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Hydrological Modeling of the Bani Basin in West Africa: Uncertainties and Parameters Regionalization

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Dedication

To my precious son, Ismail of whom I was gifted during my PhD. I did not often have enough time for you, you endured my long absences but you gave me courage and motivation. It was not easy but I did it for you!

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Abstract

In many drainage basins around the world, no runoff data are available. This situation is more pronounced in developing countries, where many river basins lack runoff data and so are ungauged. In West Africa, the general situation of insufficient data is exacerbated by the decline of the measuring network observed since the late eighties. With the aim of predicting hydrological variables in ungauged basins, regionalization methods are usually used. The main objective of this study is to make prediction of streamflow hydrographs on the Bani basin to improve the knowledge of water resources availability. Firstly, the hydrological model SWAT was calibrated on many gauged catchments on the period 1983-1992 and validated on 1993-1997 using the Generalized Likelihood Uncertainty Estimation (GLUE) approach. Secondly, the studied catchments were categorized into clusters of similar physioclimatic characteristics by the means of a multivariate statistical analysis. And finally, in each case, the entire set of optimized model parameters was transferred from gauged to ungauged catchments based on physical similarity and spatial proximity approaches, and the discharge hydrograph was simulated on the target catchment for the period 1983-1997. Results indicated that the daily model performs as good as the monthly model at catchment and subcatchment scales, despite the limited data condition underlying the hydrological modeling. On a daily basis, a good performance of the SWAT model at the whole catchment scale has been obtained as depicted by a Nash-Sutcliffe Efficiency (*NSE*) of 0.76 and 0.84 and a coefficient of determination R^2 of 0.79 and 0.87 for calibration and validation periods, respectively. In addition, the *PBIAIS* values were smaller than 25% in magnitude for both calibration and validation periods, reflecting a reasonable prediction of the water balance. Predictive uncertainties were acceptable despite being larger during high and low flows conditions. The 61% of observed data (*P-factor* = 0.61) were enclosed within a small uncertainty band (*R-factor* = 0.91). A better model performance and smaller predictive uncertainties have been achieved with monthly calibration compared to daily calibration, except for the water balance, where errors have slightly increased. A total of 12 model parameters were identified that best simulate the observed discharges. The test catchments principally aggregated into three groups: a group of northerly flat and semi-arid catchments, another group of southerly hilly and humid catchments, and a third group located in the center of the study basin, inside which, none of the descriptors seems to exert a strong control on the similarity. Overall, regionalization yielded

satisfactory to very good results at many target catchments. The best efficiencies have been recorded in the arid zone and at the whole catchment outlet with *NSE* values ranging between 0.56 and 0.83. However, predictive uncertainty showed an increase with aridity. A good mutual hydrological similarity was found in a set of catchments belonging to different physical regions, and between which, spatial proximity was found to be a better surrogate of this similarity. The knowledge of water resources availability where it is not measured is very useful for many applications such as water allocation for consumption and irrigation especially in West Africa frequently facing water deficit and food insecurity due to the impacts of a changing climate. Results also contribute to the advance in understanding of hydrological processes of a newly investigated area in the field of Prediction in Ungauged Basins (PUB), and constitute a first step toward further investigations on catchment functioning on which depends largely the success of any regionalization of hydrological information.

Keywords: Prediction in ungauged Basins, SWAT model parameters, Performance and predictive uncertainty, Multivariate statistics, Catchments similarity, Regionalization.

Résumé

De nombreux bassins de drainage à travers le monde ne disposent d'aucune mesure de débit. Les méthodes de régionalisation sont alors généralement utilisées pour les prévisions en bassins non jaugés. L'objectif principal de cette étude est de prévoir les hydrogrammes d'écoulement dans le bassin du Bani afin de contribuer à l'amélioration de la connaissance sur la disponibilité des ressources en eau. Tout d'abord, le modèle hydrologique SWAT a été calibré sur de nombreux bassins jaugés sur la période de 1983-1992 et validé sur la période 1993-1997 en utilisant la méthode « Generalized Likelihood Uncertainty Estimation (GLUE) ». Ensuite, des groupes de bassins similaires ont été déterminés en fonction de leurs caractéristiques physiographiques et climatiques et au moyen d'une analyse statistique multivariée. Deux méthodes de régionalisation basées sur le concept de similarité entre bassins, ont été utilisées : la similarité physique et la proximité spatiale. Dans les deux cas, le jeu de paramètres calés du modèle est entièrement transféré du bassin jaugé vers le bassin non jaugé pour y simuler l'hydrogramme de débits journaliers de la période 1983-1997. Les résultats indiquent une bonne performance du modèle à l'échelle journalière et mensuelle, ainsi qu'à l'échelle du bassin et des sous-basins. La performance du modèle à l'échelle du bassin global et sur un pas de temps journalier est caractérisée par un critère de Nash de 0.76 et 0.84 et un coefficient de détermination de R^2 de 0.79 et 0.87 en période de calibration et de validation, respectivement. Aussi, les valeurs absolues du PBIAIS demeurent inferieures à 25%, ce qui témoigne d'une bonne prévision du bilan d'eau. Il est à noter que les incertitudes associées demeurent satisfaisantes malgré les conditions de données limitées qui sous-tendent cette modélisation. Ainsi, 61% des débits observés (P-factor = 0.61) sont compris à l'intérieur de la bande d'incertitude dont la largeur reste adéquate (R-factor = 0.91). La calibration mensuelle a quant à elle permit d'atteindre une meilleure performance du modèle et une diminution des incertitudes à l'exception du bilan d'eau dont les erreurs de prévision semblent avoir augmenté. La calibration a également permis d'identifier 12 paramètres du modèle qui simulent au mieux les débits observés. Les bassins étudiés ont été classes en trois groupes: un groupe de bassins de plaine, semi-arides et situés au Nord, un autre groupe de bassins d'altitude qu'on rencontre dans les zones humides du Sud, et un troisième groupe situé dans le centre du bassin d'étude, à l'intérieur duquel, aucun des descripteurs semble se démarquer significativement des autres. Dans l'ensemble, la régionalisation a donné de bons résultats au niveau de plusieurs bassins cibles. Les meilleurs ont

toutefois été enregistrés dans la zone aride et à l'exutoire global du bassin, particulièrement. Cependant, on note également une augmentation des incertitudes précisément dans cette zone. Une bonne similarité hydrologique mutuelle a été mise en évidence entre certains bassins, dont le meilleur indicateur reste la proximité spatiale. La connaissance de la disponibilité des ressources en eaux, particulièrement au niveau des bassins non jauges, est d'une utilité capitale dans plusieurs domaines d'application telles que l'allocation de l'eau pour la consommation et pour l'irrigation surtout en Afrique de l'Ouest qui fait face fréquemment à la gestion des risques liés au déficit en eau et a l'insécurité alimentaire en raison des impacts du changement climatique. Ces résultats contribuent également à une meilleure compréhension du fonctionnement hydrologique d'une zone jusque-là non explorée dans le domaine de la prévision en bassins non jaugés (PUB), et constituent une première étape vers de nouvelles investigations qui contribueront à l'amélioration des prévisions de l'information hydrologique.

Mots clés : Prévisions en Bassins non jaugés, Paramètres du modèle SWAT, Performance et incertitudes liées à la prévision, Analyse multivariée, Similarité entre bassins, Régionalisation.

Table of Contents

List of Tables

List of Figures

CHAPTER I

1. Introduction

1.1. Problem statement

Water resources managers are facing challenges in many river basins across the world due to limited data availability. Climate and land use changes – be it natural or human-induced – add more complexity to this task (Pomeroy et al., 2013; Sivapalan et al., 2003). This situation is more pronounced in developing countries, where in many river basins no runoff data is available (Bormann and Diekkrüger, 2003; Kapangaziwiri et al., 2012; Mazvimavi et al., 2005; Minihane, 2013; Ndomba et al., 2008) and the existing ones are of questionable quality or at best short or incomplete.

The Niger River basin is not an exception to that fact. In the eighties and nineties, for instance, hydrometric stations were reduced to a minimum (Nkamdjou and Bedimo (2008)). To prevent the hydrologic observing system from more degradation, the Niger Basin Authority (NBA) has set the Niger-HYCOS project, which one of its specific objectives is to improve data quality of the Niger River. For this purpose, the project identified and brings assistance in the installation and the management of 105 hydrometric stations shared by nine countries drained by the River, and contributes to the capacity building of national hydrological services.

In its fifth assessment report on regional aspects of climate change, the Inter-Governmental Panel on Climate Change (IPCC, 2014) has shown that adaptation to climate change in Africa is confronted with a number of challenges among which is a significant data gap. Too many basins lack reliable data necessary to assess in details impacts of climate change on different components of the hydrological cycle and to develop strategies of adaptation related to each specific impact. Thus, there is an urgent need to predict hydrological variables in ungauged basins for building high adaptive capacity by improving: (i) water resources knowledge,

planning and management, (ii) identification and implementation of strategies of adaptation to climate change in the sector of water, and (iii) ecological studies for a sustainable development. Additionally, Blöschl et al. (2013) developed an exhaustive range of applications for which prediction in ungauged basins is needed, such as hydraulic structures design, flood and drought management, water allocation, hydropower, ecological purposes and water quality, to cite few. Another important problem that is now acknowledged by the international community is the increasing importance of uncertainty analysis in hydrology (Beven, 2008; Hrachowitz et al., 2013). Hydrological predictions should systematically integrate uncertainty analysis (Beven, 2006) and thus provide not only one situation, but a variety of possible situations on which decisions can be built (Dessai et al., 2009; Paturel, 2014). As discussed by Hulme (2011). Decision-makers need uncertainty evaluation rather than pseudo-certainty. Possible future scenarios are more needed for Prediction in Ungauged Basins (PUB) which adds to the traditional uncertainty related to hydrological modeling (related to input data, model structural errors, and parameters identification), another source of uncertainty related to model parameters transfer. However, little attention has been given to the uncertainty resulting from model parameters regionalization at ungauged sites (Wagener and Wheater, 2006), especially on the Bani catchment, where to our knowledge no such a study exists.

1.2. Scope of the study

With the aim of predicting hydrological variables in ungauged basins, regionalization procedures are usually used. Different types of regionalization methods exist, and can be divided into (He et al., 2011; Hrachowitz et al., 2013): (1) Regionalization of flow and flow metrics, and (2) regionalization of model parameters. The latter is a process-based method and involves the application of a rainfall-runoff model and the transfer of model parameters from gauged to ungauged catchments. In spite of the additional uncertainties related to input data,

model structure, parameter identification, and the need of rigorous calibration at gauged catchments (Blöschl, 2011; He et al., 2011; Wagener and Wheater, 2006), it remains a long-standing method (Wagener et al., 2004a) for flow prediction in ungauged basins. Because of runoff process results from the interaction between all important processes within a catchment, and these processes can be physical, chemical and biological (Blöschl et al., 2013). The quantification of the impact of such processes on the runoff behaviour can only be approximated by a hydrological model. The transfer of model parameters can make use of either regression-based methods or distance-based methods. The latter group of methods assumes that there exists a similarity measure, which can be used to transfer, to a certain extent, hydrological information from a catchment to another to which it is similar.

Given this background, the main objective of this thesis is to make predictions of streamflow hydrographs on the Bani basin to improve the knowledge of water resources availability. The specific objectives are to:

- Calibrate a rainfall-runoff model on many gauged catchments and identify the best model parameter sets;
- Provide a classification of catchments based on their physiographic and climatic characteristics
- And regionalize the optimized model parameters from gauged to ungauged catchment based on the physical similarity, and achieve discharge hydrograph without need of any measurement.

Specific research questions are addressed in order to achieve the aforementioned objectives: (1) To which extent does the SWAT model for the Bani catchment depend on the temporal and spatial scale?

(2) What are the SWAT model parameters that best describe the hydrological behaviour of the Bani basin?

(3) Can the use of measured sparse point rain gauge data provide valuable information for discharge simulation?

(4) What is the physio-climatic pattern of similarity between catchments?

(5) What are the dominant controls on similarity between catchments?

(6) Is there any pattern of the regionalization performance and prediction uncertainty?

(7) Which similarity-based method for regionalization performs best?

(8) Does physical similarity entail hydrological behaviour of a catchment?

By contributing to the advance in regionalization of hydrological information across regions, this work provides the first ever complete study on discharge hydrograph prediction at ungauged basins on a data-sparse large Soudano-Sahelian catchment subject to different climate, soil and land use variabilities. The originality of this work resides in the combined use of daily and subcatchment performances along with the assessment of prediction uncertainty to provide finer temporal and spatial hydrological information and its range of variations at gauged and ungauged sites. Another important output of this work is the involvement of evapotranspiration (the most important component of the water balance after rainfall especially under warm climate) in the verification of model outputs reasonability, a particular attention that has not been considered by any previous study in the region. In addition, we used point rain gauge data (as per SWAT's standard procedure) opposed to areal precipitation in order to maintain the real data condition (limited in time and space) as far as possible.

1.3. Outline of the Thesis

To address the aforementioned research questions, the Thesis is organized in 5 Chapters. ***Chapter I*** presents the general introduction of the thesis; the problem that supports the research is stated and the objectives and research questions are clearly presented.

Chapter II provides a literature review in order to estimate the current knowledge on the hydrological modeling of the study area, catchments classification and similarity frameworks and regionalization approach for flow prediction in ungauged basins.

Chapter III is dedicated to the description of the input data and the particular methods involved in the research process. First, we describe the general modeling framework of the thesis in which we tried to address the questions (1) to (3). The objectives were to assess the performance and prediction uncertainty of the SWAT model on daily and monthly time intervals and at catchment and subcatchment levels, and to identify the model parameters that best describe the hydrological functioning of the catchment. Second, we shed light on the similarity framework between catchments by addressing questions (3) and (4). The objectives were to group catchments into clusters of similar physiographic and climatic characteristics, and determine the main causes of similarity. Finally, the regionalization approach is explained that deals with questions (6) to (8). The objectives were to predict daily streamflow hydrograph at ungauged catchments based on similarity concepts, and assess the prediction uncertainty related to the model parameters transfer.

Chapter IV presents the main findings, their corresponding analysis and some discussions with regards to the current knowledge and their implications in the field of interest.

Ch***apter V*** presents a conclusion of the whole study and gives some limitations that emerged out of the research process, and some recommendations and perspectives for further work.

CHAPTER II

2. Literature review

2.1. Hydrological modeling of the Bani basin

Hydrological models are valuable tools for water resources planning and management, flood and drought prediction, ecological studies, impact studies related to change in climate and land use/land cover, and find especially good applications in PUB. Many studies successfully applied different hydrological models on the Bani catchment for different purposes taken from discharge simulation to projection of future impact of climate change on freshwater availability (**Table 2-1)**. It is important to note that the conceptual GR2M model (Makhlouf and Michel, 1994) has been extensively used in West Africa and has proved to satisfactorily reproduce monthly flows in many river basins of the region, including the Bani basin. The SWAT model (Arnold et al., 1998) has recently proved valuable in large drainage basins hydrological modeling of the African continent as a whole. The study of Schuol and Abbaspour (2006) provides monthly simulations of many river discharges in West Africa along with the associated prediction uncertainty. It can be noticed that most of the studies used interpolated input climate data, either measured or generated. For instance, Schuol and Abbaspour (2007) developed and applied a daily weather generator algorithm that uses 0.5 degree monthly weather statistics from the Climatic Research Unit (CRU) to obtain time series of daily precipitation as well as minimum and maximum temperature for West Africa. These generated weather data were then used as input for model setup and they (Schuol and Abbaspour, 2007) concluded that "discharge simulations using generated data were superior to the simulations using available measured data from local climate stations" However, the results of interpolation methods are strongly influenced by the density and spatial distribution of the measurement stations used in the interpolation (Masih et al., 2011). Such a density of data is not always available in developing countries. Beside the spatial scale of input data, one can notice that except the work by Ruelland et al. (2012), all mentioned studies in **Table 2-1**, calibrated

monthly values of the river discharge. Nevertheless, knowing daily discharge can help in many practical issues such as flood risk management, structure design, and more understanding of the hydrological processes of a catchment at finer scale, which can be smoothed out at larger scale. Moreover, only the studies with the SWAT model (Schuol and Abbaspour, 2006; Schuol et al. 2008a, 2008b) introduced the quantification of prediction uncertainty related to model calibration in the study area. At this point, reported Nash-coefficient values as well as associated prediction uncertainty vary largely between sub-basins and were principally presented as average intervals limiting thus, our understanding of model performance. As an example, Schuol et al. (2008a) presented the model performance at Douna on the calibration period as depicted by a *NSE* between 0 and 0.70, a P-factor between 60% and 80% and R-factor between 1.3 and 2.1, which makes it difficult to appreciate the real approached performance.

Table 2-1. Summary of the previous hydrological modeling studies conducted on the Bani basin.

Reference	Objectives	Study basin/area	Model	Input Rainfall	Period	Time-step	Main findings/result related to the Bani
Paturel et al. (2003)	Assess the impact of gridded data on the performance of two hydrological models	Mali, Cote d'Ivoire, Burkina Faso	GR2M, WBM	Gridded measured	1950-1995	Monthly	Robustness of the GR2M in the study area/WBM model more suitable for catchments of the Niger River,
Paturel (2014)	Hydrological scenarios	Bani	GR2M	Gridded measured	1961-1990	Monthly	The performance of the model is greater on a dry period than on a contrasted one; projected hydrological trends depend on the choice of the calibration period
Dezetter et al. (2008)	Determine the best data-model combination for runoff simulation	Guinea, Mali, Cote d'Ivoire, Burkina Faso and Niger	GR2M, WBM	Gridded measured	1902-1995	Monthly	Globally better performance of the GR2M model is recorded (including on the Bani),
Ruelland et al. (2008)	Evaluate the sensitivity of a hydrological model to methods of interpolation	Bani	Hydrostrahler	Gridded measured	1950-1992	Daily, ten-day	Inverse Distance Weighted method performs best, especially when a hydrological model is used: good *NSE* (0.76-0.85) and satisfactory (0.52-0.58) at Douna on a ten-day and daily basis, respectively,
Ruelland et al. (2012)	Simulate future water resources under a changing climate	Bani	Hydrostrahler	Gridded measured	1952-2000	ten-day	Substantial decrease in rainfall and runoff especially in the long term behavior is projected. A very good *NSE* values greater than 0.89 at Douna.
Schuol and Abbaspour (2006)	Calibration and uncertainty issues	West Africa/Niger, Senegal and Volta basins	SWAT	Generated gridded	1971-1995	Monthly	Globally satisfying results, large prediction uncertainty and negative *NSE* for the calibration period at Douna,
Schuol and Abbaspour (2007)	compare generated daily weather data to observed data from weather stations	West Africa/Niger, Senegal and Volta basins	SWAT	Generated gridded	1971-1995	Monthly	Un-calibrated simulation with generated climate data better than the simulation with measured data from weather stations,
Schuol et al. (2008a)	Estimate freshwater availability at subbasin and country levels in West Africa	West Africa/Niger, Senegal and Volta basins	SWAT	Generated gridded	1971-1995	Monthly	Globally satisfying simulations of freshwater availability as well as the associated prediction uncertainty. *NSE* at Douna between 0 and 0.70 for calibration and validation periods,

Schuol et al. (2008b)	Model monthly sub-country-based freshwater availability for Africa	African continent	SWAT	Generated gridded	1971-1995	Monthly	Globally good results although with large prediction uncertainties in many cases,
Faramarzi et al. (2013)	Assess the impact of climate change on water resources in Africa at a subbasin level	African continent	SWAT	Generated gridded	1971-1995	Monthly	Overall increase of mean water resources; subbasin and country variations,
Laurent and Ruelland, (2010)	Evaluate the contribution of the SWAT model in the understanding of streamflow generation	Bani	SWAT	Gridded measured	1952-2000	Monthly	Good performance of the model at Douna (*NSE* > 0.80) and at internal stations (*NSE* > 0.70).

2.2. Catchment classification and similarity frameworks

Hydrological similarity between catchments is an essential concept in regionalization (Blöschl, 2001; Harman and Sivapalan, 2009; Wagener et al., 2007) and could be derived by a classification scheme. As discussed by Wagener et al. (2007), the ultimate goal of classification is to understand the interaction between catchment structure, climate and catchment function. Additionally, Sawicz et al. (2011) proposed four objectives of catchment classification which are: 1) nomenclature of catchments, 2) regionalization of information, 3) development of new theory, and 4) hydrologic implications of climate, land use and land cover change. For a regionalization perspective, catchment classification consists in the search of hydrologically similar gauged catchment(s), from which hydrological information can be transferred to the ungauged catchment. However, hydrological similarity is difficult to define due to the incomplete understanding of the underlying hydrological processes (Blöschl et al., 2013) occurring at different landscapes and climates. In fact, many similarity indices exist and are related to the process they represent (Blöschl, 2006). Hence, it can be deduced that different similarity definitions exist as well. Hrachowitz et al. (2013) highlighted in their review of the decade on Prediction in Ungauged Basins (PUB) that an ideal classification scheme should thus combine catchment form, climate, and functioning.

Among the numerous classification methods, multivariate statistical analyses such as Clustering, Principal Components Analysis (PCA) are from far the most widely used. For instance, Kileshye Onema et al. (2012) used 8 physiographic and meteorological variables to organize 21 catchments located within the Nile basin, into 2 homogeneous regions by applying a multivariate statistical analysis. As for Coopersmith et al. (2012), they distinguished only six dominant classes for 331 catchments across the continental United States using four hydroclimatic similarity indices in a clustering algorithm. Using 6 different hydrological and

climatic metrics into a different clustering algorithm, Sawicz et al. (2011) were able to organize US catchments into 9 homogenous groups, and into 12 in a subsequent study (Sawicz et al., 2014), attempting to explain the impact of input metrics and temporal scale on similarity. It is worth noting the work of Raux et al. (2011) involving 24 worldwide large drainage basins, among which, the Niger basin. In fact, Raux et al. (2011) considered sixteen geomorphological and climatic variables into multivariate statistical analyses and obtained 6 clusters along with the description of the major controlling factors driving the hydro-sedimentary response of each group. Beside, different approaches have been used in order to make a classification of catchments around the world such as self-organizing maps used by Di Prinzio et al. (2011) to organize around 300 Italian catchments according to several descriptors of the streamflow regime and geomorpho-climatic characteristics.

Despite the tremendous studies that have recently been conducted, especially during the PUB decade (2003-2012), trying to define catchment classification and similarity frameworks, little attention has been paradoxically given to developing countries, where in many cases river basins are ungauged. Some few studies exist for instance on the Niger River, as in Raux et al. (2011), but still need to be deepened because large drainage basins usually encompass several climatic regions and exhibit strong environmental gradients. Therefore, it is essential to break down the scale and provide more detailed classification scheme, and this is essential especially when prediction in small ungauged catchments is foreseen. Only one *a priori* classification of the Niger basin exists and have been proposed by the Niger Basin Authority (ABN, 2007) which subdivided the whole basin into 4 physio-climatic regions: the Upper Niger, the Niger Inner Delta, the Middle Niger, and the Lower Niger. Nevertheless, a global classification at such spatial scale can still hide significant internal heterogeneities among subcatchments, hence limiting our understanding of the hydrological functioning occurring at smaller scale. In

addition, this classification falls short of providing a quantitative assessment of the degree of (dis)similarity within and between the so-called homogenous regions, and why they are similar.

2.3. Regionalization approach for flow prediction in ungauged basins

Different types of regionalization methods exist, and can be divided, as suggested by Hrachowitz et al. (2013) after He et al. (2011), into: (1) regionalization of flow and flow metrics, and (2) regionalization of model parameters. In both cases, either regression-based methods or distance-based methods can be used. The application of a rainfall-runoff model and then, transferring model parameters from gauged to ungauged catchments is a long-standing method (Wagener et al., 2004b) for flow prediction in ungauged basins. The major weakness of this method is that it adds more uncertainty related to input data, model structural errors and model parameters identification, and it requires strong calibration of model parameters at one or more gauge sites (Blöschl, 2011; Blöschl et al., 2013; He et al., 2011; Wagener and Wheater, 2006). This calibration requirement implies a certain data need that is not always fulfilled especially in developing regions (Buytaert and Beven, 2009).

A range of studies emphasized the value of model parameter regionalization based on regression methods, which consist in deriving statistical relationships between catchment attributes and the optimized model parameters (Cheng et al., 2012; Kim et al., 2015; Laaha and Blöschl, 2006a; Laaha and Blöschl, 2006b; Lyon et al., 2012; Mazvimavi et al., 2005; Mazvimavi et al., 2004; Soulsby et al., 2010a; Soulsby et al., 2010b; Viviroli et al., 2009). Notwithstanding being considered as the most common regionalization approach for flow prediction in ungauged catchment (Wagener and Wheater, 2006), statistical methods are limited in use due to the presence of equifinality in calibrated model parameters. In fact, it becomes difficult to associate individual parameters with the physical characteristics of the

catchment (because each parameter can take several values). Another drawback of these methods is that most statistical models consider linearity between catchment attributes and model parameters (Merz and Blöschl, 2004; Parajka et al., 2005) although this linearity seldom represents hydrological reality (Bárdossy, 2006). Consequently, Bárdossy (2005) suggested instead, the transfer of the complete parameter sets to ungauged sites. It is worth noting the success of simple regression methods on direct flow metrics that have been developed in West and Central Africa by ORSTOM (the current French institute for development research) method developed by Rodier and Auvray, (1965) and CIEH (the Panafrican comity in charge of hydraulic research) method by Puech and Chabi-Gonni, (1983). These methods aim at predicting the 10 percent exceedance probability discharge, generally referred to as Q10, as a function of climatic and geomorphologic variables combined into a multiple linear regression. In spite of the their simplicity, they need to be updated with new variables (due to the problem of non-stationarity in precipitation, and the impact of land use/land cover change that can affect significantly the constants used in the formulas) and to be enlarged to other catchments (have been developed only for specific catchments and climate) in order to improve their regionalization scope.

