the hydrological response at both Mulongo and Ankoro, two gauging stations in the immediate downstream of the Kamalondo wetland system. It is difficult to attribute this uncertainty to Kamalondo wetland parameters alone because many of the incremental sub-basins contributing to wetland inflows are ungauged. The issue at Mulongo is the under simulation of low flow, while the high flows at the Ankoro gauging station are over-simulated. However, the pattern of the calibrated constraint indices in this region (Chapter 8) shows that the under simulation of low flow at Mulongo cannot be attributed to incremental sub-basins (between Bukama, Kapolowe and Mulongo gauging stations), because their Q90/MMQ constraint indices are even slightly above the original constraint ranges, but maintain a spatial consistency with sub-basins of other regions. Similarly, sub-basins located between Mulongo, Luvua and Ankoro gauging stations have high flow indices slightly below the original constraint ranges and therefore they are unlikely to be responsible for the over simulation of high flow at the Ankoro gauging station. These facts highlight the need for a further understanding of the complex wetland system of Kamalondo. Short-term data collection and monitoring programme are required. Important tributaries that drain to this wetland need to be monitored by installing water level loggers and periodically collecting flow data and river bathymetry. This programme should lead to the development of rating curves of wetland input tributaries. This would partially solve the unresolved uncertainty issues at the Ankoro and Mulongo gauging stations.

The integrated modelling approach offers many opportunities in the Congo Basin. The quantified and modelled uncertainty helps to identify regions with high uncertainty and allows for the identification of various data collection and management strategies that can potentially contribute to the uncertainty reduction. The quantified channel-wetland exchanges contribute to the improvement of the overall knowledge of water resources estimation within the regions where the effects of wetlands are evident even at the monthly time scale. In contrast, ignoring uncertainty in the estimates of water resources availability means that water resources planning and management decisions in the Congo Basin will continue to be based on inadequate information and unquantified uncertainty, thus increasing the risk associated with water resources decision making.

TABLE OF CONTENT

ABSTRACT.....	i
TABLE OF CONTENT	v
ACRONYMS.....	xii
LIST OF FIGURES	xiii
LIST OF TABLES	xx
ACKNOWLEDGEMENTS.....	xxii
CHAPTER 1 : GENERAL INTRODUCTION	1
1.1 Background information	1
1.2 Problem statement	3
1.3 Aim and Objectives of the research	5
1.4 Significance of the study	7
1.5 Thesis structure	8
CHAPTER 2 : LITERATURE REVIEW	9
2.1 Introduction	9
2.2 Classification of hydrological models.....	10
2.3 Model parameter estimation, calibration and reliability measures	12
2.4 Uncertainty in water resources estimation	13
2.4.1 Input uncertainties	14
2.4.1.1 Input climate uncertainty	14
2.4.1.2 Streamflow discharge uncertainty.....	15
2.4.2 Model Structure and parameter uncertainties	17
2.4.2.1 Structural uncertainties	17
2.4.2.2 Parameter uncertainty	18

2.5 Uncertainty analysis frameworks	20
2.5.1 Methods based on the stage-discharge relationship	20
2.5.2 Methods treating different sources of uncertainty	21
2.5.2.1 Uncertainty analysis approaches within PITMAN model	22
2.5.2.2 Use of hydrological signatures in hydrological modelling	24
2.6 Wetland processes and how they affect the flow regime	27
2.6.1 Wetland and river channel exchanges	28
2.6.2 Hysteretic patterns in channel-wetland exchanges	30
2.7 Hydrodynamic modelling approaches.....	31
2.7.1 One-dimensional hydrodynamic models	32
2.7.2 Two-dimensional hydrodynamic models	33
2.7.3 Three-dimensional hydrodynamic models	33
2.7.4 Basic requirements for setting up a hydrodynamic model	34
2.7.5 Use of Earth observation techniques in hydrodynamic modelling.....	34
2.8 Review of hydrological studies in the Congo Basin	36
2.8.1 Rainfall-runoff modelling.....	36
2.8.2 Wetland and fluvial systems.....	36
2.8.2.1 Research aspects	37
2.8.2.2 Spatial coverage	37
2.8.2.3 Data collection programmes	40
2.9 Discussion	40
CHAPTER 3 : STUDY AREA AND DATASETS	41
3.1 Introduction	41
3.2 Climate and physiographic characteristics	42
3.2.1 Climate.....	42
3.2.2 Land use/Landcover	44

3.2.3 Soil and geological characteristics	45
3.2.4 Topography.....	48
3.3 Wetland systems of the Lualaba drainage system.....	50
3.3.1 Lake Kivu	50
3.3.2 Lake Tanganyika	50
3.4 Datasets	53
3.4.1 Streamflow.....	53
3.4.2 Climate.....	56
3.4.3 Physiographic data.....	57
3.4.4 River bathymetry and Landsat imagery.....	58
3.5 Concluding remarks	59
CHAPTER 4 : METHODOLOGICAL FRAMEWORK.....	60
4.1 Introduction	60
4.2 Hydrological modelling.....	62
4.2.1 PITMAN Rainfall-Runoff Model.....	62
4.2.1.1 Surface runoff	64
4.2.1.2 Sub-surface processes	65
4.2.1.3 Evaporation coefficient (R).....	66
4.2.1.4 Parameters controlling groundwater processes.....	66
4.2.1.5 Data requirement.....	67
4.2.1.6 Hydrological modelling options within PITMAN model.....	67
4.2.2 Hydrological modelling approach adopted in this study	67
4.2.2.1 Stage 1 of the modelling	68
4.2.2.2 Stage 2 of the modelling	71
4.2.2.3 Evaluation of modelling results	71
4.3 Hydrodynamic modelling.....	73

4.3.1 LISFLOOD-FP model	73
4.3.1.1 Input data requirements.....	75
4.3.1.2 Model calibration	76
4.3.1.3 Validation of the LISFLOOD-FP model	77
4.3.1.4 Types of outputs.....	78
4.3.2 Linking the PITMAN and LISFLOOD-FP models.....	78
4.3.3 Daily disaggregation framework	79
4.4 Process understanding and simulating wetland downstream impacts.....	80
4.4.1 The wetland sub-model	80
4.4.2 Quantification of wetland sub-model parameters.....	82
4.4.3 Integrated analysis of wetland hydrodynamic and morphometric characteristics...	82
4.4.4 Simulating wetlands downstream impacts on flow regimes	84
4.5 Concluding remarks	84
CHAPTER 5 : UNCERTAINTY RANGES OF HYDROLOGICAL INDICES	85
5.1 Introduction	85
5.2 Methodology	85
5.2.1 Selection of gauging stations.....	85
5.2.2 Pre-processing of flow data	87
5.2.3 Catchment classification using Self Organising Maps	87
5.2.4 Derivation of hydrological indices and their relationships.....	88
5.2.5 Spatial disaggregation of flow time series.....	90
5.2.6 Assessing the uncertainty	90
5.3 Results	91
5.3.1 Extending the record periods of the flow time series	91
5.3.2 Sub-basin classification	92
5.3.2.1 Classification by climate and physiographic attributes	92

5.3.2.2 Classification by hydrological behaviour	94
5.3.3 Developing predictive relationships of hydrological indices	97
5.3.3.1 Initial predictive relationships.....	97
5.3.3.2 Updated predictive relationships.....	99
5.3.4 Establishing uncertainty ranges of hydrological indices	99
5.4 Discussion	103
CHAPTER 6 : MODELLING HYDROLOGICAL UNCERTAINTIES	105
6.1 Introduction	105
6.2 Hydrological modelling results and validation	106
6.2.1 Simulation results in the Lualaba drainage system	106
6.2.1.1 Testing original constraint ranges in gauged headwater sub-basins.....	106
6.2.1.2 Testing original constraint ranges in sub-basins draining to Bukama gauging station.....	109
6.2.1.3 Testing original constraint ranges in sub-basins draining to Old Ponton gauging station.....	112
6.2.1.4 Testing original constraint ranges in sub-basins of the rift valley region.....	115
6.2.2 Assessing the uncertainty propagation downstream.....	118
6.2.3 Summary of the constraint revision process and re-calibration	121
6.2.4 The usefulness of constraints in constraining hydrological uncertainty.....	126
6.3 Discussion	128
CHAPTER 7 : A COMBINED MODELLING APPROACH FOR ASSESSING WETLAND DOWNSTREAM HYDROLOGICAL IMPACTS	130
7.1 Introduction	130
7.2 Overview of the methodological approach	131
7.3 Results	132
7.3.1 Disaggregating the monthly streamflow.....	132
7.3.2 Model friction and geometric parameters.....	135

7.3.3 Evaluation of the inundation extents	135
7.3.4 Process understanding of channel-wetland exchanges	139
7.3.4.1 Hydrodynamic characteristics of wetlands and hysteretic patterns	139
7.3.4.2 Estimation of wetland sub-model parameters	145
7.3.4.3 Wetland morphometric factors affecting wetland parameters	150
7.3.5 Simulating wetland downstream flow regimes	153
7.3.5.1 Simulation results up to the Ankoro gauging station	154
7.3.5.2 Simulation results within the Tanganyika basin	159
7.3.5.3 Re-calibration of some of the wetland parameters within the main PITMAN model	161
7.3.5.4 The validity of the constraints for the sub-basins in the zone of the wetlands and beyond	164
7.3.5.5 Comparing wetland parameters with those previously reported	166
7.4 Discussion	168
CHAPTER 8 : CONCLUSIONS AND RECOMMENDATIONS	171
8.1 Conclusions	171
8.1.1 Establishing the uncertainty ranges of hydrological indices	171
8.1.2 Testing the original constraint ranges to simulate hydrological uncertainties	173
8.1.3 Application of the hydrodynamic models to establish wetland parameters	177
8.1.4 Application of constraints and wetland parameters to quantify downstream wetland impacts on flow regimes	179
8.2 Recommendations	180
8.2.1 Improving constraint ranges	180
8.2.2 Testing of constraint ranges	180
8.2.3 Improving daily disaggregated wetland inflows	181
8.2.4 Improving the understanding of channel-wetland exchanges	181
8.2.5 Short term fieldwork data collection and monitoring programme	181

REFERENCES	183
APPENDICES	234

ACRONYMS

ACRU	Agriculture Catchment Research Unit
AI	Aridity Index
CRU	Climate Research Unit
CRuHM	Congo River user Hydraulics and Morphology
DEM	Digital Elevation Model
FDC	Flow Duration Curve
GRACE	Gravity Recovery And Climate Experiment
HRR	Hillslope River Routing
IWM	Index of Wetland Morphology
MAPE	Mean Annual Potential Evapotranspiration
MAR	Mean Annual Rainfall
MMQ	Mean Monthly Flow
MRFF	Maximum Return Flow Fraction
NE	Nash-Sutcliffe coefficient of efficiency
RR	Runoff Ratio
SAR	Synthetic Aperture Radar
SRTM	Shuttle Radar Topography Mission
SWAT	Soil Water Assessment Tool
SWIM	Soil and Water Integrated Model
UNIDEL	University of Delaware
WARCA	Wetland Area Ratio of the Cumulative drainage Area
WARSA	Wetland Area Ratio of Sub-basin total Area

LIST OF FIGURES

Figure 2.1. Classification of rainfall-runoff models based on process description and spatial discretisation of model inputs, parameters and outputs.	10
Figure 2.2. Screenshot of the PITMAN model interface showing the dependent index utility used to restrict the random parameter sampling within the PITMAN model.	23
Figure 3.1. The geographical location of the Congo River Basin and its major hydrographic network.	41
Figure 3.2. The spatial pattern of the aridity index (PE/P) across the Congo River Basin showing a concentric pattern.	44
Figure 3.3. The spatial pattern of land cover types across the Congo Basin. The map has been reconstructed based on the global Globcover 2009 products at a spatial resolution of 300 m.	45
Figure 3.4. Major soil groups found across the Congo Basin (derived from Dewitte et al. (2013)).	46
Figure 3.5. The spatial pattern of geology across the Congo Basin (adapted from the Africa Groundwater Atlas by Ó Dochartaigh, 2019).	47
Figure 3.6. Selected 147 sub-basins across the Congo Basin for the testing of hydrological indices ranges within the hydrological modelling uncertainty framework.	49
Figure 3.7. The Location of the five-wetland systems in the upper Congo River Basin.	51
Figure 3.8. Long-term average monthly water depth fluctuation at the outlet of Lake Kisale (at Kadia) between 1921 and 1938.	51
Figure 3.9. Lake Tanganyika basin including both lake Kivu and Tanganyika.	53
Figure 3.10. Location of the available gauging stations across the Congo Basin.	54
Figure 3.11. Streamflow monthly distributions (long-term averages) showing different flow patterns across geographic regions of the Congo Basin for selected gauging stations. (a) Northern sub-basins, (b) Equatorial belt sub-basins and (c) Southern sub-basins	55
Figure 3.12. Spatial distribution of the Curve number values across the Congo Basin. White spaces represent open water bodies.	58
Figure 4.1. The overall methodology used in this thesis, showing the interaction between different modelling components.	61
Figure 4.2. Structure of the Pitman model with its main components.	63

Figure 4.3. Catchment absorption rate following an asymmetrical triangular distribution (taken from Hughes (2013)).	65
Figure 4.4. Maximum interflow rate and maximum groundwater recharge as a function of the soil moisture content (taken from Hughes (2013)).	66
Figure 4.5. Flow diagram of the 2-stage approach to uncertainty analysis used in PITMAN model (flow diagram adapted from Hughes, 2016).	68
Figure 4.6. A utility index for checking the consistency between the constraint and parameter ranges. Here the model has failed to find out behavioural parameters due to the incompatibility between the parameter distributions and constraint limits.	70
Figure 4.7. Consistency found between the constraint and parameter ranges with almost 5000 behavioural parameter sets after 100 000 model runs during stage 1 of the modelling approach.	70
Figure 4.8. Conceptual diagram of the (a) sub-grid channel model and the (b) sub-grid cross-section (adapted from Neal et al. (2012)).	74
Figure 4.9. Schematic of the method used for the estimation of channel widths used for the sub-grid model.	75
Figure 4.10. Primary input data required for running the LISFLOOD-FP model.	76
Figure 4.11. Schematic of the methodology used for disaggregating monthly flows into daily (adjusted from Slaughter et al. (2015)).	79
Figure 4.12. Overview of the methodological approach for wetland impact assessments	84
Figure 5.1. Flowchart of the methodological approach applied for the establishment of the uncertainty ranges of hydrological indices.	86
Figure 5.2. Results of the pre-processing analysis of flow data. (a) Graphical comparison between the original flow series and the substitute series (at L_CB261 gauging station). (b) Performance statistics of the low (NE ln) and high (NE) flows.	92
Figure 5.3. Spatial distribution of the six homogenous regions of sub-basins of similar climate and physiographic properties in the Congo River Basin identified from the application of SOM.	94
Figure 5.4. Potential regression relationships between the climate/physiographic attributes and the hydrological indices within clusters formed from the 15 gauged headwater sub-basins. (a) Runoff ratio and Clay in cluster 1, (b) Q10/MMQ and AI in cluster 2, (c) Q50/MMQ and Curve number in cluster 1 and (d) Q90/MMQ and Clay in clusters 2 and 3.	96

Figure 5.5. Power regression relationships between the aridity index and the hydrological indices across the 15 headwater gauged sub-basins of the Congo River Basin. (a) Runoff ratio, (b) Q10/MMQ index, (c) Q50/MMQ index and (d) Q90/MMQ index. Regions refer to those of Figure 5.3.	98
Figure 5.6. Updated power regression relationships between the aridity index and the hydrological indices across the 26 headwater sub-basins of the Congo River Basin. (a) Runoff ratio, (b) Q10/MMQ index, (c) Q50/MMQ index and (d) Q90/MMQ index. Regions refer to those obtained Figure 5.3.	100
Figure 5.7. Final uncertainty ranges of hydrological indices derived based on the aridity index for all sub-basins of the Congo River Basin. (a) Runoff ratio index, (b) Q10/MMQ index, (c) Q50/MMQ index and (d) Q90/MMQ index. The region 6 did not appear among the plotted indices because of the lack of gauged headwater sub-basins.	101
Figure 5.8. Validation of the uncertainty ranges of the runoff ratio index across the Congo River Basin. The average runoff ratio observed over the entire Congo River Basin at the Kinshasa gauging station fits within the computed bounds.	101
Figure 5.9. Ratios of UNIDEL to CRU mean annual rainfall showing potential areas of high uncertainty in rainfall. Sub-basins located in the rift valley system (in red in the eastern part) and around the Kamalondo wetland system (in red in the southeast) have highest ratios, indicating high uncertainty.	102
Figure 5.10. Estimates of the groundwater recharge across the Congo Basin. (a) relationship with the aridity index and (b) ranges of the estimates of the mean monthly recharge over the Congo Basin.	102
Figure 6.1. Location of Lualaba gauging stations (in green circle) that are not impacted by wetland systems above the Kasongo gauging station.	107
Figure 6.2. Simulated uncertainty bounds of the flow duration curves for the gauged headwater sub-basins using the original input constraint ranges developed in Chapter 5.	108
Figure 6.3. Refined simulated uncertainty bounds of the flow duration curves for the gauged headwater sub-basins after constraint refinement.	108
Figure 6.4. Degree of uncertainty in the original and refined constraint ranges for mean monthly flow (a = MMQ) and the three percentiles of the flow duration curves (b = Q10/MMQ; c = Q50/MMQ, d = Q90/MMQ).	109

Figure 6.5. Uncertainty bounds of the flow duration curves at Nzilo gauging station (L_CB 27), using the original constraints (a) and after the refinement of constraints (b).	110
Figure 6.6. Uncertainty bounds of the flow duration curves at Bukama gauging station (L_CB 207), using the original constraints (a) and after the refinement of constraints (b).	111
Figure 6.7. Uncertainty bounds of the flow duration curves at Bukama gauging station (L_CB 207) simulated using refined constraints with channel routing parameter CL.	111
Figure 6.8. Simulated monthly streamflow at the Nzilo gauging station for the period January 1921-December 1938.	111
Figure 6.9. Simulated monthly streamflow at Bukama gauging station for the period January 1933-December 1959.	112
Figure 6.10. Uncertainty bounds of the flow duration curves at Chandawayaya gauging station (L_CB 200) using original (a) and refined (b) constraints.	113
Figure 6.11. Uncertainty bounds of the flow duration curves at Shiwa Ngandu gauging station (L_CB 202) using original (a) and refined (b) constraints.	114
Figure 6.12. Uncertainty bounds of the flow duration curves at Mbesuma Pontoon gauging station (L_CB 201) using original (a) and refined (b) constraints.	114
Figure 6.13. Uncertainty bounds of the flow duration curves at Old Ponton gauging station (L_CB 18) using original (a) and refined (b) constraints.	114
Figure 6.14. Location of the lower Lualaba sub- drainage system in the rift valley region of the Congo Basin.	115
Figure 6.15. Unsuccessful simulated uncertainty bound of the flow duration curve at Yumbi gauging station using the original constraints and CRU rainfall dataset.	117
Figure 6.16. Simulated uncertainty bound of the flow duration curve at Yumbi (L_CB191) site using region-specific constraints and UNIDEL rainfall dataset when sub-basins are ungrouped (a) and grouped (b).	117
Figure 6.17. Comparison between CRU and UNIDEL long-term mean monthly rainfall data in two different regions of the Lualaba drainage system. (a) = undulating topography of Bukama sub-drainage system and (b) = undulating to the steep topography of the lower Lualaba (rift valley) sub-drainage system.	118
Figure 6.18. Degree of uncertainty at upstream and downstream gauging stations of the upper Lualaba drainage system.	119
Figure 6.19. Location of the studied sub-basins in the Sangha drainage system.	120

Figure 6.20. Downstream uncertainty propagation across three gauging stations of the Sangha drainage system (from upstream to downstream gauging stations) for the mean monthly (MMQ), high (Q10), medium (Q50) and low (Q90) flow.	120
Figure 6.21. Mean values of the re-calibrated constraints after hydrological simulations have been validated across drainage systems for (a) runoff ratio, (b) Q10/MMQ, (c) Q50/MMQ and (d) Q90/MMQ. Dashed and plain lines represent upper and lower uncertainty bounds of original constraints.	124
Figure 6.22. Re-calibrated constraint indices along climate gradient (aridity index) depending on whether sub-basins are located in the northern or southern hemisphere across the Congo Basin.	125
Figure 6.23. Comparison between final average values of mean monthly recharge (MMR) constraint and original values derived from a global dataset. Values are plotted on a logarithmic scale for comparison purpose and the regression relationship is for the original MMR values.	125
Figure 6.24. Comparison of predictive uncertainty intervals between previous (in grey) and current (in red) studies across selected gauging stations for the (a) Mean monthly flow and three percentiles of the flow duration curve namely (b) Q10th, (c) Q50th and (d) Q90th. LB and UB are the lower and upper bounds of the predictive uncertainty intervals with respect to observed flows.	127
Figure 7.1. Scaling parameters of the disaggregation model at seven gauging stations of the Congo Basin representing different climate and physiographic regions.	133
Figure 7.2. An illustration of the disaggregation results for the median flow at selected gauging stations for October 2000-September 2004. (a) Tshiangalele wetland inflow at Kapolowe gauging station, (b) Kamalondo wetland inflow at Bukama gauging station and (c) Mweru wetland inflow at Kasenga gauging station.	134
Figure 7.3. Visual comparison between LISFLOOD-FP (using the 5 th , 50 th and 95 th percentiles of the uncertainty input time series) and Landsat imagery (MNDWI) flood extents (white areas) for the (a) Ankoro and (b) Tshiangalele wetland systems.	138
Figure 7.4. Dimensionless hysteresis of inflow volume and wetland storage volume at the Ankoro wetland system showing counterclockwise hysteresis over three consecutive hydrological years. (a)-(c) show daily hysteresis for the consecutive hydrological years 2001-2002, 2002-2003, and 2003-2004, respectively. (d)-(f) show monthly hysteresis for the	

consecutive hydrological years 2001-2002, 2002-2003, and 2003-2004, respectively. Arrows indicate the direction of loops.....	142
Figure 7.5. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows at Ankoro wetland system.....	147
Figure 7.6. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Kamalondo wetland system.....	148
Figure 7.7. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Kundelungu wetland system.....	148
Figure 7.8. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Mweru wetland.....	149
Figure 7.9. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Tshiangelele wetland system.....	149
Figure 7.10. Potential predictive equations of the scale parameter (AA) of the return flow equation when the exponent parameter BB is kept constant at a value of 1.25.....	152
Figure 7.11. Wetland impacted downstream gauging stations (in red) used for the assessment of wetland impacts on the downstream flow regime of the Lualaba drainage system.	154
Figure 7. 12. Simulated uncertainty bounds of the flow duration curve at Mulongo gauging station (L_CB150). (a) without and (b) with wetland systems when sub-basins are independently simulated.	156
Figure 7.13. Simulated streamflows (a) and monthly flow distribution (b) from one of the ensembles at the Luvua gauging station without and with the inclusion of Mweru wetland system in the basin-scale hydrological modelling.	157
Figure 7.14. Simulated uncertainty bounds of the flow duration curve at Luvua gauging station (L_CB210) in the downstream of the Mweru wetland system. (a) without and (b) with Mweru wetland system included in the modelling when sub-basins are not grouped.	158
Figure 7.15. Simulated uncertainty bounds of the flow duration curve at Ankoro gauging station (L_CB198) in the downstream of five wetland systems. (a) without and (b) with upstream	

wetlands systems included in the modelling when upstream sub-basins are independently simulated.	158
Figure 7.16. Simulated streamflows (a) and monthly flow distribution (b) from one of the ensembles at the Ankoro gauging station without and with the inclusion of all upstream wetland systems in the basin-scale hydrological modelling.	159
Figure 7.17. (a) Simulated streamflow at Lukuga gauging station over the period 1901-2014 before and after the inclusion of upstream wetland systems including Lake Tanganyika. The observed flows are available over two distinct periods 1932-1936 and 1945-1947. (b) Simulated streamflow after the inclusion of wetland function.	160
Figure 7.18. Simulated uncertainty bounds of FDCs in downstream of major wetland systems of the Lualaba drainage system after a re-calibration of some of the wetland parameters within the main PITMAN model. These are examples of Mulongo (a-b), Luvua (c-d) and Ankoro (e-f) gauging stations.	163
Figure 7.19. Variation of mean values of constraint indices with regards to the original constraint uncertainty ranges (plain and dashed lines), after adjustments have been made to constraint ranges for sub-basins within the wetland zones (Between gauging stations) and in the most downstream part, of the Lualaba drainage system.	165
Figure 7.20. Mapping of the final mean values of the constraint indices across the Lualaba drainage system for the (a) runoff ratio, (b) Q10/MMQ, (c) Q50/MMQ and (d) Q90/MMQ.	165
Figure 7.21. Observed and simulated monthly flow volumes using two different sets of wetland parameters. (a) streamflows and (b) monthly distribution of flows at Mulongo gauging station in the downstream of Kamalondo wetland system.	167

LIST OF TABLES

Table 2.1. Some of the uncertainty analysis methods applied in hydrological modelling	22
Table 2.2. Frequently used hydrological indices or signatures for catchment classification/prediction in ungauged basins and for constraining hydrological model outputs.....	26
Table 2.3. Summary of rainfall-runoff modelling studies in the Congo Basin.....	38
Table 3.1. General description of the five wetland systems	52
Table 3.2. Description of sub-basins attributes used for the classification of the Congo Basin	57
Table 3.3. Landsat images used for the validation of inundation extents between 2001 and 2004	59
Table 4.1. Description of PITMAN model main parameters.....	63
Table 4.2. Parameters of the wetland sub-model accounting for the channel–wetland exchanges	81
Table 5.1. Summary of hydrological indices used in this study	89
Table 5.2. Clusters formed based on the 15 headwater (sub-basins) gauging stations.....	95
Table 5.3. Highest R^2 of the relationship observed between physiographic attributes and hydrological indices for regions having at least 4 representative gauges. In bracket are slope of the relationship. In bold are the highest R^2 for each hydrological index.	96
Table 5.4. R^2 of the power regression relationship between hydrological and physiographic attributes across 15 gauging stations. AI and CN are potential predictors.	97
Table 6.1. Summary of the adjustment process of constraint ranges across drainage systems (LB and UB represent the lower and upper bounds of constraint ranges). The meaning of the symbols used is given at the bottom of the table.	122
Table 7.1. Calibrated friction and channel geometric parameters	135
Table 7.2. Model statistical performance of 90 m model resolution across wetland systems (Ankoro, Kamalondo, Kundelungu, Mweru and Tshiangalele) for different types of inflow inputs.....	139
Table 7.3. Model statistical performance across different spatial resolutions at selected wetland systems (Ankoro, Kundelungu and Tshiangalele) when the median flow is used.	139
Table 7.4. Attenuation of the peak flows due to wetland storage effects	141

Table 7.5. Time delay (days) between the occurrences of the peaks of channel inflow and outflow.	141
Table 7.6. Magnitude of hysteresis in channel inflow, wetland storage, inundated area, and outflow relationships across wetland systems at a daily time scale.....	143
Table 7.7. Magnitude of hysteresis in channel inflow, wetland storage, inundated area, and outflow relationships across wetland systems at a monthly time scale.	144
Table 7.8. Calibrated wetland parameters for the median flows at the five-wetland systems	147
Table 7.9. Wetland parameters of deep Lakes: Kivu and Tanganyika	150
Table 7.10. Morphometric characteristics of wetland systems.....	151
Table 7.11. Correlation matrix of wetland variables across different wetland systems. Hysteresis indices are expressed at a daily time scale.	152
Table 7.12. Wetland area ratios of the studied wetland systems	154
Table 7.13. Model performance for the ensemble with highest NE under different scenarios at Mulongo gauging station.	156
Table 7.14. Model performance for the ensemble with highest NE under different scenarios at Luvua gauging station.....	157
Table 7.15. Model performance for the ensemble having highest NE under different scenarios at Ankoro gauging station.....	158
Table 7.16. Description of sub-basins located in the region of wetlands and beyond.....	162
Table 7.17. Wetland parameters of the Kamalondo and Lake Tanganyika used in this study and the previous.....	166

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CHAPTER 1 : GENERAL INTRODUCTION

1.1 Background information

The Congo River Basin, located in central Africa, plays an essential role at regional and global scales. It is the second largest in the world in both discharge and drainage area after the Amazon. Its discharge has the potential to affect sea surface salinity and temperature (Santini and Caporaso, 2018a), contributing to regional and global ocean circulation and climate. The rainforest of the Congo Basin represents a significant source of organic matter to the Atlantic Ocean (Spencer et al., 2016a). Moreover, the volume of peatlands discovered in the Cuvette Central is capable of storing about 30 billion tons of carbon (Dargie et al., 2017), making the basin an important reservoir capable of helping to mitigate current global anthropogenic emissions. Also, the Congo Basin rainforest itself accounts for nearly 25% moisture recycling ratio (Dyer et al., 2017), meaning that its internal evaporation rate contributes to the basin precipitation. The basin has a hydroelectric potential (Alsdorf et al., 2016) of about 100 000 megawatts of which the 40 000 megawatts, from the Inga dam site alone if completed, will be the largest hydroelectric project in the world (Sanyanga, 2015; Warner et al., 2019).

Despite these opportunities, the Congo Basin faces several challenges. The need for infrastructure extension, agriculture expansion, wood and mining extraction have contributed to deforestation and land degradation (Megevand et al., 2013), with potential impacts on climate and hydrological processes (Bell et al., 2015; Ellison et al., 2017). However, less is known about the Congo Basin hydrology (Alsdorf et al., 2016) compared to other large tropical basins such as the Amazon and Orinoco rivers (Wongchuig et al., 2017). Some recent research works have investigated the climate of the basin (Bell et al., 2015; Dyer et al., 2017; Ndehedehe et al., 2019), the biogeochemistry (Spencer et al., 2009; Spencer et al., 2010; Spencer et al., 2016), changes in the forest cover (Mayaux et al., 2000; Hansen et al., 2008; Somorin et al., 2012), the impacts of wetlands (Bwangoy et al., 2010; Lee et al., 2011; Lee et al., 2015; Yuan et al., 2017; Becker et al., 2018), basin-scale hydrological modelling (Beighley et al., 2011; Tshimanga and Hughes, 2012, 2014; Aloysius and Saiers, 2017; Munzimi et al., 2019), hydrodynamic modelling (Kabuya et al., 2020a; O'Loughlin et al., 2019), soil erosion and sediment production (Coynel et al., 2005; Kabantu et al., 2018; Mushi et al., 2019) and river bathymetry and water level changes (Bos et al., 2006; O'Loughlin et al., 2013; Kim et al.,

2017; Carr et al., 2019). Alsdorf et al. (2016), reviewed the scope of some of these studies and identified the further research opportunities that exist.

Recently, the use of hydrological indices for constraining rainfall-runoff model outputs in ungauged sub-basins has been suggested as an alternative to traditional model calibration approaches (Addor, 2018). In a pilot study using 30 watersheds in the United Kingdom, Yadav et al. (2007) used streamflow indices such as high pulse count, runoff ratio and the slope of the flow duration curve to constrain uncertainty ensemble outputs from a hydrological model. Similarly, Zhang et al. (2008) used a multi-objective framework for identifying behavioural parameter ensembles for ungauged basins using suites of regionalised hydrological indices, and they concluded that regionalisation of these streamflow characteristics provided an additional way to extrapolate information from gauged to ungauged sub-basins for use in continuous basin-scale modelling. Shafii and Tolson (2015) used a large number of sub-basin response indices in a multi-objective optimisation context to achieve a level of acceptability for each index in ungauged sub-basins. Thus, there has been a growing interest in the use of hydrological indices in the context of ensemble model predictions to constrain the uncertainty of predictions in ungauged sub-basins.

Beyond these hydrological modelling efforts, other issues about the incorporation of wetland effects in hydrological simulations have been identified. The effects of wetlands may result in either the increase or decrease of a particular component of the water cycle (Bullock and Acreman, 2003; Wu et al., 2020a; Wu et al., 2020b). These effects may be different depending on some factors such as the location (e.g. Geographically Isolated Wetlands (GIW) that are surrounded by upland areas) (Golden et al., 2014a), the hydrological state (e.g. initial, residual and maximum storage capacity), the hydraulic connectivity (e.g. degree of floodplain channelization with surrounding water bodies), the morphology (e.g. storage below channel banks), and the underlying soil materials. As a result, a poorly connected wetland (e.g. GIW) to the fluvial system would have negligible impacts on the downstream flow regime compared to a highly connected wetland with well-defined hydraulic connectivity with adjacent river systems.

In an effort to improve the understanding of hydrological processes, there have been some attempts to directly or indirectly represent wetland systems within the hydrological models (Hattermann et al., 2006; Hattermann et al., 2008; Rahman et al., 2016; Evenson et al., 2016; Ameli and Creed, 2017; Evenson et al., 2018). Wang et al. (2008) incorporated wetlands into

a SWAT model using a "hydrological equivalent wetland" (HEW) concept. Different authors have reported similar applications of wetlands using SWAT (Yang et al., 2010; Golden et al., 2014; Rahman et al., 2016). Furthermore, long experience of working in different landform configurations of southern Africa led to the inclusion of earlier development of the wetland's water balance sub-model into the PITMAN model (DWA, 2008). However, the PITMAN model's original simplicity could not account for channel-wetland interactions, and therefore, the development of a wetland sub-model that accounts for the input–storage–output relationships between the river channel and the wetland systems was initiated (Hughes *et al.*, 2014). However, the complexity of hydrodynamic exchanges, which result in highly non-linear relationships among wetland hydrodynamic variables (Rudorff et al., 2014b), constrains the explicit estimation of parameters of simple wetland water balance hydrological models. Therefore, numerical simulations of wetland systems provide useful information in understanding the channel flow dynamics, wetland/floodplains storage and lag effects as well as the attenuation effects during the passage of a peak flow hydrograph. Hydrodynamic models such as LISFLOOD-FP are, therefore, appropriate tools to simulate such dynamics and thereby inform the quantification of the parameters of simple wetland water balance models (Makungu, 2019; Kabuya et al., 2020a).

1.2 Problem statement

Very few hydrological models have been applied in the Congo Basin with the aim of understanding processes taking places at different spatio-temporal scales (Beighley et al., 2011; Tshimanga and Hughes, 2012, 2014; Aloysius and Saiers, 2017). Daily time-scale hydrological models have faced tremendous challenges for simulating the diverse hydrological conditions across the basin (Beighley et al., 2011; Aloysius and Saiers, 2017; Munzimi et al., 2019). They are data demanding in terms of climate and physical sub-basin characteristics, which are not adequately available for direct use in hydrological models at finer temporal scales. Consequently, simulations are fraught with a high degree of uncertainty, which constrains their direct use (O'Loughlin et al., 2019) for practical applications (e.g. reservoir operation and inundation dynamics). In contrast, experiences in using monthly hydrological models in Southern Africa (Kapangaziwiri et al., 2012; Hughes, 2013), and specifically in the Congo Basin (Tshimanga and Hughes, 2014) have shown that many of the hydrological processes could be appropriately captured. However, Tshimanga and Hughes (2014) identified the primary sources of uncertainty in the application of monthly time step hydrological models in

the Congo River Basin. They recommended the use of regionalised hydrological indices and the inclusion of the effects of wetlands, as a means to overcome some of the problems of data scarcity and process representation, thus reducing uncertainty in hydrological simulations.

There are relatively few gauging stations within the data-scarce Congo River Basin, and many of those that do exist are located on large rivers that represent heterogeneous upstream responses, and are therefore not useful to quantify regional patterns of hydrological response at the scale of smaller sub-basins, typically used in a model setup. Besides, many of the available streamflow time series are short and the data from different stations rarely coincide in time, representing different sequences of dry and wet flow conditions such that the derived hydrological indices at different stations may not be comparable with each other, resulting in increased uncertainty. Therefore, there is a great need to appropriately quantify the uncertainty in hydrological indices to account for different sources of uncertainty such as lack of spatial representativeness and shortness of time series of available gauging stations.

Wetlands represent about 32% of the Cuvette Central's surface area (Bwangoy et al., 2010) of the Congo Basin, while there are also large wetlands present in the upper Congo Basin (Kabuya et al., 2020a). The case of the Kamalondo and other upstream (Ankoro, Kundelungu, Mweru, and Tshiangalele) wetland systems (in the upper Lualaba of the Congo Basin) have been raised since 1948 by Engineers of the National Navigation Authority who were entrusted with monitoring the gauging stations in the Lualaba drainage System (Charlier, 1955). They pointed out that the hydrodynamic functioning (filling and emptying mechanisms) of these systems was not well understood after they had observed their impacts on the alteration of the downstream flow regimes through attenuation, storage and slow release. This hydrodynamic functioning of wetlands, in the absence of observed flow data, as it is the case in the Congo, can be well understood only through the integration of the hydrological and hydrodynamic models. Hydrological models mostly compensate for the lack of observed flow data and provide input boundary conditions to hydrodynamic models, which can appropriately quantify channel-wetland exchanges. Therefore, there is a need to quantify these exchanges and provide guidance to explicitly estimate the wetland parameters rather than using a trial and error calibration approach as previously reported (Tshimanga, 2012; Tshimanga and Hughes, 2014; Hughes et al., 2014).

1.3 Aim and Objectives of the research

The limited amount of hydrological information across the Congo Basin means that the hydrological predictions will always be associated with increased uncertainty. However, the quantification of the appropriate level of uncertainty, in this basin, remains a critical issue given the multiple sources of uncertainty (Maidment et al., 2015; Westerberg and Mcmillan, 2015; Sun et al., 2018; Kiang et al., 2018; McMahon and Peel, 2019) present in hydrological data (e.g., rainfall, evapotranspiration, discharge) and the differences in the existing methods used to estimate the uncertainty (Kiang et al., 2018; McMahon and Peel, 2019). While these uncertainties can relatively be well quantified in gauged sub-basins especially if the stage-discharge information is available (Westerberg and Mcmillan, 2015; Kiang et al., 2018; McMahon & Peel, 2019), their quantification in ungauged sub-basins largely rely on the commonly used regionalisation approaches. These largely depend on the number of gauged sub-basins with sufficiently long records, thus limiting their application in regions with only limited information on individual sub-basins natural hydrology (Kabuya et al., 2020b).

This study explores existing approaches to uncertainty quantification in hydrological signatures especially for ungauged sub-basins (Yadav et al., 2007; Zhang et al., 2008; Westerberg et al., 2016) and their usefulness in constraining the hydrological model outputs in ungauged sub-basins to improve basin-wide hydrological simulations. The study accounts as well for channel-wetland exchanges in sub-basins where wetlands exert considerable influence on basin-scale hydrological processes at the monthly time scale. While some of these approaches have been successfully applied in Southern Africa (Kapangaziwiri et al., 2009; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017; Oosthuizen et al., 2018), their application in the context of the Congo Basin, however, requires a consideration of the region-specific challenges on data scarcity (Kabuya et al., 2020b). To address the above-mentioned objective, an integrated modelling framework that combines the use of hydrological indices, to quantify and predict hydrological uncertainties, and river-wetland exchange dynamics is developed. The following steps are implemented for achieving this main objective:

- To establish the uncertainty ranges of selected hydrological indices:

There exists a wide range of hydrological indices or signatures that describe different aspects of the hydrological response and their quantification depends on the type and amount of information available within a study area. Sub-basins climate and physiographic information

that have the potential to capture hydrological behaviour are often used to predict these indices from gauged to ungauged sub-basins using different regionalisation approaches. Catchment classification offers an approach for reducing the complexity of the basin to a few groups of sub-basins where the differences in climate and physiographic characteristics (and hence the hydrological indices) are assumed to be greater between the groups than within each group. The uncertainty ranges of the indices for each group are designed to reflect not only the internal homogeneity within the group, but also our lack of knowledge associated with the limited amount of streamflow data that is available to quantify the indices.

- To apply the quantified uncertainty ranges as constraints on the simulations of a hydrological model and to assess the results of the constrained simulations at downstream gauging stations:

It is expected that the application of the quantified uncertainty ranges to a hydrological model will relatively constrain the simulated uncertainty under natural hydrological conditions. Gauged headwater sub-basins reflect a lower uncertainty compared to ungauged sub-basins. However, while the application of the quantified uncertainty ranges to gauged headwater sub-basins may lead to further reductions of constraint ranges, it is important to know whether such reductions may apply to upstream-ungauged sub-basins. This can only be assessed if there are relatively downstream gauging stations where the constrained simulations can be evaluated using appropriate performance measures.

- To establish the upstream boundary conditions required for setting up a hydrodynamic model:

Hydrodynamic models often require hydrological inputs for continuous simulations of the exchanges between river channels and adjacent wetland systems. The coupling of such models requires that hydrological models provide input streamflows at a time step that is readily acceptable by hydrodynamic models. In case input streamflows are at a time step (e.g. monthly) different from that of the hydrodynamic model (e.g. daily), there is, therefore, a need to disaggregate the hydrological information.

- To calibrate a hydrodynamic model, quantify the river channel-wetland exchange dynamics and controlling factors, and use this information to quantify the wetland parameters of a basin-scale hydrological model:

In the absence of surveyed river bathymetry and flow discharges, it is very challenging to successfully calibrate and validate a hydrodynamic model. It is therefore important to choose hydrodynamic models that are not data demanding while they are computationally efficient. Such models can be validated using readily available global data sets such as the inundation extents. The channel-wetland exchange mechanisms such as filling and emptying can be quantified using hysteresis indices, known for their ability to inform on the nature of connectivity between the two systems. Often such connectivity is affected by different factors that are inherent to individual wetland systems as well as individual flood characteristics. Such understanding is useful for the quantification of wetland parameters for use in a basin-scale hydrological model.

- To quantify downstream wetland impacts on flow regimes:

The lack of knowledge in the channel-wetland exchanges can bring tremendous uncertainty in the hydrological simulations in downstream of vast wetland systems. This is the case in the Congo Basin, more specifically in the upper Lualaba drainage system where many upstream wetlands do exert considerable impacts on downstream flow regimes. It is expected that the incorporation of wetland module with appropriate parameters within basin-scale hydrological modelling will improve downstream simulations.

1.4 Significance of the study

Uncertainty is inherent to natural environmental systems (Beven, 2012; Beven, 2013) and therefore it should not be seen as a problem, but instead as a risk of a possible outcome (Beven, 2000). Adequate knowledge of how much uncertainty (Beven, 2013) is associated with different components of a sub-basin's hydrological response, expressed as hydrological indices ranges, is important for identifying model behavioural parameters (Yadav et al., 2007; Zhang et al., 2008; Addor et al., 2018) in ungauged sub-basins when constraining hydrological model outputs. Knowing how this uncertainty can propagate into model predictions offers an opportunity to identify regions with increased uncertainty and allows for the implementation of various data collection and management strategies that can potentially contribute to the uncertainty reduction (Beven, 2018). In contrast, ignoring uncertainty in estimates of water resources availability means that water resources planning and management decisions in the basin will continue to be based on inadequate information and unquantified uncertainty, thus increasing the risk associated with water resources decision making (McMillan et al., 2017;

Wilby et al., 2017; Hughes, 2019). The resulting hydrological model, which reflects natural hydrological conditions, provides an opportunity to assess the impacts of different water uses across the basin, the future environmental changes and the wetlands.

Channel-wetland exchange processes can potentially be assessed through in-situ measurements (Clilverd et al., 2013; Rahman et al., 2016). However, the complexity of these interactions in large integrated wetland systems makes in-situ measurements impractical (Alsdorf et al., 2000; Penatti et al., 2015). The use of Earth Observation (EO) data and Geographic Information System to understand these interactions has been recognised (Hughes et al., 2014; Park, 2020). However, temporal and spatial scale resolution issues (Zhang et al., 2018; Ge et al., 2019) of EO data may constrain their use in some areas and for some specific applications. Therefore, the combined modelling approach (integrating the hydrological and hydrodynamic models) offers an opportunity to understand and quantify exchange processes between river channel and wetland systems, which is crucial for improving the overall knowledge of basin-scale hydrological processes in regions where the effects of wetlands are evident.

1.5 Thesis structure

Chapter 2 deals with a review of literature on hydrological uncertainties, channel-wetland exchanges and a review of hydrological studies across the Congo Basin. The characteristics of the study area and a description of datasets used are presented in **Chapter 3**. The integrated methodological approach developed to carry out the study objectives is described in **Chapter 4**. Chapters 5 to 7 are results chapters that address each aspect of this study as outlined in the objectives. **Chapter 5** presents the results of the quantification of the uncertainty in hydrological indices. The testing of the uncertainty bounds of the hydrological indices through the application of a monthly time-step hydrological model is presented in **Chapter 6**. The establishment of the boundary conditions of the hydrodynamic model, its calibration, validation, the quantification of wetland sub-model parameters and their incorporation within basin-scale hydrological modelling for downstream impacts assessment is in **Chapter 7**, while the conclusions and recommendations are in **Chapter 8**.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

Many major human activities are dependent upon water resources. Agriculture, power production, industrial applications, water supply, fishing and health all involve the use of water, indicating our societal dependence on water (Water, 2016). About 70% of the world's population live in major river basins of the world such as Amazon, California, Colorado, Congo, Danube, Ganga-Brahmaputra, Mekong, Mississippi, Murray-Darling, Niger, Nile, Yangtze, and the Zambezi, which are all essential to the economy of the riparian countries (Syvitski et al., 2014; Lakshmi et al., 2018). However, many of these river basins lack sufficient observational hydro-climatic monitoring stations (Lakshmi et al., 2018), making it difficult to understand spatial and temporal variability of hydrological processes (Cristiano et al., 2017; Du et al., 2018). Compared to the above mentioned large river basins, the Congo appears to be the most ungauged and the less studied (Alsdorf et al., 2016), yet it plays an important role at regional and global scales (Sanyanga, 2015; Spencer et al., 2016; Dargie et al., 2017; Santini and Caporaso, 2018a; Warner et al., 2019).

Streamflow discharge is a major driver of many other processes such as the biogeochemistry and sediment transport. These processes can be understood well only if sufficient observed hydrological data are available at representative locations within the basin (Quesada-Montano et al., 2018). Hydrological and hydrodynamic models are, therefore, core tools that supplement the lack of observed data and increase the understanding of hydrological processes and the prediction of future impacts due to environmental changes (Seibert, 1999; Xu et al., 2013; Sivakumar et al., 2015; Lute and Luce, 2017; Fleischmann et al., 2018; Wang et al., 2018; Quesada-Montano et al., 2018; Geravand et al., 2020; Koo et al., 2020). However, the use of such tools is often challenging and associated with heterogeneity in parameters and state variables, nonlinearities and scale effects in process dynamics, complex or poorly known boundary conditions and initial system states (Beven, 2012; Paniconi and Putti, 2015; Beven, 2016; Singh and Marcy, 2017; Tran et al., 2018; Gupta and Govindaraju, 2019; Koo et al., 2020). Sometimes, the misinterpretation of the information contained in the available datasets can bias the modelling experiments and result in disinformation and increased level of uncertainty in hydrological predictions (Beven, 2018).

This chapter reviews some of the issues arising from the application of hydrological and hydrodynamic models. The issues include sources of uncertainty in water resources, their assessment frameworks, and the processes occurring in river channel-wetland exchanges, which are crucial for an improved understanding of hydrological processes in sub-basins with evidence of wetland effects. The chapter also presents a brief review of previous rainfall-runoff and hydrodynamic modelling studies conducted in the Congo Basin, to identify gaps for future investigations.

2.2 Classification of hydrological models

Some criteria can be used to classify hydrological rainfall-runoff models. Based on process description, rainfall-runoff models can be categorised as empirical, conceptual and physically-based models (Kokkonen and Jakeman, 2001; Jaiswal et al., 2020). On the other hand, based on the spatial discretisation of the input data, parameters and outputs, three types of rainfall-runoff models are usually termed as lumped, semi-distributed and distributed (Figure 2.1) (Khakbaz et al., 2012). On this basis, any single model can integrate both process description and spatial discretisation, such that it may be referred to as a distributed, physically-based model or a semi-distributed conceptual model, and so on.

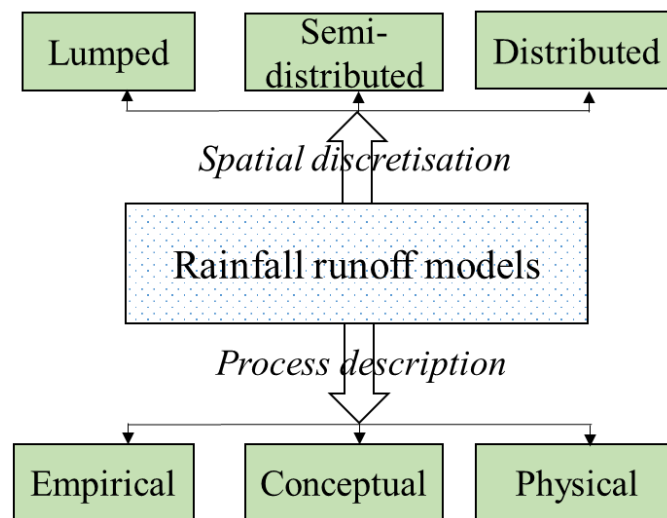


Figure 2.1. Classification of rainfall-runoff models based on process description and spatial discretisation of model inputs, parameters and outputs.

Empirical models are also referred to as data-driven models because they need only information from the existing data without really trying to account, either explicitly or implicitly, for hydrological processes. There exists a wide range of empirical models (Kokkonen and

Jakeman, 2001) including statistically based methods and the machine learning techniques which are largely used in hydro-informatics (Chandwani et al., 2015). Conceptual and physically-based models, however, describe the physical basin processes using some interconnected mathematical functions that logically compute different hydrological variables. Important features of the modelled system can be represented and interconnected to represent the direction and the order in which different hydrological processes operate in the real world (Duan et al., 1992). The main factor distinguishing physically-based from conceptual models is commonly expressed as the level of detail that is included in the model algorithms and the approach used to quantify the parameters of the model.

Physically-based hydrological models require robust numerical schemes (to represent the complexity of physical processes), high computing power, high spatial and temporal resolution of input data and parameters that are measurable (Paniconi and Putti, 2015; Singh and Marcy, 2017; Jaiswal et al., 2020). These conditions are often difficult to meet due to many issues of data availability, quality and resolution with respect to climate forcing, parameters for hydrological model conditioning and validation (Sun et al., 2017; Jaiswal et al., 2020). Some examples of such models include TOPMODEL (Beven and Kirkby, 1979; Devi et al., 2015), MIKE SHE (Refsgaard and Storm, 1995; Golmohammadi et al., 2014) and the variable infiltration capacity (VIC) model (Lohmann et al., 1998; Devi et al., 2015; Yang et al., 2019). On the other hand, conceptual rainfall-runoff models, however, use simplified mathematical conceptualisation of environmental systems, where processes are described with the help of interconnected storages (reservoirs), which represent physical elements in a basin (Devi et al., 2015; Jaiswal et al., 2020). Depending on the level of complexity in model structures, these models (conceptuals) can range from lumped to fully distributed systems. The PITMAN model is one of the examples of conceptual semi-distributed models and it represents different hydrological processes that can be readily observed within the highly heterogeneous landscapes and climates of southern Africa, where it has been successfully applied (Hughes, 2010; Kapangaziwiri et al., 2012; Hughes, 2013; Tshimanga and Hughes, 2014; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017; Oosthuizen et al., 2018).

Based on the above mentioned, a key issue is how can hydrological models be parameterised to represent relevant processes (physical realism) at a catchment scale with minimum available information, while maintaining an acceptable degree of reliability in predictions. This calls for accounting for uncertainty in hydrological modelling (Gan et al., 2018). After the next sub-

section (Section 2.3) that focuses on some measures of reliability commonly used in hydrological modelling, different sources of uncertainty in hydrological modelling are discussed (Section 2.4).

2.3 Model parameter estimation, calibration and reliability measures

Many conceptual hydrological models contain parameters that cannot be measured directly, but need a kind of adjustment to get appropriate values that can yield hydrological responses closer to the real-world (Devi et al., 2015; Jaiswal et al., 2020). This process is termed calibration. The traditional way of calibrating model parameters consists of manually adjusting parameter values through a semi-intuitive trial and error approach (Boyle et al., 2000; Kim et al., 2007). This approach is often labour intensive. Therefore, automatic calibration approaches were adopted to take advantage of the speed and power of digital computers (Boyle et al., 2000; Kim et al., 2007; Gelleszun et al., 2017).

Automatic calibration approaches aim at optimising a given objective function by selecting sets of parameters that result in a better correlation between the observed and the predicted response behaviours. Objective function refers to any performance criteria used to evaluate the performance of a model prediction. Several different criteria are in general use by hydrologists and the selection of specific performance criteria can be a challenge since each places an emphasis on different types of simulated and observed flows, e.g. high flows only, low flow only, or all flows (Krause et al., 2005). To avoid the erroneous judgement of the model performance that often results from the use of a single performance criterion, it is therefore recommended to use a multi-objective performance evaluation approach (Boyle et al., 2000; Krause et al., 2005; Khu and Madsen, 2005; Moriasi et al., 2007; Vrugt et al. 2003; Ritter and Muñoz-Carpena 2013; Bennett et al., 2013; Shafii and Tolson, 2015).

The most commonly used objective functions include the Nash-Sutcliffe coefficient of efficiency (Nash and Sutcliffe, 1970; Krause et al., 2005; Moriasi et al., 2007; Wöhling et al., 2013; Waseem et al., 2016), the coefficient of determination (Legates and McCabe, 1999) and the %Bias of the mean monthly flows (Moriasi et al., 2007). Some graphical evaluations include the streamflow hydrograph, flow duration curve and the seasonal flow distribution (Hughes and Mazibuko, 2018). The Nash–Sutcliffe coefficient of efficiency (NE) is calculated using the following expression:

$$NE = 1 - \left(\frac{\sum_{i=1}^n (Q_{Obs_i} - Q_{sim_i})^2}{\sum_{i=1}^n (Q_{obs_i} - Q_{obs}^{mean})^2} \right) \quad \text{Equation 2.1}$$

Where, Q_{Obs_i} , Q_{sim_i} and Q_{obs}^{mean} are the observed and simulated flow data and observed mean flow value at any time step, respectively. The coefficient can be a value between $-\infty$ and 1, where a NE of 1 indicates a perfect fit, while a value of $NE \leq 0$ indicates that the mean value of the observed time series would have been a better predictor than the predicted values from the model, thus indicating an unacceptable performance. In practice, values of $NE > 0.5$ have been widely accepted as simulations that are fit for practical purposes. The main drawback of this index is its sensitivity to bias in the larger values within the data series mainly because NE calculates the differences between observed and simulated flows as squared values resulting in largest values being overestimated during high flows and lower values neglected during low flow periods. To minimise this limitation, some authors have proposed either the modification of the NE (Krause et al., 2005) or the transformation of the time series before the application of the NE (Oudin et al. 2006; Pushpalatha et al. 2012; Wöhling et al., 2013).

Generally, the first step in the calibration and validation process of many hydrological models is the identification of the most sensitive parameters. This is called sensitivity analysis whereby key parameters that consistently show the greatest sensitivity to the model outputs or a particular component of the hydrological processes are identified (Parente et al., 2019; Tolley et al., 2019; Gou et al., 2020). This identification of sensitive model parameters is very important because it allows the identification of important parameters on which to concentrate during the calibration process and the unimportant (parameters that do not substantially affect the model outputs) that may be fixed at a predefined value. Some calibration and validation strategies are described in Sub-section 2.4.2.2 under parameter uncertainty.

2.4 Uncertainty in water resources estimation

Uncertainty is always present in everyday life and is inherent to natural environmental systems. Generally, it can be categorised as either aleatory or epistemic (Beven, 2013, 2016, 2018). Aleatory uncertainty is caused by randomness or natural variability of natural processes over spatial and temporal scales (Beven, 2013). This type of uncertainty is irreducible. On the other hand, epistemic uncertainty is caused by a lack of knowledge (Beven, 2016), which can be

expressed by poor measurement, and exclusion of processes in hydrological model representation. In principle, this uncertainty can be reduced by making efforts to improve our knowledge about the environmental systems to be modelled, as well as the tools and methods used. This section describes different sources of uncertainties associated with water resources estimation.

2.4.1 Input uncertainties

2.4.1.1 *Input climate uncertainty*

The main climate input data such as rainfall and evaporation/evapotranspiration demand are often subject to significant uncertainties (Westerberg et al., 2010; McMillan et al., 2012). These uncertainties can be broadly categorised as point measurement uncertainty, sampling uncertainty, neighbouring uncertainty, and equipment malfunction uncertainty (Westerberg and Mcmillan, 2015; Ehlers et al., 2019). Point measurement uncertainty, which differs across rain gauges types, arises from both systematic and random errors (Amaral et al., 2018; Ehlers et al., 2019). Appropriate approaches are used to correct systematic errors, while random errors are irreducible (Beven, 2013). Oudin et al. (2006) examined the influence of both random and systematic errors in rainfall and potential evaporation (PE) on the performance and parameter values of rainfall-runoff models. They indicated that hydrological models were almost insensitive to random errors in the PE while their performance was significantly affected by random errors in the rainfall. However, systematic errors in both rainfall and PE can have a considerable impact on model performance. This type of uncertainty may sometimes lead to inconsistent measurements that can contain more disinformation than information during the hydrological modelling process (Beven and Westerberg, 2011; Beven, 2016) and can propagate into hydrological modelling simulations (Ruelland et al., 2008; Kay and Davies, 2008; Thompson et al., 2014; Sperna Weiland et al., 2015; Sörensson and Ruscica, 2018; Terink et al., 2018; Mazzoleni et al., 2019; Cawse-Nicholson et al., 2020; Shrestha et al., 2020).

Sampling uncertainty, also called interpolation uncertainty, arises from the fact that a small sample of rainfall observations is not able to capture the spatial variability of rainfall at catchment scale (Sawunyama and Hughes, 2009; McMillan et al., 2011). This is often affected by topography, rain rate, storm type and network design (Hughes and Mantel, 2010b; Xu et al., 2013; Westerberg and Mcmillan, 2015; Sun et al., 2018). The worldwide reduction in the number of weather monitoring stations, especially rain gauges, represents a challenge to

adequately represent the spatial variability of rainfall (Xu, 2013; Walker et al., 2016; Kidd et al., 2017; Sun et al., 2018; Mazzoleni et al., 2019). This leads to potential uncertainty that is unavoidable especially in data-scarce regions. The use of global datasets of meteorological variables such as rainfall and PE constitutes another source of uncertainty (Maidment et al., 2015; Sun et al., 2018), because of the limited number and spatial coverage of surface stations, the satellite algorithms, and the data assimilation models (Cecinati et al., 2017; Bui et al., 2019).

Methods to quantify some of the above-mentioned uncertainties have been suggested before any hydrological modelling practice (Sawunyama and Hughes, 2009; Beven et al., 2011; Westerberg and Mcmillan, 2015) and sometimes this can prove difficult in cases of the absence of alternative sources of information. Global data sets are alternative sources of climate information and their uncertainty can be evaluated through intercomparisons of different global data sets using some metrics (Maidment et al., 2015; Sun et al., 2018; Nogueira, 2020). Sörensson and Ruscica (2018) performed an uncertainty assessment among nine evapotranspiration products and their results showed that the spatial patterns of maximum uncertainty differ among metrics and climate region. Olaniran et al. (2017) used the signal-to-noise ratio (SNR), correlation, root-mean-square errors and the normalised standard deviation to compare three rainfall data sets namely the Climate Research Unit (CRU) of the University of East Anglia, the Global Precipitation Climatology Centre (GPCC) and the University of Delaware (UDEL) over West Africa. Regions of low agreement among the three products were considered of high uncertainties in rainfall estimates. Similarly, Kabuya et al. (2020b) used the ratio of UNIDEL to CRU rainfall data sets and reported that large differences among the two rainfall data sets arise in high topography region of the eastern (rift valley) Congo and indicate high uncertainty in rainfall estimates.

2.4.1.2 *Streamflow discharge uncertainty*

Observed flow data can also be associated with high levels of uncertainty. A common method of obtaining continuous flow data consists of transforming measured flow levels in a natural channel cross-section into discharge estimates using a calibrated rating curve (Westerberg et al., 2011b; McMillan et al., 2012; Westerberg and McMillan, 2015; Coxon et al., 2015; Kiang et al., 2018; McMahon and Peel, 2019; Manfreda et al., 2020). The reliability of such a relationship depends on factors such as the stability of the measuring section, the stationarity of the flow conditions and the representativeness of the measurements used to construct the rating table. McMillan et al. (2012) categorised the sources of uncertainties in the rating curve

as: (i) random errors due to measurement errors, transcription and processing errors (Coxon et al., 2015; Horner et al., 2018) in the underlying stage-discharge; (ii) imperfect approximation of the true stage-discharge relationship by the rating curve model and its extrapolation beyond the observed conditions; and (iii) unsteady flow, variable backwater effects, transient flow effects (hysteresis) or changes to the channel cross-section due to sediment transport and vegetation growth (McMillan et al., 2010; Westerberg et al., 2011b). A poor representation of the rating curve model used to convert flow depths into continuous discharges may lead to consistent uncertainty in streamflow series (McMillan et al., 2012; Coxon et al., 2015; Horner et al., 2018) and affect the reliability of model simulations. For example, in the Congo Basin, technical information on rating curves and associated uncertainty are not often available (Tshimanga and Hughes, 2014) for assessing the sudden drops observed in low flows at some gauging stations.

There are other sources of uncertainty that are independent of stage-discharge relationship uncertainty. The shortness of the flow time series because of its lack of representativeness of the long-term flow regime (Westerberg et al., 2014b). The uncertainty due to the number of gauging stations used to extrapolate derived hydrological indices to ungauged sub-basins (Westerberg and McMillan, 2015; Westerberg et al., 2016; Zhang et al., 2018; Addor et al., 2018; Kabuya et al., 2020b). The uncertainty due to undocumented upstream water development infrastructures and the wetland effects (Tshimanga and Hughes, 2014; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017). Beven (2016) pointed out some forms of epistemic uncertainties that do not have stationary characteristics and that might introduce inconsistencies in streamflow series and potentially bring more disinformation in model calibration and evaluation. This is particularly the case with non-stationary conditions arising from different factors that might be localised at the gauging site (McMillan et al., 2010) or catchment scale (Ajami et al., 2017; Deb et al., 2019) due to either anthropogenic or natural induced changes in catchment properties or climate (Sen et al., 2020). These impacts are expected to affect model parameter stability and uniqueness (Li et al., 2012).

The combined effects of all these uncertainty sources can result in significant uncertainty in streamflow values. The uncertainty estimates associated with stage-discharge relationship often differ according to differences in estimating methods (Kiang et al., 2018). McMillan et al. (2012) reported on typical total uncertainties (95% uncertainty bound) for low flow ($\pm 50-100\%$), medium to high flows ($\pm 10-20\%$) and out of bank flows ($\pm 40\%$). Kiang et al. (2018)

found 3 to 17% for medium flows, 28 to 101% for low flows and the uncertainty in the extrapolated section of the rating curve ranged from 41 to 200% among different methods used. In contrast, McMahon and Peel (2019) found lowest uncertainty estimates for the median flows ranging from +4.5 to -4.2% (95% confidence band) and for individual gaugings from +29 to -22% incorporating a water level uncertainty of ± 4 mm. Westerberg et al. (2011b) quantified substantial uncertainties in discharge (-43 to +73%) due to a non-stationary rating curve.

2.4.2 Model Structure and parameter uncertainties

2.4.2.1 Structural uncertainties

In general, the model structure is how hydrological processes have been conceptualised and included in the model as mathematical equations. This includes the representation of the input, state and output variables that characterise the behaviour of the modelled system; and how these are interconnected through the mathematical functions (Lin and Beck, 2007; Blöschl et al., 2008). It also includes the spatial and temporal scales that are used in the model (Hughes, 2016). Structural uncertainty results from simplified representation of reality in models (Gupta and Govindaraju, 2019) and hence different model structures are expected to perform differently (Wagener et al., 2001; Chien and Mackay, 2014; Butts et al., 2004; Clark et al., 2017; Garavaglia et al., 2017; Jehn et al., 2019). This type of uncertainty is always present in any hydrological model because of our limited understanding of natural system's behaviour and the way this is translated into mathematical formulations (Gupta et al., 2012; Beven, 2016; Gupta and Govindaraju, 2019). While it is theoretically possible to reduce this type of uncertainty through improved understanding of the system being modelled and revisions to the model structure (Neal et al., 2012; Hughes, 2013; Nijzink et al., 2016; Hughes and Mazibuko, 2018; Ficchi et al., 2019), in practice, this is difficult in all but small experimental catchments.

Model structural uncertainty may also include both temporal and spatial scale issues. The temporal scale includes the temporal resolution at which the inputs and output variables are used. Temporal scale can refer to a model time step which is chosen according to the level of detail required for a specific application (Bennett et al., 2016; Ficchi et al., 2019), the response characteristics and the availability of the catchment's information (Reynolds et al., 2017). A major issue that relates to the temporal scale is the process representation across temporal scales, where some hydrological processes can be overlooked (Ficchi et al., 2019). Adla et al.

(2019) investigated the consequences of having different calibration and computation time-steps on model performance. They found that the daily and monthly-calibrated model parameters significantly differed, and though the monthly-calibrated model captured the patterns in monthly discharge data fairly well, it failed to characterize daily rainfall-runoff processes.

On the other hand, the spatial scale may refer to the size of the modelling units, which constrains the input data and output response spatial resolution and it takes into account the spatial heterogeneity in climate and hydrological response (Khakbaz et al., 2012; Hughes et al., 2013; Vansteenkiste et al., 2014). Haddeland et al. (2002) reported that the average annual runoff decreases with the increase in the spatial scale of the modelling units for rainfall-dominated basins simulated using a variable infiltration capacity model (VIC) (Lohmann et al., 1998; Devi et al., 2015; Yang et al., 2019) and better simulations were obtained as the size of the modelling units decreased because of accounting for spatial variability of inputs variables and parameters (Hughes et al., 2013; Tran et al., 2018).

2.4.2.2 *Parameter uncertainty*

Parameter uncertainty results from a lack of knowledge of exact parameter values due to errors in model input data and calibration data, parameter estimation methods and non-uniqueness of parameter values (Yang et al., 2008; Yeh et al., 2015; Van der Spek and Bakker, 2017; Mehdi et al., 2018; Liu et al., 2018; Motavita et al., 2019). Since parameters reflect catchment behaviour, they are usually considered as constants on the assumption that catchments conditions are stable (Zhang and Liu, 2019). However, as previously mentioned in Sub-section 2.4.1, different factors causing input uncertainties may also affect model parameters, which can be temporal and spatial scale-dependent. For instance, the presence of non-stationarities (McMillan et al., 2010; Ajami et al., 2017; Deb et al., 2019) in input and evaluation data may lead to a lack of robustness in the calibrated parameters (Andréassian et al., 2012). This will impact the temporal stability of parameters at a given measured location (Li et al., 2012; Zhang et al., 2019) where parameter values calibrated under wet (dry) conditions may fail to simulate dry (wet) conditions (Zhang and Liu, 2019).

Split sample strategies have been implemented to appropriately account for time-varying catchment conditions (Arnold et al., 2012; Bennett et al., 2013; Van der Spek and Bakker, 2017; Liu et al., 2018; Arsenault et al., 2018; Motavita et al., 2019). These strategies can be

grouped into three main approaches: Differential split- sample (Li et al., 2012; Bennett et al., 2013; Thirel et al., 2015; Broderick et al., 2016), data assimilation (Pathiraja et al., 2016; Pathiraja et al., 2018) and construction of a functional form or empirical equation between parameters and some climatic variables such as precipitation and PE (Deng et al., 2016; Deng et al., 2018). The main purpose of all these different parameter sampling strategies is to obtain parameter sets that are stable over time with good simulation ability (Arnold et al., 2012; Thirel et al., 2015; Xie et al., 2018; Arsenault et al., 2018; Zhang and Liu, 2019).

Parameter uncertainty arises also from the equifinality problem, which is an inherent characteristic of most complex hydrological models. As discussed in Section 2.2, Complex hydrological models tend to include many hydrological processes, resulting in many parameters. The lack of a single optimal parameter set from this multi-dimensional parameter space leads to the equifinality (Beven, 2006; Wang and Chen, 2013; Hughes 2016) which is a coexistence of multiple choices of parameter sets that provide equally good or acceptable model performance (Wang and Chen, 2013; Her and Seong, 2018). Her and Seong (2018) concluded that equifinality and uncertainty will be inevitably introduced into modelling as long as the amount of information available is less than required for completely constraining the parameter spaces.

