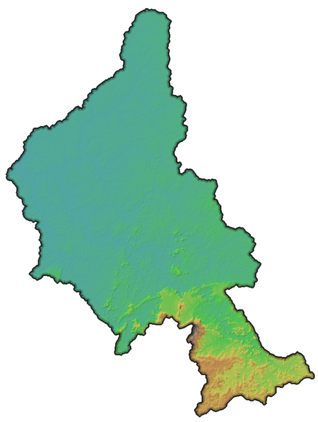
CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

FACULTY OF ENVIRONMENTAL SCIENCES

Department of Water Resources
and Environmental Modelling

# Modelling of hydrological balance in monthly time step using hydrological lumped model

## MASTER'S THESIS



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# Abstract

This study investigated the calibration performance of hydrological models applying series of split-sample to crash-test all potential combinations of calibration-validation periods under drought type (dry/wet) using lumped models: BILAN and GR2M. A sub-period focused on the drought was systematically selected based on a particular climate characteristic (precipitation, temperature, runoff) and a 7-year moving window. This approach gives a perception into calibrated parameters transferability over time under similar or different climate conditions (drought). The both lumped models yielded similar results over a set of 6 catchments in a main West African river basin located in Senegal: the Gambia river basin. The Kling-Glupta Efficiency (KGE) was the objective function to assess models efficiency. A dependency was found then between the model performance and the extent of input data. Results have shown that the calibration performance decreases within an extending simulation period width. A focus on the impact of drought type on calibration performance revealed models simulating better Dry than wet years. The analyse on how model performance would be affected when calibrated in a climate condition different to the validation (e.g calibrated in dry(wet) and validated into wet (dry) revealed that calibration over a wetter or dryer condition than the validation and vice-versa may lead to an over(under)estimation of the simulated runoff. The results also indicate a general performance loss due to the transfer of calibrated parameters to independent validation periods of −5 to −25%, on average. The shift of model parameters in time (validation) may generate significant level of errors. The outcome of this study may lead to a master of the uncertainty associated with one hydrological model and a better assessment of runoff in real world application.

Key words: rainfall runoff model; BILAN; GR2M; lumped hydrological models; Gambia river basin; Calibration; crash test

# Abstrakt

Tato studie zkoumala kalibrační výkon hydrologických modelů s použitím série rozdělených vzorků k nárazovému testování všech potenciálních kombinací kalibračních a validačních period u suchého typu (suchý / mokrý) pomocí soustředěných modelů: BILAN a GR2M. Systematicky bylo vybráno podobdobí zaměřené na sucho na základě konkrétní klimatické charakteristiky (srážky, teplota, odtok) a sedmiletého pohyblivého okna. Tento přístup umožňuje vnímat přenositelnost kalibrovaných parametrů v čase za podobných nebo odlišných klimatických podmínek (sucho). Oba soustředěné modely přinesly podobné výsledky na souboru 6 povodí v hlavním západoafrickém povodí řeky v Senegalu: v povodí Gambie. Účinnost Kling-Glupta (KGE) byla objektivní funkcí pro hodnocení efektivity modelů. Poté byla nalezena závislost mezi výkonem modelu a rozsahem vstupních dat. Výsledky ukázaly, že výkon kalibrace klesá s rostoucí šířkou simulační periody. Zaměření na dopad typu sucha na výkon kalibrace odhalilo modely simulující lepší suchá než mokrá léta. Analýza toho, jak by byl ovlivněn výkon modelu při kalibraci za jiných klimatických podmínek než je validace (např. Kalibrováno za sucha (za mokra) a validováno za mokra (za sucha)) odhalilo, že kalibrace za vlhčího nebo suššího stavu než validace a naopak může vést k nadměrnému (pod) odhadu simulovaného odtoku. Výsledky také ukazují obecnou ztrátu výkonu v důsledku přenosu kalibrovaných parametrů na nezávislé doby validace v průměru −5 až −25 %. Posun parametrů modelu v čase (validace) může generovat významnou úroveň chyb. Výsledek této studie může vést k zvládnutí nejistoty spojené s jedním hydrologickým modelem a lepšímu hodnocení odtoku v reálném světě. w

Klíčová slova: rainfall runoff model; BILAN; GR2M; lumped hydrological models; Gambia river basin; Calibration; crash test

# ČESKÁ ZEMĚDĚLSKÁ UNIVERZITA V PRAZE

Fakulta životního prostředí

# ZADÁNÍ DIPLOMOVÉ PRÁCE

Bc. Ba Doudou

Krajinné inženýrství
Environmentální modelování

Název práce

**Modelling of hydrological balance in monthly time step using the lumped hydrological model**

Název anglicky

**Modelling of hydrological balance in monthly time step using the lůumped hydrological model**

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**Cíle práce**

The aim of the thesis is to describe the calibration performance of selected lumped hydrological models.

**Metodika**

1. Choose a suitable set of river basins, prepare meteorological and hydrological data

2. Calibrate chosen hydrological models using the wet and dry period with different length

3. Evaluate the performance of lumped models and describe the impact of different calibration period on model performances

**Doporučený rozsah práce**

standard

**Klíčová slova**

lumped hydrological model, rainfall runoff modeling

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**Doporučené zdroje informací**

Coron L., Andréassian V., Perrin C ., Lerat J., Vaze J., Bourqui M., Hendrickx F. Crash testing hydrological models in contrasted climate conditions: An experiment on 216 Australian catchments. WATER RESOURCES RESEARCH, VOL. 48, W05552, doi:10.1029/2011WR011721, 2012, p. 1-17

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**Vedoucí práce**

doc. Ing. Petr Máca, Ph.D.

**Garantující pracoviště**

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Elektronicky schváleno dne 30. 11. 2020

**prof. RNDr. Vladimír Bejček, CSc.**

Děkan

V Praze dne 02. 12. 2020

# Dedication

To the young boy, in white, I dedicate this work, he might be writing after 20 years to become an Environmental Modeller...

"*Common sense is the most fairly distributed thing in the world: because everyone thinks he is so well endowed, that even those who are hardest to satisfy in everything else, have no habit of desiring more than they have. What it is unlikely that all are wrong, but this shows that the power of judging well and distinguishing truth from falsehood, which is properly what is called common sense or reason, is naturally equal in all men, and as well as the diversity of our opinions does not come from what some are more reasonable than others, but only that we conduct our thoughts in various ways, and do not see the same things . For it is not enough to have a good mind, but the key is to apply it well. The greatest souls are capable of the greatest vices as well as the greatest virtues, and those who do not work very slowly may move much more, they always follow the right path, as do those who run, and away from it*" Thus opens the Descartes' Discourse on Method, this is how we open the following paragraphs.

# Declarations

I hereby declare that I have done this thesis entitled **Modelling of hydrological balance in monthly time step using hydrological lumped model** independently, under the supervision of doc. Ing. Petr Máca, Ph.D., all texts in this thesis are original, and all the sources have been quoted and acknowledged by means of complete references and according to Citation rules of the FES.

Prague, December 2021
Doudou BA

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I would like to thank my parents and my family whose prayers, love , guidance and support are with me in whatever I pursue.

To my friends...

I can't end without thanking once more time my supervisor Dr. Máca.

To my loving and supportive wife, N.BA...

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# Glossary and Nomenclature

**climate characteristic** By climate characteristic or climate variable we mean the Precipitation (P), the Temperature (T) and the Runoff (R). 27

**drought** It's important to note that the drought referring to dry or wet years doesn't necessarily indicate a period of higher or lower temperature, that might have a misleading sense in this study, drought is utilized for periods selected based on quantiles of climate characteristics (rainfall, runofff, temperature). Periods of quantiles under twenty (20) being "Dry years" and periods of quantiles aboveeighty (80) being "Wet years". 22

**GCMs** Global Circulation Models. 1

**PD** Sub-Period selected on Dry years based on Precipitation. 29

**PW** Sub-Period selected on Wet years based on Precipitation. 29

**RD** Sub-Period selected on Dry years based on Runoff. 29

**RW** Sub-Period selected on Wet years based on Runoff. 29

**SRCC** Streamflow response to climate change. 1

**TH** Sub-Period selected based on High Temperature. 29

**TL** Sub-Period selected based on Low Temperature. 29

# Chapter 1

# Introduction

Over the last couple of years, streamflow response to climate change SRCC has been the concern of several studies worlwide including [Yapo et al. 1996; Anctil et al. 2004; Refsgaard and Madsen 2013; Lawrence et al. 2011] and many others [Andréassian et al. 2009; Hanel et al. 2012]. The SRCC studies generally start with the selection of emission scenarios, running and downscaling global circulation models GCMs at a hydrological scale to finally calibrate the hydrological models to predict runoff.

The parameters estimation (calibration) is often associated with uncertainty since hydrological models are built on observations and hypotheses, models attempting to reflect real-world behaviour will always stay inaccurate(Andréassian et al. 2009).

Many studies (Vaze et al. 2010) investigated the relevance of parameters calibrated (on historical data) to predict runoff responses (on future climate inputs). For instance (Wilby 2005; Merz et al. 2011; Brigode et al. 2013) explored models parameters transposability and the uncertainty associated with this modelling task.

(Seibert 2003) calibrated the HBV model in four Swedish catchments using periods of lower runoff peaks and validated on higher peaks, finding a decrease in model performance.

(Vaze et al. 2010) applied the DSST to four hydrological models in 61 Australian catchments and found that the models calibrated under wetter conditions performed worse on dryer periods than vice versa.

(Merz et al. 2011) calibrated a conceptual hydrological model on six consecutive 5-year periods on 273 Austrian catchments. They found that the parameters controlling snow dynamics and soil moisture processes depend significantly on the hydro-climatological conditions of the calibration period, which leads to notable biases in high flows especially in snow-affected catchments.

(Coron, Andréassian, et al. 2012) introducing a generalized split-sample tests (GSST), calibrated three rainfall-runoff models over a set of 216 catchments in southeast Australia, they also found an (over)underestimation of the average runoff volumes during parameters transfer over a wetter (drier) climate than the validation and vice versa.

(Hanel et al. 2012) applied the BILAN model at 250 Czech catchments of different sizes and climatic conditions using climate scenarios and delta model approach and found a decrease in spring and summer runoff in most of the catchments.

(Refsgaard and Madsen 2013) proposed performing Differenial Split Sample Test (DSSTs) to evaluate the trustablity of hydrological models used for climate change impact studies.

(Brigode et al. 2013) found that two hydrological models calibrated on 63 French catchments were sensitive to climatologically contrasted calibration sub-periods (dry vs wet) and that this lack of model robustness has a stronger impact on the uncertainty of hydrological projections of future streamflow as compared to the use of several multiple parameter sets.

(Fowler et al. 2016), nevertheless, conclude that the explanation to the DSST failure is often due to insufficient model calibration techniques, rather than the models themselves, which can lead to a false negative impression of the model robustness under changing climate conditions.

(Bodian, Dezetter, Diop, et al. 2018) calibrated the GR4J on two main West African Senegalese river basins (the Senegal and Gambia River Basins) using six GCMs and two RCP scenarios and multi-model ensemble. They predicted on the near future (2050 horizon) against the reference period (1971–2000) and for both river basins, a decrease of annual streamflow 8% and 22% respectively for the Senegal River Basin and the Gambia River Basin under the RCP4.5 scenario and a more pronounced decrease of 16% (Senegal River Basin) and 26% (Gambia River Basin) under RCP8.5 scenario. The Gambia River Basin being more affected by the climate change.

Recently, (Vormoor et al. 2018) calibrated the HBV model in five Norwegian catchments with mixed snowmelt/rainfall regimes under stable and contrasting conditions in terms of flood seasonality and flood generating processes (FGP). They found a general model performance loss due to the transfer of calibrated parameters to independent validation periods of $-5\%$ to $-17\%$, on average.

Finally (Berthet et al. 2020), proposed a crash-testing framework to assess the quality of hydrological forecasts in an extrapolation context using the GRP rainfall–runoff over a large set of catchments in France. They found a challenge of uncertainty quantification when forecasting high flows and significant drop in reliability when forecasting high flows in an extrapolation context and considerable variability among catchments and across lead times.

Overall, the results most of these authors found a considerable decrease in model performance after transferring calibrated parameter sets between climatologically contrasting periods.

The uncertainty associated with the parameters estimation cannot be thus neglected [Wilby 2005,Vaze et al. 2010,Merz et al. 2011].

## 1.1 Classification of Hydrological Models

Hydrological models can be classified by their structure (Empirical, Conceptual, Physical) and by their spatial processes (Lumped, Semi-Distributed or Distributed) considered in the runoff estimation.

### 1.1.1 Empirical Models

Empirical models (also referred to as data-driven models) use non-linear mathematical interactions between inputs and outputs, they are observation-oriented and rely on the precision of the input (Kokkonen et al. 2001).

The governing equation for empirical models is a function of inputs:

$$Q = f(X, Y) \tag{1.1}$$

Following (Keith Beven 2012) most empirical models are black box models, meaning very little knowledge about the internal processes controlling the runoff simulation. The forcast accuracy of empirical models decreases with a change of the HS of the catchment. Examples of Empirical models are rational method, models of unit hydrographs, regression models.

### 1.1.2 Conceptual Models

Conceptual models illustrate the water balance equation by transforming the rainfall into runoff, evapotranspiration, and groundwater. Each component in the water balance equation is deducted by mathematical equations that subdivide the rainfall input.
General equations controlling conceptual models are water balance equations that regulate surface water and storage fluctuations (Knightes 2017) (Vaze, 2012):

$$\frac{dS}{dt} = P - ET - Qs \pm GW \tag{1.2}$$

Where dS/dt is the change in reservoir storage, P is precipitation, ET is evapotranspiration, Qs is surface runoff, and GW is groundwater. Nash model, Tank model, ESMA model, PDM model, NWS R-R model are examples of conceptual models.

### 1.1.3 Physical and Theoretical Models

Physical and theoretical models are based on the knowledge of hydrological process related physics.

General laws and concepts of physics include water balance equations, mass and energy preservation, momentum and cinematics (Dingman 2015). Saint-Venant, Boussinesq, Darcy and Richard are among the equations that are adopted by physical models as mentioned (Pechlivanidis et al. 2011). The inconvenient with theoretical models is that they require a lot data and parameters. Examples of theoretical models are SHE, SHETRAN, CASC2D, Kineros...

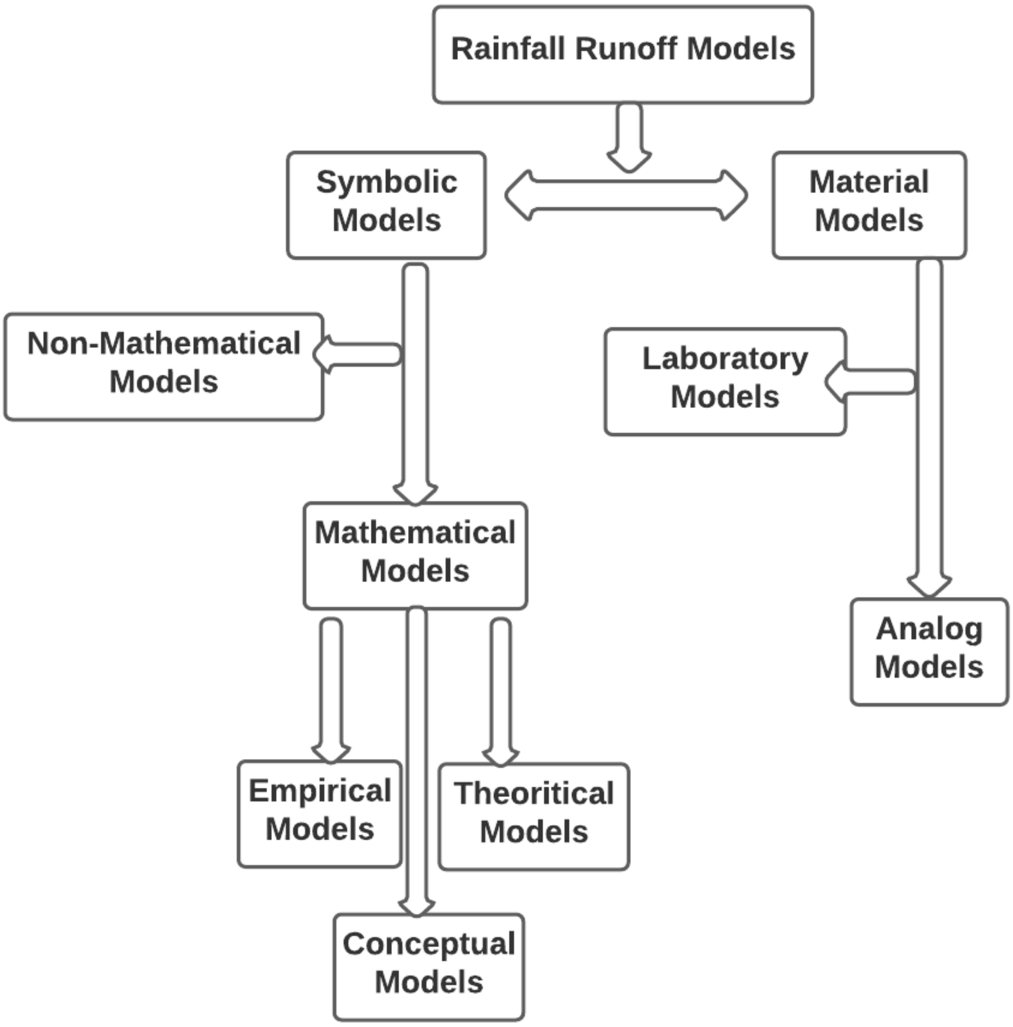



Figure 1.1: Classification of HM

### 1.1.4 Spatial representation of hydrological processes

The spatial processes provide to the model insight of the geographical representation of the catchment.

### Lumped Models

Lumped models consider the catchment as a single homogenous unit area. Spatial variability of catchment parameters is neglected in lumped models (Moradkhani et al. 2008). In a lumped model all inputs are lumped meaning average data thus by implying homogeneity over catchment, they lose data spatial resolution. Since Lumped models are hypothesis-based, they appear to overestimate (underestimate) the runoff (Knightes 2017).

### Distributed

Distributed models are the most complex since they preserve the spatial heterogeneity of inputs and parameters. (Rinsema 2014) advanced that complete distributed model subdivides the model process by small elements or grid cells and each cell (or stream) has a specific hydrological response and is calculated distinctly, but integrates communications with neighboring cells. They route the calculated runoff from each cell to the nearest cell or stream, based on physical equations used to determine flow path and natural time lags.

### Semi-Distributed

Semi-distributed models are lumped models with distributed characteristics. They may be a set of lumped parameters implemented quasi-spatially distributed that splits the catchment into smaller areas for each (Rinsema 2014). Sub-areas represent critical features in a catchment, incorporating advantages of lumped and distributed models (Pechlivanidis et al. 2011).

## 1.2 Limits of Hydrological Models: Uncertainty

Since any model isn't hundred percent accurate, the uncertainty associated with the estimation of parameters of hydrological models cannot be neglected (Coron, Andréassian, et al. 2012).

To improve models, we need rigorous testing i.e., true crash test as underlinded (Andréassian et al. 2009).

Efficient testing requires enough and varied data sets for assessing hydrological models, identifying their insufficiency (failures), to finally gain ability to improve them as mentioned in (Andréassian et al. 2009).

When building a model, hydrologists pursue a deeper understanding of physical processes and/or a benefit in their capacity to forecast flow or other hydrological variables (Andréassian et al. 2009).

But since the aim of a hydrological model is to be operational for the kind of task for which it is intended,it must demonstrate, how well it can perform before it is used. Therefore (KlemeŠ 1986) proposed a hierarchical testing scheme of hydrological simulation models which ties the nature of the test vis-à-vis the difficulty of the modelling task. The Full Klemes Crash Test (4KCT) (Andréassian et al. 2009), Generalized Split Sample test (GSST) (Coron, Andréassian, et al. 2012) or operational testing scheme (KlemeŠ 1986) is as follows:

- **Level 1 Split-sample test:** The time series are divided into two parts, one for calibration and validation and contrasting the effects of both arrangements. The model can only qualify if all case validation outcomes are acceptable and similar.

- **Level 2 Proxy-basin test:** The Proxy-basin test diagnose for the geographical transposability of a model, in this case for selected basin A and B, the model should be calibrated on basin A and validated on basin B and vice versa. Only if the two validation results are acceptable and similar can the model command a basic level of credibility with regard to its ability to simulate the streamflow in basin C adequately.

- **Level 3 Differential split-sample test:** This level should be required whenever a model is to be used to simulate flows in a given gauged basin under conditions different from those corresponding to the available flow record. This Level should be appropriate when using a model to simulate flows in a given gauged basin under conditions other than those corresponding to the available flow record. For a model supposed to predict streamflow for a wet(dry) period, it should be calibrated on a dry(wet) historic record period and tested on a wet(dry) period. The model should demonstrate its ability to perform under the transition required: from drier to wetter conditions or the opposite.

- **Level 4 Proxy-basin differential split-sample test:**

  In situations where the model is to be transposable both geographically and climately (or land-usable) the fourth stage of the Klemes crash test should be implemented. The ultimate aim of hydrological simulation being such universal transposability. By analogy, a model intended for an assessment of the impact of a wet climate scenario would have to be calibrated/validated on Ad/Bw, and on Bd/Aw, and judged adequate if results from Bw and Aw are adequate and similar. Where A and B are selected basins, d stands for dry climate, w stands for wet conditions.

## 1.3 Aim

The aim of the thesis is to crash test the BILAN and GR2M lumped models under extending width of simulation time series and under similar or varying climate conditions. It involves the following questions:

- How the simulation period width impacts the calibration performance?
- How well the model simulate the Dry against Wet periods?
- Which of the selected lumped models performs better ?
- How transferable are the optimized parameters from Calibration to Validation Period?

## 1.4 Structure of the thesis

The thesis has the following structure:

- Materials and methods
- Results
- Discussion
- Conclusion

# Chapter 2

# Materials and methods

This chapter provides a description of the study area, the catchments and hydrological data, the PET estimation, the description and calibration of hydrological models and finally the methodology to analyse the results including the objective function (KGE), the performance criteria (KGE, NSE, RMSE) and the MRC performance loss criteria.

## 2.1 Description of study area

The Gambia River Basin is a semi-arid region of West Africa located between latitudes $11°20'$ and $14°45'$ and longitudes $11°15'$ and $16°30'$ West. The Gambia River Basin is bordered by the southern Fouta Djallon Mountains (Guinean eco Climate Area), the eastern Senegal River Basin, the western Atlantic ocean, and the arid Ferlo zone of Senegal (Sudano-Sahelian eco Climate Area)(Degeorges et al. 2007). It has a thick woodland with indicators of deteriorating because of numerous environmental conditions such as drought and flooding, and anthropogenic causes, such as deforestation, bush fires, the overuse of land resources and overgrazing (Bodian, Dezetter, Diop, et al. 2018).

The basin occupies 77 100 km2, nearly 25% of the surrounding 290,000 km2 Senegal River Basin. It is located in the three countries of Guinea, Senegal and the Gambia which make up 15%, 71% and 14% of the Basin, respectively.The overall length of the Gambia River is 1180 km. Centered on the basin hydrology, the (Degeorges et al. 2007) is broken into:

- Estuarine Basin, the edge of the tidal effect, from the mouth of the Gambia to Gouloumbou, Senegal, 530 km deep, covering a region of 36 000 m2. In the basin, the Lower Freshwater River Region is the main field of pumped irrigation capacity from Kuntaur at 250 km upstream to Gouloumbou.

- Continental Basin on the river Gouloumbou, a region of 240 km from Labe in Guinea a few kilometers from the Labe at an altitude of 1125m IGN (National Geographic Institute) and covers an area of 41 000 km2.

- Guinea's Fouta Djallon Mountains, a source of the Gambia River, is also referred to as the 'Chateau d'Eau' or 'West African Water Reservoir' as it is the main source of water for large rivers such as Gambia, Senegal and Niger (Degeorges et al. 2007).