Similarity methods are suitable for addressing the aforementioned issue of non-uniqueness of model parameters, as well as for propagating prediction uncertainty from gauged to ungauged catchment. These methods are based on the search of hydrologically similar gauged catchments from which hydrological information can be transferred to the ungauged catchments. Hydrological similarity is an essential concept in regionalization (Blöschl, 2001; Harman and Sivapalan, 2009; Wagener et al., 2007). Many similarity concepts have been proposed in the literature that attempt to represent various hydrological processes occurring at different locations. For instance, (Blöschl, 2011) proposed three similarity concepts: Spatial proximity, similar catchment attributes and similarity indices. In the first concept, catchments that are

close to each other are assumed to behave hydrologically similarly. Geostatistical methods are based on this similarity measure. Many authors have indicated, for instance, the predominance of kriging methods on deterministic models in well-gauged regions (Laaha et al., 2014; Parajka et al., 2013; Salinas et al., 2013; Skøien and Blöschl, 2007). Likewise, Castiglioni et al. (2011) demonstrated that Top-kriging outperforms Physiographical-Space Based Interpolation (PSBI) at larger river branches. Nonetheless, it was pointed out that spatial proximity does not always involve functional similarity between catchments (Ali et al., 2012; Oudin et al., 2010), and thus Bárdossy et al. (2005) and He et al. (2011) suggested, instead, the application of hydrologically more meaningful distance measures. From this, it can be deduced the importance of the following concepts. Thus, catchment attributes, such as catchment size, mean annual rainfall, and soil characteristics are used as indicators of physiographic similarity. The rationale for this concept is that physio-climatic characteristics have dominant controls on runoff processes and implicitly assumes that physical similarity implies similar hydrological functioning (Oudin et al., 2010). Many studies stressed the value of parameter regionalization methods based on physiographic similarity, as a proxy for functional similarity (Dornes et al., 2008; Masih et al., 2010; Parajka et al., 2005). However, Merz and Blöschl (2009) showed that land use, soil types and geology did not exert a strong control on catchment functioning in Austria, and Oudin et al. (2010) concluded in a study involving 893 French catchments and 10 other located in the United Kingdom, that the implicit assumption of correspondence between physical and functional similarity is invalid in many catchments. The third similarity concept is based on hydrologic function characterized by similarity indices usually defined as dimensionless numbers as the ones given by Wagener (2007), which aim at representing various hydrological processes. For instance, the aridity index of Budyko is used to define similarity in climate (Sivapalan et al., 2011; Tekleab et al., 2011), and has proved to be a good indicator of catchment behavior. Nevertheless, as discussed by Blöschl (2006), different similarity indices

exist and relate to the process they represent, and there exist no unique similarity framework that could be adopted for all cases. Hrachowitz et al. (2013) highlighted the same issue in their review of the decade on Prediction in Ungauged Basins (PUB), and suggested that an ideal classification scheme should thus combine catchment form, climate, and functioning.

Another important aspect that has been highlighted during the PUB decade (2003-2012), was the increasing importance of uncertainty analysis in hydrology ((Hrachowitz et al., 2013) after (Beven, 2008)). Thus, uncertainty analysis should be integrated in any scientific paper (Beven, 2006) and should also be systematically conducted following certain guidelines (Liu and Gupta, 2007). In spite of a variety of model uncertainty assessments at well gauged catchments that have recently been conducted (Abbaspour et al., 2004; Beven and Binley, 1992; Jiang et al., 2015; Schuol and Abbaspour, 2006; Schuol et al., 2008a; Schuol et al., 2008b; Sellami et al., 2013), little attention has been given to the uncertainty resulting from model parameter regionalization at ungauged sites (Wagener and Wheater, 2006).

CHAPTER III

3. Material and Methods

In this chapter, the study area, the available input data and databases for the SWAT model, the quality control on hydro-meteorological data are described. In addition, we present all the particular methods through which research questions were answered.

3.1. The study catchment

The Bani is the major tributary of the Upper Niger River. Its drainage basin is principally located in Mali but spans in a lesser extent over Cote d'Ivoire and Burkina Faso and covers an area of about 100,000 km^2 at Douna gauging station (**Figure 3-1**). The Bani watershed was chosen for this study, on one hand, due to relatively higher data availability compared to regional situation. It thus constitutes the appropriate gauged catchment in different hydro-climatic variables. On the other hand, this watershed has not been affected by important hydraulic structures able to significantly modify its flow regime, making the hydrological modeling of that catchment more convenient.

The catchment's topography (**Figure 3-1**) is characterized by a gentle elevation that ranges from 826 m in the South and the Centre-Est to 249 m at the outlet in the North. Based on the USGS Global Land Cover Characterization (GLCC) version 2.0 (Loveland et al., 2000), croplands constitute the dominant land use category followed by shrubland and woodland (**Figure 3-3**). Major soil groups are mainly constituted by Luvisol, Acrisol and Nitosol (**Figure 3-4)**. The Bani catchment is characterized by a Sudano-Sahelian climatic regime. The river flows from south to north along a high rainfall gradient. Annual precipitation varies from 1250 mm at Odienne to 615 mm at Segou (average of the period 1981-2000). The Upstream of the watershed is formed by a crystalline and metamorphic base containing

groundwater of small storage capacity because located in the weathering products or in the cracks. The lower part is made up of large scale sandstone and alluvial deposits along the streams, inside which groundwater is much more substantial (Ruelland et al., 2009). The average annual discharge recorded at Douna gauging station between 1981 and 2000 was 184 $m^3 s^{-1}$, the smallest discharges were recorded during the years 1983, 1984 and 1987. Due to climate change, there was an abrupt decrease in rainfall in the period 1970-1971 (L'Hote et al., 2002; Ruelland et al., 2012) with a more severe impact on water resources. A decrease of more than 60% in discharge at Douna (Mahé et al., 2000; Ruelland et al., 2012) and lower contribution of baseflow to the annual flood (Bamba et al., 1996; Ruelland et al., 2009) have been reported since the seventies. Concerning future climate change impacts, the Bani basin is projected to experience substantial decrease in rainfall and runoff especially in the long term behaviour (Ruelland et al., 2012).

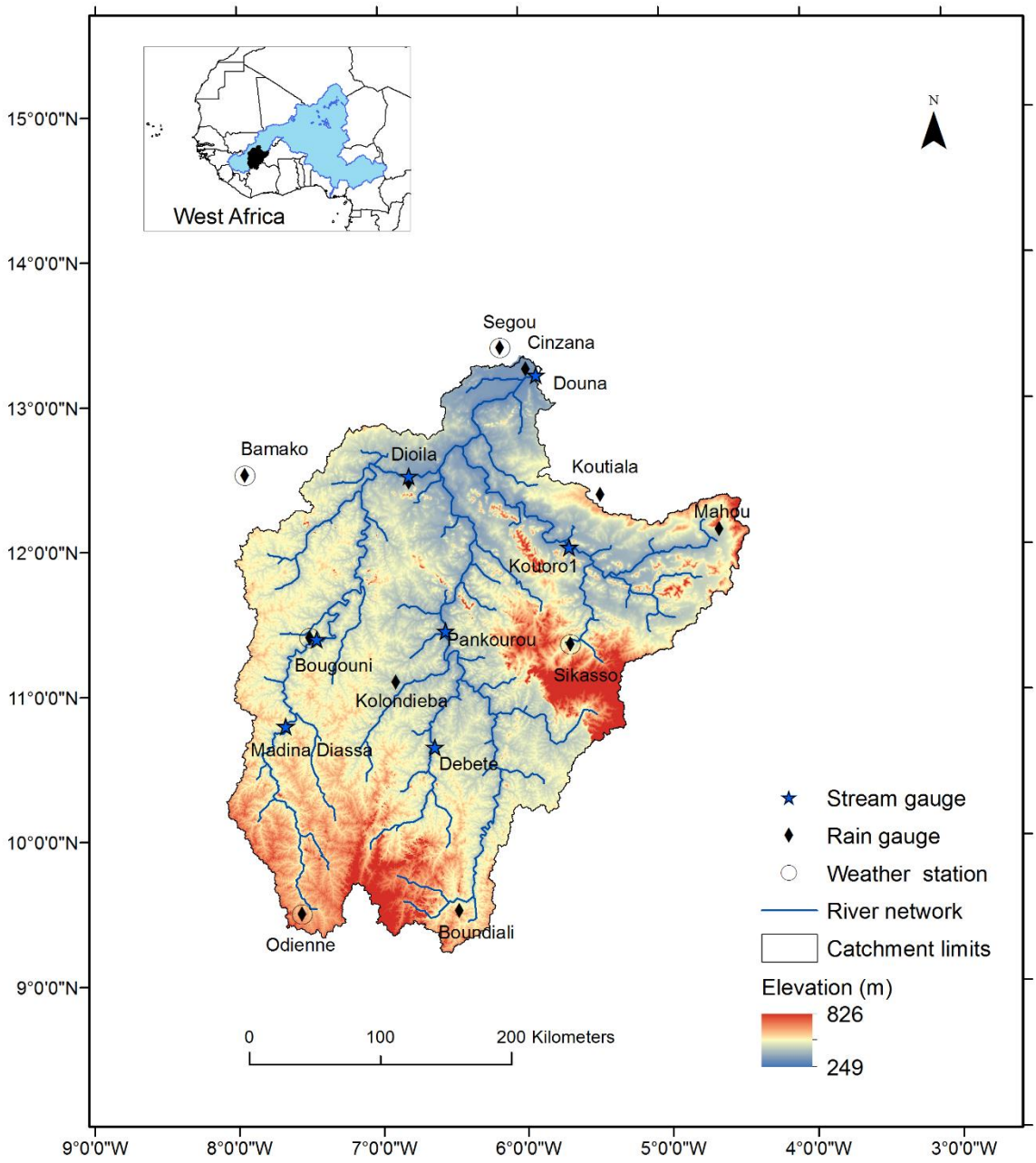


Figure 3-1. Localization of the Bani catchment and the hydro-climatic monitoring network.

3.2. Calibration and validation of the SWAT model

3.2.1. Model description

SWAT is a river basin, or watershed, scale model developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex

watersheds with varying soils, land use, and management conditions over long periods of time (Arnold et al., 1998). The model is semi-distributed, physically based and computationally efficient, uses readily available inputs and enables users to study long-term impacts (Winchell et al., 2013). For a detailed description of SWAT, see Soil and Water Assessment Tool input/Output version 2012 (Arnold et al., 2012a) and the Theoretical Documentation, Version 2009 (Neitsch et al., 2011).

The ArcSWAT (ArcGIS extension) is a graphical user interface for the SWAT model. In the present study, the recent version, ArcSWAT2012, was used for building the hydrological model of the Bani catchment.

The hydrologic cycle simulated by SWAT is based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}), \quad (1)$$

where, SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on day i (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day i (mm H_2O), E_a is the amount of evapotranspiration on day i (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O) and Q_{gw} is the amount of groundwater exfiltration on day i (mm H_2O).

SWAT divides a basin into sub-basins which are further discretized into hydrologic response units (HRUs), based on unique soil-land use combinations. The subdivision of the watershed enables the model to reflect differences in evapotranspiration for various crops and soils. Runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed. This increases accuracy and gives a much better physical description of the water balance (Neitsch et al., 2011).

Various hydrological models exist and there is no strict guideline on the selection of the model. The SWAT model uses a modified version of the Curve Number method, which was developed

in the US for specifically calculating surface runoff generation. Therefore the model is especially suitable for regions with a high share of overland flow on total runoff. Other advantages of SWAT model are that it allows a number of different physical processes (hydrologic, sediment, pollutants) to be simulated in a watershed. It has been previously validated for several large-scale watersheds throughout different climate contexts across the globe and has performed satisfactorily even in data poor and complex catchment (Bouraoui et al., 2005; Ouessar et al., 2009). SWAT is also very flexible in terms of using specific and appropriate soil and land use of the watershed to be modelled by adding them to its database. But in this context, it is worth using a low cost or free model, which West African National Hydrological services could afford due to economic constraints.

3.2.2. Input data and databases

The SWAT model for the Bani was constructed using weather data and globally and freely available spatial information described in **Table 2-1.**

Table 3-1. Input data of the SWAT model for the Bani catchment.

Data type	Description	Resolution/period	Source
		Simulation data	
Topography	Conditioned DEM	90 m	USGS hydrosheds http://hydrosheds.cr.usgs.gov/dataavail.php
Land use/ land cover	GLCC version 2	1 km	Waterbase http://www.waterbase.org/resources.html
Soil	FAO Soil Map	Scale 1:5000000	FAO http://www.fao.org/geonetwork/srv/en/main.home
River	River network map	500 m	USGS Hydrosheds http://hydrosheds.cr.usgs.gov/dataavail.php
Weather data	Rainfall, maximum and minimum temperature	Daily /1981-2000	AGRHYMET
		Calibration/verification data	
Discharge	Discharge	Daily /1983-1997	AGRHYMET/National hydrological service of Mali

PET	Potential evapotranspiration	Ten-day /1983-1998	National Meteorological Agency of Mali
Epan	Pan evaporation	Monthly /1983-1997	AGRHYMET

3.2.3. Hydro-meteorological data and quality control

Data analysis is of the utmost importance because of the quality of input data depends the quality of model results. Weather data, as input for SWAT, determine the accuracy of model simulation. Moreover, input flow data for calibration purpose need to be correct to have a realistic parameters estimation. This analysis is particularly important in West Africa, where the problematic of hydro-meteorological data constitutes a real stumbling-block to hydrological modeling of many river basins. The problem is mostly related to the decline of the measuring network observed since the late eighties (Ali et al., 2005a, 2005b) with the end of large-scale funding toward national meteorological and hydrological services for the monitoring of weather and hydrometric stations. Many of them have been abandoned or at best irregularly followed. This situation drastically affects data quality and quantity, with significant gaps that are found in the time series. As a consequence, in the present case study for instance, the length of the simulation period has been limited by the lack of data after the year 2000 at monitoring stations located in Cote d'Ivoire, and the calibration/validation period has been significantly reduced due to the presence of more missing data affecting almost all the hydrometric stations in the late nineties (from the year 1997).

The first task was to determine a common period for both climatic and discharge data because collected data time series were of varying lengths. Retained data then underwent a thorough quality control as recommended by the World Meteorological Organization (WMO) in the guide to climatological practices, third edition (WMO‑No.100, 2011). The objective of the control is to detect erroneous data in order to correct and if not possible to delete it. Three

procedures were applied: (1) completeness check, (2) plausible value check, and (3) consistency check. For this purpose, statistical techniques are a valuable tool in detecting errors and graphical displays of data constitute a complementary tool for visual examinations.

The completeness test was applied to all data in order to determine the presence of missing values and whether the available data can provide enough information about hydro-meteorological systems prevailing in the study area. Consistency test (minimum temperature is always smaller than the maximum temperature) and plausibility test (according to the knowledge on the study area, there is a plausible interval of variation of temperature values) were solely applied to temperature data. At the end of the tests, we decided which gauge or which year should be introduced into the input database.

Table 3-2. Available daily precipitation data time series: length and completeness.

Stat	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1985	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Ba																														
Bo																														
Bd																														
Ko																														
Od																														
Se																														
Si																														
*Te																														
Ma																														
Kl																														
Di																														
Ci																														

Ba: Bamako, Bo: Bougouni, Bd: Boundiali, Ko: Koutiala, Od: Odienne, Se: Segou, Si: Sikasso, Te: Tengrela, Ma: Mahou, Kl: Kolondieba, Di: Dioila and Ci: Cinzana

*: Discarded from the SWAT input climatic database

Scale of missing data

<10% missing	<20% missing	<50% missing	>50% missing	No data

Climatic data

Daily precipitation as well as daily maximum and minimum air temperatures of observed monitoring stations were used to provide SWAT with input weather variables. The location and spatial distribution of input precipitation and temperature stations are represented on **Figure 3-1**. A total of 11 rain gauges and 5 weather stations were retained and covered different climatic and physiographic subregions of the Bani. The analysis of **Table 3-2** revealed that precipitation data are complete at the majority of sites except for a few number of them: one year containing less than 20% missing data at Dioila, two years with less than 50% at cinzana and one complete missing year at Mahou. In these cases, the SWAT built-in weather generator is used to generate a value based on the provided local weather statistics and fill in missing data during run time. A part from missing values, no apparent inconsistencies were found inside precipitation data. The period of observation 1981-2000 was retained as the simulation period because it is common to all stations. Tengrela rain gauge was discarded because containing a sequence of 5 years with much more missing data which vary from 33% to 100%.

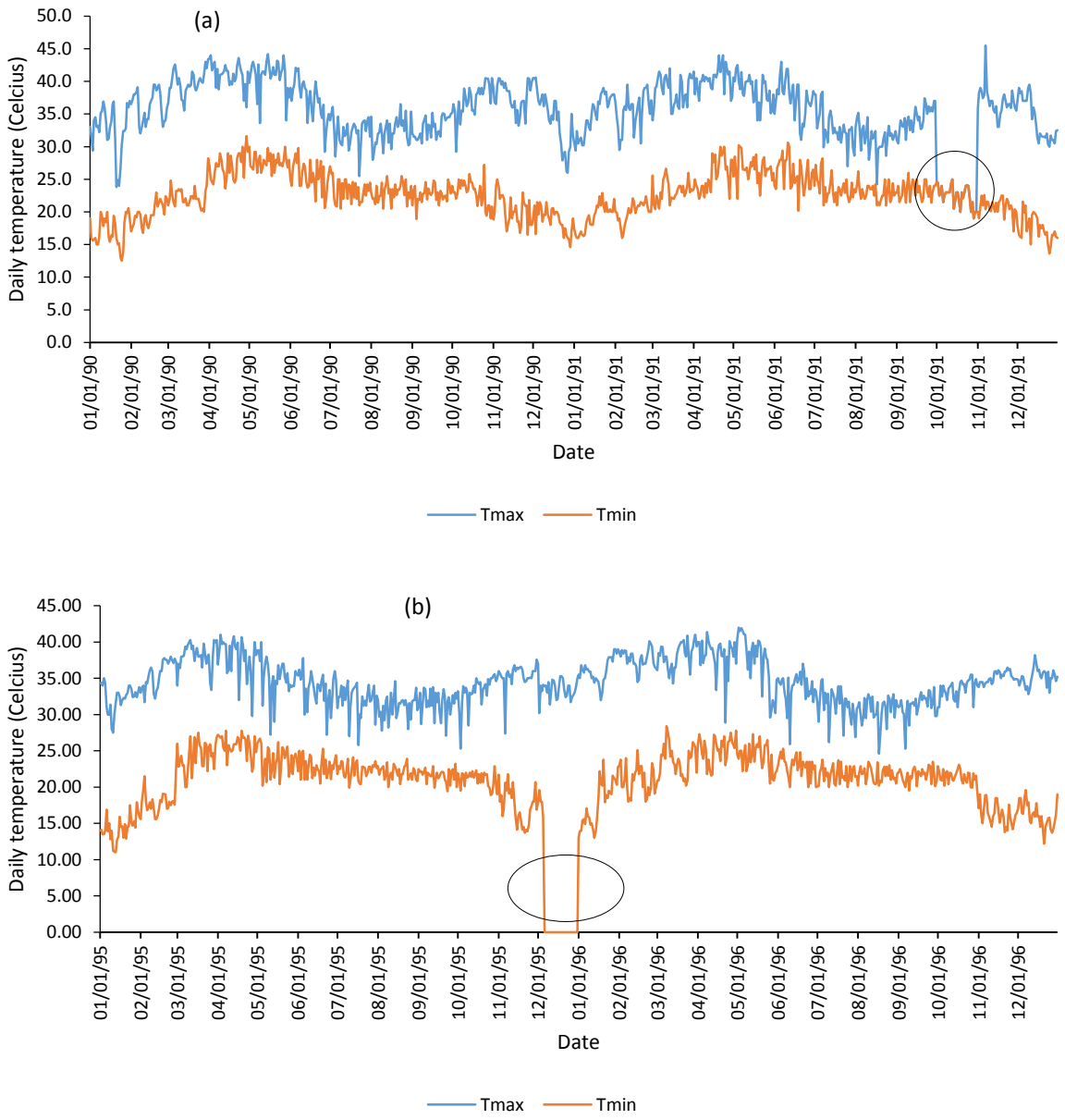


Figure 3-2. Examples of quality control test failures (a) Inconsistency in daily temperature data at Segou (b) implausible minimum temperature values at Bougouni.

Concerning temperature data, it has been noted that the original dataset contains less than 10% missing values but are scattered with errors. Therefore, a day by day meticulous analysis was conducted and many cases where temperature time series failed consistency and plausibility tests have been recorded at certain locations and dates. In such cases, the erroneous data is simply deleted and considered as missing. This technique, even though disputable, remains the

only resort in case of datasets without appropriate metadata. Above (**Figure 3-2**) are some quality control results on temperature data. **Figure 3-2 (a)** shows an example of inconsistency at the Segou weather station where maximum temperature is equal to minimum temperature of the same day and this, during the whole month of October 1991, while on **Figure 3-2 (b)** it can be detected a sequence of implausible zero values in minimum temperature of December 1995 at Bougouni.

Discharge data

Daily discharge data were available at 7 monitoring stations throughout the Bani (**Figure 3-1**). The analysis of the discharge record was mainly based on completeness test and visual analysis of hydrographs and revealed the presence of high missing data. As a consequence, 1983-1997 was kept for calibration and validation processes as it is the period which exhibits few gaps at the majority of subbasins except for Kouoro1 and Debete where 1983-1991 and 1983-1989 were available, respectively. Small existing gaps were thus filled by a simple linear interpolation. A summary description of the available discharge monitoring stations on the Bani for the present study is given in **Table 3-3**.

Table 3-3. Available discharge measurements on the Bani.

Stat_name	River	Country	Long	Lat	Elev (m)	Basin_area (km^2)	Available data
Douna	Bani	Mali	- 5.90	13.21	267	101000	1981-1997
Dioila	Baoule	Mali	- 6.80	12.52	269	31573	1981-1997
Bougouni	Baoule	Mali	- 7.45	11.40	309	14926	1981-1997
Madina Diassa	Baoule	Mali	- 7.67	10.80	327	8417	1981-1997
Kouoro 1	Banifing	Mali	- 5.68	12.02	278	14487	1983-1991
Pankourou	Bagoue	Mali	- 6.55	11.45	282	32048	1981-1997
Debete	Kankelaba	Cote d'Ivoire	- 6.63	10.65	336	5675	1981-1989

3.2.4. GIS-data and databases

Soil and land use data

The soil map of the Bani was derived from the Food and Agriculture Organization of the United Nations (FAO) Digital Soil Map of the World (DSMW) Version 3.6, completed on January 2003. The map is based on the original FAO-UNESCO Soil Map of the World published between 1974 and 1978 and available at 1:5.000.000 scale.

We utilized the GLCC United States Geological Survey's (USGS) a 1-km resolution Global Land Cover Characteristics (GLCC) map version 2.0 (Loveland et al., 2000) to build the Bani land use map. GLCC has been built with data of a 12-month period 1992-93 and therefore represents the land cover pattern of that period.

Major soils that occur in the study catchment are mainly constituted by Luvisols, Acrisols and Nitosols and cover a cumulative proportion of more than 97% of the total catchment area (**Figure 2-3**). In addition, minor inclusions of Gleysols. Lithosols, Regosols and Cambisols can be found. In the following, the description of the soils is summarized based on the FAO-UNESCO legend (FAO-UNESCO, 1977) and Bouwman (1990) who provided additional discussions on that legend.

About half of the Bani area, from the centre to the north, is covered by Luvisols and correspond to the domains of savannah and agricultural land. Ferric luvisols are mainly formed in the tropical zone with a long dry season and are essentially good for major food crops production and extensive livestock raising. They possess a clay horizon, moderate organic matter content and inherent fertility. Acrisols occur in general in warm temperate moist forest, subtropical moist forest and subtropical moist forest. They are characterized by coarse or medium texture,

strong acidity, very low availability of nutrients and an argillic horizon. This soil type is present in the highlands situated in the South of the Bani where forest constitutes the principal land use category. The principal feature of Nitosols is the high clay content which increases with depth. In addition they are characterized by high available water capacity, variable nutrients availability and high organic matter. With regards to Nitosols, they mostly occur in the centre of the study catchment under savannah and in the forested zone in a lesser extent. Lithosols and Regosols appear as inclusions in the Luvisols, while Cambisols are associated with Nitosols and Acrisols.

Databases editing

Two databases were modified to contain custom soil and land use data and their characteristics for the Bani: the user soils database and the crop database. Six soils namely Lithosol, Acrisol, Cambisol, Gleysol, Ferric Luvisol and Nitosol were entered into the user soils database. We considered 4 additional land use categories to the crop database: Forest, Savannah-Bush, Savannah and Steppe. All the aforementioned soils and land use types as well as their parametrization originate from the study by Laurent and Ruelland (2010).

A user weather generator database was created to store local weather stations including their statistics. These statistics are needed by the SWAT weather generator to fill in missing values during the running time. For this purpose, we used the excel macro WGNmaker4 (Boisramé, 2010) on the available 5 weather stations located on and around the Bani (**Figure 3-1**) to calculate statistics that are representative of the local climate conditions (Neitsch et al. 2011 for details on the required weather stations statistics).

3.2.5. Pre-processing of the SWAT input data for the Bani catchment

Four main data files are required by SWAT: Digital Elevation Model data, land use data, soil data and weather data whereas the river network data is optional. The objective of the pre-processing of these data files is to prepare the data specifically for the study catchment in order to be used in the model.