Other issues related to parameter uncertainties may arise when calibrated parameters at one gauged site have to be transferred to an ungauged location. This question of transferability of models from gauged to ungauged sub-basins was a key topic of debate during the PUB (Prediction in Ungauged Basin) decade (Sivapalan et al., 2012; Hrachowitz et al., 2013) and this can be done in many ways (Parajka et al., 2005; Zelelew and Alfredsen, 2014). There are methods based on the spatial proximity of donor catchments (Merz and Blöschl, 2004; Drogue and Ben Khediri, 2016), regressions between independently calibrated model parameters and physiographic catchment attributes (Parajka et al., 2005; Heuvelmans et al., 2006; Zelelew and Alfredsen, 2014; Wagener and Wheeler, 2006) and a regionalisation framework in which the donor sites exhibits climate and physical similarity with the receiver sites (Parajka et al., 2005; Young, 2006; Ragettli et al., 2017; Yang et al., 2019), which is called catchment classification (Parajka et al., 2005; Beck et al., 2016) through linear (Gitau and Chaubey, 2010; Zhang et al., 2018) or non-linear (Hall et al., 2002; Heuvelmans et al., 2006; Srinivas et al., 2008; Herbst and Casper, 2008; Toth, 2009; Di Prinzio et al., 2011; Ley et al., 2011; Toth, 2013; Kabuya et al., 2020b) approaches. While all these approaches revealed a certain degree of success in

specific environments, however, other authors (Wagener and Wheater, 2006) pointed out the propagation of model parameter uncertainty due to uncertainty not only in model structure but also in regionalisation techniques (Sellami et al., 2014; Neri et al., 2020). The next section deals with approaches used to account for different sources of uncertainty in hydrological modelling.

2.5 Uncertainty analysis frameworks

Hydrological systems are inherently subject to epistemic uncertainties from multiple sources such as climate inputs (e.g. rainfall and potential evapotranspiration), evaluation data (e.g. streamflow), model structure and parameter. The combined effect of all this total uncertainty can affect not only the model calibration and validation process (some measures of reliability), but also the overall hydrological model performance (Beven, 2012, 2018), translate into research conclusions and management decisions (Wilby et al., 2017), thus resulting in significant economic costs (McMillan et al., 2017). It is therefore important to provide frameworks of uncertainty analysis which can account for different sources of uncertainty by appropriately quantifying it. It must also provide ways in which uncertainty can be presented and communicated to a large range of actors. This section discusses some of the methods that are currently used for the uncertainty analysis while the sub-subsequent section will focus on wetland-channel exchanges, which might bring also some forms of uncertainty if not accounted for in basin scale hydrological modelling.

2.5.1 Methods based on the stage-discharge relationship

Methods that quantify the uncertainty directly from streamflow data can estimate uncertainty in stage-discharge relationships by focusing either on discharge gaugings (Coxon et al., 2015), stage gaugings (McMillan et al., 2012; Horner et al., 2018) or rating-curve uncertainty (Westerberg and McMillan, 2015). Kiang et al. (2018) and McMahon and Peel (2019) reviewed some of these methods as they are categorised as prediction interval using standard regression approaches (Clarke et al., 2000), prediction interval using standard approaches, and Box-Cox transformations (Westerberg et al., 2011; McMahon and Peel, 2019), methods based on Bayesian and Markov Chain Monte Carlo analysis (Westerberg and McMillan, 2015), methods that are site-specific using hydraulic analysis (Horner et al., 2018), and miscellaneous procedures (Coxon et al., 2015).

2.5.2 Methods treating different sources of uncertainty

Other methods focus only on hydrological models where structural and parametric uncertainty are quantified. Many authors point out the idea of conducting model intercomparison experiments to effectively use the diversity of modelling approaches to advance the collective quest for physical realism of hydrological models (Garavaglia et al., 2017; Clark et al., 2017; Lee et al., 2020). Structural model uncertainty has been addressed in many ways (Gupta et al., 2012; Tyralla and Schumann, 2016; Lane et al., 2019). Butts et al. (2004) used the relative performance of different acceptable model structures as a representation of structural uncertainty. Liu and Merwade (2018) and Lee et al. (2020) used Bayesian Model Averaging (BMA) to assess structural uncertainty by generating the ensemble of different model structures used in their study. These two examples describe the most popular strategy to quantify and reduce structural uncertainty (Vansteenkiste et al., 2014; Tyralla and Schumann, 2016). Table 2.1 lists some examples (not exhaustive) of uncertainty analysis methods applied in hydrological modelling while approaches used within the PITMAN model (Kapangaziwiri et al., 2012; Hughes, 2013; Tshimanga and Hughes, 2014; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017; Oosthuizen et al., 2018) are briefly described as this model is used in this study.

Table 2.1. Some of the uncertainty analysis methods applied in hydrological modelling

Name	Description	Main reference
GLUE	Generalised likelihood uncertainty estimation. It computes the total uncertainty including input data, model structure and parameter error. The method does not require detailed distribution functions of the observable variables when the number of parameters is high or data are limited. However, the fact that the method relies solely on the measure of performance of different parameter sets without the minimisation or maximisation of an objective function may lead to subjective hypotheses in the selection of the appropriate parameter sets, yielding to inconsistent uncertainty bounds.	Beven and Binley; (2014); Beven and Binley (1992), Beven and Freer (2001), Blasone et al. (2008a), Steginger et al.(2008).
SUFI-2	Sequential uncertainty fitting. It can be applied to all sources of uncertainty by combining the optimisation and uncertainty analysis through Latin hypercube sampling, which is a statistical method to generate controlled random samples.	Yang et al. (2008), Setegn et al.(2010), Wu and Chen (2015)
Parasol	Parameter solution method. It estimates parameter uncertainty in complex distributed models using a modified Shuffled complex evolution algorithm (SCE-UA). In this method, uncertainty analysis is realised with statistical concepts. The simulations generated are divided into good and not good simulations through a threshold value of the objective function as done in GLUE, leading to good parameter sets and not good parameter sets. Therefore, the predicted uncertainty is generated by equally weighing all good simulations.	Setegn et al. (2010), Yang et al. (2008).
AMALGAM	Adaptive multi-algorithm genetically multi-objective method. Originally designed for meteorological predictions. It uses the search with simultaneous and the auto-evolutionary descendent creation to guarantee fast, reliable and computationally efficient solutions in multi-objective algorithms setting.	Vrugt and Robinson (2007).
DYNIA	Dynamic identifiability analysis. For each time step, the method computes the probability distribution of parameter values in behavioural parameter sets. It then estimates the parameter sensitivity from which is derived the information available for identifying a given parameter. Details are found in the main reference.	Wagner et al. (2003)

2.5.2.1 Uncertainty analysis approaches within PITMAN model

The uncertainty analysis approaches used within the PITMAN monthly rainfall-runoff model were inspired by many of the above-mentioned approaches and are all based on random Monte Carlo sampling of the input parameter space (Hughes, 2016). An approach based on a priori model parameter estimation from physical catchment characteristics was first used to establish the input parameter space, which was further sampled through independent sampling based on Monte Carlo procedure (Kapangaziwiri et al., 2009; Kapangaziwiri et al., 2012) to account for uncertainty in hydrological prediction. The approach has been successfully applied in many parts of the Southern Africa region (Tshimanga et al., 2011; Hughes et al., 2013; Tshimanga and Hughes, 2014), but some limitations were found due to spatial scale issues of the

hydrological modelling units and the resolution of the physiographic attributes used for parameter estimation.

These approaches evolved with time as a result of new developments within the modelling framework. Initially, the modelling process used an independent sampling of sub-basin parameter set to simulate the hydrological response. This presented a big limitation as the number of sub-basins increased, given that only one gauging station may be located in the most downstream sub-basin, there was no way of constraining individual upstream sub-basin uncertainty. As a result, the total downstream uncertainty was reduced partly due to the unconstrained upstream variations of dry and wet simulations that would cancel out (Hughes, 2016). Further development to account for this drawback consisted in restricting the random parameter sampling (through a utility called the dependent index, Figure 2.2) so that groups of physically and climatically similar sub-basins would generate results based on similar ranges of parameter values (with respect to simulating generally drier or wetter conditions). While this development partially solved the problem, it was unfortunately noticed that the downstream model ensembles that were identified as behavioural were not made up of behavioural upstream sub-basins contributions. This situation led to further developments of the model inspired from previous works (Yadav et al., 2007; Zhang et al., 2008; Kapangaziwiri et al., 2012; Euser et al., 2013). The new approach is based on the use of hydrological constraint indices to quantify behavioural parameter sets for each incremental sub-basin (Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017). This overall modelling framework accounts for different sources of uncertainty and is detailed in Chapter 3 on the methodological framework.

Pitman Model (GWv 3) Uncertainty Inputs Rows = parameters Columns = Parameters Spatial Element = L_CB191						
Array Parameter	Mean	St.Dev	Dependent Index	Dist.Type	Min Value	Max Value
01. Rain Distribution Factor	0.600	0.000	1.000	0.000	0.600	1.200
02. Proportion of impervious area AI	0.000	0.000	1.000	0.000	0.000	0.000
03. Summer intercept cap.(Veg1) PI1s	1.200	0.000	1.000	0.000	1.200	2.000
04. Winter intercept cap.(Veg1) PI1w	1.200	0.000	1.000	0.000	1.200	2.000
05. Summer intercept cap.(Veg2) PI2s	2.896	0.000	1.000	3.000	2.000	3.000
06. Winter intercept cap.(Veg2) PI2w	2.896	0.000	1.000	3.000	2.000	3.000
07. % Area of Veg2 AFOR	0.730	0.000	1.000	3.000	0.000	5.000
08. Veg2/Veg1 Pot. Evap. Ratio FF	1.200	0.000	1.000	0.000	1.200	1.400
09. ST fraction for sat. excess runoff	0.860	0.000	1.000	3.000	0.300	1.000
10. Annual Pan Evaporation (mm) PEVAL	1313.550	0.000	1.000	0.000	0.000	0.000
11. Summer min.abs.rate (mm/mth) ZMINa	7.831	0.000	1.000	3.000	5.000	20.000

Figure 2.2. Screenshot of the PITMAN model interface showing the dependent index utility used to restrict the random parameter sampling within the PITMAN model.

2.5.2.2 Use of hydrological signatures in hydrological modelling

Calibration of hydrological models using traditional measures of reliability such as Nash-Sutcliffe efficiency has been challenged by many issues including (i) epistemic uncertainties in input and evaluation data that might arise from different sources as discussed in Section 2.4, (ii) sensitivity of different measures of reliability to different flow magnitudes and (iii) inability to evaluate model performance in case of lack of overlap between observation periods of discharge and model input data (Westerberg et al., 2011a; Beven, 2012). This has favoured the use of novel approaches to model calibration initially referred to as limits of acceptability (Beven, 2006b; Blazkova and Beven, 2009; Westerberg et al., 2011a; Beven, 2012; Beven and Binley, 2014; Teweldebrhan et al., 2018), which are model-independent (Almeida et al., 2016) and have the potential of constraining hydrological model outputs. These limits of acceptability were constructed in such a way to reasonably represent different sources of uncertainty (Liu et al., 2009; Westerberg et al., 2011a; Westerberg et al., 2014).

The use of flow duration curves (FDC) in the calibration of hydrological models has been one of the first attempts where some selected percentiles of the FDC were used to construct limits of acceptability around the observed uncertain FDC (Westerberg et al., 2011a). While this was relatively efficient at gauged sub-basins, there has been a need to extend the approach to the ungauged sites with the development of regionalised FDC (Westerberg et al., 2014). These were found to be useful as a basic signature constraint; however, additional signatures were required to reflect different water balance components (Yadav et al., 2007; Zhang et al., 2008; Westerberg and Mcmillan, 2015; Shafii and Tolson, 2015; Almeida et al., 2016; Ndzabandzaba and Hughes, 2017; Nijzink et al., 2018), to effectively and consistently constrain model predictive uncertainty.

Studies (Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017) conducted in the Southern Africa region used six hydrological constraints representing the main water balance components to constrain the PITMAN model outputs and establish appropriate parameter sets. They termed the parameters that passed the constraint ranges as behavioural, otherwise non-behavioural. Quesada-Montano et al., (2018) used four different constraints based on climate and runoff-process characteristics at different time-scales to reject HBV-light model parameters that failed to represent hydrological process characteristics. Nijzink et al. (2018) constrained the feasible parameter space of conceptual hydrological models using different remote sensing products of soil moisture, evaporation, and total water storage and snow

accumulation. Thus, there has been a growing interest in the use of hydrological indices for achieving acceptable levels of uncertainties in data-scarce environments. Table 2.2 provides a description of some of the most widely used hydrological indices for prediction in ungauged basins and sometimes for constraining hydrological model outputs.

While these indices have been widely used, their quantification depends on the type and amount of information available within a study area. Previous studies have often used observed data to derive the indices (Yadav et al., 2007; Zhang et al., 2008; Kult et al., 2014). Others have used earth observation products (Fang et al., 2016; López et al., 2017; Nijzink et al., 2018) or pre-existing hydrological simulations (Ndzabandzaba and Hughes, 2017). Each source of information has its strength and weaknesses, depending on the quality of the sources and the intended use of the indices. Observed data may reflect the real system processes, but are not always available at locations of interest and can be affected by water resources developments (Vicente-Serrano et al., 2017; Sabater et al., 2018; Zhang et al., 2020) and therefore not represent natural conditions (Wang et al., 2018). Earth observation products have the advantage of covering large areas and can be freely available. However, they may not be suitable due to spatial and temporal scale issues (Zhang et al., 2018; Ge et al., 2019) or because they do not directly measure the variable of interest for some specific applications. Model simulations typically cover a long period with a complete set of water balance variables from which a variety of indices can be derived (Addor et al., 2018). However, model structural and other uncertainties may impact on their value in representing real system processes (Gupta and Govindaraju, 2019).

Table 2.2. Frequently used hydrological indices or signatures for catchment classification/prediction in ungauged basins and for constraining hydrological model outputs.

Hydrological indices	Description and computation	Purpose of the study	References
Flow duration curve Percentiles	These are flows that are exceeded over a percentage of the time. They are often computed at daily or monthly time scales. Q1...Q99. The number refers to the percentage of time the flow is exceeded.	Prediction in ungauged basins, constraining hydrological models	Beck et al., 2015; Zhang et al., 2018; Addor et al., 2018
Mean Flow	It can be computed at the daily, monthly or annual basis from observed flows.	Prediction in ungauged basins, constraining hydrological models	Beck et al., 2015; Zhang et al., 2018; Addor et al., 2018 ; Ndzabandzaba and Hughes, 2017
Runoff coefficient	The percentage of mean annual precipitation that appears as runoff, or the ratio of mean annual overland flow to rainfall. It can be estimated from daily as well as monthly flow data.	Prediction in ungauged basins and catchment classification	Ley et al., 2011; Beck et al., 2015
Runoff ratio	Average annual runoff divided by average annual precipitation. It can be computed at daily as well as monthly time scales.	Constraining hydrological models	Yadav et al., 2007; Quesada-Montano et al., (2018)
Slope of the flow duration curve	The slope of part of the curve between the 33% and 66% flow exceedance values of streamflow normalized by their means.	Constraining hydrological models	Yadav et al., 2007;
Baseflow index	The ratio of base flow to mean flow. It can be computed at different time scales.	Prediction in ungauged basins	Addor et al., 2018; Beck et al., 2015; Westerberg and Mcmillan, 2015

The quantification of the uncertainty associated with hydrological signatures for constraining hydrological model parameter space can only be achieved, in the context of data scarcity, through catchment classification (Yadav et al., 2007; Kapangaziwiri et al., 2012; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017). Catchment classification is perceived as a process of identifying catchment similarity based on several attributes describing the climate and the catchment structure to come up with a synthesised understanding of how these characteristics interact to define the hydrological response (Hall et al., 2002; Wagener et al., 2007; McDonnell and Woods, 2008; Carrillo et al., 2011; Toth, 2013). Climate and physiographic characteristics that have potential relationships with sub-basin hydrological response characteristics are used for both the classification and prediction in ungauged sub-basins (Addor et al., 2018; Zhang et al., 2018).

Yadav et al. (2007) developed prediction limits of hydrological indices with associated confidence intervals. Such limits were used by both Yadav et al. (2007) and Kapangaziwiri et al. (2012) to define regional constraint uncertainty. Similarly, Ndzabandzaba and Hughes (2017) applied $\pm 15\%$ or $\pm 20\%$ uncertainty to define the constraint ranges depending on the degree of scattering in the regional relationships between the aridity index and hydrological indices. In contrast, Quesada-Montano et al. (2018) applied a subjective $\pm 20\%$ uncertainty on the runoff ratio constraints ranges inspired by uncertainty studies conducted elsewhere (Westerberg and Mcmillan, 2015). In another study by Tumbo and Hughes (2015) where it was difficult to find regional patterns in the relationships between sub-basins physical attributes and the hydrological indices, the constraint ranges were based on simple index ranges for each identified region in the Great Ruaha River basin of Tanzania. These few examples highlight the need for extracting the most possible information from the available data to constrain hydrological model outputs in the context of ungauged basins (Hrachowitz et al., 2013), including those affected by upstream wetlands.

2.6 Wetland processes and how they affect the flow regime

Wetlands are widely known for their many services such as provisioning for food and water; regulation for flood, drought, land degradation and disease; support services, such as soil formation and nutrient cycling; cultural services; and recreational, spiritual, religious and other nonmaterial benefits (De la Hera et al., 2011; Evenson et al., 2016; Thorslund et al., 2017; Guo et al., 2017). Previous studies have reported that wetlands can either increase or decrease a particular component of the water cycle since many of them are directly linked to rivers and

aquifers (Bullock and Acreman, 2003; Lee et al., 2020; Wu et al., 2020a; Wu et al., 2020b). Their dynamics in time and space strongly influence water storage, runoff, groundwater recharge and discharge processes, evapotranspiration and temporal variability of basin-scale hydrological processes (Bullock and Acreman, 2003; Acreman and Holden, 2013; Rains et al., 2016). There exists different wetland types based on their function (what wetlands do), structure (what wetland look like), and utility (how wetlands are managed) (Brinson, 2011). Hydro-climatic forcing and wetland structure within the landscape have been recognised as key drivers of wetland hydrological functioning (Bertassello et al., 2019). This section reviews process exchanges between wetlands and river systems, as well as the assessment tools for process quantification.

2.6.1 Wetland and river channel exchanges

River channels and their adjacent floodplain wetland systems develop different types of interaction that depend on the nature of connection and the characteristics of floodwater (Clilverd et al., 2013). Often, complex patterns of floodplain relief exert a considerable influence on the flow patterns of inundating waters, with sequences of filling, transmission and drying-out occurring simultaneously on floodplains (Lewin and Hughes, 1980). Depending on the topographical setting of a wetland system, the water contributing to floodplain inundation may come from groundwater rise (Bullock and Acreman, 2003; Ó Dochartaigh et al., 2019), channel bank breaching, bank spilling, tributary flooding or runoff from the adjacent valley slopes (Acreman and Holden, 2013; Grenfell et al., 2019). Water moves from channels to floodplains through two main routes: bank breaching and spilling (Hughes, 1980; Dunne and Aalto, 2013; Rudorff et al., 2014a; Park, 2020). Breaching flow is a process which can start even before the bank full stage is reached, after which more widespread bank spilling can begin (Clilverd et al., 2013; Rudorff et al., 2014a; Park, 2020). Another exchange mechanism is lateral subsurface flow (Clilverd et al., 2013; Rahman et al., 2016). At peak river discharge, when the water stage is above the floodplain water table, flow is directed from the river onto the floodplain.

Once onto the floodplain, inundating water may be transmitted to different depressional storages through different routes, depending on the nature of the transmission channels (Lewin et al., 2017). These floodplain channels are important components of the river-floodplain exchanges and are well known in playing a key role in the hydrodynamic exchange and sediment transport (Trigg et al., 2012; Lewin and Ashworth, 2014; Lewin et al., 2017). In turn,

water leaves the floodplain through return flow back to the channel (further downstream either through ebb channels or as overbank returns or lateral subsurface flow under baseflow conditions in the river) (Clilverd et al., 2013; Lewin and Ashworth, 2014) at a rate that depends on the channelization of the floodplain (Alsdorf et al., 2000), evapotranspiration or infiltration, depending on the morphology of wetland and its position with regards to the groundwater table. The inundation and recession processes are regulated by the morphological features of the wetland system and the characteristics of individual flood events (Rudorff et al., 2014a; Li et al., 2020). Wetland topography is one of the key morphological characteristics that drives the exchange processes and is one of the major sources of uncertainty in hydrodynamic modelling (Section 2.7.5).

These exchange processes can potentially affect downstream processes and therefore can be assessed through in-situ measurements. Flow data, river water levels and bathymetry at key points along the adjacent floodplain, floodplain water levels and bathymetry are needed to appropriately understand channel-wetland interactions, especially at relatively small scales (Clilverd et al., 2013; Rahman et al., 2016). However, the complexity of these interactions in large integrated wetland systems makes in-situ measurements impractical (Alsdorf et al., 2000; Penatti et al., 2015). Hydrological or hydraulic modelling (Section 2.7) is an alternative approach to understanding these interactions for larger wetland systems that might probably exert considerable influence on basin-scale hydrological processes (Rudorff et al., 2014a; Ameli and Creed, 2017; Fleischmann et al., 2018; Li et al., 2019, 2020). Reductions in peak and mean flows, event duration, flow volume, temporal variability of quickflow and baseflow have been previously reported as effects (which depending on the location and size of wetland in a basin) of wetlands on downstream hydrological processes (Wu et al., 2020a; Wu et al., 2020b).

Wetland storage processes are explicitly accounted for in some of the basin-scale hydrological models. The Soil and Water Integrated Model (SWIM) has an explicit representation of wetlands (Hattermann et al., 2006; Hattermann et al., 2008). The SWAT model integrates a wetland module to quantify hydraulic interactions between riparian depressional wetlands, rivers and aquifers (Rahman et al., 2016; Evenson et al., 2016; Evenson et al., 2018). The ACRU model has relatively detailed representation of wetlands and accounts for surface and groundwater interaction. The PITMAN model incorporates a wetland sub-model to account for channel-wetland exchanges (Hughes et al., 2014). While all of these models have their

advantages and disadvantages, they share a common problem of input data availability and difficulties in estimating the wetland parameter values. The wetland sub-model of the PITMAN model operates at a monthly time scale, does not require intensive input data, and has been widely used in Southern Africa to explicitly account for wetland-channel exchanges (Hughes et al., 2014; Tshimanga and Hughes, 2014; Tumbo and Hughes, 2015). However, all of these studies highlighted the need for guidance to explicitly estimate the wetland parameters rather than using a trial and error calibration approach, which will nearly always be difficult given the lack of both observed inflow and outflow data in the majority of wetland systems.

2.6.2 Hysteretic patterns in channel-wetland exchanges

Channel-wetland exchange processes explained above are well quantified through the use of hysteresis indices. Hysteresis is a phenomenon of the input-output relationships in which values of the outputs do not only depend on values of the input at the same time, but also on the history of the input (Camporese et al., 2014a; Norbiato and Borga, 2008). This means that the response of the output to the input is not unique. Hysteretic input-output relationships are found in many natural systems across different temporal and spatial scales (Gharari and Razavi, 2018). They can be found between inundated area-storage volume and river discharge (Hughes, 1980; Shook et al., 2013; Rudorff et al., 2014b; Zhang and Werner, 2015; Makungu, 2019), water pressure and lake water storage (Huss et al., 2007), the flux and storage for subsurface flows in hillslopes (Norbiato and Borga, 2008), nutrient concentrations and river discharges (Klein, 1984; Bača, 2010; Cartwright et al., 2014; Lloyd *et al.*, 2016) and discharge-stage relationships (Petersen-øverleir, 2006; Muste and Lee, 2013).

Rudorff et al., (2014b) found a counter-clockwise hysteresis between inundation areas and water stage in the lower Amazon floodplain. They reported that the flow dynamic between the river channel and the floodplain was driven by the complexity of the floodplain geomorphology, vegetation and multiple water sources. The inundation processes were dominated by diffuse overbank flow, while the drainage processes were dominated by wetland channels. Huang et al. (2017) identified different hysteresis types in water area-stage curves of Poyang Lake in China. Counter-clockwise, clockwise, and splayed hysteresis directions were observed at the northern, southern, and central hydrometric stations, respectively, of Poyang Lake. These hysteretic patterns were due to different water surface gradients that emerged during the rising and falling periods. All of the literature tends to support the concept that the degree of hysteresis, which can be quantified through different hysteresis indices (Langlois et

al., 2005; Fovet et al., 2015; Zhang and Werner, 2015; Lloyd et al., 2016a; Zuecco *et al.*, 2016; Zhang et al., 2017; Gharari and Razavi, 2018), in the channel-floodplain exchanges is a function of the nature of the connection and the characteristics of a specific flood event (Hughes et al., 2014; Zhang and Werner, 2015). A low degree of hysteresis implied transient flow through the wetland where the amount of inflow is balanced by a similar amount of outflow at the same time, while a high degree of hysteresis would imply more rapid inundation processes than drainage processes and highly delayed return flows (Hughes, 1980; Hughes *et al.*, 2014).

An examination of hysteresis loops can provide information regarding the time delays between variables of a channel-floodplain system (Lloyd et al., 2016b). Clockwise hysteresis is observed when larger areas and greater storage volumes, for a given stage, occur during the water-level rise period than the water-level recession period. Counter-clockwise hysteresis occurs when larger areas and greater storage volumes, for a given water stage, are obtained during the recession period (Hughes, 1980; Lewin and Hughes, 1980; Zhang and Werner, 2015; Zhang et al., 2017). Hughes (1980) explained that the counter-clockwise hysteresis observed between floodplain inundation volume and the discharge within the neighbouring Teifi River (Wales) was due to restrictions to drainage, such as slow flows through ebb channels and subsurface pathways. This is also associated with a long residence time of water within a floodplain (Jones et al., 2014; Zuijdgeest et al., 2016). Other processes such as evaporation and infiltration may negatively affect the floodplain drainage processes, contributing to a further delay in the floodplain response during the recession (Lewin and Hughes, 1980).

2.7 Hydrodynamic modelling approaches

As already discussed in the above-mentioned sections, hydrological modelling offers an opportunity to understand basin-scale hydrological processes and different modelling frameworks are used to account for hydrological uncertainty. Although some of the hydrological models have the potential to integrating wetland processes (Hattermann et al., 2006; Hattermann et al., 2008; Hughes et al., 2014; Rahman et al., 2016; Evenson et al., 2016; Evenson et al., 2018; Wu et al., 2020), they are often limited in capturing the complexity of hydrodynamic processes through channel-wetland exchanges. Hydrodynamic modelling offers an opportunity to explicitly simulate these processes and predict variables such as channel discharge, velocity and flow depths, floodplain water volume, water level and inundation extents (Zhang et al., 2017; Li et al., 2019; Liang et al., 2020; Li et al., 2020). In the majority of the cases, due to scarcity of gauge observations, hydrological models are used to provide

input hydrological boundary conditions to hydrodynamic models. This is often referred to as coupling of hydrological and hydrodynamic models (Neal et al., 2012; Komi et al., 2017; Fleischmann et al., 2018; O’Loughlin et al., 2019). This section briefly describes some of the most used hydrodynamic modelling approaches to simulate river-floodplain exchanges. They can be grouped according to their dimensionality into 1D, 2D and 3D models.

2.7.1 One-dimensional hydrodynamic models

One dimensional flow models (e.g. MIKE11 and HEC-RAS) are used to simulate flows in open channels, which are represented by a series of channel cross-sections which often include the floodplain (Kamel, 2008; Doulgeris et al., 2012; Gharbi et al., 2016; Thompson et al., 2017; Ben Khalfallah and Saidi, 2018; Shao et al., 2018). These models assume the floodplain flow to be parallel to the main channel. Large variations in flow dynamics, such as velocity and depth within a cross-section, are represented only by cross-section averaged information (Teng et al., 2017). With these models, the inundation extents are computed by linearly interpolating the values of water depths at each cross-section, thus ignoring many of the effects of floodplain topography on the flow movement (Teng et al., 2017; Vozinaki et al., 2017; Pasquier et al., 2019).

Flow dynamics in a channel are represented by solving the widely known one-dimensional Saint Venant equations using different numerical solution schemes (Doulgeris et al., 2012; Vozinaki et al., 2017; Wang and Liu, 2020). The two main equations are the continuity and momentum equations :

- Continuity

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} + q = 0 \quad \text{Equation 2.2}$$

- Momentum in its conservative form

$$\frac{1}{A} \frac{\partial Q}{\partial t} + \frac{1}{A} \frac{\partial \left(\frac{Q^2}{A} \right)}{\partial x} + g \frac{\partial h}{\partial x} - g(S_0 - S_f) = 0 \quad \text{Equation 2.3}$$

Where Q is the flow discharge [L^3T^{-1}], x is the distance between cross-sections [L], A is the cross-sectional area [L^2], t is the time [T], q is a lateral inflow term [L^3T^{-1}] which can be put to zero, g is the gravitational acceleration [LT^{-2}], h is the water depth [L], S_0 is the channel bed slope [-], and S_f is the friction slope [-].

The above equations can be solved numerically to estimate Q and h at every cross-section. The four terms included in the momentum equation (Equation 2.3) are, from left to right, the local acceleration, convective acceleration, pressure term, bed and friction slopes. Depending on which of these terms is considered or ignored, different approximation schemes (Bates and De Roo, 2000; Trigg et al., 2009; Teng et al., 2017; Vozinaki et al., 2017) can be used to simulate the propagation of flood waves along an open channel.

2.7.2 Two-dimensional hydrodynamic models

Two-dimensional flow models account for the exceeded bank full flow which is routed into and between floodplain storage units using different approximation schemes. The majority of these schemes numerically solve the two-dimensional shallow water equations (Bates et al., 2010; Neal et al., 2012; Sampson et al., 2012; Teng et al., 2017; Lai et al., 2018; Afshari et al., 2018). The 2D models can be classified into finite element, finite difference and finite volume methods (Teng et al., 2017). When discretised based on time, they can be categorised as implicit and explicit models. The implicit approach implies that the solver cannot proceed to the next time step until the whole modelling domain is solved and the explicit approach involves solving the current unit independently of the rest of the modelling domain for any given time step (Teng et al., 2017). Based on the spatial representation of the floodplain, structured mesh (rectangular grid), unstructured mesh (triangular grid), flexible mesh or raster-based (Bates and De Roo, 2000) representations are used.

2.7.3 Three-dimensional hydrodynamic models

There are relatively few studies on the use of three-dimensional (3D) models in floodplain inundation modelling as they are often regarded as unnecessary compared to two-dimensional shallow water approximations (Teng et al., 2017). Some of the published studies on the use of 3D models focus mainly on small scale inundation mapping and impact assessments of sediments and infrastructures such as buildings and dams (Booker et al., 2001; Gems et al., 2016; Rong et al., 2019). The limiting factors in the use of these schemes include the computational efficiency, which has implications for the spatial scale of the modelling (small or large scale) and the problems of accurately representing some aspects of flow dynamics such as the free water surface. For these reasons, much attention has been given to the coupling of 1D and 2D models (Ganiyu et al., 2016; Fan et al., 2017). The LISFLOOD-FP model is one

of the hydrodynamic models developed to integrate both 1D and 2D models (Bates and De Roo, 2000).

2.7.4 Basic requirements for setting up a hydrodynamic model

Regardless of the dimensionality used to represent flow dynamics in channel and floodplain, there are basic requirements for setting up a hydrodynamic model. These include the flow boundary conditions, the river network and geometry the floodplain topography and the hydraulic parameters (Kamel, 2008; Wood et al., 2016; Williams and Esteves, 2017; Lai et al., 2018; Shao et al., 2018; Geravand et al., 2020). Depending on whether the simulated processes are event-based (Afshari et al., 2018; Geravand et al., 2020) or continuous (Fleischmann et al., 2018; Pasquier et al., 2019; O'Loughlin et al., 2019), the boundary conditions can include the river water level applied to either upstream or downstream of the modelling domain (Shao et al., 2018). Similarly, the flow discharge can be applied to either upstream or downstream boundary condition, and can also be applied to the edge of the modelling domain to represent the tributary lateral flow (Li et al., 2020). The downstream boundary conditions can also be set as a discharge-stage relationship or a free fixed water surface slope (Wood et al., 2016). However, in data-scarce areas, the application of detailed 1D/2D models presents some challenges and therefore, the use of earth observation techniques provides great support during the calibration and evaluation of hydrodynamic model performances.

2.7.5 Use of Earth observation techniques in hydrodynamic modelling

The representation of the floodplain topography and the evaluation of the model performance requires the use of earth observation techniques in the absence of enough ground-based information. Their potential and limitations in hydrodynamic modelling have been extensively discussed during the last decade (Yan et al., 2015; Musa et al., 2015). The digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) remains the most widely used remote sensing product to represent the floodplain topography. However, the elevation errors in the 90 m SRTM DEM were found to have a standard deviation of 4.68 m over Africa (Rodríguez et al., 2006). The implication is that the uncertainty in topographic data can introduce substantial errors in variables such as flow depth and velocity, leading to large differences in the timing, inundation depth and extent of flood inundation (Wilson and Atkinson, 2005; Yan et al., 2015). This constitutes a major source of uncertainty in hydrodynamic modelling. To account for this type of uncertainty, recent studies have used

resampling techniques to lower the spatial resolution of the original SRTM DEM and increase the vertical accuracy (Neal et al., 2012). Others have focussed on the removal of artefacts and vegetation effects (Baugh et al., 2013).

Other issues arise during the validation process of the hydrodynamic models. Recently, the use of satellite imagery to monitor flooding extents has largely increased and is perceived to be an alternative (Heimhuber et al., 2018), or complement, to in-situ observations (Walker et al., 2020), which are not often available at the place of interest. Aerial photography probably remains the most reliable source of remotely sensed flood area and extent, because it is capable of providing high-resolution imagery (Yu and Lane, 2006; Wu et al., 2019). However, this technology is very expensive and makes its applicability in large data-scarce areas almost impossible (Chawla et al., 2020). Landsat satellite imagery offers an opportunity for mapping inundation extents (Neal et al., 2012; Mueller et al., 2016) for use in hydrodynamic modelling. However, their use is often limited by the problem of cloud-covered areas, especially in densely forested zones. It may become very challenging to distinguish water pixels from vegetation pixels, especially if open water bodies are covered by aquatic vegetation (Huang et al., 2018). As a result, the detection of water pixels may lead to an underestimation of inundated areas, thus affecting the evaluation of the modelling performance. New techniques for flood detection, especially in areas which are inaccessible by optical remote sensing, emerged with the use of Synthetic Aperture Radar (SAR) (Bates et al., 2006; Schumann et al., 2009; Wood et al., 2016; Yuan et al., 2017; Chang et al., 2020). SAR can penetrate clouds, are insensitive to weather conditions and can acquire data during day and night.

Satellites based estimates of water elevation, its temporal change, and its spatial slope in fluvial environments, as well as across lakes, reservoirs, wetlands, and floodplains offer another opportunity for the calibration and evaluation of hydrodynamic models (Jung et al., 2010; Carr et al., 2019; Park, 2020). Many hydraulic variables can be acquired using remote sensing datasets and are used in general hydraulic equations to compute variables of interests (Bjerklie et al., 2003). For example, water surface area (Pickens et al., 2020), channel slope (Cohen et al., 2018), average channel width (Andreadis et al., 2013; Yamazaki et al., 2014) and velocity of rivers (Beltaos and Kääb, 2014) can be derived from remote sensing products and used to estimate flow discharges (Zakharova et al., 2020; Chawla et al., 2020). Wetland storage volumes can be derived from the Gravity Recovery And Climate Experiment (GRACE)

satellite mission (Xie et al., 2016; Yuan et al., 2017; Hasan and Tarhule, 2020) and used for assessing model performance.

2.8 Review of hydrological studies in the Congo Basin

The Congo Basin like other large river basins of the world (Lakshmi et al., 2018) has been the focus of research, notably in climate (Dyer et al., 2017), biogeochemistry (Spencer et al., 2016), changes in the forest cover (Somorin et al., 2012), hydrology, soil erosion and sediment production, river bathymetry and water level changes. However, rainfall-runoff and hydrodynamic modelling studies have not been widely undertaken as compared to other large river basins of the world (Syvitski et al., 2014; Abdulkareem et al., 2018; Mohammed et al., 2018; Du et al., 2018; Eccles et al., 2019; Mazzoleni et al., 2019; Qi et al., 2019). This section presents a brief review of hydrological and hydrodynamic studies undertaken so far in the Congo Basin.

2.8.1 Rainfall-runoff modelling

Only very few studies on the use of rainfall-runoff models in the Congo Basin are reported in the published literature (Chishugi and Alemaw, 2009; Beighley et al., 2011; Tshimanga et al., 2011; Tshimanga and Hughes, 2014). These studies have applied hydrological models either in some parts of the Congo Basin or to the whole Congo Basin. Moreover, some have just used global climate circulation models to derive inferences on Congo Basin hydrology (Santini and Caporaso, 2018), while others have used specific hydrological models to either process understanding or future climate change impact assessment (Tshimanga and Hughes, 2012; Aloysius and Sainers, 2017). Table 2.3 presents a brief review of the rainfall-runoff modelling studies undertaken in the Congo Basin.

2.8.2 Wetland and fluvial systems

This Sub-section presents an overview of some of the published hydrodynamic studies within the Congo Basin. It covers the research aspects, their spatial coverage and data collection programmes. A discussion is then presented on the limitations of some of these studies to formulate some research questions that can be addressed to bridge the information gaps.

2.8.2.1 Research aspects

Some studies have been conducted in the Congo Basin to understand the dynamics of the central wetland system known as Cuvette Centrale. For instance, the total extent of the central wetland system of the Congo Basin (Bwangoy et al., 2010) was estimated to be 360 000 km². Other studies attempted to understand the floodplain dynamics in terms of water depths changes (Lee et al., 2015), water level variations (Kim et al., 2017), storage dynamics (Yuan et al., 2017; Becker et al., 2018), channel-wetland exchanges (Lee et al., 2011; Kabuya et al., 2020a), the characterisation of the hydrodynamic properties of the middle reach of the Congo river main stem (O'Loughlin et al., 2013; O'Loughlin et al., 2019) and the whole fluvial system including the floodplain (Jung et al., 2010).

The Congo Basin fluvial system is considered to have diffusive boundaries without clear indications of the floodplain channels connecting to the fluvial system (Jung et al., 2010). This apparent lack of connection might have led to the confirmation that the floodplain system is mainly fed by upland runoff rather than fluvial processes of river-floodplain water exchanges as it is the case in the Amazon (Lee et al., 2011). However, a recent study on the middle reach of the Congo main stem has verified that there are exchanges between the Congo floodplain and its fluvial system (O'Loughlin et al., 2019). These exchanges are deemed partly responsible for the magnitude of the flood wave propagation observed at the Kinshasa gauging station in DR Congo.

2.8.2.2 Spatial coverage

Most of the studies conducted to understand the dynamics of the Congo floodplains have mainly focused on the Cuvette Centrale (Bwangoy et al., 2010; Lee et al., 2015; Yuan et al., 2017), the middle reach of the main stem (O'Loughlin et al., 2013; O'Loughlin et al., 2019) or a sub-reach of it (Carr et al., 2019). Yet, the Congo Basin is made up of six major drainage systems which also contain extensive wetland systems. For instance, the upper Lualaba drainage system has extensive wetland systems that exert substantial effects on the downstream flow regime (Tshimanga and Hughes, 2014; Kabuya et al., 2020a). The non-inclusion of these wetland systems in the basin-scale hydrological model results in poor simulations of the timing and the attenuation of the wet season peaks at all the gauging stations located downstream of the extensive wetlands and lakes, including Kisangani gauging station, the most downstream (Tshimanga and Hughes, 2014).

Table 2.3. Summary of rainfall-runoff modelling studies in the Congo Basin

No	Author	Model type	Objective	Methodology	Findings
1	Munzimi et al. (2019)	USGS Geospatial Streamflow Model (GeoSFM), a semi-distributed hydrological model.	Simulating daily streamflow of the main stem and tributaries of the Congo Basin.	Three measures of model performance were used: R^2 , Nash, %Pbias and seasonality.	Estimating daily streamflow, model simulations provide performance for the different parts of the basin, some of which show the need for improvement.
2	Santini et al. (2018)	Multimodel ensemble of the Climate Model Intercomparison Project phase 5 (CMIP5).	Simulating freshwater flux into the ocean for the river Congo by 20 CMIP5 models.	Similarity of discharge values 'distribution within monthly and annual series as compared between models and observations; the interannual and intermonth variability, Mann-Whitney(MW-U) test not looking at a date-to-date matching, The MW-U test for monthly phasing reproduction.	The distribution of inter month and interannual anomalies of simulated flow, calculated as percent deviations from the respective long-term average, appears not significantly different from that found in observations; Most of the models appear to largely overestimate the streamflow seasonal cycle up to 4–5 times for some months.
3	Aloysius and Saiers (2017)	Spatially explicit hydrological model (SWAT).	Evaluating the impacts of climate change on water resources and associated ecosystem services.	The calibration involved minimizing an objective function defined as the sum of squared errors between observed and simulated monthly average total discharge, base flows and water yield.	Precipitation and runoff are projected to decrease in the southeast of CB. Reductions in high and low flows in streams in the southeastern region will have implications for aquatic life, channel maintenance and lake and wetland flooding.
4	Tshimanga and Hughes (2014]	Conceptual semi-distributed PITMAN model.	Understanding processes of runoff generation for hydrological prediction and water resources assessment over 99 modelling units.	The model performance was evaluated using the visual assessment of hydrographs, seasonal distributions of mean flow and flow duration curve plots, Percent Bias of the Mean Monthly Flows and Nash-Sutcliffe Coefficient of Efficiency (NE).	The objective functions and graphical evidence support the conclusion that the hydrological model applied in this study should prove to be adequate for simulating the necessary hydrological information for water resources management and planning at the basin scale. However, the study suggests future research to account for uncertainties due to input climate data, scale of modelling units, parameter space and wetland effects.

Table 2.3. (continued)

No	Author	Model type	Objective	Methodology	Findings
5	Tshimanga and Hughes (2012]	Conceptual semi-distributed PITMAN model.	Assessing the hydrological response of the Congo Basin's runoff to future changes of climatic conditions in the sub-basin scale in the northern part of the Congo Basin under A2 and B2 scenarios.	The hydrological model was initially calibrated and validated from previous studies. Use of skill test to evaluate the relative performance of GCMs in reproducing historical patterns of climate variability within the study area. The three GCMs were bias-corrected.	A decrease in runoff (more than 10% decrease in total runoff) for the near-future projections in the northern part of the Congo Basin. Very little change in rainfall from the historical conditions. A major change in evapotranspiration due to an increase in air temperature.
6	Tshimanga et al. (2011]	Conceptual semi-distributed PITMAN MODEL.	Establishing a model that is a realistic representation of the basin's hydrology using the available historical data over 66 modelling units.	The model performance was evaluated using the visual assessment of hydrographs, seasonal distributions of mean flow and flow duration curve plots, Percent Bias of the Mean Monthly Flows and Nash-Sutcliffe Coefficient of Efficiency (NE).	The hydrological behaviour of the natural system has been fairly reproduced for the major parts of the basin. Discrepancies in behavioural parameters as a result of uncertainty in rainfall input to the model.
7	Beighley et al. (2011)	Hillslope River Routing (HRR) model.	Assessing the applicability of three satellite-derived precipitation datasets (TR, CM, PE) in terrestrial rainfall-runoff modelling.	Comparison of seasonal and monthly hydrographs, Grace water anomalies and Envisat altimeter observation.	The 3 rainfall datasets capture daily, seasonal and annual variations reasonably well in most sub-basins except for the 2 equatorial sub-basins where large variability is observed. In general, the model predictions have a good agreement with GRACE observations, Envisat altimeter measurements, and mean monthly historical gauge measurements.
8	Chishugi and Alemaw (2009)	A GIS-based hydrological model, namely HATWAB, a Hybrid Atmospheric and Terrestrial Water Balance.	Computing water resource availability, simulating its spatial and temporal distribution over the CRB.	A proper methodology was not described.	Spatial and temporal variation of the main water balance components.

2.8.2.3 Data collection programmes

The majority of the fieldwork surveys undertaken in the Congo Basin by Engineers of the National Navigation Authority who were entrusted with monitoring the gauging stations are dated since the 1950s (Charlier, 1955). Recently, the Congo River user Hydraulics and Morphology project (CRuHM) has conducted two major fieldwork campaigns in 2017 and 2019 covering the middle reach of the Congo River main stem (from Kinshasa to Kisangani) (Trigg et al., 2020; Tshimanga et al., 2020b). Some of the collected data include point and spatially continuous water surface elevations, hourly continuous water level elevations at key locations along the Congo main stem and some of its major tributaries, water depths and channel bathymetry (Tshimanga et al., 2020b). The advantage of the water level elevations is the one-hour temporal resolution ever reached in the Congo Basin. Such temporal resolution is useful for practical applications such as improvement of the accuracy of the existing rating curves and flood frequency analysis studies.

2.9 Discussion

This chapter has reviewed many aspects of hydrological uncertainty including frameworks for dealing with uncertainty in hydrological modelling. However, in the Congo Basin, the literature review has shown that important gaps exist with regards to process understanding, uncertainty quantification and reduction in hydrological simulations. For instance, Beighley et al. (2011) and Aloysius and Saiers (2017) studies present some scale issues that can result in high uncertainty in modelling results. The HRR and SWAT models simulate processes at a daily time scale, while the validation of the simulated streamflow is done at a monthly time scale. This can lead to tremendous uncertainty (Adla et al., 2019) in the sense that, while the monthly calibration can capture the patterns in monthly discharges, it can fail to characterize daily rainfall-runoff processes. This was clearly shown by O'Loughlin et al. (2019) who used the HRR daily simulated flow to drive a LISFLOOD-FP inundation model in the Cuvette Centrale. They reported that the simulated daily discharge largely over and underestimated flows at different locations and decided to bias-correct the flow outputs before using them as input to the hydrodynamic model. This supports the idea that given the ungauged nature of the Congo Basin, daily time scale rainfall-runoff models present many limitations in capturing patterns of daily streamflow series and therefore, monthly time step hydrological models remain the reliable alternative.

2019) in the basin have shown the usefulness of these datasets in describing different components of the Congo Basin. In this chapter, different global datasets are used to describe the climate and physiographic properties of the study area. Also, the datasets that have been used for modelling purpose are presented and described concerning how they have been used in different chapters.

3.2 Climate and physiographic characteristics

3.2.1 Climate

The climate of the Congo River Basin is warm and humid with two distinct wet and dry seasons that vary with distance from the equator (Bultot, 1974; Samba et al., 2008). The mean temperature is approximately 25° C. The mean annual rainfall is ~2 000 mm y⁻¹ in the central parts of the basin, decreasing both northward and southward to ~1 100 mm y⁻¹. The general pattern of the Congo River Basin precipitation consists of two distinct rainy seasons: March to May (MAM) and September to November (SON), which is the wettest (Washington et al., 2013; Dyer et al., 2017). Similarly, two distinctive dry seasons span from December to February (DJF) and June to August (JJA), which is the driest (Washington et al., 2013; Dyer et al., 2017). The timing of the wet seasons in the North and South are different such that the wet season in the northern parts coincides with the dry season in the southern parts. This bimodal pattern of the rainy seasons is associated with the passage of the Intertropical Convergence Zone (ITCZ) across the equatorial belt, between 10°S and 10°N (Suzuki, 2010). Several regional dynamic climate features modulate the seasonality of the Congo Basin precipitation (Balas et al., 2007; Creese and Washington, 2018). Ndehedehe et al. (2019) reported on Pacific ENSO and other global climate indices such as the Quasi-Biennial Oscillation (QBO) and the Atlantic Multi-Decadal Oscillation (AMO) that have significant impacts on hydro-climatic extremes of the Congo Basin.

The sources of moisture over the Congo Basin have also been a subject of research interest during the last decade, even though there is a lack of agreement on the main sources. The topography of eastern Africa has been considered as a barrier to the moisture transport from the Indian ocean into the Congo Basin (McCollum et al., 2000), and hence, the Atlantic ocean would appear to be an obvious moisture source due to the strength of low-level flow from the Atlantic (Pokam et al., 2012). However, Van Der Ent and Savenije (2013) reported that the Indian ocean is the main source of moisture for the Congo Basin and rather than the Atlantic ocean. Recently, Dyer et al.

(2017) investigated the moisture contributions from different source regions to Congo Basin precipitation. They found that the Indian Ocean and evaporation from the Congo Basin itself were the dominant moisture sources and that the Atlantic Ocean was a comparatively small source of moisture. The MAM and SON rainy seasons receive about 21% of moisture from the southwestern Indian Ocean and 25% comes from the Congo Basin itself. The latter implies that a change in the Congo Basin forest would result in considerable changes in precipitation patterns across the basin, and hence would impact on hydrological processes. Bell et al. (2015) performed a set of five simulation experiments using a regional climate model (RegCM3) to investigate the potential impacts of the complete removal of the Congo Basin forests on rainfall patterns over the period of January 1989 to December 1999. They reported the presence of a dipole rainfall anomaly pattern, characterised by a decrease of about 42% in rainfall over the western Congo and an increase of about 10% in eastern Congo. This indicates that deforestation has the potential to change the climate, both locally and regionally by altering land surface properties.

The annual potential evapotranspiration is between 1 100 and 1 200 mm y^{-1} and varies little across the basin (Alsdorf et al., 2016). This pattern, together with the precipitation pattern, yields a concentric pattern of the aridity index where values increase from the Cuvette Central (located in the middle Congo: Figure 3.1) towards the north, east and south headwater tributaries of the Congo River Basin (Figure 3.2).

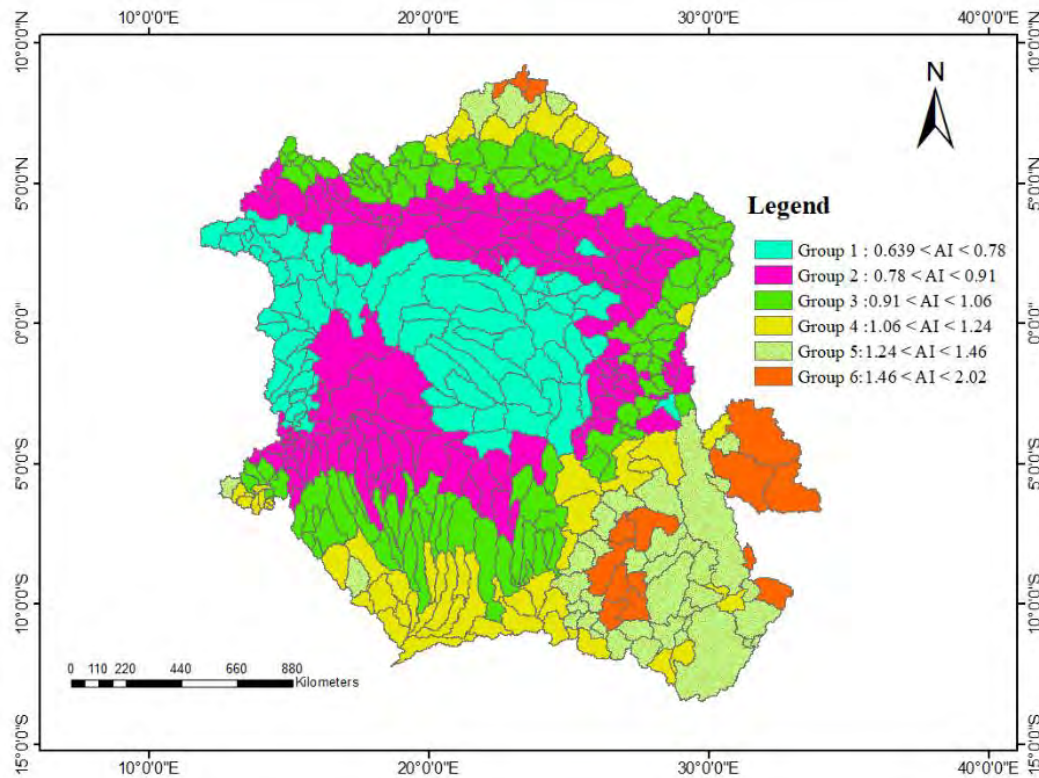


Figure 3.2. The spatial pattern of the aridity index (PE/P) across the Congo River Basin showing a concentric pattern.

3.2.2 Land use/Landcover

Land cover over the Congo Basin varies from tropical evergreen forest, with little seasonal variation, in the central parts, to savannah in the north and south (Mayaux et al., 2000; Hansen et al., 2008b). Forest constitutes the primary land cover feature and covers an area of about 2.27×10^6 km², representing about 18% of the world's tropical forests (Hansen et al., 2008b; Somorin et al., 2012), which places the Congo Basin second in the world after only the Amazon. Figure 3.3 shows the spatial pattern of land cover types across the Congo Basin. The northern and southern parts are dominated by deciduous vegetation types with a predominance of savannah. Wetlands also constitute important features of the basin, and a substantial part of the evergreen forest in the Cuvette Central is regularly flooded and constitutes an important wetland system that interacts with the river channels (O'Loughlin et al., 2019). In the southeast of the basin, there are large wetland systems made up of natural lakes and shallow wetlands of different types (Figure 3.3).

The spatial variability of the land cover is reflected to a certain extent in the variability in hydrological processes and is one of the variables used in the calculation of the SCS curve number (Williams et al., 2012; Zeng et al., 2017; Peña-arancibia et al., 2019; Yang et al., 2019), which is used in many hydrological models for runoff generation.

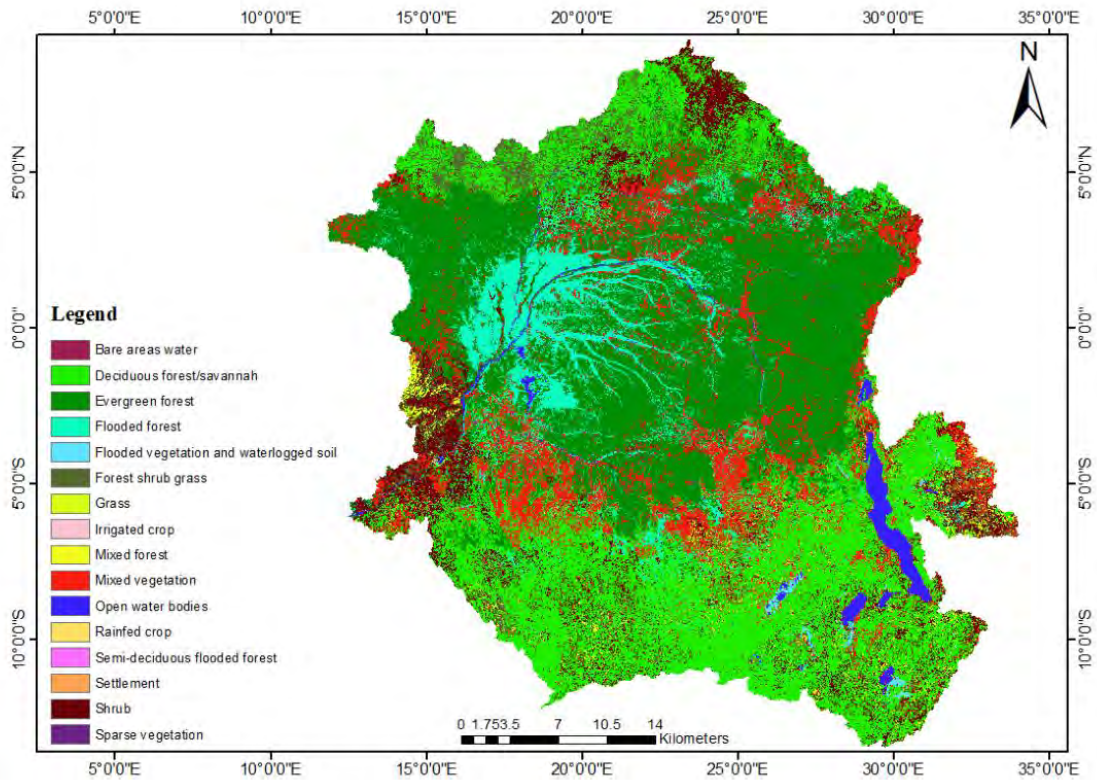


Figure 3.3. The spatial pattern of land cover types across the Congo Basin. The map has been reconstructed based on the global Globcover 2009 products at a spatial resolution of 300 m.

3.2.3 Soil and geological characteristics

The heterogeneity of the soil types and geological settings are also two of the factors affecting the spatial variability in hydrological dynamics across the Congo Basin (Tshimanga and Hughes, 2014). The soil map (Figure 3.4) of the Congo Basin, derived from the harmonisation of the soil map of Africa at the continental scale (Dewitte et al., 2013), shows the dominance of ferralsols (50.2%). These soil types occupy mainly the central part of the basin, while the south-western part is dominated by Acrinosols (14.8%). The east-southern (Lualaba drainage system) part is more

heterogeneous and is well represented by Acrisols and Cambisols, although they can also be found near the Atlantic Ocean coastal areas and in the most downstream part of the Kasai drainage system. Gleysols (5.4%) are mostly characteristics of the permanently flooded forest of the Cuvette Centrale. Plinthosols (5.1%) characterise the northern parts mostly in the Oubangui drainage system and the downstream part of the Sangha drainage system (Figure 3.1 and Figure 3.4).

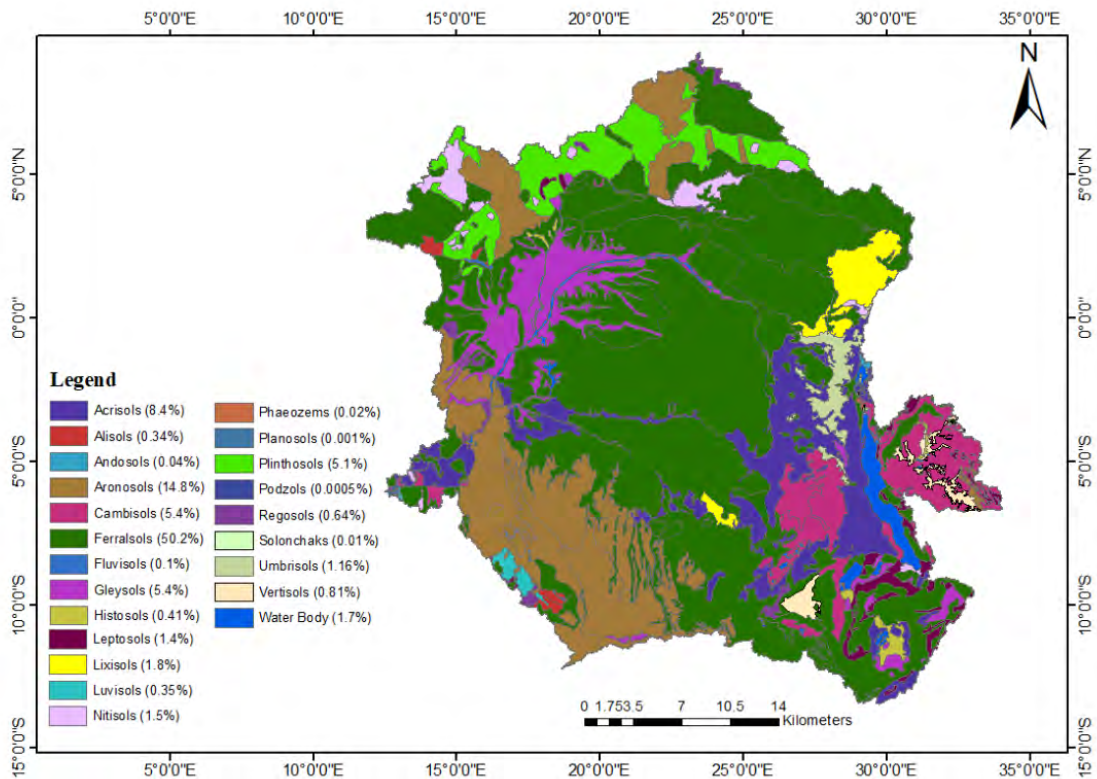


Figure 3.4. Major soil groups found across the Congo Basin (derived from Dewitte et al. (2013)).

A geological map of the Africa Groundwater Atlas (Ó Dochartaigh, 2019) is presented in Figure 3.5.

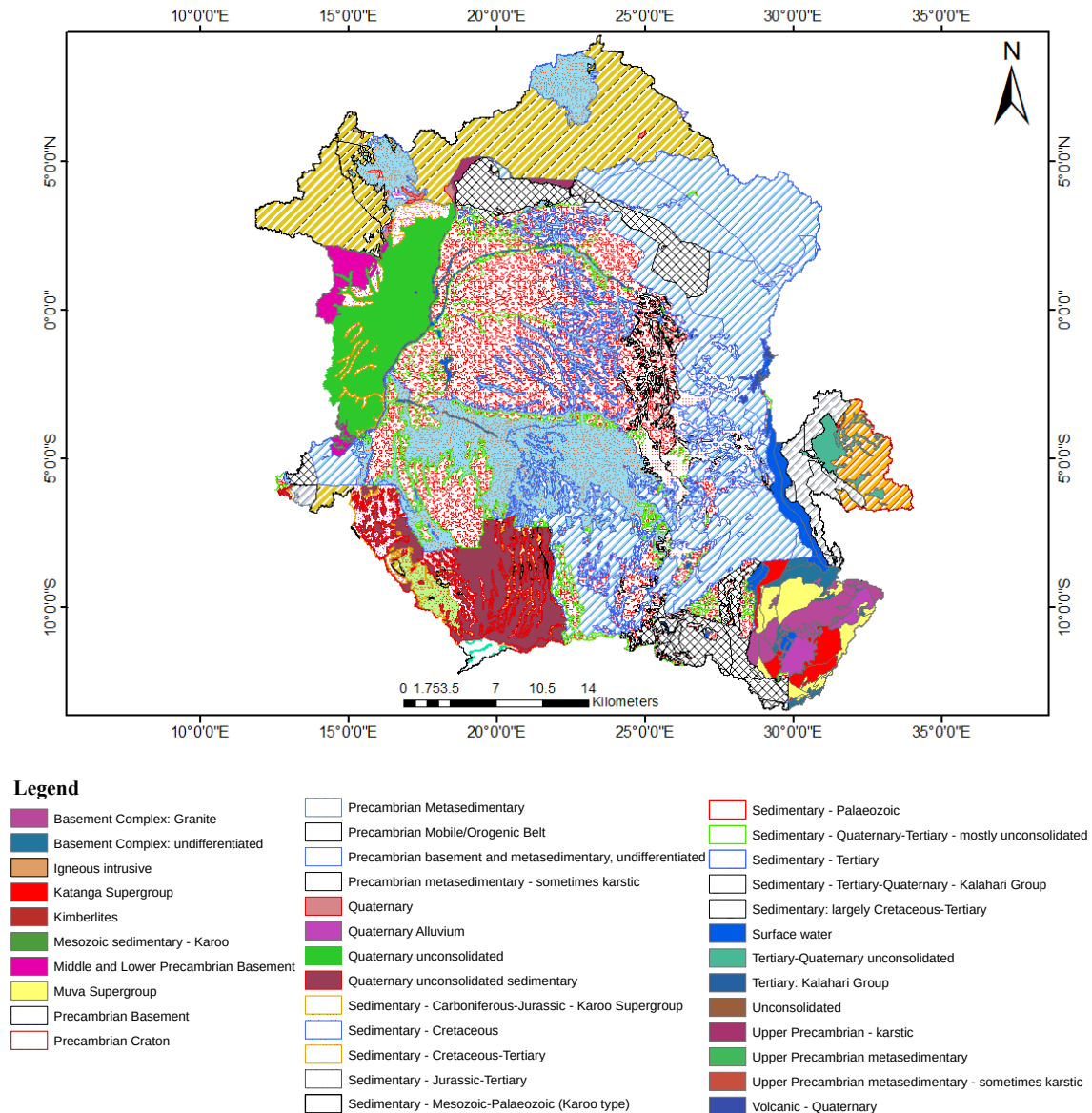


Figure 3.5. The spatial pattern of geology across the Congo Basin (adapted from the Africa Groundwater Atlas by Ó Dochartaigh, 2019).

Sedimentary rocks of the Cenozoic and Mesozoic occupy the centre of the basin, while Palaeozoic and Neoproterozoic sediments outcrop at the periphery of the basin (Kadima et al., 2011). This means that the basin is dominated by sedimentary rocks of different types (with regards to age) that translate into different hydrogeological systems with different levels of groundwater productivity. For instance, the Precambrian basement and metasedimentary undifferentiated rocks are found along the eastern part of the basin (Figure 3.5). These rocks form groundwater aquifers

with low to moderate productivity (MacDonald et al., 2012). The northern part, in the Oubangui and Sangha drainage systems, is dominated by Precambrian basement rocks with low to moderate groundwater productivity in the Oubangui region, while the western Sangha reflects a moderate to high productivity. The western part of the Congo Basin, including the Batéké plateaux system (located in the western lower part of the middle Congo: Figure 3.1) as well as the western part of the Cuvette Central, is underlain by Quaternary unconsolidated sedimentary aquifers with moderate to high productivity. In particular, the valleys of the Batéké plateaux are underlain by sedimentary Cretaceous-Tertiary aquifer systems that regulate the hydrological response in this sub-region (Laraque et al., 1998; Laraque et al., 2020). The heterogeneity observed in the geological formations of the upper Lualaba drainage system (southeast part of the Congo Basin) may be indicative of different groundwater flow regimes, which are reflected in the low flow patterns of the available streamflow data.

3.2.4 Topography

Full details of the basin topography are well documented in Runge (2007) and are not repeated here. However, one of the key topographic characteristics is the presence of topographic highs that surround the basin (Kadima et al., 2011) and form headwater areas from which the flow is produced to contribute to the main drainage systems (Oubangui River in the north-east, Sangha River in the north-west, Kasai River in the south-west and Lualaba River in the south-east: Figure 3.1) all of which converge to form the main Congo River. A major proportion of the Congo Basin topography is at a low elevation, forming a concave shape for the cumulative distribution function (CDF) of elevations, indicating a level of erosion process or sediment deposition that the basin has experienced over geological times. According to Vivoni et al. (2008), the shape of the CDF curves of basin elevations provide valuable information on the dominant basin morphological features and hence the likely dominant hydrological processes. The Congo Basin presents variable forms of these CDF curves that can be used as proxies for hydrological process understanding. Concave, convex and straight curves have been derived for different parts of the Congo Basin and suggest different underlining hydrological processes (Tshimanga et al., 2020a).

A previous study delineated the Congo Basin into 99 modelling units, 83 resulting from an analysis of the dominant slopes and elevations, while 16 sub-basins were included based on the locations

of the key gauging stations (Tshimanga, 2012). As a result, the smallest modelling unit was 533 km², while the biggest was 185 835 km². In a recent study (Tshimanga et al., 2020), a similar delineation procedure was undertaken but using a revised Digital Elevation Model (MERIT DEM: Yamazaki et al., 2017) which was corrected to remove vegetation height effects. This is particularly important for the Congo River Basin given the extent of dense tropical forest. The new delineation resulted in 403 sub-basins (Figure 3.6) that are considered appropriate to represent natural hydrological variability and that account for the current water resources management needs within the basin. For this study, the entire basin is used for the development of the hydrological indices ranges (Chapter 5) and only 147 sub-basins (Figure 3.6) are used for testing the hydrological indices ranges within the hydrological modelling uncertainty framework. These sub-basins are found in the Lualaba (93 sub-basins), Sangha (24 sub-basins), Oubangui (19 scattered sub-basins), Batéké plateaux (4 sub-basins), Kasai (4 sub-basins) and Inkisi (3 sub-basins) drainage systems. Their choice was based on the availability of the streamflow data.