The Organisation Pour la Mise En Valeur Du Fleuve Gambia (OMVG) is the Gambia River Organization to establish and operate the Gambia River. It involves Gambia, Senegal, Guinea Conakry and Guinea Bissau (Degeorges et al. 2007). A few study ((Ardoin-Bardin et al. 2009),(Bodian, Dezetter, Deme, et al. 2016),(Bodian, Dezetter, Diop, et al. 2018)) investigated the climate change influence in the Gambia river basin using GCMs scenarios and hydrological models such as GR2M, while (TRAORE 2014a) applied the GR4J and the GR2M models to describe the hydrological behaviour of the Gambia river basin at Koulountou station and (Cisse et al. 2014) analyzed the impact of climate variability on the evolution of the hydrological regime of the Senegal River Basin. This indicates a lack of analysis of climate change impact assessment on water supplies in this region.

## 2.2 Catchments and hydrological data

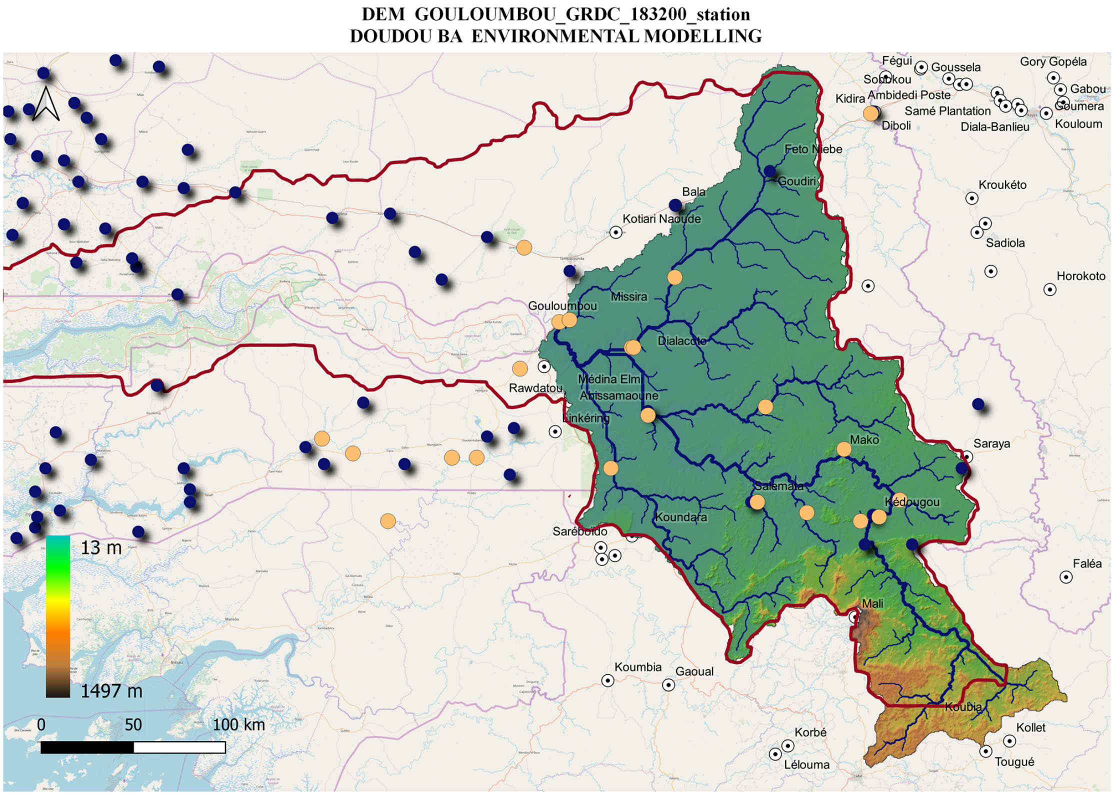
### 2.2.1 Selection of a set of catchments

This study focused on the Gambia River Basin at 6 outlets which are Gouloumbou, Kedougou, Mako, Simenti, Wassadou-amont and Wassadou aval. The Gambia River Basin covers Senegal and Conakry Guinea with a total surface area of (42000 km2) at Gouloumbou station; (7550 km2) at Kedougou, (8262 km2) at the gauging station of Mako, (20500 km2) at Simenti, (21200 km2) at Wassadou-amont and (33500 km2) at Wassadou-aval. In the Gambia River basin heights range between 13 and 1497 m (at Gouloumbou) and a total annual precipitation at of 1208 mm (at Gouloumbou). The annual average production at Gouloumbou is 87 m3/s (record 1971-1999).

Table 2.1: Catchments information from GRDC.

| grdc_no wmo | _reg su | b_reg | river | station co | untry | lat | long | area (km2) |
|---|---|---|---|---|---|---|---|---|
| *1813200* | *1* | *13* | *GAMBIA* | *GOULOUMBOU* | *SN* | *13.47* | *-13.73* | *42000* |
| *1813780* | *1* | *13* | *GAMBIA* | *KEDOUGOU* | *SN* | *12.55* | *-12.18* | *7550* |
| *1813700* | *1* | *13* | *GAMBIA* | *MAKO* | *SN* | *12.87* | *-12.35* | *10450* |
| *1813500* | *1* | *13* | *GAMBIA* | *SIMENTI* | *SN* | *13.03* | *-13.3* | *20500* |
| *1813460* | *1* | *13* | *GAMBIA* | *WASSADOU AMONT* | *SN* | *13.35* | *-13.37* | *21200* |
| *1813450* | *1* | *13* | *GAMBIA* | *WASSADOU AVAL* | *SN* | *13.35* | *-13.38* | *33500* |

Figure 2.1: DEM of Gambia river basin at Gouloumbou station




## 2.2.2 Collection of meteorological and hydrological data

In this study, monthly observed climate data (rainfall and temperature) and stream-flow were used. Monthly times series of meteorological data (rainfall and temperature) were provided by the Senegalese National Agency for Civil Aviation and Meteorology (ANACIM) with a total of seven (7) rain gauges and three (3) temperature sensor stations. Catchment and Hydrological data (runoff) were then collected from the Global Runoff Data Center (GRDC), the Water Resources Management and Planning Department of Senegal (DGPRE)and the Senegalese National Agency for Civil Aviation and Meteorology (ANACIM) with a total set of 6 catchments (Gouloumbou, Kedougou, Mako, Simenti, Wassadou-amont and Wassadou-aval) of the Gambia river basin.

## 2.2.3 Description of hydro-meteorological data

Due to the absence or inaccessibility of recent record of meteorological data , a period starting from 1970 to 1999 was selected as a reference period of 30 years which is enough for our modelling approach.

Tables 2.2, 2.3, 2.4 below show respectively the mean annual rainfall and the mean annual temperature with respectively their available records of rain gauges and temperature gauges with their quality of data (gaps(%)) and the main characteristics of the hydrographic network of the Gambia river upstream at Gouloumbou.

Table 2.2: Rain gauges information (rainfall in annual mean)

| ***Rain Guage*** | ***Lat*** | ***Lon*** | ***H (m)*** | ***Rainfall (mm)*** | ***record*** | ***gaps(%)*** |
|---|---|---|---|---|---|---|
| *Fongolim* | *12.42* | *-12.02* | *39* | *854* | *1990-2017* | *0* |
| *Goudiry* | *14.18* | *-12.71* | *-* | *656* | *1960-2017* | *19* |
| *Kedougou* | *12.56* | *-12.21* | *121* | *1200* | *1960-2017* | *0* |
| *Kidira* | *14.46* | *-12.21* | *-* | *577* | *1990-2017* | *0* |
| *Salemata* | *12.62* | *-12.8* | *84* | *808* | *1990-2017* | *0* |
| *Saraya* | *12.78* | *-11.78* | *184* | *960* | *1990-2017* | *0* |
| *Tamba* | *13.71* | *-13.68* | *-* | *752* | *1960-2017* | *0* |

Table 2.3: Temperature gauges information (annual mean of temperature)

| ***Stations*** | ***Lat*** | ***Lon*** | ***H (m)*** | ***Temperature (celcius)*** | ***record*** | ***gaps(%)*** |
|---|---|---|---|---|---|---|
| *Goudiry* | *14.18* | *-12.71* | *-* | *26.3* | *1991-2017* | *0* |
| *Kedougou* | *12.56* | *-12.21* | *121* | *28.6* | *1960-2017* | *0* |
| *Tamba* | *13.71* | *-13.68* | *-* | *28.8* | *1960-2017* | *0* |

Table 2.4: Main characteristics of the hydrographic network of the Gambia river upstream from Gouloumbou (according to Chaperon and Guiguen)

| ***Gambia River*** | ***Length*** | ***Height max (m)*** | ***Height min (m)*** | ***Drop (m)*** |
|---|---|---|---|---|
| *at Kedougou* | *243.00* | *1125.00* | *105.00* | *1020.00* |
| *at Mako* | *328.00* | *1125.00* | *75.00* | *1050.00* |
| *at Simenti* | *503.00* | *1125.00* | *10.00* | *1115.00* |
| *at Wassadou amont* | *559.00* | *1125.00* | *5.00* | *1120.00* |
| *at Gouloumbou* | *658.00* | *1125.00* | *0.00* | *1125.00* |

Figures 2.2, 2.3, 2.4 illustrate respectively 30 years record of average annual rainfall, runoff and temperature of 5 catchments of the Gambia river basin, respectively Gouloumbou (GMB), Kedougou (KDG), Mako (MKO), Simenti (SIM), Wassadout-Amont (WAM). Globally catchments have the same profiles of rainfall, runoff and temperature.

It is important to note that we are in a West African (Senegal) snow-free climate that recognizes only two seasons: a dry season that is longer with almost no rain for 7 months and a rainy season that is shorter and counts for 5 months.

The minimal annual rainfall is between 57 and 69 mm in 1983 and maximal annual runoff between 122 and 199 mm in 1994 and 1999. The minimal average runoff is between 3 and 11 mm obtained in 1983 and 1984 while the maximal annual runoff turns arround 16 and 37 mm in 1974 and 1994. Between 1974 and 1976 know the lowest temperature between 27.58 and 27.24 and the highest annual temperature between 31 and 29 Celsius in 1998 and 1980.

Figure 2.2: Mean Annual Rainfall, GMB(Gouloumbou), KDG(Kedougou), MKO(Mako), SIM(Simenti), WAM(Wassadou-Amont), WAV(Wassadou-Aval)

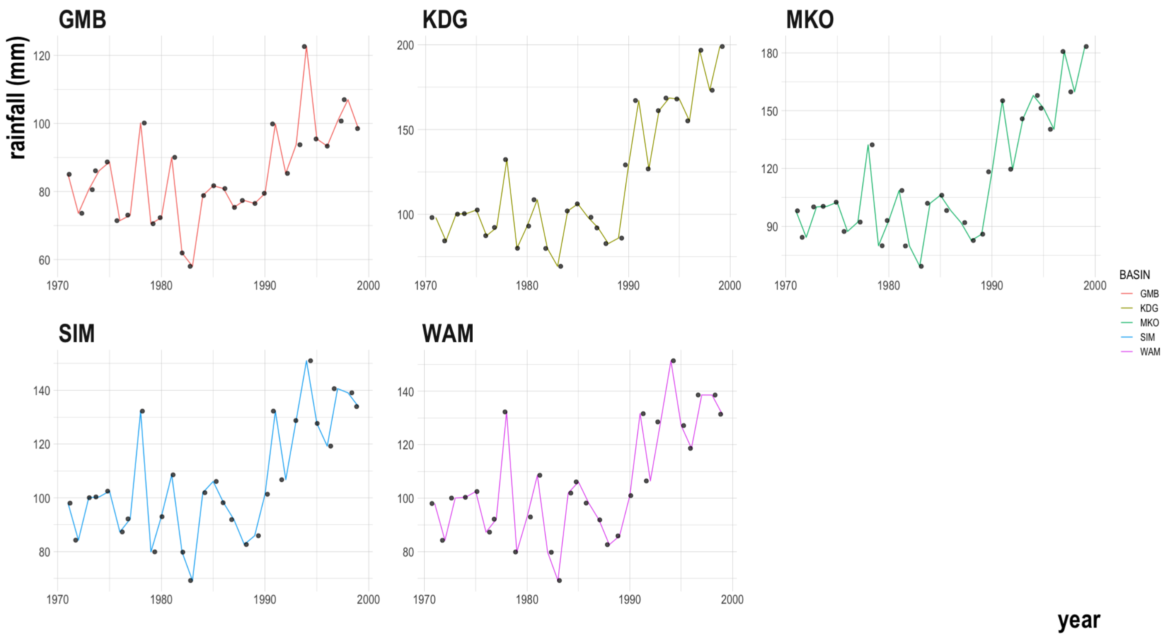



Figure 2.3: Mean Annual Runoff, GMB(Gouloumbou), KDG(Kedougou), MKO(Mako), SIM(Simenti), WAM(Wassadou-Amont), WAV(Wassadou-Aval)

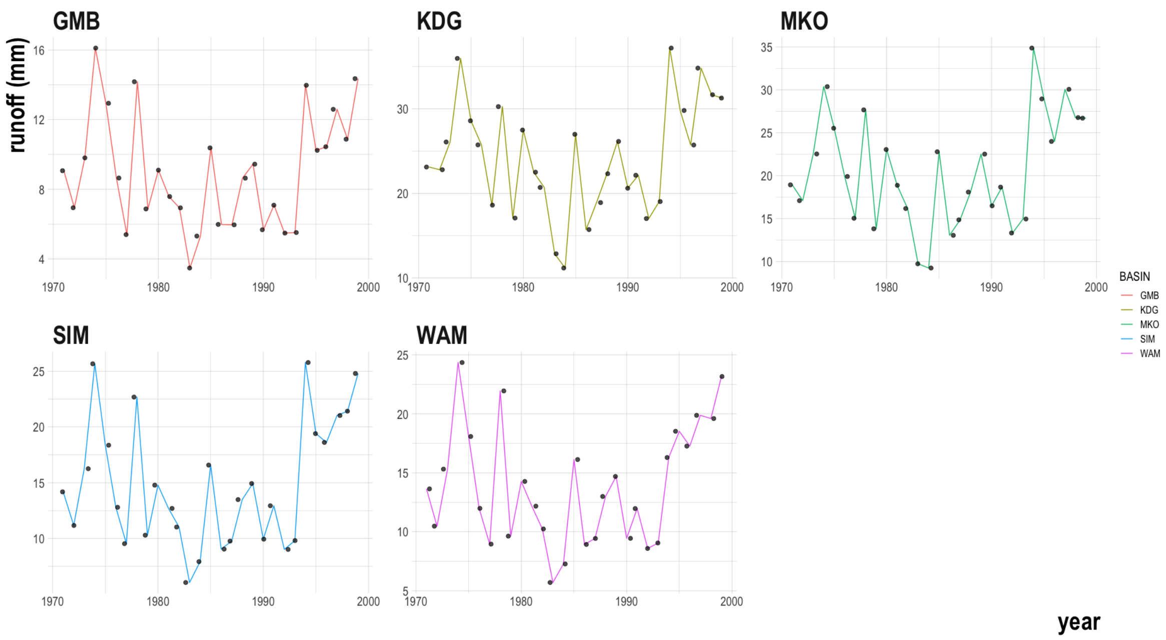
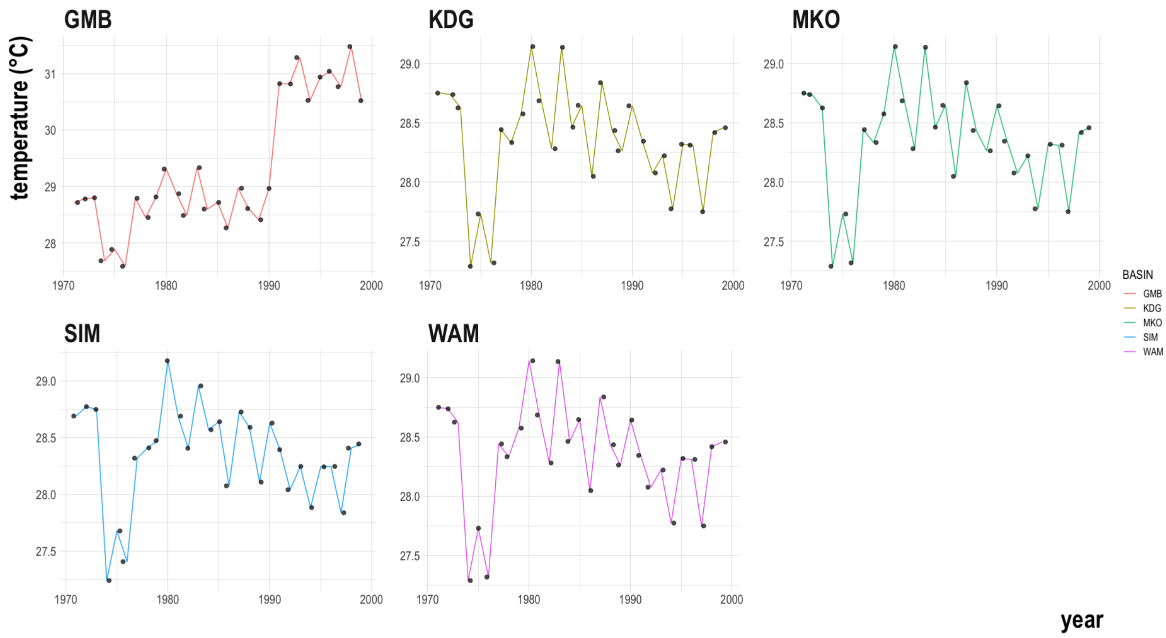


Figure 2.4: Mean Annual Temperature, GMB(Gouloumbou), KDG(Kedougou), MKO(Mako), SIM(Simenti), WAM(Wassadou-Amont), WAV(Wassadou-Aval)




### 2.2.4 Catchments delineation

A watershed (also called drainage basin, river basin, or catchment) is (Dingman 2015), the area that topographically appears to contribute all the water that passes through a specified cross section of a stream (the outlet). Watershed delineation starts with the outlet selection, which is the lowest point in the edge of a watershed where water flows out of the watershed. This location (outlet) is determined by the purpose of the analysis thus for quantitative water budgets research or stream response, the outlet typically is a stream-gauging station where streamflow is constantly monitored. The outlets are generaly located on stream junctions or where a stream joins a lake or an ocean for geomorphic study of ecosystems and stream networks. For various water resource analyses the outlet may be at a hydroelectric plant, a reservoir, a waste-discharge site, or a location where flood damage is of concern or a hydroelectric plant, canal, waste-discharge site, or place where flood risk is of significance for different water supply analyzes (Dingman 2015). In recent years, automated watershed delineations for digital elevation models (DEM), which are electronic data files on grid-point elevations, have evolved steadily and are typically accurate. The DEM elevations are based on radar reflections obtained by the satellite. In general, the original data includes many errors attributable to trees, regions with topographic shade of radar, lack of reflection of the water surface and other effects. Several web-based systems include automatic watershed delineation. In this study, catchment delineation

is performed using Qgis software (QGIS Development Team 2009) and a methodology proposed in the book Qgis for hydrological applications (Van der Kwast et al. 2019) by Dr. Hans Van der Kwast and Dr. Kurt Menke from IHE Delft Institute.
The modeling steps associated with this task include:

- Downloading our research area's DEM tiles (this can be achieved by using Qgis SRTM plugging or downloading raster files from the USGS Earth Explorer website: https:/earthexplorer.usgs.gov/),
- Fusion of tiles to build a new single DEM layer raster (mosaic),
- Reprojecting the DEM layer to the projection used for the study area,
- Subseting (clip) the DEM layer to a smaller area to reduce calculation time,
- Making hydrological DEM right by filling sinks and removal of spikes from the raw DEM (Wang and Liu algorithm is used in this case),
- Calculating the flow direction for each cell,
- Calculating the flow accumulation for each cell: how many upstream cells contribute to the runoff in each downstream cell of the DEM,
- Deriving the drainage network,
- Then calculating the catchment for the outflow point of the catchment.

For any time period of length ($\Delta$t) one can write the water-balance equation as :

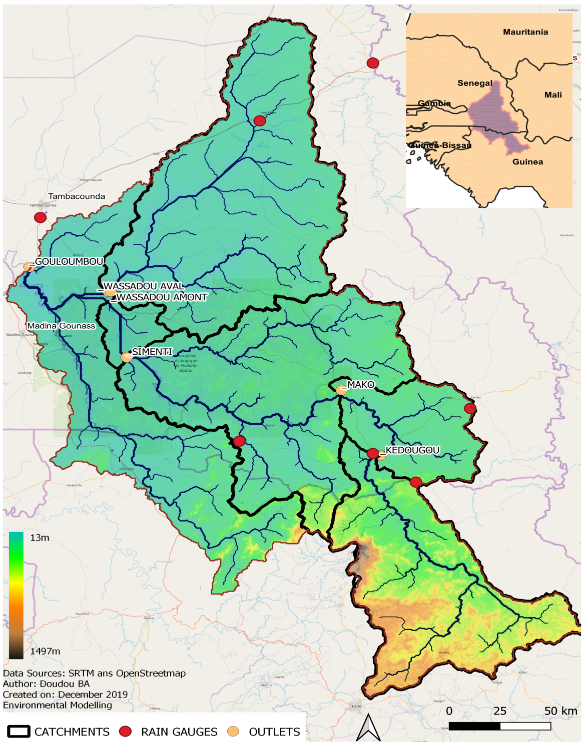
$$\Delta S = P + GWin - (ET + Q + GWout) \tag{2.1}$$

where P is precipitation (liquid and solid), GWin is ground-water inflow (liquid), Q is stream outflow (liquid), GWout is ground-water outflow (liquid), and $\Delta$S is the change in all forms of storage (liquid and solid) over the time period. ET is evapotranspiration, the total of all water that leaves a region as vapor via direct evaporation from surface-water bodies, snow, and ice, plus transpiration (water evaporated after passing through the vascular systems of plants). The sum of streamflow and ground-water outflow (Q + GWout) is called runoff.

### 2.2.5 Thiessen polygones to estimate the areal precipitation, temperature

Radar and satellite measurements provide valuable information about areal precipitation extent and are increasingly used along with gauge

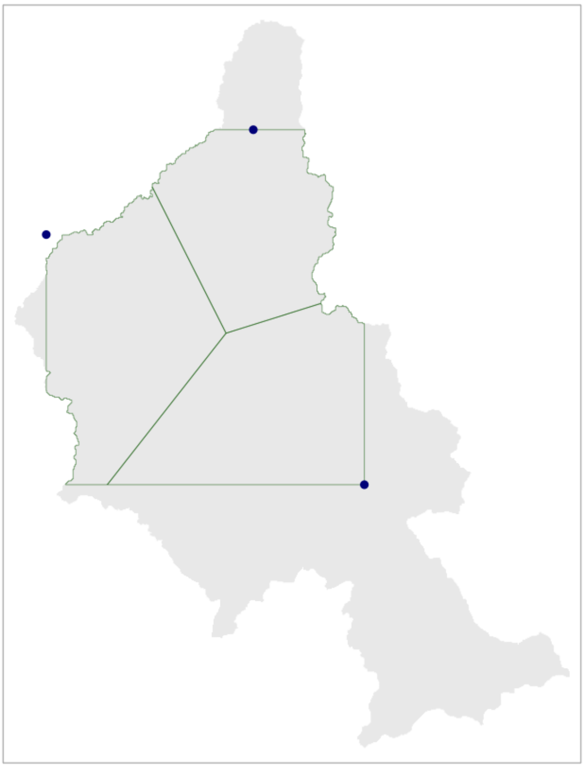
Figure 2.5: DEM of 6 Subcatchments of the Gambia river basin.




measurements to develop information on spatial distribution. However, rain gauges typically have the most precise measurements and are usually the only historical source of information; hence methods that extract calculations of spatial distribution using only measurements remain important instruments.