GIS-data pre-processing

First, it is important to install ArcGIS and ArcSWAT, the graphical user interface for the SWAT model. Then, spatial data were downloaded at addresses given in **Table 3-1** and loaded on ArcGIS. Following are the main steps for spatial data pre-processing:

- Create a Clipping box which is a square region around the Bani;
- Clip all layers by the extent of the clipping box to reduce their size;
- Project the clipped layers to Universal Transverse Mercator (UTM) coordinates because SWAT requires all input files in meter units. The Bani basin spans over 2 UTM zones: UTM Zone 29N and UTM Zone 30N. The catchment is extending only 1.58 degree into zone 30N so we projected it into Zone 29N.
- Re-clip the projected layers using the clipping box file so that any missing values that can appear at the borders due to projection deformation are eliminated.

ArcSWAT tables and text files

There are additional necessary formatting work to be done on land use, soil and weather data before incorporating them into SWAT.

The land use look up table is used to make a correspondence between SWAT land cover/plant code or SWAT urban land type code and each category in the land use map grid and was formatted as a dBase table. Therefore, the original GLCC land use types were reclassified into 3 SWAT land use classes (**Figure 3-3** and **Table 3-4**).

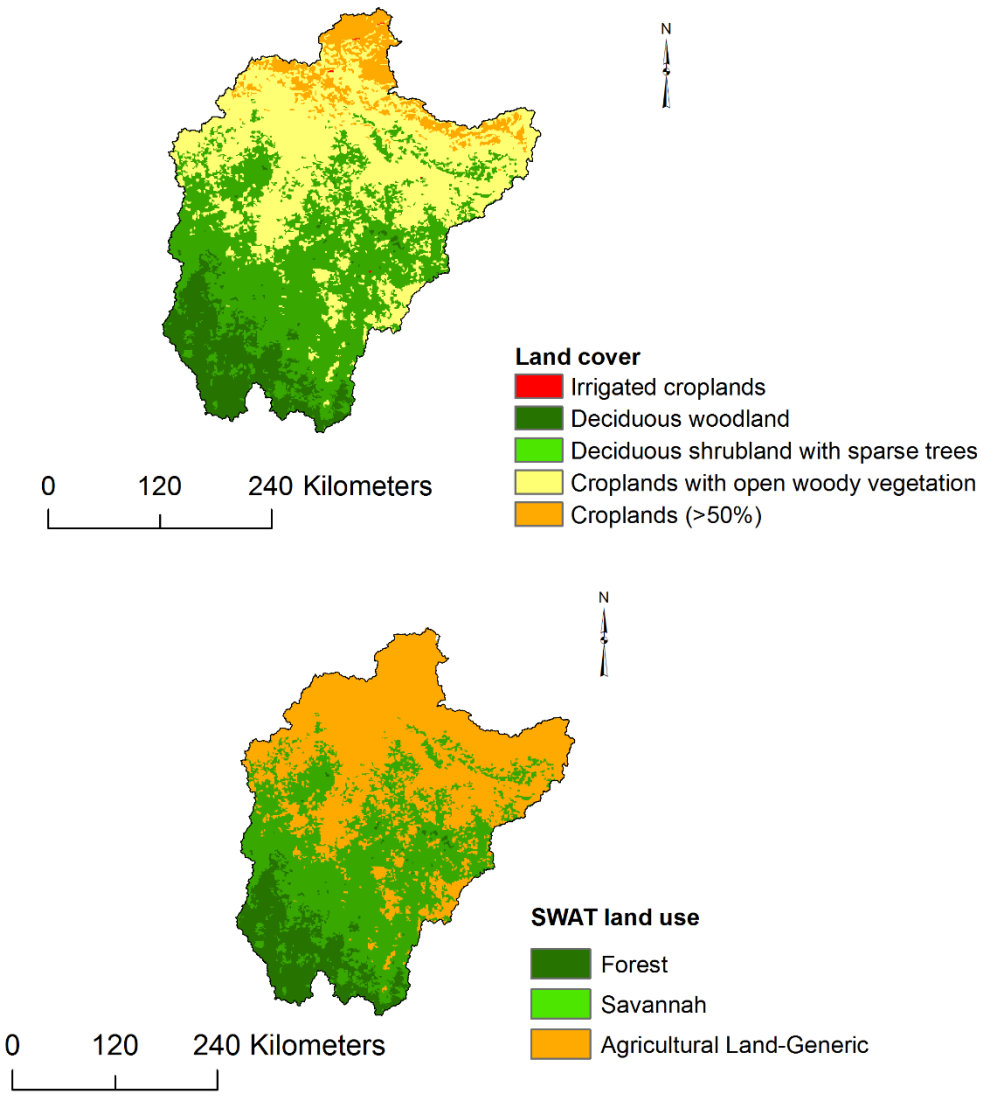


Figure 3-3. Land use/land cover maps of the Bani (a) original GLCC land cover and (b) SWAT land use classes after reclassification.

Table 3-4. Description of the SWAT land use classes of the Bani catchment.

SWAT_LU code	Description	% basin area
FORE	Forest	11.35
SAVA	Savannah	40.3
AGRL	Agricultural Land-Generic	48.35

The soil look up table (dBase) is used to make a correspondence between each category of the soil map and the soil type to be modeled. Then the FAO soil types were linked to 7 SWAT soil classes: 6 of them were previously added to the user soil database and the Regosols have been kept default due to lack of specific information on this soil in the Bani (**Figure 3-4** and **Table 3-5**).

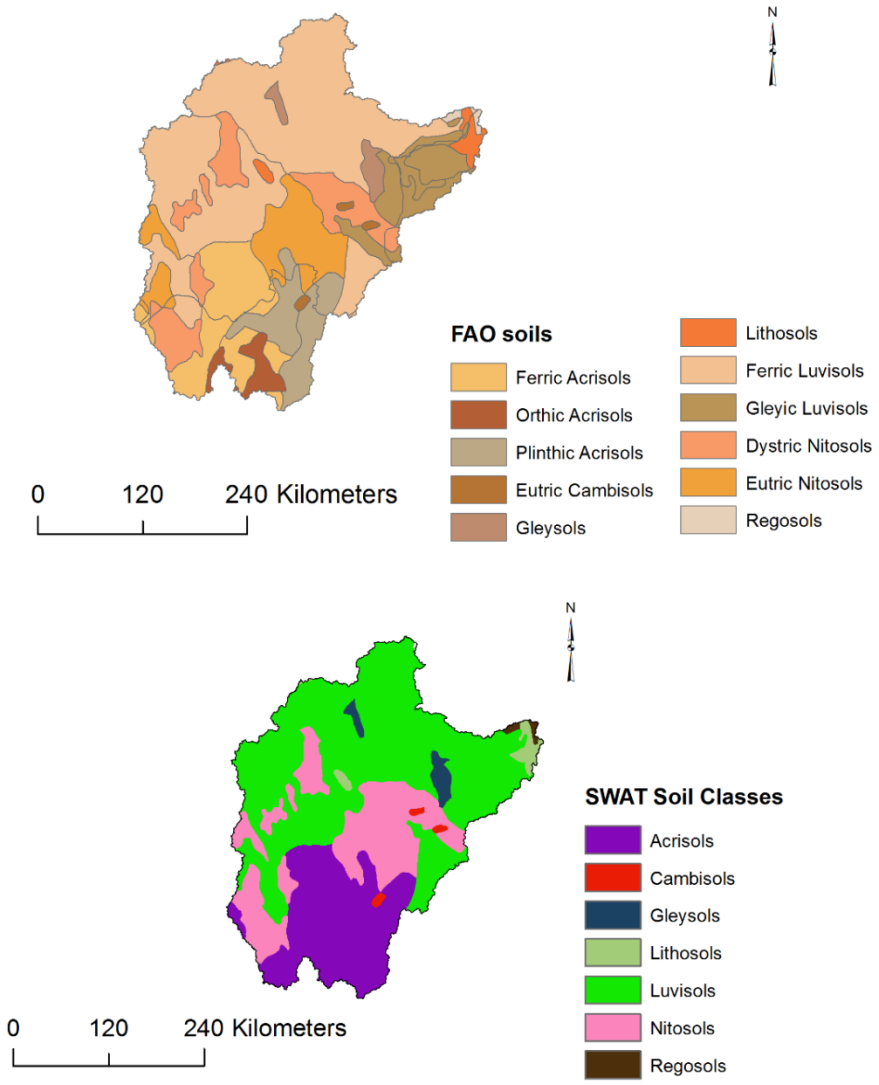


Figure 3-4. Soil maps of the Bani (a) original FAO soils and (b) SWAT soil classes after reclassification.

Table 3-5. Description of SWAT soil classes of the Bani catchment.

SWAT soil class	Description	% basin area
Li	Lithosol	1.03
Ac	Acrisol	22.89
Ca	Cambisol	0.18
Gl	Gleysol	1.21
Lu Fe	Ferric Luvisol	53.02
Ni	Nitosol	21.29
*Re33-1a-1676	Regosol	0.38

*Default FAO soil type

Another type of input files required by SWAT are the gage location tables and the data tables, both are formatted as text files. A gauge location table indicates to the model the location of rain and temperature gauges. Therefore one precipitation gage location table was created containing 11 gauges and one temperature gage location table with 5 weather stations. In addition, we edited one precipitation data file containing daily precipitation for every rain gauge and one temperature data file containing daily maximum and minimum temperatures for every weather station to provide the model with climatic information.

Table 3-6. Precipitation gauge location table.

ID	Stat_name	Lat	Long	Elevation (m)
1	*Bamako	12.53	-7.95	369
2	*Bougouni	11.41	-7.5	343
5	*Odienne	9.5	-7.56	421
6	*Segou	13.4	-6.15	276
7	*Sikasso	11.35	-5.68	368
3	Boundiali	9.52	-6.47	415
4	Koutiala	12.38	-5.46	359
8	Kolondieba	11.1	-6.9	328
9	Dioila	12.48	-6.8	319
10	Cinzana	13.25	-5.97	281
11	Mahou	12.13	-4.63	347

*: Are temperature gauges as well.

3.2.6. Model setup

The catchment was delineated and divided into sub-catchments based on the DEM. A stream network was superimposed on the DEM in order to accurately delineate the location of the streams. The threshold drainage area was kept default and additional outlets were considered at the location of stream gauging stations to enable comparison of measured discharge with SWAT results. The whole catchment was so discretized into 28 sub-catchments, which were further subdivided into 181 HRUs based on soil, land use, and slope combinations. Further parameters have been edited through the general watershed parameters and SWAT simulation menus and are reported in **Table 3-1**. Four simulations were performed based on land use and soil databases combinations: crop1soil1, crop1soil2, crop2soil1 and crop2soil2. A Nash-Sutcliffe Efficiency (*NSE*) (Nash and Sutcliffe, 1970) is thereafter calculated at Douna by comparing measured discharges against each default simulation and the one which will yield the highest *NSE* value will be kept for calibration and validation processes.

Table 3-7. Input methods for SWAT model simulation on the Bani catchment.

Code	Description	Method
	General watershed parameters	
IPET	Potential Evapotranspiration method	Hargreaves
IEVENT	Rainfall/runoff/routing option	Daily Rainfall/CN runoff/Daily routing
ICN	Daily Curve Number calculation method	Soil moisture (Plant ET at Bougouni)
IRTE	Channel water routing method	Variable storage
	SWAT simulation	
Period of simulation	-	1981-2000
NYSKIP	Warm-up period	2 years (1981 and 1982)

3.2.7. Calibration and validation procedures

It is commonly accepted in hydrology to split the measured data either temporally or spatially for calibration and validation (Arnold et al., 2012a). In addition to the split-sample method, a split-location calibration and validation approach has been performed because the global parameters set is not expected to be optimal for sub-catchments processes in view of the high heterogeneity in terms of climate, topography, soil and land use characterizing such a large-area watershed. This approach is especially needed when prediction at data sparse sites is foreseen (Moussa et al., 2007; Robson and Dourdet, 2015). In the split-sample approach, the model was calibrated using discharge data solely measured at the catchment outlet by splitting the homogenous period mentioned in section 2.3 into two datasets: two-third for calibration (1983-1992), and the other one for validation (1993-1997). To implement the split-location method, the model was calibrated at Douna and then validated at intermediate gauging stations (Bougouni and Pankourou) by turning the model on the same period (1983-1992), using the same behavioral parameters sets determined at the outlet.

Calibration was thereafter performed at Bougouni and Pankourou stations individually, and both modeling frameworks facilitated a comparative analysis of model performance and predictive uncertainty through scales. At this step, the calibration at Bougouni did not succeed within realistic range of the Curve Number (CN). Then, the daily CN calculation method was changed to Plant ET for simulation at Bougouni because soil moisture method is found to predict too much runoff in shallow soils (Arnold et al., 2012a). An additional parameter (CNCOEF) was then necessary as required by the plant ET method and fixed to 0.5 in the Edit SWAT input menu.

Calibration/validation, uncertainty analysis and sensitivity analysis were performed within the SWAT Calibration and Uncertainty Programs SWAT-CUP version 2012 (Abbaspour, 2014)

using Generalized Likelihood Uncertainty Estimation (GLUE) procedure (Beven and Binley, 1992). GLUE is a Monte Carlo based method for model calibration and uncertainty analysis. It was constructed to partly account for non-uniqueness of model parameters. GLUE requires a large number of model runs with different combinations of parameter values chosen randomly and independently from the prior distribution in the parameter space. The prior distributions of the selected parameters are assumed to follow a uniform distribution over their respective range since the real distribution of the parameter is unknown. By comparing predicted and observed responses, each set of parameter values is assigned a likelihood value. The likelihood functions selected here is principally the *NSE* as it is very commonly used and included in SWAT-CUP for GLUE performance assessment. In this study, the number of model runs was set to 10 000 and the total sample of simulations were split into “behavioral” and “non-behavioral” based on a threshold value of 0.5, a minimum threshold for *NSE* recommended by (2007) for streamflow simulation to be judged as satisfactory on a monthly time step. In that case, only simulations which yielded a $NSE \geq 0.5$ are considered behavioral and kept for further analysis.

In the calibration procedure, we included 12 parameters that govern the surface runoff and baseflow processes. The real approached baseflow alpha factor (*ALPHA_BF*) has been determined by applying the baseflow filter program developed by (1995) and modified by (1999) to streamflow data measured at the three outlets. One novelty in this study was to involve the Manning's roughness coefficient for overland flow (*OV_N*) and the average slope length (*SLSUBBSN*) parameters that are not commonly used in calibration. The reason behind this choice was to correct the tendency of the model to delay the runoff as detected by graphical analysis. The remaining parameters were chosen based on the literature (Betrie et al., 2011; Van Griensven et al., 2006; Zhang et al., 2008) and their adjusting ranges from the SWAT input/Output version 2012 document (Arnold et al., 2012b).

3.2.8. Model performance and uncertainty evaluation

To evaluate model performance, both statistical and graphical techniques were used as recommended by (Moriasi et al., 2007) based on previous published studies. The following quantitative statistics were chosen: *NSE* to quantify the relative magnitude of the residual variance ("noise") compared to the measured data variance, *PBIAS* for water balance error and R^2 to describe the degree of collinearity between simulated and measured data, and were given for the best simulation. The *NSE*, R^2 and *PBIAS* were determined using the following equations:

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)^2}, \tag{2}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)\left(Y_i^{sim} - \overline{Y^{sim}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} - \overline{Y^{sim}}\right)^2}}\right)^2, \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Y_i^{sim} - Y_i^{obs}\right)\times 100}{\sum_{i=1}^{n} Y_i^{obs}}, \tag{4}$$

Where Y_i^{sim} and Y_i^{obs} are the ith simulated and observed discharge, respectively, $\overline{Y_i^{sim}}$ and $\overline{Y_i^{obs}}$ the mean value of simulated and observed discharge, respectively and *n* the total number of observations.

The *NSE* varies between - ∞ and 1 (1 inclusive), with *NSE* = 1 being the optimal value. The optimal value of *PBIAS* is 0, with low *PBIAIS* in absolute values indicating accurate model simulation. Positive values indicate model overestimation bias, and negative values indicate model underestimation bias. R^2 ranges from 0 to 1, with higher values indicating less error variance, values greater than 0.5 are considered acceptable.

In the present study, model performance, for a monthly time step, will be judged as satisfactory if *NSE* > 0.50 and *PBIAS* ±25% for discharge (Moriasi et al., 2007) and if the graphical analysis reveals a good agreement between predicted and measured hydrographs.

The GLUE predictive uncertainties were then quantified by two indices referred to as P-factor and R-factor (Abbaspour et al., 2004). The P-factor represents the percentage of observed data bracketed by the 95% predictive uncertainty (95PPU) band of the model calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling. The R-factor is the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. For uncertainty assessment, a value of P-factor > 0.5 (i.e., more than half of the observed data should be enclosed within the 95PPU band) and R-factor < 1 (i.e., the average width of the 95PPU band should be less than the standard deviation of the measured data) should be adequate for this study especially considering limited data availability.

3.2.9. Sensitivity analysis

A Global Sensitivity Analysis (GSA) was performed after 10,000 simulations on the 12 parameters included in the calibration process. Only GSA is allowed with GLUE in SWAT-CUP and can be performed after an iteration. A t-test is then used to identify the relative significance of each parameter. T-stat provides a measure of sensitivity and p-value determines the significance of the sensitivity. A larger t-stat in absolute value is more sensitive and a p-value close to zero has more significance (Abbaspour, 2014).

3.2.10. Verification of model outputs

To evaluate the accuracy of the SWAT model to predict PET, we considered the model average annual basin output which was computed by the Hargreaves method (Hargreaves et al., 1985)

and compared it to PET values calculated with two other methods: the FAO-Penman Monteith method and the pan evaporation method. The estimates from those three methods are hereinafter referred to as PET_{har} (for average annual PET estimated by the Hargreaves method), PET_{pen} (for average annual PET estimated by the Penman-Monteith method) and PET_{pan} (for average annual PET estimated by the pan evaporation method). The modified Penman method is taken herein as the standard because it was considered to offer the best results with minimum possible error (Allen et al., 1998). Average observed ten-day PET_{pen} were collected and computed to obtain average annual value on the calibration-validation period. Monthly observed pan evaporation data were used to estimate PET_{pan}. Doorenbos and Pruitt (1975) related pan evaporation to reference evapotranspiration, ET_0 (or PET) using empirically derived coefficients. PET can be obtained by:

$$\mathrm{PET} = K_{pan} \times E_{pan} \tag{5}$$

Where E_{pan} represents the pan evaporation in mm d^{-1}, and K_{pan} the adjustment factor that depends on mean relative humidity, wind speed and ground cover.

As the pan factor in the Bani catchment could not be exactly determined due to lack of information about the pan environment and the climate, the average value of 0.7 was used in this study. The *PBAIS* was again used as the evaluation criterion representing the deviation of the predicted PET compared to the one considered as the baseline.

3.3. Catchments classification

The objective of catchment classification in this study joins the second objective of classification proposed by Sawicz et al. (2011), i.e., the regionalization of information. Indeed, a prediction in ungauged catchments is foreseen within a data sparse region where discharge data, if not measured, are incomplete or inconsistent. As discussed by (Hrachowitz et al., 2013; Sawicz et al., 2014; Wagener, 2007), a holistic classification framework should combine

physical characteristics, climate and hydrological functioning of a catchment. The major difficulty, which lies within this classification, is the data needs. Such data are not always available in developing regions. In addition, as the final objective is to transfer hydrological information from gauged to ungauged catchments which are similar, the question is how to define this similarity between them? It is evident that we need similarity metrics common for both, easily measurable and accessible. However, no discharge data are available at the ungauged site; neither are other runoff processes information even in well gauged catchments. Consequently, only precipitation and physiographic parameters remain easily available everywhere, particularly for the ungauged sites, and these are the conditions that underpin the choice of physiographic similarity to be used in this study as a proxy of hydrological functioning of a catchment.

3.3.1. Catchments and catchments' attributes

A total of 28 nested candidate catchments were selected (**Figure 3-5**), ranging in size from 92 km^2 to 10,910 km^2 and spanning across a wide range of environmental gradients of topography, precipitation, soil and land use showing a heterogeneous dataset. The study area has not been affected by important hydraulic structures able to significantly modify their flow regimes.

The choice of catchment attributes (CAs) is of great importance. Selected CAs are related to the shape (e.g., *area*, *length*) and the topography (e.g., *slope*, *elevation*) of each subbasin and its main tributary reach (e.g., *len1*, *wid1*) and were derived by application of the SWAT model (see **Table 3-1** for input spatial and climatic data). The selection of the appropriate CAs can also depend on the physical meaning of the model parameters (Mps) that will subsequently be involved in information regionalization. For instance, in the SWAT model, the Curve Number parameter (*CN2*), which was demonstrated to be the most sensitive Mps in the study area (at

the end of the modelling process), depends on the soil and land use characteristics of the catchment (Sellami, 2014). Therefore, two additional attributes related to land use and soil were considered. There exist 3 land use categories (Agricultural Land Generic, Savannah and Forest) and 3 major soil types (Ferric Luvisol, Acrisol and Nitosol, in this order).

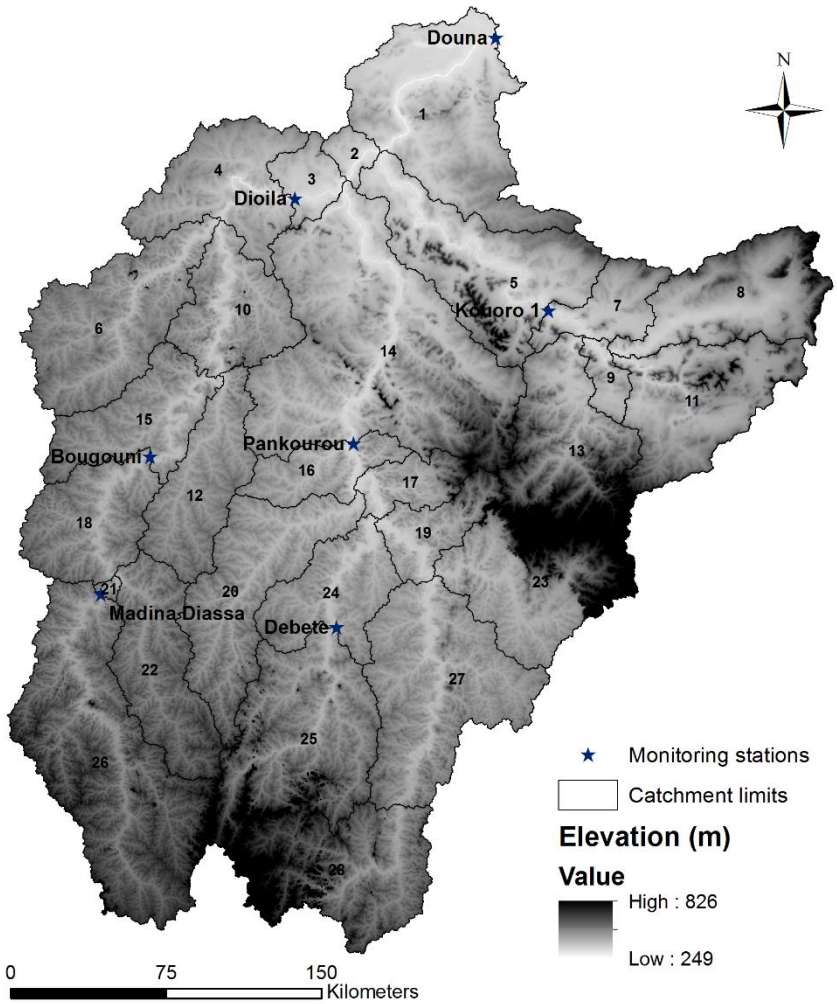


Figure 3-5. Study catchments and Digital Elevation Model of the Bani basin.

Therefore, in the preliminary analyses, we tested 10 different land use and soil combinations: 9 combinations in which we considered 1 land use and 1 soil descriptors, and 1 combination where all land uses and soils were kept at a time. These combinations were input in a Principal Component Analysis and we selected the one which yielded the smaller number of dimensions that explains the highest variability of the dataset (see the section 4.2.2 for details on the

method). So, only Agricultural Land Generic (*AGRL*) and Ferric Luvisol (*Lf*) were retained herein and represent indeed the dominant land use and soil, respectively. *AGRL* and *Lf* were calculated using the following equations:

$$\mathrm{AGRL} = \left(\frac{\mathrm{A_{AGRL}}}{\mathrm{A}}\right) * 100 \tag{6}$$

$$\mathrm{Lf} = \left(\frac{\mathrm{A_{Lf}}}{\mathrm{A}}\right) * 100 \tag{7}$$

Where A_{AGRL} is the area covered by *AGRL* within a watershed, A_{Lf} is the area covered by *Lf*, and *A* is the total area of the watershed.

Last, climatic characteristics such as long-term annual precipitation or the aridity index have a relevant impact on hydrological behaviour of a catchment (Wagener, 2007), and were commonly used in the literature. Thus, average annual precipitation was computed for each sub-catchment on the period 1981-2000. Finally, the selection ended up with 16 physiographic and climatic descriptors given in **Table 3-8**.

Table 3-8. Summary of catchment attributes derived by the SWAT model as input for multivariate statistical analysis on the Bani catchment.

Attribute	Description	Units
Slo1	Subbasin slope	%
Len1	Longest path within the subbasin	m
Sll	Field slope length	m
Csl	Subbasin tributary reach slope	m
Wid1	Subbasin tributary reach width	m
Dep1	Subbasin tributary reach depth	m
Lat	Latitude of the subbasin centroid	dd
Long	Longitude of the subbasin centroid	dd
Elev	Mean elevation of the subbasin	m
ElevMin	Minimum elevation of the subbasin	m

ElevMax	Maximum elevation of the subbasin	m
Shape_Leng	Subbasin perimeter	m
Shape_Area	Subbasin area	m^2
**P*	Average annual precipitation on the subbasin	mm
AGRL	Proportion of Agricultural Land on the subbasin	%
Lf	Proportion of ferric Luvisol on the subbasin	%

dd: decimal degree

* Calculated on the period 1981-2000

3.3.2. Multivariate statistical analyses

The proposed methodology can be separated into two main components: the clustering and the analysis of dominant controls of similarity thanks to the description of explanatory variables.