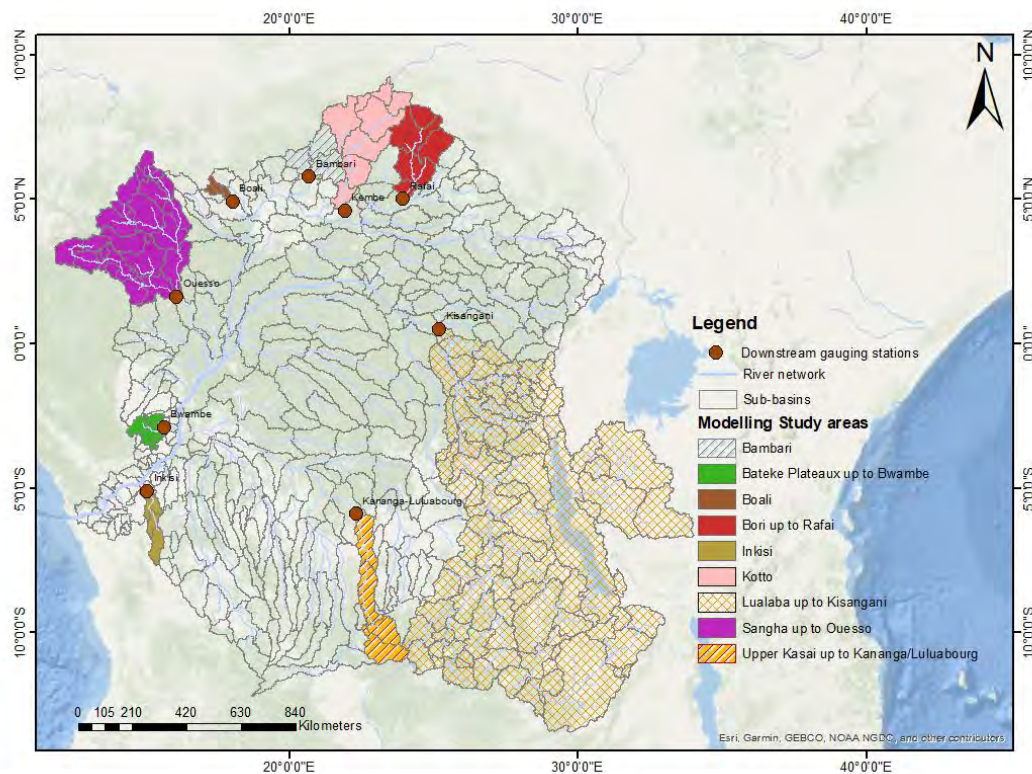


Figure 3.6. Selected 147 sub-basins across the Congo Basin for the testing of hydrological indices ranges within the hydrological modelling uncertainty framework.

3.3 Wetland systems of the Lualaba drainage system

Among the wetland systems of the upper Lualaba drainage systems, five are used for the hydrodynamic modelling (Ankoro, Kamalondo, Kundelungu, Mweru and Tshiangalele) because they are known as shallow, while two (lake Kivu and lake Tanganyika) are used without hydrodynamic modelling to derive wetland parameters based on observed information. While the Congo Basin has many wetland systems (Bwangoy et al., 2010) including those of the Cuvette Centrale, the wetland systems of the upper Lualaba are selected for the following main reasons:

- Their location and extents: they are rightly located in the upper Lualaba drainage system such that a large proportion of the Lualaba drainage system is located downstream and is hydrologically affected by their effects;
- Availability of upstream gauging stations to validate hydrological inputs to the wetlands;

Figure 3.7 shows the location of the five wetland systems used for hydrodynamic modelling. The general characteristics of these wetlands are given in Table 3.1. The long-term mean monthly water depths at the outlet of Kisale Lake (at Kadia) (Figure 3.8), one of the many lakes within the Kamalondo wetland system, indicate that April and May are the months of highest peak occurrence (Devroey, 1941), while the period September to November is the lowest.

3.3.1 Lake Kivu

Lake Kivu is one of the African Great Lakes located in the eastern Congo Basin. The lake is approximately 90 km long and 50 km at its widest, making a surface area of 2 700 km². Lake Kivu empties into the Ruzizi River (Ruzizi gauging station), which flows southwards into Lake Tanganyika (Figure 3.9). The lake has a maximum depth of 475 m and a mean depth of 220 m.

3.3.2 Lake Tanganyika

Located in eastern Africa's Great Rift Valley region, the lake basin drainage area is about 238 520 km². This area includes both lake Kivu and Tanganyika. The basin is shared by five countries namely Burundi (5.8%), DR Congo (18.3%), Tanzania (67.6%), Rwanda (1.8%) and Zambia (6.5%). The lake is the deepest in Africa (average depth: 570 m) and has the largest area (32 900 km²) among the Albertine rift lakes. The main inflows to the lake include the Ruzizi (at Ruzizi)

and Malagarasi (at Mbelagule) Rivers and the outflow is through the Lukuga River (at Lukuga) in DR Congo (Figure 3.9). The average aridity index is 1.34, but varies greatly across the sub-basins. The sub-basins of the Ruzizi River in the north of Tanganyika lake are more humid (AI: 0.81 – 0.91) than those in the eastern sub-basins (AI: 1.2 - 1.5).

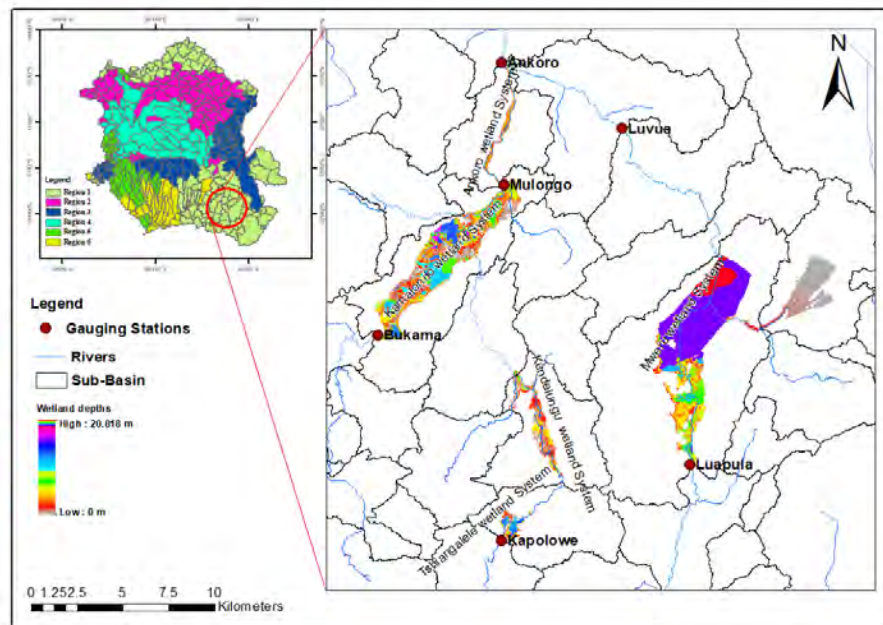


Figure 3.7. The Location of the five-wetland systems in the upper Congo River Basin.

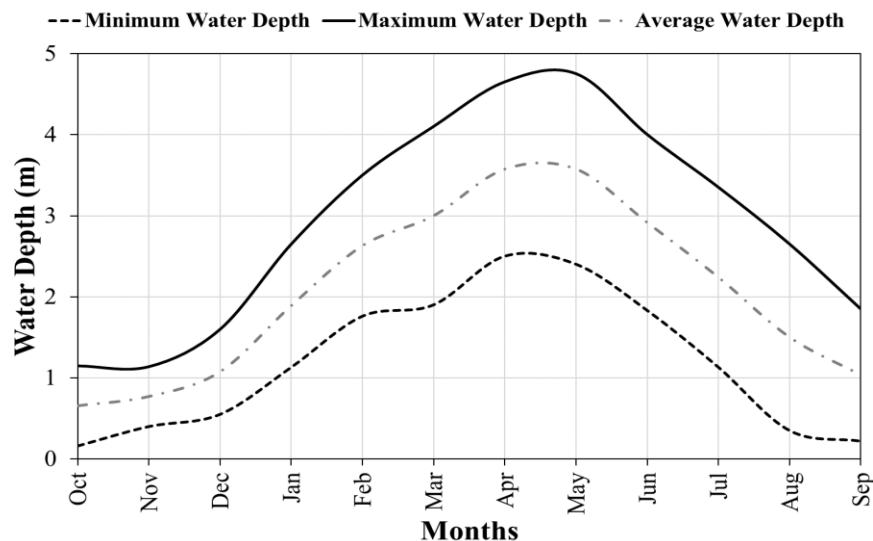


Figure 3.8. Long-term average monthly water depth fluctuation at the outlet of Lake Kisale (at Kadia) between 1921 and 1938.

Table 3.1. General description of the five wetland systems

Wetland name	General description	Climate	Inflow and Outflow
Ankoro	Located in the downstream reaches of the Kamalondo wetland system between the Mulongo and Ankoro gauging stations.	• MAR: 1112.5 mm; • MAPE: 1671.5 mm; • AI: 1.5	One main inflow from Mulongo gauging station in the south. It outflows at the north, downstream of the Ankoro gauging station.
Kamalondo	It comprises a complex mosaic of fifty to ninety lakes of various sizes within the extensive swamps of Phragmites and Cyperus papyrus, surrounded in turn by floodplains (Cotterill, 2005). It is located within a rift valley bordered by a mountainous range on the East, and the Kamina plateau on the West culminating at 1000 - 1100 m amsl. Geologically, it is believed that the Kamalondo wetland system was once covered by an ancient lake that has been infilled with sedimentation from the Lualaba, Lufira, and Lovoi rivers (Denny 1985; Bailey and Banister, 1986).	• MAR: 1015.8 mm; • MAPE: 1647.1 mm; • AI: 1.62	Four main sources: the main stem of the Lualaba River at the Bukama gauging station in the south; the Lufira River in the southeast, the Lovoi River in the west and the Kalumengongo River in the East. It outflows at Mulongo gauging station in the north.
Kundelungu	Located in the Lufira valley just downstream of the Tshiangalele wetland system. It is made up of a chain of several shallow depressions along the river course. Some authors used the name Lufira wetlands to refer to the wetlands within the Lufira valley (Hughes and Hughes, 1992), while the name Kundelungu wetland refers to its proximity to the Kundelungu national park.	• MAR: 959.6 mm; • MAPE: 1564.2 mm; • AI: 1.63	Three main inflows: outflow from the Tshiangalele wetland; Dikulwe tributary in the western part and Lufwa River in the eastern. It outflows to the Lufira falls in the north.
Mweru	It is a large wetland system in which there is the floodplain along the Luapula River before it discharges into Lake Mweru. The average depth of the lake is 7.5 m with an area and volume of 5 120 km ² and 38 200 × 10 ³ m ³ , respectively (Bos et al., 2006).	• MAR: 1114.4 mm; • MAPE: 1565.2 mm; • AI: 1.4	Two main inflows: Luapula River at Kasenga gauging station located in the south; Kalunguishi River in the east. It outflows in the north at Pweto.
Tshiangalele	It is known also as Mwadingusha Reservoir. It is roughly rectangular and extends over a length of 25 km with a maximum width of 24 km and an area of around 362.5 km ² that can exceed 440 km ² during flood periods. The system has an average and maximum depths of 2.6 m and 14 m, respectively.	• MAR: 1061.5 mm; • MAPE: 1474.2 mm; • AI: 1.4	The main inflow to the lake comes from the Lufira River, which has a gauging station at Kapolowe with interrupted periods of historical discharge observations between 1921 and 1959 (Devroey, 1948). It outflows in the north to Lufira River.

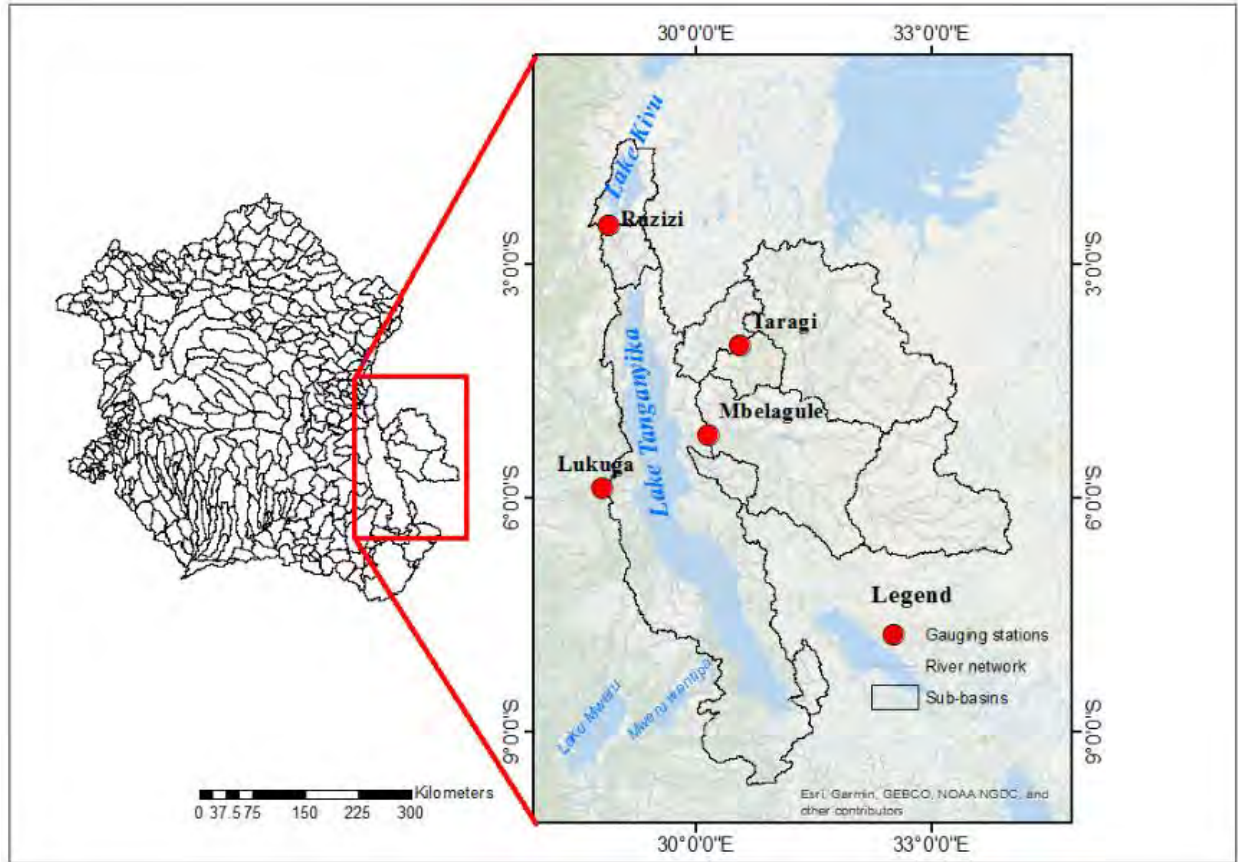


Figure 3.9. Lake Tanganyika basin including both lake Kivu and Tanganyika.

3.4 Datasets

This sub-section describes the datasets that were used to accomplish the specific objectives as outlined in the introduction Chapter. The data used in Chapter 5 and 6 for the quantification and modelling of hydrological uncertainty include: streamflow, rainfall, potential evapotranspiration and physiographic data. Other data used in Chapter 7 for the hydrodynamic modelling of river channel and wetlands include channel bathymetry and Landsat imagery.

3.4.1 Streamflow

Streamflow time series for 63 gauging stations (Figure 3.10 and Tables A.3.1 to A.3.5 in Appendix A), with different periods of record, were obtained from several sources including: the Global Runoff Data Centre (Fekete et al., 1999), the Office National de Recherche et du Developpement (Lempicka, 1971), Hydrosiences Montpellier—Système d'Informations Environnementales

(SIEREM, <http://hydrosociences.fr/sierem>) and the Annuaire hydrologique du Congo Belge (Devroey, 1951-1959). Less than 25% (15 gauging stations) of the gauging stations represent non-impacted headwater flow regimes (Figure 3.10), while the majority are located in the downstream parts of the basin and represent cumulative streamflow characteristics from relatively large catchment areas. Headwater gauging stations are useful for establishing regional variations of the hydrological indices (Chapter 5), but indices obtained from downstream stations will include mixtures of different upstream sub-basin hydrological responses and are therefore less directly useful. Gauging stations downstream of some known large wetland systems or any major water resources infrastructure, are excluded and not used to quantify the hydrological indices. However, these are used to assess and validate the impacts of wetlands simulated by the PITMAN model (Chapter 7), and therefore the validity of the wetland sub-model parameters that are estimated from the application of the hydrodynamic model (LISFLOOD-FP).

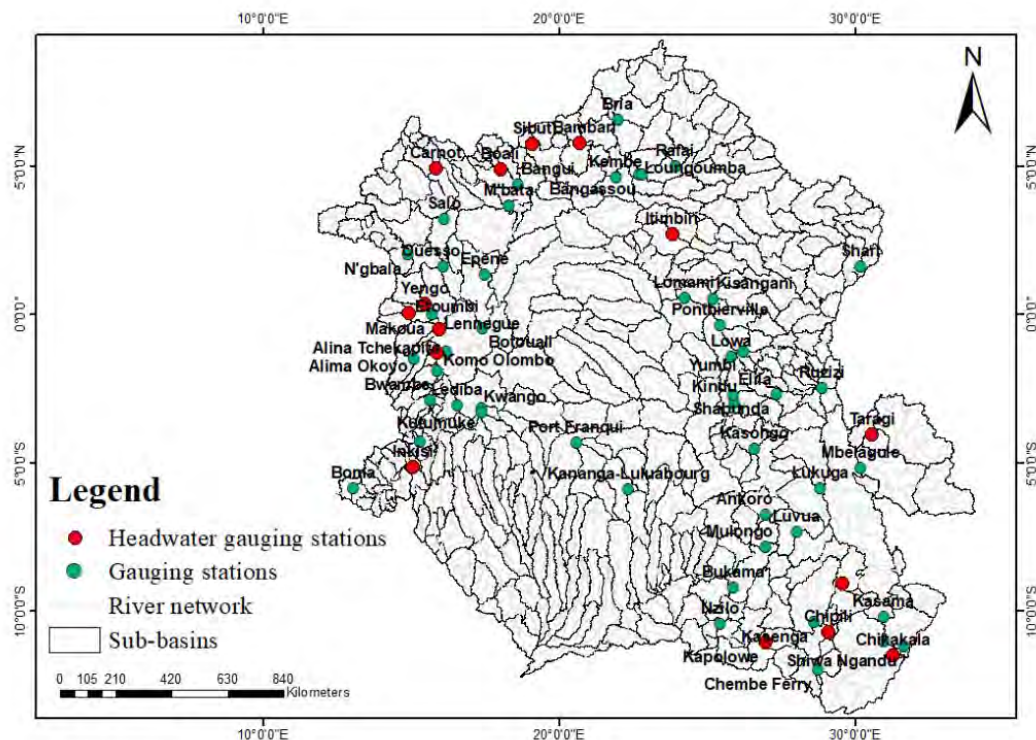


Figure 3.10. Location of the available gauging stations across the Congo Basin.

The downstream gauging stations are used in Chapter 6 to test and assess the validity of the simulated downstream uncertainty bounds that result from the regionalised uncertainty ranges of

the hydrological indices that are developed in Chapter 5. The different parts of the Congo Basin have contrasting hydrological regimes (Figure 3.11), depending on whether a gauging station is located in the north or south of the basin. Northern and southern gauging stations display a unimodal monthly distribution pattern (Figure 3.11ac), but with different wet seasons. Those located close to the equatorial line present a bimodal pattern (Figure 3.11b) and the main Congo River has a quite regular hydrological regime with relatively small variations within the hydrological year.

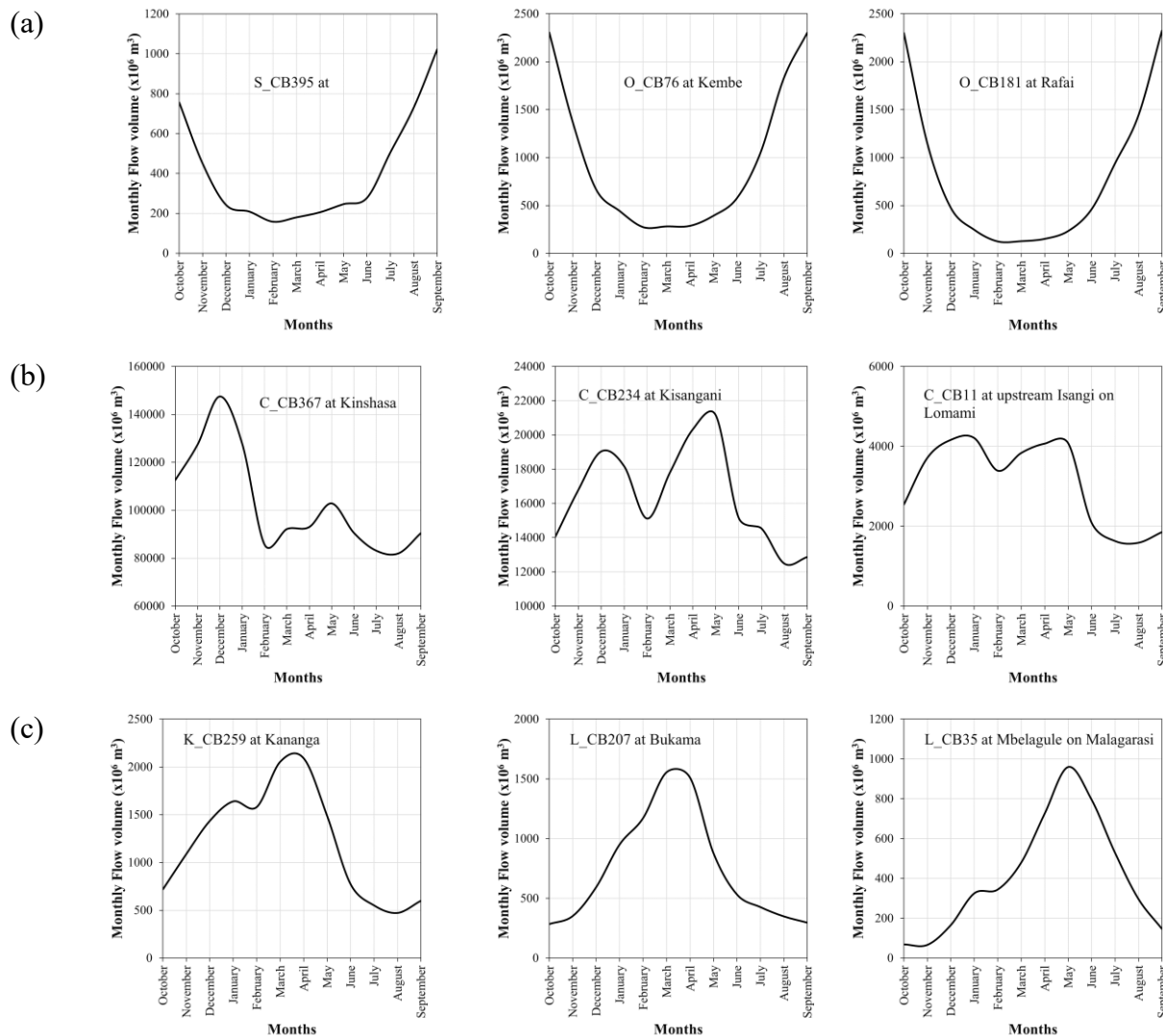


Figure 3.11. Streamflow monthly distributions (long-term averages) showing different flow patterns across geographic regions of the Congo Basin for selected gauging stations. (a) Northern sub-basins, (b) Equatorial belt sub-basins and (c) Southern sub-basins

3.4.2 Climate

The climate data used (rainfall and evapotranspiration) are from the Climate Research Unit (CRU TS 3.10) data for the period of 1901 to 2014 (Harris et al., 2014), at a spatial resolution of 0.5°. They are used:

- To derive an aridity index (the ratio of mean annual evapotranspiration to mean annual rainfall) as a potential predictor of hydrological behaviour, as reported in many hydrological studies (Beck et al., 2015; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017; Zhang et al., 2018) and the runoff ratio, in Chapter 5;
- To provide the climate forcing data for the PITMAN model (Chapter 6 and 7). However, the monthly distributions of potential evapotranspiration that are used in the model are derived from the International Water Management Institute website (<http://www.iwmi.org>) and have been computed using climate information derived from New et al. (2002) for the period centred on 1961 to 1990. The CRU rainfall data have been successfully used for hydrological modelling in the Congo Basin (Tshimanga and Hughes, 2014).

The UNIDEL (University of Delaware) rainfall dataset (covering the same period and spatial resolution) was used to check the appropriateness of the CRU rainfall data in specific areas (Sun et al., 2018). FEWS daily rainfalls are also used and they provide daily precipitation at 0.1° spatial resolution over Africa from 1983 to the present day (Novella and Thiaw, 2012). Daily rainfall data are used in two ways: first, for the disaggregation process of converting simulated monthly flows into daily, and second as daily rainfall inputs for the computation of the net potential evapotranspiration, a requirement for the hydrodynamic model.

The use of global climate datasets is justified by the lack of adequate ground-based information available for long periods and with good spatial coverage. However, the paucity of rainfall gauges over the Congo River Basin suggests that only limited observed records are used to construct and validate the global datasets, contributing to potential errors and input uncertainties (Tshimanga, 2012; Maidment et al., 2015; Sun et al., 2018). While these uncertainties are likely to be quite important for hydrological modelling, they are less likely to have a large impact on the derivation of climate indices.

3.4.3 Physiographic data

This dataset is used in Chapter 5 for the physiographic classification of the Congo Basin. It includes the topographic wetness index (TWI), slope, soil textures (fractions of silt, sand and clay) and curve number (CN). These physiographic properties (Table 3.2) have been previously reported elsewhere (Beck et al., 2015; Buchanan et al., 2014; Sørensen et al., 2006; Williams et al., 2012; Zeng et al., 2017; Peña-arancibia et al., 2019; Yang et al., 2019) as being important in understanding and regionalising sub-basin runoff responses and they were recently used in the Congo Basin for their potential in capturing basin hydrological behaviour (Kabuya et al., 2020b). Figure 3.12 suggests that high CN values (implying high runoff potential) mostly occur in the upper Lualaba drainage system (South-eastern part of the Congo Basin), south-eastern of upper Kasai drainage system, northern Oubangui drainage system and headwater sub-basins of the northern Sangha drainage system. The lowest CN values (implying low runoff potential) are observed mostly in the Cuvette Centrale (central part of the Congo Basin) and the south-western part of the Congo Basin. This heterogeneity in the CN values can be viewed as an indication of complexity in hydrological processes across the basin.

Table 3.2. Description of sub-basins attributes used for the classification of the Congo Basin

Attribute	Unit	Description	Resolution
Climate			
AI	Unitless	The aridity index is computed as $AI = PET/P$, where P is the mean annual precipitation and PET is the mean annual potential evapotranspiration. Both datasets were extracted from the Climate Research Unit (CRU TS 3.10) from 1901 to 2014 (Harris et al., 2014).	0.5°
Topography			
Slope	%	The average surface slope, computed from the MERIT DEM (Yamazaki et al., 2017)	90 m
TWI	Unitless	The average topographic wetness index, computed from the MERIT DEM (Yamazaki et al., 2017)	90 m
Land cover/Soil types			
CN	Unitless	The curve number is extracted from a global map of curve number developed by Zeng et al. (2017).	500 m
Silt	%	Soil silt content extracted from http://www.isric.org/data/AfSoilGrids (Batjes, 2017).	250 m
Clay	%	Soil clay content extracted from http://www.isric.org/data/AfSoilGrids (Batjes, 2017).	250 m
Sand	%	Soil sand content extracted from http://www.isric.org/data/AfSoilGrids (Batjes, 2017).	250 m

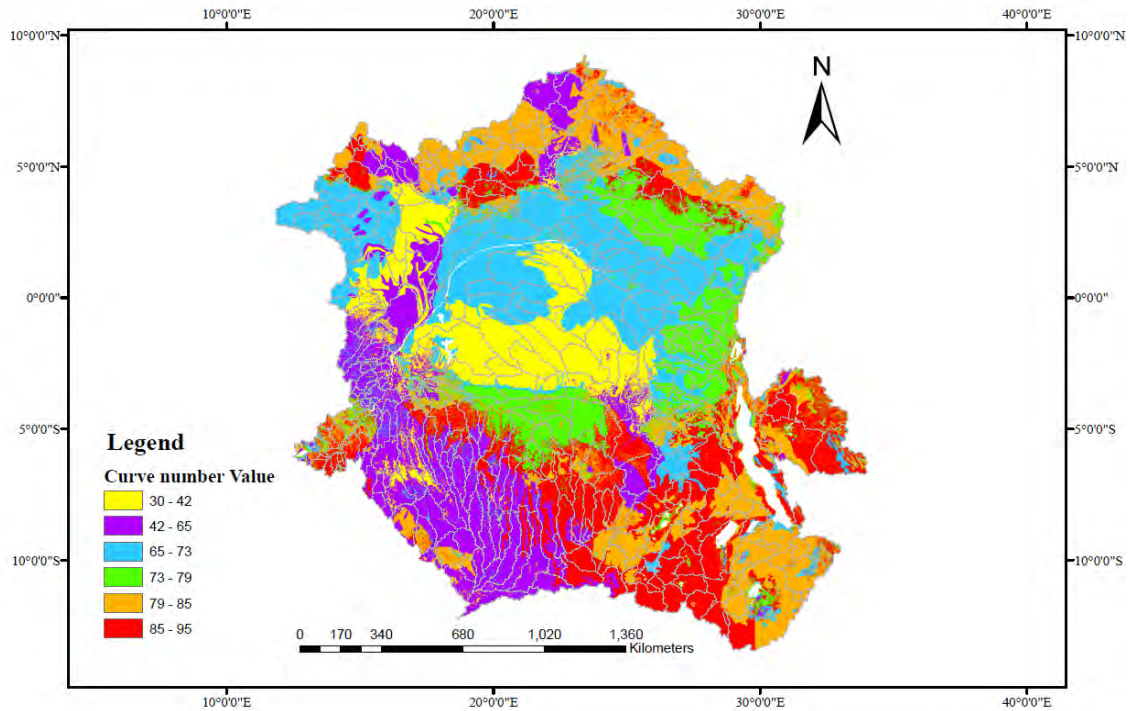


Figure 3.12. Spatial distribution of the Curve number values across the Congo Basin. White spaces represent open water bodies.

3.4.4 River bathymetry and Landsat imagery

In the Congo Basin, in-situ measurements of river bathymetry are very difficult to obtain because it is prohibitively expensive to organise fieldwork at large scales and some areas remain inaccessible because of the lack of adequate transportation infrastructure and political instability. While in-situ measurements of river bathymetry have recently become available for the main Congo River (Carr et al., 2019), the upper Congo in the Lualaba drainage system has no up to date information. The only existing information (Charlier, 1955) is related to channel widths, depths, hydraulic radius and velocity. These parameters (Table A3.6 to A3.12, in Appendix A) exist only for specific reaches over specific periods and they are used in Chapter 7 to derive the initial estimates of the hydrodynamic parameters of the LISFLOOD-FP model. Also, water levels for lakes Kivu and Tanganyika were used for the estimation of the PITMAN wetland sub-model parameters. Landsat imagery (Table 3.3) is useful for the validation of the inundation extent obtained through the application of the LISFLOOD-FP model (Chapter 7).

Table 3.3. Landsat images used for the validation of inundation extents between 2001 and 2004

Wetland system	Image dates	Landsat sensor	Bands used
Ankoro	09-Apr-02	Landsat 7	Band 2 (green)
	11-May-02	Landsat 7	and Band 5
Kamalondo	20-Feb-02	Landsat 7	(short wave
	27-Mar-03	Landsat 7	infrared)
Kundelungu	14-Mar-01	Landsat 7	
Mweru	27-Apr-02	Landsat 7	
Tshiangalele	24-Aug-02	Landsat 7	
	16-Feb-03	Landsat 7	
	21-Apr-03	Landsat 7	

3.5 Concluding remarks

This chapter has presented the characteristics of the Congo Basin including those of specific wetland systems. It clearly shows that the basin has a heterogeneous climate and physiography, which will translate into the spatial variability of its hydrological processes. The structural morphological characteristics of the wetland systems indicate potential connections between these systems and the river channels passing through them. Combined sources of information, including local in-situ observations and global datasets, are used to deal with the problems of data scarcity and short record periods. The next chapters (Chapter 5, 6 and 7) presents the research results, obtained from the application of the models and different datasets described here, while Chapter 4 presents the general methodological framework.

CHAPTER 4 : METHODOLOGICAL FRAMEWORK

4.1 Introduction

This chapter presents the integrated methodological framework that was developed for this study. The method integrates a hydrological model (PITMAN) and a hydrodynamic model (LISFLOOD-FP). The choice of the hydrological model is based on three reasons. The first is its adaptability to ungauged regions (Hughes, 2013), where it requires only minimal information that can be available in the data-scarce areas. The second is based on the number of processes represented in the model, making it suitable for regions characterised by high variability in climate and physiography (Hughes, 2016). Finally, its long history of use as a water resources assessment tool, for addressing the many societal problems associated with managing water resources, and as a scientific investigation tool in the Southern Africa region (Kapangaziwiri et al., 2012; Hughes, 2013; Tshimanga and Hughes, 2014; Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017; Oosthuizen et al., 2018). The LISFLOOD-FP model is also appropriate for data-scarce regions and represents the physical processes of channel-wetland exchanges in a relatively simplified manner, making it applicable for simulating large wetlands (Schumann et al., 2013; Rudorff et al., 2014a; Komi et al., 2017; O'Loughlin et al., 2019).

It is a common practice in hydrology to link two different models to compensate for the limitations of each one of them in achieving the overall objectives of any simulation study. The LISFLOOD-FP model requires hydrological inputs to quantify upstream boundary conditions. While direct in-situ observations may be the ideal, such data are infrequently available in the Southern Africa region. Therefore, hydrological model simulations are necessary to provide the necessary inputs. Schumann et al. (2013) used hydrological simulations from the variable infiltration capacity (VIC) model to set up the boundary conditions and simulate the hydrodynamic behaviour of the Lower Zambezi River. In similar examples (Schumann et al., 2013; Komi et al., 2017; O'Loughlin et al., 2019), both the hydrological and hydrodynamic models were fed with daily information to also output daily variables. However, the hydrological model used in this study only operates at a monthly time step, which prompted the use of an additional routine for disaggregation of the monthly output simulation to daily simulation.

This chapter describes the details of the two models (PITMAN and LISFLOOD-FP) and how they have been integrated. The overall methodological approach is illustrated in Figure 4.1. Six components of the methodological approach include: the hydrological modelling, the hydrodynamic modelling, hydrodynamic process understanding, geomorphological analysis of wetlands, wetland multi-variable analysis and the simulation of wetland downstream flow regimes. Some of the details associated with the individual components of this study are presented in subsequent Chapters.

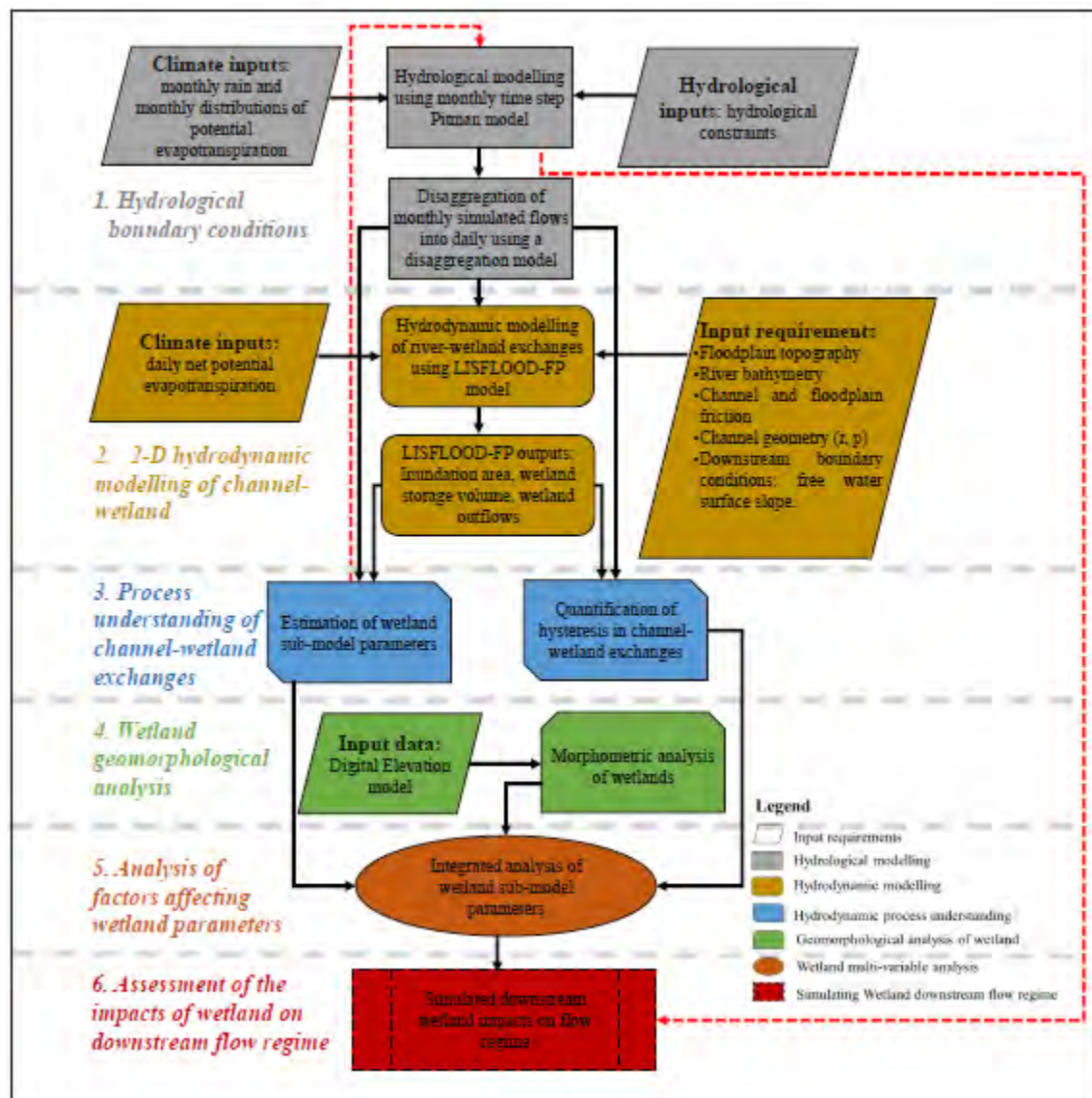


Figure 4.1. The overall methodology used in this thesis, showing the interaction between different modelling components.

4.2 Hydrological modelling

This sub-section describes the main processes of the hydrological model (PITMAN) used in this study. It also focuses on the modelling approach adopted for accounting for hydrological uncertainty analysis across the study areas.

4.2.1 PITMAN Rainfall-Runoff Model

The PITMAN model is a conceptual semi-distributed monthly time step rainfall-runoff model that was initially developed in South Africa in the 1970s (Pitman, 1973). Since then, it has undergone many revisions by the original developer and others (Hughes, 2004, 2013). However, the original conceptual form has been retained. The model consists of storages (interception, soil moisture and groundwater) linked by functions to represent the main runoff generation processes (infiltration excess, saturation excess and direct overland flow, interflow and groundwater flow) considered to occur at the sub-basin scale. Some of the revisions that have been added by the Institute for Water Research (IWR) at Rhodes University include the addition of an explicit groundwater recharge and discharge component (Hughes, 2004) as well as a saturation excess function as part of the surface runoff generation processes (Hughes and Mazibuko, 2018). Figure 4.2 illustrates the model structure, while a brief description of the model parameters is given in Table 4.1. The PITMAN model is embedded within the SPATSIM (Spatial and Time Series Information Modelling) software (Hughes, 2002; Hughes and Forsyth, 2006), which is an integrated data management and modelling software package developed at the Institute for Water Research (IWR) of the Rhodes University. SPATSIM is available at no cost from the IWR website, which also includes some guidelines on the use of SPATSIM and some of the models (including the Pitman model) that are embedded within the main framework (<https://www.ru.ac.za/iwr/research/software/>).

Many of the model components and associated parameters (Table 4.1) are well explained in many published papers (Hughes et al., 2006; Hughes, 2013; Hughes, 2015), but a brief description of the main components and parameters responsible of runoff generation is presented in the subsequent sections.

Table 4.1. Description of PITMAN model main parameters

Model Parameter	Description	Units
RDF	Rain Distribution factor	[-]
PI1 and PI2	Interception storage for two types of vegetation	mm
AFOR	The proportion of the basin area covered by the second vegetation type	%
FF	The ratio of forest/grassland potential evapotranspiration	[-]
SER	Fraction of ST at which saturation excess runoff is initiated	[-]
PEVAP	Annual sub-basin Evaporation	mm
ZMIN, ZAVE, ZMAX	Minimum, average and maximum soil absorption rate for each sub-basin	mm month ⁻¹
ST	Maximum moisture storage capacity	mm
FT	Runoff from moisture storage-runoff equation	mm month ⁻¹
POW	Power of the moisture storage-runoff equation	[-]
GW	Maximum groundwater recharge at moisture storage full capacity	mm month ⁻¹
GPOW	Power of moisture storage - groundwater recharge equation	[-]
R	Evaporation-moisture storage relationship	[-]
CL	Channel routing coefficient	Months
TL	Lag of surface and soil moisture runoff	Months
DDENS	Drainage density	km/km ²
T	Groundwater transmissivity	m ² day ⁻¹
S	Groundwater storativity	[-]
RGWS	Initial groundwater drainage slope	%
GWL	Rest water level (m below surface)	m
RSF	Riparian Strip Factor	%

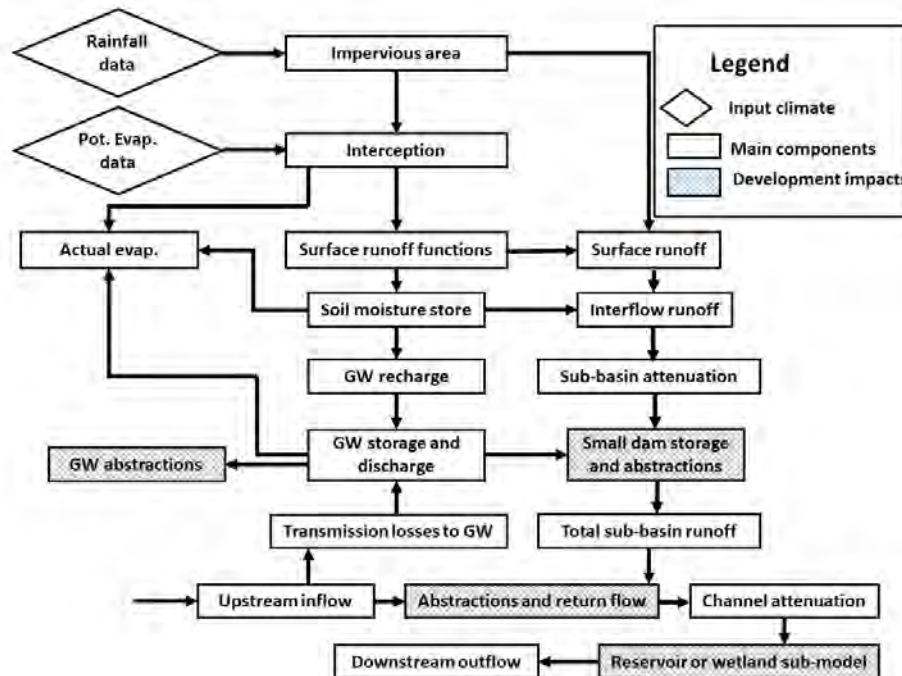


Figure 4.2. Structure of the PITMAN model with its main components.

4.2.1.1 Surface runoff

Surface runoff is generated from three possible functions (Hughes, 2013). The first contribution results from direct runoff from the proportion of the sub-basin represented by impervious areas (AI). The runoff generated is simply the product of the rainfall times the impervious area. This parameter is typically set to zero when dealing with natural sub-basins that do not have urban areas directly connected to the channel network. The second means of surface runoff is conceptualised as saturation excess runoff and uses a nonlinear relationship between the relative moisture status of the sub-area and the proportion of the sub-area contributing to the runoff. The power of the relationship is fixed, while the threshold for initiation of runoff is parameter SER in Table 4.1. As part of this function, any additions to soil moisture storage that exceeds the maximum soil moisture storage will also contribute to surface runoff (Hughes and Mazibuko, 2018).

The equation that represents the saturation excess function takes the form of:

$$SER (fraction) = \left[\frac{(S-ST*SSR)}{(ST-ST*SSR)} \right]^{SPOW} \quad \text{Equation 4.1}$$

$$SER (mm|month) = SER * Rain (mm|month) \quad \text{Equation 4.2}$$

Where S is the current depth of moisture storage (mm), ST is the maximum storage parameter (mm), SSR is the minimum storage depth (mm) for runoff to occur, and SPOW is the power of the relationship. When $S < SSR$, SER is set to zero.

The third function is based on an asymmetrical triangular distribution of catchment absorption rates defined by parameters ZMIN, ZMAX and ZAVE (Figure 4.3). In this case, the surface runoff rate (mm month^{-1}) is determined by the area under the cumulative frequency of the absorption rate at the point of intersection with the rainfall input. Recently, further development of the model introduced the asymmetry into the infiltration excess runoff function, where a ZAVE value of 0.5 represents symmetry and other values between 0 and 1, asymmetry (Hughes and Mazibuko, 2018). The sequence of the runoff modelling process is such that the saturation excess function operates first, followed by the catchment absorption function and finally, the soil moisture water balance calculations including interflow and recharge.

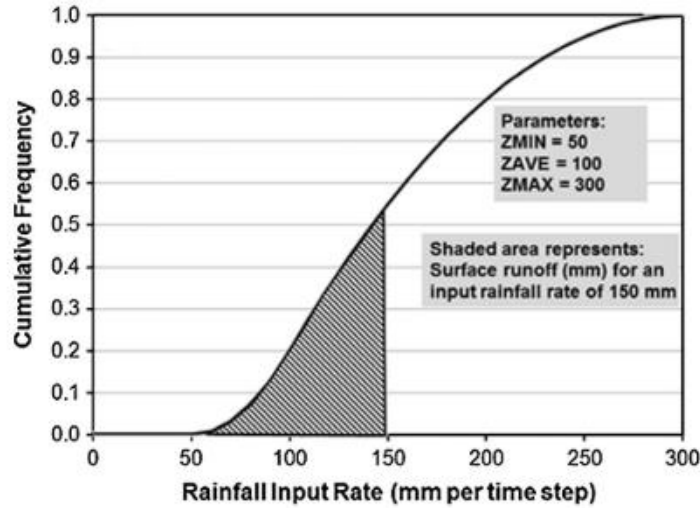


Figure 4.3. Catchment absorption rate following an asymmetrical triangular distribution (taken from Hughes (2013)).

4.2.1.2 Sub-surface processes

The sub-surface runoff processes within the PITMAN model are interflow and groundwater recharge (Figure 4.4). The interflow is the drainage from the soil moisture storage and is defined using a power equation as in Equation 4.3.

$$Q = FT \left[\frac{(ST - S)}{(ST - SL)} \right]^{POW} \quad \text{Equation 4.3}$$

Where Q is interflow, FT is the maximum interflow rate (mm month^{-1}), ST is the maximum storage (mm), SL is the storage (mm) below which the interflow ceases, S is the current storage (mm). POW is a parameter representing the power of this relationship. The groundwater component is included in the IWR version of the PITMAN model as a separate function (Hughes, 2004) rather than being associated with interflow, as it was the case in the original model (Pitman, 1973). The function uses the same type of equation as used for the interflow (Equation 4.4).

$$RE = GW \left[\frac{(ST - S)}{(ST - SLG)} \right]^{GPOW} \quad \text{Equation 4.4}$$

Where RE is Recharge, GW is the maximum recharge, SLG is the storage (mm) below which recharge ceases, and GPOW is the power parameter. The maximum interflow and recharge rates occur when the soil moisture is at its full capacity ($S=ST$) and when the moisture levels are below the saturation, the power functions (POW and GPOW) are used to determine the interflow and groundwater rates.

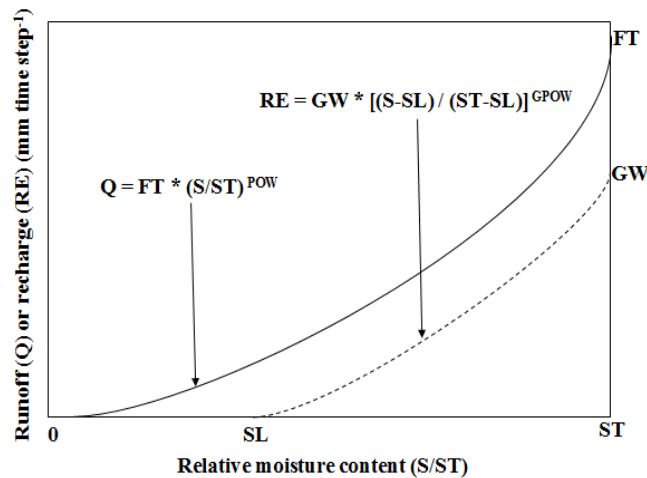


Figure 4.4. Maximum interflow rate and maximum groundwater recharge as a function of the soil moisture content (taken from Hughes (2013)).

4.2.1.3 Evaporation coefficient (R)

This parameter accounts for the reduction in evapotranspiration relative to soil moisture storage. A value close to 1 implies lower rates of evapotranspiration at low moisture states and is typically used for shallow-rooted vegetation. A value close to zero will generate higher evapotranspiration rates and applies to deep-rooted vegetation.

4.2.1.4 Parameters controlling groundwater processes

Apart from the groundwater recharge function (Sub-section 4.2.1.2), six other parameters are used to determine the geometry and water balance of the groundwater storage and the amount of the groundwater that contributes to streamflow. These parameters are the drainage density (DDENS), the groundwater transmissivity ($T \text{ m}^2 \text{ d}^{-1}$), the groundwater storativity (S), the initial groundwater drainage slope (RGWS), the rest water level (RWL in m) and the riparian strip factor (RSF %).

Further details can be found in Hughes (2004), as well as the documentation of the model available from the IWR website (<https://www.ru.ac.za/iwr/research/software/>).

4.2.1.5 Data requirement

The primary input data to the monthly step PITMAN model are catchment area, parameter sets (including mean annual potential evapotranspiration), rainfall time series and monthly distributions of evapotranspiration, while time series of observed discharge are used to calibrate and validate the model simulations when these are available. The IWR version of the model also allows for the input of a time series of monthly evapotranspiration that can over-ride the normal use of the fixed annual value and monthly distribution. Because it is challenging to obtain time series of monthly evapotranspiration, in this study, only the fixed monthly distributions of annual evapotranspiration were used as input data.

4.2.1.6 Hydrological modelling options within PITMAN model

Three modelling options are currently included within the monthly time step PITMAN model. These are the structured uncertainty, the single-run and the 2-stage uncertainty versions. The historical development of the two uncertainty versions (structured and 2-stage) is summarised in sub-section 2.5.2.1 (Hughes et al., 2010; Kapangaziwiri et al., 2012; Tshimanga, 2012; Hughes, 2015). While the uncertainty versions use ranges of parameters with defined distribution (normal, log-normal or uniform) to generate up to 10 000 ensembles using simple Monte Carlo sampling, the single-run version uses single parameter set to simulate flows for each sub-basin (Hughes et al., 2006). In general, parameters are manually calibrated but the task becomes complex when modelling many sub-basins. In this case, structured uncertainty version is run prior to the single-run in order to obtain likely behavioural parameter sets that are then used in calibrating a single-run version (Tshimanga et al., 2011).

4.2.2 Hydrological modelling approach adopted in this study

A 2-stage uncertainty version of the PITMAN model is used (Tumbo and Hughes, 2015; Hughes, 2016; Ndzabandzaba and Hughes, 2017) to simulate sub-basin hydrological responses. A schematic representation of the hydrological modelling process is shown in Figure 4.5.

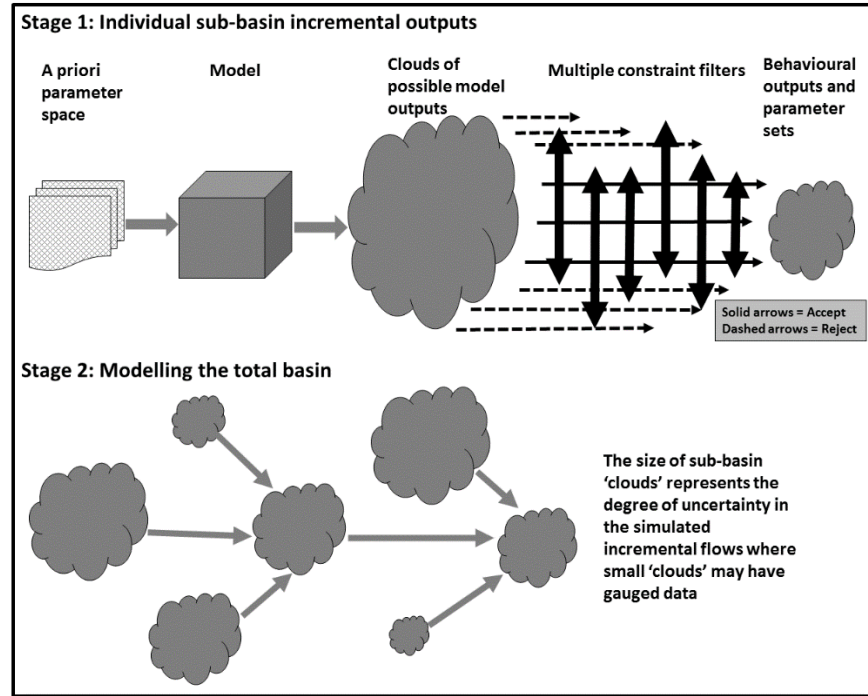


Figure 4.5. Flow diagram of the 2-stage approach to uncertainty analysis used in PITMAN model (flow diagram adapted from Hughes, 2016).

4.2.2.1 Stage 1 of the modelling

Currently, the model uses six constraints namely the mean monthly runoff volume (MMQ in $\text{m}^3 \times 10^6$); the mean monthly groundwater recharge (MMR in mm); the 10th, 50th and 90th percentiles of the flow duration curve (FDC) expressed as a fraction of MMQ and the percentage of zero flow. These constraints were judged to be the minimum number of key indices that can discriminate between different hydrological responses (Ndzabandzaba and Hughes, 2017). The first step of stage 1 of the modelling is the quantification of the constraints and associated uncertainty. As discussed in Sub-section 2.5.2.2, different approaches can be used, to quantify the constraints for each incremental sub-basin based on any available information or a regional study of hydrological response and eventually to fix the constraint ranges. This analysis is performed in Chapter 5.

Once the constraint ranges have been established, the model is set up using only model parameters responsible for a sub-basin's natural hydrology. Out of nineteen (19) parameters representing natural hydrology within the uncertainty version of PITMAN model (Table 4.1), five (5) parameters were considered as fixed values, while fourteen (14) were considered as uncertain

through the uniform probability distribution function. Parameters related to the second vegetation type such as PI2, AFOR and FF (Table 4.1) were not considered representing natural catchment hydrology and, therefore, are not used to simulate the catchment natural hydrology even at stage 2 of the modelling approach. The initial parameter ranges are established based on modelling experiences in the South Africa region, including the Congo Basin (Hughes et al., 2006; Hughes, 2013; Tshimanga and Hughes, 2014). The model then searches for parameter sets, within the input parameter space, that would generate hydrological responses falling within all the input constraint ranges used as multiple filters (Hughes, 2016). All parameter sets falling within all the input constraint ranges are behavioural and the model provides a way of saving them for use in stage 2. The model terminates once a total of 5 000 behavioural parameters is found out of 100 000 model runs (Ndzabandzaba and Hughes, 2017). In case no behavioural ensembles are found, there is a utility that can be used to identify where the problem arises and adjust both the constraint and the parameter ranges to get outputs that are evenly distributed within the constraint ranges, as well as parameter ranges that are not overly biased. This helps to make the stage 1 process run efficiently (i.e. fewer rejections and more rapid identification of behavioural ensembles). The example shown in Figure 4.6 illustrates a situation where the model did not found consistency between the constraint and parameter ranges with no behavioural ensembles found.

Experiences from using this approach have shown that when the mean monthly flow (MMQ) histogram bar is turned towards negative values, and there is no behavioural parameter set found, the problem would be that the parameter space used is not able to generate enough runoff to match the MMQ constraint range. In this case, the ranges of the parameters controlling mostly the runoff generation are adjusted towards high values. There are other situations where the constraint bars are turned towards positive values, and a similar adjustment approach is applied to bring the parameter ranges down towards low values. In Figure 4.6, the main problem is caused by the Q10/MMQ and Q50/MMQ constraints that are over and under simulated, respectively. To solve this problem, key parameters have to be adjusted. The ZMIN parameter was set between 65 and 150 mm month⁻¹, ZMAX between 400 and 800 mm month⁻¹, ST between 900 and 1800 mm, FT between 25 and 75 mm month⁻¹ and GW between 15 and 40 mm month⁻¹. A substantial reduction in ST parameter and slight changes in other parameters have consistently solved this issue as shown in Figure 4.7.

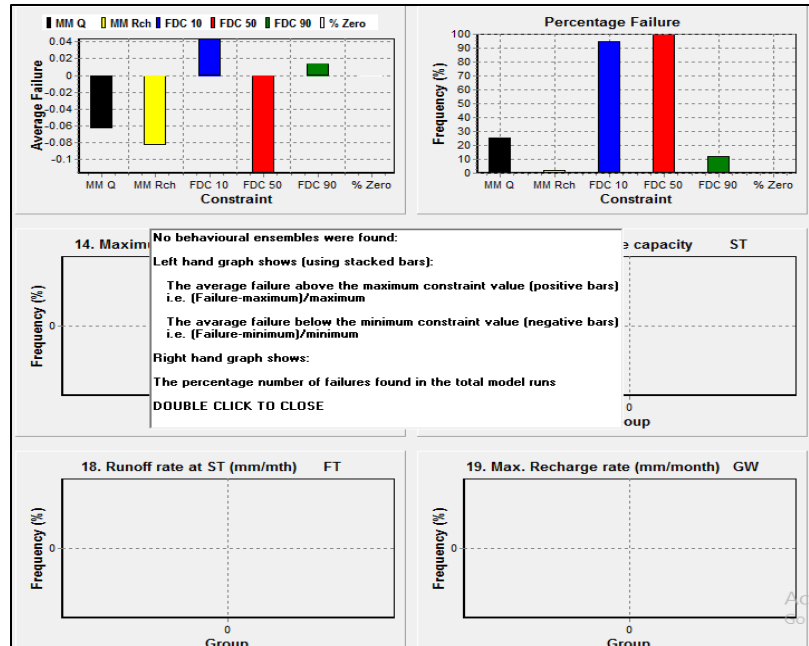


Figure 4.6. A utility index for checking the consistency between the constraint and parameter ranges. Here the model has failed to find out behavioural parameters due to the incompatibility between the parameter distributions and constraint limits.

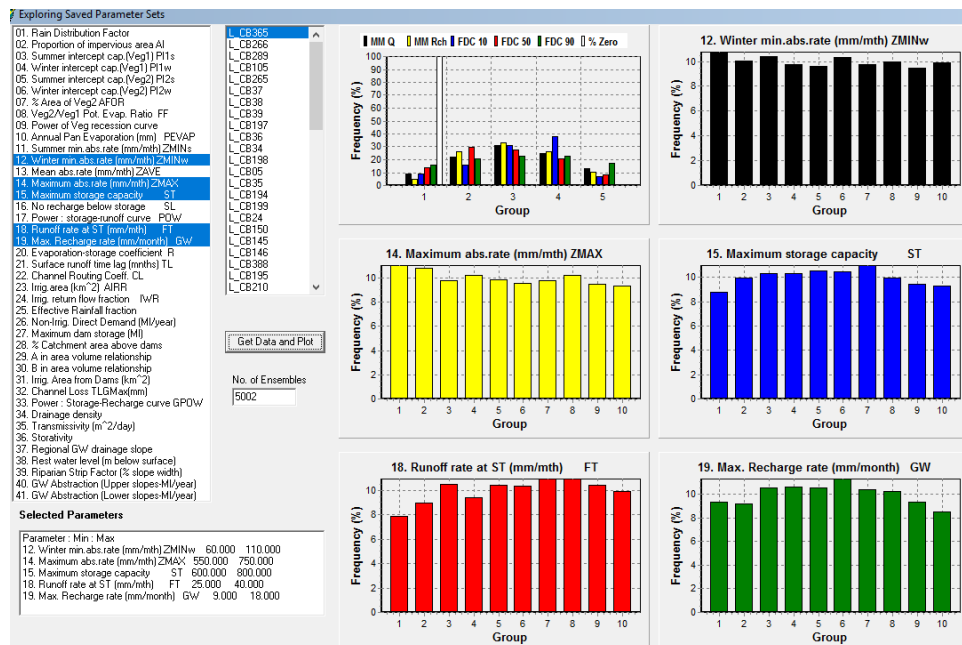


Figure 4.7. Consistency found between the constraint and parameter ranges with almost 5000 behavioural parameter sets after 100 000 model runs during stage 1 of the modelling approach.

4.2.2.2 Stage 2 of the modelling

In stage 2 of the modelling approach, the saved parameter sets (from the first stage) are re-sampled and all sub-basins connected to generate 10 000 flow ensembles at all sub-basin outlets. Any parameter not affecting the sub-basin incremental flow and any water use parameter are included to simulate either natural or development conditions. Routing parameters TL and CL (Table 4.1) were included to simulate the catchment natural hydrology. The CL parameter is only used for sub-basins where channel attenuation processes are evident, or expected, at monthly time scale. In this study, only natural hydrological conditions are simulated because the Congo Basin is well known to be underdeveloped (in terms of water infrastructures) (Nilsson et al., 2005; Santini and Caporaso, 2018) and we don't expect existing infrastructures to have significant impacts on flow records at the spatial scales of the current sub-basins used.

The size of the clouds, as shown in stage 2 of the modelling approach (Figure 4.5), represents the degree of uncertainty which is a reflection of the range of the input constraints such that a wide range represents bigger uncertainty (usually expected of ungauged sub-basins) and a small range lower uncertainty (as expected for gauged sub-basins assuming that the observed flow is consistent). The success of the implementation of 2-stage modelling mainly resides in the appropriate quantification of the uncertainty in constraints (at stage 1). If appropriately quantified, they can ensure that the downstream sub-basin outputs are composed of behavioural upstream inputs.

4.2.2.3 Evaluation of modelling results

The output file produced by the model during stage 2 is a text file with 10 000 lines, each line including the parameter values, some summary statistics, as well as five objective functions (where observed flow data exist) for each ensemble. The summary statistics include the mean monthly runoff, mean monthly recharge, the 10th, 50th and 90th percentiles of the flow duration curve expressed as fractions of mean monthly flow. The objective functions include Nash-Sutcliffe coefficient of efficiency for both untransformed (NE) and transformed values (NE {ln}) and the corresponding mean monthly runoff bias values (% Bias) and (%Bias {ln}), respectively. Another output file obtained from sorting all the 10 000 ensembles consists of five-time series extracted from the total ensemble set. These are the minimum, the 5th, 50th and 95th percentiles and the

maximum simulated flows for each month of the total time series. The 5th and 95th percentiles provide useful upper and lower bounds covering 90% of all the simulated ensembles and excluding any outliers. It is important to recognise that each of these is not a ‘real’ time series and only represent the envelopes of the ensemble set.

These uncertainty bounds are computed using the simulated cumulative streamflow and can be compared with the observed flows at both headwater and downstream gauging stations, using either the hydrographs or flow duration curves. Comparisons with observed flow data can also be used to adjust the ranges of the input constraints where necessary. Either this adjustment is performed without redefining the behavioural parameters in stage 1, or it may require a complete re-computation of behavioural parameters, depending on how far the simulations deviate from the observed flow data. The model is considered to perform well if the simulated uncertainty bounds of the flow duration curve bracket the observed flow data, but other performance measures can also be used. The uncertainty associated with the simulated hydrological response is evaluated through a simple metric which is the difference between the upper (95th) and lower (5th) bounds of the simulated ensembles divided by the mean value of the ensemble set and expressed as a percentage. This metric can be applied to any of the summary statistics referred to above.

The propagation of uncertainty downstream is affected by the dependency index. This is an input value that is used to group sub-basins together (Figure 2.2). During the parameter set sampling process within the stage 2 version of the model, all of the sub-basins with same index value are forced to have parameter sets that generate similar relatively wet/dry simulations (based on the mean monthly flow constraint). The implication is that for a given downstream sub-basin, the range of uncertainty will be higher if all upstream sub-basins have the same index value, while the range will be lower if their parameter sets are independently sampled (all different index values). Therefore, the assessment of the model results at downstream sites includes the dependency grouping of all the upstream sub-basins. After the required adjustments have been made to the constraint ranges and the results validated as far as possible with the limited available observed data, the original constraint intervals are re-evaluated using the validated bounds. The usefulness of constraints in this modelling exercise is checked against simulated uncertainty levels reported in a previous study conducted in the Congo Basin using a structured uncertainty version of the PITMAN model (Tshimanga, 2012).

4.3 Hydrodynamic modelling

The hydrodynamic modelling refers to the use of the LISFLOOD-FP model to simulate the channel-wetland exchanges in specific sub-basins of the upper Lualaba drainage system. This subsection briefly describes the LISFLOOD-FP model together with input requirements. It also presents the implementation of the model set up. This set up involves first, the simulation of the hydrological boundary conditions. These conditions are disaggregated into daily streamflows using a disaggregation model.

4.3.1 LISFLOOD-FP model

The LISFLOOD-FP model is one of the most widely used flood inundation models for research purposes. It was developed at the University of Bristol UK in its early version as a simple raster-based model (Bates and De Roo, 2000; Bates et al., 2010) and later it went through further developments to improve its physical representation of overland flow (Bates et al., 2013). The model is widely used in many flood inundation studies across the world (Pappenberger et al., 2007; Neal et al., 2012; Amarnath et al., 2015; Komi et al., 2017) and it comprises of one-dimensional solvers for the modelling of flood wave propagation in a channel and two-dimensional solvers for calculating floodplain flow.

The calculation of the flood wave propagation in a channel is based on the two basic equations of the Saint Venant Equations, namely continuity and momentum (Section 2.7.1). Within LISFLOOD-FP model, these equations are approximated in the forms of: 1D kinematic channels (Bates and De Roo, 2000), 1D diffusive channels (Trigg et al., 2009), 2D grid inertial formulation (Bates et al., 2010) and 2D inertial formulation sub-grid channels (Neal et al., 2012). Details on how these solvers work are well described in the LISFLOOD-FP user manual (Bates et al., 2013) and elsewhere (Neal et al., 2012; Amarnath et al., 2015; Komi et al., 2017) and are not repeated here.

In this study, the sub-grid model version (Neal et al., 2012) has been adopted to simulate the hydrodynamic behaviour of the channels within the wetlands. Its choice is dictated by the fact that it is computationally efficient in simulating spatially distributed dynamics of water surface elevation, wave speed, and inundation extent over large data-sparse domains. Its sub-grid

representation of channelized flows allows river channels with any width below that of the grid resolution to be simulated. The main components of the sub-grid model are given in Figure 4.8. Details on the model setup are found in Chapter 7. The sub-grid channel model uses hydraulic geometry theory to compute the channel bed elevation, which is approximated at the cell scale by:

$$z_{c,i,j} = z_{i,j} - r w_{i,j}^p \quad \text{Equation 4.5}$$

Where, r and p are coefficients that are estimated and then refined through model calibration; w is the channel width and $z_{c,i,j}$ and $z_{i,j}$ are the channel bed elevation and bank full depth, respectively. There are different ways in which the channel width can be obtained, either from remote sensing or fieldwork surveys. In this study, information on channel width was derived from remote sensing because this was the only available source. The Google Earth imagery together with the DEM and Landsat imagery were combined within a GIS environment for extracting information on channel widths (Figure 4.9).