Hydrologists are more involved in precipitation and temperature across an area than at a location. The long term average precipitation over a watershed, lake, or ground-water recharge area is the input to water balance computations. In the litterature several methods for Areal Estimation from Point Measurements are proposed among others such as Direct Weighted Averages Methods (Arithmetic Average, Thiessen Polygons, Two-Axis Method, Hypsometric Method) and Spatial Interpolation (Surface Fitting). In this study, the Direct Weighted Average Method of Thiessen Polygons is used to estimate the areal estimation of precipitation and temperature. In this method, it is presumed that the precipitation is better measured by the calculation nearest to the point. The area is then divided into G subregions based on any gauge, and the subregions are specified such that all points in each subregion are nearer to their central gauge than every other gauge. Once these subregions are identified and their areas, ag, measured, the weights are determined as wg = ag/A and the spatial average is computed as follows:

Figure 2.6: Areal Estimation of Temperature using thiessen polygons



### Estimation of the Potential Evapotranspiration

To simulate rainfall runoff model, monthly rainfall and potential evapotranspiration are needed. In the literature, there are several methods to estimate the Potential Evapotranspriration (PET). The FAO-56 Penman Monteih method is the recommended by the Food and Agriculture Organization (FAO). However, they require a great deal of climate data (wind speed, temperature, relative humidity, solar radiation) that were not available in this area. Thus, in this study is used the method derived by (Oudin et al. 2010), which only require air temperature and the latitude at the catchment outlet.

$$PET(i) = \begin{cases} \dfrac{0.408 * Re * (T(i) + 5)}{100} \\ \quad if T(i) + 5 > 0, \\ 0 \\ \quad if T(i) + 5 <= 0 \end{cases} \tag{2.2}$$

where Re denotes extraterrestrial radiation [MJ,m-2d-1] and T the air temperature(°C).

$$Re(i) = \frac{24.60}{\pi} * Gsc * dr[\omega s * sin\phi * sin\delta + cos\phi * cos\delta * sin\omega s] \tag{2.3}$$

where Gsc is a solar constant (0.082 MJ,m-2min-1), dr is the inverse relative distance Earth-Sun

$$dr = 1 + 0.033 * cos(\frac{2\pi}{365}J) \tag{2.4}$$

where J is number of the day in the year, $\delta$ is the solar declination (angular distance to the equator) [rad]

$$\delta = 0.409 * sin(\frac{2\pi}{365}J - 1.39) \tag{2.5}$$

ωs the sunset hour angle [rad]

$$\omega s = arccos[-tan\phi tan\delta] \tag{2.6}$$

and $\phi$ the catchment latitude [rad].

## 2.3 Hydrological models

There are several models used in hydrological modeling. Two lumped conceptual models are tested this study: The GR2M which successfully simulates streamflow in a West African context [Ardoin-Bardin et al. 2009; Bodian, Dezetter, Deme, et al. 2016; TRAORE 2014b; Marie-Rosine et al. 2020] and BILAN model which successfully simulates hydrological balance in Czech and European river basins but has not yet been experimented in African basins. The BILAN model is used to simulate the hydrological balance in Czech and European river basins in a number of applied research projects and hydrological studies. Example of studies where the BILAN model is used can be found in [Máca et al. 2013; Hanel et al. 2012; Vizina, Horáček, et al. 2015].

### 2.3.1 BILAN model

Bilan (Tallaksen et al. 2004) is a conceptual model developed and used at the T. G. Masaryk Research Institute of Water Management since the 1990s to simulate water balance components in a catchment. The model framework consists of a set of relations that determine fundamental concepts of water balance on the land, in the aeration zone, including vegetation cover and groundwater impact. Input data used to simulate water balance is daily or monthly time series of precipitation, air temperature and relative humidity (optional). The calibration of model parameters (applying optimization algorithm) (Máca et al. 2013) is performed using daily (monthly) observed and simulated runoff time series at the basin outlet. The model simulates daily (monthly) time series of potential evapotranspiration, actual evapotranspiration, infiltration to the soil and recharge from the soil to the aquifer. The total runoff consists of two components, which are fast runoff (direct runoff and inter flow) and slow runoff (base flow). The model has six (daily time

step) or eight (monthly time step) free parameters optimized to achieve the best match between the observed and simulated runoff.
In 2011, the original implementation of the BILAN model, written in the Pascal, was rewritten in C ++, which significantly simplified the further development of the model. Two interfaces to the model were created (described by (Beran et al. 2011)): a graphical user interface (GUI) based on the multi platform Qt library and a package for the statistical and programming environment R (R Core Team 2017). The R package allows advanced users to take advantage of bulk model processing and scripting combined with extensive capabilities provided by their own R. The newly implemented optimization algorithm using evolutionary methods was described separately (Máca et al. 2013), which provides an overview of other new features and possibilities of the model. The basics of the interconnected BILAN model are presented in the article (Vizina and Hanel 2011). A comparison of the computational algorithm for the daily and monthly versions is discussed in (Horáček et al. 2009). The monthly version of the BILAN model consider eight parameters which are defined as follows:

- **Spa** capacity of soil moisture storage [mm],
- **Grd** parameter controlling outflow from groundwater storage (base flow),
- **Alf** parameter of rainfall-runoff equation (direct runoff),
- **Dgm** temperature/snow melting factor,
- **Dgw** factor for calculating the quantity of liquid water available on the land surface under winter conditions,
- **Soc** parameter controlling distribution of percolation into interflow and groundwater recharge under summer conditions,
- **Mec** parameter controlling distribution of percolation into interflow and groundwater recharge under conditions of snow melting,
- **Wic** parameter controlling distribution of percolation into interflow and groundwater recharge under winter conditions.

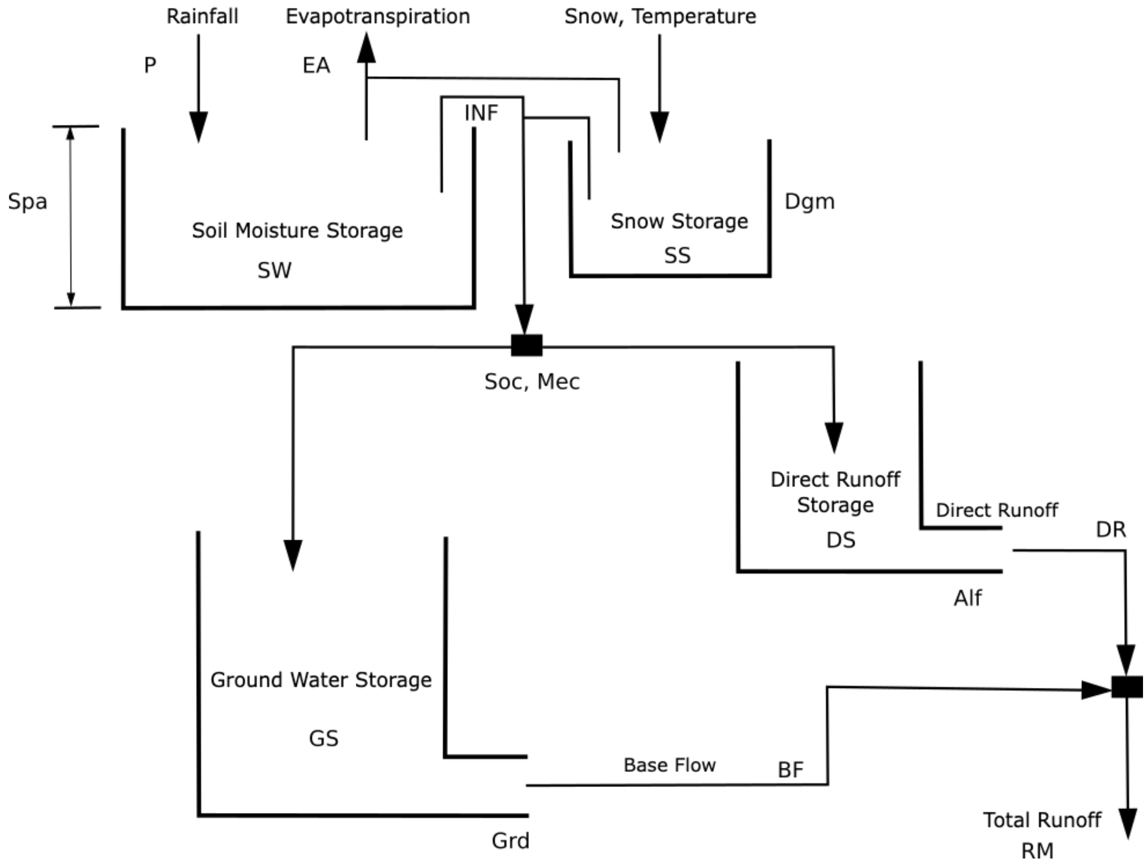
The model simulates the total runoff RM(i) as the sum of two components:

$$RM(i) = DR(i) + BF(i) \tag{2.7}$$

where *DR(i)* and *BF(i)* are direct runoff and base flow, respectively. Direct runoff occurring during the summer season due to heavy rainfall is calculated as:

$$DR(i) = Alf * P(i)^2 * \frac{SW(i-1)}{Spa} \tag{2.8}$$

Figure 2.7: Diagram of Bilan model description




where Alf is a parameter of the quadratic rainfall-runoff relationship between direct runoff and rainfall, P(i) is precipitation in the month i, SW(i − 1) is soil moisture in the month i − 1, and Spa is a parameter expressing soil moisture capacity. The precipitation reduced by the direct runoff

$$INF(i) = P(i)DR(i) \tag{2.9}$$

becomes a component of water balance in the zone of aeration.
A more detailed description of the BILAN model can be found in the T. G. Masaryk Water Research Institute website.

### 2.3.2 GR2M model

The structure of GR2M Mouelhi 2003 is based on a production store which capacity is controlled by the parameter X1 and actual contents S; and a routing store of a capacity set to 60 mm and actual contents is R, the exchange coefficient is controlled by parameter X2 (-). The production function relies on a soil moisture store.
For a precipitation P, the store level S becomes S1 and is determined by:

$$S1 = (S + X1\Phi)/(1 + \Phi(S/X1)) \tag{2.10}$$

$$\Phi = tanh(P/X1) \tag{2.11}$$

Where X1 in mm is the maximum capacity of the store (positive).
The excess rainfall P1 is calculated by:

$$P1 = P + SS1 \tag{2.12}$$

Given the potential evapotranspiration E, the level S1 becomes S2:

$$S1 = (S + 1 - \Omega)/(1 + \Omega(1 - S/X1)) \tag{2.13}$$

$$\Omega = tanh(E/X1) \tag{2.14}$$

The production store then empties with a percolation P2 and its level S, ready for the computations of the following month, given by:

$$S = S2/[(S2/X1)] \tag{2.15}$$

and

$$P2 = (S2 - S) \tag{2.16}$$

The total precipitation P3 that reaches the routing store is given by:

$$P3 = P1 + P2 \tag{2.17}$$

The level R in the routing store then becomes R1:

$$R1 = R + P3 \tag{2.18}$$

A water exchange term is then calculated:

$$F = (X21) \times R1 \tag{2.19}$$

The parameter X2 is positive and is dimensionless. The store level then becomes:

$$R2 = X2 \times R1 \tag{2.20}$$

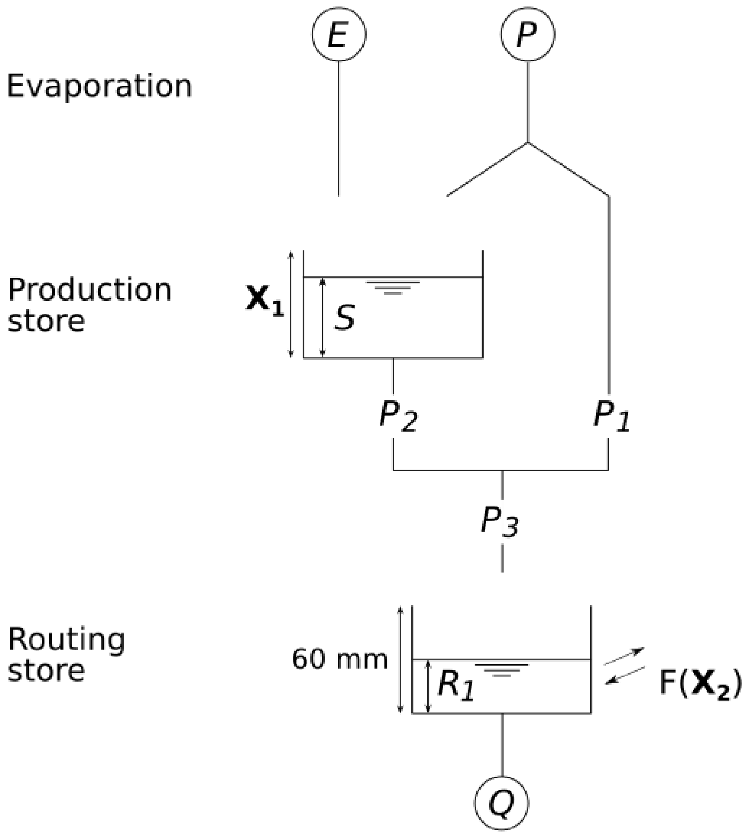
The store, with a fixed capacity equal to 60 mm, empties following a quadratic function.
The streamflow is given by:

$$Q = R2/(R2 + 60) \tag{2.21}$$

The model has two parameters to optimise during its calibration:
X1 : the capacity of the production store (mm),
X2 : the exchange coefficient (-).

The R version, airGR (Coron, Thirel, et al. 2017), was developed at the INRAE-Antony (formerly IRSTEA, HYCAR Research Unit, France), including seven rainfall-runoff models at hourly, daily, monthly and annually time step (GR4H, GR5H, GR4J, GR5J, GR6J, GR2M, GR1A) and a snow accumulation and melt model (CemaNeige). Each model core is coded in FORTRAN to ensure low computational time when mainly the calibration algorithm and the computation of the efficiency criteria are coded in R.
A more detailed description of the model is available in webgr.inrae.fr

Figure 2.8: Diagram of GR2M model description, *Source: inrae.fr*



## 2.4 Calibration and validation strategies

The method adopted in this work involves the following steps: (1) selection of calibration period; (2) calibration and validation of hydrological models; (3) Evaluation of calibrated parameters transferability.

### 2.4.1 Calibration of Hydrological models

This subsection includes the selection of the calibration period and calibration approach.

#### Selection of calibration period

In the context of (Andréassian et al. 2009)'s discussion on model evaluation, (Coron, Andréassian, et al. 2012) implemented a "crash test" methodology for models to be used in changing climatic conditions. Example of application of such methodology can be found in (Vormoor et al. 2018). This study follows the Generalized Split Sample Test (GSST) methodology proposed in (Coron, Andréassian, et al. 2012) and (Vormoor et al. 2018). The methodology can be described as follows:

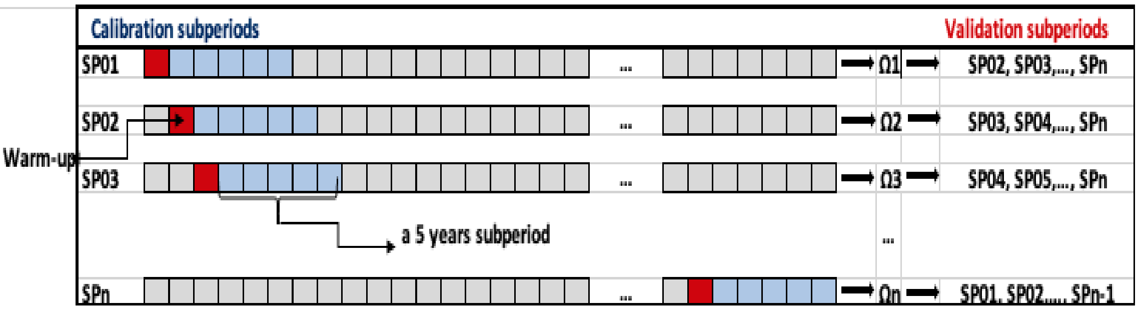
- The selection of the calibration period starts with estimation of the length of our times Series,
- Then the hydrological year is determined, and based on a particular (mean rainfall, areal temperature, average rainfall), the type of drought is selected by considering Dry years as the quantiles under twenty (20) and quantiles above eighty (80) meaning Wet years,
- Then based on the type of drought a certain number of sub-periods selected are applied the calibration-validation test.

It's important to note that the drought referring to dry or wet years doesn't necessarily indicate a period of higher or lower temperature, that might have a misleading sense in this study, drought is utilized for periods selected based on quantiles of climate characteristics (rainfall, runofff, temperature). periods of quantiles under twenty (20) being "Dry years" and periods of quantiles aboveeighty (80) being "Wet years".

The validation performances are balanced to evaluate whether they vary significantly when climatic characteristics differ between calibration and validation periods.

The GSST scheme consists of a sequence of sub-periods of same length calibration validation tests that take into account all possible configurations. To define sub-periods, a sliding window of the selected length is used. Between two periods, the window moves by 1 year, allowing the sub-periods to overlap, for each sub-period is considered a 1 year of warming period for instance for k=2 (k being the window), and a sub-period extent between 1993-1994, the preceding year (in this case 1992-1993) is always considered as warm up period. It's important to note that "Dry Years" in this analysis are distinct to "Wet Years" and they never overlap. For each calibration sub-period, the optimized parameter set is used to perform all the possible validation tests on independent sub-periods. Validation sub-periods overlapping with the calibration one are not considered to ensure strict independence of calibration and validation conditions 2.9. It's important to precise that the number of validation tests will differ for all calibration periods.

Figure 2.9: Illustration of the methodology of generation of sub-periods with a 5 year sliding window based on the principles of the split-sample test and the differential split-sample test (KlemeŠ 1986). The generalization of those schemes, i.e. the 5-year moving window, adapted from (Coron, Andréassian, et al. 2012) and (Vormoor et al. 2018).




where SPn is the Sub-Period the calibration is performed, $\Omega n$ the parameter set.

### Calibration approach

To calibrate our models monthly time series of rainfall (P) and potential evapotranspiration (PET) are needed. Monthly time series of runoff (R) will allow the model to compare the simulated runoff (Rsim) to the observed runoff (Robs). A one year warming period is created using KGE as the objective function. Next step is to set up the lower and upper boundaries of model's parameters.
For BILAN model, three major parameters are considered: The parameter controlling the capacity of soil moisture storage [mm] Spa (100, 2000), the parameter controlling the baseflow Grd (0.001, 1) and the parameter controlling the direct runoff) Alf (0.00001, 0.003) described earlier, that have impact in the runoff simulation accordingly to the geographical conditions.
It's important to note that we are in a West African (Senegal) context without snow that knows only two seasons: A Dry season that is longer with almost without rain that counts for 7 months and a rainy season that is shorter and counts for 5 months, other parameters are left default. For GR2M model that counts only 2 parameters: A parameter X1 controlling production store capacity and X2 which controls the exchange coefficient.

The most important part which is the model calibration applying optimization algorithm is crucial since this is how the best model parameters are estimated and selected. The calibration algorithm optimises the error criterion selected as objective function here the KGE.
To BILAN model is applied the Differential Evolution method (DE optim) (Mullen et al. 2011) which performs a global evolutionary optimization. The *ens-count*, which controls the number of times a single model is run and a set of parameters returned is left equal to 1 since from our observation for a 30 times *ens-count* the model returned exactly the same parameters, it was more efficient to reduce the computation time with a single parameter set return per model. For GR2M model the calibration Michel algorithm (Michel 1991) proposed in the airGR package that combines the global and local approach was used.

A screening is first performed either based on a rough predefined grid (considering various initial values for each parameter) or from a list of initial parameter sets. The best set identified in this screening is then used as a starting point for the steepest descent local search algorithm. For this search, since the ranges of parameter values can be quite different, simple mathematical transformations are applied to parameters to make them vary in a similar range and get a similar sensitivity to a predefined search step.

This is done using the TransfoParam functions. During the steepest descent method, at each iteration, starting from a parameter set of NParam values (NParam being the number of free parameters of the chosen hydrological model) and we determine the 2*NParam-1 new candidates by changing one by one the different parameters (+/- search step). All these candidates are tested and the best one kept to be the starting point for the next iteration.

At the end of each iteration, the the search step is either increased or decreased to adapt the progression speed. A composite step can occasionally be done. The calibration algorithm stops when the search step becomes smaller than a predefined threshold.

The model output is collected and with the hydroGOF package the model efficiency is determined using 3 criteria: The Kling Gupta Efficiency (KGE), the Nash-Sutcliff Efficiency (NSE) and the Root Mean Square Error (RMSE).

The calibration model code can be found in the appendix.

Automated calibration was used in the GR2M model by iteratively adjusting the parameter values until the minimum value of the selected objective function was achieved.

### 2.4.2 Methodology to Analyze the Results

Model performance criteria are often used during calibration and evaluation of hydrological models, to express in a single number the similarity between observed and simulated discharge GUPTA200980.

- NSE: Nash–Sutcliffe efficiency (NSE, Nash and Sutcliffe, 1970)

$$NSE = 1 - \frac{\sum_{i=1}^{n}((Rsim - Robs)^2}{\sum_{i=1}^{n}(Robs - \overline{Robs})^2} \tag{2.22}$$

where $Rsim$ is the simulated runoff, $Robs$ the observed runoff, and $\overline{Robs}$ the mean observed runoff.

- KGE: The Kling–Gupta efficiency (KGE; Eq. 2, Gupta et al., 2009)

$$KGE = 1 - \sqrt{(r-1)^2 + (\frac{\sigma sim}{\sigma obs} - 1)^2 + (\frac{\mu sim}{\mu obs} - 1)^2} \tag{2.23}$$

where $r$ is the linear correlation between observations and simulations, $\sigma obs$ is the standard deviation in observations, $\sigma sim$ the standard deviation in simulations, $\mu sim$ the simulation mean, and $\mu obs$ the observation mean (i.e. equivalent to $\overline{Robs}$).

A KGE or NSE = 1 indicates perfect correspondence between simulations and observations; a KGE or NSE = 0 indicates that the model simulations have the same explanatory power as the mean of the observations; and KGE or NSE < 0 indicates that the model is a worse predictor than the mean of the observations.

- RMSE: The root-mean-square error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(Rsim - Robs)^2} \tag{2.24}$$

$Rsim$ and $Robs$ being respectively the simulated and observed runoff.

- MRC:

The performance losses associated with the optimized parameters transfer to (in)dependent validation periods are assessed using MRC criterion proposed by (Coron, Andréassian, et al. 2012).

$$MRC_{C-V} = \frac{\varepsilon_C}{\varepsilon_V} - 1 \tag{2.25}$$

Where epsilon is the performance criterion (in this case RMSE) to be maximized during the calibration. The MRC theory (Vormoor et al. 2018) is that the set of calibration optimized parameters are used as a “donor” in an independent validation period which will be the

| Criterion | Range | good if | Units |
|---|---|---|---|
| NSE | $(-\infty,1)$ | 1 | [-] |
| KGE | $(-\infty,1)$ | 1 | [-] |
| RMSE | $(0, \infty)$ | 0 | [OBS] |

"receiver". Consequently, the MRC reflects the ability of the parameter set optimized on the calibration (donor) period C to simulate discharge, and particularly high flows, on the validation (receiver) period V. A null MRC-value indicates that the parameter set optimized on the Calibration period performs as well as the parameters estimated on the Validation period, while negative values indicate a decrease in the suitability of the parameter sets for the validation period. The more negative the MRC is, the less transferable the parameter set is, and a MRC-value of, say $-0.2$ means a 20 percent performance loss. A positive MRC estimate, would mean that the parameter set from the period C performs better on the period V.

# Chapter 3

# Results

In this chapter following results are presented:

- The calibration performance of BILAN and GR2M models,
- The Impact of the Drought on calibration performance,
- The optimized parameters transferability from calibration to validation period.

## 3.1 Calibration Performance

This section describes the calibration performance of BILAN and GR2M models when the simulation time series length is extending.

Figure 3.1 and 3.2 represent the box-plots of the overall calibration performance performance of respectively BILAN and GR2M model over a set of six catchments of the Gambia river basin selected in this study.

The Y axis representing the KGE which is the objective function used for the calibration. The X axis represent the sub-periods discussed on the previous chapter 2.9, which is selected on a particular climate characteristic (P,T,R) according to a drought type (either Dry or wet) and a sliding window from k=2 meaning a 2 year sub-period to k=7 that is a 7 year sub-period always with a one year of warming period. For instance for an in-dependant sub-period PD-5, P is the precipitation (T and R would mean respectively temperature and runoff) as climate characteristic selection based, D means selected on Dry year (eventually W would mean wet period) and 5 refers to a sub-period of 5 years.

Overall fair to very good calibration results are obtained for both models with KGE values ranging from a minimal value of KGE of 0.66 obtained at a 5-year Wet-Sub-Period selected on the precipitation to the highest value of 0.92 obtained at 3-year Dry-Sub-Period selected based on the runoff for the BILAN model 3.1.