Hierarchical Clustering on Principal Components

PCA and CA are frequently used in hydrological studies (Daigle et al., 2011; Kileshye Onema et al., 2012; Sawicz et al., 2011), and commonly applied in a pre-processing of a set of variables prior to the classification, to provide a convenient lower-dimensional summary of the dataset, or as a classification tool itself. PCA reduces a dataset containing a large number of variables to a dataset containing fewer new variables that are linear combinations of the original ones. These linear combinations are mutually uncorrelated and chosen to represent the maximum possible fraction of the variability contained in the original data and are called Principal Components (PCs). PCs are defined each by eigenvectors, i.e., axes aligned along the direction of the maximum joint variability of the dataset, and an eigenvalues, i.e., the variance of the PCs (Wilks, 2006). CA is an exploratory data analysis tool that attempts to separate observations into groups called clusters by using the degree of similarity between individual observations. The CA procedure implemented in this study is the hierarchical and agglomerative clustering. In the beginning of this procedure, each observation is considered as a group. In the subsequent

steps, two groups that are closest are successively merged until, at the final step, a single cluster is reached containing all the observations.

Multivariate statistics used in this study were performed under R package FactoMineR (Husson et al., 2009; Lê et al., 2008), version 1.28. The methodology utilized was based on the Hierarchical Clustering on Principal Components (HCPC) function proposed by (Husson et al., 2010). This method combines three exploratory data analysis methods, Principal Component methods, Hierarchical Clustering and Partitioning, to improve data analysis. The chosen Principal Components method was the PCA, because retained CAs are quantitative variables. PCA was used herein as a pre-process for clustering, i.e., the hierarchical clustering is solely built on the determined PCs. In that case, a reduced dataset which represents the most important variability in the observations was obtained, and leads to a more stable clustering than the one obtained from original variables (Husson et al., 2010). PCA was tested on 10 datasets each made up by the first 14 descriptors described in Table 3-1 added to a combinations of land use (numbered 1, 2 and 3) and soils (numbered a, b and c). Therefore, the resulting input datasets were hereinafter referred to as 1-a, 1-b, 1-c, 2-a, 2-b, 2-c, 3-a, 3-b, 3-c, and 123-abc, the latter referring to the dataset including all land uses and soil types. Input variables, i.e., CAs, were first standardized because they are not measured on comparable scales. The appropriate number of PCs was chosen based on the Scree plot technique (Jolliffe, 2002). The Scree plot is a graph representing the eigenvalues as a function of PCs number. On this graph, the point separating a steeply sloping portion and a gently one, corresponds to the truncated number of PCs. As the objective of PCA used in this study was for dimensionality reduction, then the combination that will give no more than 2 PCs that explain the highest percentage of the total variance of the original data, will be kept for subsequent analysis. Then, a hierarchical agglomerative clustering was performed on the PCs previously determined. The measure of distance between data points was based on the Euclidean distance (the same was used in PCA) and the

agglomerative method for merging two clusters used the Ward's criterion. This criterion is based on the Huygens theorem according to which the total inertia (variance) of a dataset can be decomposed in within-group and between-group inertia. Equation (3) gives the formula for calculating the total inertia.

$$\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}\left(x_{iqk}-\overline{x_k}\right)^2=\sum_{k=1}^{K}\sum_{q=1}^{Q}I_q\left(\overline{x}_{qk}-\overline{x_k}\right)^2+\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}\left(x_{iqk}-\overline{x_{qk}}\right)^2, \quad (8)$$

Total inertia = Between-group inertia + Within-group inertia

Where x_{iqk} is the value of the variable k for the individual i of the cluster q, $\overline{x}_{qk}$ is the mean of the variable k for cluster q, $\overline{x}_k$ is the overall mean of variable k and I_q is the number of individuals in cluster q. At the initial stage, the within-group inertia is null and the between group inertia is maximum and equal to the total inertia of the dataset as at this level, each individual represents a single-member group. At the final step, all the members are merged in a single group, the between-group inertia is therefore null and the within-group inertia is maximum and equal to the total. At each step of the algorithm, the pair of groups to be merged is chosen that minimizes the growth of within-group inertia (inversely, that maximizes the growth of between-group inertia) at each step of the algorithm.

The last step consists in choosing the appropriate number of clusters when it is not pre-assigned, that is, the stopping point of clustering that maximizes similarity within clusters and maximizes dissimilarity between clusters. HCPC function suggests an “optimal” number Q of clusters when the decrease in within-group inertia between Q - 1 and Q is from far greater than the one between Q and Q + 1 (Husson et al., 2010) for a thorough description of the HCPC function). Results of HCPC function can be presented in different ways: (1) A factor map, which displays results of the hierarchical clustering on the map induced by the first PCs, (2) a 2-dimensional dendrogram or hierarchical tree, and (3) a 3-dimensional dendrogram in which the hierarchical

tree is incorporated into the factor map. The latter representation can solely be used to get an integrated visualization of the dataset. However, dispersion of data points is somehow masked in that way. Therefore, the factor map was presented in the results section for a better visualization of individuals' dispersion on the plan formed by PCs, while the hierarchical tree offers a good insight of the variability increase between clusters.

Analysis of dominant causes of similarity between catchments

A core issue in catchment classification is to describe clusters according to the main factors that cause similarity among individuals. Addressing this issue will help knowing, in addition to which catchments are similar, why they are similar. This can be achieved through the description of input variables, i.e., CAs. A *v-test* was performed for each variable corresponding to the test: "The mean of the category is equal to the overall mean". The mean of the category is the average in the cluster and the overall mean is the average for the whole data set. An absolute value of the *v-test* greater than 1.96 means that the variable is significant. The sign of the *v-test* indicates whereas the mean of the cluster is lower or greater than the overall mean. A *p-value* less than 0.05 gives the significance of the test (more details can be found in (Husson et al., 2011).

The *v-test* is calculated with the following Equation (4):

$$v-test = \frac{\overline{x}_{qk} - \overline{x}_k}{\sqrt{\frac{S^2}{n} \times \frac{N-n}{N-1}}} \tag{9}$$

where $\overline{x}_{qk}$ is the mean of the variable k for cluster q, $\overline{x}_k$ is the overall mean of variable k, n is the number of individuals in cluster q, N is the total number of individuals and S^2 is the variance of the dataset.

3.4. Model Parameters Regionalization

3.4.1. Study catchments and modeling framework

This study was conducted on the Bani catchment for which a detailed description was given in sections *3.2* and *3.3*. A total of seven mesoscale catchments, ranging in size from 1,552 to 8,417 km^2, were selected (**Figure 3-6**) on the basis of data availability and span across different physiographic and climatic regions (catchments description is given in **Table 3-9**). It is important to note that the study area is characterized by weak data density (around 7 stream gauges per 100,000 km^2) and high distances between gauges (more than 300 km for the highest).

Calibration at gauged catchment is a prerequisite for regionalization of model parameters. To this end, we calibrated the SWAT model against a 10-year discharge record (1983-1992) and validate it on 5 other years (1993-1997) for most of the catchments. The adjustment between observed and simulated river flow has been achieved by tuning 12 SWAT model parameters identified as the most sensitive on the study area. The approach of estimating these parameters has been developed in section *3.2.7* for calibration and validation at Douna, Pankourou and Bougouni gauging stations. The same approach was adopted here for the 4 additional stations; Dioila, Kouro 1, Madina Diassa and Debete (**Figure 3-6 and Table 3-9**). We defined a behavioral parameter set, as the one which produced a simulation with a *NSE* equal to 0.5 or greater. When the calibration task identifies one or more behavioral parameter sets on a catchment, this one is considered as a donor catchment, i.e., from which the optimized model parameters could be transferred to an ungauged catchment, else it is solely considered as a target catchment, i.e., it can only receive model parameters from a potential donor.

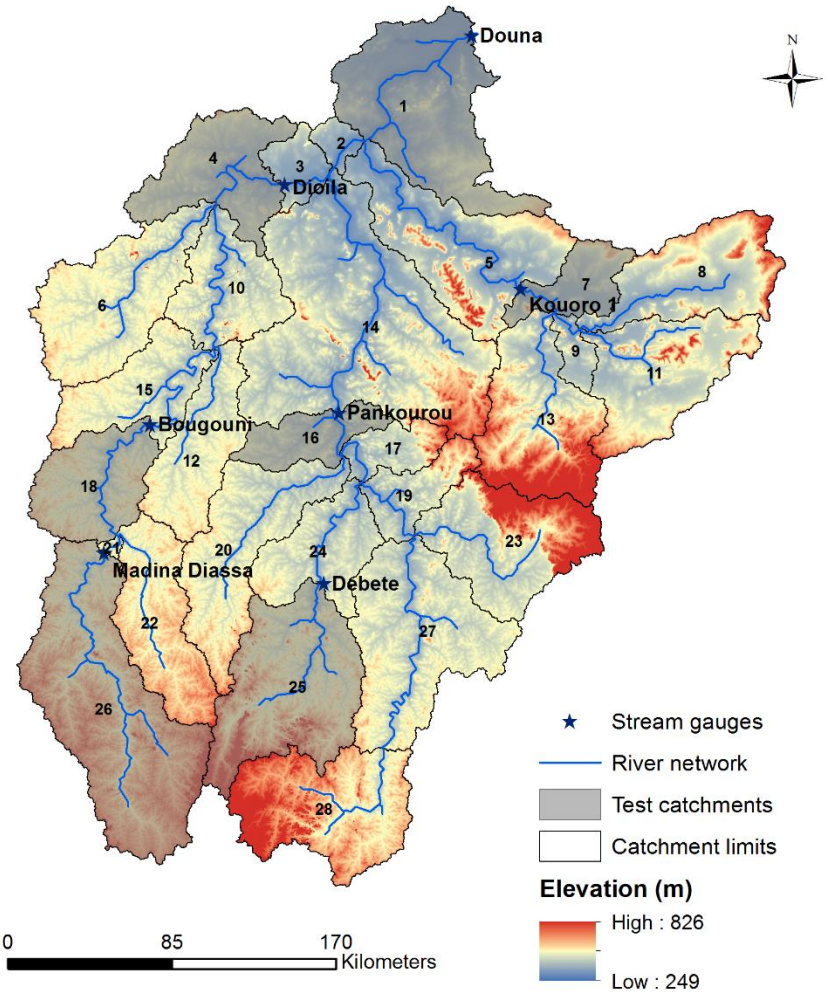


Figure 3-6. Localization of the test catchments for model parameters transfer on the Bani basin.

Table 3-9. Description of candidate catchments for model parameters regionalization.

Subbasin	Outlet	Area (km2)	*Physical cluster	Precipitation (mm)	Calibration period	Regionalization period
1	Douna	5925	C2	653	1983-1992	1983-1997
4	Dioila	3333	C2	794	1983-1992	1983-1997
7	Kouoro1	1552	C1	842	1983-1991	1983-1991
16	Pankourou	1620	C3	1036	1983-1992	1983-1997
18	Bougouni	2978	C3	1107	1983-1992	1983-1997
25	Debete	5675	C4	1294	1983-1989	1983-1989
26	Madina Diassa	8417	C4	1200	1983-1992	1983-1997

*See Chapter IV for details.

3.4.2. Regionalization approaches and similarity frameworks

In this study, the objective of the regionalization is to predict the entire discharge hydrograph, i.e., the time series of river discharge, at ungauged basins. The hydrograph has the advantage to be "… *the most complete runoff signature*…" Blöschl et al. (2013) because resulting from the interaction between all the processes within a catchment. So, all the other signatures can be derived from it. We applied 2 regionalization techniques based on similarity measure between gauged and ungauged catchments. The first approach is the spatial proximity, according to which catchments that are geographically close to each other are expected to have similar behavior. The nearest neighbor method is especially relevant in the case of very data sparse region (Goswami et al., 2007). In this study, the entire model parameter set is transposed from the closest donor to the receptor catchment. The distance measure between catchments is defined by the geographical distance between catchments' centroids. In the physical similarity approach, the search of donor catchment was restricted to the same cluster as the target catchment. As an important step in physiographic similarity, a classification scheme was conducted prior to the regionalization (in Chapter III) to determine clusters of similar catchments based on their physioclimatic characteristics. A combined method can be interpreted as when the donor is physically similar to the ungauged catchment and is located in its vicinity as well.

However it has been pointed out that the MPs from the nearest catchment will not necessarily result in the best simulation at the target catchment (Oudin et al., 2008). In addition, many authors (Patil and Stieglitz, 2012; Viviroli et al., 2009) suggest the use of multiple neighbors in order to find the best regionalization efficiency. But such an approach is not possible in the present study because we are in a case of very data-sparse region. The stream gauge density considered is low, (1 gauge per 14300 km^2) and a gauge catchment can be very far from an ungauged catchment. Therefore, to avoid misleading effects of small number of test

catchments, we considered all the possible cases on model parameters transfers without any consideration of spatial or physical similarity. In other words, if *n* is the total number of donors, at a target *i*, we transferred one by one, the parameter set of the *n-1* donors, resulting in *n-1* individual simulations. The entire set of optimized SWAT model parameters is transposed without any modification from the donors to the target catchment to achieve discharge hydrograph without need of any measurement. The resulting simulations were then discussed according to the aforementioned regionalization methods to draw conclusions and hypotheses related to which method performs best.

3.4.3. Evaluation of the regionalization performance and prediction uncertainty

The aim of this step is to assess the performance and prediction uncertainty of parameters regionalization in reproducing flows in ungauged basins. For this assessment, the Nash-Sutcliffe Efficiency (*NSE*) was calculated between the simulated and observed hydrographs for the entire simulation period 1983-1997. The length of the regionalization period has been chosen long enough to cover both calibration and validation periods at gauged catchments. So, we can test at a time the reliability of the transfer of MPs to perform under different flow conditions of space (from gauged to ungauged) and time (from calibration to validation period). The performance was judged as satisfactory if *NSE* > 0.50 and *PBIAIS* < ±25%, and if the graphical analysis reveals a good agreement between predicted and measured hydrographs. Regarding uncertainty assessment, the P-factor was used to measure the percentage of observed data enclosed within the uncertainty band whose width is represented by the *R-factor*. In this study, we define adequate prediction uncertainty when we obtained a value of *P-factor* > 0.5 (i.e., more than half of the observed data are enclosed within the 95PPU band) and *R-factor* < 1 (i.e. the average width of the 95PPU band is less than the standard deviation of the measured data) especially considering limited data availability.

3.4.4. Assessment of the hydrological similarity

Many definitions of hydrological similarity exist. Following Oudin et al. (2010), hydrological similarity between two catchments can be defined as the ability of the optimized parameter set of one to adequately simulate the streamflow of the other. This assumption explains the use of a rainfall-runoff model for making prediction in ungauged catchments.

Our objective is to explore the relationship between spatial proximity and physical similarity on one hand, and hydrological similarity on the other. To this end, the performances of the resulting hydrographs are compared in order to identify the approach that gives the highest performance. We adopted the criterion defined by Oudin et al. (2010) who suggest that two catchments A and B are hydrologically similar "if, on target catchment A, the efficiency reached by the model using the parameters obtained by calibration on catchment B is greater than 0.9 of the model efficiency obtained in calibration on catchment A, then this catchment B is considered as hydrologically similar to catchment A". That means, all catchments should be calibrated so that a comparison between efficiencies obtained by calibration and by regionalization is feasible. We adapted this definition to our context of data scarcity and say: if the performance reached at the target using the parameters obtained at the donor is greater than 0.5, 0.65 or 0.75 the performance reached by calibrating at the target, then the hydrological similarity between donor and target can be judged as satisfactory, good or very good, respectively. In addition, the transfer of parameters from one to another should work in both ways in order to call the catchments "mutually similar".

Chapter IV

4. Results and Discussions

4.1. Multi-site Validation of the SWAT Model on the Bani Catchment: Model Performance and Predictive Uncertainty*

*Results published in Chaibou Begou et al. (2016)

Reference:

J. Chaibou Begou, S. Jomaa, S. Benabdallah, P. Bazie, A. Afouda, and M. Rode, (2016). Multi-site validation of the SWAT model on the Bani catchment: Model performance and predictive uncertainty. Water, 8, 178.

The objective of this Chapter is to assess the performance of the SWAT model and its predictive uncertainty on the Bani at catchment and subcatchment levels. More specifically, this meant to:

(i) set up a hydrological model for the Bani catchment using the SWAT program;

(ii) calibrate the model at the catchment outlet at daily and monthly time steps and assess the prediction performance and uncertainty;

(iii) evaluate the spatial performance of the watershed-wide model within the catchment by validating it at two internal stations

(iv) And calibrate the model at the sub-catchments separately and provide a comparative assessment of the model performance at different spatial scales.

4.1.1. The catchment scale model

Global model performance and predictive uncertainty

In the preliminary analyses we tested different land use and soil databases and kept for subsequent analysis the simulation of databases combination crop2soil2, which yielded the highest default, i.e. before calibration, performance (*NSE* = 0.09). The impact of land use database was not so significant, but the type of soil database used to setup the model was very decisive in obtaining a simulation with the smallest overall error. SWAT-CUP output results are presented as 95PPU as well as the best simulation (**Table 4-1**).

Overall, calibration and validation of the hydrological model SWAT on the Bani catchment at the Douna outlet yielded good results in terms of *NSE* and R^2 for both daily and monthly timesteps. 364 simulations for daily calibration against 588 for monthly calibration returned a $NSE \geq 0.5$ and were thus considered as behavioral. Satisfactory to very good *NSE* and R^2 values were obtained and were greater than 0.75 for the best simulations. Moreover, it can be noticed

that the performance is slightly lower for daily calibration compared to monthly calibration, but always higher for the validation period. Only one year (1984) over ten showed very low performance with a *NSE* of 0.23.

Table 4-1. Model performance statistics and predictive uncertainty indices of the SWAT model for the Bani catchment at Douna, Pankourou and Bougouni discharge gauging stations.

Time step	Criterion	Calibration (1983-1992)			Validation (1993-1997)		
		Douna	Pankourou	Bougouni	Douna	Pankourou	Bougouni
Daily	*NSE*	0.76	0.73	0.66	0.85	0.77	0.37
	R^2	0.79	0.74	0.68	0.87	0.83	0.57
	PBIAS (%)	- 12.23	6.08	- 15.01	- 23.26	- 19.57	- 59.53
	P-factor	0.61	0.68	0.60	0.62	0.63	0.51
	R-factor	0.59	0.41	0.57	0.51	0.29	0.35
Monthly	*NSE*	0.79	0.78	0.72	0.85	0.81	0.47
	R^2	0.82	0.78	0.76	0.88	0.91	0.68
	PBIAS (%)	- 15.78	5.93	- 13.14	- 26.91	- 19.54	- 58.40
	P-factor	0.65	0.71	0.58	0.70	0.67	0.55
	R-factor	0.65	0.45	0.54	0.55	0.31	0.32

The water balance prediction can be considered as accurate at a daily time-step but become hardly satisfactory for monthly calibration, which is characterized by higher PBIAIS values showing increasing errors in the prediction. For example, the PBIAIS values increased from daily to monthly time intervals: from - 12% to - 16% in the calibration period and from - 23% to - 27% in the validation period (**Figure 4-1**). With regard to high flow events, visual analysis of simulated and observed hydrographs represented in Figure 3 came out with the following results: timing of peak is well reproduced although simulation tends to underestimate peak flows especially during dry years (e.g., 1983, 1984, and 1987).

The predictive uncertainty of the model, as indicated by the P-factor and R-factor, is adequate, though being larger during peak flow and recession periods (reflected by larger 95PPU band). On a daily basis for instance, 61% of the observed discharge data are bracketed by a narrow

95PPU band depicted by the R-factor < 1 (**Figure 4-1**). It has been noted that the entire uncertainty band is, however, very large during the year 1984.

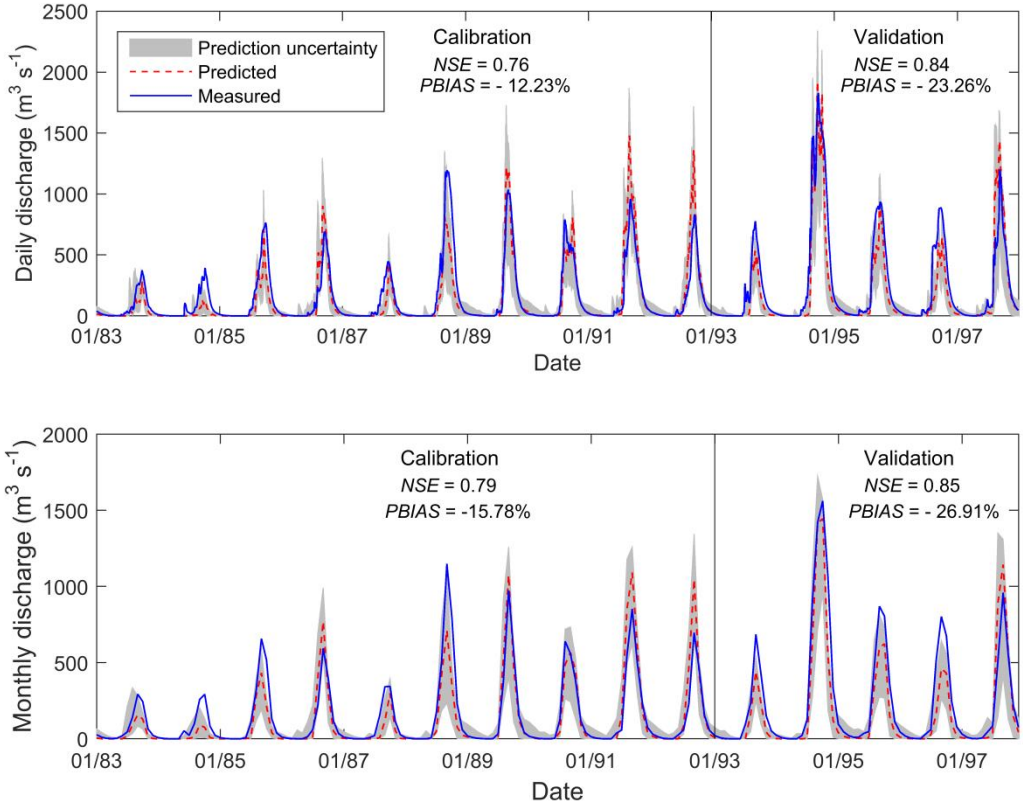


Figure 4-1. Simulated and observed hydrographs at Douna station at (a) daily and (b) monthly timesteps along with calculated statistics on calibration and validation periods.

Verification of average annual basin values

Table 4-2 reports the average annual values of the SWAT model simulated on the Bani catchment. However, there are not available data to enable a full verification of all model outputs at the watershed scale. In this case, we focused on available PET and biomass for which there exist regional values.

Table 4-2. Average annual basin values of precipitation (P), Evapotranspiration (ET), Potential Evapotranspiration (PET) and biomass as SWAT outputs on the Bani catchment.

Period	P (mm)	ET (mm)	PET (mm)[a]	Biomass (ton ha-1)		
				Agricultural Land Generic	Savannah	Forest
Calibration (1983-1992)	960.4	895	1925.7	1.18	0.27	3.09
Validation (1993-1997)	1049.5	975	1925.1	1.72	0.53	5.51

[a] Average annual PET estimated by the Hargreaves method (herein used by SWAT).

The analysis of **Table 4-2** came out with several results. On average, PET_{har} presented a positive *PBIAS* of 11% compared with observed PETpen herein equal to 1737 mm and the latter is very close to PET_{pan} estimated to 1755 mm. These results give a clear advocate of overestimation of PET by the SWAT model over the Bani catchment, an overestimation that can be attributed to the Hargreaves method used herein by the model to compute PET.

To further investigate the model's accuracy, we evaluated predicted biomass values over the calibration/validation period against reported values for the study area. Simulated biomass was on average 4.3 ton ha^{-1} for forest and 1.45 ton ha^{-1} for agricultural land and both are in the ranges of observed values in the region (Laurent and Ruelland, 2010; Marie et al., 2007). Nevertheless, this component is far underestimated for savannah with a simulated value of 0.4 ton ha^{-1}.

Sensitivity analysis

There is a wide range of uses for which sensitivity analysis is performed. Based on the 12 selected SWAT parameters (*ALPHA_BF* being fixed), a GSA was used herein for identifying sensitive and important model parameters in order to better understand which hydrological processes are dominating the streamflow generation in the Bani catchment.

Sensitivity analysis results of 10 000 simulations are summarized in **Table 4-3**. The first three most sensitive parameters (*CN2*, *OV_N* and *SLSUBBSN*) are directly related to surface runoff, reflecting therefore the dominance of this process on the streamflow generation in the Bani catchment. Processes occurring at soil level followed at the second position as pointed out by the sensitivity of *ESCO* and *SOL_AWC*. Groundwater parameters happened in the last position demonstrating the low contribution of the latter to flows measured at the Douna outlet. The same sensitive parameters were identified by daily and monthly calibrations with only different ranks for soils parameters (*ESCO* and *SOL_AWC*).

Table 4-3. Sensitivity of the calibrated SWAT model parameters on the Bani catchment at Douna on a daily time interval.