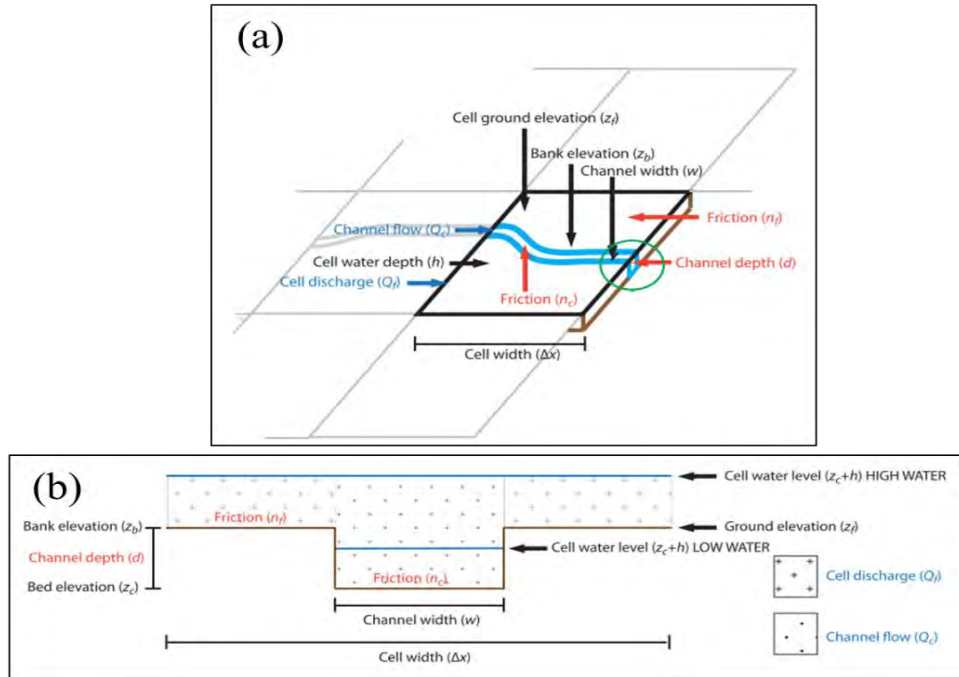


Figure 4.8. Conceptual diagram of the (a) sub-grid channel model and the (b) sub-grid cross-section (adapted from Neal et al. (2012)).

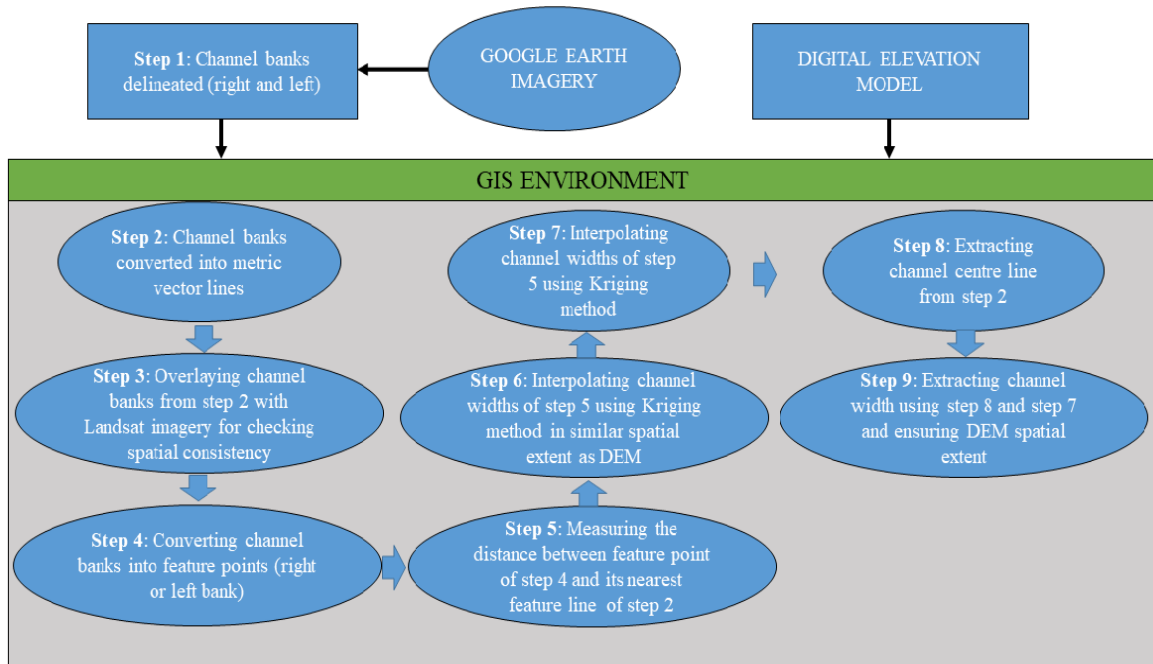


Figure 4.9. Schematic of the method used for the estimation of channel widths used for the sub-grid model.

4.3.1.1 Input data requirements

The input data requirements for running the LISFLOOD-FP model are summarised in Figure 4.10. A digital elevation model is used to represent the floodplain topography (Bates and De Roo, 2000), while the channel geometry includes the channel bed slope, width and bank full depth. The channel friction is the Manning roughness coefficient and is often set at a single value. In contrast, the floodplain friction can either be a uniform or a distributed Manning value, depending on the land cover properties. The boundary conditions represent the flow conditions at the upstream, downstream and the edge of the modelling domain. Finally, the model time step can be a fixed time step defined by the user or an adaptive time step computed by the code to maintain model stability.

These input data are presented in different file types, which are either compulsory or optional for running the model, depending on the purpose of the study. Some of these file types are the parameter file, channel information file, boundary condition file, time-varying boundary condition file, digital elevation model file, sub-grid model river width file, and sub-grid model bank elevation

file. Details of the format of these files are described in the LISFLOOD-FP user manual (Bates et al., 2013).

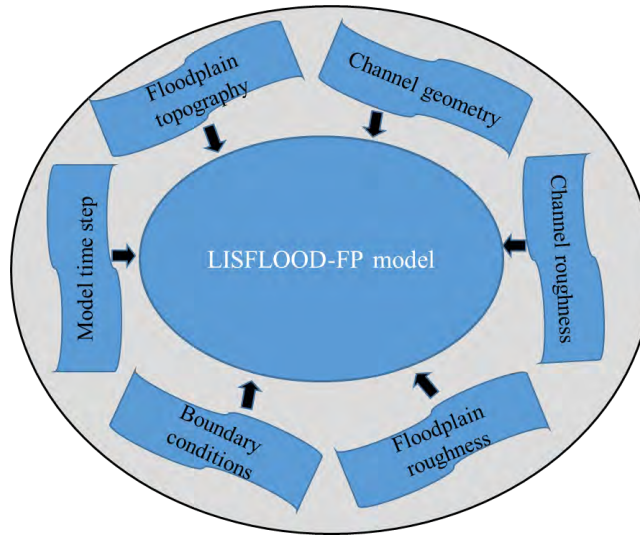


Figure 4.10. Primary input data required for running the LISFLOOD-FP model.

4.3.1.2 Model calibration

The friction and channel geometry parameters need calibration. While the channel friction is often set at a single value, the floodplain friction can either be a uniform or a distributed Manning value, depending on the land cover properties. Chow (1959) provides values for channel friction ranging from $n_c = 0.03$ (for clean channels) to $n_c = 0.1$ (for weedy and rocky reaches). Manning's friction for floodplain can vary from pasture short grass ($n_p = 0.03$) to heavy stands of timber and a few fallen trees ($n_p = 0.12$). In this study, the initial values for the channel roughness were set from the range (n_c : 0.017- 0.051) of the computed values based on observed historical channel hydraulic characteristics within the study region (Charlier, 1955). Increments of 0.005 starting from $n_c = 0.017$ were used for the channel friction to assess the model sensitivity while channel geometry parameters were kept fixed within the computed ranges (e.g. r : 0.038-0.16). Similarly, the scale parameter (r) of the sub-grid model was varied in 0.025 increments ranging from 0.038 to 0.168 while the channel friction was kept to its optimal value (value that has yielded the highest performance). This sensitivity analysis was performed for individual wetland systems and calibrated values were used to simulate the wetland hydrodynamic. It has to be noted that the

historical conditions covered the period March 1949-October 1953. Land cover maps were used to estimate values of floodplain roughness.

4.3.1.3 Validation of the LISFLOOD-FP model

Landsat images acquired on specific dates of the simulation period were used to extract inundation areas using the Modified Normalised Difference Water Index (MNDWI) (Xu, 2006; Wang *et al.*, 2008; Rokni *et al.*, 2014). Only Landsat images of Landsat 7 –ETM+ (Table 3.2) were available across the study areas during 2000-2004 hydrological years. The equation 4.6 gives the computation of the MNDWI index as following:

$$MNDWI = \frac{bgreen - bswir1}{bgreen + bswir1} \quad \text{Equation 4.6}$$

Where bgreen stands for the green band (band 2) with a wavelength between 0.525–0.605 μm ; bswir1 is the short wave infrared band (band 5) with a wavelength between 1.55–1.75 μm .

Four performance measures, namely flood area index (FAI), Pierce Skill Score (PSS), Accuracy and Bias (Bennett *et al.*, 2013) are used for the validation of the hydrodynamic modelling results. These measures use the binary maps of flood extents from both model simulations and Landsat imagery acquired on the same dates. These performance measures were used in similar studies conducted elsewhere (Hunter *et al.*, 2005; Pappenberger *et al.*, 2007) and Chapter 7 gives details on how they have been used in the validation process. Equations 4.7 to 4.10 give mathematical expressions of these performance measures.

- Flood Area Index (FAI) = $A/(A+B+C)$ Equation 4.7

Where A is the number of pixels correctly predicted as wet. B is the number of pixels observed wet but predicted dry. C is the number of pixels observed dry but predicted wet. FAI ranges between 0 and 1 with 0 for a model with no overlap between observed and modelled, and 1 for a model with perfect overlap.

- Pierce Skill Scores (PSS) = Hit – false alarm rate Equation 4.8

$$\text{Hit} = A/(A+B) \text{ and false alarm rate} = C/(C+D)$$

Where, D is obtained by subtracting the sum of A, B and C from the total number of pixels in the modelling domain.

- $\text{Accuracy} = (A+D)/n$, Equation 4.9

where n is the total pixel number within the modelling domain.

- $\text{Bias} = (A+C)/(A+B)$ Equation 4.10

4.3.1.4 Types of outputs

The LISFLOOD-FP model generates a variety of outputs depending on the purpose of the simulation. The main output file is known as the mass file, which contains details on the model mass balance, including the channel input and output discharge (downstream discharge), as well as the floodplain water volume and inundation extents. These are the outputs useful for the implementation of this research. They are used to calibrate the wetland sub-model parameters as it is described in Section 4.4. Other file types include channel and floodplain water depths, in raster format, which can be visualised in a GIS environment for further processing.

4.3.2 Linking the PITMAN and LISFLOOD-FP models

The PITMAN model operates at a monthly time scale, while the LISFLOOD-FP is at a sub-daily time scale and therefore the monthly simulations from the PITMAN model need to be disaggregated into a daily time series through a daily disaggregation model (Slaughter et al., 2015: see Section 4.3.3 below). A review of past studies in the Congo Basin (Chapter 2) has shown that the application of daily hydrological models in the Congo Basin (Beighley et al., 2011; Aloysius and Saiers, 2017; Munzimi et al., 2019) presents limitations in not capturing the magnitude of streamflow volumes (O'Loughlin et al., 2019) and, therefore, those simulations are not suitable for use as boundary conditions to hydrodynamic models. On the other hand, monthly hydrological simulations obtained with the PITMAN model (Tshimanga et al., 2011; Tshimanga and Hughes, 2014) have shown that the model has the potential to appropriately capture the timing, seasonality and magnitude of main hydrological processes occurring across the Congo Basin and hence, its simulations can represent well the real basin processes.

The disaggregated daily streamflow is used to provide the boundary inflow conditions required by the LISFLOOD-FP model. In turn, the outputs (wetland flow storage volumes and outflow

hydrographs) from the LISFLOOD-FP model are used to calibrate the parameters of wetland sub-model of the main monthly PITMAN model. The basin-scale model (main PITMAN model) is then re-run using calibrated wetland parameters to improve the understanding of channel-wetland exchanges and quantify wetland impacts on the downstream flow regime.

4.3.3 Daily disaggregation framework

The overall framework used for the disaggregation of monthly flows into daily is inspired by Slaughter et al. (2015). Six key steps of this process are schematised in Figure 4.11.

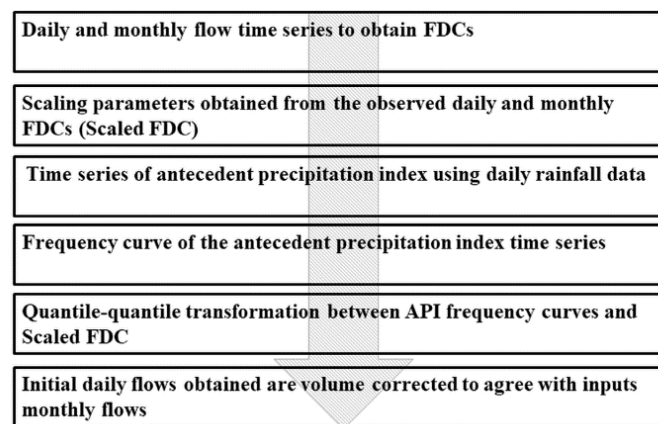


Figure 4.11. Schematic of the methodology used for disaggregating monthly flows into daily (adjusted from Slaughter et al. (2015)).

The approach has been applied in some case studies (Hughes and Slaughter, 2015) in Southern Africa. In this thesis, the scaling parameters are obtained from the observed daily and monthly time series of flows at eight gauging stations covering different climate and physiographic regions of the Congo Basin. The simulated monthly flows to be disaggregated are obtained from the first run of the monthly PITMAN model (Chapter 6) for sub-basins with wetland systems in the upper Lualaba drainage system.

In step 1 of the disaggregation approach, the simulated monthly flow time series is used to construct a flow duration curve (FDC), the second step quantifies the scaling parameters that are used to scale monthly flow quantiles to generate a daily FDC. In steps 3 and 4, daily rainfall data are used to create a continuous time series of an antecedent precipitation index (API) and the

associated exceedance frequency distribution using decay (K) and threshold (P_{thresh}) parameters to account for the runoff response dynamics of catchments with different sizes and physical characteristics. In step 5, the initial daily flow time series is generated from the antecedent precipitation index time series using a quantile-quantile transformation method and finally in step 6, the initial daily flow values are volume corrected to ensure the same volume as the monthly flow data.

4.4 Process understanding and simulating wetland downstream impacts

After the model has been validated, the channel-wetland exchanges are quantified using both PITMAN wetland sub-model parameters and hysteresis indices that are believed to be affected by some wetland morphometric characteristics. Finally, downstream wetland impacts on flow regime are simulated using the calibrated wetland parameters and the main PITMAN model. Methodological components 3, 4, 5 and 6 (Figure 4.1) are covered in this sub-section.

4.4.1 The wetland sub-model

The wetland sub-model was developed as a sub-component of the rainfall-runoff basin-scale hydrological monthly model (PITMAN) to account for wetland storage processes that are expected to have downstream impacts on the flow regime even at the monthly time scale (Hughes et al., 2014). Since its conceptual design, the sub-model has been applied in many studies to account for the impacts of wetlands (Hughes et al., 2014; Tshimanga and Hughes, 2014; Tumbo and Hughes, 2015; Kabuya et al., 2020a), thus improving the downstream basin-scale hydrological simulations.

The exchanges taking place between the river channels and their adjacent floodplains/wetland or natural lakes are quantified within the sub-model through some components and parameters (Table 4.2).

Table 4.2. Parameters of the wetland sub-model accounting for the channel–wetland exchanges

Parameter name	Description
Local catchment area (km ²)	The maximum inundated area including a wetland area
Residual wetland storage, RWS (MCM)	Wetland storage below which there is no return flow
Initial storage (MCM)	Initial wetland storage at the start of a simulation
$A \text{ in Area } (m^2) = A * Volume^B (m^3);$	The coefficient in a power relationship between the wetland volume and area, when both are expressed in m ³ and m ² , respectively.
$B \text{ in Area } (m^2) = A * Volume^B (m^3);$	The exponent in a power relationship between the wetland volume and area, when both are expressed in m ³ and m ² , respectively.
Channel capacity for spillage (MCM), Qcap	Channel capacity for the spill to the wetland to occur. Below this threshold, there is no spill from the channel to the wetland
Channel Spill Factor (Fraction), QSF in SPILL= QSF*(Q-QCap)	With Q: the channel upstream flow and SPILL: the flow volume added to the wetland
AA in (Ret Flow= AA*(Vol/RWS) ^{BB}	The coefficient in a power relationship between the ratio of the wetland storage volume over the residual wetland storage and the return flow
BB in (Ret Flow= AA*(Vol/RWS) ^{BB}	The exponent in a power relationship between the ratio of the wetland storage volume over the residual wetland storage and the return flow
Annual Evaporation (mm)	Annual evaporation from the wetland (distributed into monthly values using a table of calendar month percentages)
Annual Abstraction (MCM)	Annual water abstractions from the wetland (distributed into monthly values using a table of calendar month percentages).
Max Return flow Fraction	A parameter used to restrict the return flow. Three options determine how the return flow fraction is dealt with.

The return flow is restricted in three ways through the Maximum Return Flow Fraction (MRFF) parameter:

- If the MRFF is positive and less than 1 (e.g. MRFF = 0.95), the model limits the return flow by the volume of the channel inflow relative to the channel capacity for spillage. The immediate effect of this is that the return flow can be severely reduced while the channel is still spilling onto the wetland.

- If the MRFF is positive and greater than 1: The return flow, in this case, is not limited by the inflow volume relative to the capacity for spillage, but rather the two processes, spilling and return flow, can occur simultaneously. In practice, a value of 10.95 for MRFF is typical of many wetland systems in the upper Congo Basin.
- The last way of constraining the return flow is to give a negative value to the MRFF. In this case, no return flow is allowed when the channel is spilling, and the positive fractional value only applies to return flows when spilling ceases.

4.4.2 Quantification of wetland sub-model parameters

The quantification of wetland parameters is based on the outputs of the LISFLOOD-FP model after it has been validated. LISFLOOD-FP provides a mass file that contains a summary of the wetland water balance in terms of daily time series of the total wetland inflows, outflows, inundated area, and wetland volume. This information is used to quantify the parameters. The first step involves the aggregation of the daily information into monthly totals. In the second step, the algorithms of the PITMAN wetland model are reproduced in a simple spreadsheet so that the spilling and return flow parameters can be estimated through manual calibration and visual comparison with the LISFLOOD-FP output values, while the area-volume relationship parameters are directly derived from LISFLOOD-FP model outputs.

For deep lakes (lake Kivu and Tanganyika), the LISFLOOD-FP model was not used, as the model is designed for shallow water systems. For these lakes, the PITMAN wetland parameters were estimated using different sources of information including observed flow discharge and lake storage volume. Some simplifications of the parameter values were achieved by setting the residual storage to zero and assuming that water level fluctuation lies between the minimum and maximum lake levels (i.e. the volume of water below the lake outlet minimum level is effectively ignored). However, a key issue for lakes is that the spill factor and the channel capacity for spillage are always 1 and 0, respectively.

4.4.3 Integrated analysis of wetland hydrodynamic and morphometric characteristics

As shown in the general methodological framework (Figure 4.1), wetland hydrodynamic characteristics (exchanges) are quantified using hysteresis indices suggested by Lloyd *et al.* (2016)

and Zuecco *et al.* (2016). To maintain consistency in the computation of the hysteresis indices, the standardised time series of the independent variables were divided into equal steps of 0.05 between 0.1 and 0.95, and linear interpolation was used to get corresponding values of the dependent variables at the same intervals. A value of HI_{Lloyd} of zero represents no hysteretic pattern and positive values indicate clockwise, while negative values anticlockwise. Similarly, Clockwise hysteresis is characterised by $HI_{Zuecco} > 0$, anticlockwise hysteresis with $HI_{Zuecco} < 0$, and no hysteresis happens when $HI_{Zuecco} = 0$ or for the case of symmetrical eight-shaped or complex loop. GIS techniques are used to derive morphometric characteristics of wetlands that might affect the inundation and drainage dynamics. Such characteristics may include the wetland average slope as well as the proportion of wetland volume below channel water level. The principle behind the latter characteristics is that the raising and lowering of water surface profiles along the river course can be used to infer likely patterns of inundation during different levels of flooding (Lidzhegu *et al.*, 2019) and can, therefore, be used to differentiate different wetland systems.

The index of wetland morphology (IWM) which can collectively represent the heterogeneity of the wetland morphology, gives an indication of the wetland storage volume below channel water level. The computation of this index is solely based on the DEM analysis within the GIS environment and involves the following steps:

- Determining the cross section profiles along the river course at reasonable intervals following the morphology of the main river. The length of each profile is long enough to capture the total width of the wetland system;
- Assigning an elevation value to cross section profiles and interpolating to create Triangular Irregular Network (TIN) of water surface for each height below and above the channel water level;
- Computing the surface difference between the water surface profiles of TIN and a reference surface (DEM);
- Constructing height-volume curves corresponding to different height below and above channel water levels.
- Standardising volume-height curves and estimating the fraction of the wetland volume below the channel water level. This index is a definite integral.

4.4.4 Simulating wetlands downstream impacts on flow regimes

The quantification of the wetland downstream impacts on flow regimes is assessed by including calibrated wetland parameters and hydrological constraints into the main PITMAN model (calibrated in Chapter 6) as shown in the general methodological framework (Figure 4.1). The impacts are evaluated through a comparison between hydrological simulation results with and without the inclusion of wetland systems. Figure 4.12 shows the overall procedure used for the simulation of the impacts of wetlands on the downstream flow regime of the Lualaba River.

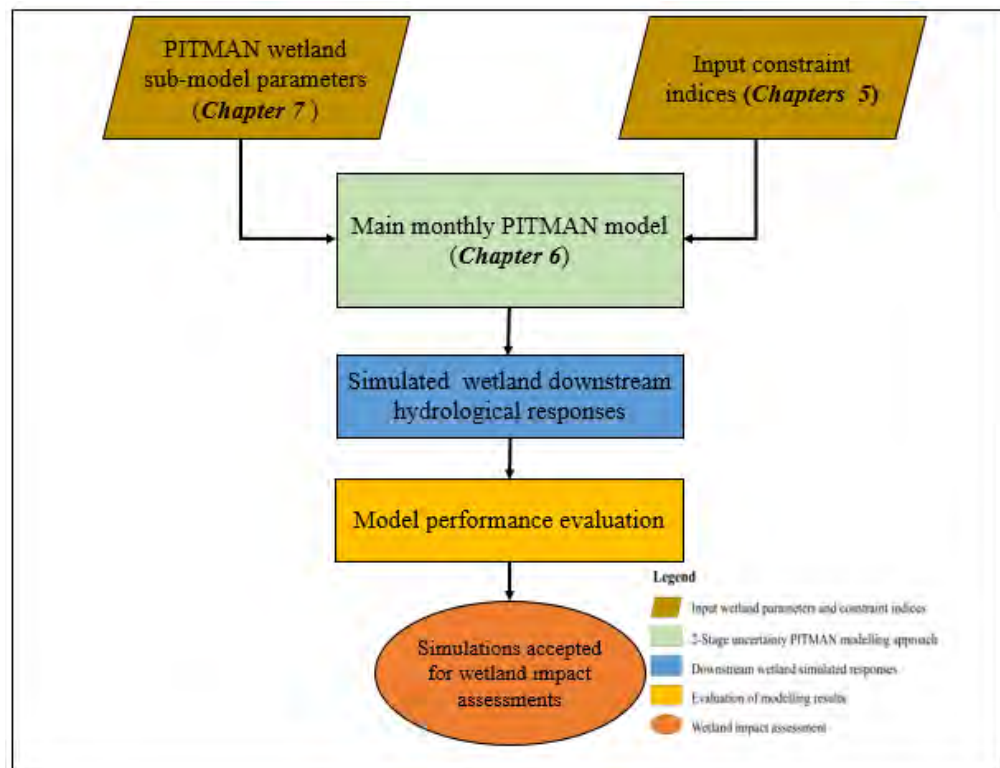


Figure 4.12. Overview of the methodological approach for wetland impact assessments

4.5 Concluding remarks

This chapter has shown the methodological approach to hydrological uncertainty quantification (see Chapter 5) and modelling (see Chapter 6). It has also justified the choice made for using these two models (PITMAN and LISFLOOD-FP) to understand the river channel-wetland exchanges at a basin-scale (see Chapter 7). These chapters provide the main results obtained from the implementation of this integrated methodological modelling framework.

CHAPTER 5 : UNCERTAINTY RANGES OF HYDROLOGICAL INDICES

5.1 Introduction

Information about sub-basin long-term hydrological behaviour is essential for hydrological analysis, modelling and water resources management. Hydrological indices, or signatures, have been used for runoff prediction (Kult et al., 2014; Zhang et al., 2018), model selection (Jothityangkoon et al., 2001; McMillan et al., 2011), model evaluation and optimisation (Shafii and Tolson, 2015), uncertainty analysis (Westerberg and Mcmillan, 2015; Westerberg et al., 2016), catchment classification (Ley et al., 2011; Sawicz et al., 2011) and ensemble predictions (Yadav et al., 2007; Zhang et al., 2008; Tumbo and Hughes, 2015; Hughes, 2016; Ndzabandzaba and Hughes, 2017). The reliability of the hydrological indices is affected by uncertainties in the available observed data, as well as by the methods used to transfer these indices from gauged to ungauged sites. This chapter presents the results of the establishment of the uncertainty ranges of hydrological indices used for modelling in this research. Specifically, the chapter focuses on (i) providing a basis for extrapolating the hydrological indices from gauged to ungauged sub-basins, (ii) identifying potential predictors of hydrological behaviour and (iii) quantifying uncertainty ranges of the hydrological indices which are referred to as hydrological constraints in Chapter 6.

5.2 Methodology

Figure 5.1 shows the methodological approach implemented for the establishment of the uncertainty ranges of hydrological indices.

5.2.1 Selection of gauging stations

Among the available sixty-three gauging stations across the Congo Basin (Tables A3.1 to A3.5 in Appendix A), only fifteen were selected for the quantification of the hydrological indices. Some criteria were used to select these gauging stations:

- (i) The gauging station should reflect the headwater flow regime: The headwater flow regime represents a sub-basin's flow response to input climate. It does not represent cumulative

streamflow characteristics from large catchment areas. But, it represents the natural flow that is not affected by large wetland systems, or any major water infrastructure (Tumbo and Hughes, 2015; Ndzabandzaba and Hughes, 2017);

- (ii) The gauging station should not be drained by physiographically or climatically heterogeneous upstream contributing areas: It is assumed that climate and physiographic data can be used to assign hydrological indices to ungauged sub-basins based on regionalised relationships. Therefore, only gauging stations located in homogenous regions are used to avoid possible effects of climate and physiographic heterogeneity;
- (iii) The length of the data record should be at least five continuous years to ensure that the quantified hydrological indices would capture most of the temporal hydrological variability (Merz et al., 2009).

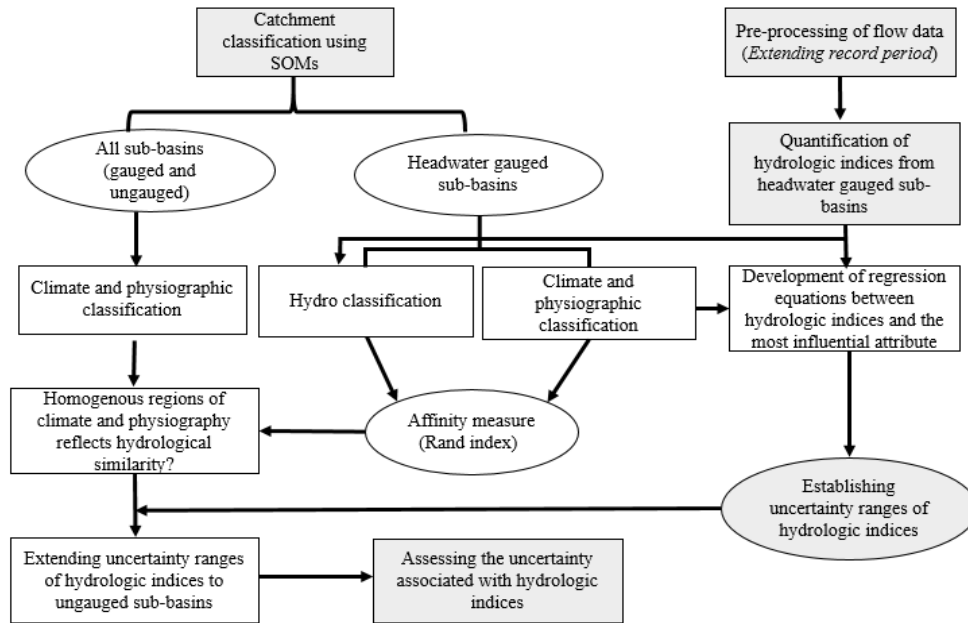


Figure 5.1. Flowchart of the methodological approach applied for the establishment of the uncertainty ranges of hydrological indices.

5.2.2 Pre-processing of flow data

Many of the selected streamflow time series are short and have different record periods, which might affect the representativeness of derived hydrological indices. Therefore, the data were pre-processed using a spatial interpolation approach (Hughes and Smakhtin, 1996) to extend the observed flow series to common record periods. This approach assumes that flows occurring simultaneously at sites in reasonable proximity to each other correspond to similar percentage points on their respective duration curves. Its implementation requires the identification of key gauging stations within each region that have the longest record periods so that they can be used as source gauges for extending the flow series of gauging stations in their vicinity. While the method allows for the use of up to 5 source gauges with different weighting factors (Hughes and Smakhtin, 1996), only one source gauge is used in this study due to the limited number of available gauges. However, the selection of source gauge was based on the spatial proximity. The outputs consist of both a patched (filling missing data periods) and extended time series, as well as a time series representing estimates for all months (substitute time series). The latter can then be used to compare with the original observed flow data and the reliability of the method assessed using typical objective functions (such as the Nash coefficient of efficiency).

5.2.3 Catchment classification using Self Organising Maps

Due to the largely ungauged nature of the Congo River Basin, catchment classification offers a possible approach for reducing the complexity of the basin to a few groups of sub-basins where the differences in climate and physiographic characteristics (and hence the hydrological indices) are assumed to be greater between the groups than within each group. In this regards, Self-Organizing Maps (SOM) offer an opportunity to analyse, organise and cluster various types of data through non-linear relationships, which represent the internal similarity of the variables. They have been used in many hydrological applications (Hall et al., 2002; Srinivas et al., 2008; Herbst and Casper, 2008; Toth, 2009; Di Prinzio et al., 2011; Ley et al., 2011; Toth, 2013).

The classification was based on the use of the Viscovery SOMine software (<https://www.viscovery.net/somine/>), which was used to classify the Congo Basin into homogenous regions. The appropriate number of regions was based on the use of the ANOSIM R statistic (Clarke, 1993; Warton et al., 2012) rather than specific metrics which often result in

contrasting results (Charrad et al., 2014; Agarwal et al., 2016). In addition to the ANOSIM R statistic, the adequacy of the overall classification results was assessed based on a quantization error (also known as Euclidean distance) defined as the average of the squared distance of all data records associated with a node in the output layer. It should be as small as possible and is often used as the basis for assigning input vectors (sub-basins) to nodes. Therefore, sub-basins that have similar quantization error were assigned to the same region.

Apart from the classification of the all 403 sub-basins, other classification schemes were performed using only the selected fifteen sub-basins with observed data (used to derive hydrological indices). These were based on climate and physiographic attributes on the one hand, and hydrological indices on the other hand. The purpose of these classifications was to assess the degree of affinity between the physiographic and hydrological classifications of the fifteen gauged headwater sub-basins and thereby identify physiographic attributes that would better explain specific aspects of hydrological indices and provide a basis to transfer hydrological indices to ungauged sub-basins.

The Rand affinity index (Rand, 1970; Di Prinzio et al., 2011; Ssegane et al., 2012) was calculated (Equation 5.1) to assess the affinity between classifications.

$$R = \frac{a+b}{a+b+c+d} \quad \text{Equation 5.1}$$

Where R varies between 1 (perfect agreement between the two pools of clusters) and 0 (no agreement). The meaning of the terms a, b, c and d is given under the following assumptions: Given two classifications (C1 and C2) of the same dataset, a pair of sub-basins can be assigned to the same class or different clusters in C1 and C2. The variable “a” is defined as the number of sub-basin pairs that are in the same cluster in both classifications C1 and C2; variable “b” is the number of sub-basin pairs that are in different clusters in C1 and C2; variable “c” is the number of sub-basin pairs that are in the same cluster in C1 but in different clusters in C2; while variable “d” is the number of sub-basin pairs that are in different clusters in C1 but in the same cluster in C2.

5.2.4 Derivation of hydrological indices and their relationships

Table 5.1 shows the six hydrological indices for which uncertainty ranges have to be derived. Their choice is based on the fact that they are used in the current version of the PITMAN model, already

described in Chapter 4. These indices have been previously used in similar studies in southern Africa (Tumbo and Hughes, 2015; Hughes, 2016; Ndzabandzaba and Hughes, 2017). The 10th, 50th and 90th percentiles are considered here to represent the minimum number of key indices that can characterise the shape of the flow duration curve, and therefore the main response variability of the sub-basins. The majority of the sub-basins used are greater than 2 000 km², and there are no very arid areas, suggesting that zero flows at a monthly time scale under natural conditions are very unlikely. The mean monthly recharge index is the most uncertain within the Congo Basin for there are no ground-observed measurements of this index across the basin. However, the estimates that are used are taken from the global database of the annual long-term average groundwater recharge (Döll and Fiedler, 2008) at a spatial resolution of 0.5° by 0.5°, which represents about 55 km by 55 km at the equator and slightly decreases either moving to south or north poles of both the longitude and the latitude.

Table 5.1. Summary of hydrological indices used in this study

Hydrological indices	Unit	Description
Mean monthly flow (MMQ)	m ³ *10 ⁶	Long term mean monthly flow
Q10th, Q50th and Q90th expressed as fractions of MMQ	unitless	Flow duration curve percentiles computed from monthly flows
Mean monthly recharge (MMR)	mm	long term mean monthly groundwater recharge
Percentage of zero flow	%	the percentage of time there is zero flow at the site

This database is based on the Water GAP Global Hydrology Model WGHM which was calibrated against observed long-term average river discharge at 1235 gauging stations across the world. Its main drawback for use in the Congo Basin is that no validation was carried out across the basin and therefore the recharge values are expected to be very uncertain. The early version of the groundwater global database (Döll and Flörke, 2005) was previously used in the Congo Basin (Tshimanga, 2012; Tshimanga and Hughes, 2014) for catchment classification and elsewhere (Döll and Fiedler, 2008; Mohan et al., 2018). However, the dataset provides initial estimates of the range of the index that can be further refined during the modelling exercise (in Chapter 6).

Potential predictors (Table 3.2) that exhibit some consistent relationships with hydrological indices (Yadav et al., 2007) were identified and possible relationships explored. It is assumed that any relationships used to estimate hydrological indices in un-gauged sub-basins will necessarily be uncertain, and therefore, 90% regression confidence limits are used to quantify the degree of uncertainty.

5.2.5 Spatial disaggregation of flow time series

The number of headwater gauging stations (15) is a relatively small sample set to develop reliable relationships between the hydrological indices and sub-basin physiographic attributes. A spatial disaggregation approach was therefore implemented to distribute some of the downstream flow time series to individual upstream sub-basins and thereby increase the number of sub-basins for the analysis. Only gauging stations with less than six sub-basins and without any identified upstream anthropogenic impacts and that are not influenced by wetland effects are included, and in fact, only two such situations exist. This approach involves an iterative process. First, the initial regression relationships (developed from the gauged headwater sub-basins) provide initial estimates of the hydrological indices for the sub-basins lying upstream of the gauging station. This step ensures that sub-basin relative differences in response are consistent with the initial relationships. Second, the flow percentile indices are converted to absolute values (i.e. not as fractions of MMQ) and are summed to give cumulative values at the downstream gauging station. All of the cumulative index values are compared to the observed gauging station values and correction factors determined for each index and each sub-basin. Third, these correction factors are then applied to the sub-basin initial estimates, and the FDC indices converted back to fractional values by dividing by MMQ. Clearly, the indices for the additional sub-basins are less certain than those derived from the gauged headwaters. The approach is justified based on the very limited number of gauged headwater sub-basins and at least allows some of the response characteristics of the two larger gauged catchments to be included in the second round of regression analysis.

5.2.6 Assessing the uncertainty

The rainfall data constitute the main source of uncertainty. It has been acknowledged that the reliability of a rainfall dataset is mainly limited by the number and the spatial coverage of surface stations (Sun et al., 2017) and the CRU rainfall dataset used in this study is based on a very limited

amount of observed rainfall data. Previous studies reported on the lack of agreement between different interpolated rainfall datasets (Sun et al., 2017). The consistency of the CRU and the UNIDEL (Sun et al., 2017) datasets is checked by computing ratios of UNIDEL to CRU mean annual rainfall. Regions where the computed ratio is high (e.g. >1.15) were identified as potential areas of high uncertainty where the uncertainty ranges of the indices would need further refinement. As already noted in Section 5.2.4, the width of the 90% confidence limits represents the degree of uncertainty in the hydrological indices.

5.3 Results

5.3.1 Extending the record periods of the flow time series

The original and extended record periods (after spatial interpolation), as well as the source gauging stations used for the record extension (Table A5.13 in Appendix A), have resulted in extended flow time series that ensure the representativeness of the computed hydrological indices and minimize the differential effects of the number of wet and dry periods represented in short record periods. The reliability of the extended flow time series is assessed by comparing the observed flows with the substitute time series (i.e. all months estimated from the source gauge). For example, Figure 5.2a shows a comparison between the original and substitute series. The general pattern of the observed streamflow series is well reproduced and therefore the extended and infilled records should be adequately reliable. Figure 5.2b shows the Nash coefficients of efficiency for the fits between the observed and substitute time series for all the stations that were extended and the results are considered satisfactory. The final hydrological indices were therefore derived from the extended streamflow series (i.e. a combination of observed, patched and extended data).

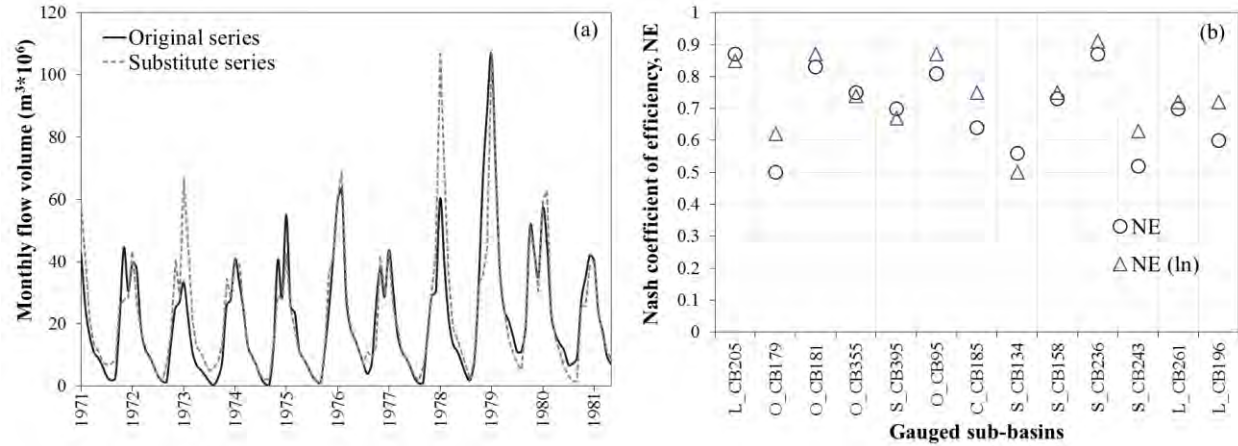


Figure 5.2. Results of the pre-processing analysis of flow data. (a) Graphical comparison between the original flow series and the substitute series (at L_CB261 gauging station). (b) Performance statistics of the low (NE ln) and high (NE) flows.

5.3.2 Sub-basin classification

5.3.2.1 Classification by climate and physiographic attributes

During the training process of different map sizes, as required by SOM techniques, a map size of 2 000 nodes (Kabuya et al., 2020b) was judged appropriate to adequately represent the input climate and physiographic attributes in the classification. The appropriate number of clusters was six because all the between-group dissimilarity values (with six clusters) are above 0.53 and are significantly different with a global R of 0.7 at a p-value of 0.001%. On the other hand, the ANOSIM statistic R associated with other numbers of clusters (3, 5, 7, 8, 9 and 10) has shown low dissimilarity ($0.25 < R < 0.48$) between some clusters (Kabuya et al., 2020b).

The spatial distribution of the six climate and physiographic regions resulting from the classification of the all 403 sub-basins of the Congo Basin is shown in Figure 5.3. These groups are coherent and preserve a high degree of spatial proximity. Approximately 28% of sub-basins are assigned to Region 1, 19.4% to Region 2 and 3, 14.6% to Region 4, 11.6% to Region 5 and 7.2% to Region 6.

Region 1 is characterized by high values of aridity index (AI), medium content of clay and flat to undulating topography (slope). These three attributes account for more than 75% to the within-

group similarity. Sub-basins are mostly located in the south-eastern and northern parts of the Congo Basin. The presence of high values of curve number suggests the potential of the sub-basins to be dominated by surface hydrological processes.

Region 2 is dominated by soil texture with a high content of clay resulting in a decrease of silt content with medium to high values of curve number. These attributes contribute by more than 85% to the overall similarity within the region. These conditions suggest the potential of the region to have limited infiltration rates while maintaining relatively high levels of humidity ($AI < 1$) on flat to undulating topography. The majority of the sub-basins are located in the northeastern part of the Cuvette central, while the others are within the Sangha drainage system.

Region 3 is mostly dominated by high clay content, high slope and low aridity, accounting for more than 85% of the within region similarity. In contrast to region 2, this region is characterised by high silt content and high slope, suggesting the dominance of sub-surface processes, particularly interflow. The sub-basins are mostly located in the eastern mountainous region of the Congo, known as the Rift Valley. Similar conditions are found in the south of the Cuvette central and the lower Congo River before draining into the Atlantic Ocean.

Region 4 represents most of the sub-basins located in the Cuvette centrale, the central part of the Congo Basin. More than 80% of within-group similarity is controlled by CN, Slope and Silt. Low values of curve number suggest high infiltration rates resulting in a predominance of sub-surface processes over surface processes and relatively low runoff ratios. The climate is humid with the lowest values of the aridity index and flat to undulating topography. These conditions suggest a depositional environment that favours the formation of wetlands and channels with a high degree of sinuosity and braiding.

Region 5 describes Clay, Slope and Silt as representing more than 70% of the within-group similarity. The soil characteristics (low clay and silt) imply the dominance of the infiltration processes, resulting in high storage capacity. Sub-basins of the Batéké plateau system, located in the western part of the Congo Basin, are found in this group and are mostly characterized by v-shaped valleys with deep soils. A humid climate ($AI < 1$) on undulating to steep topography characterizes this region.

Region 6 has almost similar characteristics as region 5, but the difference is that region 6 has a more arid climate ($0.94 < AI < 1.3$) and flat to undulating topography. The sub-basins are located in the southern part of the Kasai drainage system. Clay, Silt and AI account for more than 75% to the within-group similarity.

Figure 5.3 illustrates that Region 1 has the highest number (8) of gauged headwater sub-basins, while Region 6 has none.

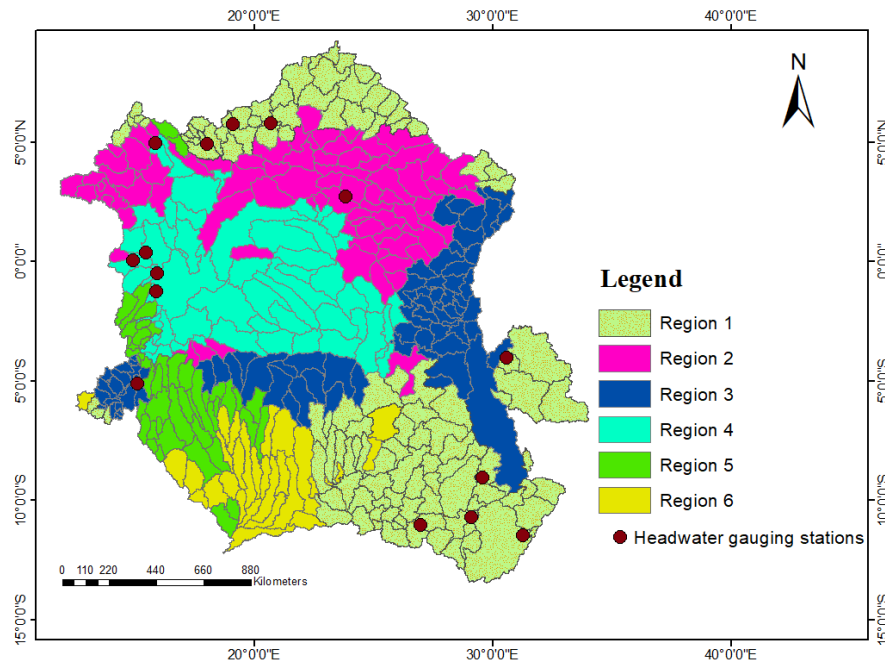


Figure 5.3. Spatial distribution of the six homogenous regions of sub-basins of similar climate and physiographic properties in the Congo River Basin identified from the application of SOM.

5.3.2.2 Classification by hydrological behaviour

Based on the distribution of gauged sub-basins, two independent classifications, each having five groups, were performed using a similar approach as highlighted in Section 5.3.2.1. The formed clusters of both hydrological and physiographic classifications of the 15 headwater-gauging stations when all indices of the hydrological behaviour are used are shown in Table 5.2. The comparison (overlay) between the physiographic and hydrological classifications was performed using Rand index. Only the three fractions of the FDC indices and runoff ratio were used to

represent sub-basin response behaviour, while five climate and physiographic attributes represented sub-basins physical properties. Overall, there exists a high degree of affinity (Rand index = 73%) between the physiographic and hydrological classifications (SOM all indices). This suggests that the climate and physiographic attributes used in this classification can capture different components of the sub-basin's hydrological response, and therefore climate and physiographic regions reflect hydrological similarity.

Table 5.2. Clusters formed based on the 15 headwater (sub-basins) gauging stations

Hydrological classification					Climate and physiographic classification				
Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Group 1	Group 2	Group 3	Group 4	Group 5
S_CB395	S_CB236	O_CB179	O_CB355	S_CB243	S_CB236	S_CB395	L_CB205	C_CB138	S_CB158
O_CB176	S_CB134	L_CB203	L_CB205		S_CB134	O_CB355	L_CB203	L_CB196	C_CB185
L_CB196	C_CB138	L_CB261			S_CB243	O_CB179	L_CB261		
C_CB185	S_CB158					O_CB176			

Due to the limited number of gauged headwater sub-basins, some clusters (Table 5.2) are made up of less than 3 sub-basins. This result implies that predictive equations for the hydrological indices in most of the clusters cannot be developed, due to a lack of enough sample points. For those clusters where there are 4 representative gauges, Table 5.3 illustrates that there are potentially strong relationships between the physiographic/climate attributes and the hydrological indices. Figure 5.4 shows the shape of the relationships between each hydrological index with individual climate/physiographic attribute. These relationships are regionally variable and therefore, because of a lack of enough gauging stations to represent some clusters, they cannot be extrapolated to all the sub-basins in the Congo. The possibility of developing general relationships across all of the Congo Basin was explored. Table 5.4 shows that when all the sub-basins are included in the regression analysis, the aridity index is revealed as the best single predictor of hydrological behaviour, with CN second. The other attributes do not appear to offer any additional predictive value. Where the curve number develops consistent relationships with the Q10/MMQ and Q50/MMQ, the aridity index shows the highest predictive power (Table 5.4). This study has therefore retained the aridity index as the best predictor of hydrological indices.

Table 5.3. Highest R^2 of the relationship observed between physiographic attributes and hydrological indices for regions having at least 4 representative gauges. In bracket are slope of the relationship. In bold are the highest R^2 for each hydrological index.

	AI	Slope	CN	Silt	Clay
RR	0.96 (-ve)	0.59 (+ve)	0.64 (+ve)	0.96 (-ve)	0.98 (-ve)
Q10/MMQ	0.97 (+ve)	0.94 (+ve)	0.79 (+ve)	0.67 (+ve)	0.35 (-ve)
Q50/MMQ	0.75 (-ve)	0.63 (-ve)	0.95 (-ve)	0.64 (-ve)	0.44 (-ve)
Q90/MMQ	0.46 (-ve)	0.46 (-ve)	0.08 (-ve)	0.55 (-ve)	0.97 (+ve)

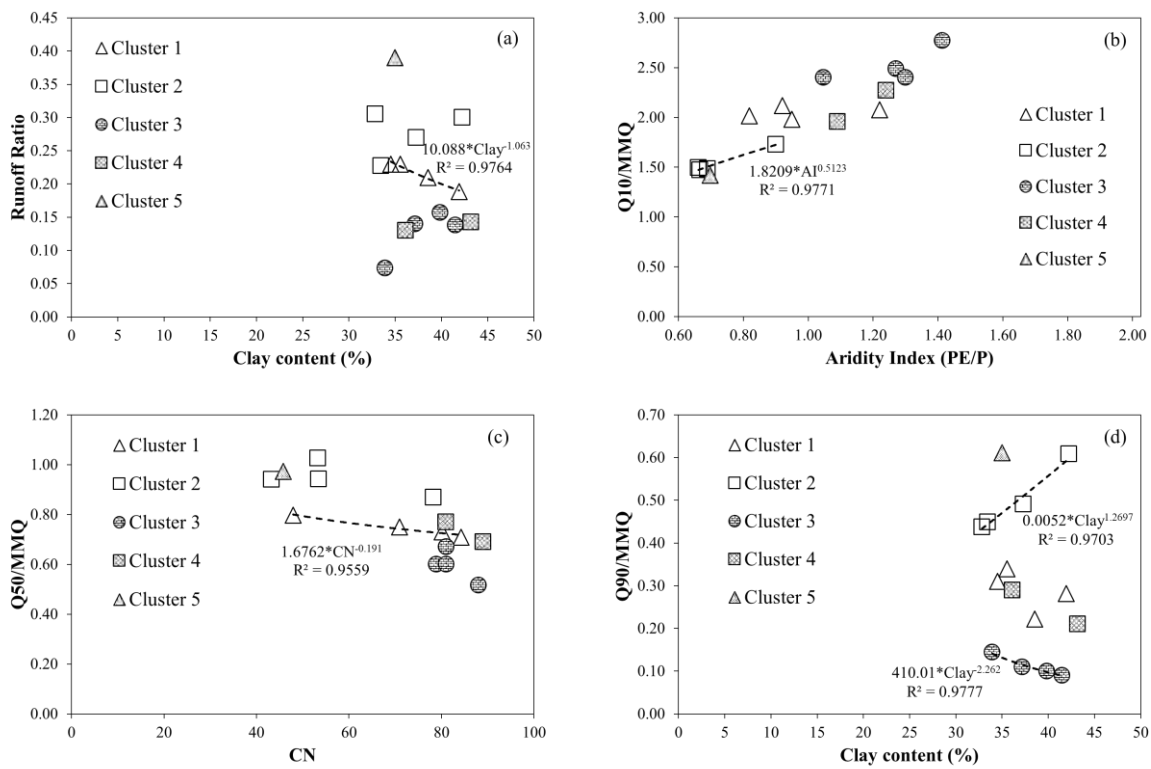


Figure 5.4. Potential regression relationships between the climate/physiographic attributes and the hydrological indices within clusters formed from the 15 gauged headwater sub-basins. (a) Runoff ratio and Clay in cluster 1, (b) Q10/MMQ and AI in cluster 2, (c) Q50/MMQ and Curve number in cluster 1 and (d) Q90/MMQ and Clay in clusters 2 and 3.

Table 5.4. R^2 of the power regression relationship between hydrological and physiographic attributes across 15 gauging stations. AI and CN are potential predictors.

	AI	Slope	CN	Silt	Clay
RR	0.63	0.26	0.35	0.06	0.15
Q10/MMQ	0.85	0.12	0.61	0.11	0.12
Q50/MMQ	0.82	0.16	0.59	0.00	0.13
Q90/MMQ	0.73	0.29	0.24	0.05	0.18

5.3.3 Developing predictive relationships of hydrological indices

5.3.3.1 Initial predictive relationships

Initial predictive relationships between the aridity index and the hydrological indices using the 15 gauged headwater sub-basins are shown in Figure 5.5. Figure 5.5a shows the plot of the runoff ratio (RR) as a function of aridity index (AI). The majority of gauging stations representing sub-basins located in the southeast and north of the Congo River Basin (Region 1) show high values of aridity index and a low runoff ratio ($RR < 0.25$) potential. Within the humid region (Region 4: $AI < 0.75$) there is very little variation in aridity, but some variations in runoff ratio and therefore the aridity index alone is not a very good predictor for this area. In general, while two discernible relationships could have been established between the AI and the runoff ratio, it would have been difficult to determine the basis on which ungauged sub-basins could have been assigned to either relationship, given the fact that observed gauging stations of the same region would be on different regression lines. Therefore, a single regression relationship ($R^2 = 0.63$) is derived between the aridity index and the runoff ratio index.

Figure 5.5b presents a positive power relationship ($R^2 = 0.85$) between the aridity index and the Q10/MMQ index and this relationship is consistent with previous observations made about those areas which are expected to be more dominated by surface runoff relative to sub-surface processes and vice-versa. The sub-basins of Region 4 are located at the bottom end of the regression line, suggesting relatively low surface runoff contributions, while the sub-basins of Region 1 are spread throughout the regression line.

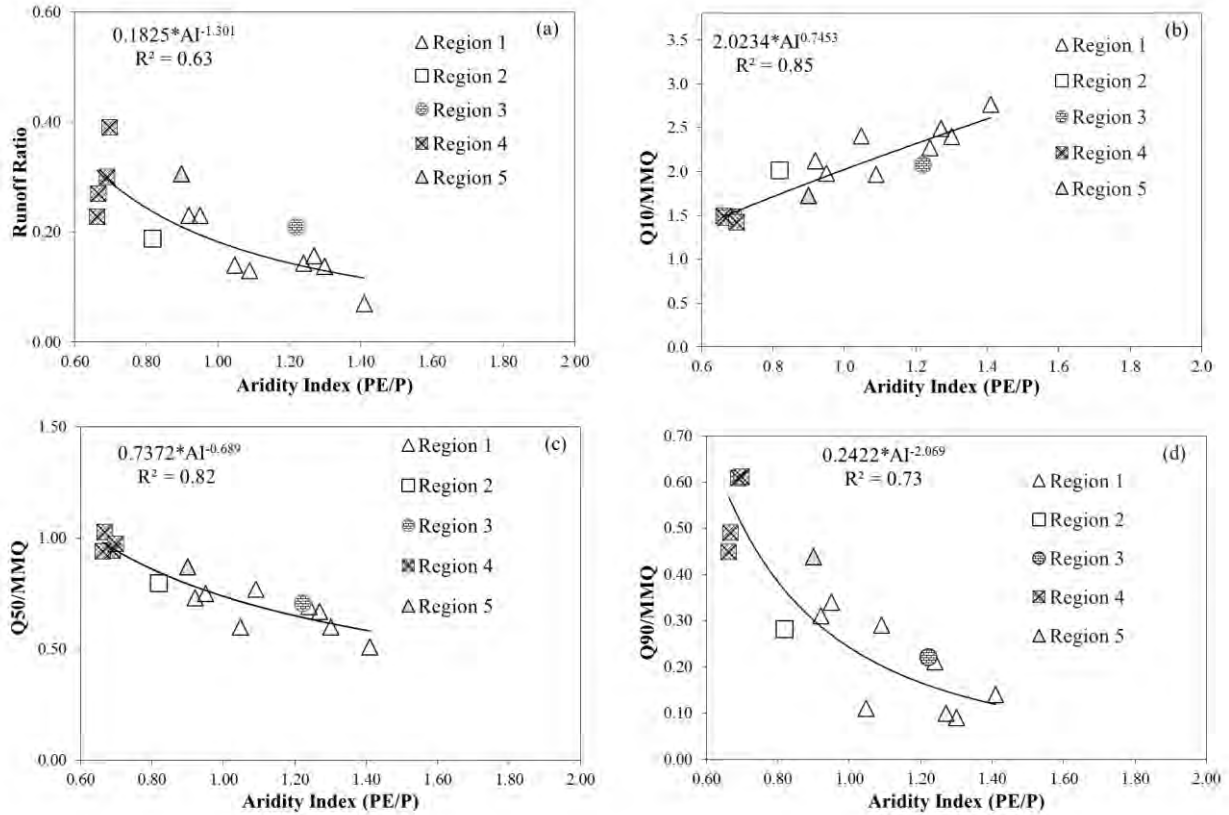


Figure 5.5. Power regression relationships between the aridity index and the hydrological indices across the 15 headwater gauged sub-basins of the Congo River Basin. (a) Runoff ratio, (b) Q10/MMQ index, (c) Q50/MMQ index and (d) Q90/MMQ index. Regions refer to those of Figure 5.3.

The Q50/MMQ index (Figure.5.5c) shows a positive power relationship ($R^2 = 0.82$) with the aridity index and follows a similar trend to the runoff ratio, where high values of aridity index are associated with low indices. The Q90/MMQ index also exhibits a positive power relationship (Figure.5.5d) but with a higher degree of scattering ($R^2 = 0.73$). Comparing Figures 5.5b and 5.5d suggests that Regions 2 and 4 have regimes with low variability, while Region 3 is more variable and Region 1 is represented by flow regimes of different degrees of variability. The low variability observed in the flow regimes of sub-basins representing regions 2 and 4 may also be partly attributed to their closeness to the equatorial line, where the bimodal flow pattern becomes evident. Without more data points it is difficult to predict if areas with higher aridity indices (Figure 3.2) would have very low Q90/MMQ indices and possibly zero flows for some of the time. This could

depend on the spatial scale of the sub-basins, in that aggregation of contributions from different parts of a large sub-basin, coupled with the effects of flow routing, suggest that zero flow conditions are unlikely. However, small sub-basins might experience zero flows, but the majority of the sub-basins used in the current modelling units are greater than 2 000 km², limiting the possibility of zero flow at a monthly time scale.

5.3.3.2 Updated predictive relationships

Through the application of the spatial disaggregation procedure (Section 5.2.5), additional sub-basins were added to the initial relationships. While these values are more uncertain than those used in initial relationships, they have been included to expand the data set before calculating regression line confidence intervals to quantify the uncertainty ranges of the hydrological indices. Figure 5.6 shows the updated relationships of the hydrological indices. A comparison between Figures 5.5 and 5.6 suggests that the shapes of the relationships have hardly changed, while most of the R² values have slightly decreased and therefore the final uncertainty bounds will be similarly increased.

5.3.4 Establishing uncertainty ranges of hydrological indices

The 90% confidence intervals of the hydrological indices are shown in Figure 5.7. These confidence intervals represent the degree of uncertainty that varies according to the type of the hydrological index, with greater relative uncertainty in the runoff ratio and the Q90/MMQ indices, while relatively low uncertainty characterises the Q10/MMQ and Q50/MMQ indices. Some limited independent estimates (Snel, 1957; Laraque et al., 1998) of runoff ratio (Figure 5.8) suggest that many of the reported runoff ratios fit within the computed bounds. Notable exceptions are some estimates for the rift valley region (eastern Congo River Basin). There are quite large uncertainties in the rainfall data (e.g. ratios of UNIDEL to CRU >1.15) for these steep areas (Figure 5.9), but even if a different rainfall data set is used (UNIDEL), the estimated runoff ratios remain well outside the computed uncertainty bounds (Figure 5.8).

In contrast, the independent estimates in flat to undulating topography (0.5 to 5%) regions (Cuvette Centrale, Northeast Congo, upper Lualaba and Southeast Kasai), generally fall within the uncertainty bounds regardless of which rainfall data set is used (Figure 5.8). The average runoff

ratio (0.24) for the whole Congo River Basin (Laraque and Olivry, 1996) also falls within the uncertainty bounds.

The averaged MMR (Figure 5.10) values over each sub-basin were correlated to the aridity index and a consistent relationship was found. This relationship shows a similar trend to some of the other hydrological indices such as RR, Q10/MMQ and Q90/MMQ. It is recognised that these values are potentially model dependent (Döll and Fiedler, 2008) and, therefore, subject to large uncertainty.

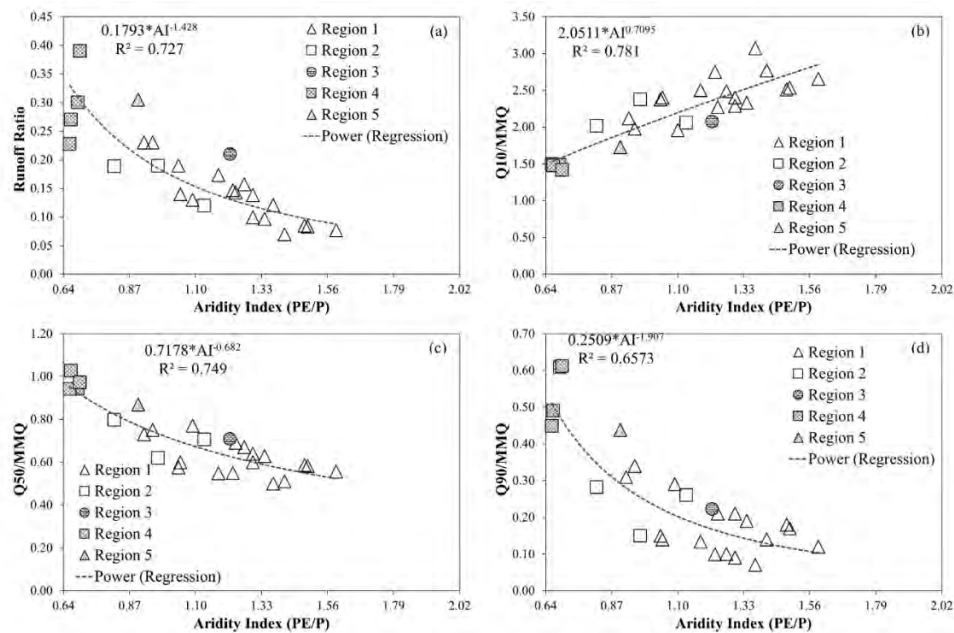


Figure 5.6. Updated power regression relationships between the aridity index and the hydrological indices across the 26 headwater sub-basins of the Congo River Basin. (a) Runoff ratio, (b) Q10/MMQ index, (c) Q50/MMQ index and (d) Q90/MMQ index. Regions refer to those obtained Figure 5.3.

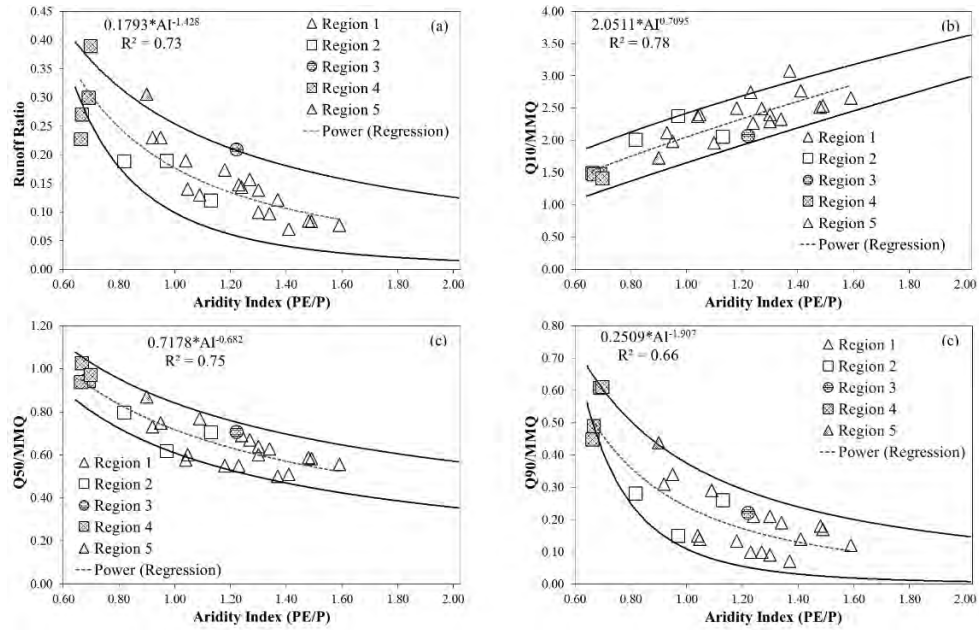


Figure 5.7. Final uncertainty ranges of hydrological indices derived based on the aridity index for all sub-basins of the Congo River Basin. (a) Runoff ratio index, (b) Q10/MMQ index, (c) Q50/MMQ index and (d) Q90/MMQ index. The region 6 did not appear among the plotted indices because of the lack of gauged headwater sub-basins.

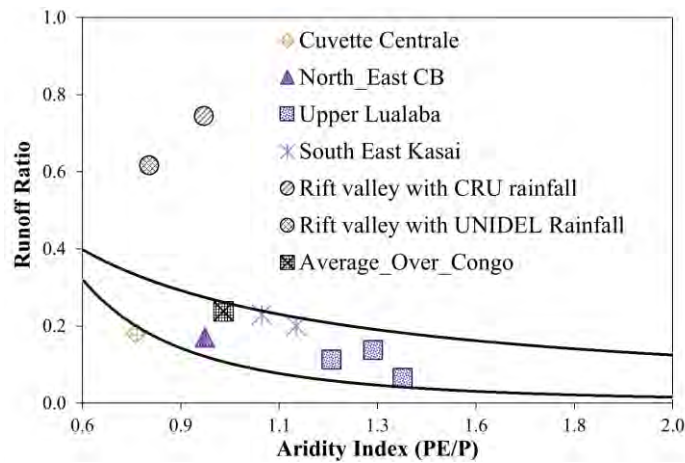


Figure 5.8. Validation of the uncertainty ranges of the runoff ratio index across the Congo River Basin. The average runoff ratio observed over the entire Congo River Basin at the Kinshasa gauging station fits within the computed bounds.

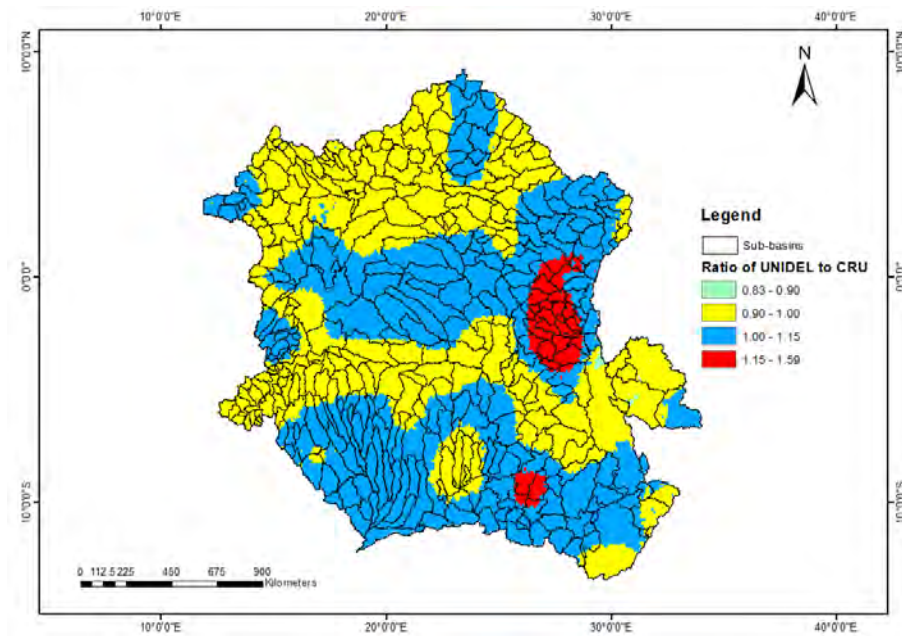


Figure 5.9. Ratios of UNIDEL to CRU mean annual rainfall showing potential areas of high uncertainty in rainfall. Sub-basins located in the rift valley system (in red in the eastern part) and around the Kamalondo wetland system (in red in the southeast) have highest ratios, indicating high uncertainty.