Figure 3.1: Boxplot of overall Calibration Performance of BILAN model

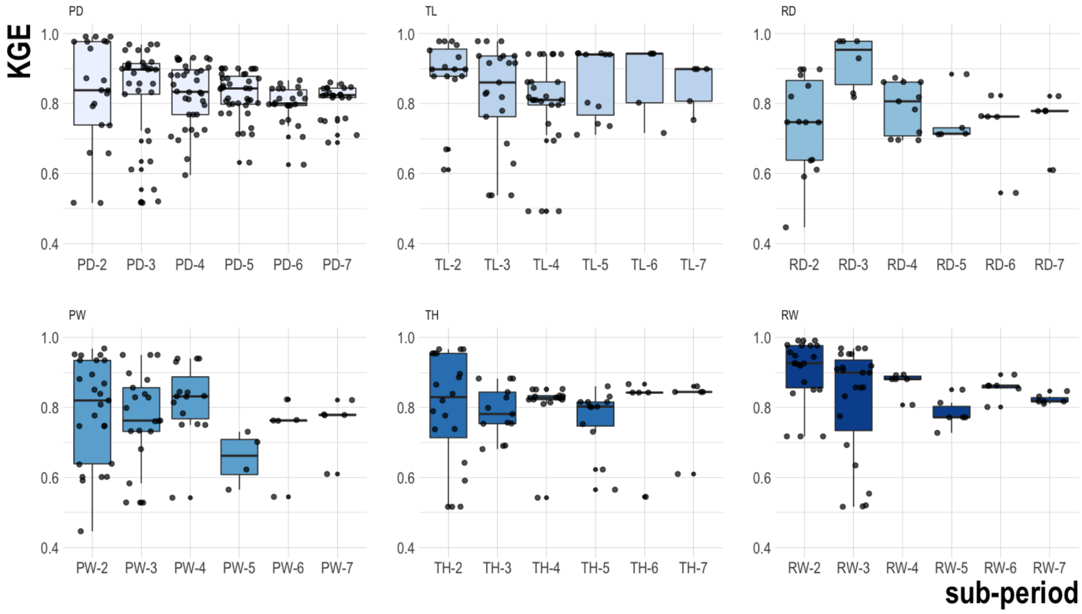
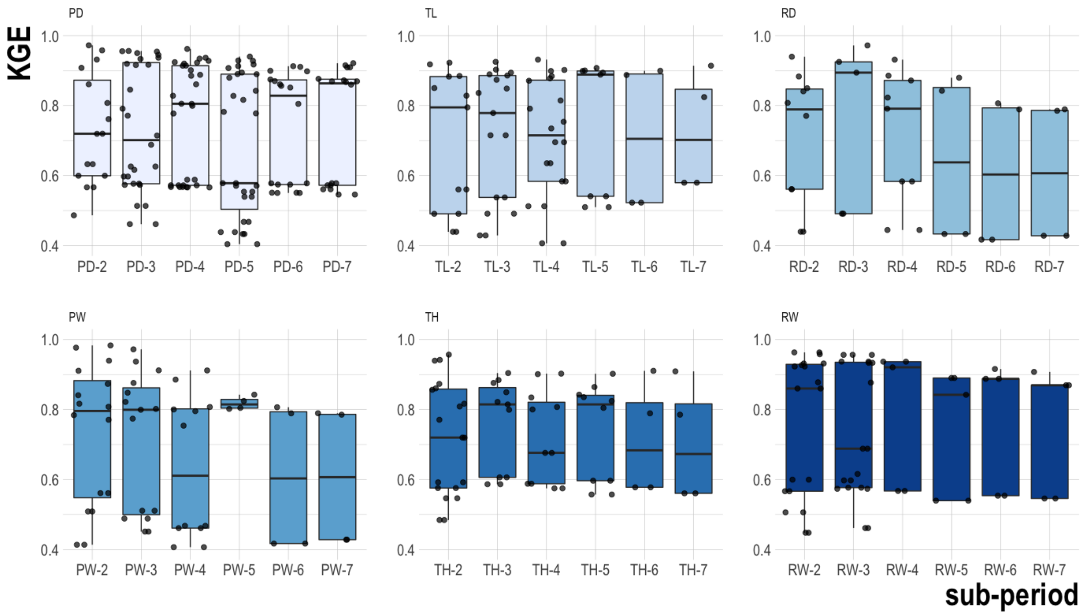



Figure 3.2: Boxplot of overall Calibration Performance of GR2M model



Tables 3.1 and 3.2 give insight into the overall calibration performance of BILAN and GR2M models over a set of six catchments of the Gambia river basin in terms of KGE, NSE, and RMSE.

For the GR2M model, the KGE ranges from the lowest value of 0.61 obtained at 6 and 7-year dry-sub-period selected on runoff (RD6 and RD7) and a maximal value of 0.79 obtained at a 4-year Wet-Sub-Period runoff based (RW4) 3.1.

Overall, the results highlight that and for both hydrological models, the calibration performance decreases as the simulation period length increases.
The box plots in figures 3.1 and 3.2 illustrate the distribution of the overall calibration performance of both models in terms of KGE over six catchments of the Gambia river basin for all 7-year moving window of each climate characteristic derived on the drought type.

For the BILAN model it is noticed an average overall decrease of 0.0009% per sub-period with respectively for PDs, PWs, RWs, TLs an average decrease per K (-.55%, -.25%, -1.56%, -.67%) and an average increase of 0.99% and 2% at RDs and THs. The GR2M model shows an average decrease of 0.006% with an increase of (0.48%, 0.016% and 0.81%) in PDs,PWs and TLs and a decrease of (-0.88%, -0.11% and -0.35%) at RDs, RWs and THs.

However the validation Performance appears poor to good for the GR2M model, KGE values ranging from -0.17 obtained at a 4-year Wet-Sub-Period (PW4) as the poorest result obtained and a maximal value of 0.63 obtained at RW6 and TL5. Lowest and Highest values of KGE are obtained both for shorter and longer time series 3.4.
The BILAN model showing the poorest value of validation KGE of (-6.34, -5.58, -5.31, -2.91, -1.43) obtained at (TH2, TL2, PD2, RW2, RD2) which are either dry or wet periods selected from all climate variables (P,T,R) but are all of a 2-year sub-period followed by the 3-year Sub-Periods with second lowest values ranging from (0.21 to 0.46) and the best values of (0.70, 0.42, 0.57, 0.74, 0.71, 0.76) obtained respectively at (7, 5, 4, 6, 6, 6)-year sub-period which may lead to think that the BILAN model might during validation period simulate better longer period time series than the shorter ones (2 or 3-year).
This result can be even proven by the validation performance Box-Plot 3.3 which demonstrates a tendancy of increase of the validation performance of BILAN model, for all Sub-Period except the Wet-Sub-period Precipitation based (PW). An average validation performance increase is though noticed in the rate of 0.45% for the BILAN model and a decreasal of GR2M validation performance of -25% per sub-period. validation variation rates are as follow and respectively for BILAN and GR2M model PD (3.66, 37.36) , PW (24.78%, -134.44%) , RD (-2.23% , -85.39%) , RW (-8.08%, 15.21%), TH (-11.57%,4.29%) and TL ( -3.84%, 10.84%), a positive value meaning an improvement and a negative value meaning

Table 3.1: Overall Calibration Performance of BILAN and GR2M models

| Period | BILAN | | BILAN | BILAN | GR2M | GR2M | GR2M |
|---|---|---|---|---|---|---|---|
| | K | KGE | NSE | RMSE | KGE | NSE | RMSE |
| PD | 2 | 0.83 | 0.72 | 8.98 | 0.73 | 0.71 | 11.72 |
| | 3 | 0.83 | 0.69 | 10.29 | 0.73 | 0.70 | 11.49 |
| | 4 | 0.83 | 0.70 | 11.66 | 0.76 | 0.72 | 11.25 |
| | 5 | 0.83 | 0.71 | 15.50 | 0.68 | 0.64 | 17.61 |
| | 6 | 0.80 | 0.64 | 13.94 | 0.74 | 0.69 | 12.45 |
| | 7 | 0.81 | 0.67 | 13.69 | 0.74 | 0.69 | 12.60 |
| PW | 2 | 0.79 | 0.66 | 20.30 | 0.66 | 0.64 | 21.58 |
| | 3 | 0.77 | 0.62 | 21.15 | 0.67 | 0.65 | 20.80 |
| | 4 | 0.82 | 0.74 | 17.93 | 0.64 | 0.61 | 22.31 |
| | 5 | 0.66 | 0.53 | 13.19 | 0.82 | 0.85 | 6.61 |
| | 6 | 0.73 | 0.65 | 21.73 | 0.61 | 0.58 | 24.09 |
| | 7 | 0.75 | 0.66 | 20.48 | 0.61 | 0.59 | 23.03 |
| RD | 2 | 0.74 | 0.62 | 21.42 | 0.65 | 0.64 | 20.66 |
| | 3 | 0.92 | 0.87 | 10.76 | 0.75 | 0.74 | 17.81 |
| | 4 | 0.79 | 0.69 | 18.77 | 0.71 | 0.69 | 18.01 |
| | 5 | 0.75 | 0.69 | 20.39 | 0.65 | 0.63 | 21.93 |
| | 6 | 0.73 | 0.65 | 21.73 | 0.61 | 0.58 | 24.09 |
| | 7 | 0.75 | 0.66 | 20.48 | 0.61 | 0.59 | 23.03 |
| RW | 2 | 0.91 | 0.82 | 8.22 | 0.76 | 0.73 | 11.56 |
| | 3 | 0.82 | 0.66 | 10.25 | 0.73 | 0.70 | 11.22 |
| | 4 | 0.87 | 0.77 | 9.85 | 0.79 | 0.74 | 10.42 |
| | 5 | 0.78 | 0.62 | 13.33 | 0.74 | 0.69 | 11.71 |
| | 6 | 0.86 | 0.73 | 11.10 | 0.76 | 0.71 | 11.74 |
| | 7 | 0.82 | 0.68 | 12.67 | 0.75 | 0.69 | 12.20 |
| TH | 2 | 0.73 | 0.50 | 12.94 | 0.72 | 0.71 | 11.54 |
| | 3 | 0.79 | 0.65 | 14.44 | 0.76 | 0.74 | 12.19 |
| | 4 | 0.81 | 0.69 | 16.88 | 0.72 | 0.69 | 16.07 |
| | 5 | 0.77 | 0.63 | 15.32 | 0.74 | 0.72 | 12.42 |
| | 6 | 0.79 | 0.66 | 16.58 | 0.71 | 0.69 | 15.18 |
| | 7 | 0.80 | 0.66 | 15.77 | 0.70 | 0.67 | 14.97 |
| TL | 2 | 0.89 | 0.80 | 12.12 | 0.70 | 0.68 | 17.24 |
| | 3 | 0.82 | 0.70 | 16.29 | 0.72 | 0.70 | 17.50 |
| | 4 | 0.80 | 0.66 | 18.00 | 0.71 | 0.68 | 17.80 |
| | 5 | 0.86 | 0.77 | 14.02 | 0.73 | 0.71 | 17.35 |
| | 6 | 0.87 | 0.79 | 13.47 | 0.71 | 0.68 | 18.03 |
| | 7 | 0.85 | 0.74 | 16.50 | 0.72 | 0.69 | 18.33 |

Table 3.2: Overall Validation Performance of BILAN and GR2M models

| Period | BILAN K | BILAN KGE | BILAN NSE | BILAN RMSE | GR2M KGE | GR2M NSE | GR2M RMSE |
|---|---|---|---|---|---|---|---|
| PD | 2 | -5.31 | -43.92 | 24.89 | 0.47 | 0.58 | 14.72 |
| | 3 | 0.30 | -0.17 | 16.09 | 0.53 | 0.61 | 12.69 |
| | 4 | 0.62 | 0.50 | 15.36 | 0.51 | 0.65 | 12.63 |
| | 5 | 0.49 | 0.48 | 32.99 | 0.17 | 0.15 | 26.91 |
| | 6 | 0.69 | 0.54 | 16.56 | 0.59 | 0.64 | 12.71 |
| | 7 | 0.70 | 0.61 | 16.69 | 0.61 | 0.65 | 12.74 |
| PW | 2 | 0.14 | -1.85 | 28.33 | 0.23 | 0.35 | 28.41 |
| | 3 | 0.35 | 0.44 | 43.52 | 0.16 | 0.15 | 32.14 |
| | 4 | 0.34 | 0.49 | 46.50 | -0.17 | -0.31 | 40.82 |
| | 5 | 0.42 | 0.50 | 22.96 | 0.34 | 0.35 | 13.46 |
| | 6 | 0.29 | 0.42 | 55.50 | 0.12 | 0.03 | 34.98 |
| | 7 | 0.24 | 0.37 | 59.41 | 0.03 | -0.09 | 35.03 |
| RD | 2 | -1.43 | -9.13 | 31.87 | 0.28 | 0.36 | 26.63 |
| | 3 | 0.21 | -0.18 | 19.33 | 0.55 | 0.65 | 19.65 |
| | 4 | 0.57 | 0.56 | 32.87 | 0.19 | 0.07 | 29.22 |
| | 5 | 0.36 | 0.41 | 48.42 | -0.08 | -0.26 | 39.99 |
| | 6 | 0.29 | 0.42 | 55.50 | 0.12 | 0.03 | 34.98 |
| | 7 | 0.24 | 0.37 | 59.41 | 0.03 | -0.09 | 35.03 |
| RW | 2 | -2.91 | -22.24 | 22.32 | 0.35 | 0.48 | 14.51 |
| | 3 | 0.42 | -0.02 | 14.90 | 0.54 | 0.65 | 11.87 |
| | 4 | 0.74 | 0.68 | 13.57 | 0.43 | 0.65 | 11.94 |
| | 5 | 0.67 | 0.55 | 16.75 | 0.50 | 0.61 | 12.69 |
| | 6 | 0.74 | 0.65 | 14.44 | 0.63 | 0.67 | 11.66 |
| | 7 | 0.72 | 0.60 | 15.82 | 0.64 | 0.66 | 12.00 |
| TH | 2 | -6.34 | -72.81 | 24.12 | 0.39 | 0.44 | 15.50 |
| | 3 | 0.44 | 0.35 | 17.28 | 0.47 | 0.45 | 15.79 |
| | 4 | 0.46 | 0.28 | 22.45 | 0.44 | 0.53 | 18.25 |
| | 5 | 0.62 | 0.52 | 20.20 | 0.45 | 0.55 | 14.89 |
| | 6 | 0.71 | 0.58 | 20.04 | 0.50 | 0.54 | 16.62 |
| | 7 | 0.67 | 0.61 | 19.88 | 0.47 | 0.51 | 16.42 |
| TL | 2 | -5.58 | -38.91 | 29.70 | 0.45 | 0.59 | 19.03 |
| | 3 | 0.37 | 0.11 | 19.49 | 0.53 | 0.63 | 18.62 |
| | 4 | 0.64 | 0.56 | 25.22 | 0.38 | 0.43 | 22.45 |
| | 5 | 0.73 | 0.61 | 17.85 | 0.63 | 0.71 | 15.87 |
| | 6 | 0.76 | 0.66 | 16.68 | 0.52 | 0.64 | 17.46 |
| | 7 | 0.72 | 0.66 | 21.21 | 0.61 | 0.64 | 18.36 |

a loss between sub-periods.

Figure 3.3: Boxplot of overall Validation Performance of BILAN model

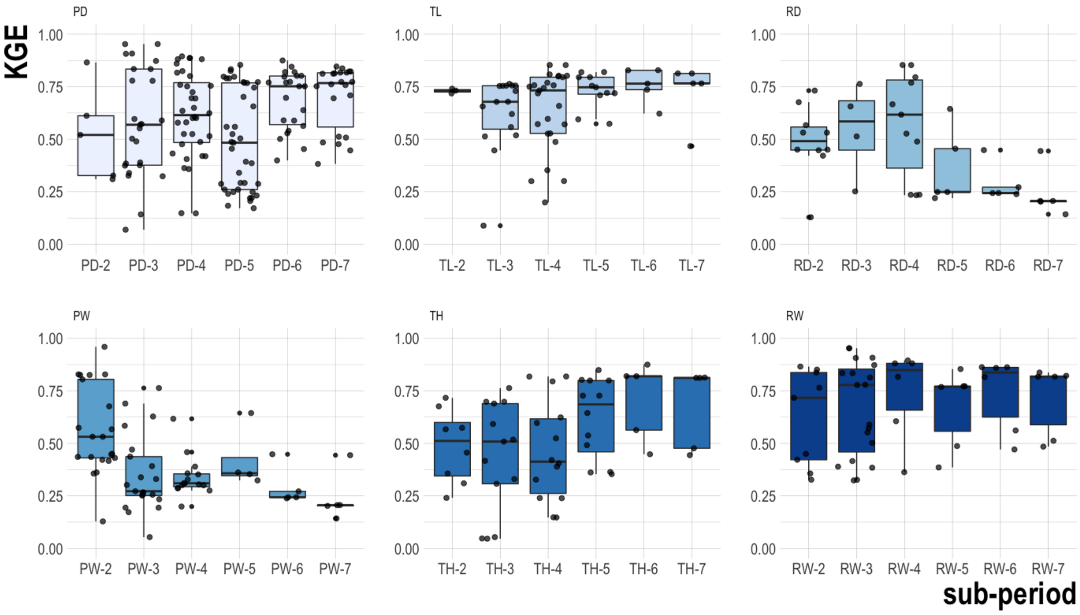
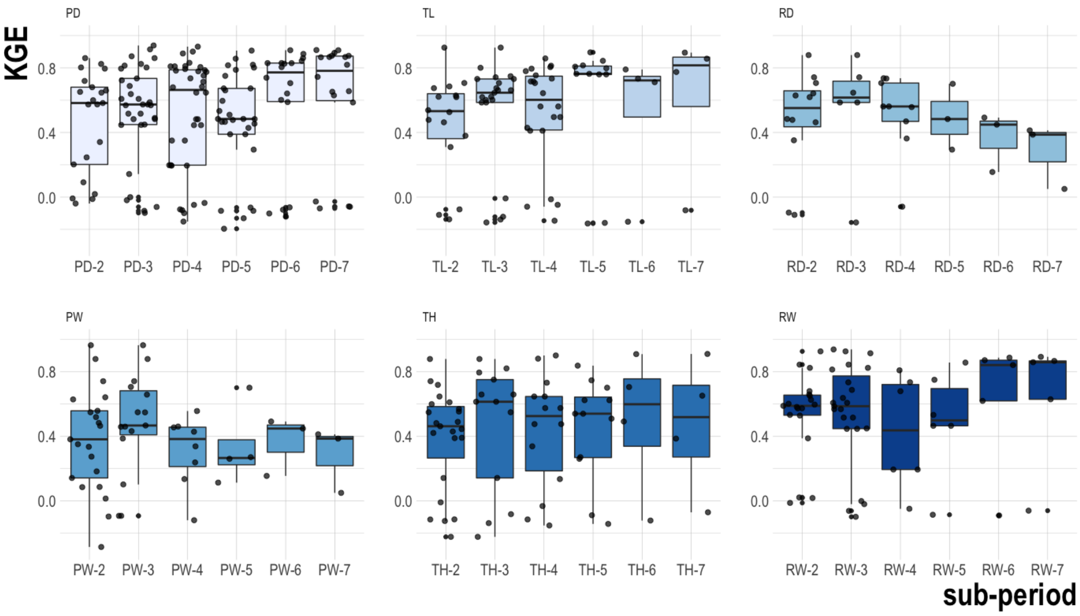



Figure 3.4: Boxplot of overall Validation Performance of GR2M model

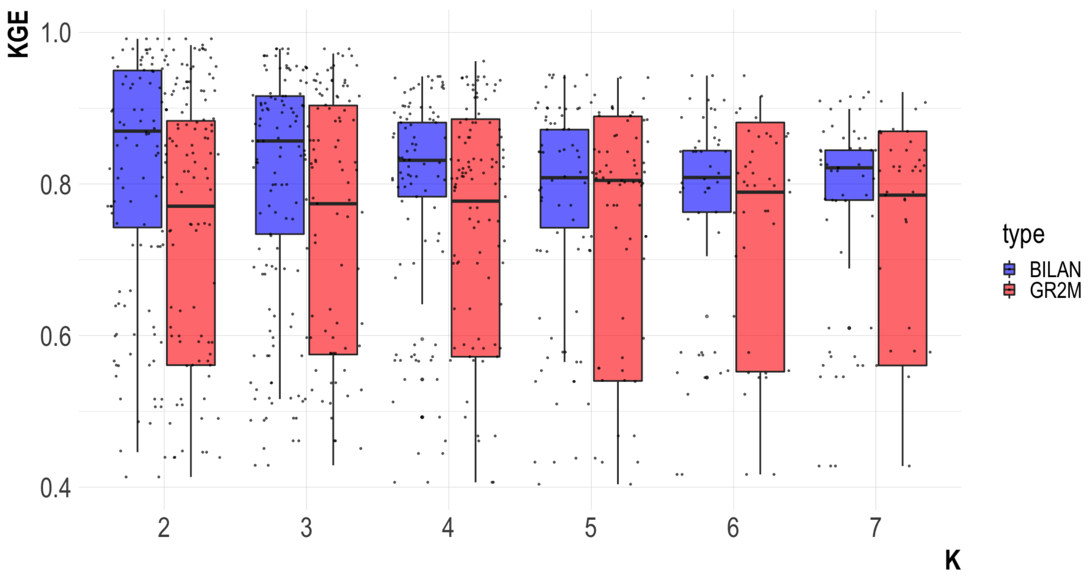



Figures 3.5 and 3.6 illustrate respectively the overall calibration and validation performance of BILAN and GR2M models with overall

together the climate variables influence analyzed. The BILAN model calibration performance prevails over the GR2M model and along all time series for all K windows but decreasing constantly with increasing of the simulation width. As an opposite, the GR2M model has tendency to slightly increase it's performance with an increasing simulation period length. The median value of KGE for both models being arround 0.8.

The validation results show an increasing/decreasing performance but a competitive result for both models which take over one another with a median value of KGE arround 0.5.

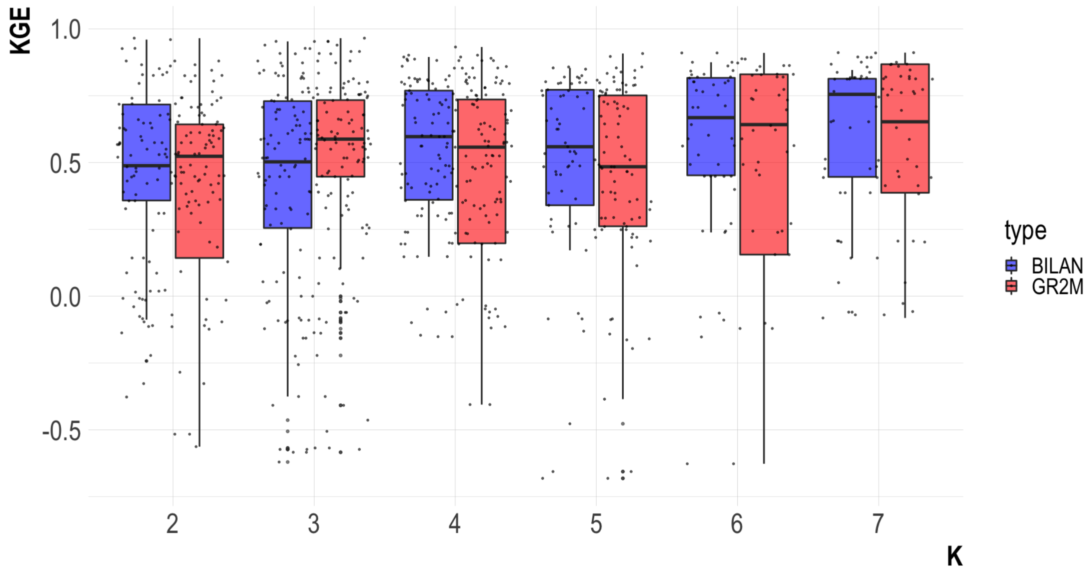
Figure 3.5: Overall calibration performance of BILAN and GR2M model without distinction of climate variable.




Figures 3.8 and 3.9 illustrate the comparison of the overall Calibration against Validation Performance of BILAN and GR2M models without distinction of climate variables influence.
The BILAN model performs well and better in calibration than validation but with a decreasing performance of the calibration and a validation performance that seems increasing within an extending period simulation length. The GR2M model performs well and better in calibration than in validation but has a slightly constant KGE values when the simulation period increases. The median calibration performance being arround 0.8 and a median validation performance turning around 0.5 for both models.