Parameter	Description	Input calibration range	Global Sensitivity analysis	
			t-stat	p-value
CN2	SCS runoff curve number II (-)	± 20%	- 54.03083	0.00000
OV_N	Manning's "*n*" value for overland flow (-)	0.01-30	11.41603	0.00000
SLSUBBSN	Average slope length (m)	10-150	8.87352	0.00000
ESCO	Soil evaporation compensation factor (-)	0.01-1	- 6.08880	0.00000
SOL_AWC	Available water capacity of the soil layer (mm H_2O/mm sol)	± 20%	2.89864	0.00376
GW_DELAY	Groundwater delay (days)	0.0-50	1.81341	0.06980
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	0.0-4000	- 1.51853	0.12891
REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm H_2O).	0-500	- 0.64939	0.51610
RCHRG_DP	Deep aquifer percolation fraction (-)	0-1	0.46408	0.64260
GW_REVAP	Groundwater "revap" coefficient (-)	0.02-0.2	- 0.12613	0.89963
SURLAG	Surface runoff lag coefficient (-)	0.05-24	- 0.07433	0.94075
ALPHA_BF	Baseflow alpha factor (d^{-1})	0.034-0.034	ND	ND

ND: Not Determined

Spatial validation

The results of the spatial validation were divergent according to the location (**Figure 4-2**). For instance at Pankourou, the same parameters sets determined at Douna produced a good simulation on a monthly basis (satisfactory for daily validation) whereas predictive uncertainty remained adequate and all met our requirements (*NSE* > 0.5, P-factor > 0.5 and R-factor < 1). In addition, the water balance was reasonably predicted at both timesteps. In contrast, it has been recorded a complete loss of model performance at Bougouni with unsatisfactory *NSE* values and more uncertainty related to input discharge as expressed by a lower percentage of observed data (P-factor = 0.55 et 0.57 for daily and monthly validation) inside the 95PPU band (**Figure 4-2**). Accordingly, important uncertainty could be attributed to observed discharge at Bougouni.

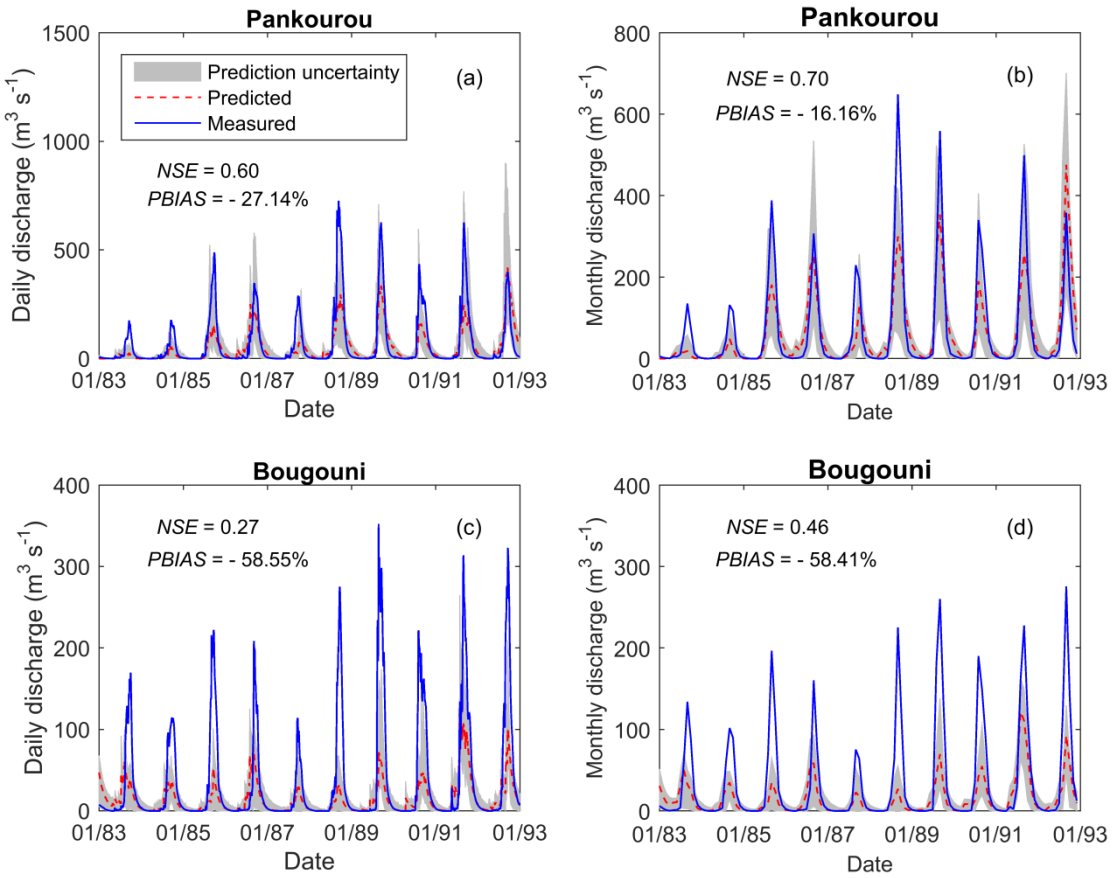


Figure 4-2. Spatial validation of the SWAT model on the Bani catchment. The model was turned at Pankourou ((a) daily and (b) monthly timesteps) and at Bougouni ((c) daily and (d) monthly

timesteps) by using the same behavioral parameter sets determined at the Douna outlet on the period 1983-1992.

4.1.2. The subcatchment model

Statistical evaluation results of the subcatchment calibration are presented in **Table 4-1** and time series of observed and simulated hydrographs are shown on **Figures 4-3** and **Figure 4-4.** Good to very good performance was obtained at Pankourou with accurate predictive uncertainty. However the validation period remained unsatisfactorily simulated at Bougouni. A comparative analysis of the catchment and subcatchment calibration performances came out with the following results:

- When calibrated separately, the prediction at Pankourou was slightly better, but greatly improved at Bougouni compared to when the catchment wide model was applied.
- The total uncertainty of the model is smaller at Pankourou (smaller R-factor and larger P-factor) than at the whole catchment, but larger at Bougouni.
- The water balance is better simulated at both internal stations compared to the watershed-wide water balance as depicted by smaller PBIAIS values, except always in the validation period at Bougouni.
- The model performance in terms of *NSE* and R^2 was higher at the watershed-wide level than at the sub-watershed level.

Overall, these results revealed that further calibration at the internal gauging stations was synonymous with gain of performance at the subcatchment level.

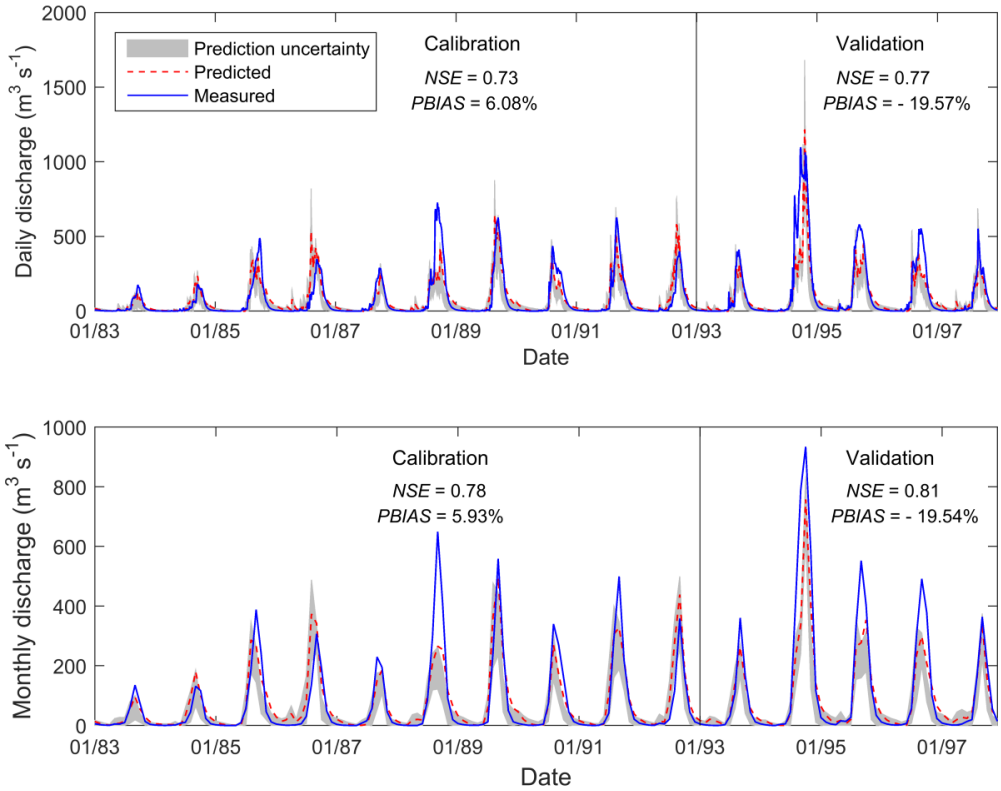


Figure 4-3. Simulated and Observed hydrographs at Pankourou station at (a) daily and (b) monthly timesteps along with calculated statistics on calibration and validation periods.

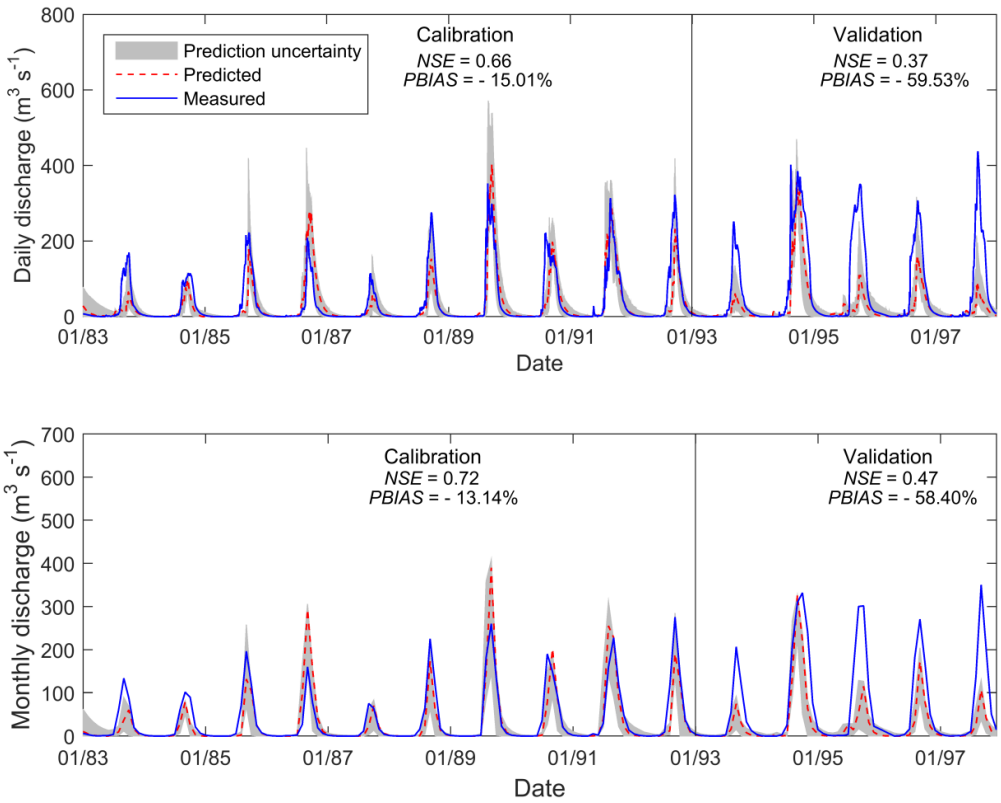


Figure 4-4. Predicted and measured discharges at Bougouni station at (a) daily and (b) monthly intervals during the calibration and validation periods with their corresponding statistics.

4.1.3. Discussion and conclusions

Model performance and predictive uncertainty

In an effort to assess the performance of the SWAT model on the Bani catchment, we calibrated and validated the model at multiple sites on daily and monthly timesteps by using measured climate data. There were no statistically significant differences in model performance among time intervals. Using guidelines given in Moriasi et al. (2007), the overall performance of the SWAT model in terms of *NSE* and R^2 can be judged as very good especially considering limited data conditions in the studied area. On a monthly basis, we obtained at the Douna outlet a *NSE* value equal to 0.79 for the calibration period (0.85 for the validation period). These results are greater than the ones of the studies by Schuol and Abbaspour (2006) and Schuol et al. (2008a) at the same outlet. Schuol and Abbaspour (2006) reported indeed a negative *NSE* (between -1 and 0) for the monthly calibration and a value ranging between 0 and 0.7 for monthly validation, while (Schuol et al., 2008a) obtained a *NSE* between 0 and 0.70 for both monthly calibration and validation. However, Laurent and Ruelland (2010) reported a greater performance (*NSE* values varying between 0.81 and 0.91 for calibration and validation period, respectively) but on a coarser time step (average annual basis). The water balance is less well simulated, especially for monthly time step with a *PBIAIS* greater than 25% in absolute value. The quantified predictive uncertainties are surprisingly satisfactory. At the end of the daily calibration, the model was able to account for 61% of observed discharge data (65% for monthly calibration) in a narrow uncertainty band. The quantified predictive uncertainties obtained herein are close to the results of (Schuol et al., 2008a) who estimated the observed discharge data bracketed by the 95PPU between 60% and 80% for monthly calibration (40% and 60% for monthly validation). However, one explanation that could be attributed to the

small uncertainty band we obtained, is that model predictive uncertainty derived by GLUE depends largely on the threshold value to separate “behavioral” from “non-behavioral” parameter sets (Mantovan and Todini, 2006; Montanari, 2005).This means, a high threshold value (as in this case) will generally lead to a narrower uncertainty band (Blasone et al., 2008; Viola et al., 2009; Xiong and O’Connor, 2008) but this will be achieved at the cost of bracketing less observed data within the 95PPU band. In addition, GLUE accounts partly for uncertainty due to the possible non-uniqueness (or equifinality) of parameter sets during calibration and could therefore underestimate total model uncertainty. For instance, Sellami et al. (2013) showed that the GLUE predictive uncertainty band was larger and surrounded more observation data when uncertainty in the discharge data was explicitly considered. Engeland and Gottschalk (2002) demonstrated that the conceptual water balance model structural uncertainty was larger than parameter uncertainty. In spite of all the aforementioned limitations of GLUE, we succeeded in enclosing interestingly most of the observed data within a narrow uncertainty band (the sought adequate balance between the two indices) hence increasing confidence in model results. These are encouraging results showing, on one hand, the good performance of the SWAT model on a large soudano-sahalian catchment under limited data and varying climate conditions and, on the other hand, the capability of observed climate and hydrological input data of this catchment, even though contested, to provide reliable information about hydro-meteorological systems prevailing in the region.

It has been also noted that the model did not perform well during the year 1984 particularly (lower performance and larger uncertainty). This loss of performance can be attributed to the disruption in rainfall-runoff relationship consequence of consecutive years of drought, which has prevailed in the beginning of the eighties. The over-predicted PET on the Bani catchment could be attributed to the Hargreaves method, which could give a greater estimate of PET than it actually is. Ruelland *et al.* (2012) applied a temperature-based method given by Oudin *et al*.

(2005) and provided a similar estimate of PET (1723 mm) than the values calculated herein by the Penman and pan evaporation methods hence corroborating our results. These results demonstrated the valuable of pan evaporation measurements for estimating PET and that the simple pan evaporation method appears to be suited for application in the study area and can be used when all the climatic data required by the Penman method are missing.

As far as biomass is concerned, the underestimation of this component in savannah could be explained by inappropriate specification of all categories in the land use map grid to be modelled by SWAT as savannah or inaccurate savannah characteristics added in the SWAT database and directly affecting biomass production such as *BIO_E* and *LAI* parameters, among others.

Advance in understanding of hydrological processes

The GSA confirms what has already been reported on and around the Bani catchment about the contribution of hydrological processes to streamflow generation. In order to better understand the origin of flows at Kolondieba (a tributary of the Bani River), Dao et al. (2012) showed that Groundwater contribution to the hydrodynamic equilibrium at the outlet of watershed Kolondieba is small and the direct flow from the soil surface governs the runoff process. This fact can be explained by the double impact of a general impoverishment of shallow aquifers due to reduction in precipitation in West Africa in general since the great drought of the seventies as well as a concurrent increase of the recession coefficient of the Bani river as demonstrated by Bamba *et al.* (1996) and Mahé (2009) with a decrease of baseflow contribution to total flow in absolute and relative values as corollary.

Spatial performance

The results of different calibration and validation techniques showed varying predictive abilities of the SWAT model through scales. Firstly, it can be derived from these findings that model performance in terms of *NSE* and R^2 was higher on the watershed-wide level than on the sub-watershed level. However, this could be attributed to a compensation between positive and negative errors of processes occurring at a larger scale (Cao et al., 2006; Wellen et al., 2015). This suggests that calibrating a model only at the basin outlet leads to an overconfidence in its performance than at the sub-basin scale. Secondly, individual calibration of subcatchment processes expectedly improved model accuracy in predicting flows at the internal gauging stations, due to reducing heterogeneities with downsizing space, and is especially beneficent while the donor and receiver catchments are substantially different. Finally, prediction uncertainty appears to decrease with reducing spatial scale but increases with humidity as shown by the lower performance recorded at Bougouni. The inability of the model to perform during the validation period at Bougouni could be attributed to the structure of the validation period which is substantially different to that of calibration, and is solely composed by average to wet years while in contrast, it is noted the occurrence of dry, average and wet years during the calibration period.

These results have an important role to play in the calibration and validation approaches of large-area watershed models and constitutes a first step to model parameters regionalization for prediction in ungauged basins.

Conclusions

In this study, the performance of the widely-used SWAT model was evaluated on the Bani catchment using both split-sample and split-location calibration and validation techniques on daily and monthly intervals. The model was calibrated at the Douna outlet and at two internal

stations. Freely available global data and daily observed climate and discharge data were used as input for model simulation and calibration. Calibration and validation, uncertainty and sensitivity analyses were performed with GLUE within SWAT-CUP. Both graphical and statistical techniques were used for hydrologic calibration results evaluation. Evapotranspiration and biomass production outputs were verified and compared to regional values to make sure these components were reasonably predicted. Sensitivity analysis contributed to a better understanding of the hydrological processes occurring at the study area. Final results showed a good SWAT model performance to predict daily as well as monthly discharge at Douna with acceptable prediction uncertainty despite the poor data density and the high gradient of climate and land use characterizing the study catchment. This performance is somehow lower at internal sub-catchments level when the global parameters sets are applied, especially at the one with higher humidity and dominated by forest. However, subcatchment calibration induced an increase of model performance at intermediate gauging stations as well as a decrease of total uncertainty. With regard to predicted PET, this component is overestimated by the model when the Hargreaves method is applied in that specific region while biomass production remained low in savannah land use category. The GSA revealed the predominance of surface and subsurface processes in the streamflow generation of the Bani River.

Overall, this study has shown the validity of the SWAT model for representing globally hydrological processes of a large-scale soudano-sahelian catchment in West Africa. Given the high spatial variability of climate, soil and land use characterizing the catchment, additional calibration is however needed at subcatchment level to ensure that predominant processes are captured in each subcatchment. Accordingly, the importance of spatially distributed hydrological measurements is demonstrated and constitute the backbone of any type of progress in hydrological process understanding and modeling. The calibrated SWAT model for

the Bani can be used to assess the current and future impacts of climate and land use change on water resources of the catchment, a more and more necessary information awaited by water resources managers. Knowing this information, a strategy of adaptation in response to the current and future impacts can be clearly proposed and the vulnerability of population can therefore be reduced. More widely, this impact study can increase the transferability of the model parameters from the Bani subcatchment to another ungauged basin with some similarities, and then predicting discharge without the need of any measurement. These findings are very useful especially in West Africa, where many river basins are ungauged or poorly gauged.

4.2. Catchment Classification: Multivariate Statistical Analysis for Physiographic Similarity*

*From the original idea of Chaibou Begou et al., 2015

Reference:

J. Chaibou Begou, P. Bazie and A. Afouda, (2015). Catchment classification: multivariate statistical analyses for physiographic similarity in the Upper Niger Basin. IJERA Vol. 5, Issue 9, (Part - 1), pp.60-68

The main objective of this chapter was to determine a physiographic and climatic similarity framework between catchments located on the Bani basin. The specific objectives were to:

(1) Perform a hierarchical clustering of catchments based on their physiographic and climatic characteristics

(2) And determine the main factors that control similarity between catchments.

This study provides the first ever quantification of similarity among catchments with respect to physiographic characteristics on a large tropical river basin at finer spatial scale. Neither descriptors, nor statistics themselves are actually novel in the broad literature, but their combined use in that particular area to evaluate the gain of homogeneity with increasing number of clusters is sought. In other words, the questions that will be addressed in this study are:

(i) Can the Bani be further separated into similar groups of catchments based on physio-climatic characteristics?

(ii) If so, what are the dominant controls on similarity between catchments?

(iii) And how much do we gain in system homogeneity when moving from the whole dataset to the optimal number of groups?

4.2.1. Catchments clustering

In this section, a brief description of the intermediate results of PCA is given. PCA was repeated 10 times and the most successful result was recorded on the combination 1-a, that permitted to determine 2 PCs which explains the highest cumulative variance (76.10%) as compared to other combinations that gave either smaller variance or more PCs. Results can be visualized on

Figure 4-5. The percentage of the joint variability of the original dataset explained by each dimension is also given. The subsequent clustering was then performed on retained PCs.

Results of the hierarchical clustering are presented on **Figures 4-5 and 4-6**. **Figure 4.5** displays results of the hierarchical clustering on the map induced by the first PCs. Four clusters were identified that maximize the within-group similarity while maximizing the between-group dissimilarity. Cluster 1 (C1) contains 5 catchments (4 catchments if we consider the number 21 as an outlier).

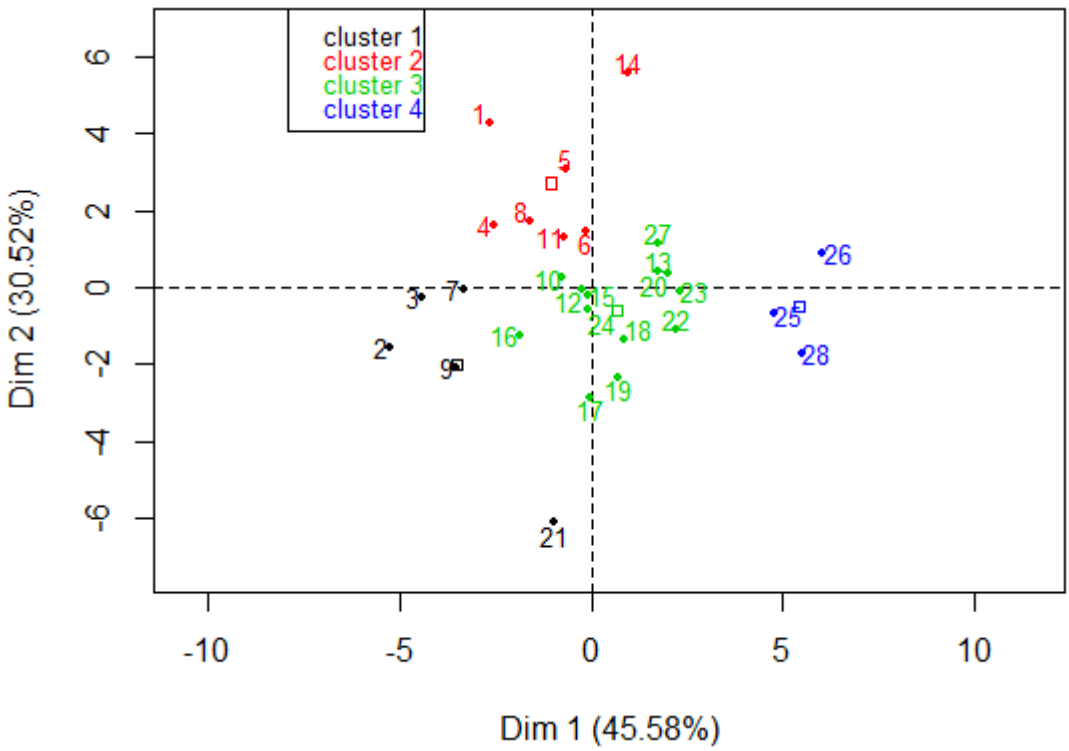


Figure 4-5. Hierarchical clustering representation on the map induced by the first 2 Principal Components on the Bani catchment. Sub-catchments are coloured according to the cluster they belong to, the barycenter of each cluster is represented by a square and Dim1 and Dim2 are the first two Principal Components on which the hierarchical clustering is built.

It is worth noting that these catchments have the smallest sizes in the dataset and their metrics (especially the area) could provide a bias in the distribution. In this group C1, it is found Kouoro 1 (sub-catchment 7). The second cluster (C2) is made up of 7 subbasins, among which, Douna

and Dioila (subbasins 1 and 4, respectively). The third Cluster (C3) represents a large mixing of 13 similar subbasins, such as Pankourou (subbasin 16) and Bougouni (subbasin 18). Finally, cluster 4 (C4) is considered as being well dissimilar to other clusters and is formed by the combination of 3 catchments; the well-known are Debete (25) and Madina Diassa (26).

Beside the optimal number of clusters suggested by the HCPC algorithm, one can look for a reorganization of clusters by examining the hierarchical tree illustrated on **Figure 4.6**. The tree represents the inertia loss as a function of clustering steps. The point at each two catchments that are merged is represented by the horizontal branch linking them, and the inertia loss attributed to this merging is read by projecting orthogonally the horizontal branch on the vertical axis. First, it can be noticed that C3 and C4 are closest to one another (the horizontal branch linking them is lower than the one linking C1 and C2 and could be merged into one cluster by increasing the variability of the system by 1.98. Then, the other merging possibility is between C1 and C2 but at the expense of increasing the variability by 2.94. Therefore, this classification into 2 clusters (C3+C4, C1+C2) could be envisaged depending on the application, which the classification is intended for.

In addition, the analysis of the barplot of within-group inertia (**Figure 4-6**) highlights an important outcome: The loss of inertia (variability) or inversely the gain of homogeneity in the system with increasing number of clusters. It is worth noting that the loss of inertia when moving from one cluster to two, is equal to 3.62, from 2 clusters to 3, 2.94, and from 3 to 4, 1.98 (can be read on the barplot). So, from a single cluster to the optimal number of 4 clusters, we reduced the variability by 8.54 and gained, therefore, in more system homogeneity.