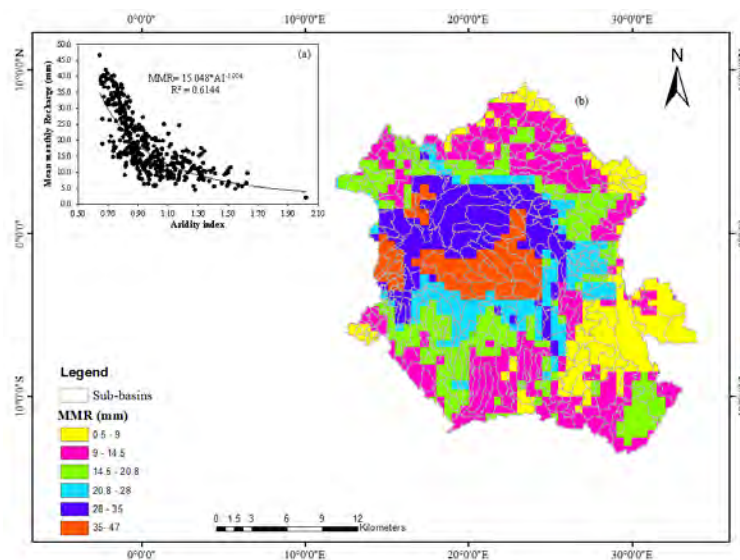


Figure 5.10. Estimates of the groundwater recharge across the Congo Basin. (a) relationship with the aridity index and (b) ranges of the estimates of the mean monthly recharge over the Congo Basin.

5.4 Discussion

This chapter aimed at establishing uncertainty ranges of hydrological indices that have to be used to constrain the outputs of hydrological models. However, it is difficult to establish such ranges in the context of data-scarce areas such as the Congo Basin and therefore, a region-specific approach was developed and identified the aridity index as the best predictor. In-depth discussion is provided in Kabuya et al. (2020b).

The identification of the aridity index as the best predictor (Table 5.4) of hydrological indices in the Congo Basin is perhaps not surprising. The aridity index was found by Zhang et al. (2018) to be one of the most influential attributes that correlated well with mean discharge as well as the 10th and 50th percentiles of the flow duration curve. In the southern African region, the aridity index showed consistent relationships with the runoff ratio (Ndzabandzaba and Hughes, 2017). However, there was a clear distinct regional difference, which was partly related to the substantial topographic and climate variations across the small country of Eswatini (Ndzabandzaba and Hughes, 2017). Such regional differences were less evident in the Congo Basin possibly because of the relatively small number of headwater gauging stations that did not consistently cover different identified climate and physiographic regions (Kabuya et al., 2020b). Tumbo and Hughes (2015) also found regional differences in the link between aridity and hydrological response indices, but they were not able to quantify regression relationships, and their result was based on simple index ranges for each identified region in the Great Ruaha River basin of Tanzania.

There have been situations where the aridity index did not reveal the best predictor of some aspects of the hydrological response. Gnann et al. (2019) have shown that the variability of low flow in humid sub-basins of the United Kingdom and the United States could not be primarily attributed to the aridity index and that the aridity index is the key determinant of low flows only in arid regions. The results presented in our study tend to support this conclusion in that the uncertainty range for Q90/MMQ index is quite large and there is no real trend in the values for Region 4 (Figure 5.7d).

Unavoidably, the developed uncertainty ranges of the hydrological indices account for several different sources of uncertainty. These uncertainties could be due to the uncertainty in the rainfall (Figure 5.9 and 5.10; Maidment et al., 2015; Sun et al., 2018) and evapotranspiration estimates,

affecting the aridity index estimates. Also, the length of the streamflow records (Westerberg et al., 2014b; Van der Spek and Bakker, 2017), the number of the gauging stations used, their spatial distribution and their extrapolation to ungauged areas (Westerberg and Mcmillan, 2015; Westerberg et al., 2016; Zhang et al., 2018; Addor et al., 2018; Kabuya et al., 2020b), the percentage of missing data, the reliability of rating curves (McMillan et al., 2012; Kiang et al., 2018) used to convert raw stage data into streamflow, and stage observational errors can all add uncertainty to the developed ranges. The average uncertainty obtained for the Q10/MMQ and Q50/MMQ indices (Figure 5.7) is less than what has been previously reported for Kasai and Lualaba drainage systems. The 38% and 32% uncertainty bounds for Q10/MMQ and Q50/MMQ indices, respectively, are lower than the 41% reported by Charlier (1955) and Lempicka (1971). The uncertainty results are reasonably consistent with previous studies on the uncertainty in hydrological signatures (Westerberg and McMillan, 2015) in other parts of the world. Westerberg et al. (2016) reported that the uncertainty in hydrological signatures varied with signature type, with the highest uncertainties ($\pm 30\text{-}40\%$) found in high and low flow characteristics due to the uncertainty in the observed discharge and the regionalization procedure.

CHAPTER 6 : MODELLING HYDROLOGICAL UNCERTAINTIES

6.1 Introduction

Hydrological modelling results are often affected by different sources of uncertainty (Westerberg et al., 2010; McMillan et al., 2012; Beven, 2013, 2016, 2018; Westerberg and Mcmillan, 2015; Liu et al., 2018; Ehlers et al., 2019; Gupta and Govindaraju, 2019; Motavita et al., 2019). Traditional calibration approaches are not able to account for these uncertainties because of the ungauged nature of many sub-basins (Boyle et al., 2000; Vrugt et al. 2003; Krause et al., 2005; Khu and Madsen, 2005; Moriasi et al., 2007; Ritter and Muñoz-Carpena 2013; Bennett et al., 2013). Some approaches to predictions in ungauged sub-basins have therefore focused on the use of regionalised hydrological indices to constrain hydrological models and identify behavioural parameter sets (Yadav et al., 2007; Zhang et al., 2008; Tumbo and Hughes, 2015; Hughes, 2016; Ndzabandzaba and Hughes, 2017; Quesada-Montano et al., 2018; Nijzink et al., 2018) to simulate hydrological responses with acceptable levels of uncertainty. The confidence intervals of hydrological indices developed in Chapter 5 provide the uncertainty ranges of constraints for each sub-basin of the Congo Basin and represent the long-term averages of hydrological responses across sub-basins.

This Chapter assesses the value of using uncertainty bounds of hydrological indices in constraining the outputs of the PITMAN model across the Congo Basin. Specifically, the focus is on the following:

- Quantifying behavioural parameter sets that match behavioural hydrological responses across 147 sub-basins selected for this study;
- Assessing the results of the constrained simulations at downstream gauging stations;
- Assessing the uncertainty propagation downstream;
- Revising the final constraints in line with original constraint bounds;
- Assessing the value of constraints in limiting simulated uncertainty;

6.2 Hydrological modelling results and validation

There are two possible steps in the refinement of the constraint ranges. The first is to modify the regionalised ranges for the sub-basins that are headwater gauged sites. This may involve either a shift, or a reduction in the ranges, or both. The objective of this exercise is to reduce the uncertainty in those sub-basins where there are observed data that are considered acceptably reliable. This is equivalent to reducing the size of the ‘clouds’ of uncertainty (Figure 4.5) in the gauged sub-basins. The second step is to determine whether any of the changes in the constraint ranges can be considered applicable to other sub-basins that are not gauged. This is a much more difficult objective and can only be applied when there are downstream gauged data to decide whether any changes to the constraint ranges in the upstream ungauged sub-basins are appropriate. This is equivalent to reducing the size of the ‘cloud’ in the most downstream sub-basin of Figure 4.5 on the basis that it is gauged and therefore should not be too uncertain. Behavioural model parameter ranges across drainage systems are given in Appendix B (Tables B6.1 to B.6.7) together with performance statistics (Table B6.8 in Appendix B) for the original and refined constraint ranges. The constraint refinement process presented for the Lualaba drainage system has shown different directions in which changes were made and reflects the general pattern observed in other drainage systems such as Oubangui, Sangha and upper Kasai. A summary of these adjustments is provided in Section 6.2.3, while Sections 6.2.2 and 6.2.4 focus on the uncertainty propagation downstream and the value of the constraint indices, respectively.

6.2.1 Simulation results in the Lualaba drainage system

A total of 93 sub-basins were delineated in the Lualaba drainage system and the majority of these are located downstream of wetland systems, whose results are presented in Chapter 7 (Section 7.4.5), while this sub-section deals only with sub-basins that are in the upstream parts of the drainage system and presents some of the results. Figure 6.1 shows the upstream gauging stations that are not impacted by wetland systems.

6.2.1.1 *Testing original constraint ranges in gauged headwater sub-basins*

Four sub-basins were among those used in Chapter 5 for the development of the original constraint ranges, and the simulated uncertainty bounds (Figure 6.2) of the flow duration curves (FDCs)

shows that the general pattern of the flow regimes is adequately simulated, but improvements could be made to some of the constraint ranges. Figure 6.3 presents the simulated FDCs after the constraint ranges were refined, while Figure 6.4 illustrates the changes made to the constraint ranges (degree of uncertainty). Only small changes were made for Taragi (L_CB196), while the main change for Chikakala (L_CB203) involved a small shift upwards in the Q50/MMQ range and a decrease in the range and upper value of the Q90/MMQ constraint.

For Kapolowe (Figure 6.3c), the ranges of all constraints were reduced with the upper bound of Q90/MMQ being decreased and the lower bound of Q90/MMQ being increased. For Chipili (Figure 6.3d), the main changes were reductions in the upper values of the Q10/MMQ and Q90/MMQ constraints. The main parameter changes were to those that determine the low flows and their range of uncertainty (FT, GW and R). The main issue for these four sub-basins is that all of the changes to both constraints and parameters are relatively small, suggesting that the original constraint values are broadly applicable and did not need to be changed very much.

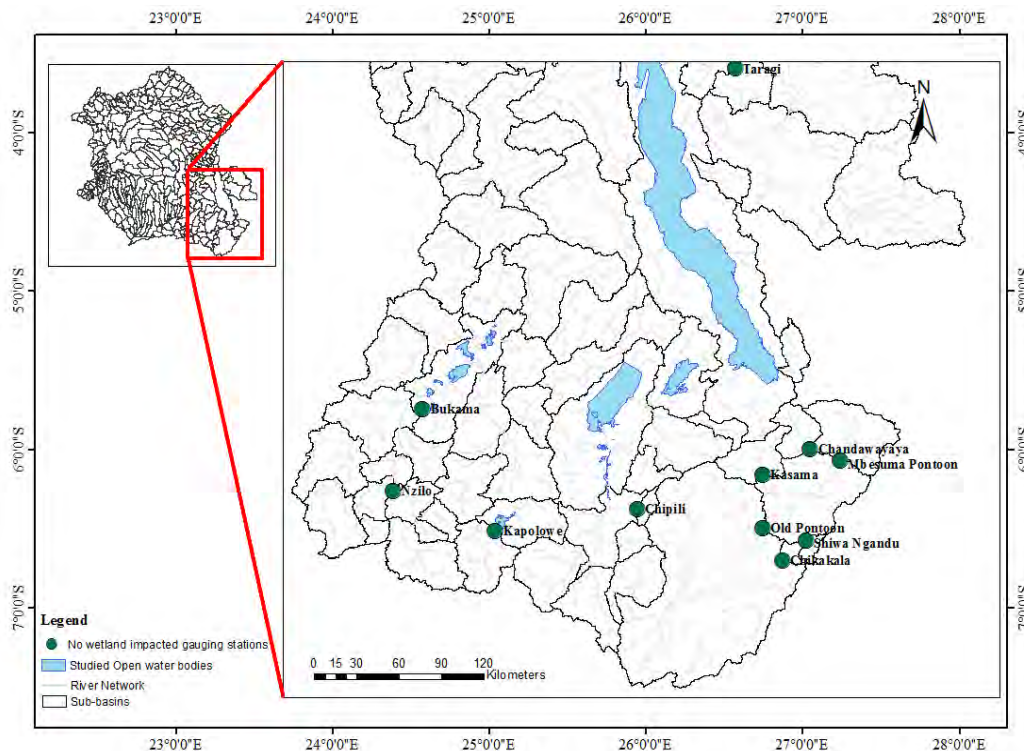


Figure 6.1. Location of Lualaba gauging stations (in green circle) that are not impacted by wetland systems above the Kasongo gauging station.

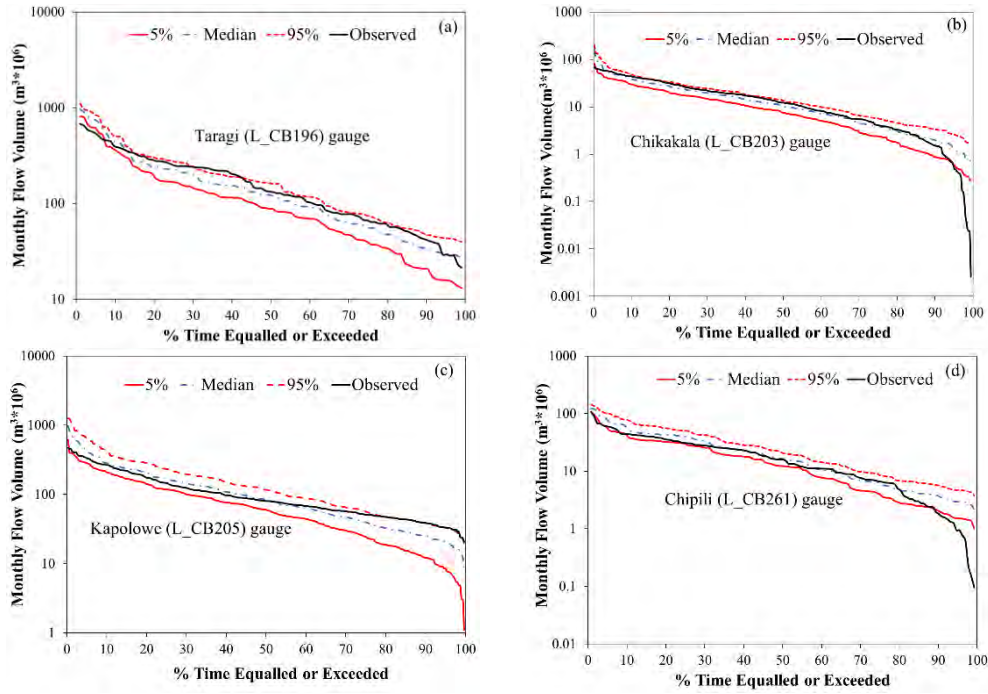


Figure 6.2. Simulated uncertainty bounds of the flow duration curves for the gauged headwater sub-basins using the original input constraint ranges developed in Chapter 5.

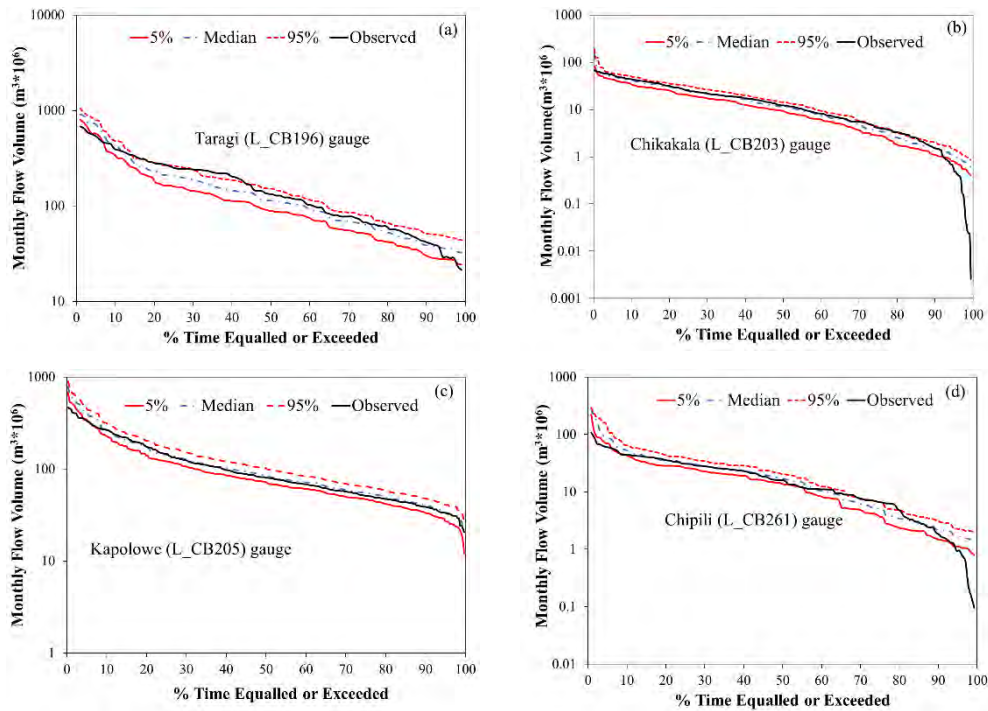


Figure 6.3. Refined simulated uncertainty bounds of the flow duration curves for the gauged headwater sub-basins after constraint refinement.

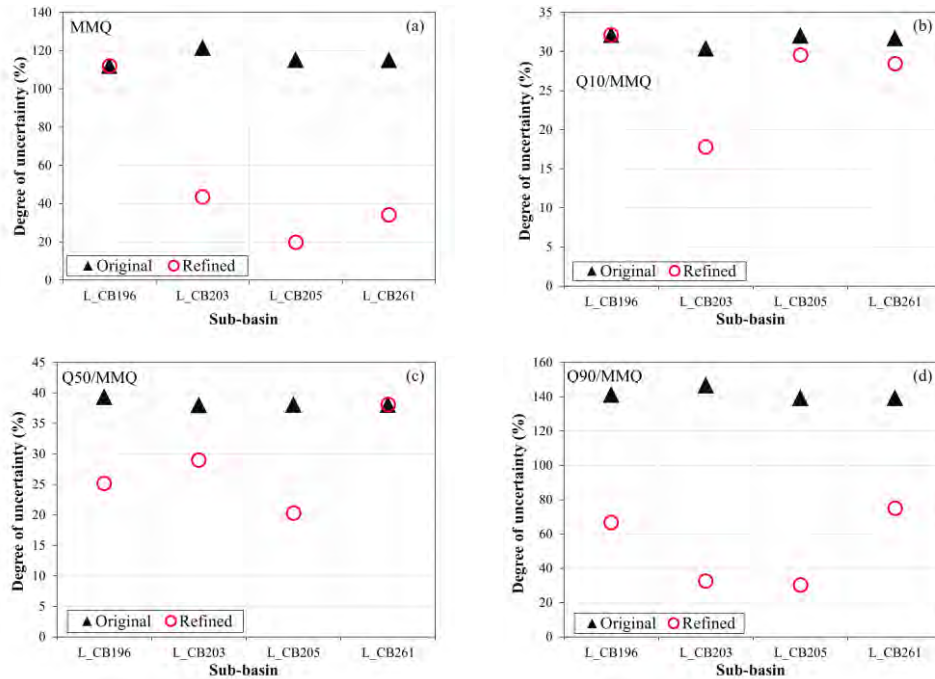


Figure 6.4. Degree of uncertainty in the original and refined constraint ranges for mean monthly flow (a = MMQ) and the three percentiles of the flow duration curves (b = Q10/MMQ; c = Q50/MMQ, d = Q90/MMQ).

6.2.1.2 Testing original constraint ranges in sub-basins draining to Bukama gauging station

There are only two gauging stations (Nzilo and Bukama) located in this sub-drainage system (Figure 6.1). Nzilo (L_CB27) is located in the upstream part where it drains three sub-basins with a cumulative area of 17 927 km², while Bukama (L_CB207) drains ten sub-basins, with a cumulative area of 61 385 km².

The results (Figure 6.5a) for the Nzilo show an under-simulation of the low flow regime and an over-simulation of high flows, while the middle part of the FDC is well simulated. The constraints for all three sub-basins, including the gauged, were adjusted (Figure 6.5b) in proportion to their contribution to the total runoff at the gauging station. The parameter changes required were mainly a decrease in FT and an increase in GW.

Further downstream at Bukama gauging station (L_CB207), the simulation results using the original constraints also show an under simulation of the low flow responses (Figure 6.6a). Proportionally (based on relative sub-basin areas) increasing the low flow constraints across all

sub-basins draining to this gauging station resulted in improved simulations (Figure 6.6b). However, these refinements have required changes to be made not only to FT and GW parameter ranges as it is the case with the upstream Nzilo gauging station, but also to ST and POW parameter ranges that have slightly shifted towards lower values.

The downstream sub-basin L_CB207 has an incremental area of 11 319 km² and is possibly subject to channel attenuation effects. The inclusion of the channel routing (CL) parameter in step 2 further improves the model performance, largely by reducing the very high flows, but with increased uncertainty in some parts of the FDC (Figure 6.7). The simulated streamflows at Nzilo (Figure 6.8) and Bukama (Figure 6.9) for one of the ensembles show that the general pattern of monthly flows is well simulated. The model somewhat over-simulates the high flow values in some years and these are essentially flows that occur less than 6% of the time.

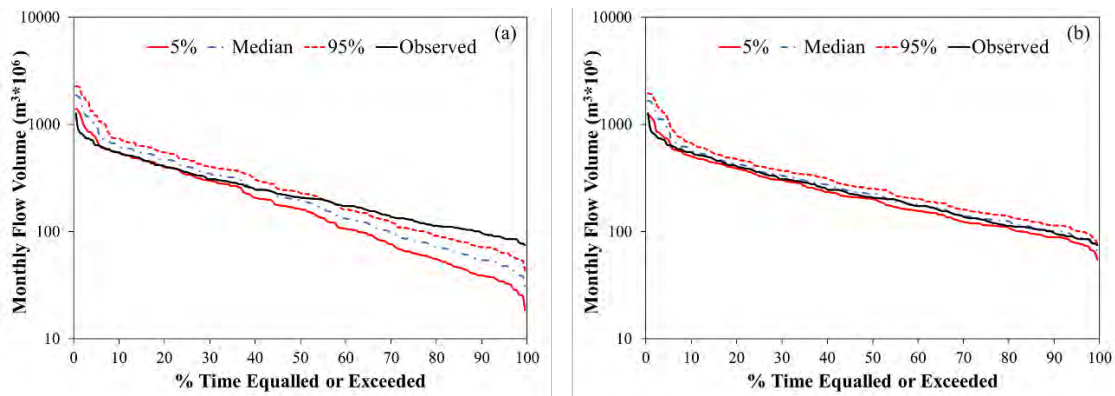


Figure 6.5. Uncertainty bounds of the flow duration curves at Nzilo gauging station (L_CB 27), using the original constraints (a) and after the refinement of constraints (b).

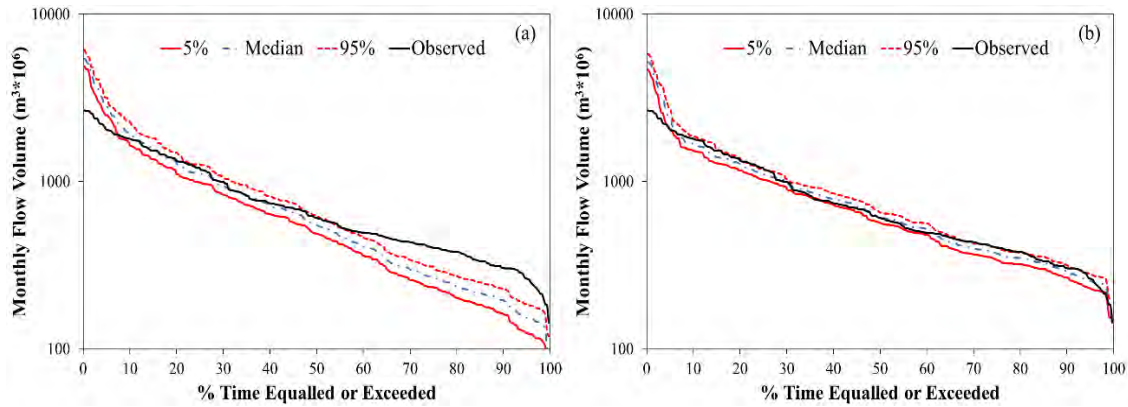


Figure 6.6. Uncertainty bounds of the flow duration curves at Bukama gauging station (L_CB 207), using the original constraints (a) and after the refinement of constraints (b).

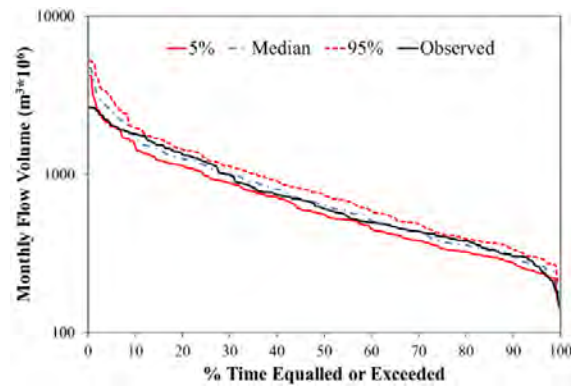


Figure 6.7. Uncertainty bounds of the flow duration curves at Bukama gauging station (L_CB 207) simulated using refined constraints with channel routing parameter CL.

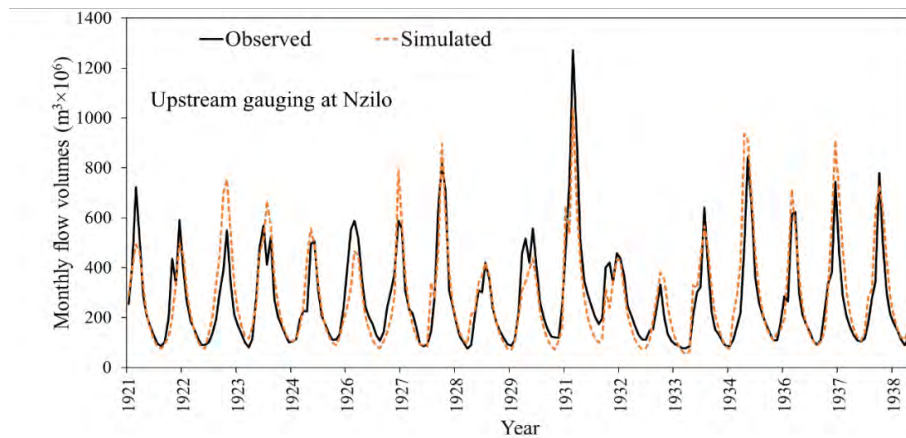


Figure 6.8. Simulated monthly streamflow at the Nzilo gauging station for the period January 1921-December 1938.

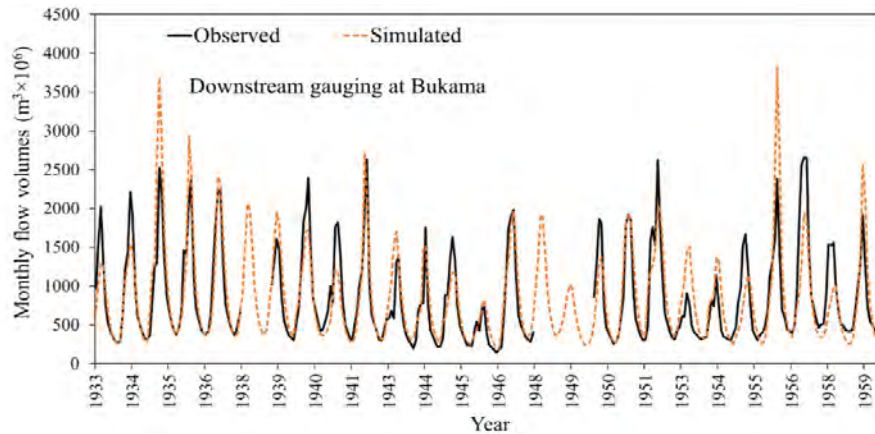


Figure 6.9. Simulated monthly streamflow at Bukama gauging station for the period January 1933-December 1959.

6.2.1.3 Testing original constraint ranges in sub-basins draining to Old Ponton gauging station

The Old Ponton gauging station is located in sub-basin L_CB18 part of the eastern sub-drainage system of Chambeshi-Luvua (Figure 6.2) upstream of the Bangweulu wetland system. It drains four sub-basins representing a cumulative area of 34 745 km² and all of them fall into climate and physiographic region 1 (Figure 5.3). Two of the upstream sub-basins (L_CB200 and L_CB202) are gauged, but L_CB200 (Chandawayaya) has only three years of data (1978-1981), while L_CB202 (Shiwa Ngandu) has the longest record period (1964-1992). L_CB201 (Mbesuma Pontoon: 1974-2004) and L_CB18 (Old Ponton: 1972-2004) are in downstream with longest record periods.

The results indicate that substantial changes to all the original constraint ranges are required for L_CB200 (Figure 6.10), while moderate changes to the low flow constraints are required at L_CB202 (Figure 6.11). Substantial changes in L_CB200 seem to have affected the portion of FDC beyond 50th percentile in the immediate downstream gauge located in L_CB201 (Figure 6.12) and any attempts to bring this part of FDC down did not solve this issue. However, the much larger changes required for L_CB200 may be a reflection of the very short observed data record. Only small changes were necessary at the most downstream sub-basin (L_CB18) (Figure 6.13), which represents 30% of the total drainage area. The changes in constraint ranges were accompanied by only slight changes in the model parameter space for L_CB202, suggesting that it was wide enough

to generate behavioural simulations within the refined constraint ranges. However, quite large changes to the ST and GW parameters for sub-basin L_CB200 were required.

More than 20% ensembles for L_CB200 have NE values ranging between 0.4 - 0.68 with %Bias ranging from -5.5% to 9.9%, while all ensembles have NE (ln) values ranging from 0.67 to 0.84 with %Bias (ln) between -9.9% and 9.9%. Although the simulated flows bracket the observed in sub-basin L_CB202 (Figure 6.11b), values of NE for high flows are below 0.5 across all ensembles, whereas 67% ensembles have low flow statistics above 0.5. This issue highlights the limitations of the traditional measures of reliability in situations of epistemic uncertainty. The use of uncertainty bounds provides a better way of evaluating model performance (Westerberg et al., 2011a; Beven, 2012).

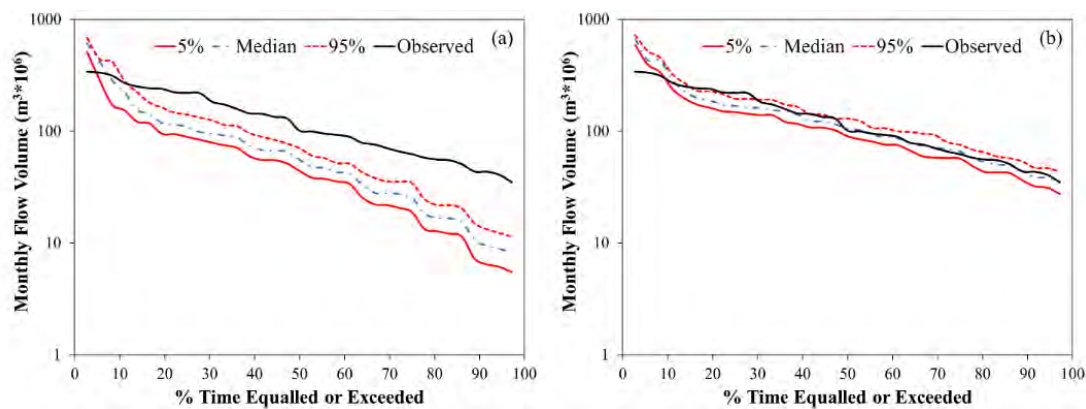


Figure 6.10. Uncertainty bounds of the flow duration curves at Chandawayaya gauging station (L_CB 200) using original (a) and refined (b) constraints.

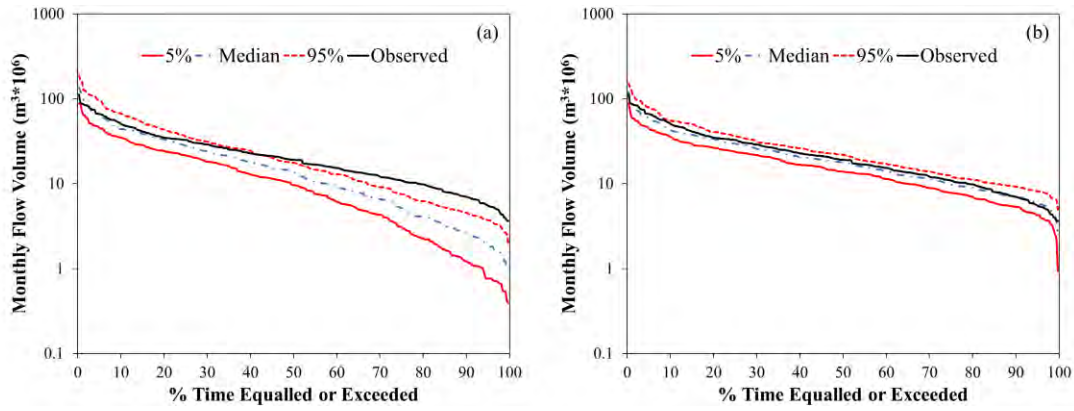


Figure 6.11. Uncertainty bounds of the flow duration curves at Shiwa Ngandu gauging station (L_CB 202) using original (a) and refined (b) constraints.

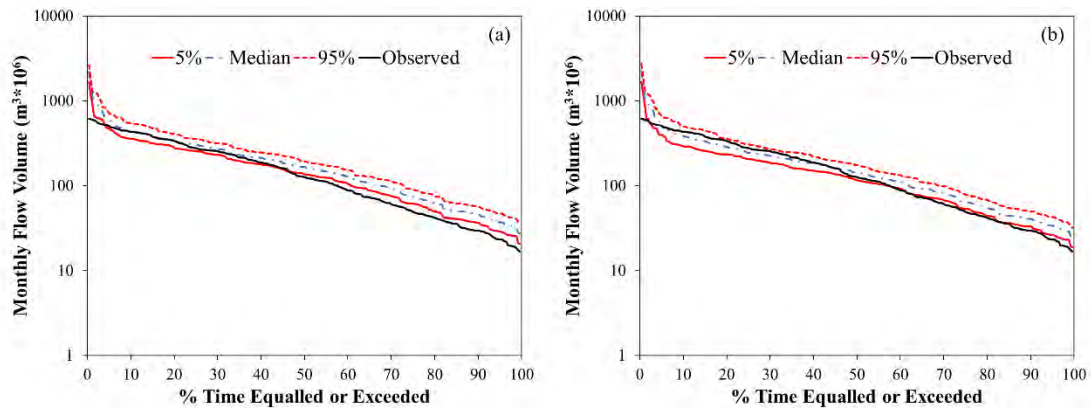


Figure 6.12. Uncertainty bounds of the flow duration curves at Mbesuma Pontoon gauging station (L_CB 201) using original (a) and refined (b) constraints.

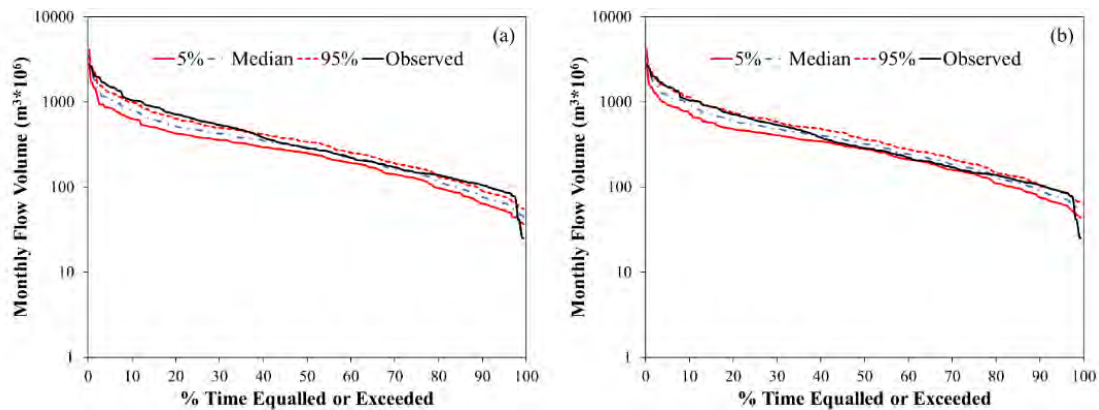


Figure 6.13. Uncertainty bounds of the flow duration curves at Old Ponton gauging station (L_CB 18) using original (a) and refined (b) constraints.

6.2.1.4 Testing original constraint ranges in sub-basins of the rift valley region

These sub-basins are located in the lower Lualaba drainage system and are not influenced by wetland systems of the upper Lualaba. They display a unique flow regime which is different from the upstream sub-basins of Lualaba (Kabuya et al., 2020b). They are responsible for the sudden change of the flow regime between Elila (L_CB394) and Lowa (L_CB 393) gauging stations (Tshimanga, 2012). Two gauging sites are available, both with short records. Shabunda (L_CB192) has two sub-basins, while Yumbi (L_CB191) has 12 sub-basins (Figure 6.14). It has already been noted that the ability of the input CRU rainfall data to represent real rainfall patterns for this area is questionable, and this issue is also dealt with in this sub-section.

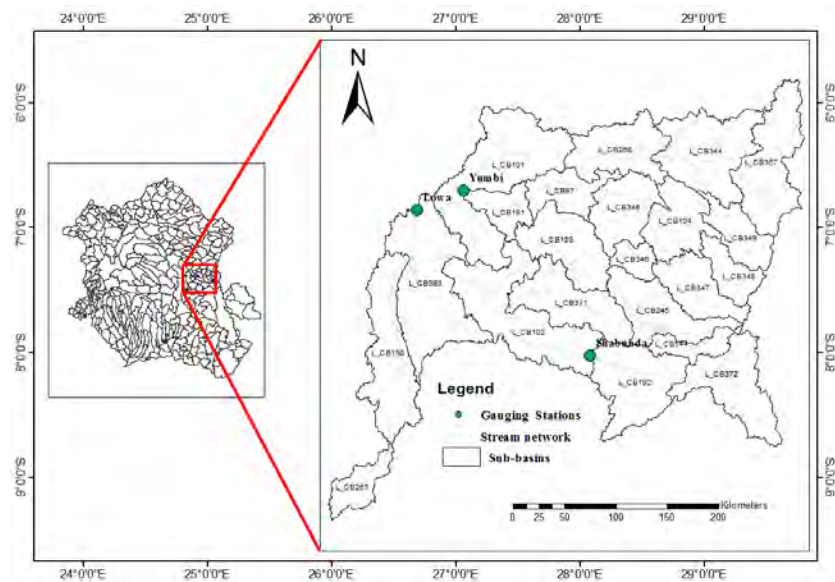


Figure 6.14. Location of the lower Lualaba sub- drainage system in the rift valley region of the Congo Basin.

The use of the original constraint ranges generates highly biased simulations at Shabunda and Yumbi compared with observed flows (Figure 6.15). The runoff ratio (using sub-area weighted rainfall for all upstream sub-basins) at Yumbi is about 0.58 and 0.74 when the UNIDEL and CRU rainfall datasets are used, respectively. However, the runoff ratio from the predictive equations varies between 0.09 and 0.32. Even if the higher values of the UNIDEL rainfall data are used to convert the predicted runoff ratios into MMQ the simulations remain too low. The MMQ constraints for all the upstream sub-basins were therefore increased to reflect the observed data

signals and the other constraints were similarly adjusted. UNIDEL rainfall was also used in this region on the assumption that a 74% runoff ratio based on the use of CRU data would be unrealistic. To achieve simulations that match the new constraints it was necessary to use ranges for the main runoff generation parameters that were quite different from the sub-basins discussed previously in this chapter. For example, FT parameter values were increased from between 10 and 40 mm month⁻¹ to between 60 and 170 mm month⁻¹ depending on sub-basin, and this is likely to be a reflection of the steeper topography.

The hydrological simulations using the UNIDEL rainfall dataset with the refined constraints have successfully bracketed the observed flow duration curve when all sub-basins are grouped (Figure 6.16b) and some portions of the flow duration curve are outside the uncertainty bound when sub-basins are independently simulated (Figure 6.16a). The uncertainty associated with the three percentiles and the mean monthly flow is within an acceptable range. The full uncertainty for the Q10, Q50, Q90 and MMQ is 12.9%, 14.6%, 8.7% and 13%, respectively with grouped sub-basins and even less for independent sub-basins.

The simulation results for this area highlight the effects of the forcing rainfall dataset on the model performance (Terink et al., 2018; Mazzoleni et al., 2019; Cawse-Nicholson et al., 2020; Shrestha et al., 2020). The CRU rainfall data in the rift valley region of the lower Lualaba appear to be very uncertain especially in the mountainous regions. The upper Lualaba sub-region is characterised by flat to undulating (2 – 6%) topography and falls into climate and physiographic Region 1 (Figure 5.3), whereas the rift valley region is characterised by undulating to steep (9 – 25%) topography and is included in Region 3. The comparison between the two rainfall datasets in these two sub-regions reveals that (Figure 6.17a) there is a small (7%) difference in the lower topography sub-region, but a much greater difference (20%) in the steeper sub-region (Figure 6.17b). This difference was previously highlighted through regional comparisons of the ratio of UNIDEL to CRU mean annual rainfall totals (Figure 5.9). This result is consistent with previous studies conducted elsewhere (Maidment et al., 2015; Sun et al., 2018; Nogueira, 2020) that have noted that the CRU data are not always appropriate to adequately represent rainfall patterns in mountainous regions.

The constraint refinement process conducted in the Lualaba drainage system has shown different directions in which changes were made and these reflect the general pattern observed in other drainage systems such as Oubangui, Sangha and upper Kasai. A summary of these readjustments is provided in Section 6.2.3, while the next section focuses on uncertainty propagation downstream.

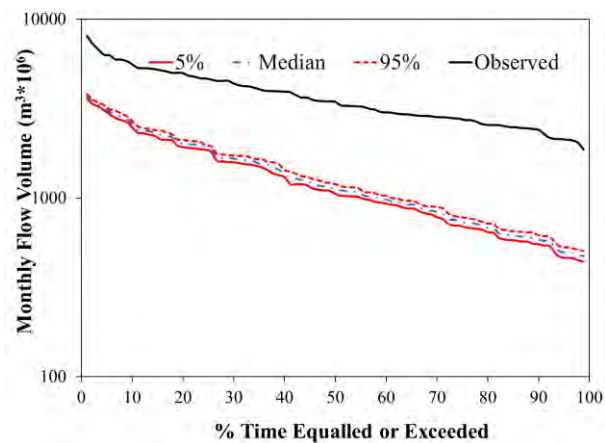


Figure 6.15. Unsuccessful simulated uncertainty bound of the flow duration curve at Yumbi gauging station using the original constraints and CRU rainfall dataset.

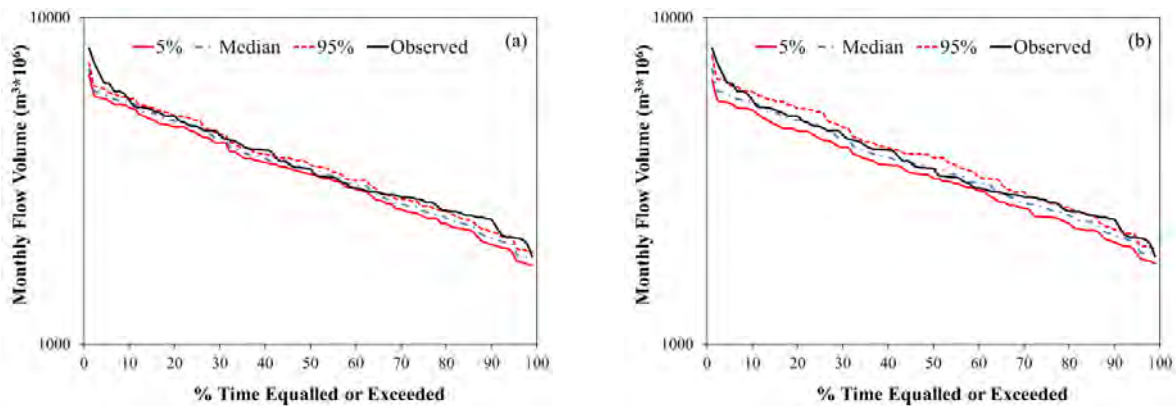


Figure 6.16. Simulated uncertainty bound of the flow duration curve at Yumbi (L_CB191) site using region-specific constraints and UNIDEL rainfall dataset when sub-basins are ungrouped (a) and grouped (b).

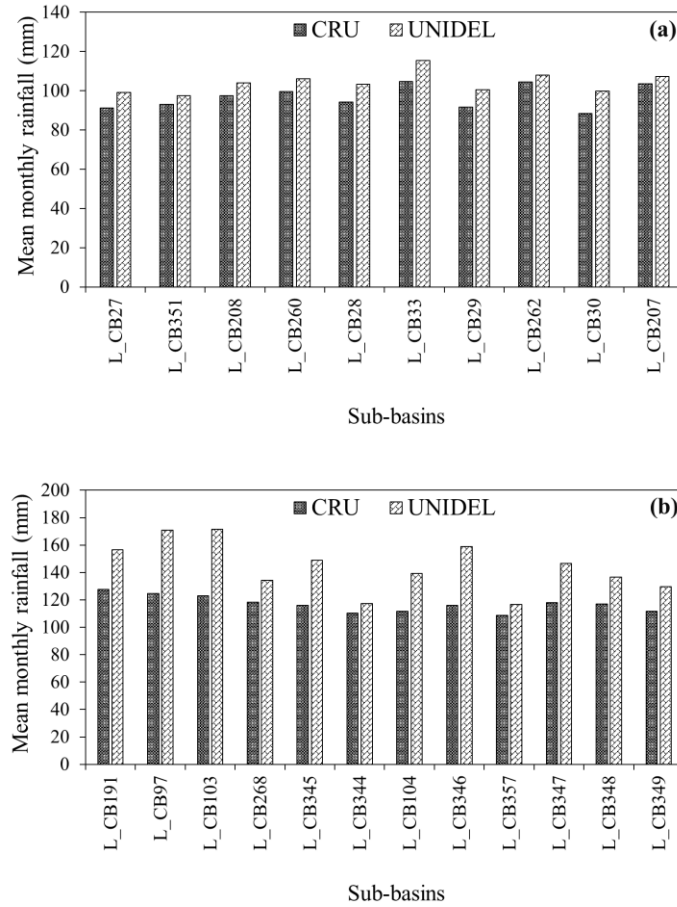


Figure 6.17. Comparison between CRU and UNIDEL long-term mean monthly rainfall data in two different regions of the Lualaba drainage system. **(a)** = undulating topography of Bukama sub-drainage system and **(b)** = undulating to the steep topography of the lower Lualaba (rift valley) sub-drainage system.

6.2.2 Assessing the uncertainty propagation downstream

As already noted (Section 4.2.2.2), grouping sub-basins should increase the overall uncertainty as this removes the random combinations of relatively wet and dry simulations from the upstream sub-basins. In this section, examples of the uncertainty propagation downstream are presented for Lualaba and Sangha drainage systems. Figure 6.18 illustrates the different degrees of uncertainty associated with no grouping and grouping of sub-basins in the Lualaba between Nzilo and Bukama gauging stations. For the upstream gauging station (Nzilo) where only three sub-basins were grouped, the uncertainty has slightly decreased for MMQ, Q10 and Q90, while it has increased for

Q50. At the downstream gauging station (Bukama), with more upstream sub-basins, the grouping of sub-basins has resulted in increased uncertainty across all of the response variables, as would be expected from simple statistical considerations. In general, the simulated upstream and downstream uncertainty lies within the range of 20% to 35% across hydrological response types.

In Sangha drainage system (Figure 6.19), the grouping of sub-basins involved assigning different group index values to sub-basins according to their physiographic region (Figure 5.3). Only six sub-basins drain to Carnot gauging, while twelve and twenty-four drain to Salo and Ouesso gauging stations, respectively. Results show that the uncertainty propagation from upstream (Carnot) to downstream (Ouesso) gauging stations decreases when sub-basins are independently simulated (Figure 6.20). Further, the difference in the degree of uncertainty between independent and grouped sub-basins increases downstream. This is probably due to the larger number of simulated sub-basins. Also, the lower levels of uncertainty for independent sub-basins is related to the larger number of sub-basins in this system (Sangha) than in the Lualaba.

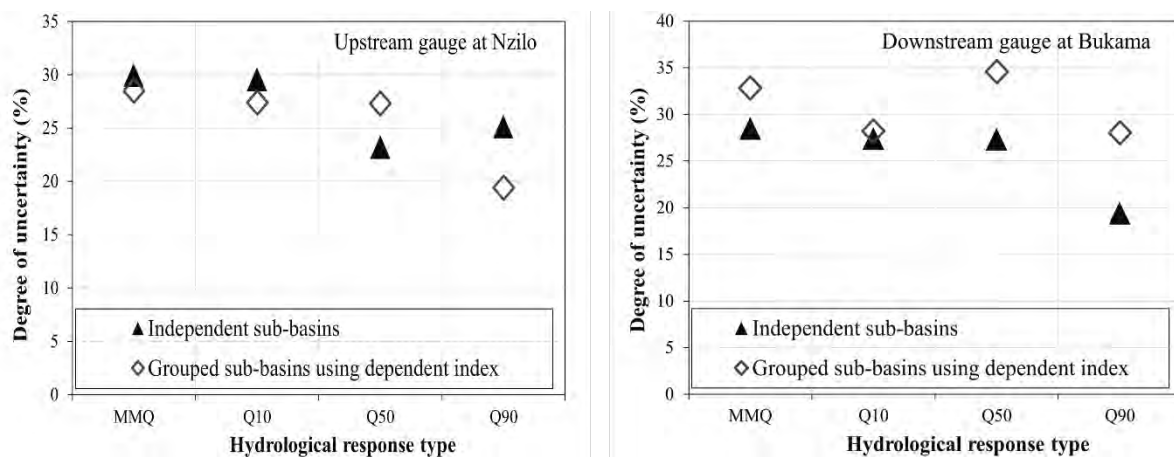


Figure 6.18. Degree of uncertainty at upstream and downstream gauging stations of the upper Lualaba drainage system.

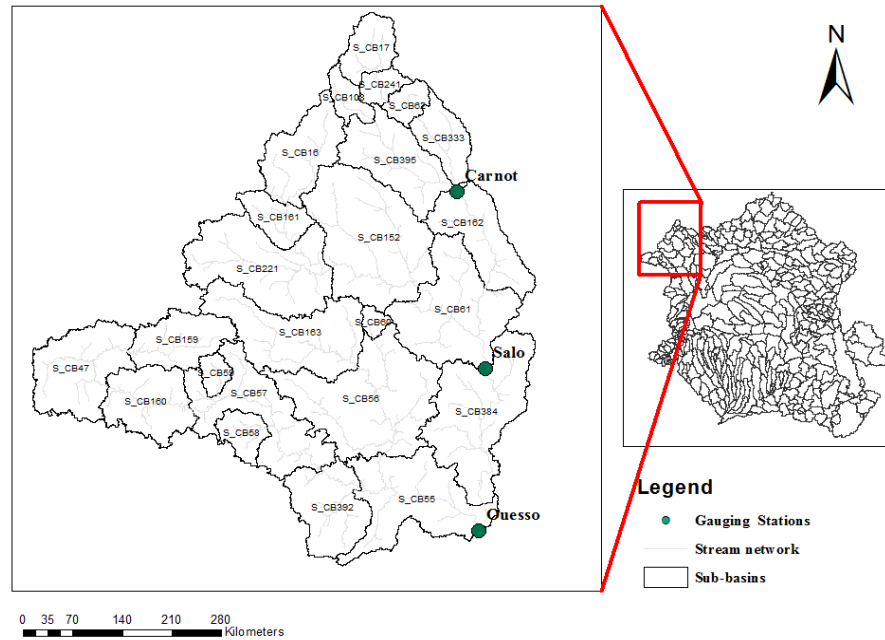


Figure 6.19. Location of the studied sub-basins in the Sangha drainage system

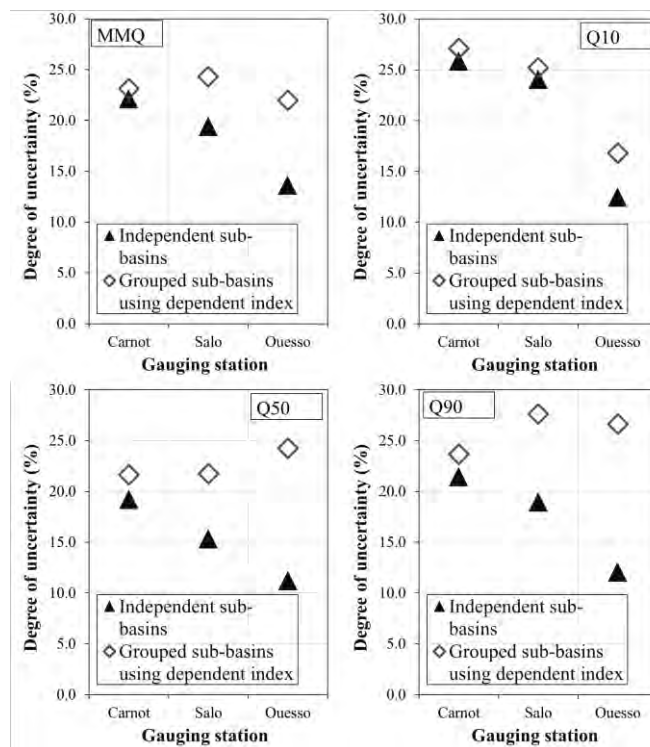


Figure 6.20. Downstream uncertainty propagation across three gauging stations of the Sangha drainage system (from upstream to downstream gauging stations) for the mean monthly (MMQ), high (Q10), medium (Q50) and low (Q90) flow.

6.2.3 Summary of the constraint revision process and re-calibration

The application of the original constraints generated satisfactory simulation results in some areas, while in others both small and large adjustments were required to fully capture some aspects of the observed hydrological responses. Table 6.1 summarises the patterns of changes made to original constraint ranges. In general, the low flow constraint (Q90/MMQ) ranges have substantially increased in the Lualaba drainage system, whereas the high flow constraint (Q10/MMQ) ranges display a decreasing pattern. The Q50/MMQ constraint ranges have relatively increased (shifted up), while the lower limits of MMQ have mostly increased and the upper bounds have either remained unchanged, decreased or increased. In the Oubangui and Sangha drainage systems, many of the original constraint ranges did not require adjustments. However, adjustments in low flow constraint ranges mainly involved increases and were rarely decreased. In the upper Kasai and Inkisi sub-drainage systems, substantial increases of the constraint ranges, particularly MMQ, Q50/MMQ and Q90/MMQ, were required. The Rift valley and Batéké plateaux sub-drainage systems have shown unique hydrological responses that resulted in complete changes of the original constraint ranges.

The starting point for a re-calibration of the regionalisation of the constraints is illustrated in Figure 6.21 which compares the original constraint bounds with the actual values obtained after the hydrological simulations have been compared with the observed data. The revised constraint values plotted in Figure 6.21 are the mean values of the re-calibrated constraint ranges. The majority of sub-basins fit within the original uncertainty bounds. The number of points within original bounds reflects the percentage success while the number outside reflects the percentage failure of the original uncertainty bounds to represent hydrological responses at the sub-basin level. In general, the results have shown that Q10/MMQ and Q50/MMQ have got the highest percentage success (75%) while the runoff ratio and Q90/MMQ have 65% and 58%, respectively. This higher success may be justified by the fact that the degree of uncertainty associated with the Q10/MMQ and Q50/MMQ constraints was lower in the original constraint ranges whereas it was greater in the runoff ratio and Q90/MMQ constraints (Kabuya et al., 2020b).

Table 6.1. Summary of the adjustment process of constraint ranges across drainage systems (LB and UB represent the lower and upper bounds of constraint ranges). The meaning of the symbols used is given at the bottom of the table.

Sub-basin	Gauging	Number of sub-basins	Drainage system	MMQ		Q10/MMQ		Q50/MMQ		Q90/MMQ	
				LB	UB	LB	UB	LB	UB	LB	UB
L CB196	Taragi	1	Lualaba	No	No	No	No	++	No	+++	++
L CB203	Chikakala	1	Lualaba	+++	No	+	++	++	+	+++	---
L CB205	Kapolowe	1	Lualaba	+++	--	-	-	++	+	+++	+++
L CB261	Chipili	1	Lualaba	+++	--	--	--	No	No	No	---
L CB27	Nzilo	3	Lualaba	+++	--	--	--	++	++	+++	+++
L CB207	Bukama	10	Lualaba	No	No	---	---	++	++	+++	+++
L CB200	Chandawayaya	1	Lualaba	+++	+++	--	--	++	++	+++	+++
L CB202	Shiwa Ngandu	1	Lualaba	+++	+++	--	--	+++	++	+++	+++
L CB18	Old Ponton	4	Lualaba	++	No	No	No	No	No	+++	No
L CB191	Yumbi	12	Lualaba	+++	+++	--	--	+++	+++	+++	+++
O CB179	Sibut	1	Oubangui	No	--	+++	++	---	---	+++	+++
O CB355	Bambari	3	Oubangui	++	---	-	--	++	-	+++	++
O CB176	Boali	3	Oubangui	--	No	++	+	-	-	-	---
O CB95	Bria	6	Oubangui	No	No	-	-	No	No	+	+
O CB76	Kembe	8	Oubangui	No	No	No	No	No	No	No	No
O CB181	Rafai	5	Oubangui	No	No	No	No	--	--	-	---
S CB395	Carnot	6	Sangha	No	No	No	No	No	No	No	No
S CB61	Salo	12	Sangha	++	++	No	No	No	No	+++	++
S CB55	Ouessou	24	Sangha	---	---	++	+	--	--	+	-
K_CB259	Kananga-Luluabourg	4	Upper Kasai	+++	No	--	--	+++	+++	+++	+++
C CB138	Inkisi	3	Lower Congo	+++	+++	-	--	++	++	++	+
C CB169	Bwambe	4	Sangha	+++	+++	--	--	+++	+++	+++	+++

+: Slight increase of <5%; ++: Increase of <25%; +++: High increase of >25%; -: Slight decrease of <5%

---: Decrease of <25%; ----: High decrease of >25%; No: No changes made to original constraint ranges

The sub-basins of the rift valley and Batéké plateaux regions, in relation to runoff ratio and Q50/MMQ constraints, show a consistent hydrological similarity although there exists a noticeable difference in Q90/MMQ constraints (Figure 6.21d). Sub-basins of Oubangui and Sangha drainage systems fit well within the original uncertainty bounds, except some points of Oubangui that fall outside constraint bounds (Figure 6.21c). Sub-basins of Oubangui show a large degree of scattering that indicates spatial variability of hydrological processes in relation to Q50/MMQ and Q90/MMQ constraints. The variation of constraints along the climate gradient is well explained based on the sub-drainage pattern rather than on climate and physiographic regions (Figures B.6.1 and B.6.2 in Appendix B).

An analysis of the re-calibrated constraints shown in Figure 6.21 reveals two major patterns that can be grouped into northern and southern sub-basins (Figure 6.22). The northern sub-basins include mainly the Sangha and Oubangui drainage systems and others north of the equator, while the southern sub-basins include all drainage systems south of the equator. On this basis, a variation of constraints along the climate gradient is represented by two equations for each constraint index. This has the advantage of reducing uncertainty in the regional constraint index estimation process, especially for the MMQ and Q90/MMQ constraints. There are some sub-basins of the upper Lualaba drainage that depart from the general pattern of southern sub-basins regarding Q90/MMQ (Figure 6.22d). These two sub-basins behave similarly as some sub-basins of the northern Oubangui, but the underlying geological formations are not the same. The majority of the Oubangui sub-basins are underlain by Precambrian basement formations (Figure 3.5), while those in the upper Lualaba have a high degree of spatial heterogeneity in the geological formations (O'Dochartaigh, 2019), which can influence the spatial variability of the low flow regime.

Figure 6.23 illustrates that the re-calibrated mean monthly recharge (MMR) constraints in the Sangha and Oubangui drainage systems are well outside the original values that were derived from the global dataset (Döll and Fiedler, 2008). Since the original MMR values are model dependent, it was expected that their use in this modelling exercise would constitute one of the major sources of uncertainty associated with low flows. On the other hand, the majority of the sub-basins in the upper Lualaba, Rift valley, Kasai and Inkisi have shown average values of groundwater recharge within the original range, suggesting that this global dataset of groundwater recharge can still be useful in constraining the groundwater components of a hydrological model.

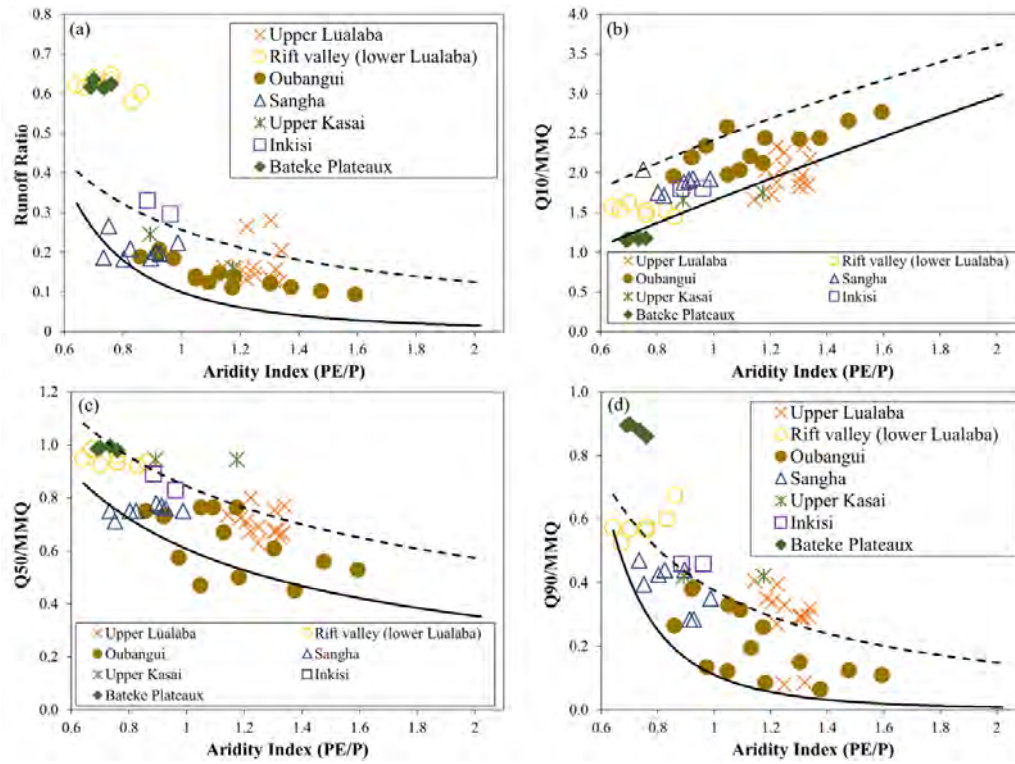


Figure 6.21. Mean values of the re-calibrated constraints after hydrological simulations have been validated across drainage systems for (a) runoff ratio, (b) Q10/MMQ, (c) Q50/MMQ and (d) Q90/MMQ. Dashed and plain lines represent upper and lower uncertainty bounds of original constraints.

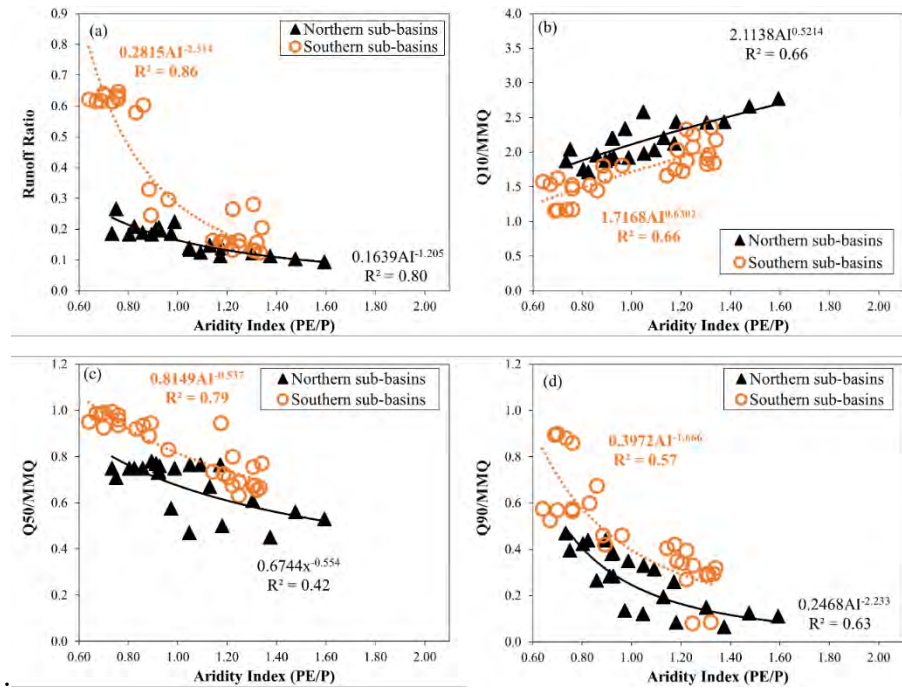


Figure 6.22. Re-calibrated constraint indices along climate gradient (aridity index) depending on whether sub-basins are located in the northern or southern hemisphere across the Congo Basin.

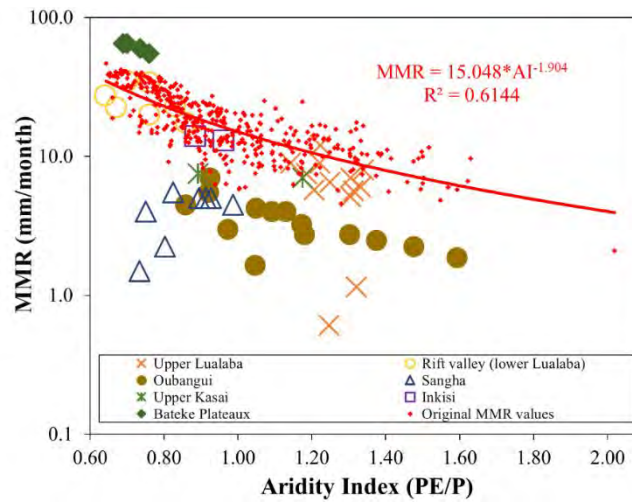


Figure 6.23. Comparison between final average values of mean monthly recharge (MMR) constraint and original values derived from a global dataset. Values are plotted on a logarithmic scale for comparison purpose and the regression relationship is for the original MMR values.

6.2.4 The usefulness of constraints in constraining hydrological uncertainty

This sub-section assesses the value of using constraints to constrain hydrological model outputs. This assessment is done by comparing the predicted uncertainty intervals of the hydrological response simulated in this study and the results obtained in a previous study where the structured uncertainty version of the PITMAN model was used (Tshimanga, 2012). An error index (defined as the percentage difference between the simulated and observed monthly flow volumes) is computed for the mean monthly flow and the three percentiles of the flow duration curve across selected gauging stations in the Oubangui, Sangha and Lualaba drainage systems (Figure 6.24). Positive values of this error imply an over-estimation of the prediction, and negative values the under-estimation. In general, the results show that the current study has simulated a lower hydrological uncertainty compared to the previous study. In the current study, although a similar pattern is reproduced across drainage systems, the predictive uncertainty intervals are smaller across gauging stations (Figure 6.24a) and hydrological response type.