The graph 3.7 represent the hydrograph of the monthly observed (R OBS) and Simulated Runoff (R BILAN) and (R GR2M) at Gouloumbou catchment on an independant 6-year sub-period during calibration. The GR2M model has tendency to underestimate high flows or overestimate low flows while the BILAN model simulates very well high flows but has

Figure 3.6: Overall validation result of BILAN and GR2M model without distinction of climate variable.




tendency to underestimate low flows.

Figure 3.7: Monthly Observed Runoff (R OBS) and Simulated Runoff of BILAN and GR2M model, at GOULOUMBOU catchment, during Calibration on an in-dependant 6 year sub-period

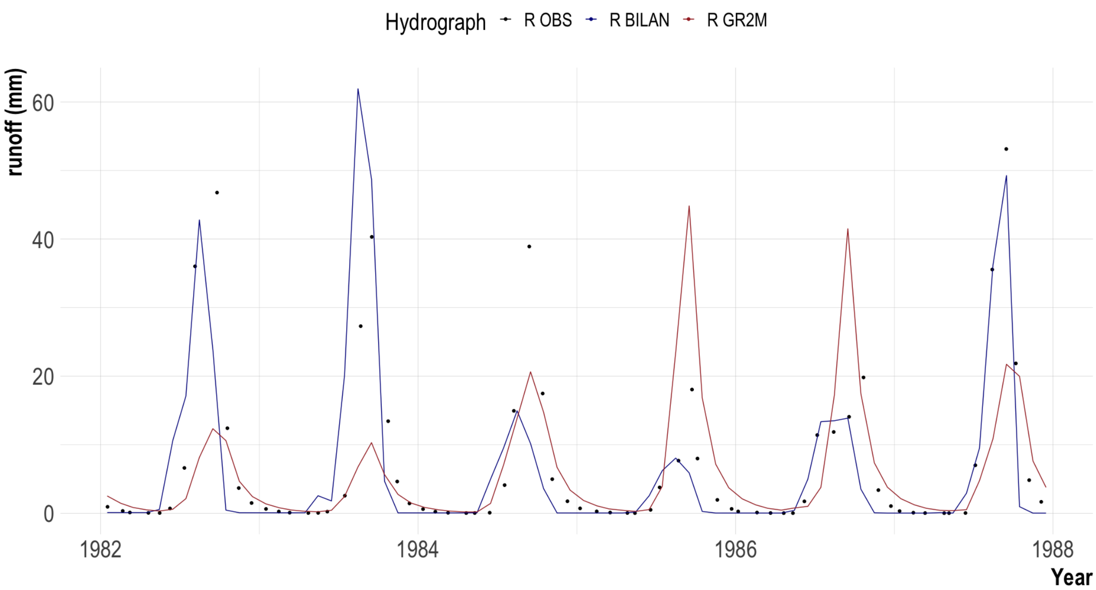


Figure 3.8: Comaparion of Calibration-Validation Performance of BILAN model

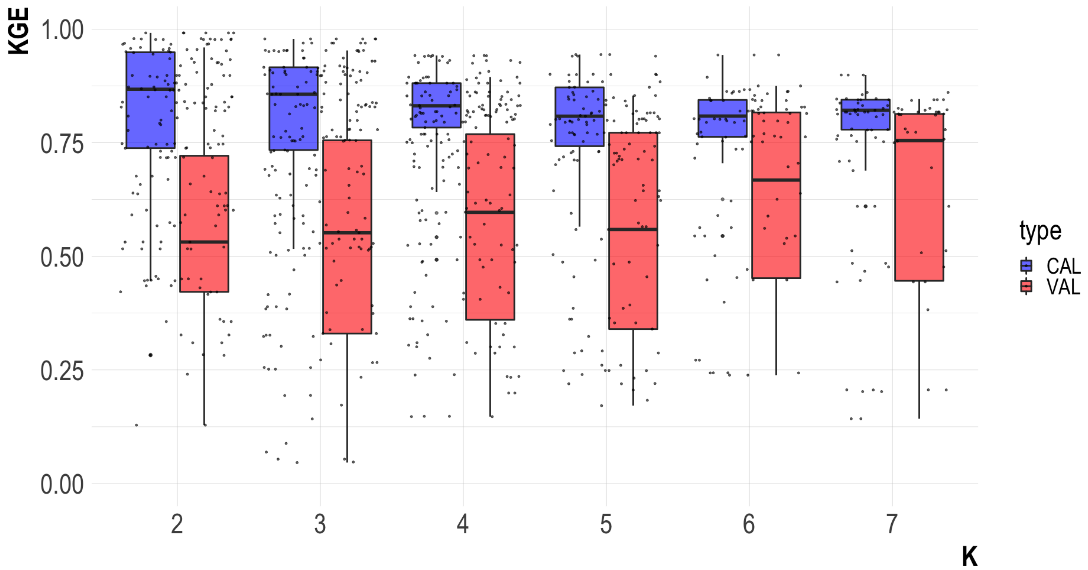
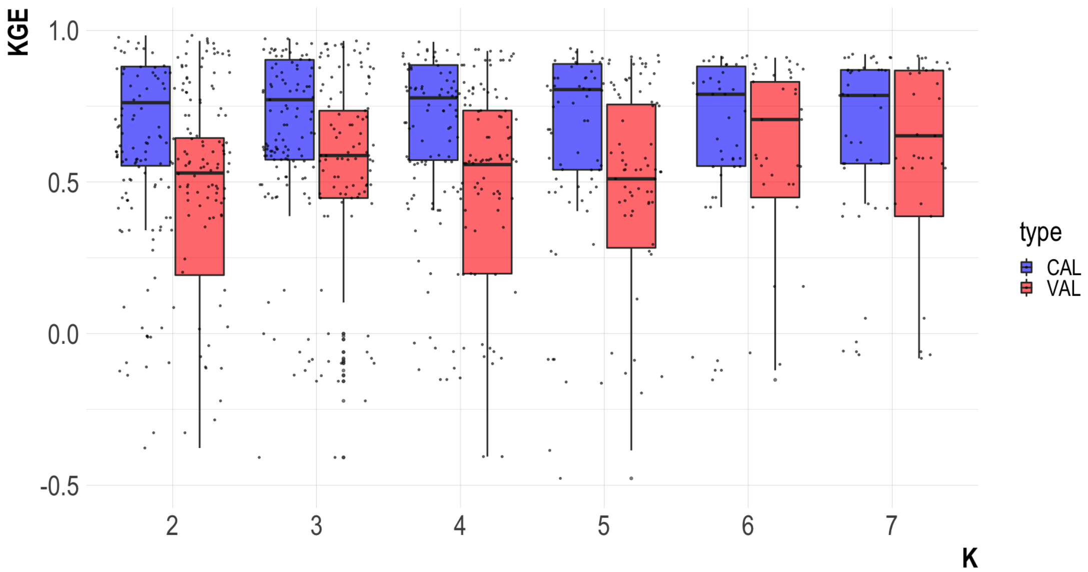



Figure 3.9: Comaparion of Calibration-Validation Performance of GR2M model



## 3.2 Impact the drought type on model performances

This section investigates the impact of the drought on the calibration performance by comparing performances obtained on Dry and Wet years.

Figures 3.10, 3.11 and 3.12, 3.13 show the impact of the drought on respectively calibration and validation performance of BILAN and GR2M model.

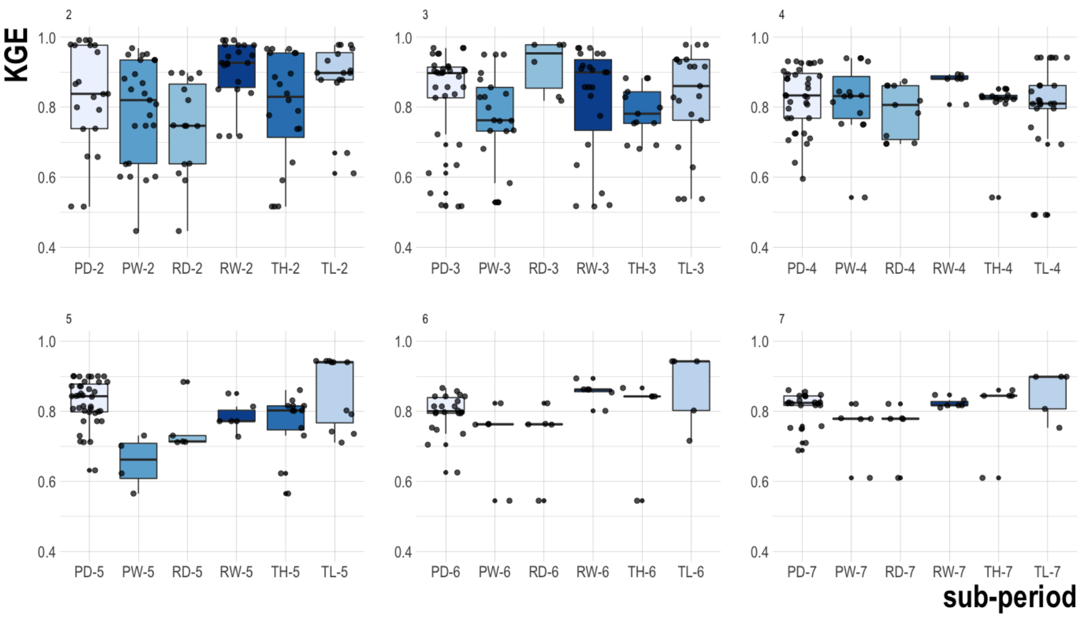



Figure 3.10: Boxplot of the impact of drought on BILAN model Calibration performance

Results show a BILAN model that has tendency to simulate better dry years for shorter time series and wet years for longer time series during calibration 3.14 but simulating better dry periods than wet periods 3.17 during validation.

The GR2M results reveal that wet periods are better simulated than Dry periods during calibration 3.16 and the opposite is noticed during validation 3.17. The medians of the calibration performance are in dry periods and in wet periods respectively for the BILAN model 0.85 and 0.6 and for GR2M model 0.7 and 0.8.

Figure 3.11: Boxplot of the impact of drought on GR2M model Calibration performance

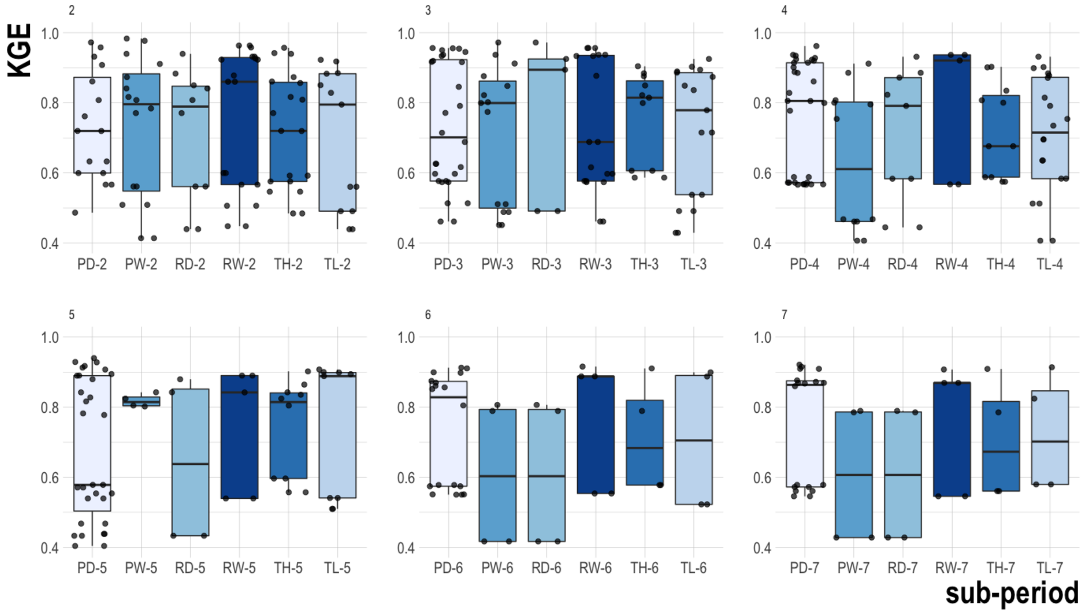



Figure 3.12: Boxplot of the impact of drought on BILAN model Validation performance

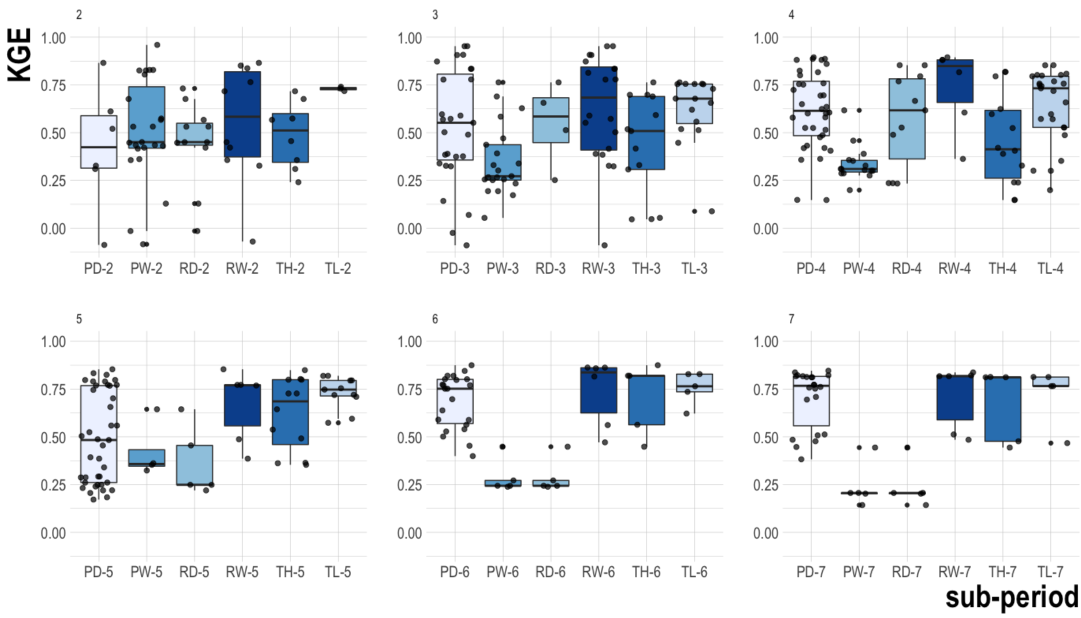


Figure 3.13: Boxplot of the impact of drought on GR2M model Validation performance

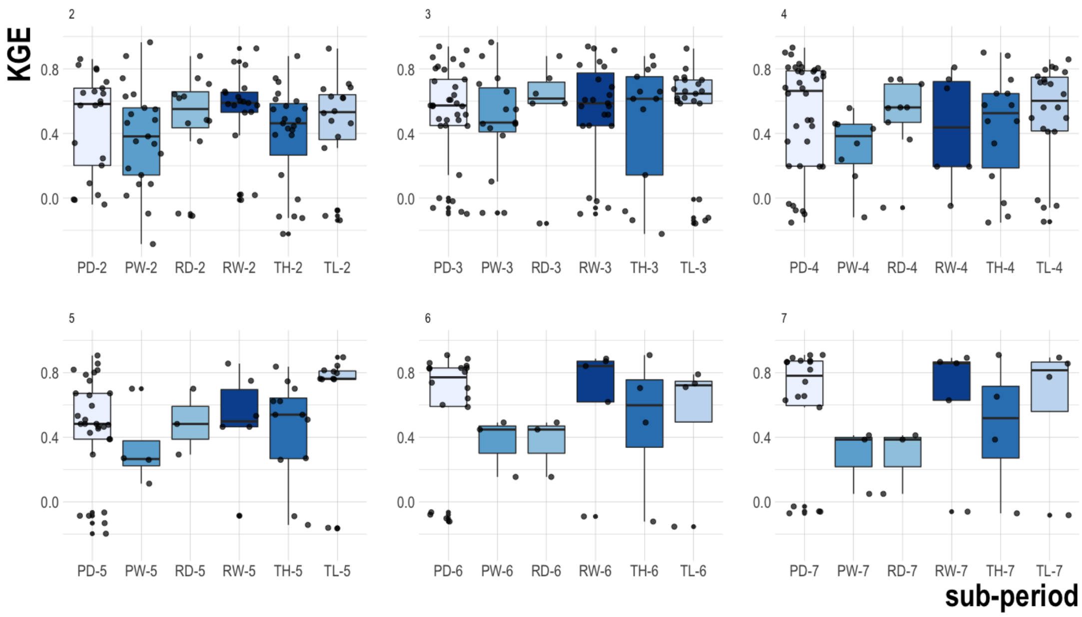



Figure 3.14: Impact of Drought on Calibration Performance of BILAN model

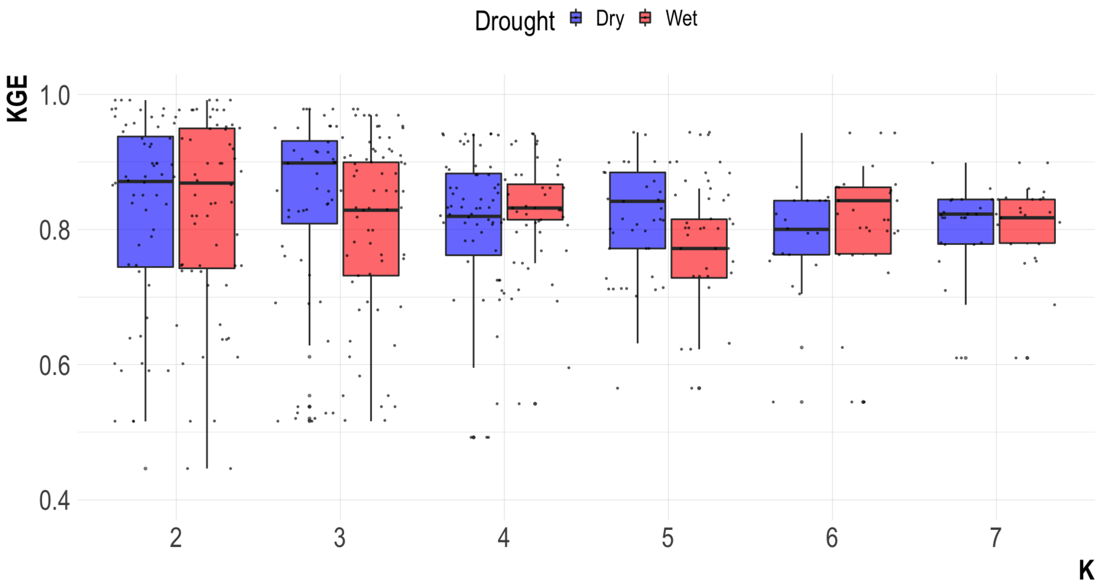


Figure 3.15: Impact of Drought on Validation Performance of BILAN model

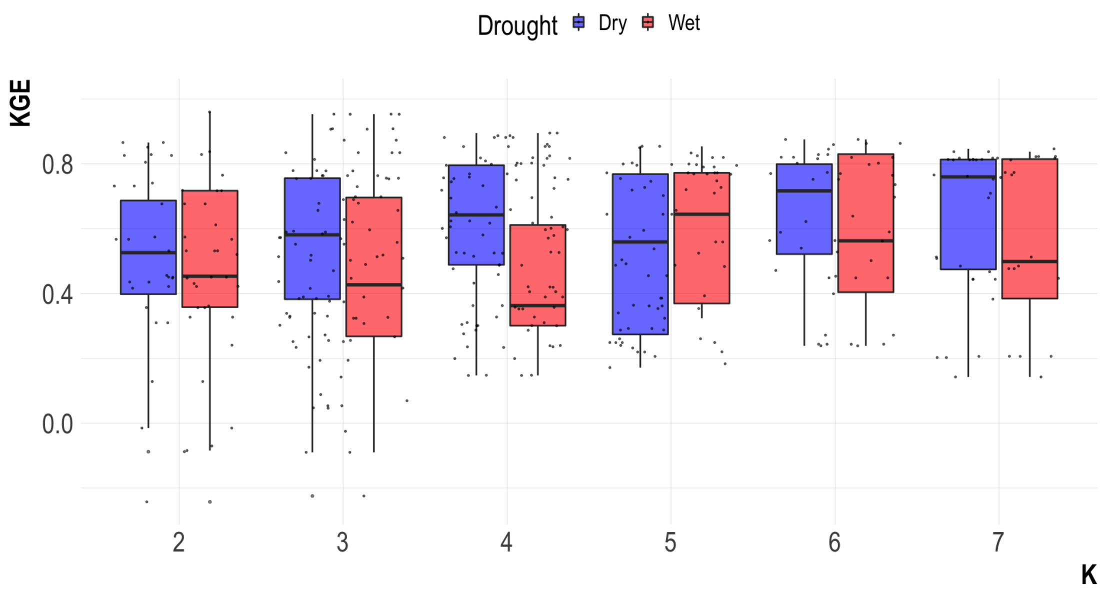



Figure 3.16: Impact of Drought on Calibration Performance of GR2M model

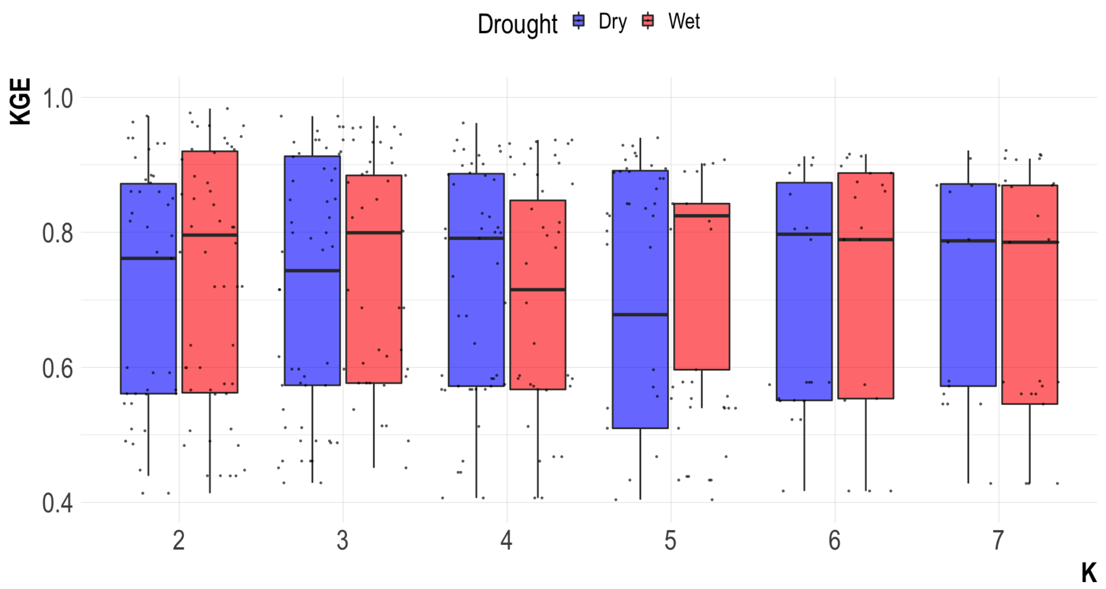
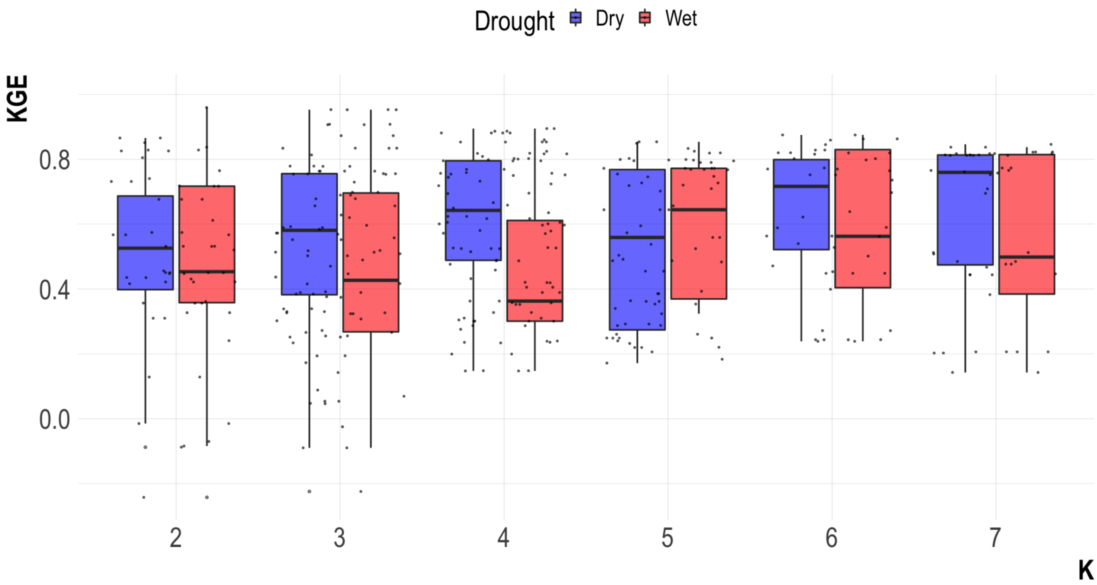


Figure 3.17: Impact of Drought on Validation Performance of GR2M model



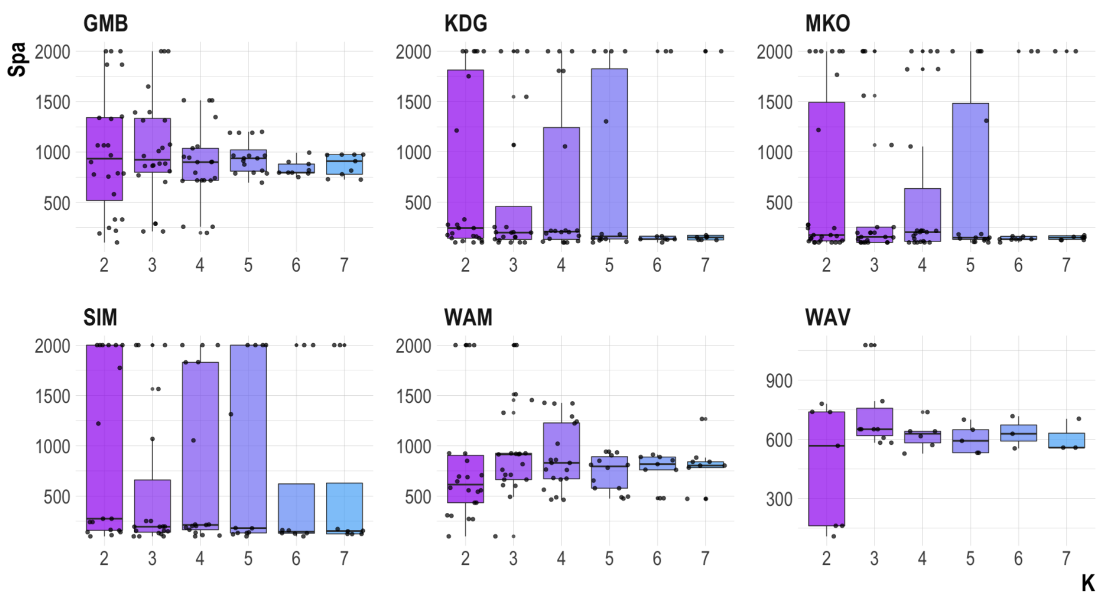
## 3.3 Parameters transferability

This section tends to investigate the performance loss during optimized parameters transfer from calibration to validation. It is subdivided in two subsections: The Distribution of the optimized parameters where an analysis of the distribution of the calibrated parameters is provided for each single catchment and a diagnosis of the parameters transferability from calibration to validation period using MRC criterion.