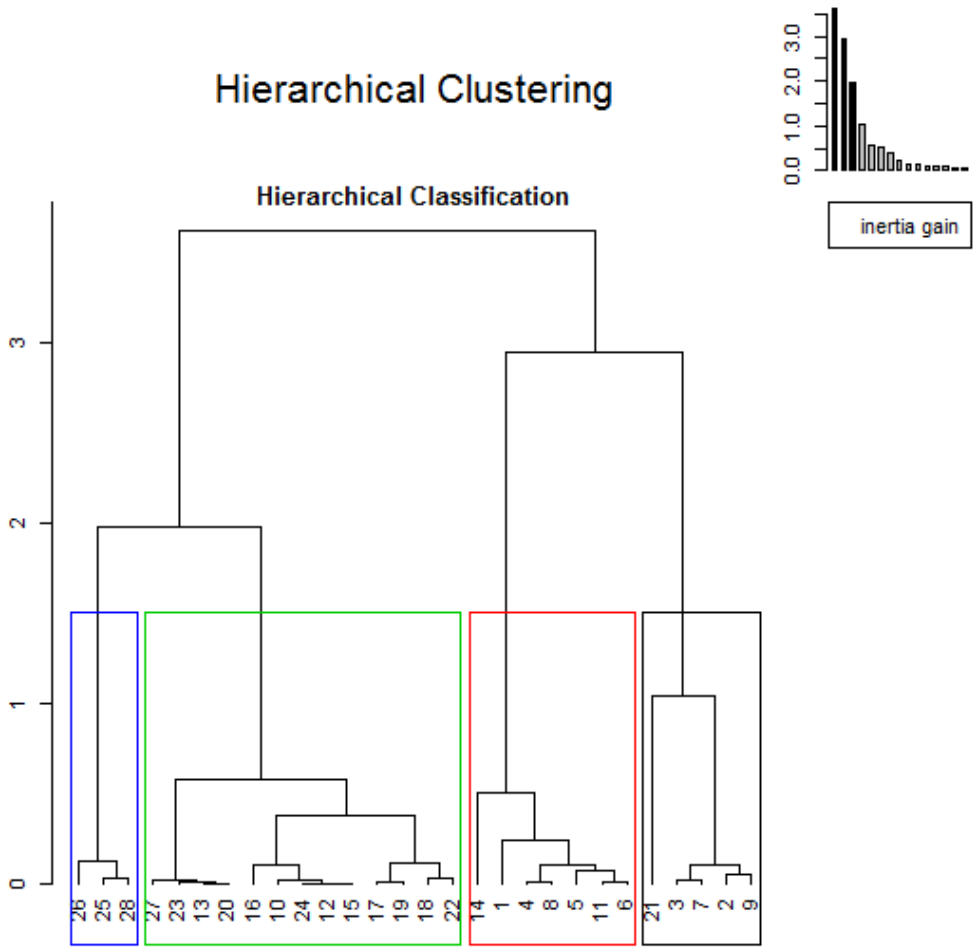


Figure 4-6. Hierarchical dendrogram of the Bani catchment. Each rectangle represents a cluster of similar catchments. The barplot (inertia gain) gives the decrease of within-group variability with increasing number of clusters.

4.2.2. Major controlling factors of similarity

It is important to explain the causes of similarity inside each cluster by determining attributes that are exerting strong control on each cluster. The description of input variables is given in **Table 4-4**. Results are also enriched by the analysis of the spatial distribution of clusters given in **Figure 4-7**.

Table 4-4. Description of hierachical clusters. In bold, positive *v-test* values indicate the variable that has a value greater than the overall mean, and in italic, negative *v-test* values refer to the variable that has a value smaller than the overall mean. All *v-test* values are significant at the probability $p = 0.05$.

Variable	*v-test*	Mean in category	Overall mean	*p-value*
		Cluster 1		
Shape_Area	*- 2.96*	728.24	3623.44	0.003104
Len1	*- 3.43*	56277.76	135344.70	0.000601
Wid1	*- 3.52*	62.95	166.14	0.000428
Shape_Leng	*- 3.62*	192137.08	465762.00	0.000296
Dep1	*- 3.78*	1.69	3.24	0.000160
		Cluster 2		
AGRL	**2.97**	87.75	50.81	0.002936
Lat	**2.76**	12.17	11.41	0.005818
Lf	**2.74**	91.25	56.71	0.006213
ElevMin	*- 2.68*	265.57	285.96	0.007257
P	*- 3.00*	829.56	1011.18	0.002674
		Cluster 4		
Slo1	**3.95**	3.53	2.12	0.000080
ElevMax	**3.41**	801.67	559.00	0.000654
Elev	**3.25**	405.79	352.47	0.001171
ElevMin	**2.77**	321.00	285.96	0.005648
P	**2.67**	1279.97	1011.18	0.007662
Lat	*- 3.16*	9.94	11.41	0.001557

Within C1, the most significant attributes are related to catchment and reach shape (*Dep1*, *Shape_Leng*, *Wid1*, *Len1* and *Shape_Area*, in this order) and are all characterized by below average values (negative *v-test* values). These catchments have the smallest sizes in the dataset. The most significant parameter in C2 is the precipitation, which is below the average. Catchments of C2 experience have the lowest annual precipitation and highest latitude, which are in line with their location in the North and the semi-arid part of the basin. In addition, they have the lowest minimum elevation (*ElevMin*), which confirms the proximity to the outlet of

the basin. Accordingly, C2 is assimilable to the group of northerly semi-arid catchments situated in the valleys. With respect to the significance of *AGRL* and *Lf* attributes, C2 can further be defined as the group of basins dominated by agricultural lands and where ferric Luvisols constitute the major soil type. In the center of the study basin, C3 forms another homogenous region inside which, none of the descriptors seems to have a significant impact. Migrating southward this time, in the headwaters of the Bani, we find catchments belonging to C4 where the topography exerts the strongest control on the similarity. The highest topographic attributes are recorded in this group (*Slo1*, *ElevMin*, *Elev* and *ElevMax*). These catchments receive more precipitation than the other catchments of the Bani and have the lowest latitude. As opposed to C2, C3 is therefore analogous to a group of southerly and humid catchments situated in the highlands of the Bani. Overall it seems that attributes which vary along a south-north gradient (topography, latitude and precipitation) constitute the driving forces that control the physical similarity.

Likewise, pursuing the search for more indicators of similarity, the spatial distribution of physically similar catchments (**Figure 4-7**) revealed that similar catchments mostly lie in a joint homogenous region, or at least in its surroundings. Therefore similar catchments are found to be close to each other. It appears from this result that spatial proximity plays an important role as an indicator of physical similarity in the study area, which is in line with the significance of the geographic descriptor (latitude) demonstrated here for two clusters.

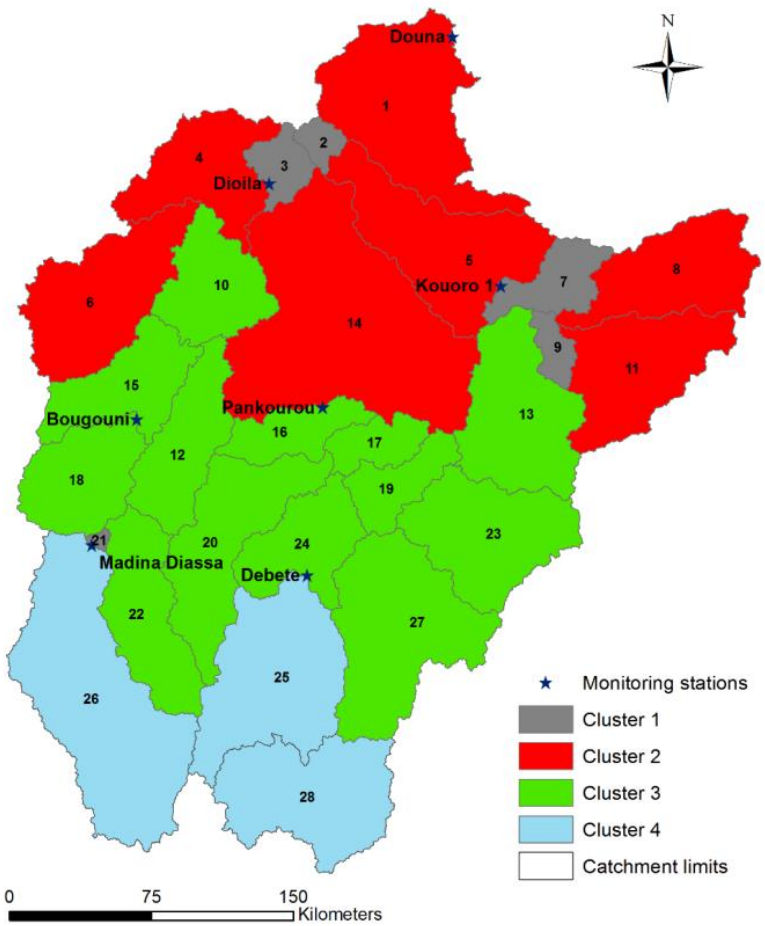


Figure 4-7. The spatial distribution of clusters of physically similar catchments on the Bani basin

4.2.3. Discussion and conclusions

Discussion

Overall, results of this study showed that the Bani can be organized into 4 major clusters of similar catchments based on physiographic and climatic characteristics. In addition, topographic variability, climatic indicators and geographical position of the sub-catchment were demonstrated to be the most important causes of similarity between catchments, and permitted to propose a kind of nomenclature of clusters: The group of northerly flat and semi-arid catchments, and the one of southerly hilly and humid catchments. The former is further characterized by the dominance of cultivated lands and ferric Luvisols soil type. Globally, an

important gain of system homogeneity has been obtained when moving from a single group of catchments to the optimal number of 4 clusters. The contiguity of the defined clusters indicates that physical similarity somehow depends on spatial proximity of the catchments. These results expectedly answer the questions posed at the beginning of this work. However, due to limited availability of literature on this area, it is difficult to show how these results fit in with existing knowledge on that topic. A broader comparison can only be made about the dominant controls on similarity in different contexts. For instance, Kileshye Onema et al. (2012) demonstrated that topographic parameters (e.g., mean stream slope, minimum elevation, and maximum elevation) provide the major categorization of catchments of the equatorial Nile, and proposed the same nomenclature of flat and hilly regions. Likewise, Raux et al. (2011) showed that the whole Niger basin is close to the group of basins characterized by topographic parameters (hypsometry and mean elevation), which can be considered as the major driving forces of its hydro-sedimentary response. As regard to the influence of spatial proximity on physical similarity, many authors (Coopersmith et al., 2012; Shu and Burn, 2003) have demonstrated that catchment classes are geographically contiguous in many cases. The rationale of this concept is that climatic and landscape controls on the rainfall–runoff relationship are expected to vary smoothly in space and therefore, spatial proximity could entail similarity in catchment response (Blöschl, 2011).

Conclusions and perspectives

It is important to note that no cluster analysis can produce a definitive classification because the results are depending on the dataset used and other kind of subjective choices (choice of classification algorithm and distance metric, (Sawicz et al., 2011)). It is also acknowledged that the actual limitation that could arise within this study was the absence of geological descriptors, limiting thus our understanding of subsurface controls. However, it was demonstrated through

a global sensitivity analysis performed in the previous chapter (see Chapter III) that groundwater parameters exert a lower contribution to streamflow generation in that region. Therefore, the assumption that geological parameters could have a lower impact on the hydrological functioning of the catchment could sound acceptable. In spite of the limitations discussed above, these are encouraging results, showing on one hand the relevance of physical characteristics to give information about the spatial similarity characterizing a large tropical river basin, and on the other, the value of statistical analyses (such as the HCPC function) as a pertinent tool for exploring similarity among catchments. Concerning the assumption of correspondence between physical and functional similarity made in this study, Oudin et al. (2010) pointed out that this assumption may not always be verified. We try to verify this assumption in the following Chapter by applying two similarity approaches of model parameter transfer within and between the so-called similar catchments, and discussed the conditions which favour hydrological similarity. The use of other similarity concepts (such as runoff similarity) applied to the same catchments could also give a good platform for discussion.

4.3. Predicting Daily Discharge Hydrograph in Ungauged Basins Based on Similarity Approach

The objective of this study chapter was to contribute to the advance in streamflow prediction in ungauged catchments and uncertainty assessment resulting from regionalization of model parameters based on similarity concepts. The specific objectives were to:

(1) Transfer the SWAT model parameters from gauged to ungauged catchments to simulate daily discharge hydrograph,

(2) Make a comparative assessment of regionalization methods based on spatial proximity and physical similarity

(3) And propagate and evaluate the prediction uncertainty related to the hydrological information transfer.

Predicting streamflow hydrographs in ungauged sites is germane for a wide range of applications such as water resources allocations, design of hydraulic structures, flood and drought risk management, impact of climate and land use change studies.

4.3.1. Calibration at gauged catchments

In the preliminary, we calibrated the SWAT model at 7 gauged catchments. The calibration task ended up with 5 catchments where the *NSE* were greater than 0.5, hereinafter referred to as donor catchments. The two other catchments are solely target catchments. Results of the successful calibrations are summarized in **Table 4-5**.

Overall, calibration of the hydrological model SWAT on the Bani catchment yielded good results for the calibration period at all the gauged catchments. Good to very good *NSE* and R^2 values were obtained and were greater than 0.65. The highest performance has been recorded at the catchment outlet of Douna with a *NSE* of 0.76. Similarly, the water balance prediction component was accurately reproduced (*PBIAIS* < ± 25%).

Table 4-5. Performance statistics and prediction uncertainty indices of the SWAT model for the Bani catchment. In bold, *NSE* values greater than 0.5, and *PBIAIS* less than ±25% in absolute values.

Period	Criterion	Douna	Pankourou	Bougouni	Dioila	Debete
Calibration (1983-1992)	*NSE*	**0.76**	**0.73**	**0.66**	**0.66**	**0.69**
	R^2	0.79	0.74	0.68	0.67	0.69
	PBIAS (%)	**- 12.2**	**6.08**	**- 15.0**	**6.64**	**- 2.50**
	P-factor	0.61	0.68	0.60	0.34	0.44
	R-factor	0.59	0.41	0.57	0.55	0.58
Validation (1993-1997)	*NSE*	**0.85**	**0.77**	0.37	**0.57**	0.45
	R^2	0.87	0.83	0.57	0.8	0.54
	PBIAS (%)	**- 23.2**	**- 19.5**	- 59.5	- 38.0	**- 13.2**
	P-factor	0.62	0.63	0.51	*0.33*	*0.20*
	R-factor	0.51	0.29	0.35	0.33	0.36

The prediction uncertainty was adequate (*P-factor* > 0.5 and *R-factor* < 1) for most of the stations unless at Dioila and Debete where uncertainty band could not account for the majority of the observations. However, it can be noticed a loss of performance during the validation period (poor *NSE* at Bougouni and Debete of about 0.37 and 0.45, respectively and higher *PBIAIS* values at Bougouni and Dioila of about -59.53 and -38.00, respectively). These results prelude a weak regionalization performance of certain stations especially Bougouni where the model could not adequately reproduce flows under different conditions to that of calibration period (**Table 4-5**).

4.3.2. Prediction of discharge hydrographs in ungauged basins

Regionalization performance at ungauged catchments

All catchments, including the donor catchments, were considered in turn as ungauged while the others were considered as potential donors. A total of 30 model parameters transfers have, therefore, been executed. Seven of them (that represent 23% of the total regionalization) have yielded good performances in terms of both *NSE* and *PBIAIS*, and have been found on four catchments over seven. Results of the model parameters transfers are summarized in **Table 4-6**.

NSE values vary between 0.52 and 0.83, with a median of 0.60. Moreover, good *PBIAIS* values have been obtained showing accurate prediction of the water balance component, and range between 5.67 and 25% in absolute values. It is important to underline the somewhat lower performance of one additional simulation obtained at Pankourou (donor = Debete, *NSE* = 0.56, *PBIAIS* = 41.75%), but which will be considered hereinafter at a successful regionalization (despite the higher errors in water balance prediction). Overall, good predictions have been obtained and the best performance has been achieved at the whole catchment outlet of Douna (*NSE* = 0.83 and *PBIAIS* = 5.67%) with the use of the parameter set determined at Pankourou.

Table 4-6. Performance of the SWAT model parameters transfer inside the Bani catchment. In bold, above-threshold statistics of a satisfactory regionalization, while in italic below-threshold statistics.

Donor / Target	Douna		Dioila		Pankourou		Debete	
	NSE	*PBIAIS*	*NSE*	*PBIAIS*	*NSE*	*PBIAIS*	*NSE*	*PBIAIS*
Douna	×	×	**0.73**	**- 6.93**	**0.83**	**5.67**	- 0.58	111.1
Dioila	**0.56**	**- 25.0**	×	×	**0.60**	**- 17.7**	- 0.30	85.8
Pankourou	**0.68**	**- 7.95**	*0.49*	*- 39.1*	×	×	**0.56**	41.8
Debete	**0.52**	**- 6.36**	0.11	- 70.4	**0.59**	**19.4**	×	×

Dependency of regionalization performance at ungauged catchment on calibration performance at gauged catchment.

It should be noted that in the present study we used a process-based method, i.e., a rainfall-runoff model, to predict streamflow in ungauged basins. Therefore, the performance of a regionalization method firstly depends on the quality of the calibration task. If we compare the performance obtained at ungauged catchments (**Table 4-6**) to the performance of the calibration at gauged catchments (**Table 4-5**), it can be derived that in general, a good regionalization was obtained by applying parameter sets that already showed a certain ability to perform on the validation period at gauged sites. For instance, a good performance has been achieved for both calibration and validation periods at Douna, Pankourou and Dioila stream gauges, and the same stream gauges yielded good regionalization results. None of the transfers from Bougouni gave a satisfactory simulation; little performance has been obtained with the parameters of Debete. It is important to recall here that the model has already shown a weak robustness in performing under a different time period at those catchments.

Assessment of the prediction uncertainty at ungauged catchments

The total uncertainty in ungauged catchments results from the cumulative effect of model calibration uncertainty (related to input data, model structural errors and model parameters identification) and model parameters transfer. As such, it can be awaited an increase of uncertainty from the donor (where the rainfall-runoff model has been calibrated) to the target catchment (where

the model parameters have been transferred). The resulting uncertainty statistics are presented on **Figure 4-8**.

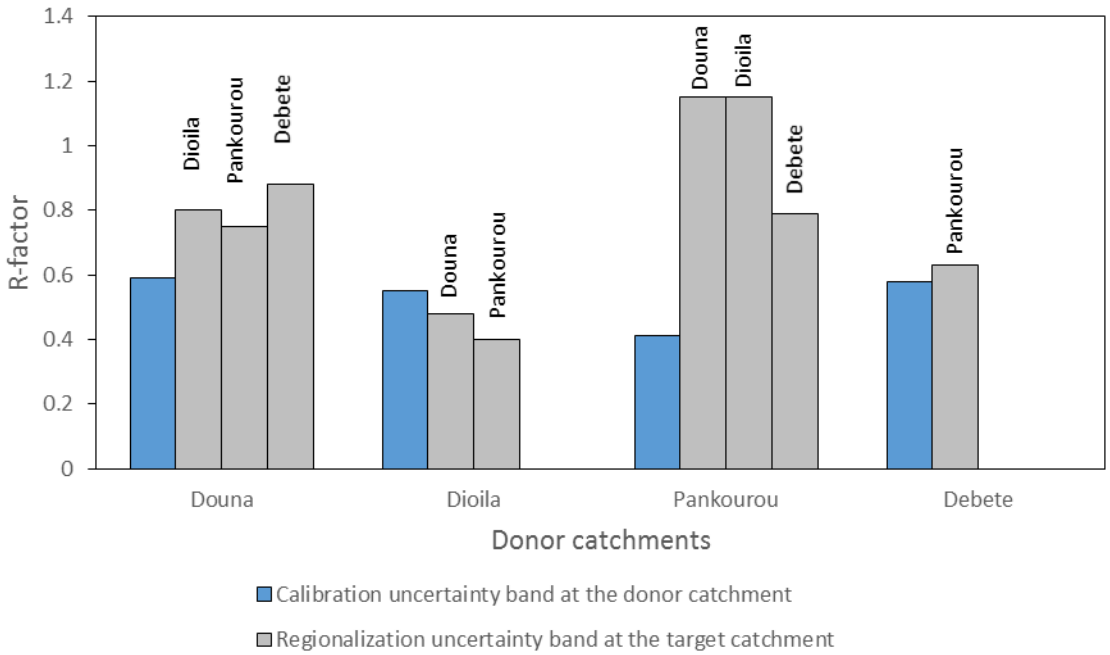
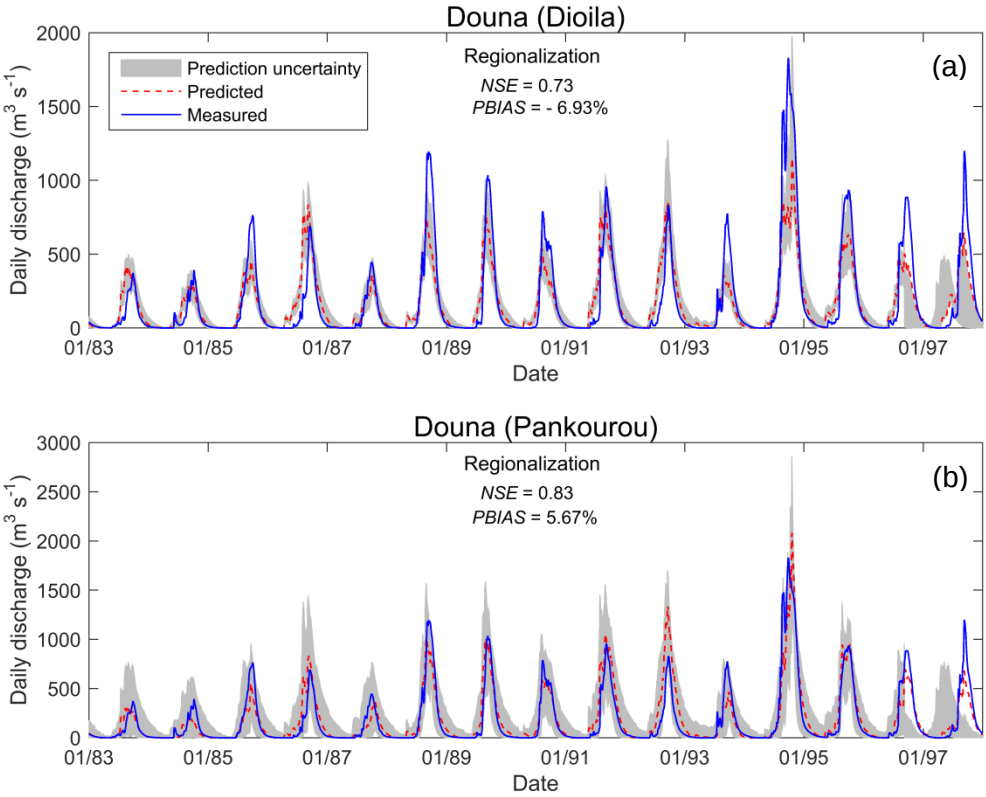


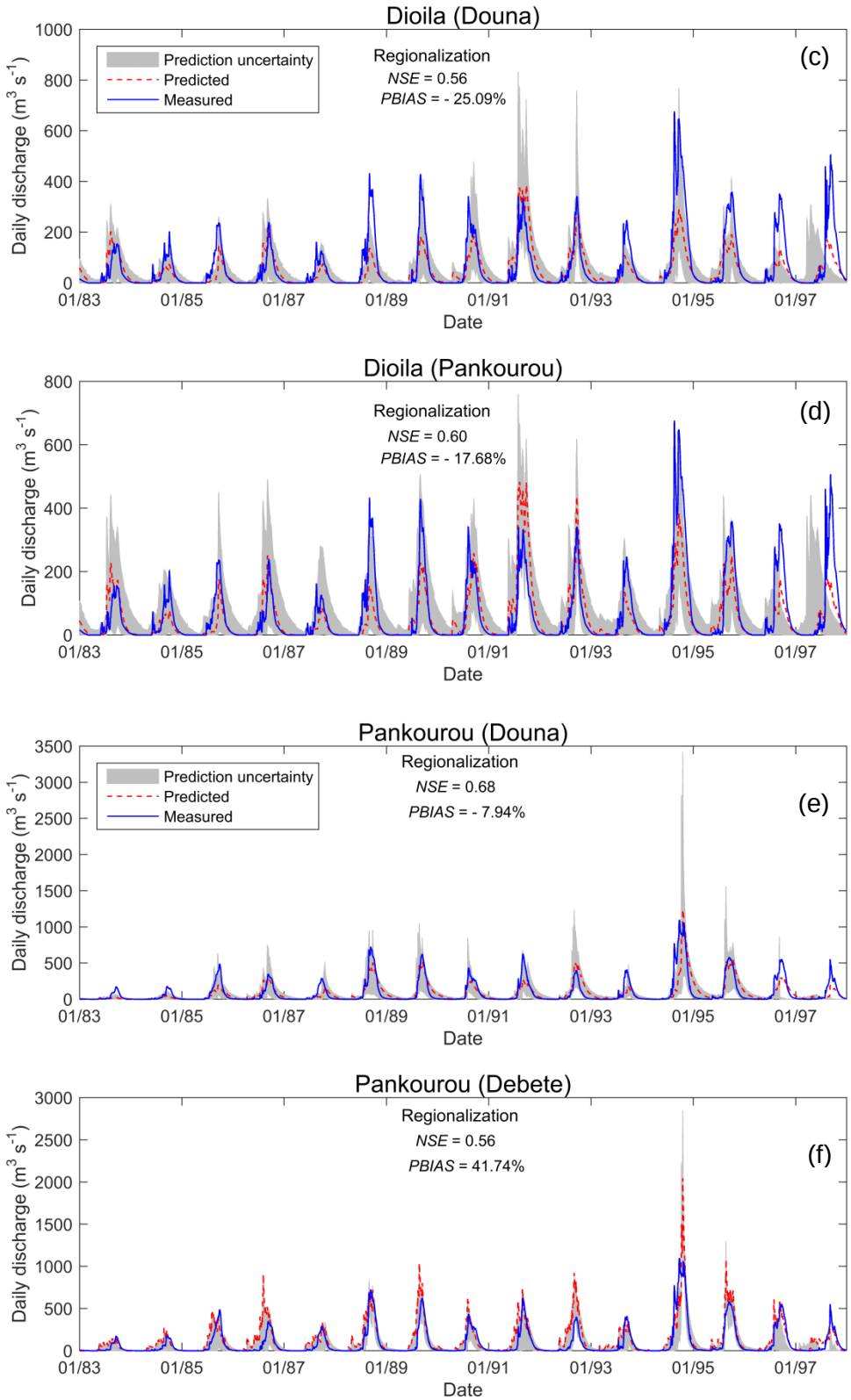
Figure 4-8. Prediction uncertainty band of model parameters transfer at ungauged catchments (in gray) represented by *R-factor* values. In blue, initial uncertainty band at the donor catchment.