However, although the total uncertainty in the current study is lower compared to the previous, there is a slight increase of the upper uncertainty bound associated with high flows at the Bria gauging station (O_CB95) (Figure 6.24b) in the Oubangui and similar behaviour is observed with low flows at Taragi gauging station (L_CB196) in the Lualaba, where the lower uncertainty bound is higher compared to a previous study (Figure 6.24d). It can be, therefore, said that the uncertainty reduction in this study is primarily attributed to the use of constraints that have adequately quantified the uncertainty level and identified appropriate behavioural parameter sets that have substantially captured main hydrological processes across drainage systems

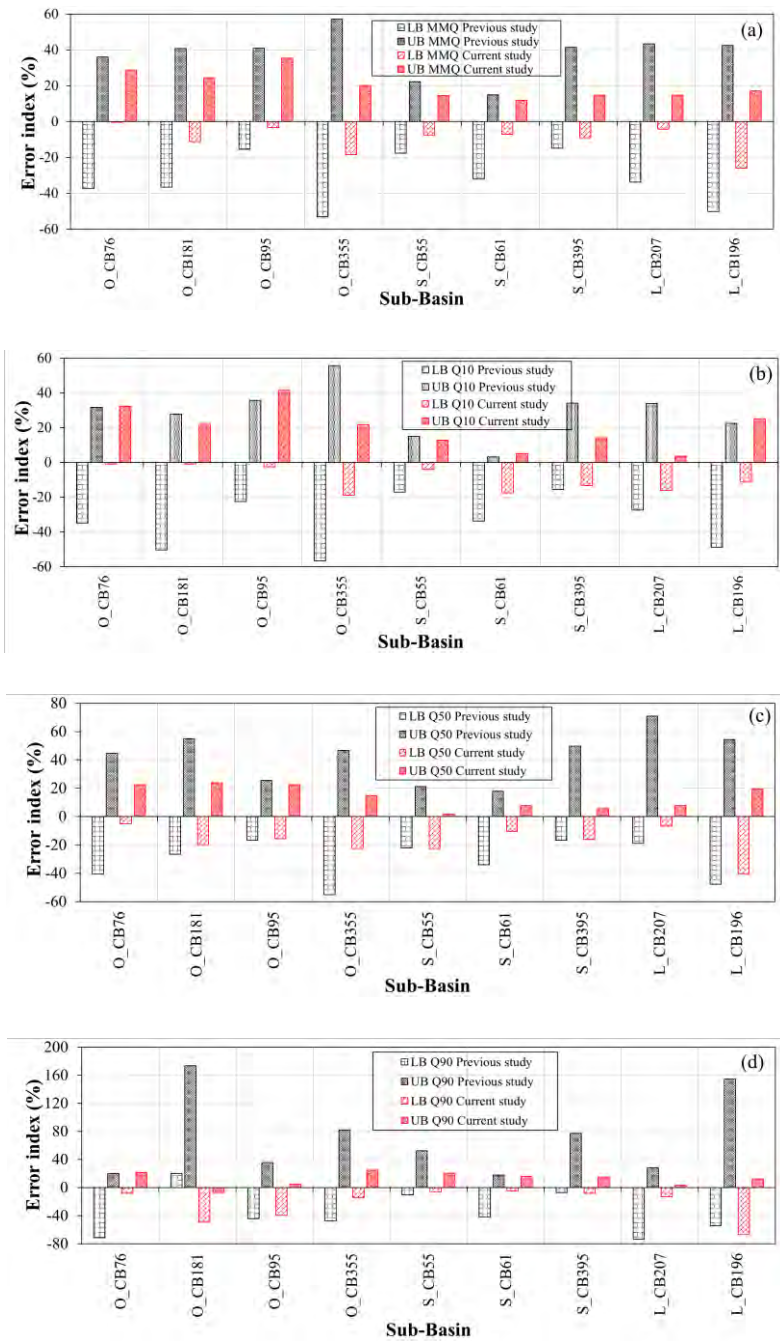


Figure 6.24. Comparison of predictive uncertainty intervals between previous (in grey) and current (in red) studies across selected gauging stations for the (a) Mean monthly flow and three percentiles of the flow duration curve namely (b) Q10th, (c) Q50th and (d) Q90th. LB and UB are the lower and upper bounds of the predictive uncertainty intervals with respect to observed flows.

6.3 Discussion

This Chapter has discussed the testing of the original constraint index uncertainty bounds developed in Chapter 5, across the different drainage systems of the Congo Basin. The main issue was whether the changes made to the original constraints at headwater-gauged sub-basins can be applied to ungauged upstream sub-basins to meet the observed flow at downstream gauging stations. Other issues associated with extreme flows (low and high) arise during the modelling process. These two issues are discussed below.

The simulations at downstream gauging stations present some challenges when they do not reproduce observed conditions. There have been only very few cases that did not require any constraint adjustment at all (Table 6.1). This is, for example, the case with Kembe and Carnot gauging stations located in Oubangui and Sangha drainage systems, respectively. Ideally, only gauged sub-basin's constraints can be easily revised based on the observed flow. However, the refinement made to gauged sub-basins alone may fail to substantially affect the results if ungauged upstream sub-basins exert a major impact on defining downstream hydrological response. This is the case for the majority of gauging stations used in this analysis where improvement of constraint ranges at the downstream gauged site alone did not affect the overall results and therefore adjustments were required in ungauged sub-basins. These adjustments aimed at adjusting constraint ranges of a particular aspect of hydrological response in the same proportion across all ungauged upstream sub-basins contributing to the same downstream gauging station. The approach was successfully applied by Ndzabandzaba and Hughes (2017) who reported relatively small changes in the order of 10 – 15%. In this study, however, major changes, sometimes beyond 100%, were required for the MMQ and Q90/MMQ (Table 6.1) constraints because the original ranges were too wide (Kabuya et al., 2020b). Sometimes the full range of constraints was completely changed because of the uniqueness of place issue (Beven, 2000) that limits our ability to generalise hydrological response hypotheses (original constraint ranges) across the Congo Basin.

There are portions of the hydrological response that are very difficult to capture even after major revisions have been made to constraint ranges. High and low flows that occur less than 6% and beyond 90%, respectively, are over-simulated irrespective of drainage systems. While the use of

the channel routing parameter CL can solve some of the high flow problems through peak flow attenuation, often this is done at the expense of other aspects of the hydrological response where the predictive uncertainty increases (Figure 6.7). However, it should be noted that these over-simulations could be a result of the inadequate quality of the input climate data (Oudin et al. 2006; Westerberg et al., 2010; McMillan et al., 2012; Ehlers et al., 2019) as well as of the flow data used to validate the model outputs (Westerberg et al., 2014b; Beven 2016; Van der Spek and Bakker, 2017; McMahon and Peel, 2019; Manfreda et al., 2020). Basically, it is unrealistic to expect the CRU regional rainfall to be able to adequately represent the real rainfall in individual months and therefore we will always expect relatively poor simulations of peak wet season runoff. What is important is that the key wet and dry seasons are identified, which they seem to be in most cases.

CHAPTER 7 : A COMBINED MODELLING APPROACH FOR ASSESSING WETLAND DOWNSTREAM HYDROLOGICAL IMPACTS

7.1 Introduction

In this chapter, the term wetland covers a large variety of fluvial wetland systems (Von der Heyden and New, 2003; Acreman and Holden, 2013; Hughes et al., 2014) and their effects may lead to either the increase or decrease of a particular component of the water cycle (Bullock and Acreman, 2003). Wetland systems are widely known for their potential to exert a considerable influence on basin-scale hydrological processes (Rudorff et al., 2014a; Ameli and Creed, 2017; Fleischmann et al., 2018; Li et al., 2019; Li et al., 2020). Through their storage effect, wetlands can affect the timing and attenuate the peak of downstream streamflow hydrographs, thus modifying the sub-basin flow regime. Wu et al. (2020a) quantified streamflow regulation services of wetlands with respect to quickflow and baseflow responses and found significant effects on the variability of quickflow and baseflow across temporal and spatial scales. The inclusion of wetland processes in many hydrological models has contributed to improved simulation efficiency and accordingly improvement of downstream basin-scale processes representation (Hughes et al., 2014; Lee et al., 2018).

Previous attempts to model the upper Congo River Basin (Lualaba) identified the need to account for wetland effects in a basin-scale hydrological model (Tshimanga, 2012; Tshimanga and Hughes, 2014; Hughes et al., 2014). This part of the basin is partly characterised by the presence of large wetland systems that considerably affect the downstream flow regime of the Lualaba River. Understanding the river channel-wetland exchange processes would provide a means to appropriately quantify wetland parameters, needed for simulating the downstream impacts. A combined modelling approach (hydrological and hydrodynamic) offers an opportunity for understanding channel-wetland exchanges and their underlying factors. These exchanges are explicitly represented through the use of a 2-D hydrodynamic river-wetland model (LISFLOOD-FP) to inform the choice of PITMAN wetland model parameters (Makungu, 2019; Kabuya et al., 2020a).

The overall objective of this chapter is to account for processes in channel-wetland exchanges and thereby improving the simulation of downstream hydrological responses in the Lualaba drainage system of the Congo Basin. Specifically, the chapter aims at:

- Establishing the upstream boundary conditions required for setting up a hydrodynamic model;
- Calibrating and validating the LISFLOOD-FP hydrodynamic model for specific sites;
- Quantifying the hysteretic patterns observed in river channel-wetland exchanges and the underlying factors affecting these patterns;
- Quantifying the wetland parameters of the PITMAN wetland sub-model;
- Simulating wetland downstream impacts on hydrological responses.

7.2 Overview of the methodological approach

Figure 4.10 has shown the main requirements for setting up the LISFLOOD-FP model at the five sites shown in Figures 3.7. These requirements include:

- *The boundary conditions:* These conditions define the input stream flows into the modelling domain and are derived from the monthly flow time series provided by the PITMAN model (Chapter 6). Three different inputs are used, representing the lower (5%), median, and the upper (95%) uncertainty bounds of the simulated streamflow, after they have been disaggregated into daily flows (Section 4.3.3). Only four hydrological years (2000 – 2004) were used due to the availability of satellite daily rainfall (to force the disaggregation process) over the study areas and the presence of the highest flow peaks in the simulated monthly flows over 2000-2004 hydrological years. The downstream boundary conditions at all five sites were defined as a free water surface slope, computed using Google Earth topography. A warm-up period of one year (October 2000-September 2001) was initiated to provide the initial storage conditions in the wetlands.
- *Input climate data:* In addition to daily rainfall (Novella and Thiaw, 2012), monthly distributions of potential evapotranspiration collected from the International Water Management Institute website (<http://www.iwmi.org>) were converted into daily time series of potential evapotranspiration over the simulation period. Net evapotranspiration values were computed from the daily rainfall and evapotranspiration.

- *Channel bathymetry, roughness and hydraulic parameters:* Since the channel sub-grid model (Neal et al., 2012) is used to represent channel widths, a specific approach presented in Figure 4.9 was implemented to estimate channel widths at all sites. As indicated in Section 3.4.4, historical field survey data (Table A3.6 to A3.12, in Appendix A) are used to derive initial estimates of both channel friction and hydraulic parameters that are refined through calibration (Section 4.3.1.2), while a land-use map (Figure 3.3) was used for estimating floodplain roughness values.
- *Floodplain topography:* The MERIT DEM (Yamazaki et al., 2017b), at different spatial resolutions (90 m, 270 m and 360 m), was used to represent the floodplain topography.

The overall hydrodynamic model setups at the different study sites are visually presented in Appendix C (Figures C7.1 to C7.5).

7.3 Results

The results include the disaggregation of monthly flows to provide input daily flows for the hydrodynamic model, the calibration and validation procedures of the LISFLOOD-FP model, the derivation of the hydrodynamic and morphometric characteristics of wetlands, the calibration of wetland sub-model parameters and finally, the simulation of the hydrological responses at gauging stations located downstream of wetland systems.

7.3.1 Disaggregating the monthly streamflow

The disaggregated streamflow boundary conditions used to drive the LISFLOOD-FP model were obtained through the application of the disaggregation model. This model normally requires the calibration of both scaling and Antecedent Precipitation Index (API) parameters. The scaling parameters (A, B, and C) for the conversion of monthly to daily FDCs were calibrated based on an analysis of the observed daily flow data at different gauging stations including Bukama (Figure 7.1). These observed daily flow data were available only for the period 1950-1960, over which the satellite daily rainfall data (ARC2) were not available to calibrate the API parameters ($P_{\text{threshold}}$ and decay K). This lack of satellite daily rainfall data prompted the use of default API parameter values that are based on previous studies (Hughes and Slaughter, 2015). A threshold value ($P_{\text{threshold}}$) of

5 mm of rainfall and the antecedent precipitation factor (decay K) of 0.999 were used and Figure 7.2 illustrates some of the results.

The fact that the monthly flows were simulated using CRU monthly rainfall data (Chapter 6) and the disaggregation process is driven with a satellite (ARC) daily rainfall dataset does not pose any problems as the seasonality and frequency characteristics of the daily rainfall are the important issues in the disaggregation process (Slaughter et al., 2015). Hughes and Slaughter (2015) concluded that the success of the disaggregation depends mainly upon the accuracy of the monthly streamflow used and the timing, but not the absolute values, of the daily rainfall data.

Simulated daily streamflow obtained in this study are expected to reflect an acceptable level of uncertainty as their corresponding monthly flows were judged acceptable (e.g. Figures 6.3c and 6.7), but the use of the uncalibrated API parameters may further increase the uncertainty which can still be contained within the predictable uncertainty bounds. Overall, the most important issue is to obtain realistic inflow patterns that could be used as boundary conditions in the LISFLOOD-FP model, so that the outputs can be used to determine realistic parameters for the PITMAN wetland model.

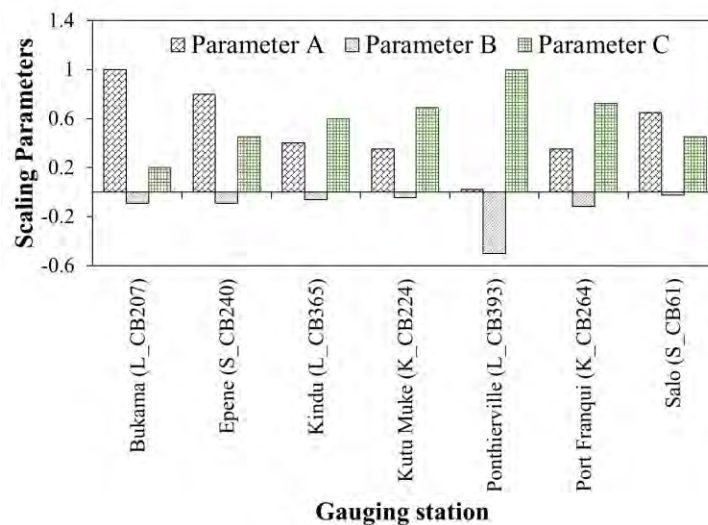


Figure 7.1. Scaling parameters of the disaggregation model at seven gauging stations of the Congo Basin representing different climate and physiographic regions.

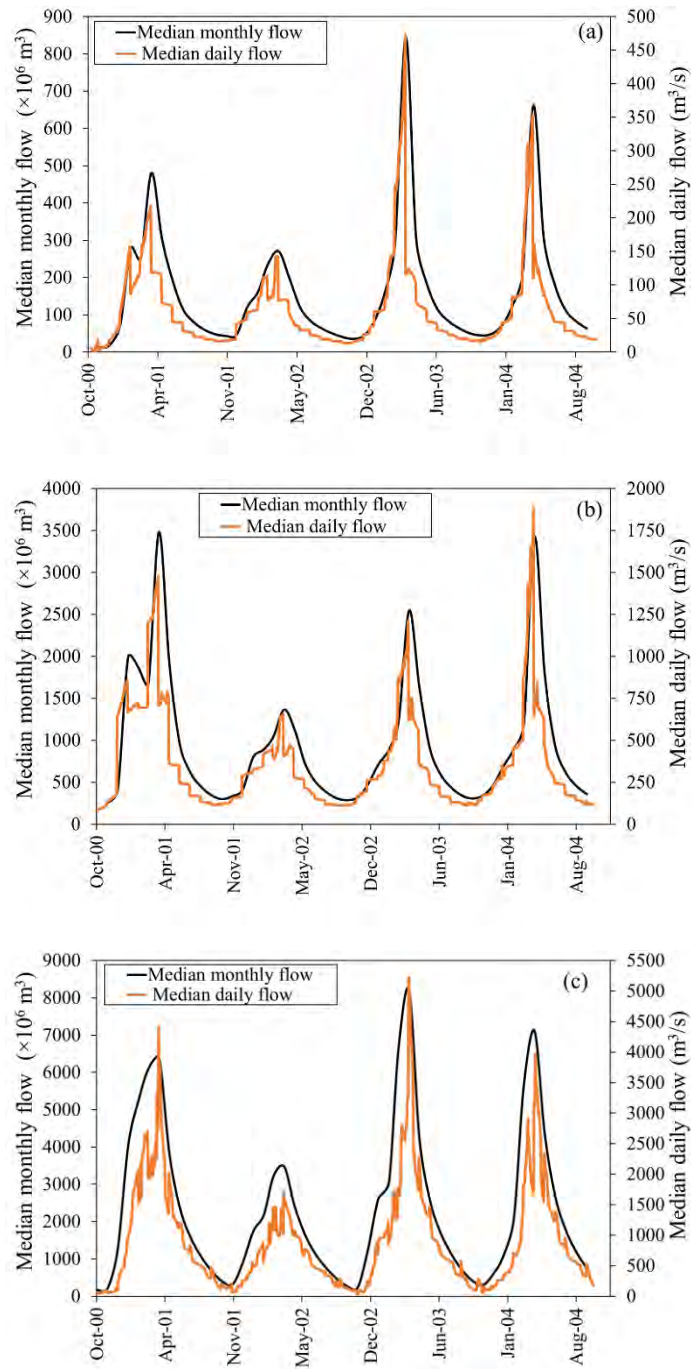


Figure 7.2. An illustration of the disaggregation results for the median flow at selected gauging stations for October 2000-September 2004. (a) Tshiangalele wetland inflow at Kapolowe gauging station, (b) Kamalondo wetland inflow at Bukama gauging station and (c) Mweru wetland inflow at Kasenga gauging station.

7.3.2 Model friction and geometric parameters

Table 7.1 lists the calibrated values of the four hydraulic parameters. These values are within the acceptable ranges for natural channels and floodplains (Chow, 1959; Arcement and Schneider, 1989). The calibrated channel friction parameter values obtained for the Ankoro, Kundelungu, Mweru and Tshiangalele wetland systems are consistent with the range (n_c : 0.017 – 0.051) of the channel roughness computed from historical field survey data (Table A3.6 to A3.12, in Appendix A) of the Lualaba drainage system reported by Charlier (1955). For the Kamalondo wetland system, the calibrated channel friction is outside this range and possibly might represent typical sluggish, weedy and deep pool channels (Chow, 1959; Arcement and Schneider, 1989) colonised sometimes by aquatic vegetation, which describes current conditions within the Kamalondo wetland system (Cotterill, 2004, 2005). Furthermore, the calibrated channel hydraulic parameter values for the five-wetland systems are within the range of acceptable values for r (0.025-0.175) and p (0.67-0.82) parameters (Neal et al., 2012).

Table 7.1. Calibrated friction and channel geometric parameters

Wetland	Parameters			
	Friction		Channel geometry	
	n_c	n_{fp}	r	p
Ankoro	0.028	0.075	0.115	0.739
Kamalondo	0.07	0.1	0.12	0.72
Kundelungu	0.05	0.035-0.07	0.13	0.75
Mweru	0.05	0.07	0.115	0.739
Tshiangalele	0.045	0.08	0.13	0.67

Footnote: n_c and n_{fp} are channel and floodplain roughness parameters

r and p are the hydraulic parameters of the channel depth –width relationship

7.3.3 Evaluation of the inundation extents

Figure 7.3 provides an example of the visual illustration of the comparison between the simulated and Landsat inundation extents for the Ankoro (top image) and Tshiangalele (bottom image) wetland systems. The inundation extents of past floods are very difficult to evaluate due to the limited access to cloud-free inundation satellite images, and Landsat images used in this evaluation were taken during either the rising or the recession period of the flow hydrographs. Images

reflecting the occurrence of the inundation peaks were not of good quality for the evaluation purpose. The patterns of the inundation extents (Figure 7.3) are well reproduced in comparison to Landsat imagery (MNDWI) when the 5th and median flows are used as wetland inflows. The image acquired on 21/April/2003 at Tshiangalele wetland system represents the recession period, while the 16/February/2003 image represents the rising limb. The month of August represents the period of low flow within the Tshiangalele wetland system. The results show smaller inundation extents during the rising period compared to the recession period. The highest peak flows are expected to occur between March and April and the April image is expected to be indicative of the maximum flood extent in this wetland.

Table 7.2 provides the model performance statistics across the wetland systems, and in general, satisfactory results were obtained for the different validation dates especially for flows representing the 5th and median flow uncertainty bounds. These results show that the model was able to reproduce both low and high flow patterns. A Flood Area Index (FAI) above 0.5 implies that the model has satisfactorily captured the general pattern of flow dynamics. However, the model performance can be affected by the spatial resolution used to represent the processes. For example, it is generally recognised that the elevation errors of a normal SRTM DEM of 90 m resolution have a standard deviation of 4.68 m over Africa (Rodriguez et al., 2006). The magnitude of these errors, although lower on flat terrain, can still pose problems for inundation models in wetlands where the depth of flooding is typically believed to be a few metres (Sanders, 2007). However, if we believe that the vertical accuracy of the MERIT DEM increased by 39% to 58% (Yamazaki et al., 2017b), then the representation of the low lying areas (wetlands) is expected to be improved compared to the original SRTM DEM. This means that the expected vertical errors in the MERIT DEM (90m resolution) are within the range of 1.96 m to 2.85 m. Therefore, to guarantee a better representation of the floodplain topography in minimising vertical errors, this study attempted to average the MERIT DEM vertical error over 9 and 16 cells. This is expected to result in vertical errors of 0.95 m and 0.49 m for spatial resolutions of 270 m and 360 m, respectively, considering the reduction in random noise error in the cell elevation to be proportional to $1/\sqrt{N}$, where N is the number of cells (Neal et al., 2012). The results of this attempt are shown in Table 7.3 where the model performance has increased for the 270 m resolution data

at Ankoro and Kundelungu, while the performance has remained almost the same for the Tshiangalele wetland system.

The validation results using performance measures of inundation extents are consistent with other studies conducted elsewhere. For instance, the values found for the FAI at Ankoro (0.51-0.63), Kamalondo (0.33-0.41) and Kundelungu (0.58-0.66) were lower compared to previous studies (Bates and De Roo, 2000; Horritt and Bates, 2001; Wilson et al., 2007; Komi *et al.*, 2017) and relatively high compared to the results from other data-sparse environments, such as the FAI value of 0.38 reported by Amarnath et al. (2015) when modelling the flood risk extent using LISFLOOD-FP in a complex watershed of Mundeni Aru River Basin in Sri Lanka. They justified the low value of FAI by the differences in the dates of the simulated inundation extents (3 February 2011) and SAR satellite map analysis (6 February 2011). Similarly, Makungu (2019) found FAI values that were generally below 0.5 using Landsat imagery across different wetland systems in Zambia and Tanzania and attributed these low values to the wetting and drying ability of the LISFLOOD-FP model (Neal et al., 2012). Moreover, values of FAI for Mweru (0.74-0.75) and Tshiangalele (0.63-0.70) are comparable to previous studies (Bates and De Roo, 2000; Horritt and Bates, 2001; Wilson et al., 2007; Komi *et al.*, 2017) and high compared to that of 0.61 determined by Sayama et al. (2012) for the 2010 Pakistan flood in the Kabul River basin.

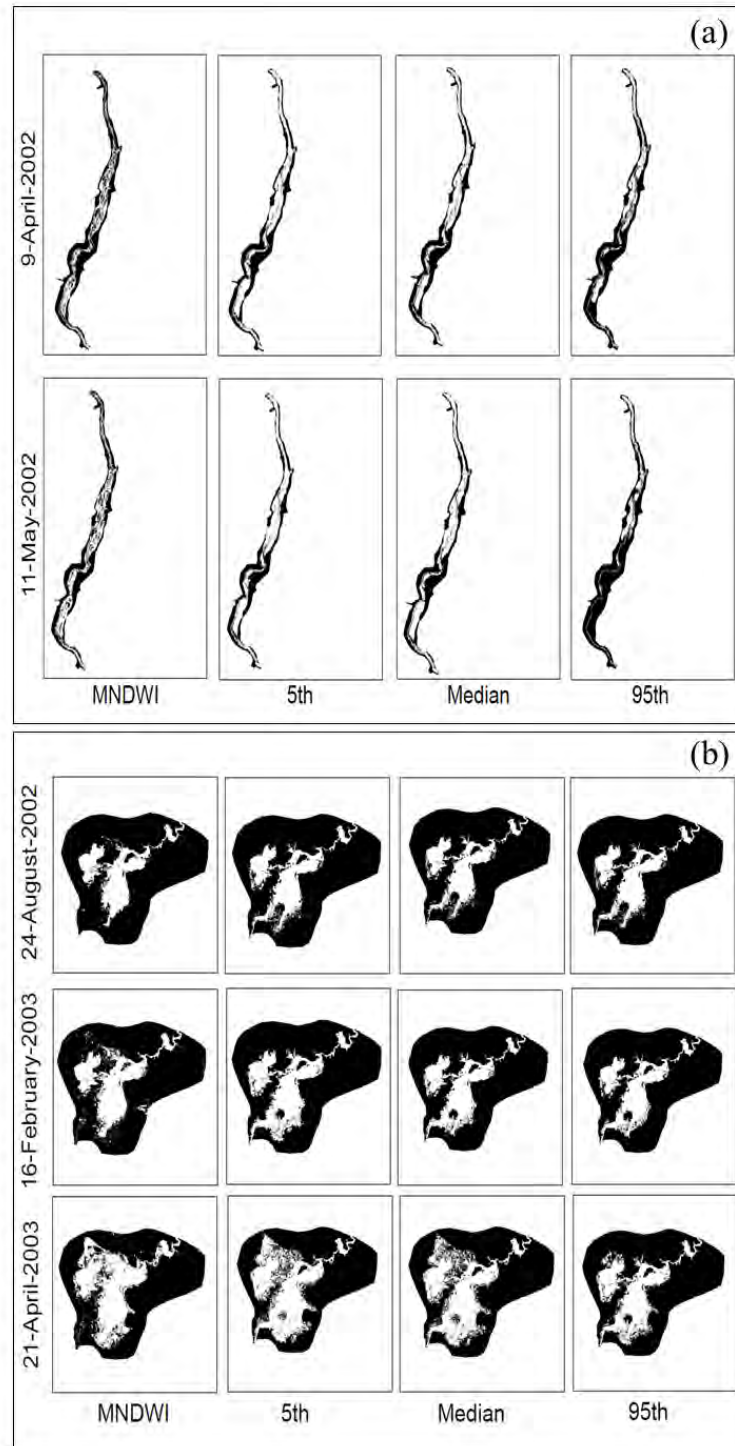


Figure 7.3. Visual comparison between LISFLOOD-FP (using the 5th, 50th and 95th percentiles of the uncertainty input time series) and Landsat imagery (MNDWI) flood extents (white areas) for the (a) Ankoro and (b) Tshiangalele wetland systems.

Table 7.2. Model statistical performance of 90 m model resolution across wetland systems (Ankoro, Kamalondo, Kundelungu, Mweru and Tshiangalele) for different types of inflow inputs.

Wetland	Validation dates	5 th flows				Median flows				95 th flows			
		FAI	Bias	PSS	Accuracy	FAI	Bias	PSS	Accuracy	FAI	Bias	PSS	Accuracy
L_CB198	09-Apr-02	0.54	1.35	0.54	0.79	0.51	1.26	0.54	0.77	0.41	0.94	0.4	0.75
	11-May-02	0.56	1.18	0.56	0.78	0.55	1.14	0.54	0.77	0.27	0.54	0.2	0.68
L_CB150	20-Feb-02	0.39	2.46	0.5	0.63	0.4	2.41	0.51	0.65	0.41	2.37	0.53	0.66
	27-Mar-03	0.33	2.99	0.4	0.54	0.33	2.96	0.41	0.55	0.34	2.91	0.42	0.56
L_CB404	14-Apr-01	0.59	0.99	0.49	0.74	0.58	0.97	0.48	0.74	0.58	0.98	0.48	0.74
L_CB23	27-Apr-02	0.74	1.13	0.66	0.83	0.74	1.13	0.67	0.84	0.75	1.05	0.71	0.85
L_CB350	28-Aug-02	0.69	1.09	0.8	0.93	0.7	1.08	0.81	0.93	0.65	0.93	0.71	0.91
	16-Feb-03	0.63	1.07	0.72	0.89	0.65	0.99	0.72	0.9	0.54	0.69	0.55	0.84
	21-Apr-03	0.65	1.08	0.7	0.86	0.64	0.99	0.68	0.86	0.59	0.82	0.61	0.85

Table 7.3. Model statistical performance across different spatial resolutions at selected wetland systems (Ankoro, Kundelungu and Tshiangalele) when the median flow is used.

Wetland	Validation dates	90 m				270 m				360 m			
		FAI	Bias	PSS	Accuracy	FAI	Bias	PSS	Accuracy	FAI	Bias	PSS	Accuracy
L_CB198	09-Apr-02	0.51	1.35	0.54	0.79	0.56	1.59	0.63	0.77	0.53	1.57	0.58	0.75
	11-May-02	0.56	1.18	0.56	0.78	0.63	1.39	0.65	0.8	0.58	1.37	0.56	0.76
L_CB404	14-Apr-01	0.59	0.99	0.49	0.74	0.66	1.1	0.61	0.8	0.59	0.98	0.5	0.75
L_CB350	16-Feb-03	0.63	1.07	0.72	0.89	0.53	0.63	0.53	0.82	0.51	1.2	0.64	0.87
	21-Apr-03	0.65	1.08	0.7	0.86	0.65	0.73	0.64	0.84	0.6	1.15	0.67	0.85

7.3.4 Process understanding of channel-wetland exchanges

7.3.4.1 Hydrodynamic characteristics of wetlands and hysteretic patterns

The simulated hydrodynamic characteristics of the wetlands provide insights into the differences between wetlands and their capability in affecting downstream flow regimes. Some of these characteristics include the attenuation (%) of the peak flows (computed as the % difference between the upstream and downstream flood peaks divided by the upstream flood peak) and the time delay between the occurrence of peaks in the upper and downstream parts of the wetlands. Table 7.4 shows that the attenuation of peak flows is temporal scale-dependent for the Ankoro,

Kamalondo, Kundelungu, and Mweru wetland systems, while it is largely independent of temporal scale for the Tshianganalele wetland system.

The time delay defines the time between the occurrence of the peak inflow and outflow hydrographs. This time varies across wetland systems and hydrological years (Table 7.5). The lowest time delay is observed at Tshianganalele (1 to 5 days), while the longest is at Mweru (45 to 52 days). The magnitude of the time delays can be directly associated with the hydrological characteristics of the flood hydrograph as well as the wetland morphometric characteristics, including connectivity between the channel and the main wetland storage areas.

The hydrodynamic exchanges across wetland systems result in different hysteretic patterns in the relationships between variables involved in the wetland inundation and drainage processes. These variables are notably the channel inflow, the wetland storage volume, the inundated area and the outflow volume. The resulting hysteretic effects are evaluated qualitatively through the graphical plot of the two variables and quantitatively through the use of the hysteresis indices referred to in this study (Section 4.4.3). An example relationship between the channel inflow and the wetland storage for the Ankoro wetland system at both daily and monthly time steps is shown in Figure 7.4, while Tables 7.6 and 7.7 show the magnitude of the hysteretic patterns.

The results for inflow versus storage (Tables 7.6 and 7.7) show consistent anticlockwise (negative index values) hysteretic patterns across all wetland systems and years. In the Ankoro wetland system (Figure 7.5) the hysteresis is lower in the dry year (2001-2002) compared to the wet year (2003-2004) using a daily time step. A comparison across wetland systems shows that Mweru has higher hysteresis followed by Tshianganalele, Kundelungu, Kamalondo and Ankoro. The Mweru wetland system is large in extent and the flow from the channel to the wetland takes a long time to reach the most distant part of the wetland system. It also has the highest peak attenuation and lag times (Tables 7.4 and 7.5).

The hysteretic patterns found in the drainage processes (storage volume versus outflow) include both anticlockwise and weakly clockwise at the daily scale. At both daily and monthly time scales (Tables 7.6 and 7.7), the Kamalondo wetland has a higher degree of hysteresis compared to the other wetland systems. This can be explained by the presence of numerous depressions and natural lakes that are present within the Kamalondo wetland system (Table 3.1). Hydrodynamic modelling

of this system only accounted for visible channels from the main rivers to these storage systems, and some drainage channels were not visible at the spatial resolution of the Landsat images used, and this may have affected the hysteresis patterns. The lowest hysteresis found in the Tshiangalele wetland system at a daily time scale indicates a high degree of connectivity between the wetland storage and the main channel.

The two hysteresis indices (Lloyd *et al.*, 2016a; Zuecco *et al.*, 2016) used in this study can capture the hysteresis found in channel-wetland exchanges. They are consistent with each other in capturing the direction and the extent of the hysteresis loops. However, in many cases, the magnitude of the HI_{Zuecco} index was always slightly lower than the HI_{Lloyd} index (Table 7.6 and 7.7). Far from being a disadvantage, this provides a better way of expressing the ranges in which the hysteresis varies across different natural systems under study. In general, the differences in the degree of hysteresis quantified through these two indices varied between 12 and 15%.

Table 7.4. Attenuation of the peak flows due to wetland storage effects

Hydrological Year (HY)	% of Peak flow attenuation (Daily/Monthly)				
	Ankoro	Kamalondo	Kundelungu	Mweru	Tshiangalele
2000-2001	1.7/0.3	12.4/7.3	21.0/6.6	71.6/48.3	20.8/24.5
2001-2002	2.1/4.0	16.4/7.6	20.8/11.3	60.3/47.1	27.4/14.3
2002-2003	2.0/4.6	15.0/6.9	15.6/7.4	75.5/57.7	37.2/36
2003-2004	2.7/5.0	19.0/7.7	20.7/8.9	71.7/58.7	34.3/33.1

Table 7.5. Time delay (days) between the occurrences of the peaks of channel inflow and outflow.

Hydrological Year (HY)	Wetland systems				
	Ankoro	Kamalondo	Kundelungu	Mweru	Tshiangalele
2000-2001	4	13	7	45	1
2001-2002	6	26	6	49	5
2002-2003	5	16	4	48	1
2003-2004	5	14	13	52	2

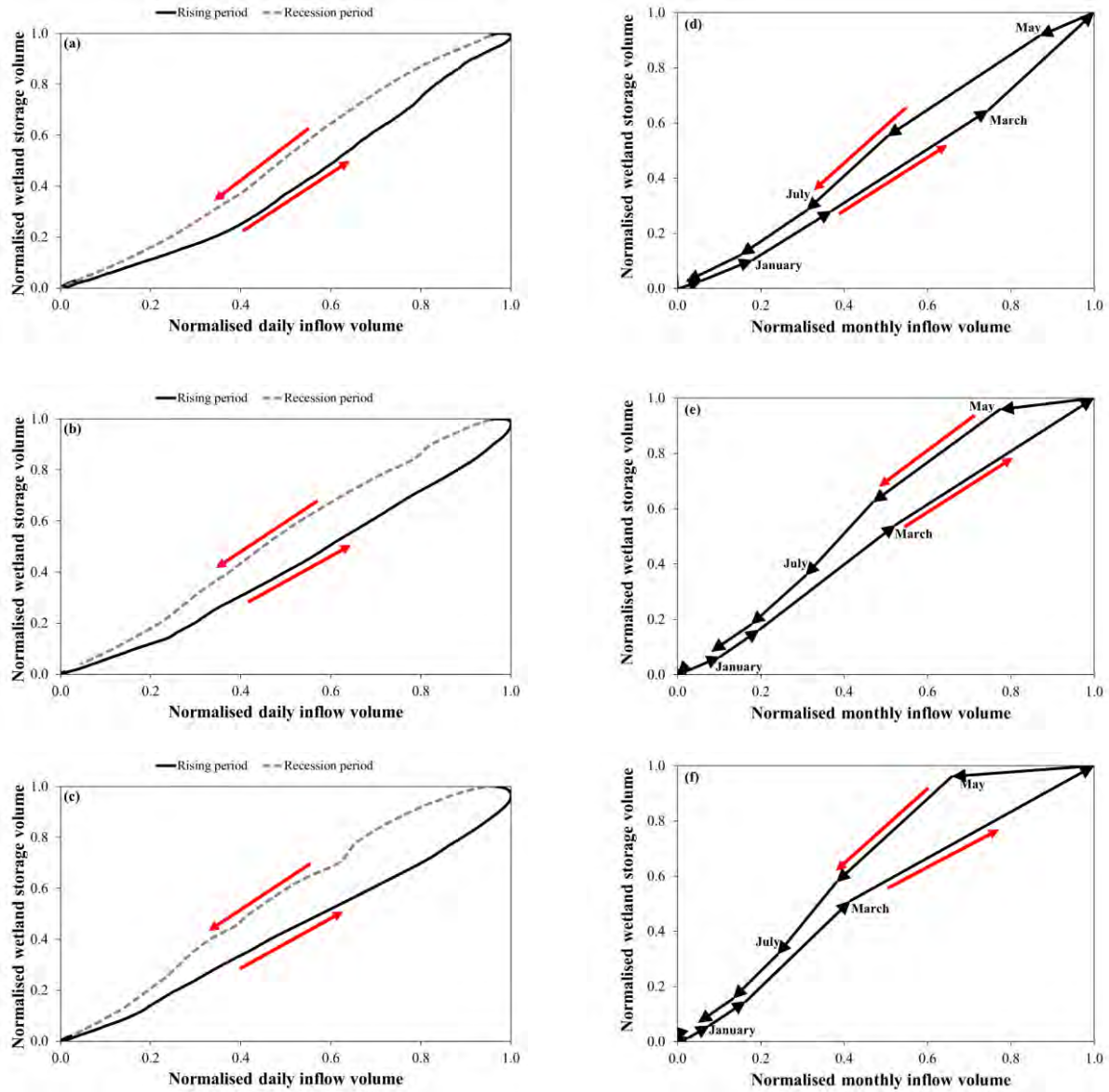


Figure 7.4. Dimensionless hysteresis of inflow volume and wetland storage volume at the Ankoro wetland system showing counterclockwise hysteresis over three consecutive hydrological years. (a)-(c) show daily hysteresis for the consecutive hydrological years 2001-2002, 2002-2003, and 2003-2004, respectively. (d)-(f) show monthly hysteresis for the consecutive hydrological years 2001-2002, 2002-2003, and 2003-2004, respectively. Arrows indicate the direction of loops.

Table 7.6. Magnitude of hysteresis in channel inflow, wetland storage, inundated area, and outflow relationships across wetland systems at a daily time scale.

Hydrological Year (HY)	Ankoro		Kamalondo		Kundelungu		Mweru		Tshiangalele	
	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index
<i>Magnitude of channel inflow-wetland storage hysteresis</i>										
2001-2002	-0.091	-0.103	-0.146	-0.168	-0.067	-0.078	-0.376	-0.443	-0.201	-0.235
2002-2003	-0.108	-0.124	-0.153	-0.178	-0.253	-0.284	-0.392	-0.457	-0.204	-0.235
2003-2004	-0.128	-0.146	-0.194	-0.221	-0.274	-0.323	-0.486	-0.592	-0.285	-0.325
<i>Average</i>	-0.109	-0.125	-0.164	-0.189	-0.198	-0.229	-0.418	-0.497	-0.230	-0.265
<i>Magnitude of channel inflow-inundated area hysteresis</i>										
2001-2002	-0.112	-0.130	-0.069	-0.079	0.010	0.012	-0.057	-0.073	-0.229	-0.283
2002-2003	-0.109	-0.127	-0.081	-0.096	-0.011	-0.010	-0.070	-0.083	-0.277	-0.323
2003-2004	-0.105	-0.122	-0.107	-0.121	-0.003	0.003	-0.087	-0.096	-0.420	-0.502
<i>Average</i>	-0.109	-0.126	-0.085	-0.099	-0.002	0.002	-0.071	-0.084	-0.309	-0.370
<i>Magnitude of wetland storage - inundated area hysteresis</i>										
2001-2002	-0.022	-0.028	0.056	0.040	0.085	0.104	0.143	0.224	-0.048	-0.057
2002-2003	-0.017	-0.020	0.036	0.043	0.054	0.071	0.380	0.483	-0.147	-0.173
2003-2004	-0.014	-0.016	0.032	0.039	0.071	0.090	0.243	0.334	-0.145	-0.185
<i>Average</i>	-0.018	-0.021	0.042	0.040	0.070	0.088	0.255	0.347	-0.113	-0.139
<i>Magnitude of wetland storage - outflow hysteresis</i>										
2001-2002	-0.018	-0.020	-0.151	-0.176	-0.016	-0.022	-0.126	-0.167	0.000	-0.006
2002-2003	-0.036	-0.041	-0.189	-0.222	-0.020	-0.031	-0.107	-0.144	0.008	0.005
2003-2004	-0.051	-0.058	-0.204	-0.242	-0.015	-0.027	-0.138	-0.178	0.000	-0.002
<i>Average</i>	-0.035	-0.040	-0.181	-0.213	-0.017	-0.027	-0.124	-0.163	0.002	-0.001

Table 7.7. Magnitude of hysteresis in channel inflow, wetland storage, inundated area, and outflow relationships across wetland systems at a monthly time scale.

Hydrological Year (HY)	Ankoro		Kamalondo		Kundelungu		Mweru		Tshiangalele	
	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index	HI _{zuecco} index	HI _{Lloyd} index
<i>Magnitude of channel inflow-wetland storage hysteresis</i>										
2001-2002	-0.084	-0.095	-0.181	-0.209	-0.103	-0.119	-0.529	-0.597	-0.309	-0.352
2002-2003	-0.094	-0.106	-0.168	-0.194	-0.099	-0.114	-0.539	-0.619	-0.294	-0.336
2003-2004	-0.109	-0.123	-0.191	-0.221	-0.105	-0.120	-0.588	-0.672	-0.287	-0.328
<i>Average</i>	-0.095	-0.108	-0.180	-0.208	-0.102	-0.118	-0.552	-0.629	-0.297	-0.339
<i>Magnitude of channel inflow-inundated area hysteresis</i>										
2001-2002	-0.107	-0.123	-0.119	-0.135	0.005	0.008	-0.084	-0.098	-0.377	-0.428
2002-2003	-0.161	-0.185	-0.110	-0.128	-0.017	-0.017	-0.089	-0.106	-0.262	-0.298
2003-2004	-0.156	-0.180	-0.122	-0.140	-0.019	-0.015	-0.087	-0.100	-0.268	-0.304
<i>Average</i>	-0.141	-0.163	-0.117	-0.135	-0.010	-0.008	-0.087	-0.101	-0.302	-0.343
<i>Magnitude of wetland storage - inundated area hysteresis</i>										
2001-2002	-0.029	-0.034	0.061	0.070	0.107	0.127	0.268	0.306	-0.068	-0.076
2002-2003	-0.100	-0.115	0.039	0.047	0.092	0.111	0.376	0.452	-0.146	-0.190
2003-2004	-0.099	-0.114	0.030	0.035	0.100	0.121	0.337	0.386	-0.130	-0.147
<i>Average</i>	-0.076	-0.088	0.043	0.051	0.100	0.120	0.327	0.381	-0.114	-0.138
<i>Magnitude of wetland storage - outflow hysteresis</i>										
2001-2002	-0.018	-0.021	-0.180	-0.206	0.003	0.003	-0.111	-0.126	0.002	0.001
2002-2003	-0.009	-0.008	-0.163	-0.186	0.007	0.007	-0.104	-0.116	0.045	0.058
2003-2004	0.010	0.017	-0.165	-0.188	0.027	0.030	-0.072	-0.081	0.030	0.043
<i>Average</i>	-0.006	-0.004	-0.169	-0.193	0.012	0.013	-0.096	-0.108	0.026	0.034

7.3.4.2 Estimation of wetland sub-model parameters

The wetland sub-model parameters are calibrated in a spreadsheet version of the PITMAN wetland routine to achieve visual correspondence between the wetland storages and outflow volumes for the PITMAN wetland sub-model compared to LISFLOOD-FP at a weekly time step (Section 4.4.2). This process was conducted such that some parameters (e.g. the first five from Table 7.8) were derived directly from LISFLOOD-FP outputs, whereas the remaining were obtained through manual calibration. The calibration of return flow parameters resulted in better fits when the BB parameter was fixed at a value of 1.25 and this helps to reduce the equifinality in the parameters of the return flow function.

The calibrated wetland parameters (Table 7.8 and Figure 7.5) show that the maximum inundated area for Ankoro is 411 km² and the residual storage is 420*10⁶ m³, which represents about 30% of the maximum wetland storage. This is the storage volume that remains in the wetland without returning back to the channel and can be subject only to evapotranspiration losses and infiltration. For the Kamalondo wetland system, the LISFLOOD-FP and PITMAN wetland sub-models show good agreement in reproducing the pattern of wetland storages as well as of outflows (Figure 7.6). The residual storage represents about 48% of the maximum wetland storage, while the initial storage at the beginning of the wet season is slightly above the residual storage and represents 50% of the maximum wetland storage. This means that the wetland system keeps releasing water to the channel even during the dry season. Spilling parameter values (Table 7.8) indicate that the wetland system is dominated by natural lakes with a channel spill factor of 1.0 and the channel capacity for spillage of zero. This implies that all channel inflow ends up being completely attenuated by the lakes in both high and low water seasons. The process parameterisation of the Kundelungu wetland system shows that the LISFLOOD-FP and PITMAN wetland sub-model outputs are consistent with each other (Figure 7.7). The Kundelungu wetland receives only about 55% of the channel inflow, while the residual and initial storages represent 24% and 13% of the maximum wetland storage, respectively (Table 7.8). The low values of the initial storages compared to residual storages at both the Ankoro and Kundelungu wetland systems may be an indication that these systems are disconnected from the channel during the dry seasons. At the full storage capacity, both wetlands return the maximum fraction of 0.95, while Kamalondo returns 0.84, but when the storage is double the residual storage, the return is 0.95 (maximum) in the Ankoro, 0.83 in the Kamalondo and only 0.48 in the Kundelungu. This may highlight the role of wetland channels

within the Kundelungu system where the connectivity seems to decrease as the wetland storage depletes. The plot of the wetland storages for Mweru wetland system shows reasonable consistency between the PITMAN and LISFLOOD-FP patterns of storage and outflow (Figure 7.8).

The parameterisation of the Mweru wetland processes indicates that although the wetland system is an integrated river-floodplain-lake type, the impact of the lake is more dominant. This justifies the assignment of value of zero to the channel capacity for spillage and 1.0 to the channel spill factor (Table 7.8). The implication is that the wetland inflows are completely attenuated by the lake and the downstream flow regime is expected to be completely different from the upstream flow regime. However, the return flow parameters show that the wetland is always returning flow to the channel regardless of the season and the peaks of both wetland storage and outflow volume are very sensitive to changes in the AA parameter, such that the calibrated value of 0.025 represents the best compromise for reproducing the general pattern of both storage volume and outflow volume. The Tshiangalele wetland is another type of river-floodplain-lake wetland system and the Pitman parameters have been successfully calibrated to reproduce the LISFLOOD-FP model results (Figure 7.9). Compared to Mweru, the Tshiangalele wetland returns back to the channel a fraction of 0.95 (maximum) and 0.83 at the full storage capacity and when the storage is double the residual storage, respectively, while Mweru returns 0.17 and 0.15, respectively.

For natural lakes such as Kivu and Tanganyika, LISFLOOD-FP was not used in the estimation of wetland parameters (Section 4.4.2). Lake storage volumes above the minimum lake water level were estimated by multiplying the lake area with the flow depth, computed from differences in lake water levels, and the relationships between flow discharges and flow volume above the minimum lake water level were constructed to estimate return flow parameters. The calibrated parameters can account for the flow dynamics above the lowest lake water level. As for all lakes, channel spilling parameters are assigned values of zero and 1.0.

Table 7.8. Calibrated wetland parameters for the median flows at the five-wetland systems

Parameter name	Wetland systems				
	Ankoro	Kamalondo	Kundelungu	Mweru	Tshiangalele
Local Catchment area (km ²)	411	5068	1144	7050	372
Residual wetland storage, RWS (MCM)	420	5400	180	5500	205
Initial storage (MCM)	400	5600	100	12000	230
A in Area (m ²)=A*Volume (m ³) ^B	29809	654846	5* 10 ⁶	1*10 ⁷	33939
B in Area (m ²)=A*Volume (m ³) ^B	0.4527	0.4891	0.2626	0.2731	0.447
Channel capacity for spillage (MCM)	20	0	20	0	0
Channel Spill Factor (Fraction)	0.55	1	0.55	1	1
AA in (Ret Flow= AA*(Vol/RWS) ^{BB}	0.6	0.35	0.2	0.025	0.35
BB in (Ret Flow= AA*(Vol/RWS) ^{BB}	1.25	1.25	1.25	1.25	1.25
Annual Evaporation (mm)	1671.53	1504.31	1564.25	1565.23	1474.25
Annual Abstraction (MCM)	0	0	0	0	0
AA scaling factor	0	0	0	0	0
Max Return flow Fraction	0.95	0.95	0.95	0.95	0.95

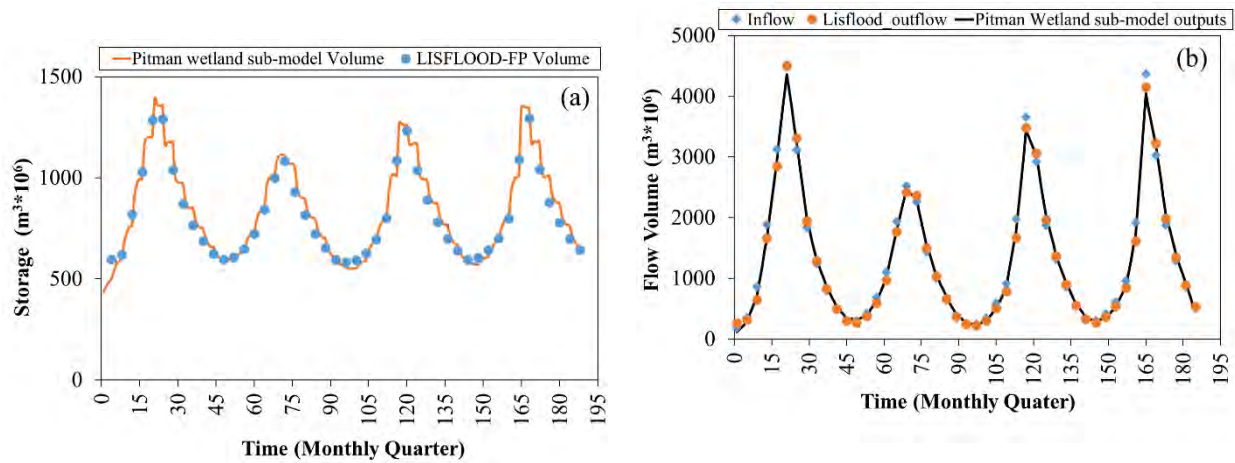


Figure 7.5. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows at Ankoro wetland system.

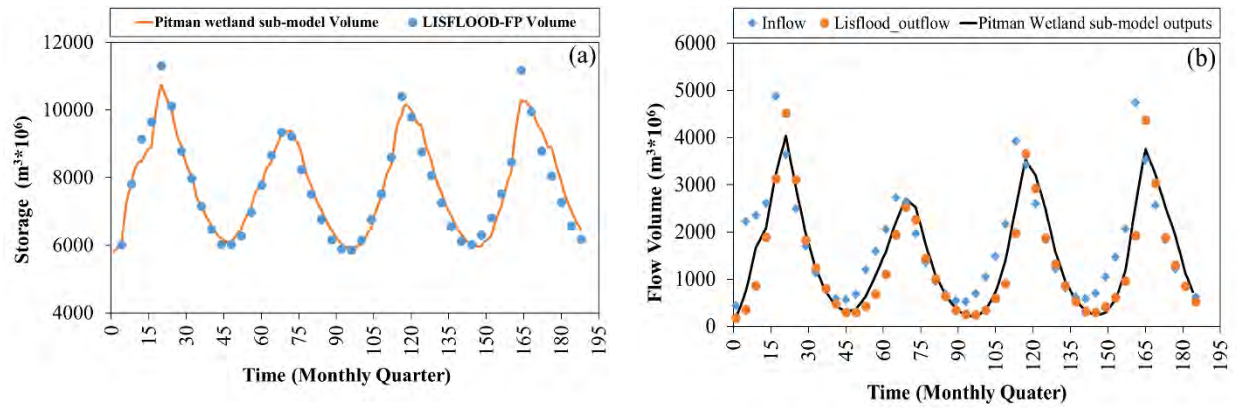


Figure 7.6. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Kamalondo wetland system.

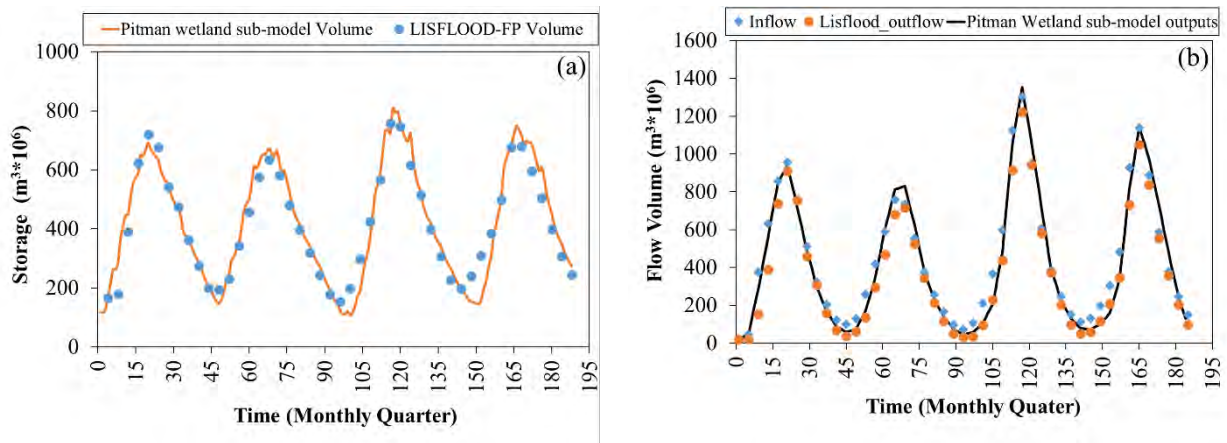


Figure 7.7. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Kundelungu wetland system.

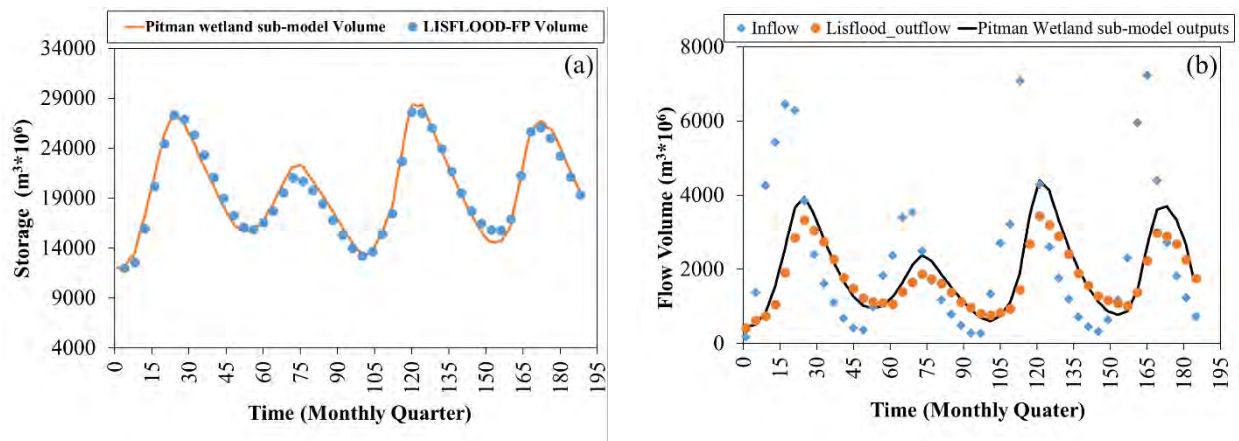


Figure 7.8. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Mweru wetland.

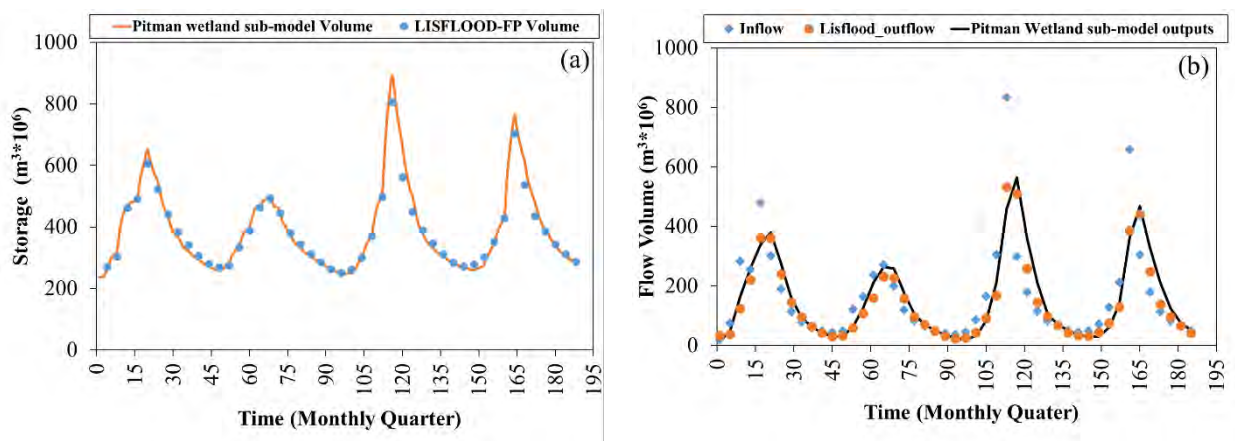


Figure 7.9. Graphical visualisation of the correspondence of the LISFLOOD-FP and PITMAN wetland sub-model wetland storages (a) and outflows (b) for the median flows of Tshiangelele wetland system.

Table 7.9. Wetland parameters of deep Lakes: Kivu and Tanganyika

Parameter name	Parameter values for deep Lakes	
	Lake Kivu	Lake Tanganyika
Local Catchment area (km ²)	2700	32900
Residual wetland storage, RWS (MCM)	0	0
Initial storage (MCM)	2000	45000
A in Area (m ²)=A*Volume (m ³) ^B	2.70E+10	3.29E+10
B in Area (m ²)=A*Volume (m ³) ^B	0	0
Channel capacity for spillage (MCM)	0	0
Channel Spill Factor (Fraction)	1	1
AA in (Ret Flow= AA*(Vol/RWS)) ^{BB}	0.0079	0.0004
BB in (Ret Flow= AA*(Vol/RWS)) ^{BB}	1.25	1.25
Annual Evaporation (mm)	1120.09	1330
Annual Abstraction (MCM)	0	0
AA scaling factor	0	0
Max Return flow Fraction	0.95	0.95

7.3.4.3 Wetland morphometric factors affecting wetland parameters

It is generally recognised that channel-wetland exchanges are affected by not only the characteristics of flood events, but also the morphometric characteristics of wetland systems. The approach applied by Lidzhegu et al. (2019) using GIS techniques was implemented to derive the proportion of wetland area below the channel water level. This index has the potential to discriminate likely patterns of inundation during different levels of flooding (Lidzhegu et al., 2019) between different wetland systems. As indicated in Section 4.4.3, this metric can collectively represent the heterogeneity of the wetland morphology (IWM). Table 7.10 shows the main wetland morphometric characteristics.

An integrated analysis of wetland sub-model parameters including morphometric and hysteretic characteristics allows the identification of factors that might impact on wetland parameters. Such analysis is crucial because it provides a means of deriving wetland parameters in areas where the hydrodynamic simulations are not available. Table 7.11 shows a correlation matrix of all the wetland variables estimated in this chapter. Average hysteresis indices presented in Tables 7.6 were used to represent different hysteretic behaviours observed across the studied wetland systems at a daily time scale. In general, it is observed that the inundation and drainage processes slightly affect the channel capacity for spillage parameter.

The channel spill factor (QSF) parameter is positively correlated with the inundation and drainage processes. The scale parameter (AA) of the return flow equation is negatively correlated with the hysteresis found in the channel inflow-wetland storage and wetland storage-

inundated area relationships. This parameter affects negatively both the time delay of wetland systems and the attenuation of peak flows. A low value of the AA parameter will lead to a highly delayed flow hydrograph, contributing to a greater attenuation of peak flow and which also appears to be related to the wetland average slope (Figure 7.10).

The residual storage parameter is positively and highly correlated with the storage-outflow hysteresis, such that greater residual storage induces a high degree of hysteresis, contributing also to a highly delayed outflow. IWM is related to the two parameters of channel spilling and is highly correlated with the attenuation of peak flows which has also an implication for the hysteresis found in channel inflow versus storage. The length of the wetland affects the time delay of the flood wave. Similar conclusions are reached when considering hysteresis developed at a monthly time scale (Table C7.1 in Appendix C) and indicate that the time scales of the studied wetland hydrodynamic processes do not affect the estimates of the wetland parameters of the PITMAN model.

Table 7.10. Morphometric characteristics of wetland systems

Characteristics	Wetland names				
	Ankoro	Kamalondo	Kundelungu	Mweru	Tshiangalele
IWM	0.01	0.03	0.01	0.07	0.07
Wetland width (km)	2 to 11	20 to 40	13 to 25	28 to 45	3 to 19
Wetland length (km)	166	200	115	212	45
Wetland average slope (%)	1.20	0.72	0.33	0.01	0.83

Table 7.11. Correlation matrix of wetland variables across different wetland systems. Hysteresis indices are expressed at a daily time scale.

	Inf_St	Inf_Area	St_Area	St_Outfl	Qcap	QSF	AA	Res. storage	Ini. storage	Rs_St/T_St	Time Lag (days)	IWM	% of attenuation	Average slope (%)
Inf_St														
Inf_Area	-0.04													
St_Area	-0.73	0.67												
St_Outfl	0.24	-0.37	-0.55											
Qcap	0.55	0.47	-0.14	0.53										
QSF	-0.55	-0.47	0.14	-0.53	-1.00									
AA	0.88	-0.30	-0.76	0.27	0.41	-0.41								
Res. storage	-0.52	0.30	0.69	-0.95	-0.66	0.66	-0.49							
Ini. storage	-0.80	0.28	0.85	-0.75	-0.60	0.60	-0.68	0.91						
Rs_St/T_St	0.58	0.03	-0.27	-0.61	-0.19	0.19	0.50	0.37	-0.04					
Time Lag (days)	-0.86	0.35	0.92	-0.63	-0.47	0.47	-0.75	0.81	0.98	-0.22				
IWM	-0.78	-0.56	0.19	-0.10	-0.84	0.84	-0.57	0.36	0.53	-0.36	0.50			
% of attenuation	-0.99	0.00	0.71	-0.26	-0.59	0.59	-0.86	0.54	0.81	-0.54	0.86	0.81		
Average slope (%)	0.85	-0.44	-0.82	0.29	0.29	-0.29	0.99	-0.49	-0.68	0.50	-0.76	-0.46	-0.82	
Length (km)	-0.23	0.65	0.74	-0.83	-0.09	0.09	-0.20	0.79	0.73	0.36	0.70	-0.17	0.24	-0.28

Legend: *Inf_St*: stands for channel inflow-storage hysteresis, *Inf_Area*: channel inflow-inundated area hysteresis, *St_Area*: storage-inundated area hysteresis, *St_Outfl*: storage-outflow hysteresis, *Qcap*: channel capacity for spillage, *QSF*: channel spill factor, *AA*: scale parameter of the return flow equation, *Res. Storage*: Residual storage, *Ini. storage*: Initial storage, *Rs_St/T_St*: a fraction of the residual storage related to maximum wetland storage, *IWM*: index of wetland morphology.

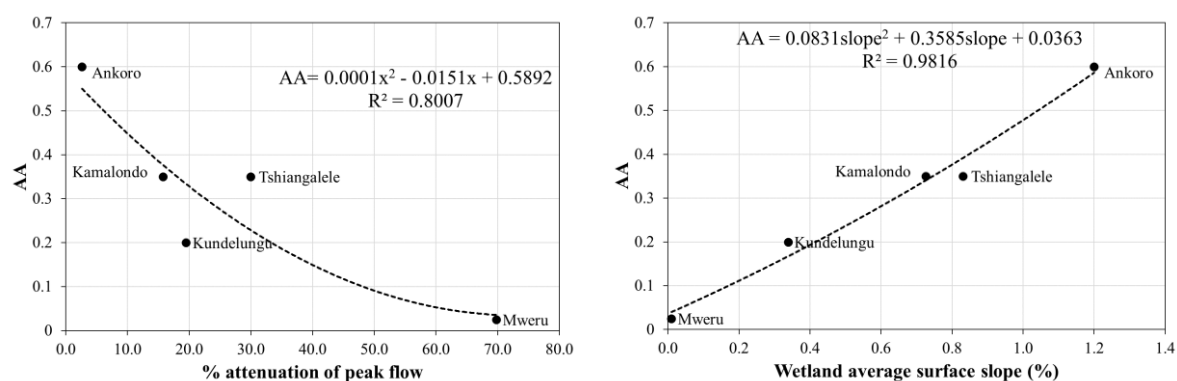


Figure 7.10. Potential predictive equations of the scale parameter (AA) of the return flow equation when the exponent parameter BB is kept constant at a value of 1.25

7.3.5 Simulating wetland downstream flow regimes

The information generated in Section 7.3.4.2 is used for the simulation of the wetlands downstream flow regime. Wetland sub-model parameters (Table 7.8 and 7.9) are included in the hydrological modelling of the Lualaba drainage system to improve model performance and consequently reduce the uncertainty due to the lack of knowledge in channel-wetland exchanges. It is expected that these LISFLOOD-FP informed wetland parameters would need further re-calibration within the main PITMAN model to improve some of the hydrological response aspects. Hydrological simulations downstream of wetland systems are conducted in two different ways. The first is to consider the effect of individual wetland systems on the downstream flow regime in terms of model performance (based on the best model performance in the ensemble set) and uncertainty. The second is to consider the combined effects of all upstream wetlands. Obviously, the impacts are expected to be different across wetland systems and they can be more pronounced at gauging stations located immediately downstream rather than at those located further downstream.

Table 7.12 lists the wetland systems and their corresponding area ratios with respect to individual sub-basin area as well as upstream cumulative area, while Figure 7.11 shows the downstream gauging stations (in red) affected by upstream wetland systems. Tshiangalele (L_CB350) and Ankoro (L_CB198) wetland systems represent only than 5% of their sub-basin total area (WARSA), while Kundelungu (L_CB404) represents 11% and others have areas greater than 20% of their sub-basins's area. This % ratio is further reduced when the cumulative drainage area is considered (WARCA). The key question is whether the size of the wetland (% ratio) can be linked to its potential in modifying downstream processes at local and larger scales?

Since the main hydrological modelling approach is based on the use of constraints, this section verifies whether the original constraints are valid in the region of wetlands and further downstream, across the Lualaba drainage system. The subsequent sub-sections present the main simulation results.

Table 7.12. Wetland area ratios of the studied wetland systems

Wetland system	Number of sub-basins	Wetland area (km ²)	Sub-basin area (km ²)	WARSA (%)	Cumulative area (km ²)	WARCA (%)	D. gauging station
Tshiangalele	2	372	8667	4.29	17253	2.2	Mulongo
Kundelungu	5	1144	10317	11.09	41713	2.7	Mulongo
Kamalondo	20	5068	18239	27.79	156545	3.2	Mulongo
Mweru	18	7050	31809	22.16	215644	3.3	Luvua
Ankoro	42	355	8265	4.30	426746	0.1	Ankoro
Tanganyika	10	32900	95430	34.48	238520	13.8	Lukuga
Kivu	1	2700	7378	36.60	7378	36.6	Ruzizi

D. gauging station stands for downstream gauging station.

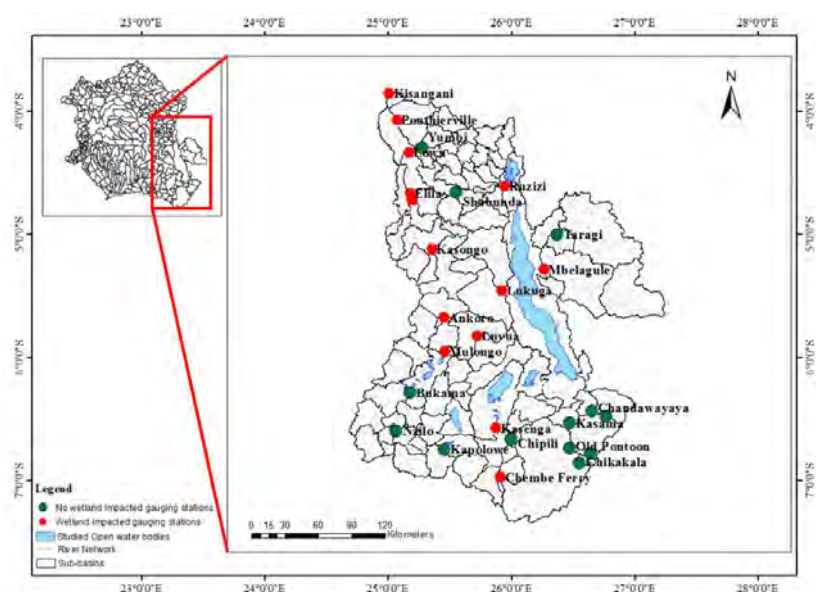


Figure 7.11. Wetland impacted downstream gauging stations (in red) used for the assessment of wetland impacts on the downstream flow regime of the Lualaba drainage system.