### 3.3.1 Distribution of the Optimized Parameters

The tables 3.3, 3.4 and 3.5 below provide a summary of the optimized parameters in terms of average on the sub-period the calibration was performed. The tables 3.3, 3.4 and 3.5 provide a summary of the optimized BILAN's (Spa, Grd, Alf) and GR2M's (X1 and X2) parameters in terms of average on the sub-period the calibration was performed and for each basin. Globally the decrease is noticed in the BILAN model Spa

Figure 3.18: BILAN model Spa parameter




and Grd parameters within an extending simulation period width and respectively turning arround for Spa Gouloumbou (1000), Kedougou, Mako and Simenti (250), Wassadou-Amont and Wassadou-Aval (600) and for Grd : Gouloumbou (0.1, 0), Kedougou, Mako and Simenti (0.6, 04) and Wassadou-Amont (-.6, 0) and Wassadou-Aval (0.02, 0).

The BILAN model Alf optimized parameter seems increasing with an increasing simulation length and for all Basins with values turning arround Gouloumbou (0.0015,0.0027), Kedougou and Simenti (0.0003 and 0), Mako (0, 0.0003), Wassadou-Amont (0.001, 0.0018), Wassadou-Aval (0.0025, 0.003).

Figure 3.19: BILAN model Grd parameter

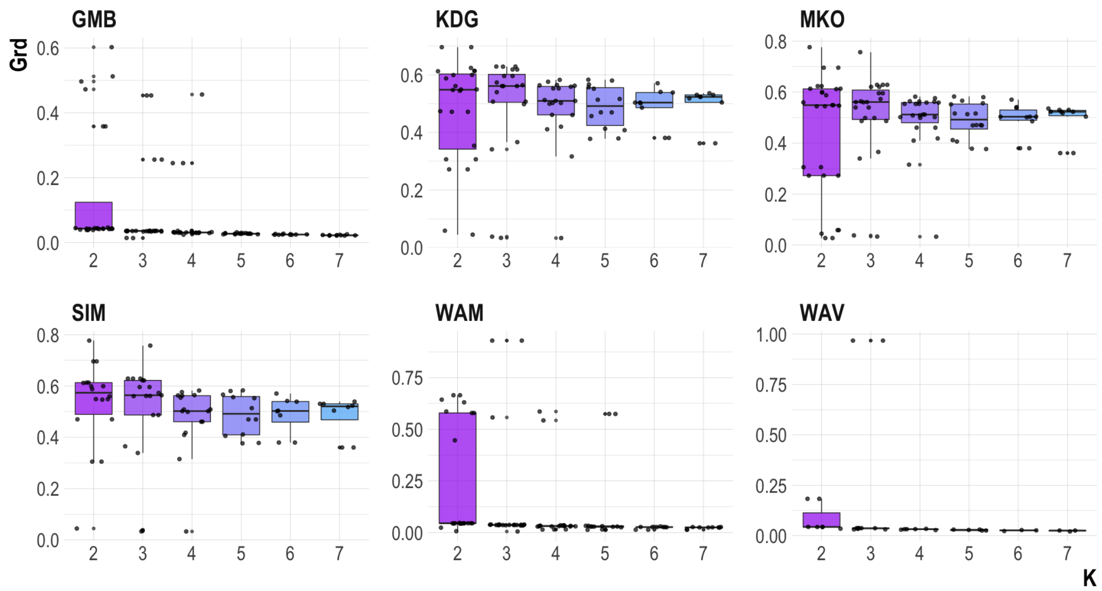
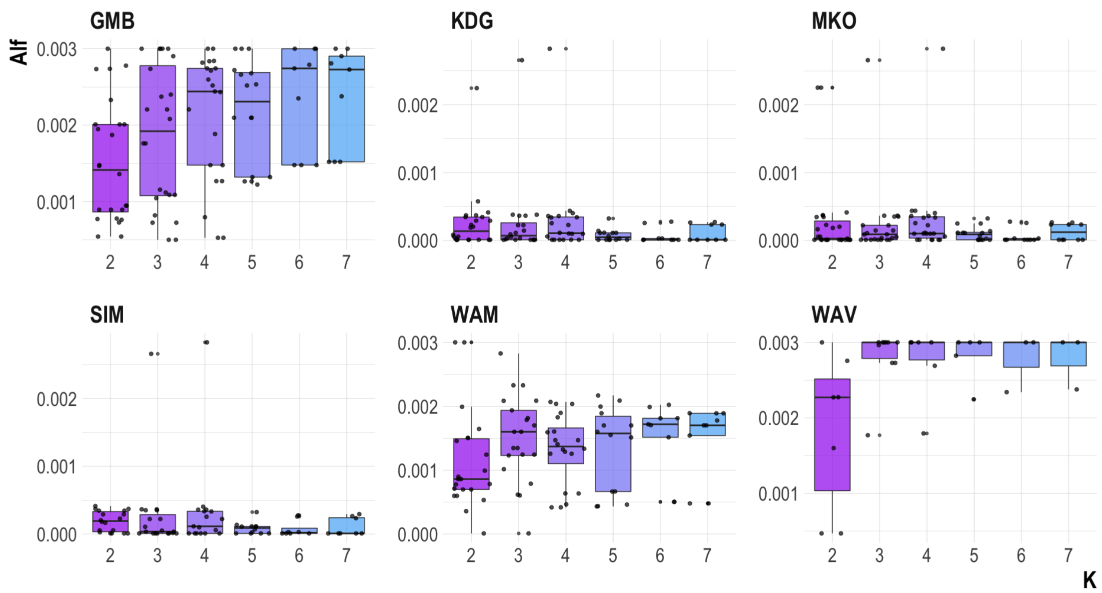



Figure 3.20: BILAN model Alf parameter



The Highest value of the Spa turns arround 1000 for Gouloumbou catchment, under 500 for Kedougou, Mako and Simenti and arround 600 for Wassadou-Amont and Wassadou-Aval. The Highest value of the Spa turns arround 1000 for Gouloumbou catchment, under 500 for Kedougou, Mako and Simenti and arround 600 for Wassadou-Amont and Wassadou-Aval. The highest value of the Grd arround 0.6 are obtained at Kedougou, Mako adn Simenti, the lowest value arround 0.1 are obtained at Gouloumbou, Wassadou-Amont and Wassadou-Aval. The Alf parameter increasing and between 0.001 to 0.003.

Table 3.3: BILAN model Optimized Parameters Spa, Grd and Alf

| Period | Gouloumbou | | | | Kedougou | | | Mako | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | K | Spa | Grd | Alf | Spa | Grd | Alf | Spa | Grd | Alf |
| PD | 2 | 773 | 0.0431 | 0.0025 | 227 | 0.4815 | 0.0003 | 179 | 0.5896 | 0.0002 |
| | 3 | 968 | 0.0315 | 0.0026 | 177 | 0.5885 | 0.0002 | 163 | 0.6138 | 0.0002 |
| | 4 | 858 | 0.0910 | 0.0024 | 150 | 0.5189 | 0.0001 | 150 | 0.5193 | 0.0001 |
| | 5 | 860 | 0.0288 | 0.0028 | 987 | 0.4837 | 0.0001 | 988 | 0.4835 | 0.0001 |
| | 6 | 861 | 0.0258 | 0.0028 | 132 | 0.5078 | 0.0001 | 131 | 0.5080 | 0.0001 |
| | 7 | 824 | 0.0238 | 0.0028 | 139 | 0.5188 | 0.0001 | 138 | 0.5189 | 0.0001 |
| RD | 2 | 1468 | 0.0414 | 0.0015 | 1380 | 0.4423 | 0.0001 | 1380 | 0.2940 | 0.0000 |
| | 3 | 548 | 0.2447 | 0.0015 | 155 | 0.5957 | 0.0000 | 155 | 0.5958 | 0.0000 |
| | 4 | 1192 | 0.0319 | 0.0021 | 1109 | 0.4127 | 0.0002 | 1109 | 0.4121 | 0.0002 |
| | 5 | 1191 | 0.0258 | 0.0021 | 2000 | 0.3774 | 0.0001 | 2000 | 0.3768 | 0.0001 |
| | 6 | 795 | 0.0244 | 0.0015 | 2000 | 0.3808 | 0.0000 | 2000 | 0.3800 | 0.0000 |
| | 7 | 974 | 0.0218 | 0.0015 | 2000 | 0.3620 | 0.0000 | 2000 | 0.3609 | 0.0000 |
| TL | 2 | 644 | 0.2904 | 0.0016 | 138 | 0.5651 | 0.0002 | 137 | 0.5651 | 0.0002 |
| | 3 | 1039 | 0.1198 | 0.0020 | 374 | 0.4419 | 0.0007 | 374 | 0.4418 | 0.0007 |
| | 4 | 893 | 0.0325 | 0.0026 | 681 | 0.4377 | 0.0008 | 684 | 0.4375 | 0.0008 |
| | 5 | 878 | 0.0294 | 0.0026 | 130 | 0.5745 | 0.0001 | 130 | 0.5746 | 0.0001 |
| | 6 | 902 | 0.0251 | 0.0027 | 128 | 0.5705 | 0.0000 | 128 | 0.5706 | 0.0000 |
| | 7 | 909 | 0.0231 | 0.0028 | 171 | 0.5359 | 0.0003 | 171 | 0.5358 | 0.0003 |
| PW | 2 | 1208 | 0.1059 | 0.0013 | 1950 | 0.3992 | 0.0001 | 1953 | 0.3100 | 0.0000 |
| | 3 | 1038 | 0.0797 | 0.0013 | 1886 | 0.3262 | 0.0000 | 1889 | 0.3256 | 0.0000 |
| | 4 | 829 | 0.1020 | 0.0011 | 1934 | 0.4646 | 0.0000 | 1940 | 0.4639 | 0.0000 |
| | 5 | 1029 | 0.0270 | 0.0015 | 2000 | 0.3808 | 0.0000 | 2000 | 0.3800 | 0.0000 |
| | 6 | 795 | 0.0244 | 0.0015 | 2000 | 0.3620 | 0.0000 | 2000 | 0.3609 | 0.0000 |
| | 7 | 974 | 0.0218 | 0.0015 | 474 | 0.6239 | 0.0003 | 475 | 0.6240 | 0.0003 |
| RW | 2 | 400 | 0.3506 | 0.0014 | 188 | 0.5786 | 0.0002 | 186 | 0.5743 | 0.0002 |
| | 3 | 1073 | 0.0290 | 0.0023 | 203 | 0.5021 | 0.0004 | 202 | 0.5021 | 0.0004 |
| | 4 | 902 | 0.0326 | 0.0027 | 134 | 0.4695 | 0.0000 | 134 | 0.4696 | 0.0000 |
| | 5 | 913 | 0.0296 | 0.0030 | 159 | 0.5383 | 0.0003 | 159 | 0.5386 | 0.0003 |
| | 6 | 787 | 0.0271 | 0.0028 | 125 | 0.5301 | 0.0000 | 124 | 0.5304 | 0.0000 |
| | 7 | 726 | 0.0230 | 0.0027 | 123 | 0.3746 | 0.0006 | 123 | 0.3749 | 0.0006 |
| TH | 2 | 1323 | 0.1057 | 0.0010 | 100 | 0.5188 | 0.0001 | 100 | 0.5192 | 0.0001 |
| | 3 | 1313 | 0.0904 | 0.0010 | 138 | 0.5411 | 0.0002 | 138 | 0.5417 | 0.0002 |
| | 4 | 488 | 0.1381 | 0.0009 | 123 | 0.4863 | 0.0000 | 127 | 0.4936 | 0.0001 |
| | 5 | 972 | 0.0269 | 0.0016 | 132 | 0.5035 | 0.0000 | 132 | 0.5036 | 0.0000 |
| | 6 | 795 | 0.0244 | 0.0015 | 151 | 0.5232 | 0.0002 | 150 | 0.5232 | 0.0002 |
| | 7 | 974 | 0.0218 | 0.0015 | | | | | | |

Table 3.4: BILAN model Optimized Parameters Spa, Grd and Alf

| Period | Simenti | | | | Wassadou-Amont | | | Wassadou-Aval | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | K | Spa | Grd | Alf | Spa | Grd | Alf | Spa | Grd | Alf |
| PD | 2 | 206 | 0.6954 | 0.0003 | 647 | 0.2510 | 0.0018 | 450 | 0.1131 | 0.0014 |
| | 3 | 163 | 0.6142 | 0.0002 | 720 | 0.1850 | 0.0019 | 713 | 0.2221 | 0.0029 |
| | 4 | 150 | 0.5195 | 0.0001 | 805 | 0.0319 | 0.0017 | 618 | 0.0315 | 0.0027 |
| | 5 | 989 | 0.4834 | 0.0001 | 657 | 0.0916 | 0.0011 | 591 | 0.0282 | 0.0029 |
| | 6 | 132 | 0.5082 | 0.0001 | 831 | 0.0273 | 0.0018 | 635 | 0.0255 | 0.0027 |
| | 7 | 138 | 0.5189 | 0.0001 | 827 | 0.0251 | 0.0018 | 631 | 0.0234 | 0.0027 |
| RD | 2 | 1381 | 0.4414 | 0.0001 | 1519 | 0.2222 | 0.0008 | | | |
| | 3 | 155 | 0.5958 | 0.0000 | 914 | 0.0373 | 0.0021 | | | |
| | 4 | 1109 | 0.4118 | 0.0002 | 991 | 0.2875 | 0.0009 | | | |
| | 5 | 2000 | 0.3764 | 0.0001 | 578 | 0.5743 | 0.0007 | | | |
| | 6 | 2000 | 0.3795 | 0.0000 | 479 | 0.0135 | 0.0005 | | | |
| | 7 | 2000 | 0.3604 | 0.0000 | 473 | 0.0138 | 0.0005 | | | |
| TL | 2 | 137 | 0.5650 | 0.0002 | 488 | 0.3739 | 0.0010 | | | |
| | 3 | 374 | 0.4418 | 0.0007 | 1424 | 0.0373 | 0.0015 | | | |
| | 4 | 686 | 0.4375 | 0.0008 | 1165 | 0.0284 | 0.0012 | | | |
| | 5 | 130 | 0.5746 | 0.0001 | 919 | 0.0291 | 0.0020 | | | |
| | 6 | 128 | 0.5706 | 0.0000 | 912 | 0.0265 | 0.0020 | | | |
| | 7 | 173 | 0.5391 | 0.0003 | 1267 | 0.0243 | 0.0018 | | | |
| PW | 2 | 1955 | 0.3983 | 0.0001 | 1040 | 0.2638 | 0.0005 | | | |
| | 3 | 1891 | 0.3253 | 0.0000 | 1053 | 0.1591 | 0.0005 | | | |
| | 4 | 1943 | 0.4636 | 0.0000 | 539 | 0.2051 | 0.0005 | | | |
| | 6 | 2000 | 0.3795 | 0.0000 | 479 | 0.0135 | 0.0005 | | | |
| | 7 | 2000 | 0.3604 | 0.0000 | 473 | 0.0138 | 0.0005 | | | |
| RW | 2 | 476 | 0.6240 | 0.0003 | 515 | 0.3297 | 0.0008 | 503 | 0.0900 | 0.0021 |
| | 3 | 186 | 0.5747 | 0.0002 | 805 | 0.2602 | 0.0016 | 740 | 0.2684 | 0.0029 |
| | 4 | 202 | 0.5021 | 0.0004 | 860 | 0.0348 | 0.0015 | 640 | 0.0325 | 0.0030 |
| | 5 | 134 | 0.4697 | 0.0000 | 941 | 0.0327 | 0.0017 | 531 | 0.0305 | 0.0030 |
| | 6 | 159 | 0.5388 | 0.0003 | 761 | 0.0264 | 0.0017 | 628 | 0.0264 | 0.0030 |
| | 7 | 124 | 0.5305 | 0.0000 | 803 | 0.0268 | 0.0019 | 558 | 0.0257 | 0.0030 |
| TH | 2 | | | | 645 | 0.0451 | 0.0020 | 423 | 0.0391 | 0.0019 |
| | 3 | | | | 789 | 0.0355 | 0.0018 | 793 | 0.0341 | 0.0018 |
| | 4 | | | | 944 | 0.0312 | 0.0018 | 699 | 0.0257 | 0.0022 |
| | 5 | | | | 816 | 0.0283 | 0.0017 | | | |
| | 6 | | | | 889 | 0.0265 | 0.0018 | | | |
| | 7 | | | | 841 | 0.0252 | 0.0017 | | | |

Globally the decrease of X1 parameter of GR2M model is noticed when the simulation period width increases and respectively turning arround for Gouloumbou (1000), Kedougou, Mako and Simenti (250), Wassadou-Amont and Wassadou-Aval (600) and for Grd : Gouloumbou (0.1, 0), Kedougou, Mako and Simenti (0.6, 04) and Wassadou-Amont (-.6, 0) and Wassadou-Aval (0.02, 0).

Figure 3.21: GR2M model X1 parameter

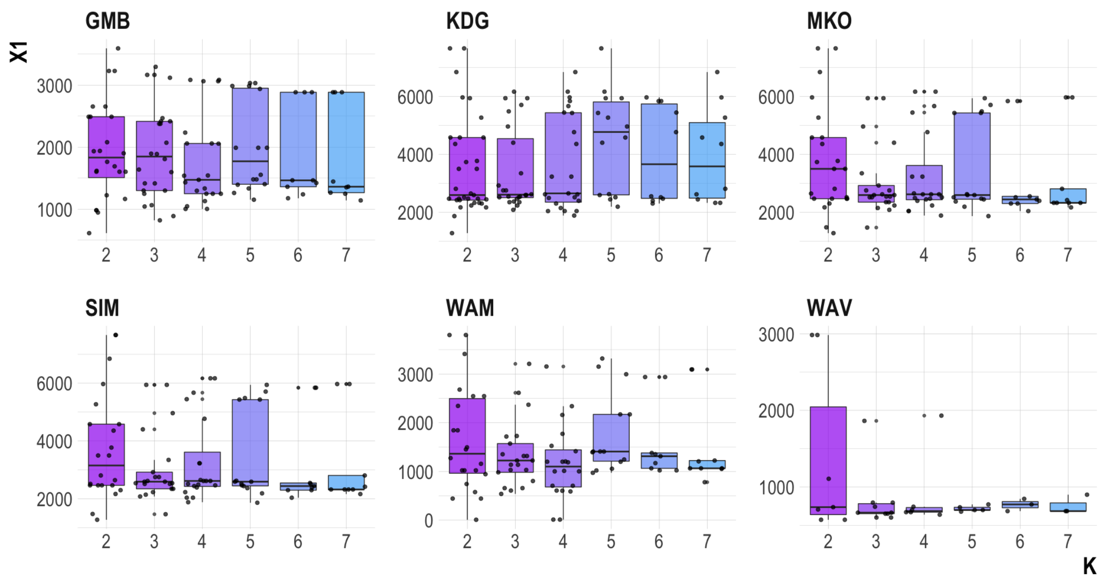



Figure 3.22: GR2M model X2 parameter

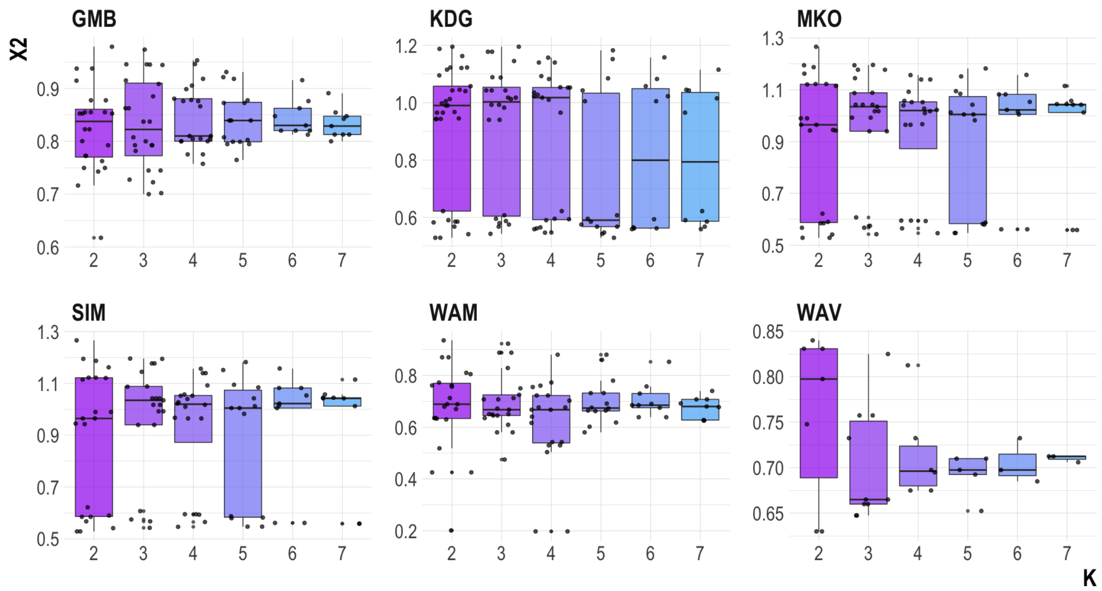


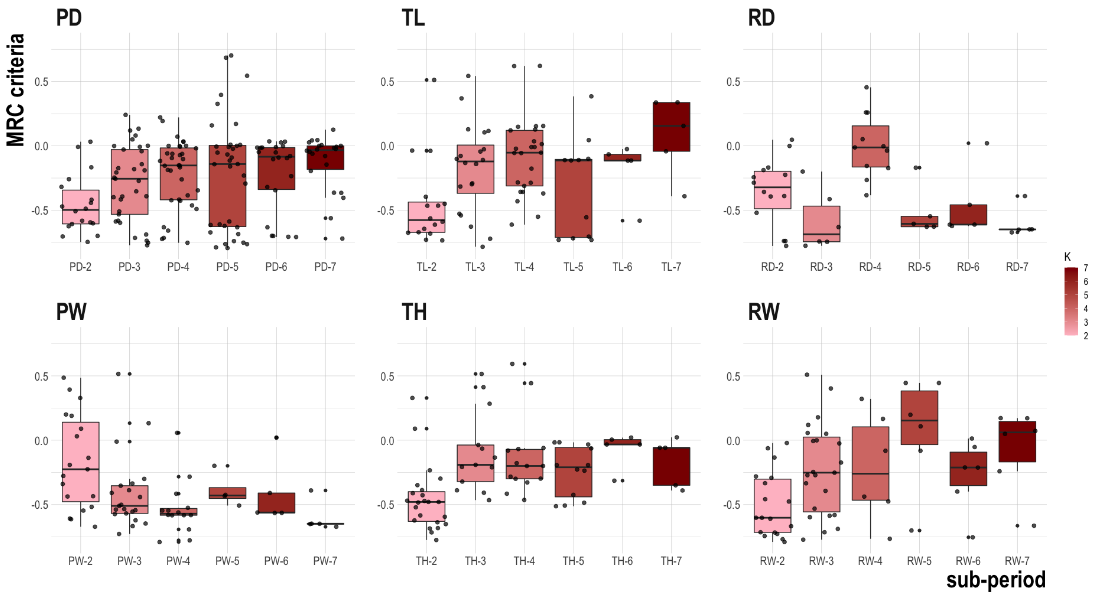
Table 3.5: GR2M Optimized Parameters : X1, X2