R-factor values became greater as one moves from gauged to ungauged catchment (except for the case of Dioila) representing therefore larger uncertainty band related to model parameters transfer. As an example, the *R-factor* values increased from 0.51 at the donor Douna, to 0.75 and 0.88 successively at Pankourou and Debete. The largest uncertainty band has been recorded at Douna and Dioila (*R-factor* = 1.15). However, the relative tendency of the *P-factor* is not straightforward; depending on the case, the regionalization can be accompanied by a decrease or an increase of the percentage of observed data bracketed by the 95PPU. But in general, more of 50% of the observed discharges were included in the uncertainty band unless again the transfer from Dioila. In fact, few

behavioral simulations (9) have been obtained by the calibration task, and a small *P-factor* (**Table 4-5**). The choice of a high threshold value (0.5) to separate behavioral to non-behavioral simulations, can have the impact of reducing the prediction uncertainty at that station.

To complete the assessment, graphical analysis of **Figure 4-9** revealed the presence of larger uncertainty band around high flows, especially exacerbated during the year 1994, which has been a very humid year due to the exceeding precipitations recorded all over the study area. In addition, one can note the displacement of that uncertainty band aside of the predicted and observed hydrographs during the last year (1997), which could be an artifact of the model. Overall, it can be deduced from what preceded that there is an increase of the prediction uncertainty from gauged to ungauged catchments.




Dioila (Douna)
Prediction uncertainty
Predicted
Measured
Regionalization
NSE = 0.56
PBIAS = - 25.09%
(c)
Daily discharge (m3 s-1)
Date
Dioila (Pankourou)
Regionalization
NSE = 0.60
PBIAS = - 17.68%
(d)
Pankourou (Douna)
Regionalization
NSE = 0.68
PBIAS = - 7.94%
(e)
Pankourou (Debete)
Regionalization
NSE = 0.56
PBIAS = 41.74%
(f)
01/83
01/85
01/87
01/89
01/91
01/93
01/95
01/97

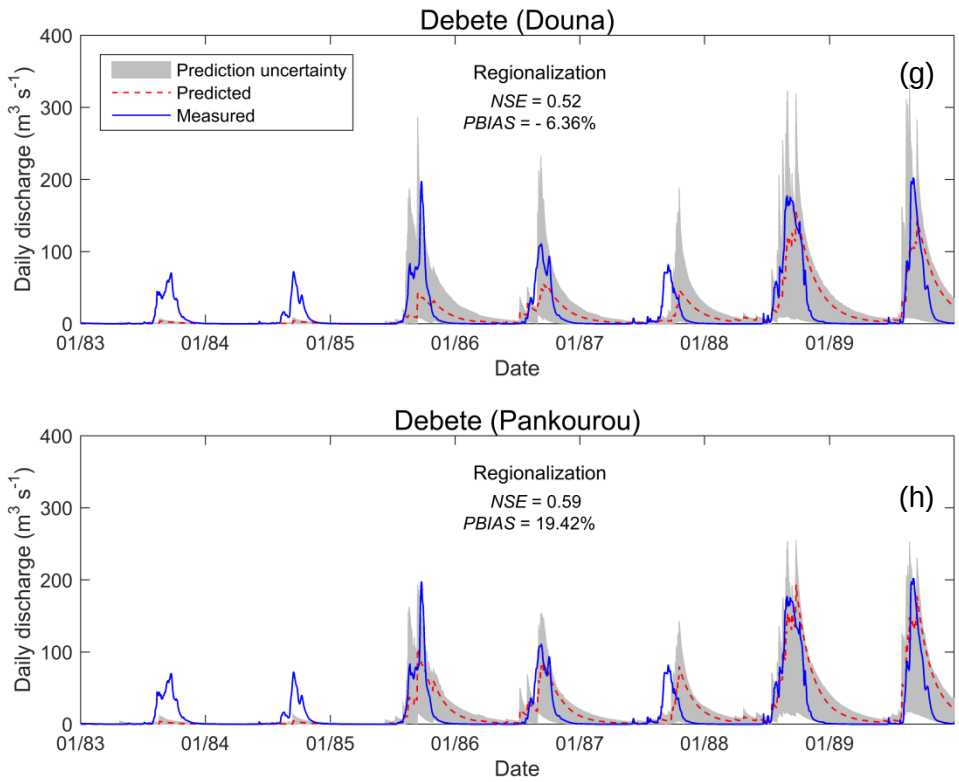


Figure 4-9. Measured and predicted discharge on the target catchments (Douna (a)-(b), Debete (c)-(d), Dioila (e)-(f) and Pankourou (g)-(h)) using different donor catchments. Note that the title of each subplot (for example Douna (Dioila) in subplot (a)) means Target (Donor) catchment, respectively.

Is there any physiographic or climatic pattern of hydrograph prediction?

Figure 4-10 shows the spatial location of the ungauged sites where regionalization yielded at least one satisfactory result with respect to the evaluation criteria defined in section 3.2.8. Most of the successful regionalization simulations are located in the half-north of the study area, which actually spans over semi-arid (aridity index between 0.2 and 0.5) and dry sub-humid (aridity index between 0.5 and 0.65) zones. Overall the total catchments with satisfactory regionalizations, 3 over 4 are located in that region and recorded the highest performances which range between 0.56 and 0.83. Only one successful catchment is located in the humid region (aridity index > 0.65) with lower performance between 0.52 and 0.59 (**Figure 4-10**). Consequently, hydrograph prediction

performance appears to be higher in semi-arid than in humid region although prediction uncertainty tends to increase more in semi-arid catchments.

Moreover, there is a tendency that the regionalization performs better among hydrologically connected catchments without consideration of any physioclimatic region, as describe by the performances obtained between Douna and Dioila on one hand, Douna, Pankourou and Debete on the other. In fact, these stations control nested catchments which flows successively contribute to the flows of the one situated downstream. But this characteristic was not found on the other river (Baoule River) connecting Madina Diassa, and Bougouni where the regionalization did not succeed at all.

Definition of hydrological similarity

In this case, we evaluated the best similarity method as the one which best describes hydrological similarity between gauged and ungauged catchments. To assess that hydrological similarity, we compared at each target catchment the performance obtained by calibration, and the performance obtained by using the optimized parameters of the donor catchments. Results are presented in **Table 4-7**.

Table 4-7. Ratio between regionalization performance and calibration performance at target catchment.

Target catchment	Douna	Dioila	Pankourou	Debete
Douna	-	96%	109%	-
Dioila	85%	-	91%	-
Pankourou	93%	68%	-	77%
Debete	75%	-	86%	-

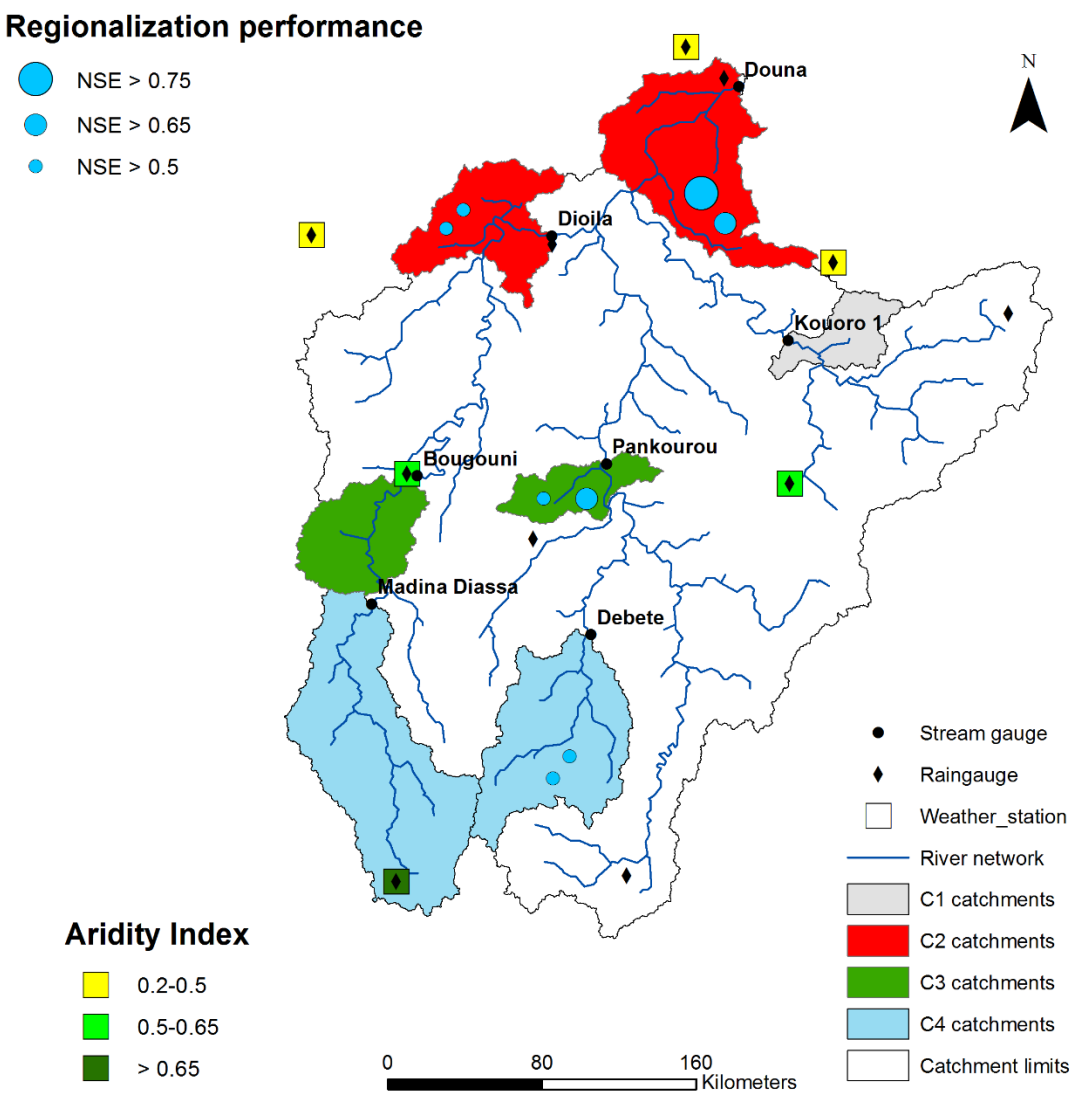


Figure 4-10. Spatial pattern of the discharge hydrograph regionalization. The number of symbols inside each catchment represents the number of simulation with *NSE* greater than 0.5. The aridity index was calculated on the period 1983-1998.

All regionalization models reached efficiency greater than 0.75% of the efficiency obtained by calibration at the target catchment. Pankourou is the outlet whose parameters produced the highest performance at the other target catchments (109% at Douna, 91% at Dioila and 86% and Debete). The performance achieved at Douna is even greater than the performance achieved by calibration (ratio = 109%). Therefore, taken two by two, there exist a very good hydrological similarity

between Douna and Dioila, Douna and Pankourou, Douna and Debete, Dioila and Pankourou, and Pankourou and Debete. However, only Douna and Dioila, Douna and Pankourou, and Pankourou and Debete, can be considered as mutually hydrologically similar because parameters set of one is suitable for the other, and vice versa.

If we try to relate this hydrological similarity with the regionalization approaches utilized herein, results revealed that the hydrologically similar catchments are two by two nested an can be treated as the immediate upstream and downstream neighbors. Therefore, there exists a tendency of spatial proximity to best describe, even though partially, the hydrological similarity between catchments.

4.3.3. Discussion and conclusions

Does hydrograph prediction depend on climate?

With the aim of predicting discharge hydrographs at ungauged catchments on the Bani basin, we calibrated the SWAT model on many gauged catchments and then transfer model parameters to ungauged sites based on similarity approaches. Results showed good predictability of the regionalization in dry sub-humid to semi-arid catchments as depicted by highest *NSE* ranging between 0.56 and 0.83, while it decreases to 0.52 and 0.59 in more humid catchments. However, prediction uncertainty was found to increase with aridity. Many authors have reported in the broad literature, however, a decreasing performance with aridity (Parajka et al., 2013; Patil and Stieglitz, 2012; Salinas et al., 2013) and have attributed this finding to the presence of more heterogeneities in hydrological variables leading to non-linear rainfall-runoff relationships in arid zones. In our case the weakness of the regionalization in humid catchments may be explained by a non-stationarity of hydrological behavior on the simulation period potentially due to changes in climate

and land use characteristics. The calibration of the model has already given inadequate results in the temporal validation. Therefore, in addition to the difference of hydrological behavior between catchments (spatial transposability), there should be a temporal disruption in rainfall-runoff relationship between calibration and validation periods. Abrate et al.(2013) showed for instance the appearance of a new break in the hydrological series of the Niger River during the year 1994/95 (this year falls inside our validation period) with a return to wetter conditions. However, one could expect the impact of the hydrological break to be the same or uniformly distributed on the basin. But we rather think that the consequences of that new regime on catchments rainfall-runoff relationship, should have been different in humid than in arid catchments. One can discuss the limited length of the herein calibration-validation period (15 years) to derive any statistically significant tendency, but Sawicz et al. (2014) were able to detect the presence of non-stationarity of hydrological behavior between catchments by comparing their hydrological signatures between 10-year periods and concluded that the change in catchment functioning is mainly attributed to change in precipitation characteristics. In addition, the land use map utilized herein for model setup has been built with data of a 12-month period 1992-93 and therefore represents the land cover pattern of that period. We hypothesized that this land cover map could not be suitable to capture the temporal and spatial variability of that attribute in the study catchments.

Is there any physiographic pattern of regionalization efficiency?

We obtained the highest regionalization efficiencies at the whole catchment outlet. This result can be explained by the effect of catchment size on the prediction performance. Parajka et al. (2013) have reported in their review on runoff-hydrograph prediction studies, an increasing prediction performance with increasing catchment size. The catchment's size effect in hydrological models in general creates a kind of compensation between positive and negative errors of processes at a

larger scale (Cao et al., 2006; Wellen et al., 2015) leading to an overconfidence in the model performance with increasing area. As a reminder, the same catchment (i.e., Douna) has yielded the highest calibration performance as well (see Chapter III). Another aspect that can be regarded the hydrological dependency of flows (nestedness) between donor and target catchments. Douna receives flows from all the internal outlets involved in the regionalization; this could be in favor to a successful transfer of parameters between the upstream and the downstream of the basin.

The efficiency reached by using parameters borrowed from Pankourou was surprisingly even better than the efficiency reached by calibration. This raises an important issue of whether regionalization can outperform calibration at a given location? First, , it should be noted that in spite of the high regionalization performance obtained at Douna in terms of *NSE* and *PBIAIS*, the prediction is however accompanied with uncertainty higher than the one obtained by calibration. Therefore, the result should be interpreted with caution. Second, we could not attribute the performance reached by calibration at Douna to a local optimum which is not possible with GLUE because this method was constructed instead to avoid the problem of model parameters non-uniqueness. In conclusion, we could not explain with the data used in this study why regionalization outperformed calibration at Douna.

Which similarity method performs best?

The results support a good advocacy of spatial proximity predominance over the study area. In fact, a good hydrological similarity has been found principally between nested (situated along the same river branch) catchments, such as Douna and Dioila on one branch, Douna, Pankourou and Debete on another, and decreases with increasing distance. The rationale behind this influence is that there exists a hydrological connection between nested catchment flows so that one can assume their parameters to be similar. Merz and Blöschl (2004) used this kind of spatial proximity

approach and transferred the average parameters of immediate upstream and downstream neighbors. They concluded that this method performs best among other regionalization techniques. More widely, spatial proximity have been proved in many review studies (Blöschl et al., 2013; Parajka et al., 2013; Salinas et al., 2013; Viglione et al., 2013) to be the best regionalization approach. However, our result is conditioned by the limited data availability characterizing our study, and also the dependency between physical similarity and spatial proximity as discussed in Chapter III. The rationale of this relation is that catchment structure and climate are noted to vary smoothly in space. Consequently, physioclimatic regions frequently appear to be contiguous making it difficult sometimes to differentiate between the influence of physical similarity and spatial proximity, which we called the combined method as described between Douna and Pankourou lying in the same physiographic region and being geographically close.

Estimation of hydrological similarity between catchments

Last, but not the least, we have demonstrated that the Pankourou catchment was the most hydrologically similar to the other catchments involved in the regionalization. At all the target catchments, the efficiency reached by applying parameters from Pankourou not only exceeded the others efficiencies, but is also greater than 80% of the efficiency reached by calibration at the same catchments. Pankourou can therefore be considered as the paragon of the Bani catchment, and neither spatial proximity nor physical similarity can fully explain this hydrological behaviour. We suggest that further work been carried out on such catchment, and on the similarity relationships it has in common with other catchments to advance the understanding of hydrological similarity.

Conclusions

In this study, the performance of the similarity approach for discharge hydrograph prediction in ungauged catchments was evaluated on the Bani basin. We utilized a process-based method, i.e., a regionalization of model parameters. For this purpose, we calibrated the SWAT model at 5 gauged catchments (termed as donor catchments) on a daily basis for the period 1983-1992 and validated it on the period 1993-1997, and considered 2 additional gauged catchments where the model has not been calibrated. For the regionalization purpose, each catchment (including the donor catchments) was considered in turn as ungauged, while the others were considered as potential donor. Then the optimized model parameter set was entirely transposed from the gauged to the ungauged catchment to achieve discharge hydrograph. Due to limited availability of gauged catchment, all donors were considered for each ungauged catchments without any consideration of spatial proximity or physical similarity. The resulting simulations were thereafter discussed according to both similarity methods (spatial proximity and physical similarity).

Final results showed a good SWAT model performance to predict daily discharge by calibration at gauged catchments. However, poor performance has been recorded in the validation period at catchments situated in humid region. In addition, the study showed higher regionalization performance and prediction uncertainty in arid zone, where spatial proximity seem to explain, in most cases, hydrological similarity between catchments. Overall, this study shows evidence on the hydrological similarity inside a group of 4 catchments spanning over different environmental regions. The exemplar of this group is

the catchment controlled by the Pankourou outlet whose parameters seem to represent all the other catchments.

However, it is worth noting that the major limitations that arose within this study is mainly the limited climate data availability (rain gauge density, time series length) and the weak density of the discharge gauges which can impact the model parameter identification and the comparative assessment of regionalization methods, respectively. In addition, the success of physical similarity can be masked by many subjective choices such as catchment descriptors, classification algorithm, and especially the absence of geological and subsurface descriptors limiting therefore the impact of groundwater flows on the classification result. These issues emphasized the challenging task of prediction in ungauged basins in developing countries where even the few existing gauged catchments are "ungauged" in a certain extent, in terms of geological, soil, socioeconomic information, to cite few.

In spite of these limitations, this study represents a first step towards an advance in hydrological processes understanding for better prediction in ungauged catchments, especially where it is more needed, i.e. in developing countries. To our knowledge, this is the first ever study on prediction in ungauged catchments on the Bani river, using a process-based method for a complete hydrograph simulation. Results of this study can be used in many water resources management's strategies. However, the backbone of any management is the data availability. Therefore, the developed regionalization model can be used to generate data where it is not measured. From filling gaps in discharge time series, to data forecast, from daily discharge to annual discharge volume, many applications can be found according to the objective it is intended for: water allocation to irrigation,

industry, hydraulic structure design, ecological studies, and climate and land use change impact studies, among others. Due to the limited accuracy of the model to simulate high flows, we recommend that the model should be improved before being used in any flood forecast.

Chapter V

5. Conclusions and Perspectives

5.1. Conclusions

This thesis is devoted to predicting streamflow hydrographs in ungauged basins. Firstly, we calibrated the SWAT model on the Bani catchment on a daily time interval and identified the most sensitive model parameters that will subsequently be used in a regionalization scheme. Secondly, all the subcatchments generated at the watershed delineation pre-processing were grouped into clusters of similar physiographic and climatic characteristics by the means of a multivariate statistical analysis. Finally, the optimized model parameters were transferred between catchments based on physical similarity and spatial proximity approaches to achieve daily streamflow hydrograph simulations which will be compared to their observed counterparts.

Final results demonstrated a good SWAT model performance to predict daily as well as monthly discharge at catchment and subcatchment levels with adequate prediction uncertainty. From the calibration task, 12 model parameters were clearly identified as the ones that best represent the hydrological functioning of the catchment, and the most sensitive of them are related to surface runoff process. The underlying limited data conditions seem to favour a good hydrological modeling of the study area. The study has also come out with a physical classification of subcatchments into 3 major groups: a group of northerly flat and semi-arid catchments, another group of southerly hilly and humid catchments, and a third group located in the center of the study basin, inside which, none of the descriptors seems to exert a strong control on the similarity. This similarity is mainly interpreted by the topography, the precipitation and the latitude, i.e. the geographical position, of the catchments. Then, a comparative performance assessment of the regionalization methods based on similarity is provided. First, it was highlighted the existence of

a climate and scale patterns of the regionalization efficiency. There are noted increasing performance and larger prediction uncertainty with aridity and catchment area. In addition, spatial proximity was found to perform best. However, with the data used in this specific case study, we could not shed light on the assumption of correspondence between physical and hydrological similarity.

We used a physically based model to predict discharge at gauged catchments and evaluated the associated prediction uncertainty, therefore providing a range of possible discharge estimations on a specific period of time on which decisions can be built. But the model has the advantage that it can accommodate to changes in time, climate and environment. Because of that, it can be used for water resources forecast and impact studies, by updating input data. This knowledge will help in the evaluation of current and future hydrological impacts of climate and land use changes, and the development of appropriate strategies of adaptation to climate change.

The knowledge of water resources availability in small ungauged catchments can also contribute to the development of irrigation. In a context where rain-fed agriculture remains the most threatened economic sector by climate change and is mainly subsistence-oriented, irrigation has become an alternative solution in West Africa facing frequently hydro-meteorological droughts. The development of irrigation will help limiting the exposure of the rural population to food insecurity.

Beside the practical implications, the outcomes of this thesis are also very useful for the science by improving the understanding of local hydrological processes. From the predominance of surface runoff in streamflow generation and the limit of the so-defined physical similarity to

explain hydrological similarity between catchments, possible research ways towards new definitions of hydrological processes are outlined.

Many difficulties and limitations arose at different steps of the regionalization process. Limited hydro-meteorological data, with many gaps, inconsistencies and varying lengths, and coarse information on soil and land use for Africa, can successively impact the prediction performance and uncertainty of the calibrated and regionalized hydrological models.

It is also acknowledged that the actual limitation that could arise within the classification was the absence of geological descriptors, limiting thus our understanding of groundwater controls. Moreover, this classification is very sensitive to the dataset used, the classification algorithm, the distance metric, making it difficult to extrapolate beyond the catchment of interest.

5.2. Perspectives and recommendations

Data constitute the backbone of any water resources management. Therefore, to improve model accuracy and reduce prediction uncertainties, additional data have to be used. This suggests that:

- We need to densify the hydro-meteorological measuring network to collect information at the maximum amount of points possible. And more, not only data quantity is required, but also data of good quality which are measured following accepted guidelines and are easily traceable to their sources in order to facilitate quality control procedures.
- Exploiting new measurement technologies such as remote sensing can help keep pace with the evolving water issues.
- Spatial data are also concerned. It is important to note that the use of globally available data with very coarse resolution is not always suitable especially for small catchments.

The use of the new land use map developed by AGRHYMET on West Africa could be a promising tool for enhanced hydrological modeling in that region.

While we know that physical similarity does not necessarily entail hydrological similarity between catchments involved in this study, we do not know which elements do contribute to that behaviour and how. We need further investigations on functional characteristics, e.g. runoff signatures, and the way they affect catchment rainfall-runoff response. This, in turn, will enhance the development of more suitable classification and regionalization methods.

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Appendices

Appendix A: Published article 1

Appendix B: Published article 2

Appendix A: Published article 1

RESEARCH ARTICLE OPEN ACCESS

Catchment classification: multivariate statistical analyses for physiographic similarity in the Upper Niger Basin

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Abstract
The objective of this study was to determine physiographic similarity, as indicator of hydrologic similarity between catchments located in the Upper Niger Basin, and to derive the dominant factors controlling each group singularity. We utilized a dataset of 9 catchments described by 16 physical and climatic properties distributed across a wide region with strong environmental gradients. Catchments attributes were first standardized before they underwent an integrated exploratory data analysis composed by Principal Component Analysis (PCA) followed by Hierarchical Clustering. Results showed a clear distribution into 2 major clusters: a group of easterly flat catchments and another of westerly hilly catchments. This nomenclature came from the interpretation of the main factors, topography and longitude, that seem to control the most important variability between both clusters. In addition, the hilly catchments were designated to be dominated by forest and ACRISOL soil type, two additional drivers of similarity. The outcome of this study can help understanding catchment functioning and provide a support for regionalization of hydrological information.
Keywords: catchments, Hierarchical Clustering, physiographic similarity, Principal Component Analysis, Regionalization.