7.3.5.1 Simulation results up to the Ankoro gauging station

All five wetland systems for which the LISFLOOD-FP model was used are located upstream of the Ankoro gauging station, draining 42 sub-basins representing a cumulative area of 426 746 km² (Table 7.12 and Figure 7.11). Hydrological simulations are assessed at Mulongo, Luvua and Ankoro gauging stations. Assessments at Mulongo accounts for the effect of three wetland systems namely Tshiangalele, Kundelungu and Kamalondo where individual and combined effects are evaluated. Evaluations at Luvua accounts for only the effect of the Mweru wetland system, while the effects of all upstream wetlands are evaluated at the Ankoro gauging station.

The Modelling results (Table 7.13) obtained at Mulongo gauging station show that the exclusion of all the three-wetland systems in the modelling framework results in low model performance with high %Bias for both high and low flows. However, including the Tshiangalele and Kundelungu wetland systems individually slightly improved model simulations but still with high %Bias, largely because they are located in the upstream sub-basins and that their impact on the downstream part is buffered. The inclusion of the Kamalondo wetland system substantially improves the model performance for both high and low flows with the %Bias in the range of $\pm 5\%$ mainly due to its proximity to the Mulongo gauging station and its size. The model performance is further improved when Kamalondo and one of the other wetland systems are included in the modelling while adding the third wetland makes very little difference. Figure 7.12 illustrates the model performance before and after the wetlands are included (using sub-basin inputs that are not grouped). The figure shows over-simulation of moderate to high flows and under-simulation of low flows. This under-simulation of low flows may be due to the quality of the observed flows at this gauging station, a situation previously reported (Mahé, 1993; Tshimanga, 2012). Most of the time series from this dataset are short (1950-1959) and have been generated based on rating curves developed from a limited number of measurements. However, it is also possible that the Kamalondo wetland parameters could be further calibrated to produce an improved simulation.

The results obtained at Luvua gauging station for the period 1950-1958 show poor performance without the inclusion of the Mweru wetland when upstream sub-basins are independently simulated (Table 7.14). The inclusion of Mweru wetland system in the modelling has substantially improved the model performance and contributed to the attenuation of peak flows as well as the timing of flood hydrographs (Figure 7.13a). This has improved the seasonality ($NE = 0.903$) of the monthly flows (Figure 7.13b) such that peak flows correctly occur in May. Most of the hydrological response characteristics (Figure 7.14) are well captured when the Mweru wetland system is included.

The Ankoro gauging station is just downstream of Mulongo and Luvua gauging stations. The effect of different modelling scenarios of upstream wetland systems on the modelling performance is given in Table 7.15. As pointed out before, the inclusion of all upstream wetland systems has substantially improved the performance by reducing the %Bias for both high and low flows. The inclusion of Mweru wetland alone improves the performance more so than the other two wetlands, while including Mweru and Kamalondo produces similar results to the

model run where all upstream wetlands are included. This is largely because both Kamalondo and Mweru are large in extent and therefore they exert major impacts on downstream flow conditions. Both wetlands have high peak delay times (Table 7.5) and Mweru alone has a very high peak flow attenuation effect (Table 7.4). While including the wetlands improves the uncertainty bands of the FDCs (Figure 7.15), there remains quite a high level of over-simulation. Again, this might be related to the quality of the observed flow, but may also suggest that further calibration of the wetland parameters is required. The simulated streamflows from one of the ensembles (for independent sub-basins) have adequately captured the general pattern of the observed flow (Figure 7.16a).

Table 7.13. Model performance for the ensemble with highest NE under different scenarios at Mulongo gauging station.

SN	Modelling Scenarios	NE	NE(ln)	%Bias	%Bias (ln)
1	No wetlands included in model run	0.33	0.47	13.37	10.84
2	Only Tshiangalele wetland (L_CB350)	0.41	0.52	11.10	7.13
3	Only Kundelungu wetland (L_CB404)	0.40	0.49	11.80	7.87
4	Only Kamalondo wetland (L_CB150)	0.62	0.54	-0.55	-4.43
5	Only Tshiangalele and Kundelungu wetlands	0.38	0.49	8.80	3.80
6	Only Tshiangalele and Kamalondo wetlands	0.67	0.59	-2.28	-4.17
7	Only Kundelungu and Kamalondo wetlands	0.65	0.53	1.09	-2.95
8	All wetlands included in model run	0.66	0.56	-1.14	-4.56

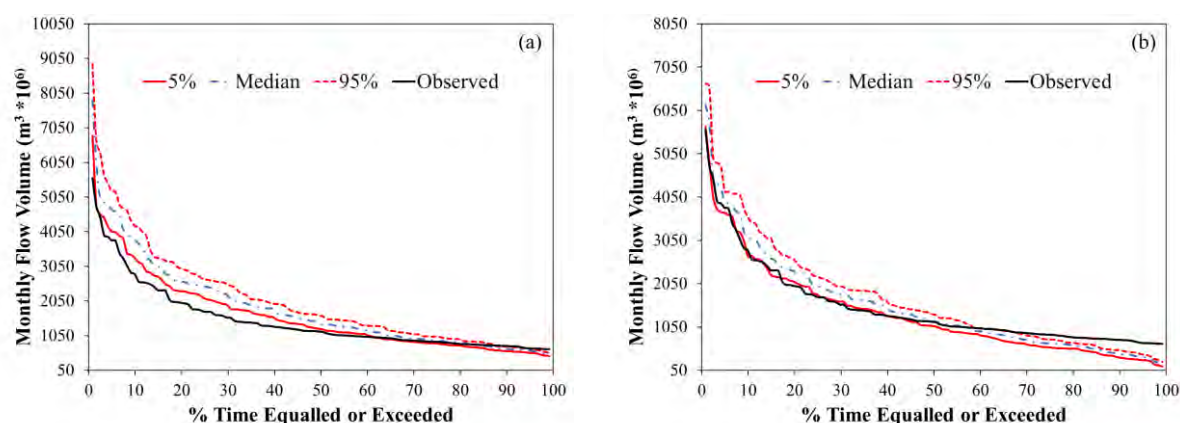


Figure 7. 12. Simulated uncertainty bounds of the flow duration curve at Mulongo gauging station (L_CB150). (a) without and (b) with wetland systems when sub-basins are independently simulated.

Table 7.14. Model performance for the ensemble with highest NE under different scenarios at Luvua gauging station.

SN	Modelling Scenarios	NE	NE(ln)	%Bias	%Bias (ln)
1	No wetland included in the model run with independent sub-basins	0.505	0.402	4.41	-3.183
2	Wetland included in the model run with independent sub-basins	0.912	0.847	0.259	4.162

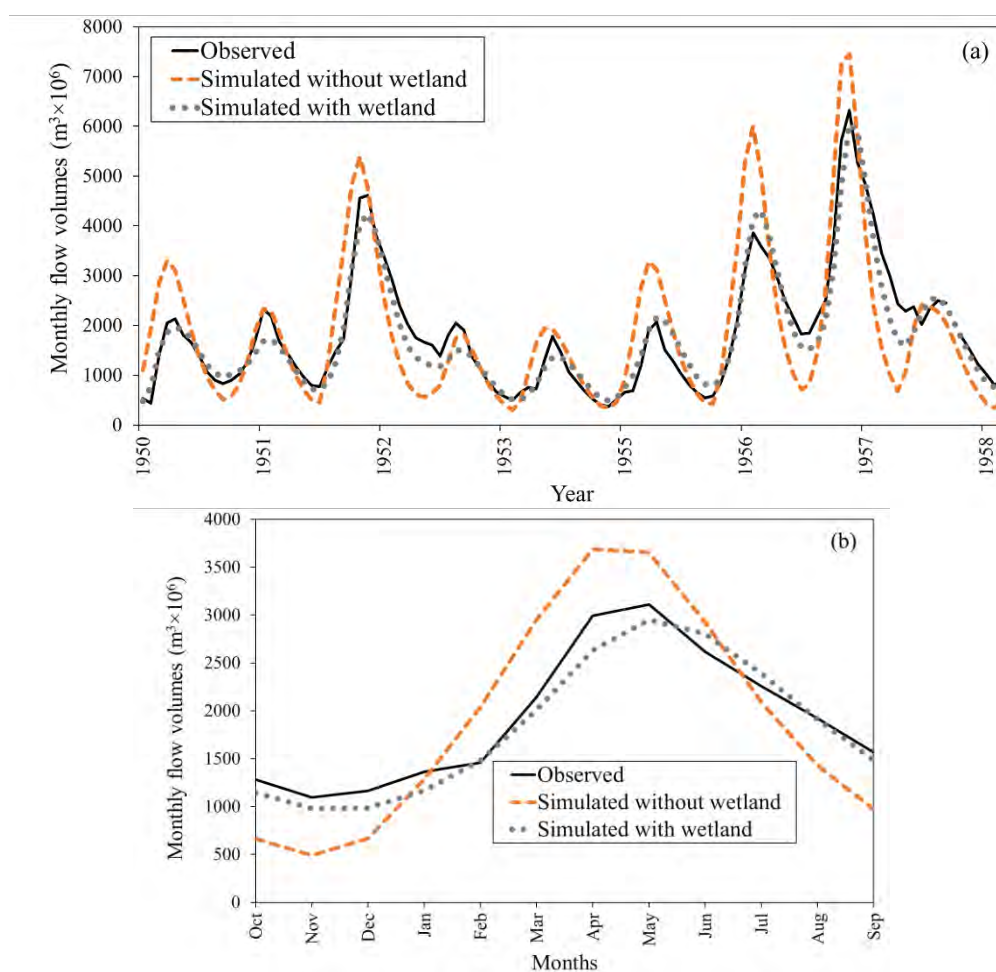


Figure 7.13. Simulated streamflows (a) and monthly flow distribution (b) from one of the ensembles at the Luvua gauging station without and with the inclusion of Mweru wetland system in the basin-scale hydrological modelling.

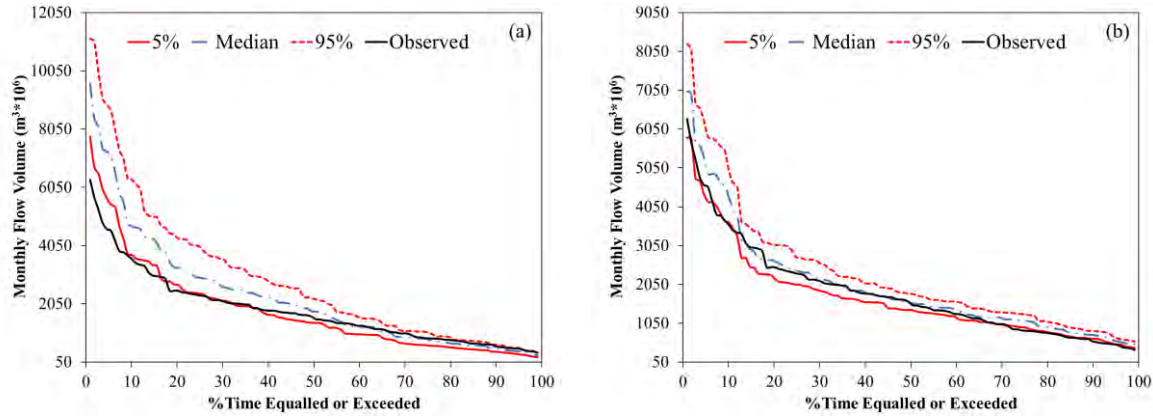


Figure 7.14. Simulated uncertainty bounds of the flow duration curve at Luvua gauging station (L_CB210) in the downstream of the Mweru wetland system. (a) without and (b) with Mweru wetland system included in the modelling when sub-basins are not grouped.

Table 7.15. Model performance for the ensemble having highest NE under different scenarios at Ankoro gauging station.

SN	Modelling Scenarios	NE	NE(ln)	%Bias	%Bias (ln)
1	No upstream wetlands included in the model run	0.71	0.74	10.05	6.53
2	Only Ankoro wetland (L_CB198)	0.76	0.73	10.24	9.54
3	Only Kamalondo wetland (L_CB150)	0.76	0.74	4.06	-1.33
4	Only Mweru wetland (L_CB23)	0.88	0.90	4.44	6.01
5	Only Kamalondo and Mweru wetlands	0.90	0.90	-2.22	-2.17
6	All wetlands included in the model run	0.90	0.89	0.78	0.05

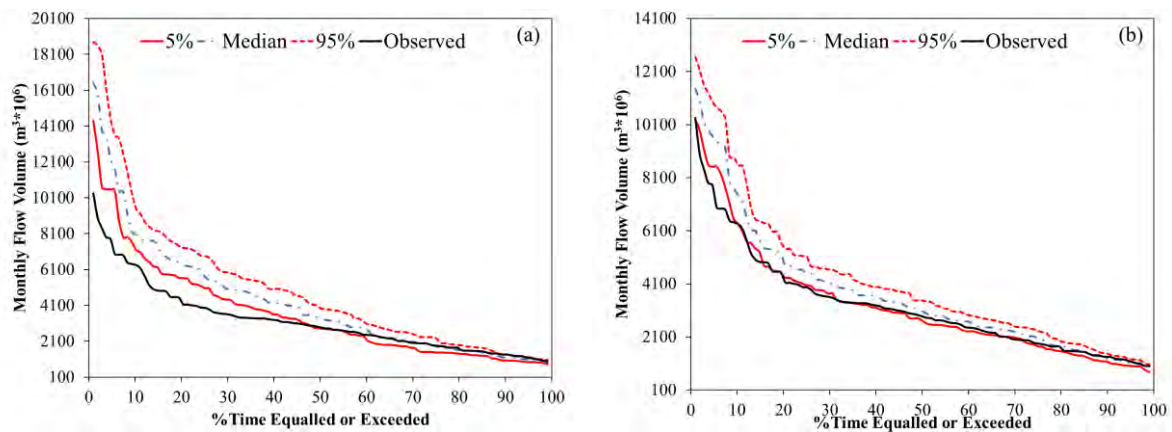


Figure 7.15. Simulated uncertainty bounds of the flow duration curve at Ankoro gauging station (L_CB198) in the downstream of five wetland systems. (a) without and (b) with upstream wetlands systems included in the modelling when upstream sub-basins are independently simulated.

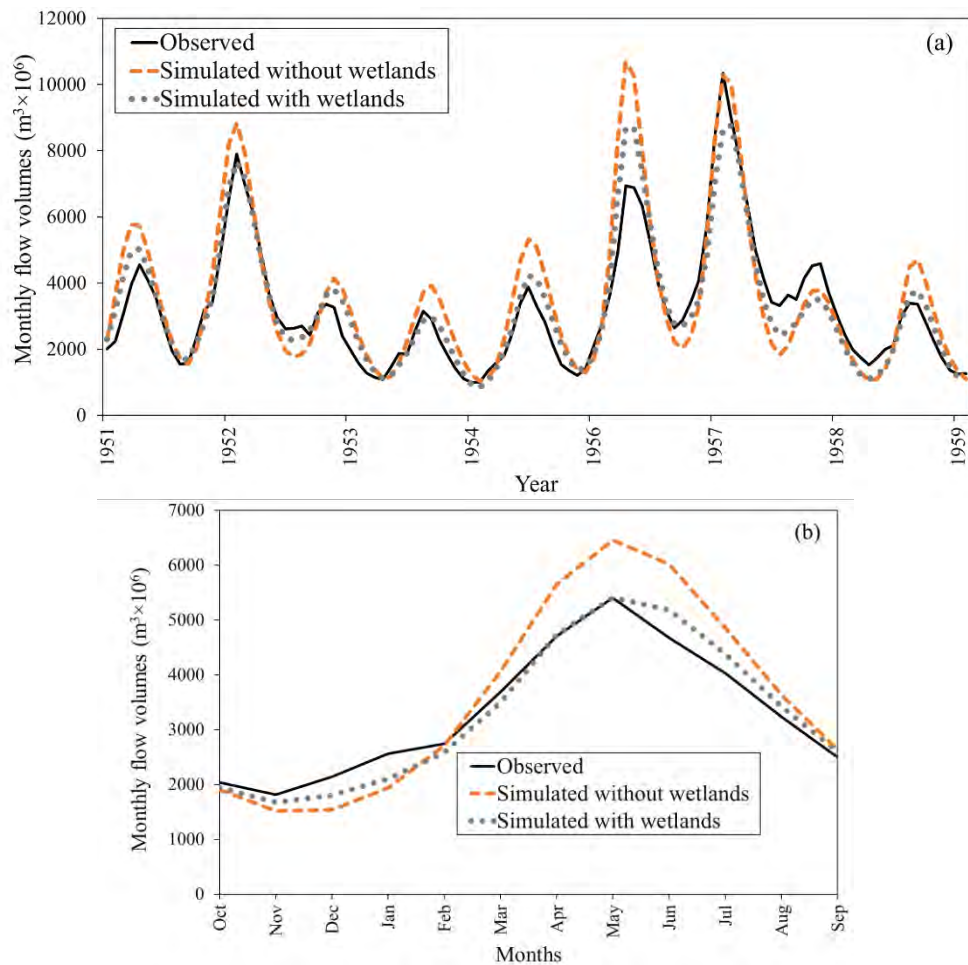


Figure 7.16. Simulated streamflows (a) and monthly flow distribution (b) from one of the ensembles at the Ankoro gauging station without and with the inclusion of all upstream wetland systems in the basin-scale hydrological modelling.

7.3.5.2 Simulation results within the Tanganyika basin

The historical information at Lukuga (Charlier, 1955) gauging station includes discontinuous flow series that were generated based on rating curves developed under different flow conditions. These rating curves express relationships between Lake Tanganyika water level fluctuations and streamflow discharges in the Lukuga River. Wetland parameters (Table 7.9), developed using this interaction between lake and river, are used to simulate downstream flow conditions at both Lukuga and Ruzizi (Figure C7.6 in Appendix C) gauging stations, but only the results at Lukuga are presented (Figure 7.17).

The model has appropriately simulated the timing of flow hydrographs (Figure 7.17b) and the highest model efficiency across the ensembles over the period 1932-1936 is 0.66 and 0.63 for both high and low flows, respectively. This efficiency increases over the period 1945-1947 to

0.68 and 0.74 for high and low flows, respectively. Lake Tanganyika exerts a huge flow attenuation (Figure 7.17a) of about 116% at the Lukuga gauging station. Simulated flows at Lukuga gauging station are highly dependent on upstream flows coming mainly from major tributaries such as Ruzizi, Malagarasi and Lufubu rivers. The simulated long-term mean flow over the period 1901-2014 is about $503.3 \times 10^6 \text{ m}^3$, which represents 58% of the total inflows from these major tributaries. This means that any impact in these upstream sub-basins would impact on the flow regime at the Lukuga gauging station. Also, the $503.30 \times 10^6 \text{ m}^3$ flow simulated at Lukuga gauging station represents only about 10% of downstream flow observed at Kasongo gauging station (on Lualaba River), while ignoring the Lake Tanganyika effects would generate an excessive flow (about $1900 \times 10^6 \text{ m}^3$), resulting in an over-simulation at downstream gauging stations.

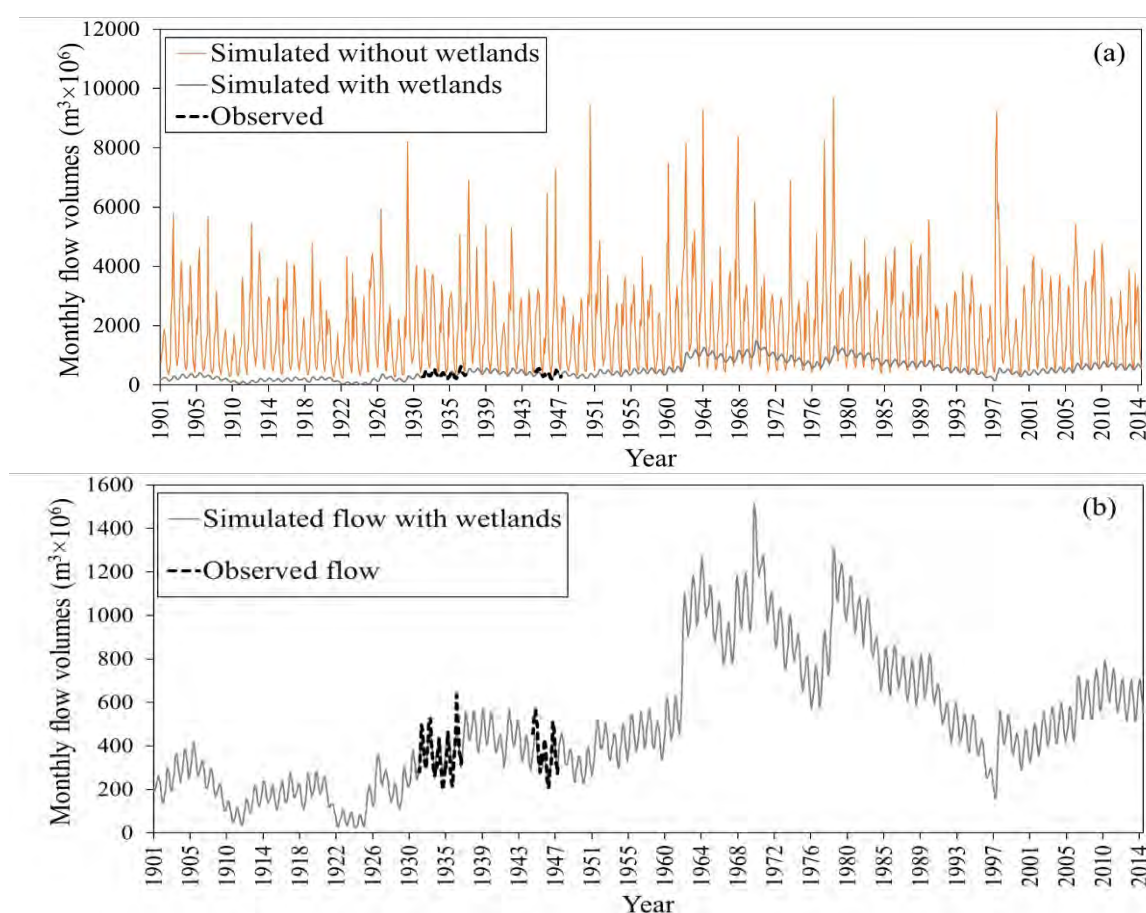


Figure 7.17. (a) Simulated streamflow at Lukuga gauging station over the period 1901-2014 before and after the inclusion of upstream wetland systems including Lake Tanganyika. The observed flows are available over two distinct periods 1932-1936 and 1945-1947. (b) Simulated streamflow after the inclusion of wetland function.

7.3.5.3 Re-calibration of some of the wetland parameters within the main PITMAN model

The initial wetland parameters of the PITMAN wetland sub-model (Table 7.8) together with the behavioural parameters of the main PITMAN model (Chapter 6) were used to simulate the impacts of wetlands on downstream flow regimes of the Lualaba drainage system (Section 7.3.5.1). Simulated uncertainty bounds of flow duration curves suggested that the inclusion of wetlands substantially improved the uncertainty bands, but there remained a high level of over-estimation of flow volume (e.g. Figures 7.12b and 7.15b) at some gauging stations. This over-estimation may partly be related to the uncertainty in wetland parameters and the parameters of the ungauged incremental sub-basins contributing to the wetlands. The lack of wetland bathymetry especially for the Kamalondo and Mweru wetland systems may underestimate the attenuation effects of these wetlands and therefore add uncertainties in the estimated wetland parameters. The validation process of the hydrodynamic modelling of these wetlands (Section 7.3.3) was performed against the inundation areas because of the unavailability of flow gauge during the modelling period. The lack of wetland bathymetry may directly affect the residual wetland storage (RWS) and indirectly the two parameters of the return flow function (AA and BB). These parameters together with the wetland evaporation rate can vary within a certain uncertainty bound which represent the uncertainty in the validation process (of the hydrodynamic models) as well as in the lack of wetland bathymetry. On the other hand, the total area of the ungauged incremental sub-basins between Bukama, Kapolowe and Mulongo gauging stations represent about 43% of the cumulative area up to the downstream of the Kamalondo wetland system and that between Kasenga and Luvua gauging stations represent 34% (Table 7.16). This means that the flow contribution from these sub-basins has the potential to affect the wetland outflow and therefore any constraint refinement in these areas is expected to more or less affect the wetland outflow. Whereas the sub-basins located between Mulongo, Luvua and Ankoro gauging stations represent only about 6% of the cumulative drainage area and their contribution is therefore unlikely to affect the simulated flow at the Ankoro gauging station.

To account for the uncertainty in wetland parameters and improve the simulations of downstream wetland systems at Mulongo, Luvua and Ankoro gauging stations, an attempt for a re-calibration of some of the wetland parameters, within the main PITMAN model, consisted of slightly decreasing the AA parameter of the return flow function, while increasing the residual storage (RWS). This would potentially increase the wetland storage volume and create

additional attenuation of the wetland outflow while maintaining the inundation pattern. The recalibration of these two parameters was combined with an increase of the wetland evaporation parameter (which remained within the uncertainty range of the evaporation rate parameter of the main PITMAN model). A similar approach was applied for the Mweru wetland system as both Kamalondo and Mweru have major impacts on the downstream flow regime, but for Mweru, only the evaporation was increased as the changes in RWS and AA parameters affect negatively the downstream monthly flow distribution. The results have shown that the simulated downstream flow regimes are improved (Figure 7.18). However, there is still an unresolved issue at Mulongo (Figure 7.18b) where the Kamalondo wetland seems to have insufficient water to release during the low water season. Even if the low flow constraint indices of the incremental sub-basins are increased, the problem is not solved, indicating the complexity of flow dynamics, which need to be further understood in future investigations.

Table 7.16. Description of sub-basins located in the region of wetlands and beyond

Groups of sub-basins	Number of sub-basins	Description
Between Chembe Ferry and Kasenga gauging stations	6	No wetland. These sub-basins generate the main wetland inflows for the Mweru wetland system
Between Kasenga and Luvua gauging stations	6	The Mweru wetland sub-basin is the largest in this group with three sub-basins inflowing into Mweru wetland while two sub-basins are in downstream of Mweru wetland. They represent 34% of the cumulative area.
Between Bukama, Kapolowe and Mulongo gauging stations	9	Bukama and Kapolowe gauging stations are the main inflows in this region with three wetland systems: Tshiangalele, Kundelungu and Kamalondo. Kamalondo wetland sub-basin is the largest and the most downstream in this group and represent 43% of the cumulative area.
Between Mulongo, Luvua and Ankoro	2	Only the Ankoro wetland lies in this group and represent 6% of the cumulative area.
Tanganyika	10	Lake Kivu is a headwater sub-basin with a gauging station at Ruzizi which discharge into lake Tanganyika after crossing one sub-basin. Five sub-basins in the eastern part of lake Tanganyika drain to Melagule gauging station which discharge directly into lake Tanganyika. Two other sub-basins drain as well to lake Tanganyika which has an outlet at Lukuga gauging station.
Between Ankoro, Lukuga and Kasongo gauging station	6	No wetland.
Between Kasongo and Kindu gauging stations	4	No wetland.
Between Kindu and Elila gauging stations	4	No wetland.
Between Elila and Lowa gauging stations	22	No wetland. Twelve sub-basins of rift valley regions were calibrated in chapter 6 (Section 6.2.14). The remaining ten sub-basins are calibrated in this chapter.
Between Lowa and Ponthierville gauging stations	2	No wetland.
Between Ponthierville and Kisangani gauging stations	3	No wetland.

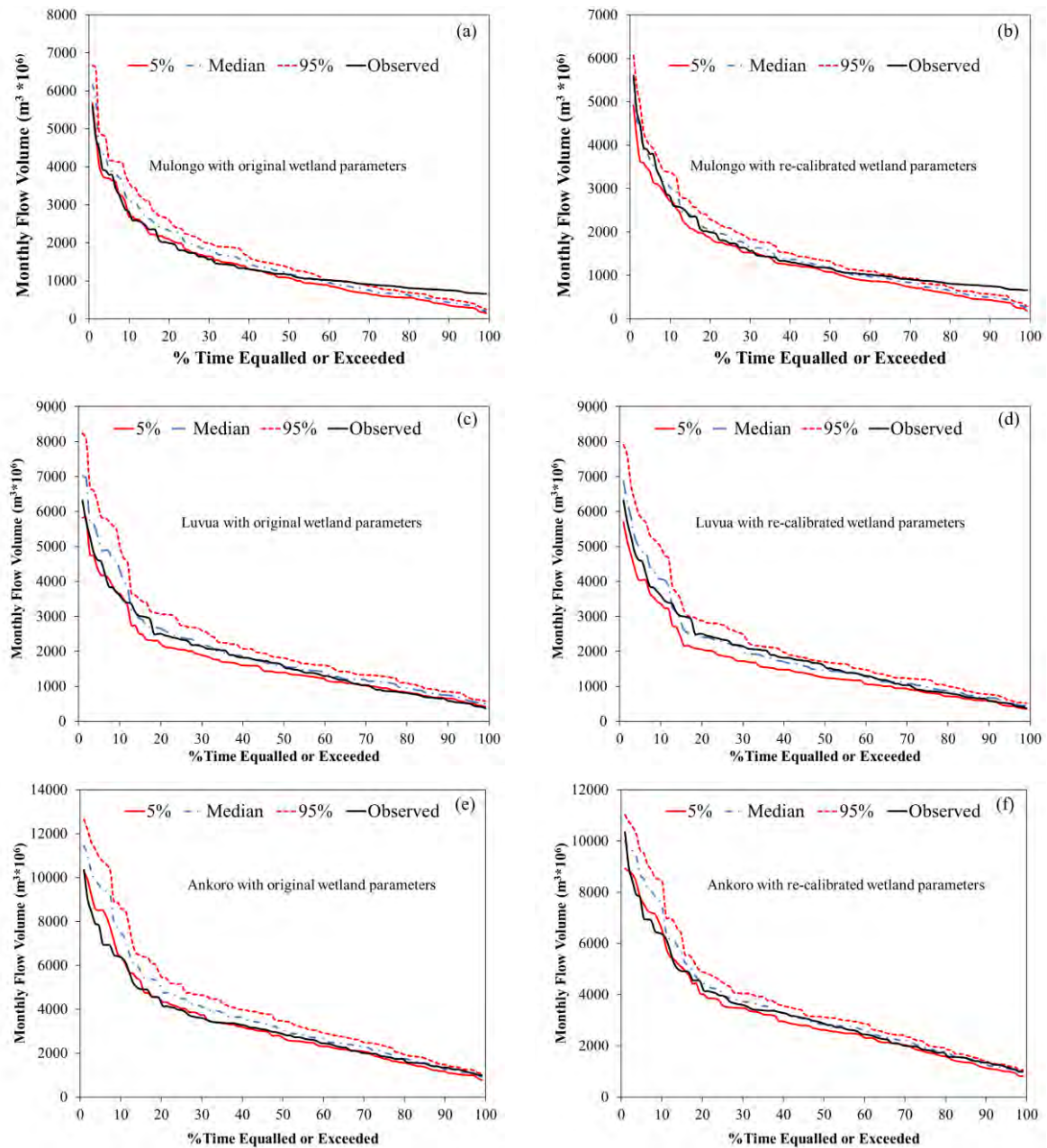


Figure 7.18. Simulated uncertainty bounds of FDCs in downstream of major wetland systems of the Lualaba drainage system after a re-calibration of some of the wetland parameters within the main PITMAN model. These are examples of Mulongo (a-b), Luvua (c-d) and Ankoro (e-f) gauging stations.

7.3.5.4 The validity of the constraints for the sub-basins in the zone of the wetlands and beyond

As discussed earlier in Chapter 6, the use of the original constraints required some adjustments to match the downstream observed hydrological responses. These adjustments can be minor or major, depending on how the simulated response departs from the observed flow. For the sub-basins located in the region of the wetlands, the main question is whether some changes to the constraints (as seen in Chapter 6) are still required even after the wetland parameters have been included in the modelling framework. The answer to this question largely depends on the location of the evaluating gauging stations with respect to the upstream wetland systems. There are very few situations where the evaluation gauging station is in the sub-basin immediate downstream of a wetland. In such situations, only minor adjustments were required for some constraints while major ones were required for the majority of sub-basins located in the downstream part of the Lualaba drainage system. Table 7.16 shows different groups of sub-basins from upstream to downstream depending on the location of the gauging stations. Only three groups of sub-basins located between Bukama, Kapolowe and Mulongo for the first group, between Kasenga and Luvua for the second group and between Mulongo, Luvua and Ankoro have been the most challenging during the constraint analysis and refinement process. It has been difficult to say whether the mismatch between the simulated flow and the observed at downstream gauging stations was due to the wetland parameters or to the incremental sub-basin responses. The experience of constraint refinement within other groups of sub-basins not having wetland systems was used to guide the refinement process within the region of wetlands.

Figure 7.19a shows the runoff ratios plotted against the aridity index for sub-basins located either in the region of wetlands or downstream. For example, the runoff ratio of the majority of the sub-basins fit well within the original uncertainty bounds, except for sub-basins between Elila and Ponhierville gauging stations. These sub-basins display similar hydrological behaviour as those of the Rift valley region with runoff ratios highest than 35% (Figure 7.20a). These sub-basins mostly exhibit climate and physiographic characteristics different from those of upstream and belong mainly to Regions 2, 3 and 4 (Figure 5.3), which were not substantively represented in the original constraint relationships. However, the high and medium flow indices of this region are well simulated within the original uncertainty bounds (Figure 7.19bc), whereas those of some sub-basins within the wetland region are slightly outside the original ranges.

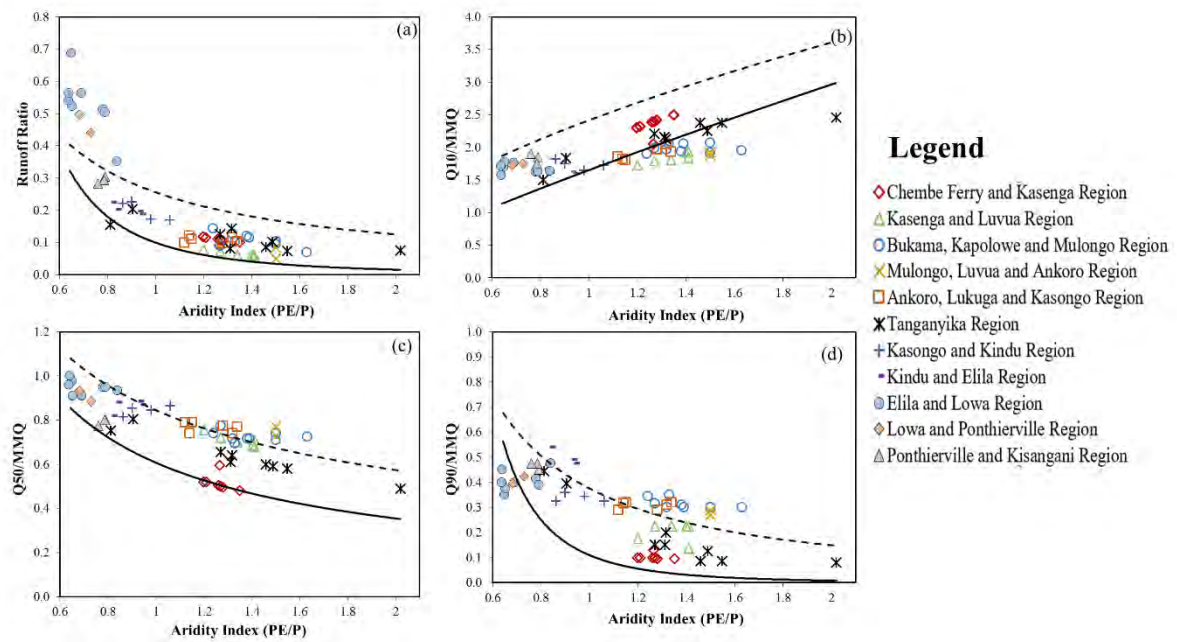


Figure 7.19. Variation of mean values of constraint indices with regards to the original constraint uncertainty ranges (plain and dashed lines), after adjustments have been made to constraint ranges for sub-basins within the wetland zones (Between gauging stations) and in the most downstream part, of the Lualaba drainage system.

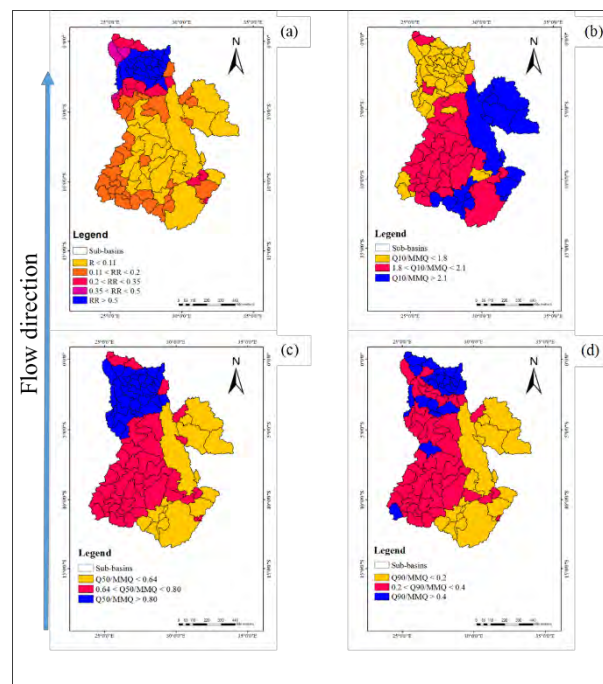


Figure 7.20. Mapping of the final mean values of the constraint indices across the Lualaba drainage system for the (a) runoff ratio, (b) Q10/MMQ, (c) Q50/MMQ and (d) Q90/MMQ.

7.3.5.5 Comparing wetland parameters with those previously reported

The parameters determined from the LISFLOOD-FP wetland simulations should be more appropriate than those estimated through trial and error calibration during the previous study (Tshimanga, 2012). Table 7.17 shows the two sets of parameters for the Kamalondo and Lake Tanganyika wetlands. One of the major differences lies in the way in which Lake Tanganyika was dealt within the model. In this study, only the lake volume above the minimum outlet level was included and this affects the storage volume-area parameters. It was further assumed that the lake area above the minimum lake level remains constant. It was also assumed that Kamalondo operates in a similar way to a natural lake (zero channel capacity and a spill factor of 1.0) because a major proportion of the inflow ends up in lake Kisale (Figure 3.8). In contrast, the previous study considered the wetland system as a single unit which exchanges a much smaller fraction of its flow with the adjacent water bodies. An example of simulated streamflow (Figure 7.21a) using these two sets of wetland parameters illustrates that the new parameters result in better model performance for the Kamalondo wetland system. The ensemble with the highest performance (NE and NE {ln}) using the new parameters has values of 0.72 and 0.61, respectively, whereas the previous wetland parameters generated values of 0.5 and 0.51, respectively. The seasonality of the simulated monthly flow distribution is also improved with a NE of 0.98 against 0.67 based on previous wetland parameters (Figure 7.21b).

Table 7.17. Wetland parameters of the Kamalondo and Lake Tanganyika used in this study and the previous

Parameter name	Wetland parameter values			
	Kamalondo		Tanganyika	
	In this study	In previous study	In this study	In previous study
Local Catchment area (km ²)	5068	12000	32900	33000
Residual wetland storage, RWS (MCM)	8100	24000	0	1.89*10 ⁷
Initial storage (MCM)	5600	42000	45000	1.9*10 ⁸
A in Area (m ²)=A*Volume (m ³) ^B	654846	381	3.29*10 ¹⁰	77.15
B in Area (m ²)=A*Volume (m ³) ^B	0.4891	0.8	0	0.65
Channel capacity for spillage (MCM)	0	5000	0	0
Channel Spill Factor (Fraction)	1	0.6	1	1
AA in (Ret Flow= AA*(Vol/RWS) ^{BB}	0.175	0.45	0.4	0.8
BB in (Ret Flow= AA*(Vol/RWS) ^{BB}	1.25	9.32	1.25	800
Annual Evaporation (mm)	1504.31	1500	1330	1450
Annual Abstraction (MCM)	0	0	0	0
AA scaling factor	0	0	1000	1000
Max Return flow Fraction	0.95	0.95	0.95	0.95

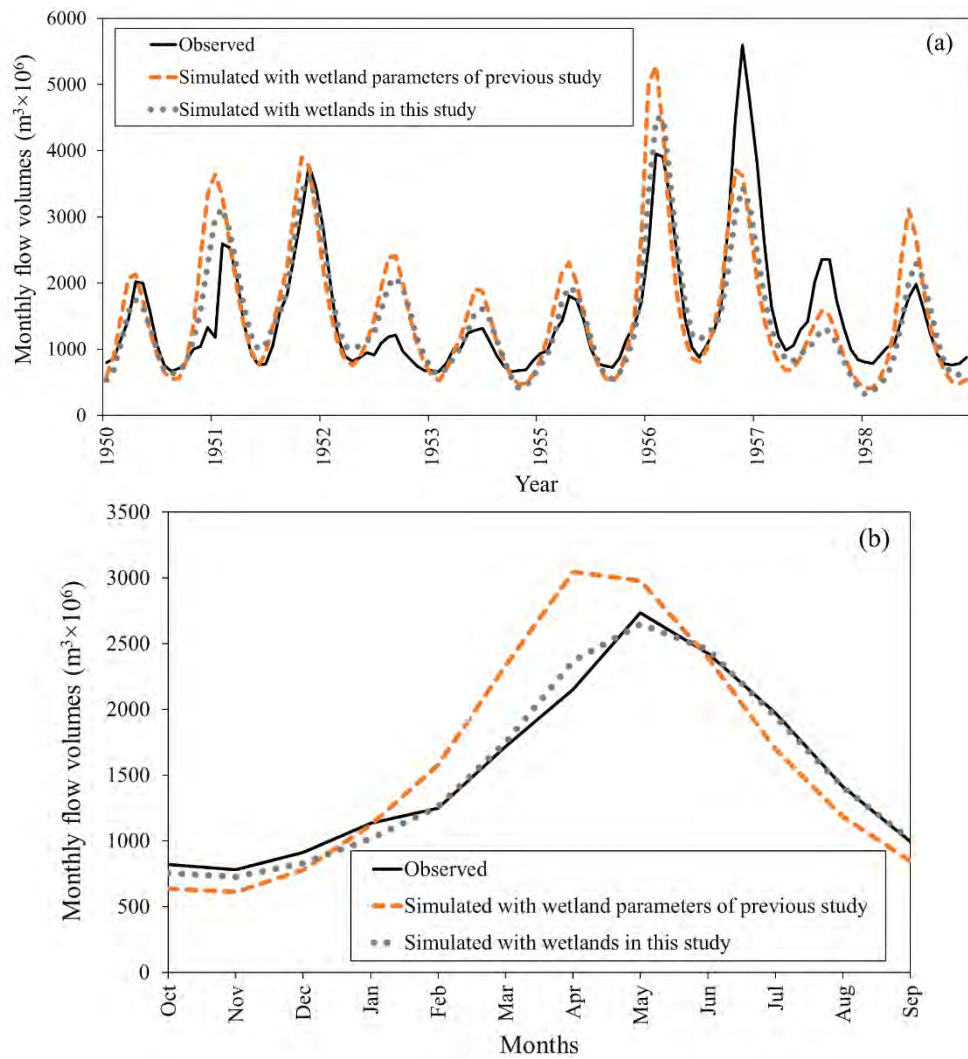


Figure 7.21. Observed and simulated monthly flow volumes using two different sets of wetland parameters. (a) streamflows and (b) monthly distribution of flows at Mulongo gauging station in the downstream of Kamalondo wetland system.

7.4 Discussion

This chapter has focussed on the estimated PITMAN wetland parameters from an understanding of wetland hydrodynamic behaviour, simulated through the use of the LISFLOOD-FP model. Hydrological input boundary conditions for driving the hydrodynamic behaviour were simulated through the monthly time step PITMAN model (Chapter 6). These monthly stream flows were disaggregated into daily stream flows using a disaggregation model (Slaughter et al., 2015).

The hydrodynamic models of the different wetland areas have been partially validated using independent estimates of inundation extents available from remote sensing. Both visual inspection of the simulated inundation extents and the magnitude of the performance statistics show acceptable model performance across a range of measures. However, some of the uncertainties associated with the model performance (Tables 7.2 and 7.3) may be due to the quality of the Landsat images, the resolution of the model, the lack of field surveys of lake bathymetry (for some wetlands such as Kamalondo and Mweru) and the limitations of the water detection index (MNDWI) used. Although Landsat imagery has been successful in reproducing inundation extents in other flood monitoring studies (Marcus and Fonstad, 2008; Mueller et al., 2016), there are some limitations encountered in this study region. These limitations include the persistent cloud cover during flood events and the inability of the sensor to map flooding beneath the aquatic vegetation covering a major part of the Kamalondo wetland system (Welcomme, 1979; Hughes and Hughes, 1992). Alternative remote sensing products such as Synthetic Aperture Radar (SAR) images (Sanyal and Lu, 2004; Schumann et al., 2009) would provide an opportunity to overcome such limitations inherent to optical remote sensing. Other remote sensing products such as water level elevation and storage volumes (Kim et al., 2017; Yuan et al., 2017; Becker et al., 2018) can also be used for the validation purpose, but this was beyond the scope of this study which focussed only on inundation extent as a validation that the flow volume exchanges between river channels and their adjacent floodplains are being simulated realistically.

Process understanding of channel-wetland exchanges has provided a basis for differentiating wetland systems based on their filling and emptying mechanisms. Kamalondo and Tshiangelala wetland systems have similar mechanisms of spilling and returning flows (Table 7.8). The spilling is similar to natural lakes where the total channel inflow is discharged into the wetland system, thus modifying completely the downstream flow signal. This type of functioning is

also found in the Mweru wetland system. The release of flow back to the channel is slower in the Mweru wetland than Ankoro (Figure 7.10b). The calibration of wetland sub-model parameters using LISFLOOD-FP outputs (Figures 7.5 to 7.9) reveals that all wetlands have the potential to attenuate peak flows even at the monthly time scale. However, only Mweru and Kamalondo wetlands increase and decrease, respectively, the downstream base flows, while Kundelungu, Ankoro and Tshiangalele show small or no such low flow impacts.

The quantification of hysteresis indices in channel-wetland exchanges has helped to understand the nature of connectivity across wetland systems and to draw inferences on factors driving their dynamics. The highest degree of hysteresis was found in the Mweru wetland system, indicating a highly delayed return flow (Hughes et al., 2014). The smallest was found in Ankoro, implying a transient flow through the wetland where most of the inflow would return almost simultaneously to the channel (Hughes, 1980; Hughes *et al.*, 2014). The analysis of factors determining the PITMAN wetland model parameters has revealed the possibility of deriving these parameters using wetland morphometric characteristics in areas where hydrodynamic models are not available (Kabuya et al., 2020a). The correlation matrix (Table 7.11) of wetland variables shows potential relationships between wetland parameters and some of the morphometric characteristics, although the sample size of only five wetlands is not high enough to be statistically conclusive. All these relationships need to be further explored in future for understanding wetland processes in ungauged areas.

The simulation results highlight the importance of including wetland systems into modelling and are consistent with many studies conducted elsewhere (Bullock and Acreman, 2003; Golden et al., 2014b). Wetlands have improved the timing and the occurrence of peak flow hydrographs, the attenuation of peak flows as well as the seasonality of monthly flow distribution (e.g. Figures 7.13, 7.14, 7.18). The wetland impacts are exerted differently depending on the size of wetland and its location (Wu et al., 2020a; Wu et al., 2020b). Small wetlands like Ankoro and Tshiangalele have no substantial effect on downstream flows, whereas large wetlands such as Kamalondo and Mweru have very large impacts (Tables 7.13 and 7.15), but the combined effects of all upstream wetlands can contribute to large downstream impacts. While the simulation results are generally acceptable, the attenuation effects of wetlands at some gauging stations (Figure 7.12b and 7.15b) were not strong enough to capture a large portion of the observed flows. This suggested the need for a re-calibration of some of the wetland parameters (within an acceptable uncertainty bound) within the main

PITMAN model and such re-calibration may be justified by the fact that some large wetlands such as Kamalondo and Mweru lacked bathymetry information that might have affected some LISFLOOD-FP parameters. It has been difficult at this point to confirm whether some of the over-simulations of the hydrological responses at Mulongo and Ankoro gauging stations were due to the wetland parameters or to the parameters of the incremental sub-basins within the wetland region. However, the variation of the constraint indices in this region (Figure 7.19) is consistent with other regions that have no wetlands, indicating that much attention has to be directed to wetland parameters especially for the Kamalondo wetland, which is more complex due to a large number of natural lakes.

CHAPTER 8 : CONCLUSIONS AND RECOMMENDATIONS

8.1 Conclusions

The overall objective of this thesis was to improve hydrological simulations by appropriately quantifying the uncertainty and constraining hydrological model outputs in ungauged sub-basins of the Congo Basin. An integrated methodological framework that involved the use of hydrological indices and the inclusion of channel-wetland exchanges was implemented to account for different sources of uncertainty. The main conclusions achieved and recommendations are presented in the subsequent sub-sections.

8.1.1 Establishing the uncertainty ranges of hydrological indices

The ungauged nature of many river basins makes the reliable assessment of water resources under present and future environmental changes very difficult. The lack of reliable forcing and model evaluation information will always result in highly uncertain estimates of water resources. It is difficult to appropriately quantify the uncertainty associated with these estimates because of the existence of multiple uncertainty sources (Lin and Beck, 2007; Blöschl et al., 2008; Westerberg et al., 2010; McMillan et al., 2012; Mehdi et al., 2018; Liu et al., 2018; Mazzoleni et al., 2019; Manfreda et al., 2020), which are treated differently depending on the availability of data and existing uncertainty methods. However, approaches that can account for different sources of uncertainties do exist. One such approach includes the establishment of the uncertainty ranges of hydrological indices or signatures. These are the characteristics of a sub-basin's long-term hydrological behaviour and may reflect the dynamics of the different components of the catchment water balance such as climate, water storage and different runoff processes. Indices, such as long-term mean monthly flow volume and percentiles of the flow duration curve, can be readily obtained from observed streamflow data that represent headwater flow regimes. These headwater flow regimes are useful for establishing regional variations of the hydrological indices, but there are relatively few gauging stations within the data scarce Congo River Basin (Figure 3.10) and many of those that do exist are located on large rivers that represent heterogeneous upstream responses, and therefore are not useful to quantify regional patterns of response at sub-basin scales. In addition, many of the available headwater streamflow time series are short and the data from different stations rarely coincide in time, representing different sequences of dry and wet flow conditions such that the derived indices at different stations may not be comparable with each other. To overcome these challenges,

this study has shown that the short streamflow time series could firstly, be extended to obtain common record periods of streamflow time series to ensure the representativeness of the computed hydrological indices and minimize the differential effects of the number of wet and dry periods represented in short record periods (Section 5.3.1). Secondly, the computed hydrological indices can be used to develop regional relationships with the sub-basins physical characteristics. However, the low number of headwater gauging stations make the initial relationships highly uncertain because of a lack of spatial representativeness. This is overcome by including in the initial relationships additional downstream gauging stations that have a relatively small number (< 6) of upstream sub-basins that do not have any identified anthropogenic impacts and are not influenced by wetland effects. A spatial disaggregation approach of flow time series was implemented and is justified because of the very limited number of gauged headwater sub-basins, and at least the approach allowed some of the response characteristics of the larger gauged catchments to be included in the second round of regression analysis (Section 5.3.3.2).

Ideally, catchment classification offers an approach for reducing the complexity of the basin to a few groups of sub-basins where the differences in climate and physiographic characteristics (and hence the hydrological indices) are assumed to be greater between the groups, than within each group. The climate and physiographic characteristics should represent different aspects of a sub-basin's properties including climate, topography, land cover/land use, soils and geology (Hall et al., 2002; Wagener et al., 2007; McDonnell and Woods, 2008). The latter is the most difficult to quantify, yet it is an important attribute that is likely related to sub-surface processes and low flow responses (Carlier et al., 2018). The catchment classification performed in this study resulted in six homogeneous regions (using self-organising maps) presenting a high level of internal similarity (Section 5.3.2.1). Attributes representing the climate (aridity index), the topography (slope) and land cover/soil types (curve number, %silt and %clay) were found to have potential relationships with sub-basin response characteristics, namely the runoff ratio and the three percentiles (Q10th, Q50th and Q90th) of the flow duration curve expressed as fractions of the mean monthly flow. These response characteristics are considered to represent the minimum number of key indices that can characterise the main response variability of the sub-basins. The identified physiographic regions represent the hydrological similarity because the overlay between the hydrological and physiographic classifications (Section 5.3.2.2) of the fifteen headwater gauging stations revealed a higher degree of affinity (Rand index = 73%). This indicates that hydrological indices from gauged sub-basins can be transferred to ungauged

with a high degree of confidence. Generally, such procedures require each identified physiographic region to have a predictive equation of hydrological response based on potential climate and physiographic predictors. However, the success of this approach largely depends on the number of gauged headwater sub-basins (per identified region) which, at the scale of the Congo Basin, were not sufficient to develop individual predictive relationships for each region, limiting the application of commonly used regionalisation approaches for prediction in ungauged sub-basins (Yadav et al., 2007; Westerberg et al., 2016).

An approach based on generic predictive equations for the whole basin using the aridity index was adopted and produced acceptable levels of uncertainty, as measured by the width of the confidence intervals around the regression relationships, of the hydrological response indices (Kabuya et al., 2020b). These intervals can account for different sources of uncertainties (rainfall and evapotranspiration estimates, a lack of spatial representativeness of the available observed streamflow data, shortness of data series and other factors such as geology). The intervals are less than 41% for both Q10/MMQ and Q50/MMQ indices across the basin, while a greater degree of uncertainty is associated with the runoff ratio and the Q90/MMQ indices. Similarly, the mean monthly recharge (MMR) is associated with a high degree of uncertainty because these estimates are model-dependent (Döll and Fiedler, 2008) and they have not been validated across the Congo Basin. However, these original uncertainty ranges provide the first estimates of hydrological indices that relatively and appropriately reflect the level of uncertainty that is intended to constrain the outputs from hydrological models.

8.1.2 Testing the original constraint ranges to simulate hydrological uncertainties

The hydrological modelling approach implemented in this thesis accounts for the uncertainty analysis for gauged and ungauged sub-basins. The modelling approach can be applied anywhere with the same type of hydrological model. Other models such as HBV-light uses four different constraints based on climate and runoff-process characteristics at different time-scales (Quesada-Montano et al., 2018) and reject model parameters that fail to represent hydrological process characteristics. The particularity of the modelling approach implemented in this study, however, is that it is run in two stages. In stage 1, the uncertainty ranges of hydrological indices are used as filters for each sub-basin to quantify behavioural parameters (5 000 parameters sets) of the model (PITMAN) that are consistent with the constraint ranges under natural hydrological conditions. A key issue in stage 1 is to make sure that the behavioural hydrological responses cover the full range of input constraints as well as

parameter ranges that are not overly biased to make the stage 1 run efficiently with fewer rejections and more rapid identification of behavioural ensembles. However, achieving this depends partly upon the compatibility among the six constraints used, given that the mean monthly recharge constraint was highly uncertain, so it had to be frequently adjusted to be consistent with the low flow constraint index (Q90/MMQ). In the case of the Congo Basin, the mean monthly recharge index remained within the initial ranges for most of the sub-basins located in the southern hemisphere, while substantial changes occurred for those located in the northern hemisphere (Figure 6.23). In stage 2, the saved parameters are re-sampled by the model after other parameters (e.g. channel routing, wetland parameters, water uses) have been added to simulate cumulative hydrological responses, which are evaluated at any outlet where there is a gauging station with sufficient observed data. In this study, simulations were produced only under natural conditions. There were some parameters such as PI2, AFOR and FF, related to a second type vegetation (afforestation), which were not considered to represent natural catchment hydrology and, therefore, were not used to simulate the catchment natural hydrology even at stage 2 of the modelling approach. Also, parameters representing current water resources development (such as irrigation reservoirs and hydropower dams) were not used because the Congo Basin is well known to be underdeveloped in terms of water infrastructures (Nilsson et al., 2005; Santini and Caporaso, 2018) and existing infrastructure is not expected to have significant impacts on flow records at the spatial scales of the sub-basins used. Even though, care was taken to consider only flow records that existed before any infrastructure was implemented.

The testing of the original constraint ranges was performed across the entire drainage system of the Lualaba and Sangha. Some scattered sub-basins of Oubangui, Kasai, Inkisi and Batéké plateaux were also used for the testing, making a total of 147 sub-basins out of 403 (Figure 3.6), but representing different climate and physiographic regions. A key issue in this modelling exercise was whether the quantified original constraint ranges could appropriately simulate hydrological uncertainty bounds at both headwater and downstream gauging stations. Another issue was whether the constraint refinements made at gauged headwater sub-basins could be applied to the ungauged upstream sub-basins. A third issue was associated with the propagation of uncertainty downstream. This relates to whether the upstream ungauged sub-basins should be independently simulated, or that the random sampling of behavioural parameters should be restricted by grouping upstream ungauged sub-basins to preserve the uncertainty downstream. The results presented have clearly shown that the use of the original

uncertainty ranges has captured most of the hydrological response aspects at the gauged headwater sub-basins, and only small changes were made to high and medium flow constraint indices, while substantial changes were made to the MMQ and Q90/MMQ (Section 6.2.4) constraints in some sub-basins. As expected, the simulated uncertainty at downstream sites is relatively lower when sub-basins are independently simulated, and higher when they are grouped.

Generally, modelling experiences in this thesis have shown three types of refinement actions that were made to the original constraints. The first refinement consists of shifting the full range of a constraint index either towards higher or lower values, depending on the degree to which the simulated uncertainty bounds depart from the observed flow. The second refinement consists of reducing the constraint range by decreasing the upper and increasing the lower limits. The third consists of increasing or decreasing either side of the constraint range. Adjustments made at gauged headwater sub-basins involved the last two refinement procedures, while the first was essentially applied to ungauged sub-basins. The spatial distribution of gauging stations in the Congo Basin is such that the majority are located in the downstream parts where they drain many upstream ungauged sub-basins. This is where the constraint adjustment process becomes a difficult task, especially where the simulated uncertainty bounds at the downstream gauged sub-basin substantially depart from the observed flow. The results have also shown that adjustments made to the downstream gauging station alone do not substantially improve the simulations, but if the constraints are adjusted at the upstream ungauged sub-basins in proportion to their contribution to downstream gauging stations, substantial improvements are observed at the downstream gauging stations. This was the only way of dealing with this issue of constraint refinement in a data-scarce area such as the Congo Basin. However, it is important to ensure that the direction in which the constraint refinement process is conducted, in the upstream ungauged sub-basins, would realistically represent hydrological responses. While this is still a difficult question to answer given the very limited knowledge about hydrological responses in ungauged sub-basins, the pattern of the simulated flow at the evaluation downstream gauging station remains the only means for directing the refinement process in the upstream ungauged sub-basins.

The assessment of parameter sampling approaches has shown that independent sampling of the saved parameter sets results in a lower uncertainty at downstream gauging stations, while the grouping of sub-basins contributes to increased uncertainty downstream, as would be expected

from simple statistical considerations. The key issue is whether the random parameter sampling should be independent or restricted, but this largely depends on the amount of the available observed information. Independent random sampling in the context of hydrological indices ranges is more realistic when downstream gauging stations are available for evaluating the reliability of model simulations. On the other hand, the grouping of sub-basins to restrict random sampling of parameters would be a good idea to preserve the uncertainty in situations where downstream gauging stations are not available. In such situations, independent sampling of parameters might under-estimate the realistic uncertainty.

The testing of the original constraint ranges has also shown their limitations in regions displaying unique hydrological responses. It is not surprising for the Congo Basin to face such situations because of its higher degree of climate and physiographic heterogeneity which is expected to translate into higher spatial variability of hydrological processes. Examples of such regions include some areas of very steep topography on the eastern borders of the basin (Rift valley) and the Batéké plateaux. The runoff ratio of these two regions were largely outside the computed original ranges (Figure 6.21a). Across the studied sub-basins, the re-calibrated hydrological constraint indices have shown two patterns based on whether the sub-basins are in the northern or southern hemisphere (Figure 6.22). Sub-basins located in the northern hemisphere exhibit low RR values that increase towards the equator whereas those in southern latitudes (considering sub-basins in the upstream of wetlands) have the highest RR values that further increase towards the equator. While the similar trend is maintained for the Q50/MMQ and Q90/MMQ constraints, the pattern is different for the Q10/MMQ constraints that show high values for northern sub-basins and low values for southern, but in both cases, the constraint indices decrease towards the equator. This understanding has shown the potential of establishing two predictive equations for each constraint index depending on whether sub-basins are in the north or south of the equator. This may contribute to the reduction of the uncertainty associated with MMQ and Q90/MMQ constraint indices compared to what was initially observed in the original constraint ranges.

The main conclusions regarding the testing of the original uncertainty ranges of hydrological indices are as follow:

- The use of the constraint indices to constrain the hydrological model to simulate behavioural hydrological responses has contributed to establishing realistic and reduced uncertainty ranges across the sub-basins compared to a previous study;

- Re-calibrated constraint indices ranges have the potential to include different sources of uncertainty and can be used for simulating the sub-basin's hydrological conditions including current water resources development and environmental change impacts assessment.

8.1.3 Application of the hydrodynamic models to establish wetland parameters

The lack of knowledge in channel-wetland exchanges can lead to increased uncertainty in basin-scale hydrological response. Many studies have demonstrated the importance of incorporating wetland modules or functions as part of the hydrological model structures. Among these, the PITMAN model has an explicit wetland function that accounts for channel-wetland exchanges. However, the application of this wetland sub-model across different parts of the Southern Africa region highlighted the need to explicitly estimate the wetland parameters rather than using a trial and error calibration approach, which will nearly always be difficult given the lack of both observed inflow and outflow data in the majority of wetland systems. This study implemented an integrated approach to link the monthly time step PITMAN and sub-daily time step LISFLOOD-FP models. Uncertain hydrological responses (from the main PITMAN model) were used to provide input boundary conditions for the 2D-hydrodynamic LISFLOOD-FP model. These hydrological boundary conditions were first disaggregated into daily using a disaggregation model which provides the likely patterns of daily flow discharges. Generally, the uncertainty in daily disaggregated flows may be related to both the quality of the simulated monthly flows and the daily rainfall used in the disaggregation process.

Five wetland systems of the upper Lualaba drainage system namely the Ankoro, Kamalondo, Kundelungu, Mweru and Tshiangalele were selected for analysis as the combined effect of these exert a considerable impact on the downstream flow regimes. The ungauged nature of these wetland systems implies that it is difficult to validate the hydrodynamic simulations, and the only validation method adopted in this study was through the use of the inundation extents derived from Landsat imagery. Simulation results, using both visual inspection and statistical measures, have generally shown reasonable results that were encouraging compared to other studies (e.g. Sayama et al., 2012). However, some of the uncertainty in the channel-wetland exchange processes is related to the lack of wetland bathymetry (Kamalondo and Mweru) and limited information used to validate the hydrodynamic models. The simulated wetland storage volumes, inundation extents, channel input inflows and outflows were used to understand the functioning of the different wetlands. This can be quantified through the use of both hysteresis

curves and indices. Dry hydrological years characterised by low peaks have lower hysteresis indices compared to wet years. Wetland systems with a low surface slope were more hysteretic compared to wetlands with high surface slope. Similarly, wetlands with a considerable storage volume below the channel water level were more hysteretic compared to those with only a small proportion. It was demonstrated that the degree of hysteresis in channel-wetland exchanges translates into the wetland attenuation power. The attenuation power of individual wetland systems is linked to the size of the wetland. Small wetlands, such as Ankoro has a lower attenuation power (low hysteresis), while a large wetland such as Mweru has a higher attenuation power (high hysteresis). Counterclockwise hysteresis was observed across all five wetland systems in inflow-storage and storage-outflow relationships, but the magnitude of these hysteresis indices varied across the wetland types and with flood magnitude. The highest degree of hysteresis was observed in Mweru wetland system and indicated a highly delayed response characterised by a slow-release due to the extent of the wetland and the time that the flow from the channel to the wetland takes to reach the most distant part of the wetland system. The lowest hysteresis was observed in Ankoro wetland and indicated a transient flow through the wetland where most of the inflow would return almost simultaneously to the channel.

The understanding of channel-wetland exchanges from LISFLOOD-FP simulations, after validation, provides a means of calibrating the wetland parameters of the wetland sub-model of PITMAN model. Inundated area, residual storage and storage volume-inundated area relationship parameters are directly derived from LISFLOOD-FP outputs. The spilling and return flow parameters are manually calibrated until the PITMAN model outputs correspond with the LISFLOOD-FP outputs. However, the analysis of these LISFLOOD-FP informed calibrated wetland parameters with wetland morphometric characteristics has shown that there is a potential to estimate some of these parameters using morphometric characteristics. One example is the scale parameter of the return flow function (AA), which shows a good relationship with the average wetland surface slope when the coefficient parameter (BB) of the same function is kept constant to a value of 1.25. The same parameter (AA) is a good indicator of the wetland emptying mechanism. A small AA indicates a wetland that slowly releases its flow, resulting in a highly delayed and attenuated hydrological response. This understanding would provide a means of deriving wetland parameters in areas where the hydrodynamic simulations are not available, although the number of wetlands used in this study is not statistically enough to develop conclusive relationships.

8.1.4 Application of constraints and wetland parameters to quantify downstream wetland impacts on flow regimes

The PITMAN hydrological model calibrated in different drainage systems of the Congo Basin reflects natural hydrological conditions. The model can be used for different impact assessment studies. Its application in the Lualaba drainage system, for assessing the impacts of wetlands on downstream hydrological regimes, has revealed the usefulness of incorporating wetland information within basin-scale hydrological modelling. All upstream wetlands in the Lualaba drainage system have different degrees of impacts on the downstream hydrological regime. These differences are caused by the size and location of individual wetland in the basin. If the local sub-basin is significantly larger with respect to the wetland system, the potential of the wetland to modify downstream flow regime is negligible. Similarly, if the wetland is farther from the basin outlet, its potential to modify downstream flow regime can be buffered. Experiences in modelling the upper Lualaba drainage system have shown that the Tshiangalele and Kundelungu wetland systems have a negligible impact on downstream flow regime at the regional scale. However, their potential to modify downstream flow regime is evident only at the local scale (Figures 7.7, 7.9 and Table 7.13). On the other hand, Kamalondo and Mweru wetland systems exert considerable impacts at both local and regional scales because they are large in extents. The inclusion of these wetlands in basin-scale modelling has improved the model performance and reduced the simulated hydrological uncertainty.

While the original constraint indices are still relevant in the region of the wetlands and further downstream of the Lualaba drainage system, there remains an unresolved uncertainty issue related to the under- and over-estimation of some aspects of the hydrological response at both Mulongo and Ankoro gauging stations. It is, however, difficult to attribute this uncertainty to Kamalondo wetland parameters alone because many of the incremental sub-basins contributing to wetland inflows are ungauged. The issue at Mulongo is the under simulation of low flow, while the high flows at the Ankoro gauging station are over-simulated (Figure 7.18). However, the pattern of the calibrated constraint indices in this region (Section 7.3.5.4) shows that the under simulation of low flow at Mulongo cannot be attributed to incremental sub-basins (between Bukama, Kapolowe and Mulongo gauging stations), because their Q90/MMQ constraint indices are even slightly above the original constraint ranges, but maintain a spatial consistency with sub-basins of other regions (Figure 6.21 and 7.19). Similarly, sub-basins located between Mulongo, Luvua and Ankoro gauging stations have high flow indices slightly

below the original constraint ranges and therefore they are unlikely to be responsible for the over simulation of high flow at the Ankoro gauging station. These facts highlight the need for a further understanding of the complex wetland system of Kamalondo.