| Period | Gouloumbou | | | Kedougou | | Mako | | Simenti | | W-Amont | | W-Aval | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | K | X1 | X2 | X1 | X2 | X1 | X2 | X1 | X2 | X1 | X2 | X1 | X2 |
| PD | 2 | 1477 | 0.8 | 5746 | 0.56 | 2535 | 1.04 | 2135 | 1.07 | 1800 | 0.71 | 1778 | 0.73 |
| | 3 | 1570 | 0.8 | 5484 | 0.58 | 2267 | 1.03 | 2267 | 1.03 | 911 | 0.66 | 692 | 0.69 |
| | 4 | 1422 | 0.8 | 5540 | 0.58 | 2380 | 1.03 | 2380 | 1.03 | 1268 | 0.71 | 937 | 0.72 |
| | 5 | 1322 | 0.8 | 5618 | 0.57 | 3983 | 0.79 | 3983 | 0.79 | 2064 | 0.66 | 704 | 0.70 |
| | 6 | 1398 | 0.8 | 5508 | 0.57 | 2323 | 1.03 | 2323 | 1.03 | 1215 | 0.71 | 809 | 0.70 |
| | 7 | 1328 | 0.8 | 5265 | 0.59 | 2306 | 1.03 | 2306 | 1.03 | 1140 | 0.70 | 793 | 0.70 |
| RD | 2 | 2011 | 0.8 | 5249 | 0.74 | 5249 | 0.74 | 5249 | 0.74 | 1611 | 0.66 | | |
| | 3 | 1358 | 0.8 | 2752 | 1.17 | 2752 | 1.17 | 2752 | 1.17 | 1317 | 0.88 | | |
| | 4 | 1766 | 0.8 | 4450 | 0.79 | 4450 | 0.79 | 4450 | 0.79 | 1523 | 0.60 | | |
| | 5 | 1990 | 0.8 | 5433 | 0.55 | 5433 | 0.54 | 5433 | 0.54 | 2172 | 0.66 | | |
| | 6 | 2885 | 0.8 | 5844 | 0.56 | 5844 | 0.56 | 5844 | 0.56 | 2938 | 0.63 | | |
| | 7 | 2885 | 0.8 | 5971 | 0.56 | 5971 | 0.55 | 5971 | 0.55 | 3093 | 0.62 | | |
| TL | 2 | 1483 | 0.8 | 2940 | 1.14 | 2940 | 1.14 | 2940 | 1.14 | 1881 | 0.87 | | |
| | 3 | 1314 | 0.8 | 2909 | 1.12 | 2909 | 1.12 | 2909 | 1.12 | 1289 | 0.77 | | |
| | 4 | 1280 | 0.9 | 3436 | 0.96 | 3436 | 0.96 | 3436 | 0.96 | 688 | 0.53 | | |
| | 5 | 1431 | 0.9 | 2569 | 1.16 | 2569 | 1.16 | 2569 | 1.16 | 1401 | 0.87 | | |
| | 6 | 1361 | 0.9 | 2547 | 1.15 | 2547 | 1.15 | 2547 | 1.15 | 1380 | 0.85 | | |
| | 7 | 1362 | 0.8 | 2807 | 1.11 | 2807 | 1.11 | 2807 | 1.11 | 781 | 0.62 | | |
| PW | 2 | 2228 | 0.8 | 2854 | 0.97 | 5746 | 0.57 | 5746 | 0.57 | 1390 | 0.51 | | |
| | 3 | 2475 | 0.8 | 3253 | 0.89 | 5313 | 0.57 | 5313 | 0.57 | 2477 | 0.64 | | |
| | 4 | 2735 | 0.8 | 2740 | 0.98 | 5462 | 0.58 | 5462 | 0.58 | 1775 | 0.48 | | |
| | 5 | 2737 | 0.8 | | | | | | | | | | |
| | 6 | 2885 | 0.8 | 2490 | 1.03 | 5844 | 0.56 | 5844 | 0.56 | 2938 | 0.63 | | |
| | 7 | 2885 | 0.8 | 2529 | 0.99 | 5971 | 0.55 | 5971 | 0.55 | 3093 | 0.62 | | |
| RW | 2 | 1299 | 0.78 | 3386 | 0.86 | 3386 | 0.86 | 3386 | 0.86 | 1771 | 0.63 | 806 | 0.72 |
| | 3 | 1809 | 0.82 | 2498 | 0.99 | 2498 | 0.99 | 2498 | 0.99 | 1013 | 0.64 | 679 | 0.68 |
| | 4 | 1249 | 0.8 | 2618 | 0.96 | 2618 | 0.96 | 2618 | 0.96 | 1200 | 0.66 | 672 | 0.67 |
| | 5 | 1480 | 0.87 | 2592 | 1.0 | 2592 | 1.00 | 2592 | 1.00 | 1409 | 0.73 | 699 | 0.71 |
| | 6 | 1176 | 0.8 | 2392 | 1.02 | 2392 | 1.02 | 2392 | 1.02 | 1064 | 0.69 | 685 | 0.69 |
| | 7 | 1141 | 0.8 | 2322 | 1.04 | 2322 | 1.04 | 2322 | 1.04 | 1064 | 0.70 | 685 | 0.71 |
| TH | 2 | 2714 | 0.8 | 2378 | 1.10 | 2378 | 1.10 | 2378 | 1.10 | 1627 | 0.75 | 1845 | 0.83 |
| | 3 | 2813 | 0.79 | 2155 | 1.11 | 2155 | 1.11 | 2155 | 1.11 | 1168 | 0.73 | 1863 | 0.82 |
| | 4 | 3074 | 0.79 | 2104 | 1.08 | 2104 | 1.08 | 2104 | 1.08 | 933 | 0.67 | | |
| | 5 | 2670 | 0.81 | 2315 | 1.06 | 2315 | 1.06 | 2315 | 1.06 | 1014 | 0.66 | | |
| | 6 | 2885 | 0.8 | 2298 | 1.08 | 2298 | 1.08 | 2298 | 1.08 | 1022 | 0.68 | 773 | 0.65 |
| | 7 | 2885 | 0.8 | 2322 | 1.04 | 2322 | 1.04 | 2322 | 1.04 | 1054 | 0.67 | | |

### 3.3.2 Parameters transferability: The MRC criterion

The Boxplots 3.24 and 3.23 show the performance loss of BILAN and GR2M models using the MRC criteria calculated on the Root Mean Square Error (RMSE). Globally for both BILAN and GR2M models a median performance loss of around 25% is noticed for all periods without distinction of climate characteristic.

Figure 3.23: Boxplot of overall Performance loss of BILAN model using MRC to RMSE




However an improvement of the performance loss is noticed as long as the simulation period width increases. For BILAN model is ranges from -50% for 2-year sub-periods to -8% for 7-year sub-periods 3.25 and for the GR2M model values of performance losses are between -50% to -20% 3.26.

Figure 3.24: Boxplot overall Performance loss of GR2M model using MRC to RMSE

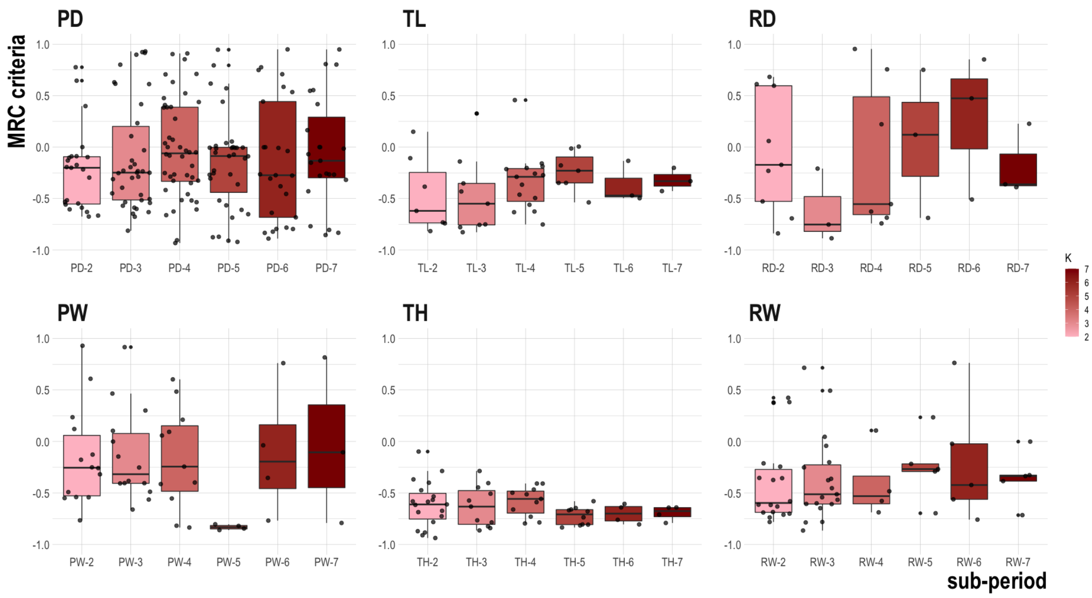



Figure 3.25: Boxplot overall Performance loss of GR2M model using MRC to RMSE without distinction of Period

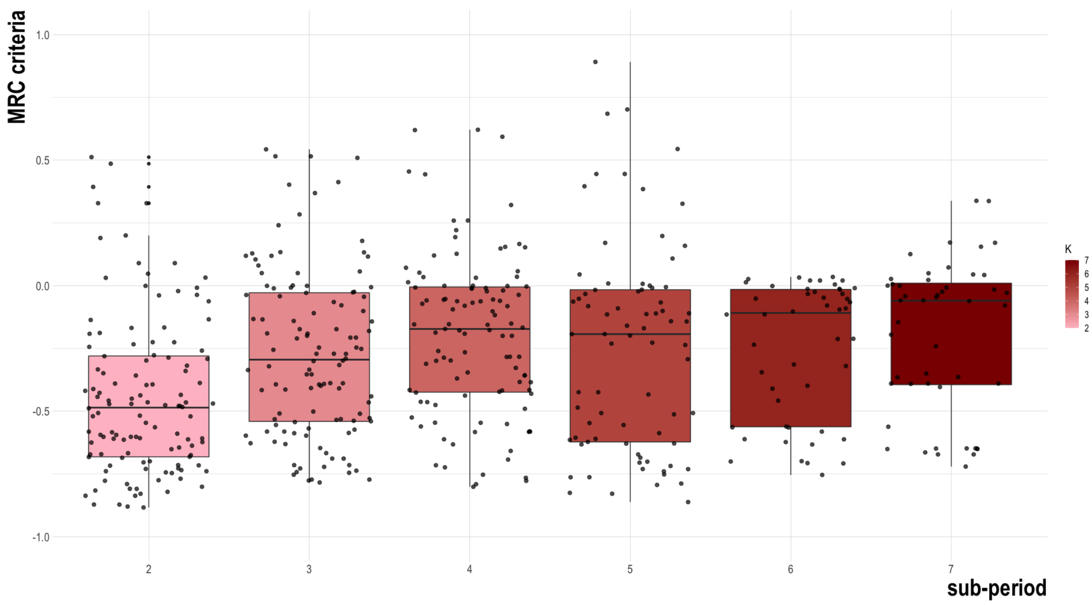
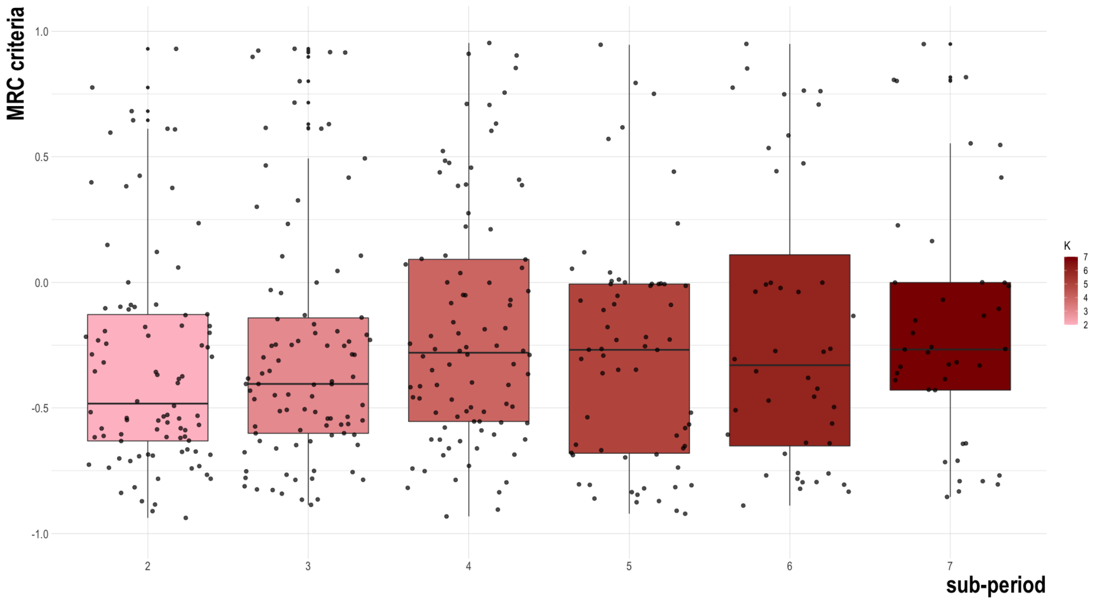


Figure 3.26: Boxplot overall Performance loss of GR2M model using MRC to RMSE without distinction of Period




The boxplots 3.27 and 3.28 show the overall performance loss of respectively BILAN and GR2M using MRC criteria RMSE without distinction of period with. Overall, BILAN and GR2M models have tendency to perform better in dry periods (PD,RD,TL) than wet periods (PW,RW,TH).

Figure 3.27: Boxplot overall Drought Performance loss of BILAN model using MRC to RMSE without distinction of Period

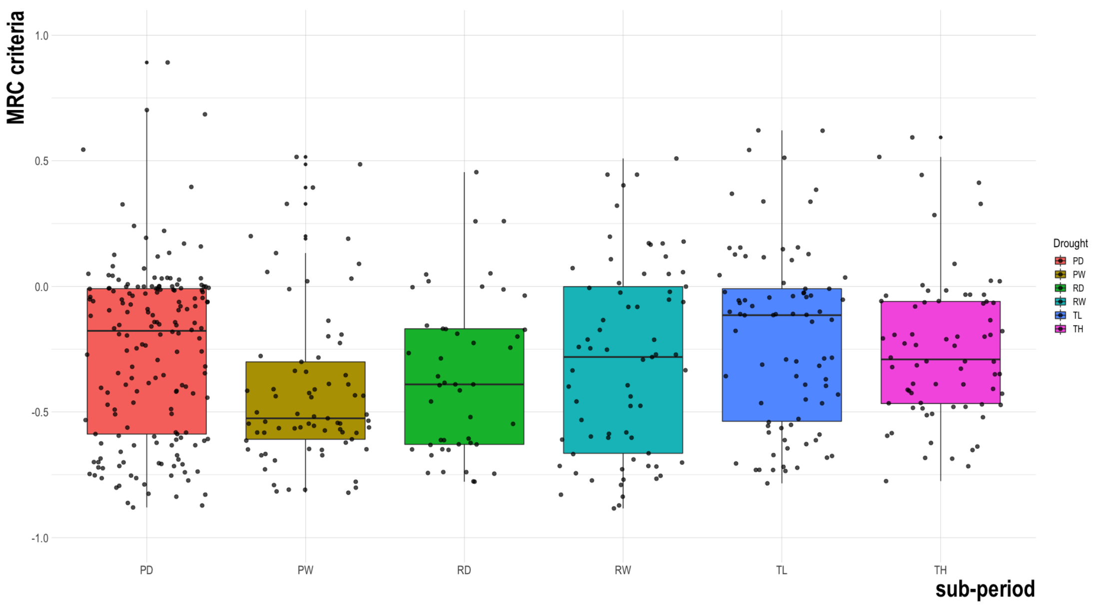
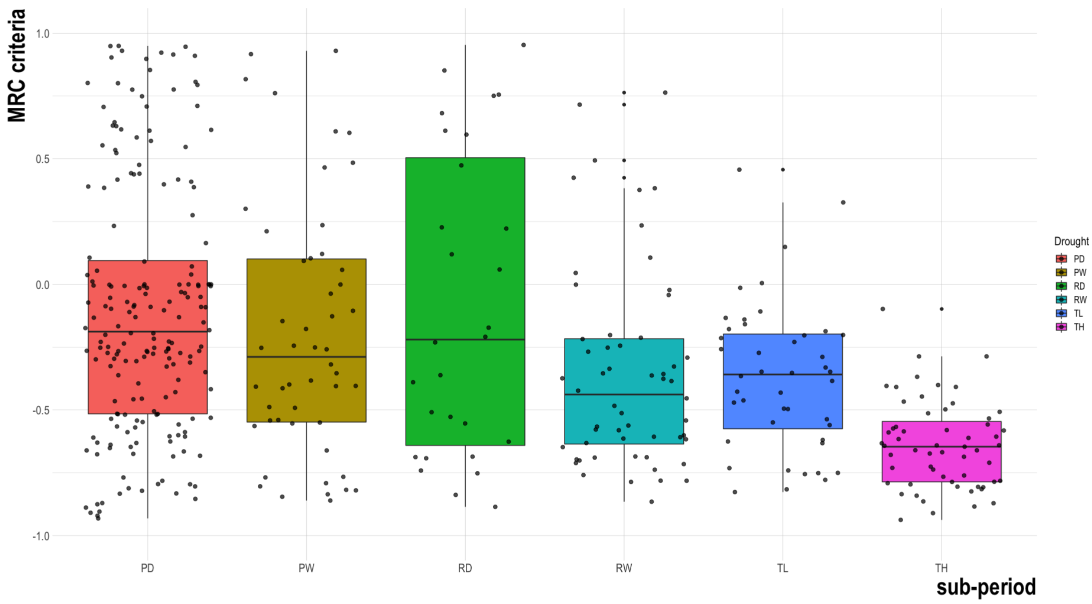


Figure 3.28: Boxplot overall Drought Performance loss of GR2M model using MRC to RMSE without distinction of Period



# Chapter 4

# Discussion

This chapter examines the study's approaches and findings and the relevance of the findings for future climate change researches.

## 4.1 Methodological approach

Applying BILAN and GR2M models to six catchments of the Gambia river basin, a systematical crash test was performed along a 30-year time series.

Systematically, calibration sub-periods were selected distinguished by quantiles under 20 "Dry Years" and over 80 "Wet Years," as determined by climate characteristics and using a 7-year moving window. It's important to note that "Dry Years" in this analysis are distinct to "Wet Years" and they never overlap.

This type of modelling approach , earlier proposed by (KlemeŠ 1986) was widely used in several studies such as (Coron, Andréassian, et al. 2012) finding an (over)underestimation of the average runoff volumes during parameters transfer over a wetter (drier) climate than the validation and vice versa.

(Vaze et al. 2010) applied the to four hydrological models in 61 Australian catchments and found that the models calibrated under wetter conditions had performed worse on dryer periods than vice versa.

(Brigode et al. 2013) found that two hydrological models calibrated on 63 French catchments were sensitive to climatologically contrasted calibration sub-periods (dry vs wet) and that this lack of model robustness has a stronger impact on the uncertainty of hydrological projections of future streamflow as compared to the use of several multiple parameter sets.

(Vormoor et al. 2018) found a general model performance loss due to the transfer of calibrated parameters to independent validation periods of −5% to −17%, on average.

The results obtained in this study are similar to the findings of previous studies.

Results indicated an overall performance loss during parameters transfer ranging from -25% to -5% as previously found (Vormoor et al. 2018) and a model performance decreasing with an extending width of simulation period.

Results also indicate that the BILAN model simulates very well high flows but has tendency to underestimate low flows while GR2M model has tendency to overestimate low flows and underestimate high flows, similar result was found in (Coron, Andréassian, et al. 2012).

Also results demonstrated that the calibration performance of both models is sensitive to the drought (Dry or Wet Periods), annd that both BILAN and GR2M models perform better in dry periods (PD,RD,TL) than wet periods (PW,RW,TH) as previously found (Brigode et al. 2013).

Finally overall the results the BILAN model performs better than the GR2M model.

## 4.2 Critical discussion of the results

The Evaluation of modelling results should be based on the knowledge of how and why these results were obtained including the input data and the calibration methods. Hydrological models possess different internal structures and their concepts applied for the solution of water balance also differ.

Overall the results, decent to very good calibration performance were obtained for both models, with KGE values ranging from 0.66 to 0.92 for BILAN and 0.61 to 0.79 for GR2M during calibration and -6.34 to 0.46 and -0.17 to 0.63 for BILAN and GR2M models during validation, respectively.

The analysis of parameters distribution without distinction of climate characteristic or drought type implies for all catchments a BILAN model Spa and Grd parameters decrease but a slightly increasing Alf parameter and a decrease of GR2M X1 and X2 parameters for all catchments.

The highest value of the Spa turns around 1000 for Gouloumbou catchment, under 500 for Kedougou, Mako and Simenti and arround 600 for Wassadou-Amont and Wassadou-Aval.

The highest value of the Grd arround 0.6 are obtained at Kedougou, Mako and Simenti, the lowest value around 0.1 are obtained at Gouloumbou, Wassadou-Amont and Wassadou-Aval. The Alf parameter values were found between 0.001 to 0.003.

Globally, there are two categories of catchments, the first category consists of Gouloumbou, Wassadou-Amont and Wassadou-Aval, and the second category consists of Kedougou, Mako and Simenti.

The highest Spa and lowest Grd are found in the first group of catchments, which have outlets next to each other and a larger catchment area, meaning that soil moisture capacity contributes the most to total runoff RM. The second group, which has outlets near by, has a smaller catchment area, the highest Grd, and the lowest Spa, implying that the baseflow determines total runoff.

The GR2M parameter X1 decreases between 4000 and 2000 for Kedougou, Mako, Simenti and decreases between 2000 and 1000 for Gouloumbou, Wassadou-Amont and Wassadou-Aval. The X2 parameter looks slightly constant between 1 and 0.8 for all catchments.