8.2 Recommendations

Based on the outcomes of this study, the following recommendations are suggested:

8.2.1 Improving constraint ranges

- ❖ The main limitation for extending the predictive equations of the hydrological indices to ungauged sub-basins is related to the spatial representativeness of the observed streamflow gauging stations. The majority of the sub-basins used to develop the uncertainty ranges are found in region 1, even after the inclusion of the disaggregated gauging station data. While the developed uncertainty ranges of hydrological indices can be applied with high confidence in sub-basins representing the climate and physiographic properties of region 1 (upper Lualaba and northern Oubangui), less confidence can be ascribed to their application in the other regions where some aspects of the hydrological behaviour may not have been captured. To improve the original constraint ranges, it is necessary to explore other approaches to quantify hydrological indices of the ungauged headwater sub-basins of other physiographic regions (e.g. Regions 2, 3, 5 and 6) identified in this study. These approaches may include the use of multiple information sources of remote sensing products. For example, global maps of different discharge characteristics (<http://water.jrc.ec.europa.eu>) can be explored. However, in the absence of validation data, these estimates will remain very uncertain.

8.2.2 Testing of constraint ranges

- ❖ The approach used in this study for testing the constraint indices needs to be extended to other major parts of Kasai, Oubangui and Central Congo drainage systems.
- ❖ The approach needs to be assessed under current conditions. This implies the collection of water use information in sub-basins containing water resources development infrastructures as well as land use change information (e.g. deforestation). This supposes also that the modelling units be reduced at a spatial scale that can capture the effects of such development. Under the current conditions, afforestation parameters of

the PITMAN model can be included especially for the northern sub-basins (e.g. Sangha) where previous studies attributed high values of AFOR parameter to these sub-basins.

8.2.3 Improving daily disaggregated wetland inflows

- ❖ The quality of the disaggregated daily flow depends on the daily climatic data inputs and the simulated monthly flow. The study used the default API parameter values and ARC2 daily rainfall data. To improve the disaggregated daily estimates, daily discharge data that overlap the daily rainfall estimates (e.g CHIRPS) should be identified and used to obtain the likely ranges of the API parameter values within the Congo Basin.

8.2.4 Improving the understanding of channel-wetland exchanges

- ❖ There is a potential to derive some of the wetland sub-model parameters from wetland morphometric characteristics, but the number of wetlands used in this study is not sufficient to reach statistically conclusive results. It is therefore recommended to extend the implementation of the hydrodynamic modelling to other wetland systems such as those of the Cuvette Centrale and the Bangweulu in the upper Lualaba system.
- ❖ The LISFLOOD-FP model does not account for surface water-groundwater exchanges. The same is true for the wetland sub-model of the PITMAN model. Given that there may be wetlands in which this type of interaction is important, future investigations should look at the possibility to include these aspects in both models.

8.2.5 Short term fieldwork data collection and monitoring programme

- ❖ To improve the constraint indices ranges, short-term gauging programmes at selected sites can help to extend the amount of observed data at key locations.
- ❖ For wetlands that have apparent channelization connected to the river system, it is important to account for these channels as they have the potential to control the inundation and drainage processes. Drainage channels were overlooked in this study, especially in the Kamalondo wetland system, while some of the inundation channels were represented. Further information on channel widths and depths will help in calibrating the r and p parameters of the sub-grid model of the LISFLOOD-FP model.

This calls for a short-term fieldwork survey of river channel bathymetry, which can potentially be extended using remote sensing data.

- ❖ The ungauged nature of many wetland systems has made the validation of the hydrodynamic models difficult, and they were only partially validated using the inundation areas detected using Landsat imagery. Other sources of data such as remote sensing of water level altimetry, SAR images and wetland storage estimates may be used to improve the validation results. Moreover, there is a need for a short-term data collection and monitoring programme of complex wetland systems such as Kamalondo. Important tributaries that drain to this wetland need to be monitored by installing water level loggers and periodically collecting flow data and river bathymetry. This programme should lead to the development of rating curves of wetland input tributaries. This would partially solve the unresolved uncertainty issues at the Ankoro and Kamalondo gauging stations.

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APPENDICES

Appendix A:

Table A3.1. List of available gauging stations located in the central Congo Basin drainage system.

SN	Station Name	Longitude	Latitude	Drainage Area		Sub-basin Code	Period of records	Months	% of missing
				Km ²	% basin				
1	Boma	13.05	-5.86	3681853	99.88	C_CB401	1950-1959	120	0
2	Bwambe	15.65	-2.90	12295	0.33	C_CB169	1951-1994	509	19.25
3	Inkisi	15.07	-5.13	12824	0.35	C_CB138	1950-1959	120	22.5
4	Itimbiri	23.84	2.71	35056	0.95	C_CB185	1950-1959	120	0
5	Kinshasa	15.30	-4.30	3623147	98.29	C_CB367	1903-2006	1248	0
6	Kisangani	25.19	0.51	961648	26.09	C_CB234	1950-1959	120	0
7	Lomami	24.24	0.56	107037	2.90	C_CB11	1950-1959	120	0
8	Shari	30.16	1.60	4294	0.12	C_CB220	1950-1959	120	0

Table A3.2. List of available gauging stations located in the Kasai drainage system.

SN	Station Name	Long	Lat	Drainage Area		Sub-basin Code	Period of records	Months	% of missing
				Km ²	% basin				
1	Kananga-Luluabourg	22.31	-5.90	46336	1.26	K_CB259	1952-1970	228	0.87
2	Kutumuke	17.38	-3.18	744201	20.19	K_CB224	1950-1982	396	3.28
3	Kwango	17.37	-3.30	269694	7.32	K_CB52	1950-1959	120	0
4	Lediba	16.56	-3.06	887772	24.08	K_CB223	1950-1959	120	0
5	Port Franqui	20.58	-4.33	239805	6.51	K_CB264	1932-1982	612	2.12

Table A3.3. List of available gauging stations located in the Oubangui drainage system.

SN	Station Name	Longitude	Latitude	Drainage Area		Sub-basin Code	Period of records	Months	% of missing
				Km ²	% basin				
1	Bambari	20.67	5.78	29851	0.81	O_CB355	1952-1975	282	21.3
2	Bangassou	22.82	4.73	120252	3.26	O_CB232	1952-1994	504	75.9
3	Bangui	18.61	4.37	490124	13.30	O_CB369	1936-2005	840	0
4	Boali	18.03	4.91	4793	0.13	O_CB176	1949-1988	468	48.931624
5	Bria	22.00	6.56	60685	1.65	O_CB95	1954-1978	300	9.66
6	Kembe	21.92	4.61	77924	2.11	O_CB76	1954-1978	300	9.66
7	Loungoumba	22.69	4.70	23862	0.65	O_CB77	1966-1972	80	20
8	M'bata	18.30	3.66	30919	0.84	O_CB82	1951-1975	300	3.33
9	Rafai	23.94	5.01	52527	1.42	O_CB181	1952-1973	249	16.06
10	Sibut	19.08	5.73	2538	0.07	O_CB179	1951-1991	483	45.13

Table A3.4. List of available gauging stations located in the Lualaba drainage system.

SN	Station Name	Long	Lat	Drainage Area		Sub-basin Code	Period of records	Months	% of missing
				Km ²	% basin				
1	Ankoro	26.95	-6.75	426746	11.58	L_CB198	1951-1959	107	0
2	Bukama	25.86	-9.19	61385	1.67	L_CB207	1933-1959	324	11.11
3	Old Pontoon	31.07	-10.95	34745	0.94	L_CB18	1972-2004	396	20.7
4	Chandawayaya	31.70	-9.78	4666	0.13	L_CB200	1978-1981	36	2.7
5	Chembe Ferry	28.76	-11.97	115882	3.14	L_CB239	1957-1981	300	0
6	Chikakala	31.28	-11.49	1147	0.03	L_CB203	1970-2004	419	17.89
7	Chipili	29.09	-10.71	1321	0.04	L_CB261	1971-1981	132	0.75
8	Elila	25.89	-2.74	826304	22.42	L_CB394	1950-1959	120	0
9	Kapolowe	26.95	-11.04	8586	0.23	L_CB205	1933-1959	324	7.4
10	Kasongo	26.58	-4.53	759189	20.59	L_CB105	1950-1959	120	0
11	Kindu	25.93	-2.95	796878	21.62	L_CB365	1933-1959	324	0
12	Lowa	25.82	-1.41	923965	25.06	L_CB393	1950-1959	90	1.11
13	Luapula/Kasenga	28.62	-10.36	158867	4.31	L_CB206	1950-1959	121	0.82
14	Lukuga	28.81	-5.87	238520	6.47	L_CB36	1932-1959	322	74.53
15	Luvua	28.01	-7.34	243252	6.60	L_CB210	1950-1959	108	0
16	Kasama	30.96	-10.18	6366	0.17	L_CB230	1969-2006	444	2.36
17	Mbelegule	30.31	-5.08	123300	3.34	L_CB35	1976-1980	60	0
18	Mbesuma Pontoon	32.16	-10.00	16572	0.45	L_CB201	1974-2004	363	29.47
19	Mulongo	26.98	-7.84	156545	4.25	L_CB150	1950-1959	120	0
20	Nzilo	25.41	-10.43	17927	0.49	L_CB27	1921-1938	216	0
21	Ponthierville	25.45	-0.35	923965	25.06	L_CB393	1950-1959	120	0
22	Ruzizi	28.89	-2.49	7378	0.20	L_CB195	1950-1959	108	0
23	Shabunda	27.34	-2.69	10703	0.29	L_CB192	1952-1956	54	1.85
24	Shiwa Ngandu	31.60	-11.20	1008	0.03	L_CB202	1964-1992	336	10.41
25	Taragi	30.57	-4.04	8395	0.23	L_CB196	1971-1979	108	5.55
26	Yumbi	26.23	-1.24	42322	1.15	L_CB191	1952-1959	90	1.11

Table A3.5. List of available gauging stations located in the Sangha drainage system

SN	Station Name	Long	Lat	Drainage Area		Sub-basin Code	Period of records	Months	% of missing
				Km ²	% basin				
1	Alima Okoyo	15.08	-1.48	8022	0.22	S_CB166	1952-1975	286	3.84
2	Alina Tchekapita	16.17	-1.27	20643	0.56	S_CB167	1963-1975	156	1.28
3	Botouali	17.42	-0.48	29053	0.79	S_CB374	1949-1975	324	1.54
4	Carnot	15.86	4.94	18559	0.50	S_CB395	1954-1971	216	19.9
5	Epene	17.48	1.35	9831	0.27	S_CB240	1956-1980	300	24
6	Etoumbi	14.92	0.05	10492	0.28	S_CB236	1951-1970	240	16.6
7	Komo Olombo	15.87	-1.28	1866	0.05	S_CB134	1963-1975	154	2.59
8	Lenneque	15.93	-0.50	11159	0.30	S_CB243	1953-1970	216	15.74
9	Makoua	15.70	0.01	15290	0.41	S_CB228	1952-1971	237	8.43
10	N'gbala	14.89	2.02	38346	1.04	S_CB392	1956-1975	240	24.16
11	Nkeni-Gambona	15.87	-1.89	6118	0.17	S_CB168	1952-1975	288	1.38
12	Ouessou	16.07	1.62	158284	4.29	S_CB55	1959-1983	300	0
13	Salo	16.12	3.20	71424	1.94	S_CB61	1953-1994	492	34.95
14	Yengo	15.45	0.36	11686	0.32	S_CB158	1961-1980	237	21.51

Table A3.6. River channel bathymetry in the upstream of the Ankoro gauging station

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Upstream Ankoro	13-Apr-49	227	6.7	4.83	0.425
	29-Jan-52	227	7.5	5.6	0.514
	22-Aug-52	227	9	6.44	0.483
	27-Oct-52	222	6.3	4.53	0.252
	18-Feb-53	225	7.2	4.55	0.28
	13-Apr-53	228	6.8	5.42	0.3
	22-May-53	211	6.8	5.27	0.41
	20-Jul-53	222	5.8	4.05	0.24
	05-Sep-53	205	5.35	3.75	0.27
	25-Nov-53	206	5.15	3.54	0.29

Table A3.7. River channel bathymetry in the upstream of the Mulongo gauging station

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Mulongo	11-Apr-49	190	6.7	3.77	0.637
	02-Feb-52	190	7.5	5.05	0.694
	20-Aug-52	190	9	4.58	0.64
	28-Oct-52	180	6.3	3.15	0.53
	21-Jan-53	180	7.2	3.48	0.6
	26-Mar-53	187	6.8	3.63	0.62
	26-May-53	185	6.8	3.91	0.56
	16-Jul-53	175	5.8	3.02	0.54
	23-Nov-53	174	5.35	2.62	0.5

Table A3.8. River channel bathymetry in the upstream of the Bukama gauging station

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Bukama	02-Apr-49	211	3.45	3.11	0.586
	17-Feb-52	211	5.7	4.59	0.727
	09-Aug-52	207	1.8	1.67	0.483
	30-Oct-52	203	1.5	1.27	0.445
	15-Jan-53	204	2.7	2.42	0.6
	24-Mar-53	211	3.3	2.78	0.57
	09-Mar-54	210	3.2	2.83	0.578

Table A3.9. River channel bathymetry in the upstream of the Lovoi outlet

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Lovoi	09-Feb-52	74	2.9	2.4	0.756
	18-Aug-52	74	1.3	1.03	0.404
	19-Jan-53	76	1.8	1.59	0.62

Table A3.10. River channel bathymetry in the upstream of the Lufira outlet

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Lufira (outlet)	08-Apr-49	110	3	2.46	0.525
	11-Feb-52	96	3.9	3.33	0.618
	29-May-53	130	2.3	1.8	0.48
	30-Mar-54	134	3.5	3.26	0.61

Table A3.11. River channel bathymetry in the upstream of the Kasenga gauging station

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Kasenga	25-Feb-52	410	9.7		
	31-Jul-52	406	6.8		
	16-Dec-52	406	4.5		
	14-Jan-53	406	4.5		
	16-Mar-53	406	6		
	20-Sep-53	406	6.6		

Table A3.12. River channel bathymetry in the upstream of the Pweto/Mweru outlet

Station name	Date	Width (m)	Depth (m)	Hydraulic radius (m)	Velocity (m/s)
Pweto/Mweru outlet	01-Mar-52	225	9.5		
	23-Jul-52	240	10.3		
	10-Nov-52	230	7		
	09-Dec-52	230	6.8		
	26-Feb-54	155	10		
	26-May-54	174	8		

Table A5.13. Extended flow record periods of gauging stations used for the derivation of hydrological indices in the Congo River Basin

Gauging station	Sub-basin code	Original record period	Extended record period	Source gauging station
Bambari	O_CB355	1952 - 1975	1949 - 1988	O_CB176
Boali*	O_CB176	1949-1988	Not available	Not available
Bria [@]	O_CB95	1954 - 1978	1949 - 1988	O_CB176
Carnot	S_CB395	1954 - 1971	1949 - 1988	O_CB176
Chikakala*	L_CB203	1970-2004	Not available	Not available
Chipili	L_CB261	1971 -1981	1970 - 2004	L_CB203
Etoumbi	S_CB236	1951 - 1970	1951 - 1980	S_CB158
Inkisi [#]	C_CB138	1950-1959	Not extended	Not available
Itimbiri	C_CB185	1950-1959	1949 - 1988	O_CB176
Kapolowe	L_CB205	1933 - 1959	1921 - 1959	L_CB27
Komo Olombo	S_CB134	1963 - 1975	1951 - 1980	S_CB158
Kouyou Linnegue	S_CB243	1953 - 1970	1951 - 1980	S_CB158
Rafai [@]	O_CB181	1952 - 1973	1949 - 1988	O_CB176
Sibut	O_CB179	1951 - 1991	1949 - 1988	O_CB176
Taragi	L_CB196	1971 - 1979	1970 - 2004	L_CB203
Yengo	S_CB158	1961 - 1980	1951 - 1980	S_CB236

* Gauging stations having a long period of records with no need of extension.

gauging station with record period not extended because of lack of donor gauge in its vicinity.

@ New gauging stations added for the spatial disaggregation procedure.

Appendix B:

Table B6.1. Behavioural PITMAN model parameter ranges across gauged Oubangui Sub-basins (Mean, distribution type, Minimum and Maximum values are in first, second, third and fourth row, respectively).

Sub-basins	RDF	PII	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
O_CB76	0.6	1.5	1	1479.32	50	0.18	900	1800	4	15	15	0.6	0.25	0	3.5	0.43	40	0.003	0.01	15	1.86
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.6	1479.32	40	0.1	800	1200	3	30	5	0	0.15	0	3	0.2	30	0.001	0.001	10	0.6
	1.2	4	1	1686	100	0.5	1100	1800	4	50	15	0.6	0.25	0.6	4	0.7	70	0.03	0.018	50	2
O_CB95	0.6	1.5	1	1608.73	75	0.18	900	1800	4	15	15	0.6	0.25	0	3.5	0.43	40	0.005	0.01	15	1.8
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.3	1608.73	50	0.15	800	1400	3	10	5	0.3	0.15	0	3	0.2	20	0.001	0.001	10	0.6
	1.2	4	1	1769	120	0.4	1100	1800	4	35	20	0.7	0.8	0.6	4	0.7	50	0.03	0.018	50	2
O_CB176	0.8	1.5	1	1401.62	50	0.18	900	1800	4	15	15	0.6	0.25	0	3.5	0.43	40	0.003	0.01	25	2
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	3	0.4	1401.62	35	0.1	600	1500	3	22	12	0.15	0.15	0	3	0.2	40	0.001	0.001	10	0.6
	1.2	5	0.8	1597.14	70	0.5	900	1800	4	45	25	0.6	0.25	0	4	0.7	75	0.03	0.018	50	2
O_CB179	0.8	2.796	0.607	1498.99	96.823	0.23	690.324	1735.92	4.13	17.683	5.489	0.436	0.25	0	3.39	0.43	64.686	0.003	0.01	25	1.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.504	1498.99	42	0.161	554	1502	3.5	7	3	0.206	0.25	0	3.008	0.43	40.527	0.003	0.01	5	0.5
	0.8	4	0.759	1783	99	0.349	699.371	1798.99	4.5	17	8	0.698	0.25	0	4	0.43	69.934	0.003	0.01	25	1.5
O_CB181	0.6	1.5	1	1524.74	50	0.18	900	1800	4	15	15	0.6	0.25	0	3.5	0.43	40	0.003	0.01	25	1.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.5	0.4	1524.74	40	0.1	400	950	2.5	12	5	0	0.15	0	3	0.2	50	0.001	0.001	10	0.6
	1.2	3	1	1829	100	0.5	800	1400	4.5	35	12	0.5	0.25	0	4	0.7	70	0.03	0.018	50	2
O_CB355	0.6	1.75	1	1540.41	90	0.25	650	1800	3.75	28	10	0.325	0.25	0	3.5	0.43	57	0.005	0.01	25	1.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.7	1540.41	60	0.2	500	1600	3.5	15	5	0.15	0.15	0	3	0.2	40	0.001	0.001	10	0.6
	1.2	3	1	1694	120	0.5	800	1850	4.5	40	15	0.5	0.25	0	4	0.7	74	0.03	0.018	50	2

Table B6.2. Behavioural PITMAN model parameter ranges across gauged Sangha Sub-basins (Mean, distribution type, Minimum and Maximum values are in first, second, third and fourth row, respectively).

Sub-basins	RDF	PII	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
S_CB55	0.8	2.2	1	1195.6	100	0.5	900	1200	4	20	25	0.2	0.25	0	3.5	0.44	42	0.008	0.008	25	2.5
				3	3	3	3	3	3	3	3	3	3			3		3			3
	0.6	3	0.8	1195.6	40	0.15	500	900	3	14	0	0	0.25	0	3	0.2	40	0.001	0.001	5	2
	0.8	5	1	1500	120	0.4	1000	1300	4	35	5	0.3	1	0.6	4	0.5	75	0.1	0.01	30	2.8
S_CB61	0.8	2.2	1	1281.9	100	0.5	900	1200	4	20	25	0.2	0.25	0	3.5	0.5	20	0.005	0.01	20	1.5
				3	3	3	3	3	3	3	3	3	3			3		3			
	0.6	3	0.6	1281.9	25	0.15	700	900	3	18	5	0	0.25	0	2.5	0.2	15	0.001	0.001	5	0.2
	0.8	5	0.9	1506	80	0.6	1000	1300	4	45	17	0.4	1	0.3	4	0.5	40	0.1	0.01	30	2.8
S_CB395	0.8	2.2	1	1360.52	100	0.5	900	1200	4	20	25	0.2	0.25	0	3.5	0.5	20	0.005	0.01	25	2
				3	3	3	3	3	3	3	3	3	3			3		3			
	0.6	1.2	0.7	1360.52	25	0.15	800	1200	3.5	30	8	0	0.25	0	2.5	0.2	20	0.001	0.001	5	0.2
	0.8	3	1	1496	100	0.6	1000	1500	4.5	55	18	0.6	1	0	4	0.5	40	0.1	0.01	30	2.8

Table B6.3. Behavioural PITMAN model parameter ranges across Batéké plateaux Sub-basins (Mean, distribution type, Minimum and Maximum values are in first, second, third and fourth row, respectively).

Sub-basins	RDF	PI1	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
C_CB169	0.75	1.2	1	1249.46	25	0.5	900	2400	1.8	62	248	0.9	0.25	0	2	0.45	5	0.04	0.001	10	0.2
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	1.2	0.5	1186	0	0.35	750	2300	1.8	70	220	0.7	0	0	1.8	0	5	0	0	0	0
	1.2	1.3	0.85	1311	80	0.65	1000	2700	2.5	120	350	1	0	0	2.5	0	10	0	0	0	0.5
C_CB328	0.75	1.2	0.3	1217.1	25	0.5	900	2400	1.8	60	280	0.9	0	0	2	0.45	5	0.04	0.002	10	0.2
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	1.25	0.6	1156	25	0.35	700	2300	1.8	50	220	0.8	0	0	2	0	5	0.003	0.004	0	0
	1.2	3	1	1257	50	0.65	1000	2600	2.5	100	290	1	0	0	2.5	0	20	0.1	0.1	0	0.5
C_CB329	0.75	1.2	0.3	1260.21	25	0.5	900	2400	1.8	62	255	0.9	0	0	2	0.45	5	0.04	0.001	10	0.2
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	1.25	0.3	1197	20	0.35	700	2300	1.8	55	220	0.8	0	0	1.8	0	5	0.003	0.004	0	0
	1.2	3	1	1323	50	0.65	1200	2600	2.5	100	320	1	0	0	2.5	0	20	0.1	0.1	0	0.5
C_CB330	0.75	1.2	0.3	1247.87	25	0.5	900	2400	1.8	62	248	0.9	0.25	0	2	0.45	5	0.04	0.001	10	0.2
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	1.25	0.5	1185	20	0.4	600	2300	1.8	55	200	0.8	0	0	1.8	0	3	0.003	0.004	0	0
	1.2	3	1	1310	55	0.6	900	2600	2.5	100	290	1	0	0	2.5	0	15	0.1	0.1	0	0.5

Table B6.4. Behavioural PITMAN model parameter ranges across gauged Lualaba Sub-basins (Mean, distribution type, Minimum and Maximum values are in first, second, third and fourth row, respectively).

Sub-basins	RDF	PI1	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
L_CB18	0.8	2.758	0.655	1604.698	87.675	0.484	846.365	1210.296	4.379	42.3	18.96	0.016	0.25	0	4.01	0.45	33.945	0.01	0.003	30	0.5
		3	3	3	3	3	3	3	3	3	3	3			3						
	0.6	2	0.3	1591.46	50	0.25	600	1200	3.5	30.0	10.00	0	0.15	0	3.5	0	25	0.001	0.001	5	0.85
	0.8	4	0.8	1700	100	0.65	900	1500	4.5	45.0	20.00	0.4	0.25	0	4.5	0	50	0.01	0.01	30	2.5
L_CB27	0.6	2.71	1	1702.12	144	0.32	856	776	4.51	33.3	34.21	0.51	0.25	0	4.46	0.451	20.87	0.008	0.015	25	0.597
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.9	1477.37	100	0.15	700	600	4	22.0	15.00	0.15	0	0	3.5	0	10	0.001	0.001	5	0.2
	0.8	4	1	1713	150	0.5	900	800	5	35.0	35.00	0.55	0.25	0.06	4.5	0	30	0.1	0.01	30	0.8
L_CB35	0.692	2.1	0.65	1618.74	130	0.375	750	700	3.75	35.0	6.50	0.325	0.25	0	3.25	0.45	27.5	0.008	0.003	23.841	1.781
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.6	1618.74	100	0.15	600	550	3	25.0	3.00	0.15	0.15	0	2.5	0	20	0.001	0	5	1
	1.2	3	1	1860	160	0.6	900	1000	4.5	45.0	15.00	0.5	0.25	0.6	4	0	35	0.1	0	30	2.5
L_CB36	0.6	2.1	0.65	1478.28	175	0.4	1500	1150	3.75	45.0	7.50	0.3	0.25	0	3.75	0.5	30	0.003	0.003	29.967	1.266
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.3	1478.28	150	0.2	800	600	3.5	15.0	5.00	0.1	0	0	3	0	20	0.001	0	5	1.2
	0.8	3	1	1578	200	0.6	1600	1000	4	30.0	10.00	0.5	0	0.6	4.5	0	40	0.1	0	30	2.8
L_CB105	0.609	2.182	1	1431.47	147.864	0.426	1072.13	721.134	4.251	32.9	15.51	0.538	0.25	0	3.629	0.45	27.403	0.008	0.009	16.308	0.538
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.9	1431.47	90	0.15	900	600	4	15.0	8.00	0.15	0.15	0	3.5	0.2	40	0.001	0.001	5	0.5
	0.8	4	1	1639	150	0.6	1200	950	4.5	30.0	18.00	0.5	0.25	0.6	4.5	0.5	75	0.1	0.01	30	2
L_CB150	0.6	3.904	0.873	1653.61	123.546	0.501	940.578	862.422	4.291	21.1	40.09	0.29	0.25	0.56	3.945	0.451	22.407	0.008	0.015	10	0.625
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	3	0.5	1647.1	120	0.25	850	700	3.5	15.0	30.00	0	0	0	3	0	5	0.001	0.001	5	0.2
	0.8	5	1	1800	150	0.6	1400	1200	4.5	35.0	55.00	0.4	0.25	0.6	4	0	30	0.1	0.01	30	1.5
L_CB191	0.6	1.2	0.86	1313.55	7.831	0.141	333.917	1160.97	1.886	113.4	161.88	0.595	0.25	0	1.923	0.4	40	0.005	0.1	25	0.2
		3	3	3	3	3	3	3	3	3	3	3			3						
	0.6	1.2	0.3	1234	5	0.125	200	800	1.8	120.0	160.00	0.5	0.15	0	1.8	0.2	30	0.001	0.001	5	0.2
	1.2	2	1	1358	20	0.4	450	1200	2.5	180.0	220.00	1	0.25	0.8	2.5	0.5	45	0.1	0.01	30	2
L_CB192	0.8	1.2	1	1334.8	25	0.303	300	750	2	70.0	110.00	0.85	0.25	0	2	0.45	5	0.008	0.004	10.927	0.2
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.3	1334.8	0	0.15	150	400	1.8	30.0	30.00	0.1	0.15	0	1.8	0.2	5	0.001	0.001	5	0.2
	1.2	2	1	1430	80	0.4	400	800	2.5	80.0	60.00	1	0.25	0	2.5	0.5	25	0.1	0.01	30	2
L_CB196	0.6	2.1	1	1486.06	80	0.5	575	675	3.5	27.5	27.50	0.8	0.25	0	3.5	0.45	52.5	0.005	0.003	25	2
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.3	1486.06	60	0.4	600	700	3	10.0	27.00	0.25	0.15	0	3	0	40	0.001	0	0	1.2
	0.8	4	0.7	1600.49	100	0.6	800	900	4	25.0	40.00	0.6	0.25	0.6	4	0	65	0.1	0	0	2.8

Table B6.4. (continue)

Sub-basins	RDF	PI1	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
L_CB200	0.8	2.36	0.788	1565.66	41.713	0.502	1262.16	1023.81	3.051	54.9	36.38	0.554	0.25	0	3.866	0.45	33.733	0.01	0.006	25	0.5
		3	3		3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.5	1561.76	30	0.25	1000	900	3	45.0	30.00	0.3	0.15	0	3	0.2	20	0.001	0	5	0.2
	0.8	2.5	0.8	1600	80	0.65	1300	1100	4	60.0	45.00	0.6	0.25	0	4	0.5	60	0.01	0.01	30	1.2
L_CB201	0.6	3.706	0.845	1778.283	146.849	0.454	648.741	1103.354	4.206	17.3	7.13	0.016	0.25	0	4.033	0.45	6.337	0.009	0.006	10	0.984
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	3	0.3	1632.23	70	0.25	600	900	3	8.0	0.50	0	0.15	0	3.5	0.2	5	0.001	0	10	0.5
	0.8	4	1	1800	150	0.5	900	1150	4.5	20.0	10.00	0.25	0.25	0	4.5	0.5	15	0.01	0.01	30	1.2
L_CB202	0.8	3.258	0.951	1597.2	56.297	0.58	979.839	1058.76	3.645	63.8	47.78	0.557	0.25	0	3.838	0.45	7.317	0.01	0.004	10	0.379
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.5	1505.84	35	0.25	700	1000	3.5	50.0	45.00	0.125	0.15	0	3.5	0.2	5	0.001	0.001	10	0.2
	1.2	4	1	1600	60	0.65	1000	1300	4.5	65.0	60.00	0.6	0.25	0	4.5	0.5	50	0.01	0.01	30	1.2
L_CB203	0.61	4.62	0.994	1614.54	44.512	0.61	903.23	1008.09	3.626	67.2	5.93	0.204	0.25	0	3.214	0.45	38.663	0.01	0.004	10	1.189
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	3	0.9	1516.44	40	0.25	700	900	3.5	55.0	2.00	0	0.15	0	3	0.2	5	0.001	0.001	10	0.5
	1.2	5	1	1615	80	0.65	1000	1100	4.5	70.0	9.00	0.3	0.25	0	4.5	0.5	50	0.01	0.01	30	1.2
L_CB205	0.75	4.66	0.61	1550	144.249	0.426	866.201	943.113	4.02	38.2	39.12	0.118	0.25	0	3.729	0.451	11.684	0.008	0.015	25	0.994
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	3	0.45	1455.49	100	0.35	600	850	4	20.0	25.00	0	0	0	3	0	10	0.001	0.001	5	0.5
	0.8	5	0.7	1700	150	0.7	900	1000	5	40.0	40.00	0.4	0.25	0.06	4	0	30	0.1	0.01	30	1.2
L_CB206	0.6	3.108	0.77	1577.609	85.895	0.342	961.364	1002.957	4.17	17.3	2.82	0.545	0.25	0.423	3.881	0.45	21.843	0.007	0.005	6.283	1
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.7	2	0.5	1512.96	70	0.15	700	950	3.5	8.0	2.00	0.15	0	0	3	0	10	0.001	0.001	5	0.5
	1.2	4	0.8	1671	130	0.5	1000	1200	4.5	20.0	10.00	0.6	0.25	0.6	4	0	50	0.01	0.01	30	2
L_CB207	0.65	2.14	0.93	1815.69	143.99	0.384	677.526	730.699	4.243	29.3	23.76	0.274	0.25	0	3.773	0.45	25.293	0.016	0.004	14.995	1.361
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.9	1555.6	140	0.25	600	500	3.5	20.0	15.00	0	0.15	0	3.5	0.2	8	0.001	0.001	5	0.5
	0.8	4	1	1840	180	0.5	900	800	4.5	37.0	30.00	0.5	0.25	0.6	4.5	0.5	30	0.1	0.01	15	1.5
L_CB210	0.6	3.203	0.991	1576.468	137.212	0.207	889.007	1189.962	3.681	12.3	5.40	0.389	0.25	0.312	3.897	0.45	19.253	0.002	0.007	14.172	0.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	3	0.8	1556.26	80	0.15	600	950	3	8.0	4.00	0.1	0	0	3.5	0	5	0.001	0.001	5	0.2
	0.8	5	1	1700	150	0.5	900	1200	4	15.0	20.00	0.5	0.25	0.6	4	0	30	0.01	0.01	30	2.5
L_CB230	0.8	1.541	0.828	1631.075	119.281	0.254	1155.229	1359.127	3.129	49.2	44.31	0.492	0.25	0	3.144	0.45	37.5	0.008	0.004	30	0.5
		3	3	3	3	3	3	3	3	3	3	3			3						
	0.6	1.5	0.3	1561.69	95	0.25	950	1150	3	35.0	42.00	0.35	0.15	0	3	0	25	0.001	0.001	5	0.2
	0.8	3	0.9	1660	140	0.65	1200	1400	4	50.0	60.00	0.7	0.25	0	4	0	50	0.01	0.01	30	1.2
C_CB234	0.6	1.25	1	1292.65	106.789	0.303	661.734	995.401	4.591	22.0	28.78	0.519	0.25	0	3.829	0.45	10.758	0.008	0.004	10.927	0.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.8	1.2	0.7	1292.65	30	0.15	400	500	3	10.0	10.00	0.5	0.15	0	3	0.2	10	0.001	0.001	5	0.2
	1.2	2	1	1392	80	0.6	800	900	4	35.0	40.00	1	0.25	0	4	0.5	45	0.1	0.01	30	2
L_CB239	0.6	3.093	0.811	1774.52	76.955	0.624	869.672	1395.88	4.094	24.0	5.94	0.242	0.25	0	4.494	0.45	39.63	0.009	0.004	29.835	0.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	3	0.8	1534.35	70	0.25	600	1200	3.5	12.0	2.00	0	0.15	0	3.5	0	25	0.001	0.001	5	0.5
	1.2	4	1	1800	140	0.65	900	1500	4.5	25.0	10.00	0.3	0.25	0.6	4.5	0	48	0.01	0.01	30	1.2
L_CB261	0.646	2.947	1	1556.7	56.436	0.313	802.802	1071.05	4.043	41.8	4.70	0.175	0.25	0	3.836	0.45	8.319	0.008	0.006	5	1.079
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	1.5	0.8	1497.08	30	0.25	680	900	3	30.0	0.50	0.12	0	0	3.5	0	5	0.001	0.001	5	0.2
	0.8	3	1	1576.56	90	0.5	900	1100	4.5	48.0	5.00	0.55	0.25	0	4	0	10	0.009	0.01	30	1.2
L_CB365	0.8	1.879	1	1332.02	99.32	0.173	863.999	924.078	3.87	31.4	19.64	0.957	0.25	0	4.195	0.45	21.995	0.008	0.006	10	1.951
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.6	1332.02	60	0.15	550	600	3	25.0	9.00	0.15	0.15	0	3.5	0.2	40	0.001	0.001	5	0.2
	1.2	4	1	1551	110	0.4	750	800	4	40.0	18.00	1	0.7	0.6	4.5	0.5	75	0.1	0.01	15	2
L_CB366	0.8	1.3	1	1271.25	106.789	0.303	661.734	995.401	4.591	22.0	28.78	0.519	0.25	0	3.829	0.45	10.758	0.008	0.004	10.09	0.5
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.3	1271.25	0	0.15	200	500	3	5.0	30.00	0.6	0.15	0	2.5	0.2	5	0.001	0.001	5	0.2
	1.2	2	1	1371	50	0.4	400	800	4	30.0	60.00	1	0.25	0.6	4	0.5	25	0.1	0.01	30	2
L_CB393	0.8	1.2	1	1288.38	40	0.303	350	750	2	75.0	90.00	0.85	0.25	0	3.829	0.45	20	0.05	0.002	27	0.2
		3	3	3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.3	1288.38	0	0.15	200	500	3	15.0	60.00	0.6	0.15	0	1.8	0.2	5	0.001	0.001	5	0.2
	1.2	2	1	1388	30	0.45	500	800	4	45.0	80.00	1	0.25	0.6	3	0.5	25	0.1	0.01	30	2
L_CB394	0.647	2.402	1	1325.17	151.701	0.306	800	950	4.2	39.9	22.00	0.126	0.25	0	3.481	0.45	16.744	0.022	0.002	8.117	1.869
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.8	1325.17	60	0.1	500	700	3	20.0	5.00	0.15	0.25	0	3	0.2	35	0.001	0.001	5	0.2
	1.2	4	1	1537	150	0.6	950	1050	4	45.0	30.00	0.7	1	0.6	4	0.5	70	0.1	0.01	30	2

Table B6.5. Behavioural PITMAN model parameter ranges across the upper Kasai Sub-basins (Mean, distribution type, Minimum and Maximum values are in first, second, third and fourth row, respectively).

Sub-basins	RDF	PI1	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
K_CB106	0.6	2	1	1547.1	64.091	0.381	697.181	1146.42	2.958	41.544	11.527	0.404	0.25	0	3.408	0.45	25.263	0.05	0.004	15	1.5
		3		3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.7	1547.1	40	0.2	600	900	3	25	10	0.1	0.15	0	2.5	0.2	25	0.001	0.001	10	0.2
	0.8	4	1	1856	70	0.5	1000	1250	4	48	35	0.6	0.25	0	3.5	0.5	50	0.1	0.01	30	2
K_CB141	0.6	2	1	1453.74	69.406	0.292	728.43	1200	3.553	30.127	20.389	0.364	0.25	0	3.284	0.45	32.339	0.05	0.004	15	1
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.7	1453.74	45	0.25	650	900	3	30	10	0.25	0.15	0	3	0.2	30	0.001	0.001	10	1
	0.8	4	1	1635	70	0.5	900	1250	4	50	30	0.6	0.25	0	4	0.5	50	0.1	0.01	30	2.5
K_CB155	0.6	2	1	1537.96	48.204	0.386	827.875	1007.09	3.401	32.924	14.414	0.402	0.25	0	3.185	0.45	23.727	0.05	0.004	15	1
		3		3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.7	1537.96	40	0.2	600	900	3	20	10	0.25	0.15	0	2.5	0.2	20	0.001	0.001	10	0.2
	0.8	4	1	1730	70	0.5	900	1200	4	45	30	0.6	0.25	0	3.5	0.5	50	0.1	0.01	30	2
K_CB259	0.6	2	1	1358.74	57.305	0.418	731.727	1034.54	3.852	49.765	21.881	0.316	0.25	0	3.983	0.45	30.021	0.05	0.004	15	0.75
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.8	1358.74	45	0.25	650	750	3	40	8	0.25	0.15	0	3	0.2	30	0.001	0.001	10	0.2
	0.8	4	1	1495	70	0.5	900	1100	4	60	28	0.6	0.25	0.6	4	0.5	50	0.1	0.01	30	2

Table B6.6. Behavioural PITMAN model parameter ranges across the Inkisi Sub-basins (Mean, distribution type, Minimum and Maximum values are in first, second, third and fourth row, respectively).

Sub-basins	RDF	PI1	SER	PEVAP	ZMIN	ZAV	ZMAX	ST	POW	FT	GW	R	TL	CL	GPOW	DDENS	T	S	RGWS	GWL	RSF
C_CB07	1.2	2	1	1271	30	0.6	520	650	4	40	70	0.4	0.25	0	3.7	0.45	30	0.05	0.05	25	1.13
		3		3	3	3	3	3	3	3	3	3			3		3				
	0.6	1.2	0.3	1271	15	0.25	900	700	3	60	50	0.2	0	0	3	0	40	0.003	0.004	0	0.4
	1.2	3	1	1371	60	0.6	1300	1050	4	90	70	0.6	0	0	4.5	0	70	0.1	0.1	0	2
C_CB138	1.2	2	1	1285.73	31	0.6	590	680	3.9	40	60	0.4	0.25	0	5	0.45	30	0.05	0.03	25	1.13
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	1.2	0.3	1285.73	15	0.15	1000	650	3	60	50	0.15	0	0	3	0	30	0.003	0.004	0	0.5
	1.2	3	1	1385	60	0.6	1300	1050	4.5	90	70	0.6	0	0	4.5	0	70	0.1	0.1	0	2
C_CB321	1.2	2	1	1292.53	25	0.6	500	600	4	40	70	0.4	0	0	5	0.45	30	0.05	0.05	25	1.13
		3		3	3	3	3	3	3	3	3	3			3		3				
	0.6	2	0.1	1292.53	15	0	1000	700	3	65	50	0.25	0	0	3	0	20	0.003	0.004	0	0.4
	1.2	3.5	1	1421	60	0	1300	1050	4	80	70	0.65	0	0	4.5	0	50	0.1	0.1	0	2
K_CB259	0.6	2	1	1358.74	57.305	0.418	731.727	1034.54	3.852	49.765	21.881	0.316	0.25	0	3.983	0.45	30.021	0.05	0.004	15	0.75
		3	3	3	3	3	3	3	3	3	3	3			3		3				3
	0.6	2	0.8	1358.74	45	0.25	650	750	3	40	8	0.25	0.15	0	3	0.2	30	0.001	0.001	10	0.2
	0.8	4	1	1495	70	0.5	900	1100	4	60	28	0.6	0.25	0.6	4	0.5	50	0.1	0.01	30	2

Table B6.7. Model performance statistics across drainage systems with original and revised constraints.

Sub-basin	NE				NE (ln)				%Bias				%Bias(ln)			
	Original		Refined		Original		Refined		Original		Refined		Original		Refined	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
L_CB196	-0.12	0.65	0.31	0.71	-0.18	0.74	0.51	0.83	-27.12	21.14	-30.79	13.01	-31.13	24.12	-33.10	19.08
L_CB203	-0.43	0.69	0.07	0.69	0.52	0.60	0.52	0.60	-9.97	29.99	-26.94	15.56	-29.96	9.99	-27.96	26.55
L_CB205	-0.09	0.69	-0.04	0.71	-0.12	0.76	0.58	0.79	-11.98	16.00	-1.98	20.08	-14.98	23.00	-10.98	20.79
L_CB261	-0.57	0.64	-2.52	0.46	-0.15	0.71	0.67	0.78	-15.57	39.98	3.89	44.45	-39.91	45.12	-20.13	40.44
L_CB27	-2.38	0.74	-0.40	0.78	-0.66	0.72	0.65	0.82	-23.58	41.16	2.92	10.00	-44.30	17.67	-7.14	9.99
L_CB207	-1.00	0.50	-0.33	0.67	0.00	0.69	0.66	0.79	-17.01	30.36	-3.98	14.51	-34.41	6.53	-8.73	13.02
L_CB200	-0.43	0.44	-0.18	0.68	-2.70	0.17	0.67	0.85	-49.01	-15.98	-5.56	10.00	-66.63	-36.24	-9.99	9.95
L_CB201	-1.73	0.47	-1.60	0.52	0.28	0.74	0.40	0.76	-26.08	51.04	-27.20	46.20	-23.51	74.30	-22.09	52.72
L_CB202	-0.34	0.39	-0.32	0.48	-1.49	0.56	0.08	0.62	-53.70	-11.36	-30.73	12.99	-59.16	-7.63	-32.14	21.12
L_CB230	0.21	0.67	0.13	0.69	0.01	0.72	0.44	0.77	-27.00	6.83	-17.21	22.40	-33.18	9.17	-21.62	28.09
L_CB18	-0.50	0.55	0.21	0.58	0.09	0.63	0.33	0.68	-22.10	34.59	-37.44	4.58	-17.23	55.27	-34.75	13.00
L_CB191	0.03	0.26	0.22	0.65	0.13	0.32	0.19	0.66	-11.14	5.29	-6.78	3.75	-10.79	3.99	-4.44	5.47
O_CB176	0.09	0.68	0.36	0.74	0.42	0.71	0.55	0.74	-21.46	16.80	-30.82	16.03	-21.01	16.38	-28.95	19.44
O_CB355	-1.37	0.53	-0.45	0.68	0.31	0.77	0.43	0.79	-22.29	49.50	-25.81	23.46	-29.89	40.52	-31.02	25.29
O_CB95	-1.99	0.61	-2.34	0.52	0.40	0.82	0.32	0.81	-18.79	53.81	-20.20	70.38	-33.03	36.06	-36.52	48.28
O_CB76	-0.71	0.66	-0.37	0.72	0.72	0.87	0.48	0.87	-10.48	39.51	-13.80	49.73	-17.16	33.69	-17.99	51.08
O_CB181	0.05	0.64	-0.11	0.62	0.56	0.82	0.56	0.83	-18.57	36.66	-24.42	41.40	-13.51	50.20	-32.95	39.35
S_CB395	0.35	0.71	0.32	0.70	0.62	0.71	0.61	0.71	-11.27	16.34	-12.37	18.57	-13.68	20.61	-15.40	22.06
S_CB61	0.09	0.78	0.17	0.77	0.59	0.81	0.66	0.82	1.68	30.78	-12.26	22.57	1.06	30.47	-14.71	23.26
S_CB55	-0.27	0.62	0.00	0.86	0.46	0.78	0.60	0.87	14.49	37.70	-10.12	17.89	13.83	36.26	-16.07	17.88
K_CB259	-3.02	0.03	-0.02	0.74	-0.97	0.53	0.41	0.75	-18.68	20.80	-20.37	17.77	-38.66	2.28	-22.13	17.94
C_CB138	-0.88	0.19	0.33	0.67	-1.05	0.30	0.50	0.79	-41.10	-22.00	-18.92	4.66	-46.84	-26.73	-19.35	7.87
C_CB169	-0.18	1.19	-0.75	0.21	-0.28	0.12	-0.87	0.23	-17.89	-2.15	-9.21	4.28	-12.96	2.18	-9.05	4.16

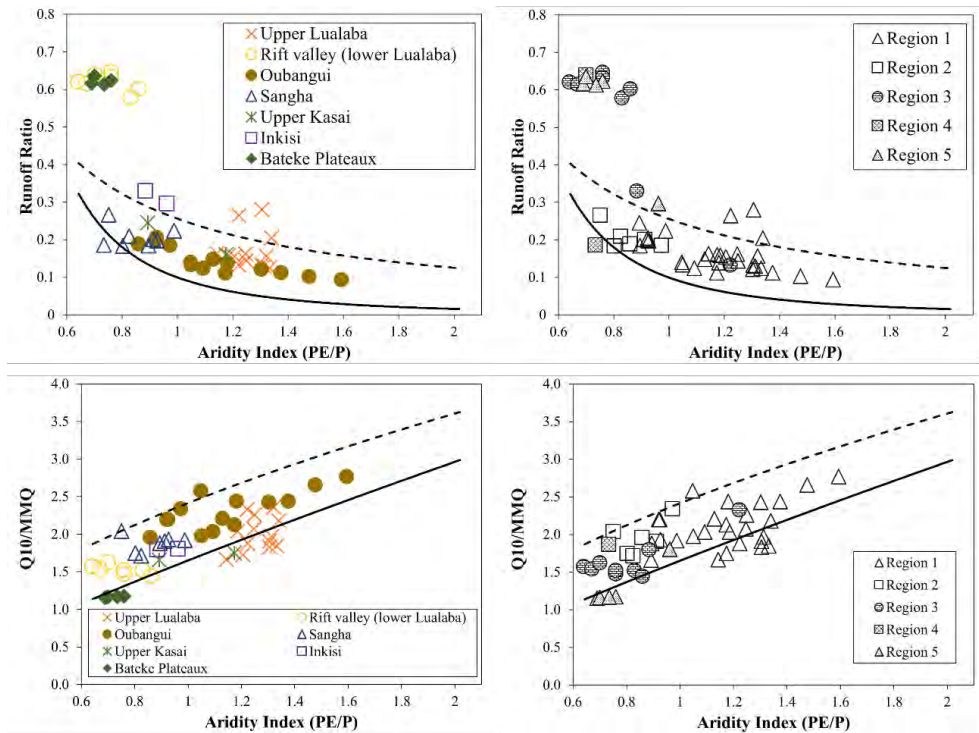


Figure B6.1. Comparing the variation of constraint indices along the climate gradient based on sub-drainage (left figures) and on climate and physiographic regions (right figures) for runoff ratio and Q10/MMQ constraints.

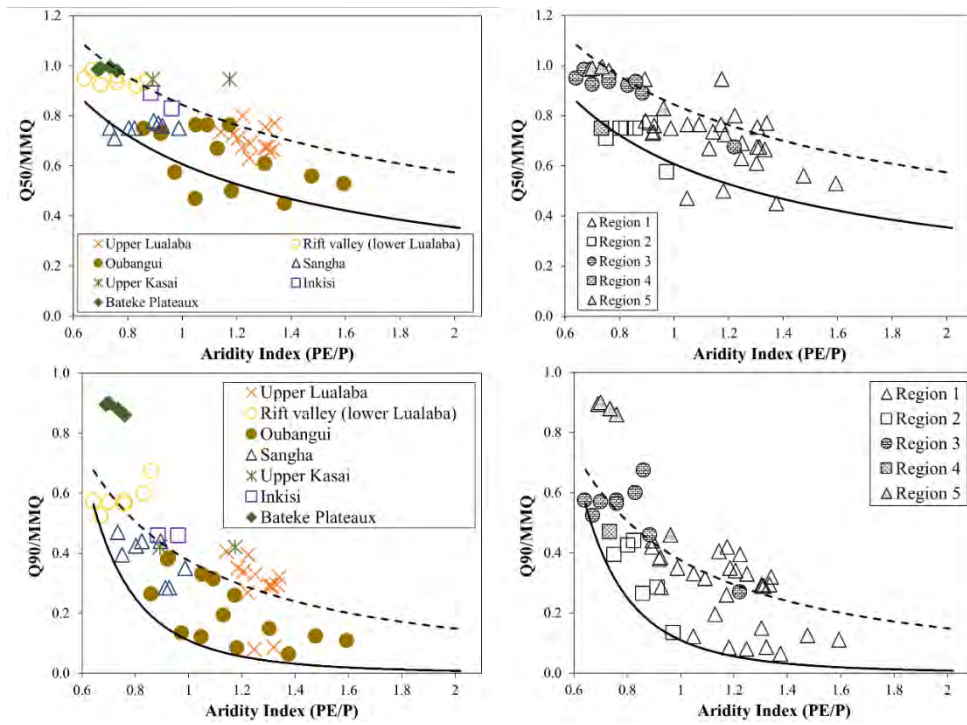


Figure B6.2. Comparing the variation of constraint indices along the climate gradient based on sub-drainage (left figures) and climate and physiographic regions (right figures) for Q50/MMQ and Q90/MMQ constraints.

Appendix C:

Table C7.1. Correlation matrix of wetland variables across different wetland systems. Hysteresis indices are expressed on a monthly scale.

	Inf_St	Inf_Area	St_Area	St_Outfl	Qcap	QSF	AA	Res. storage	Ini. storage	Rs_St/T_St	Time Lag (days)	IWM	% of attenuation	Average slope (%)
Inf_St														
Inf_Area	0.15													
St_Area	-0.67	0.63												
St_Outfl	0.28	-0.27	-0.46											
Qcap	0.71	0.48	-0.23	0.54										
QSF	-0.71	-0.48	0.23	-0.54	-1.00									
AA	0.72	-0.38	-0.86	0.25	0.41	-0.41								
Res. storage	-0.58	0.25	0.67	-0.94	-0.66	0.66	-0.49							
Ini. storage	-0.82	0.26	0.85	-0.71	-0.60	0.60	-0.68	0.91						
Rs_St/T_St	0.42	-0.07	-0.34	-0.65	-0.19	0.19	0.50	0.37	-0.04					
Time Lag (days)	-0.84	0.35	0.92	-0.59	-0.47	0.47	-0.75	0.81	0.98	-0.22				
IWM	-0.88	-0.51	0.31	-0.10	-0.84	0.84	-0.57	0.36	0.53	-0.36	0.50			
% of attenuation	-0.97	0.05	0.79	-0.23	-0.59	0.59	-0.86	0.54	0.81	-0.54	0.86	0.81		
Average slope (%)	0.66	-0.51	-0.91	0.26	0.29	-0.29	0.99	-0.49	-0.68	0.50	-0.76	-0.46	-0.82	
Length (km)	-0.25	0.58	0.63	-0.80	-0.09	0.09	-0.20	0.79	0.73	0.36	0.70	-0.17	0.24	-0.28

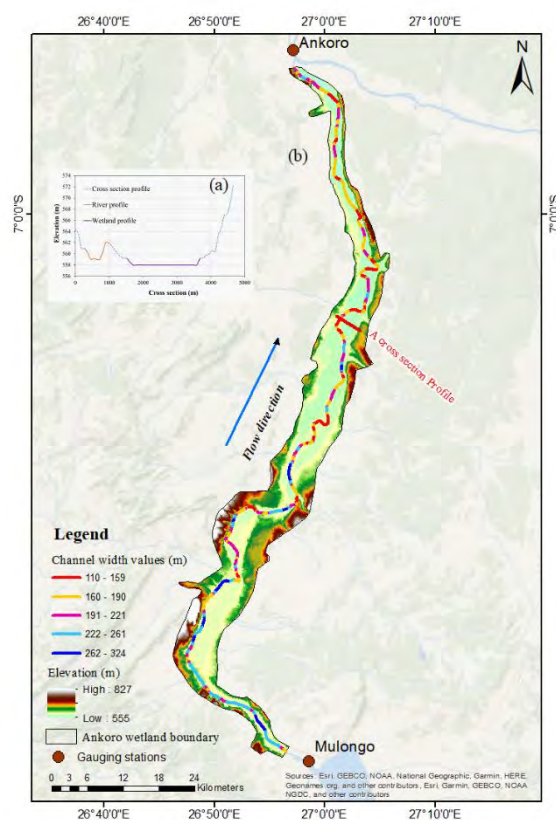


Figure C7.1. The Ankoro wetland system. (a) A cross-section profile showing a morphological structure of channel-wetland connection. It shows that the wetland system is located below channel banks. (b) Floodplain topography and channel widths.

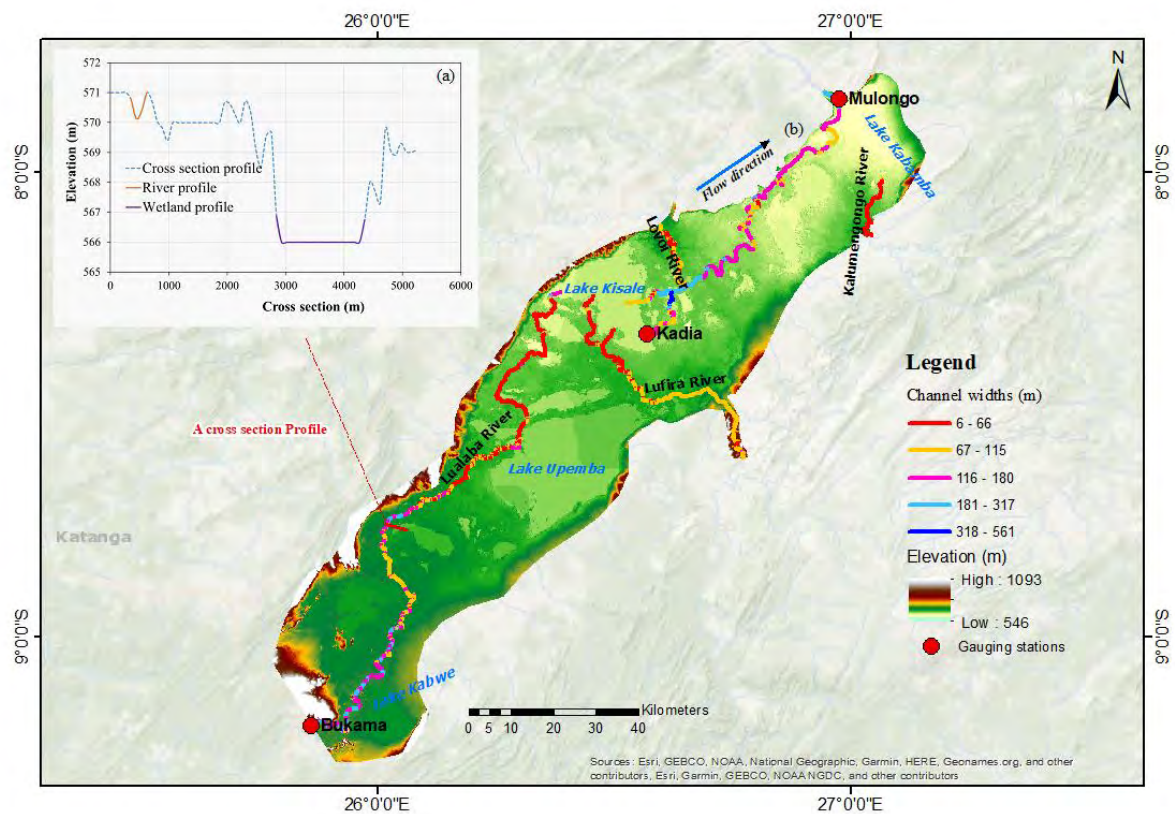


Figure C7.2. The Kamalondo wetland system. (a) A cross-section profile showing a morphological structure of channel-wetland connection with wetland system located below channel banks. (b) Floodplain topography and channel widths.

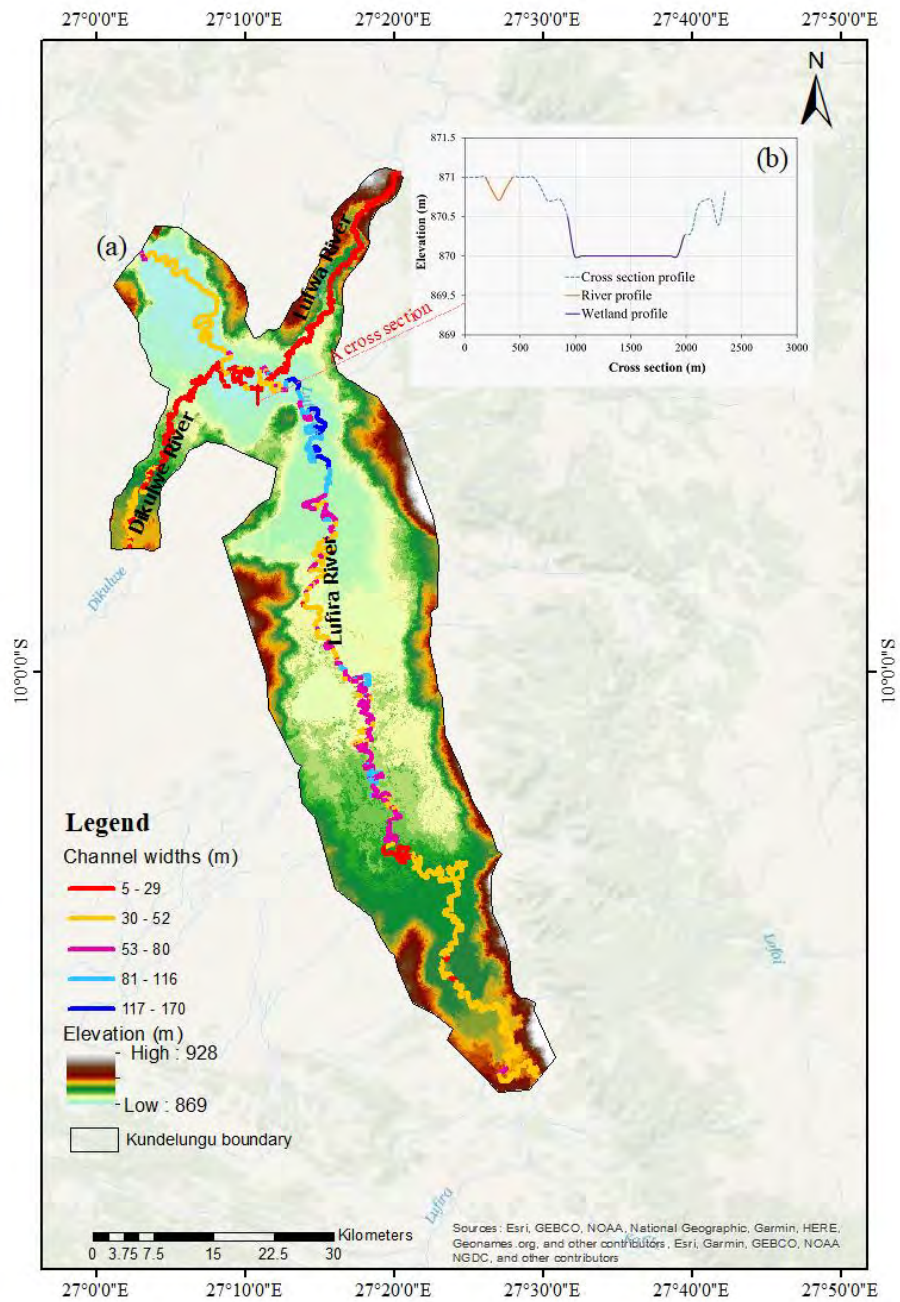


Figure C7.3. The Kundelungu wetland system. (a) Floodplain topography and channel widths. (b) A cross-section profile showing a morphological structure of channel-wetland connection. It shows that the wetland system is located below channel banks.

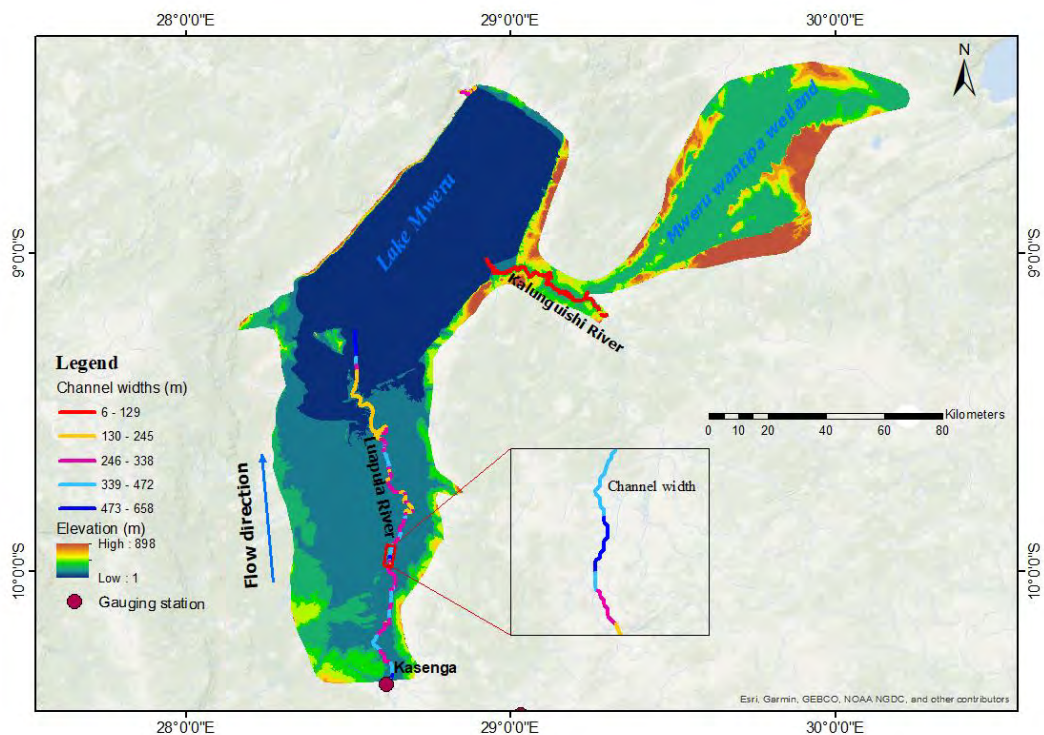


Figure C7.4. The topographic setting of Mweru wetland system.

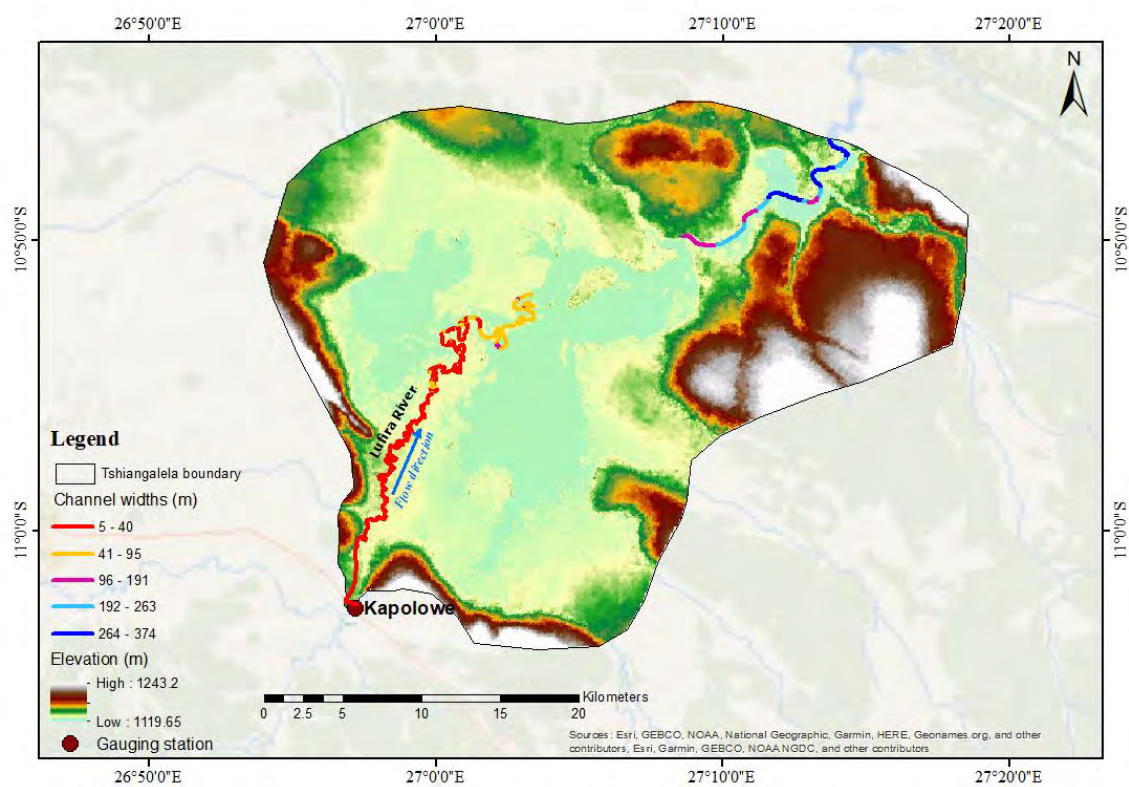


Figure C7.5. The topographic setting of the Tshiengalele wetland system in the upper Lualaba drainage system.

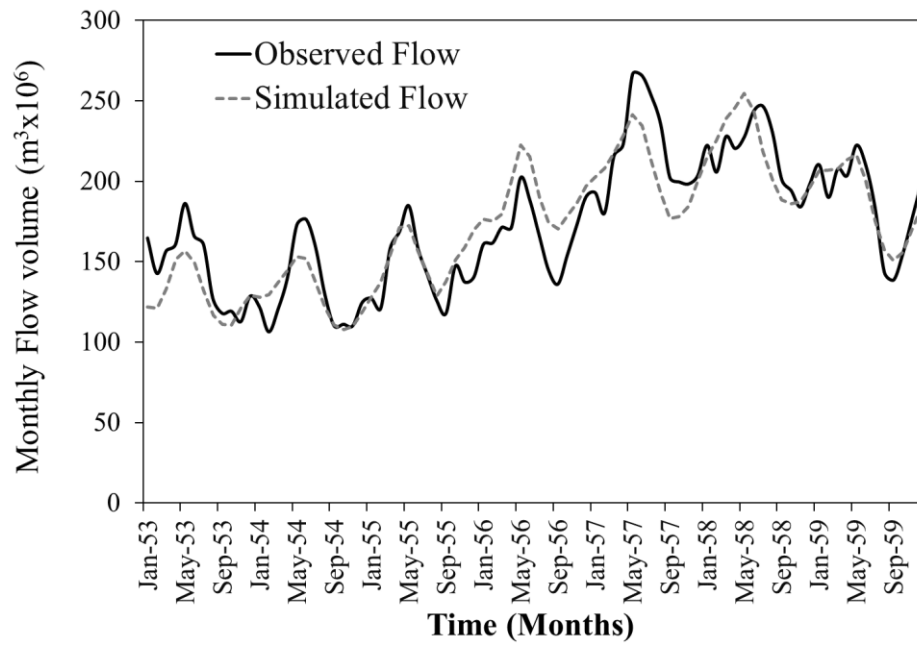


Figure C7.6. Simulated streamflow at the Ruzizi gauging station after the inclusion of Lake Kivu for the period 1953-1959.