The calibration of BILAN and GR2M models on six catchments with a 7 year sliding window over a 30 years time series has yielded into the similar results for both models with performance loss noticed within an extending simulation period width. This result can be explained by the limits of hydrological models, indicating that models would be unable to correctly estimate runoff at a certain extent.

Also, the performance loss ranging from -25% to -5% noticed during parameters transfer from calibration to validation period giving an idea on the robustness of hydrological models that loose their accuracy when using optimized parameters to an independent validation period.

The BILAN model simulated better dry years (median KGE=0.85) than Wet years (median KGE = 0.6) but has tendency to underestimate low flows while the GR2M model seems to perform better during wet years calibration ( median KGE= 0.8) than dry years (median KGE= 0.7) but might underestimate high flows or overestimate low flows.

The BILAN model compared to the GR2M performs better but it is important to highlight the comment of one the pioneers of hydrologic modelling, (Linsley 1982), who argued that "because almost any model with sufficient free parameters can yield good results when applied to a short sample from a single catchment, effective testing requires that models must be tried on many catchments of widely differing characteristics, and that each trial cover a period of many years" (p. 14–15).

One approach to address these limitations is to build and test of hydrological models on broad and diversified catchment sets, and to always present the findings of model-related discussions with model output distributions obtained on a significant number (a few hundred or more) of catchments as mentioned (Andréassian et al. 2009). This approach will ensure the generality of hydrological models, diagnose their failures, and improve them rather than using ad hoc solutions that could well be valid on only a single catchment.

This will allow to verify that the proposed models have a wide capacity to reflect hydrological behaviour and, as a result, that their implementation context is not limited to a few catchments and stationary space-time conditions.

Since this study deals with lumped conceptual models which to remind, average the input data implying homogeneity over the catchment. Therefore the spatial resolution of the data is lost reason why they have tendency to overestimate or underestimate the runoff. Lumped models are conceptual models with simplified description of hydrological processes, that represents the average response of a process over a watershed. For example, groundwater response over the entire watershed might be simulated as a single linear reservoir. Spatial variability in groundwater response might be simulated as a simple function of the land surface.

But, for (Refsgaard and Henriksen 2004) the roles and expectations of model developers and model users may differ since most users are interested in a single or a limited number of catchments for which they wish to establish the best possible model.

As for model improvement, (Andersson 1992) reminded that "a certain change of model structure can improve the model performance for some basins whereas it is unchanged or deteriorated for other basins.

It is therefore important to test the new model for a large set of basins and for long time series before drawing conclusions of a general model improvement"

In this scope (K. Beven 2007) added that "more may be learned from model rejection than acceptance; rejection of a hypothesis, when properly justified, is an important stage in model development and improvement."

It is a common belief among hydrologists that the structure of a catchment model is climate or region-specific reason why it is important in a model to keep only those driving processes that the modeller deems active in a given catchment.

It is therefore natural to think that a single case-study could be enough to discover and dissect the main small-scale physical processes controlling the movement of water in a catchment.

A hydrologist using a model should know the limits of the model structure, based on the implementation of a complete crash test. A site-specific model, developed on a single site, may be very successful, but the question is: will it remain so in the long run? (Andréassian et al. 2009)

It is also important to address the question of data quality since it is crucial when working on a few catchment set from data originated from regional or national hydrological and meteorological databases that have their own data quality check procedures, are not obviously perfect but only acceptable.

But since a model evaluation is only meaningful in a comparative framework (a model can only be ranked good in comparison with alternative models), (Linsley 1982) objects that "if the data are too poor for the use of a good simulation model they are also inadequate for any other model." Therefore, in intercomparison studies, data errors should not spoil the conclusions on the relative efficiency of several models (or model versions).

To conclude (KlemeŠ 1986) wrote that the power of this four-level testing scheme was "rather modest, and [that] even a fully successful result [could] be seen only as a necessary, rather than a sufficient, condition for model adequacy vis-'a-vis the specific modelling objective"

## 4.3 Significance of the results for future climate change studies

Climate change may affect the water supply in energy production and agriculture sectors, which are the two main elements of economic growth in Africa.

The outcome of this study may lead to a better understanding of the calibration performance of hydrological models and help OMVG authorities to better assess the water resources in a realistic mean.

Findings demonstrate the importance of careful selection of calibration periods and the need of using a variety of optimized parameter sets for future climate change research.

In this regard, it is appropriate to calibrate hydrological models for periods long enough to incorporate as many applicable processes as the observation data allows, or for periods that more closely represent possible future conditions.

A certain number of aspects regarding the uncertainty and the parameters transfer, such as:

- the selection of research catchments,
- the quality of input data,
- the selection of calibration periods,
- the selection of hydrological models,
- the calibration method
- and the use of variety of optimized parameters

need to be carefully considered.

The alteration of one or more of these aspects may lead to different outcomes and different conclusions.

The outcome of this study may lead to a master of the uncertainty associated with hydrological model and a better assessment of runoff for future climate change studies.

# Chapter 5

# Conclusion

Applying BILAN and GR2M models to six Senegalese catchments of the Gambia river basin, a systematical crash test was perform to test all potential combinations of calibration-validation period was along a 30-year time series. Systematically, calibration sub-periods were selected distinguished by quantiles under 20 ”Dry Years” and over 80 ”Wet Years,” as determined by climate characteristics and using a 7-year sliding window.

A crash test of hydrological models robustness when subjected to an extending simulation period width (moving window) were performed and thus a diagnois of the performance losses associated with calibrated parameters transfer to validation periods under similar and/or different climate conditions (drought).

The calibration of BILAN and GR2M models over six Senegalese catchments tributaries of the Gambia river basin using a 7 year sliding window over a 30 years time series yielded similar results : A performance loss noticed within an extending simulation period width. This result can be explained by the limits of hydrological models, indicating that models would be unable to correctly estimate runoff at a certain extent.

Overall, decent to very good calibration results were obtained for both models, with KGE values ranging from 0.66 to 0.92 for BILAN and 0.61 to 0.79 for GR2M during calibration.

Also the BILAN model simulates very well high flows but has tendency to underestimate low flows while GR2M model has tendency to overestimate low flows and underestimate high flows. The calibration performance of both models is sensitive to the drought (Dry or Wet Periods), and that the BILAN model simulates better Dry years (median KGE=0.85) than Wet years (median KGE = 0.6) while the GR2M model seems performing better during Wet years calibration ( median KGE= 0.8) than Dry years (median KGE= 0.7).

Also, a performance loss ranging from -25% to -5% noticed during parameters transfer from calibration to validation period indicate the robustness of hydrological models loose their accuracy when using optimized parameters to an independent validation period. A performance loss that is more pronounced on wet years than dry years.

The analyse of parameters distribution without distinction of climate characteristic or drought type implies for all catchments a BILAN model Spa and Grd parameters decrease but a slightly increasing Alf parameter and a decrease of GR2M X1 and X2 parameters for all catchments.

The Highest value of the Spa turns arround 1000 for Gouloumbou catchment, under 500 for Kedougou, Mako and Simenti and arround 600 for Wassadou-Amont and Wassadou-Aval.

The highest value of the Grd arround 0.6 are obtained at Kedougou, Mako and Simenti, the lowest value arround 0.1 are obtained at Gouloumbou, Wassadou-Amont and Wassadou-Aval. The Alf parameter increasing and between 0.001 to 0.003.

Globally, there are two categories of catchments, the first category consisting of Gouloumbou, Wassadou-Amont and Wassadou-Aval, and the second category consisting of Kedougou, Mako and Simenti.

The highest Spa and lowest Grd are found in the first tier of catchments, which have outlets next to each other and a larger catchment area, meaning that soil moisture capacity contributes the most to total runoff RM. The second tier, which has outlets near by, has a smaller catchment area, the highest Grd, and the lowest Spa, implying that the baseflow determines total runoff.

The GR2M parameter X1 decreases between 4000 and 2000 for Kedougou, Mako, Simenti and decreases between 2000 and 1000 for Gouloumbou, Wassadou-Amont and Wassadou-Aval. The X2 parameter looks slightly constant between 1 and 0.8 for all catchments.

The BILAN model compared to the GR2M overall performed better.

The outcomes of the study demonstrate the importance of careful selection of calibration periods and the need of using a variety of optimized parameter sets for future climate change research.

The particularity of the Gambia River Basin shared by many countries requires a powerful "win-win" cooperation between all the stakeholder countries. Therefore, OMVG will remain the ideal motor to enhance new strategies and policies to tackle the negative effect of climate change.

Climate change may affect the water supply in energy production and agriculture sectors, which are the two main elements of economic growth in Africa.

The findings of this study may lead to think of a negative impact of climate change, particularly on dry periods and high flows.

This study will thus be helpful for future climate change studies to pay more attention to a certain number of aspects regarding the uncertainty associated with hydrological models and the parameters transposability, such as:

- the selection of research catchments,
- the quality of input data,
- the selection of calibration periods,
- the selection of hydrological models,
- the calibration method

- and the use of variety of optimized parameters

need to be carefully considered.

It is also important to calibrate hydrological models for periods long enough to incorporate as many applicable processes as the observation data allows, or for periods that more closely represent possible future conditions.

The alteration of one or more of these aspects may lead to different outcomes and different conclusions.

The outcome of this study may lead to master the uncertainty associated with hydrologicals model and a better assessment of runoff for future climate change studies.

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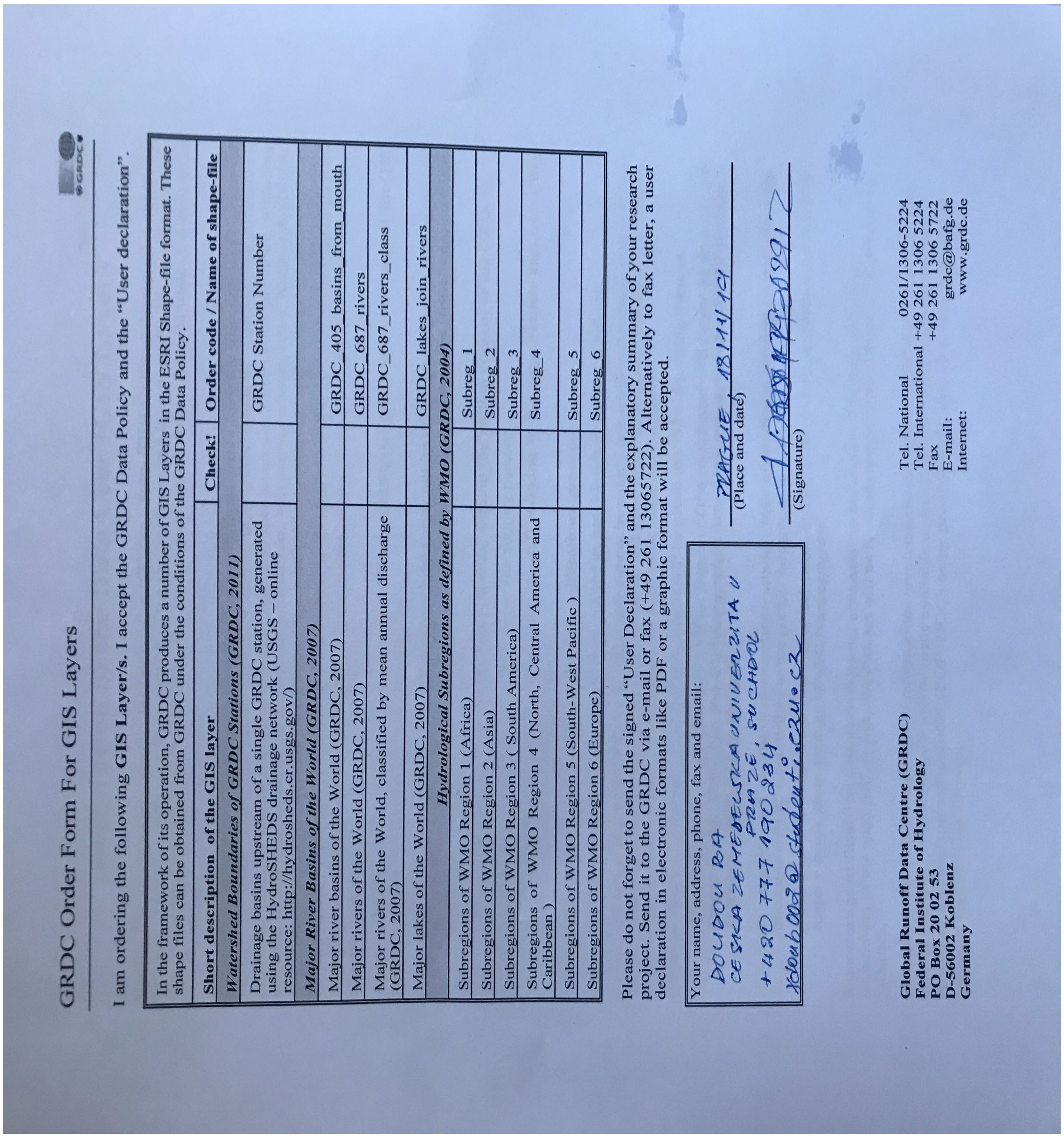
# Appendix A

# List of Appendix



GRDC Order Form For GIS Layers

I am ordering the following **GIS Layer/s.** I accept the GRDC Data Policy and the "User declaration".

In the framework of its operation, GRDC produces a number of GIS Layers in the ESRI Shape-file format. These shape files can be obtained from GRDC under the conditions of the GRDC Data Policy.

| Short description of the GIS layer | Check! | Order code / Name of shape-file |
|---|---|---|
| *Watershed Boundaries of GRDC Stations (GRDC, 2011)* | | |
| Drainage basins upstream of a single GRDC station, generated using the HydroSHEDS drainage network (USGS – online resource: http://hydrosheds.cr.usgs.gov/) | | GRDC Station Number |
| *Major River Basins of the World (GRDC, 2007)* | | |
| Major river basins of the World (GRDC, 2007) | | GRDC_405_basins_from_mouth |
| Major rivers of the World (GRDC, 2007) | | GRDC_687_rivers |
| Major rivers of the World, classified by mean annual discharge (GRDC, 2007) | | GRDC_687_rivers_class |
| Major lakes of the World (GRDC, 2007) | | GRDC_lakes_join_rivers |
| *Hydrological Subregions as defined by WMO (GRDC, 2004)* | | |
| Subregions of WMO Region 1 (Africa) | | Subreg_1 |
| Subregions of WMO Region 2 (Asia) | | Subreg_2 |
| Subregions of WMO Region 3 ( South America) | | Subreg_3 |
| Subregions of WMO Region 4 (North, Central America and Caribbean ) | | Subreg_4 |
| Subregions of WMO Region 5 (South-West Pacific ) | | Subreg_5 |
| Subregions of WMO Region 6 (Europe) | | Subreg_6 |

Please do not forget to send the signed "User Declaration" and the explanatory summary of your research project. Send it to the GRDC via e-mail or fax (+49 261 13065722). Alternatively to fax letter, a user declaration in electronic formats like PDF or a graphic format will be accepted.

Your name, address, phone, fax and email:
DOUDOU BA
CESKA ZEMEDELSKA UNIVERZITA V PRAZE, SUCHDOL
+420 777 190234
xdoub002@studenti.czu.cz

PRAGUE, 18/11/19
(Place and date)

(Signature)

**Global Runoff Data Centre (GRDC)**
**Federal Institute of Hydrology**
**PO Box 20 02 53**
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Tel. National 0261/1306-5224
Tel. International +49 261 1306 5224
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E-mail: grdc@bafg.de
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Figure A.1: GRDC ORDER

CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

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A Monsieur le Directeur General de
L'Agence Nationale de l'Aviation Civile
et de la Météorologie ANACIM
Aéroport Léopold Sédar SENGHOR
BP: 8184 Dakar-Yoff

**Objet :** Demande de mise à disposition de données chronologiques pluviométriques et climatologiques.

Cher Directeur General,

Je suis un Étudiant Sénégalais en Modélisation Environnementale à l'Université Czech des Sciences vivantes à Prague.

Le sujet de mon Msc thesis porte sur la Modélisation de la balance Hydrologique a pas de temps journaliers utilisant les modèles globaux.

Ma zone d'étude concerne les bassins des fleuves Sénégal, Gambie, Casamance, Sine Saloum, elle encadre les régions suivantes (SENEGAL, MALI, MAURITANIE, GAMBIE, GUINEE.B ET GUINEE.C)

C'est à ce propos que je vous transmets ma demande pour me fournir les données chronologiques (journalières, mensuelles, annuelles, les stations et les coordonnées des stations, etc…) de précipitations et de températures (humidité, insolation,) des stations sur les listes en pièces jointes sur une période de 1960 à nos jours.

Monsieur le Directeur General, je veux travailler pour mon pays, publier pour mon pays, servir alors mon pays, c'est dans cette logique que je me suis interdit de faire de l'Europe (dont je dispose déjà les données en objet) ma zone d'étude.

Je serai à votre disposition toute information complémentaire.
Je vous transmets mes salutations, les meilleures.

PJ : grdcSN.xlsx ; stations_et_postes_pluvio_senegal.csv

Doudou BA

Figure A.2: ANACIM ORDER

The modelling approach was to create a function called CalFun in which are included all the model set up and calibration and with lapply function available in the dplyr package Wickham et al. 2018 We perform iterations along our list of subperiods to calibrate. The lapply function [lapply(X, FUN, ...)], returns a list of the same length as X, each element of which is the result of applying FUN to the corresponding element of X. In this modelling approach X meaning our list of sub-periods as model input and the FUN meaning our CalFun function defined below. X is a list of data frames, the lenght of the list X being the number of models (sub-periods, input or time series) to calibrate. The Bilan model is initialized with the function *bil.new*, with the *modif* option to customize the model to later set up a warming up period. Then model values are set using *bil.set.values* and the input data which is a data frame of monthly time series of rainfall (P), runoff(R) and Potential Evapotranspiration (PET). Using the R package HydroGOF (Mauricio Zambrano-Bigiarini 2020)

*bil.get.values* and with the hydroGOF package we calculated the model efficiency using 5 criteria: The Kling Gupta Efficiency (KGE), the Nash-Sutcliff Efficiency, the Mean Absolute Error (MAE), the Mean Square Error (MSE) and the Root Mean Square Error (RMSE).

```
library(airGR)
data(L0123001)
PotEvap <- PE_Oudin(JD = as.POSIXlt(BasinObs$DatesR)$yday + 1,
                    Temp = BasinObs$T,
                    Lat = 0.8, LatUnit = "rad")
```

PET ESTIMATION

```
FunGR1<-function(x,y,w){

# set strings as factors to false
options(stringsAsFactors = F)

b=bil.new('m')
bil.set.values(b, x, init_date = startDTM[[j]])
bil.pet(b, "latit", 13.35)
y<-bil.get.values(b)

y<-data.frame(DTM=x$DTM,
              P=y$vars$P,
              T=y$vars$T,
              R=y$vars$R,
              PET=y$vars$PET)
return(y)
}


input<-data
```

```
startDTM=list()
for(j in 1:length(input)){
startDTM[[j]]<-input[[j]][["DTM"]][1]
print(startDTM)
}

PETestm<-input%>%
  lapply(FunGR1)

input2<-PETestm

CalFun<-function(x,y,z,m,k) {#model setup}

b=bil.new('m', modif = 'critvars')
 bil.set.values(b, x,
 init_date = startDTM[[j]])
 bil.pet(b, "latit", 13.35)
y<-bil.get.values(b)
y<-data.frame(P=y$vars$P,
              T=y$vars$T,
              R=y$vars$R,
              PET=y$vars$PET)
              }

#Setting warump period
warmup<-1:12
KGEwarmUp<- function(sim){
obst<-y$R[-warmup]
simt<-sim[-warmup]
-1*hydroGOF::KGE(sim = simt, obs = obst)}

#Setting model parameters

 bil.set.params.lower(b, list(Spa =100,Grd= 0.001,
                             Alf=0.00001))
 bil.set.params.upper(b, list(Spa = 2000, Grd= 1,
                             Alf=0.003))

 bil.set.optim(b, method = "DE", crit = "NS",
     DE_type = "best_one_bin", n_comp = 4,
     comp_size = 10, cross = 0.95, mutat_f = 0.95,
     mutat_k = 0.85, maxn_shuffles = 30,
     n_gen_comp = 15, ens_count = 1, seed = 446,
     weight_BF = 0, init_GS = 5)

#Setting modif critvars
 bil.set.critvars(model = b,
                  weights = c(1),
                  obs_vars = c('R'),
                  mod_vars=c("RM"),
```

```
                    obs_values=c(-1),
                    crits=c('custom'),
                    funs=c(KGEwarmUp))

#Optimizing the model
m<-model<-bil.optimize(b)
#Res get val
res=bil.get.values(b)
bilget<-bil.get.ens.resul(b)
z<-bilget

resCal<-input%>%
lapply(CalFun)
```

### A.0.1 Validation of Bilan model

Similary to the model calibration we create a function to perform an automatized model validation using the r lapply function.

```
ValFun<-function(x,y,z,m,k,o){}

  for(i in 1:nrow(a)){
  bil.set.params.curr(b, list(Spa=a$Spa[i],
                              Dgw=a$Dgw[i],
                              Alf=a$Alf[i],
                              Dgm=a$Dgm[i],
                              Soc=a$Soc[i],
                              Wic=a$Wic[i],
                              Mec=a$Mec[i],
                              Grd=a$Grd[i] ))

     #run model
    m<-bil.run(b)
    #Res get val
    res=bil.get.values(b)
    z<-res

bilget<-bil.get.ens.resul(b)
o<-bilget


k<-list(KGE,NSE,MAE,MSE,RMSE)

result<-list(x,y,z,m,k,o)

# print(res)
saveRes[[i]]=res

saveRes = rbind(saveRes)
```

```
saveRes

  }
return(list(saveRes,k))

}

a<-pk7
input<-K7

startDTM=list()
for(j in 1:length(input)){
startDTM[[j]]<-input[[j]][["DTM"]][1]
print(startDTM)
}

saveVal<-input%>%
  lapply(ValFun)
```

## A.1 Calibration and Validaion of GR2M model

### A.1.1 Calibration

```
FunGR2<-function(x,l,k,z){#model setup}


#Model Setup
BasinObs<-x

#Run model ------------------------------------------------
#Preparation of the InputsModel object

w<-CalInputs<- CreateInputsModel(FUN_MOD = RunModel_GR2M,
                                 DatesR = x$DTM,
                                 Precip = x$P,
                                 PotEvap = x$PET)


#Selection of simulation and warmup periods

begWarm<-substring(x$DTM[1],1,7)

endWarm<-substring(x$DTM[12],1,7)

begRun<-substring(x$DTM[13],1,7)

endRun<-substring(x$DTM[nrow(x)],1,7)
```

```
list(begWarm,endWarm,begRun,endRun)

CalWarmUp<- seq(which(format(x$DTM, format="%Y-%m")==begWarm),
           which(format(x$DTM, format="%Y-%m")==endWarm))

CalRun <- seq(which(format(x$DTM, format="%Y-%m")==begRun),
         which(format(x$DTM, format="%Y-%m")==endRun))

CalRunOpt <- CreateRunOptions(FUN_MOD = RunModel_GR2M,
            InputsModel = CalInputs, IndPeriod_Run = CalRun,
            IndPeriod_WarmUp = CalWarmUp)

## preparation of CalibOptions object
CalOpt <- CreateCalibOptions(FUN_MOD = RunModel_GR2M,
FUN_CALIB = Calibration_Michel)

## calibration
CalOutput <- Calibration_Michel(InputsModel = CalInputs,
              RunOptions = CalRunOpt,
              InputsCrit = InputsCrit, CalibOptions = CalOpt,
              FUN_MOD = RunModel_GR2M)
## simulation
p<-CalParam <- CalOutput$ParamFinalR

k<-CalOutput <-  RunModel_GR2M(InputsModel = CalInputs,
              RunOptions = CalRunOpt, Param = CalParam)

z<-list(KGE,KGE2,NSE,RMSE)

result<-list(w,k,z,p)
return(result)

resCalGR<-input%>%
lapply(FunGR2)
```

### A.1.2 Validation

Similiarly to the calibration method we create a Validation function that we call

```
FunGR2<-function(x,l,k,z){the model setup}
```

, to which we apply the dplyr lapply function defined earlier.

```
model setup:

for(i in 1:nrow(a)){
ValParam<- c(X1=a$X1[[i]], X2=a$X2[[i]])
```