I. Introduction

A core issue in hydrology is to make prediction of hydrological variable where it is not measured. This situation is of particular importance especially in developing countries where many river basins are ungauged [1-5]. This lack of information constraints water resources management and constitutes a stumbling block to adaptation to climate change in the sector of water hence increasing the vulnerability of rural population, particularly.

With the aim of predicting hydrological variables in ungauged basins, regionalization procedures are usually used. Different types of regionalization exist, and can be classified as [6] in: 1) regression methods, and 2) methods based on distance measures between gauged and ungauged sites. The former methods consist in deriving statistical relationships between catchment attributes and the optimized model parameters. Notwithstanding being considered as the most common regionalization approach for flow prediction in ungauged catchment [7], statistical methods are limited in use due to the presence of equifinality in calibrated model parameters. In fact, it becomes difficult to associate individual parameters with the physical characteristics of the catchment (each parameter can take several values) and thus, instead, complete parameter sets should be transferred to ungauged sites [8]. Another drawback of these methods is that most statistical models consider linearity between catchment attributes and model parameters [9, 10]. Consequently, in order to address the issue of model parameters non-uniqueness and propagate prediction uncertainty from gauged to ungauged catchment, similarity methods should be suitable.

Hydrologic similarity is an essential concept in regionalization [11-13]. Many similarity concepts have been proposed in the literature that attempt to represent various hydrologic processes occurring at different locations. [14], for instance, proposed three similarity concepts: spatial proximity, similar catchment attributes and similarity indices. In the first concept, catchments that are close to each other are assumed to behave hydrologically similarly. Geostatistical methods are based on this similarity measure. Many authors have indicated, for instance, the predominance of kriging methods on deterministic models in regions where the gauging network is sufficiently dense (e.g. [15, 16]). Nonetheless, it was pointed out that spatial proximity does not always involve functional similarity between catchments [17, 18], and thus[19, 20] suggest, instead, the application of hydrologically more meaningful distance measures. In the second concept, catchment attributes, such as catchment size, mean annual rainfall, and soil characteristics are used as indicators of physiographic similarity. Many studies stressed the value of parameter regionalization methods based on physiographic similarity, as a proxy for functional similarity ([10,

21, 22]. The third similarity concept is based on hydrologic function defined by similarity indices such as the aridity index of Budyko (e.g. [23, 24]), which has proved to be a valuable measure of catchment behavior.

Similarity of hydrological function between catchments could be derived by a classification scheme. As discussed by [13], the ultimate goal of classification is to understand the interaction between catchment structure, climate and catchment function. Additionally, [25]proposed four objectives of catchment classification which are: 1) nomenclature of catchments, 2) regionalization of information, 3) development of new theory, and 4) hydrologic implications of climate, land use and land cover change. Many authors attempted to classify catchments around the world into similar groups. For instance, [26]used 8 physiographic and meteorological variables to organize 21 catchments located within the Nile basin, into 2 homogeneous regions by applying a multivariate statistical analysis. In a different approach, [27]used self-organizing maps to classify around 300 Italian catchments according to several descriptors of the streamflow regime and geomorphoclimatic characteristics. As for [28], they distinguished only six dominant classes for 331 catchments across the continental United States using four similarity metrics. It is worth noting the work by[29]involving 24 worldwide large drainage basins, among which, the Niger basin. In fact, [29]considered sixteen geomorphologic and climatic variables into multivariate statistical analyses and obtained 6 clusters along with the description of the major controlling factors driving the hydrosedimentary response of each group. However, large river basins, as it is the case in [29], usually encompass several climatic regions and exhibit strong environmental gradients. Consequently, a global classification at such spatial scale can still hide significant internal heterogeneities among subcatchments, hence limiting our understanding of the hydrological functioning occurring at smaller catchments. Therefore, it is essential to break down the scale and provide more detailed classification scheme, and this is essential especially when prediction in small ungauged catchments is foreseen. However, only one a priori classification of the Niger basin exists and have been proposed by the Niger Basin Authority (e.g. [30]) which subdivided the whole basin into 4 physio-climatic regions: the Upper Niger, the Niger Inner Delta, the Middle Niger, andthe Lower Niger. Nevertheless, this classification falls short of providing a quantitative assessment of the degree of (dis)similarity within and between the so-called homogenous regions.

In the light of these examples, the main objective of this study was to classify subcatchments of the Upper Niger into similar groups according to their physio-climatic parameters. The specific objectives were to: 1) reduce the dimension of the input dataset containing catchment attributes by a Principal Component Analysis, and 2) perform a hierarchical clustering of subcatchments based on the reduced dataset. This study provides the first ever quantification of similarity among catchments with respect to physiographic characteristics on a large tropical river basin at finer spatial scale. Nor descriptors, neither statistics themselves are actually novel in the broad literature, but their combined use in that particular area to evaluate the gain of homogeneity with increasing number of clusters, is.The questions that will be addressed in this study were: (i) can the Upper Niger further be separated into similar groups of catchments based on their physical characteristics, and if so, (ii) what are the dominant controls of similarity between catchments.

II. Material and methods

2.1. The study area

The present study was conducted within the Upper Niger (Fig. 1). This basin is composed by to mutually independent subbasins: the Upper Niger subbasin controlled by the Koulikoro gauging station and the Banisubbasin at the Douna outlet, each covering an area of 120,000 km2 and 101,000 km2, respectively. The study area is shared by four West African countries: Guinea, Cote d'Ivoire, Mali and Burkina Faso, in a lesser extent. To avoid confusion, the parent basin is called the Upper Niger and its subbasin upstream Koulikoro is called the Upper Niger subbasin.

Altitudes are unevenly distributed across the Upper Niger. The extreme west and south of the basin are hilly zones. The Tinkissosubcatchment, for instance, is situated in the Fouta-Djalon Mountain, which culminates at more than 1000 m in the region of Dabola[31]. Similarly, the south of the basin is shaped into plateau and mountains, the most important of which is situated between Milo and Dion rivers and reaches its highest point at 1500 m. In contrast, the Bani watershed's topography is gently sloping, with altitudes ranging from 249 m to 826 m. Average annual precipitation (period 1981-2000) varies from 1500 mm y-1 in the humid Guinean zone in the south-west (region of Kissidougou) to 620 mm y-1 in the Sahelian zone in the North-east (region of Segou). The vegetation is dominated by the presence of closed evergreen forest in the highlands of the Fouta Djalon Mountain, whereas the Baniis mainly the domain of savannah with small spots of deciduous forest. ACRISOL is the most important soil grouping on the majority of subcatchments, except at the subcatchments controlled by Bougouni and Kouro1 gauging stations.

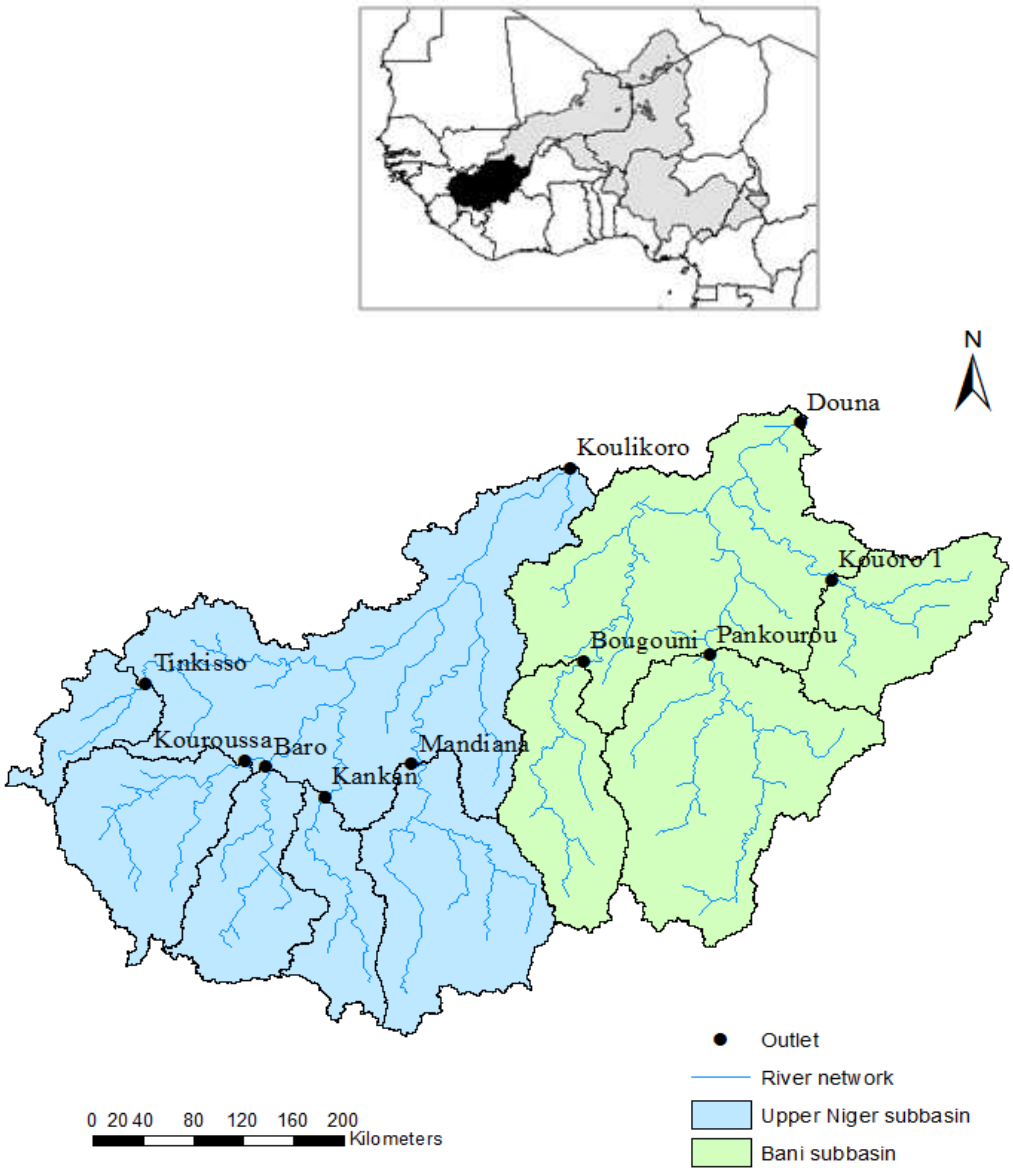

Figure 1: localization of the Upper Niger basin and the study catchments

2.2 Catchments and catchments' attributes

A total of 9 candidate catchments were selected and range in size from 6379 km^2 to 101,456 km^2 and were hereinafter given the name of their corresponding outlet. For example, Bougouni referred to the subcatchment controlled by the Bougouni outlet. Three of them are included in the Bani, while five are located on the Upper Niger subbasin, (Fig. 1), and are referred to as Group I and Group II, respectively. The Dounasubbasin, which is actually the Bani, is the biggest catchment and was added on purpose to test similarity across spatial scale. In addition to belonging to two hydrologically non-connected subbasins, Group I and Group II individuals were chosen to be non-nested sites in order to provide a better structure of independence between subcatchments. Furthermore, these subcatchments have not been affected by anthropogenic activities able to significantly modify their flow regime and have been chosen to be located in the headwaters of both subbasins.

This study make the implicit assumption that the physical similarity based on the selected catchment attributes, is a proxy of hydrological functioning of a catchment. Therefore the choice of catchment attributes (CAs) is of great importance. Selected CAs are related to the shape (e.g. area, length) and the topography (e.g. slope, elevation) of each subbasin and its main tributary reach and were derived by application of the SWAT model (at watershed delineator and HRU analysis processing steps required for SWAT model setup). The same input spatial data (Table 1) were used to characterize Group I and Group II subcatchments. The selection

of the appropriate CAs can also depend on the physical meaning of the model parameters (Mps) that will subsequently be involved in information regionalization. For instance, in the SWAT model, the curve number parameter (CN2) which is considered among the most sensitive Mps, depends on the soil and land use characteristics of the catchment [32]. Therefore, two other characteristics related to land use and soil were considered as descriptors: Forest and ACRISOL. Forest represents the proportion of area covered by forest, and ACRISOL gives information about the soil texture based on the relative proportion of sand, silt and clay. As ACRISOL remains the dominant soil in the majority of the study catchments, its proportion is used to indicate the presence of more than 35% of clay in each catchment. Forest and ACRISOL were calculated using the following equations:

$$\text{Forest} = \left(\frac{Af}{A}\right) \times 100 \quad (1)$$

$$\text{ACRISOL} = \left(\frac{Aacs}{A}\right), \quad (2)$$

Where*Af* is the area covered by forest within a watershed, *Aacs* is the area covered by ACRISOL, and A is the total area of the watershed.

Last, it is very common to use climatic characteristics such as long-term annual precipitation as indicator of similarity. Thus, average annual precipitation was computed for each subcatchment on the period 1981-2000. A detailed description of the 16 CAs is given in Table 2.

Table 1:Input data for SWAT model to derive catchments attributes on the Upper Niger basin.

Data type	Description	Resolution/period	Source	Processing
Topography	Conditioned DEM	90 m	USGS hydrosheds[a]	SWAT Watershed Delineator
River	River network	500 m	USGS Hydrosheds[a]	SWAT Watershed Delineator
Land use/cover	GLCC version 2	1 km	Waterbase[b]	SWAT HRU Analysis
Soil	FAO Soil Map	Scale 1:5000000	FAO [c]	SWAT HRU Analysis
Precipitation data	Rainfall	Daily/1981-2000	AGRHYMET	Arithmetic mean

[a]http://hydrosheds.cr.usgs.gov
[b]http://www.waterbase.org
[d]http://www.fao.org/geonetwork

Table 2:Summary of catchment attributes derived by the SWAT model as input for multivariate statistical analyses on the Upper Niger basin.

Attribute	Description	Units
Slo1	Subbasin slope	%
Len1	Longest path within the subbasin	m
Sll	Field slope length	m
Csl	Subbasin tributary reach slope	m
Wid1	Subbasin tributary reach width	m
Dep1	Subbasin tributary reach depth	m
Lat	Latitude of the subbasin centroid	-
Long	Longitude of the subbasin centroid	-
Elev	Mean elevation of the subbasin	m
ElevMin	Minimum elevation of the subbasin	m
ElevMax	Maximum elevation of the subbasin	m
Shape_Leng	Subbasin perimeter	m
Shape_Area	Subbasin area	m^2
[a]P	Average annual precipitation on the subbasin (mm)	mm
Forest	Proportion of forest on the subbasin	%
ACRISOL	Proportion of ACRISOL on the subbasin (%)	%

[a] Calculated on the period 1981-2000

2.3 Multivariate statistical analyses

Multivariate statistics used in this study are Principal Components Analysis (PCA) and Cluster Analysis (CA), and were performed under R package FactoMineR[33, 34], version 1.28.

PCA and CA are frequently used in hydrological studies [25, 26,35], and commonly applied in a pre-processing of a set of variables prior to the classification, to provide a convenient lower-dimensional summary of thedataset, or as a classification tool itself. PCA reduces a dataset containing a large number of variables to a dataset containing fewer new variables that are linear combinations of the original ones. These linear combinations are chosen to represent the maximum possible fraction of the variability contained in the original data and are called Principal Components (PCs). CA attempts to separate observations into groups of similar characteristics called clusters.

The methodology utilized in this study was based on the Hierarchical Clustering on Principal Components (HCPC) function proposed by [36]. This method combines three exploratory data analysis methods, Principal Component methods, Hierarchical Clustering and partitioning, to improve data analysis.The chosen Principal Components method is the PCA, because retained CAs are quantitative variables. PCA was used herein as a pre-process for clustering, i.e., the hierarchical clustering is solely built on the determined PCs. In that case, the clustering is more stable than the one obtained from original variables [36]. Input variables, i.e., CAs, were standardized because they are not measured on comparable scales. The appropriate number of PCs was chosen based on the scree plot technique [37]. Then, a hierarchical agglomerative clustering was performed on the PCs previously determined. The measure of distance between data points was based on the Euclidean distance (the same was used in PCA) and the agglomerative method for merging two clusters used the Ward's criterion. According to this criterion, the total inertia (variability) is decomposed in within-group and between-group inertia, and the pair of groups to be merged is chosen that minimizes the growth of within-group inertia. Equation (3) gives the formula for calculating the total inertia of a dataset:

$$\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}\left(x_{iqk}-\overline{x_k}\right)^2=\sum_{k=1}^{K}\sum_{q=1}^{Q}I_q\left(\overline{x_{qk}}-\overline{x_k}\right)^2+\sum_{k=1}^{K}\sum_{q=1}^{Q}\sum_{i=1}^{I_q}\left(x_{iqk}-\overline{x_{qk}}\right)^2, \quad (3)$$

Total inertia = Between-group inertia + Within-group inertia

Where x_{iqk} is the value of the variable k for the individual i of the cluster q, $\overline{x_{qk}}$ is the mean of the variable k for cluster q, $\overline{x_k}$ is the overall mean of variable k and I_q is the number of individuals in cluster q.

The last step consists in choosing the appropriate number of clusters when it is not preassigned, that is, the stopping point of clustering that maximizes similarity within clusters and maximizes dissimilarity between clusters. HCPC function suggests an "optimal" number Q of clusters when the decrease in within-group inertia between Q - 1 and Q is from far greater than the one between Q and Q + 1 (see [36]for a thorough description of the HCPC function). Results of HCPC function can be presented in different ways: (1) a factor map, which displays results of the hierarchical clustering on the map induced by the first PCs, (2) a 2-dimensional dendrogram or hierarchical tree, and (3) a 3-dimensional dendrogram in which the hierarchical tree is incorporated into the factor map. The latter representation can solely be used to get an integrated visualization of the dataset. However, dispersion of data points is somehow masked in that way. Therefore, the factor map was presented in the results section for a better visualization of individuals' dispersion on the plan formed by PCs, while the hierarchical treeoffers a good insight of the variability increase between clusters.

III. Results

3.1 Catchments clustering

It is interesting to briefly describe the intermediate result of PCA. It permitted to determine 2 PCs that explain 81.33% (63.84% for Dim1 and 17.49% for Dim2) of the total variance of the original data set. The subsequent clustering was then performed on these PCs. Results are presented on Fig. 2 and Fig. 3.

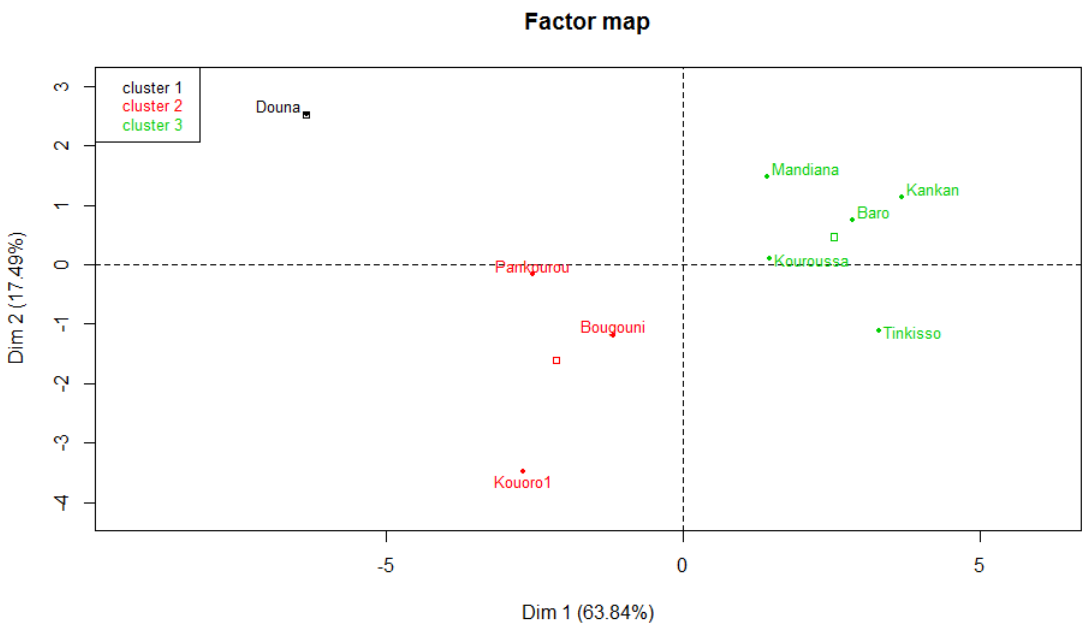

Figure 2: Hierarchical clustering representation on the map induced by the first 2 Principal Components on the Upper Niger basin. Catchments are colored according to the cluster they belong to, the barycenter of each cluster is represented by a square and Dim1 and Dim2 are the first two Principal Components on which the hierarchical clustering is built.

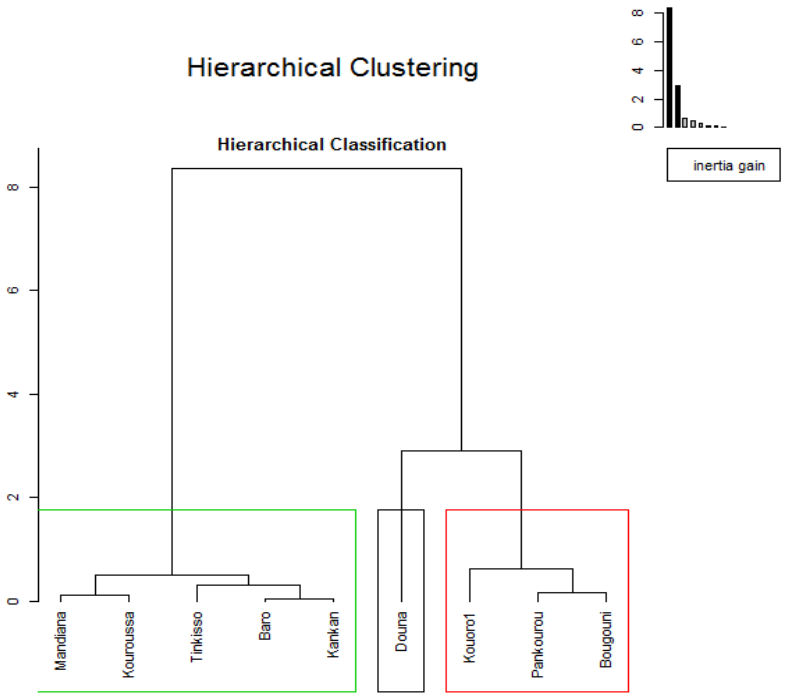

Figure 3: hierarchical clustering of the Upper Niger catchments. On the hierarchical classification or tree, each rectangle represents a cluster of similar catchments. The barplot(inertia gain) gives the decrease of within-group variability with increasing number of clusters.

Table 3: Description of hierachical clusters. In bold, positive v.test value indicating that the variable has a value greater than the overall mean, and in italic, negative v.test value indicating that the variable has a value smaller than the overall mean . All v.test values are significant at the probability p = 0.05

Variable	v.test	Mean in the category	Overall mean	p-value
Cluster 2				
Long	**2.01**	- 6.43	- 8.32	0.045
Elev	*- 1.97*	376.51	454.59	0.048
Cluster 3				
Elev	**2.63**	520.42	454.59	0.0084
ElevMin	**2.58**	344.6	314	0.0097
Slo1	**2.48**	5.6	4.21	0.0131
Forest	**2.35**	79.01	52.54	0.0186
ElenMax	**2.34**	1219.2	1029.78	0.0194
Csl	**2.24**	0.18	0.13	0.0252
Acrisol	**2.01**	62.06	46.36	0.0442
Long	*- 2.49*	- 9.81	-8.32	0.0126

IV. Discussion and conclusions

Overall, results of this study showed that the Upper Niger can be classified into 2 major clusters of similar catchments based on physiographic characteristics. In addition, topographic variability and geographical position of the subcatchment were demonstrated to exert a stronger control on separating clusters, and permitted to propose a kind of nomenclature of clusters: the group of easterly flat catchments assigned to the Bani, and the one of westerly hilly catchments, assigned to the Upper Niger subbasin. The latter is further characterized by the dominance of Forest and ACRISOL as the major soil type. These results expectedly answer the questions posed at the beginning of this work. However, due to limited availability of literature on this area, it is difficult to show how these results fit in with existing knowledge on that topic. A broader comparison can only be made about the dominant controls on similarity in different contexts. For instance, [26]demonstrated that topographic parameters (e.g., mean stream slope, minimum elevation, and maximum elevation) provide the major categorization of catchments of the equatorial Nile, and proposed the same nomenclature of flat and hilly regions. Likewise, [29]showed that the whole Niger basin is close to the group of basins characterized by topographic parameters (hypsometry and mean elevation), which can be considered as the major driving forces of its hydrosedimentary response.

Nonetheless, it is important to note that no cluster analysis can produce a definitive classification because the results are depending on the dataset used and other kind of subjective choices (choice of classification algorithm and distance metric, [25]). It is also acknowledged that the actual limitation that arose within this study was the absence of geologicaldescriptors, limiting thus our understanding of subsurface controls. In spite of the limitations discussed above, these are encouraging results, showing on one hand the relevance of physical characteristics to give information about the spatial dissimilarity characterizing a large tropical river basin, and on the other, the value of statistical analyses (such as the HCPC function) as a pertinent tool for exploring similarity among catchments. Concerning the assumption of correspondence between physical and functional similarity made in this study, [18]pointed out that this assumption may not always be verified. Further studies can try to find out its validity in the present case study, by evaluating, for instance, the performance of a regionalization method to transfer information within and between clusters. The use of other similarity concepts (such as similarity indices) applied to the same catchments could also give a good platform of discussion.

V. Acknowledgements

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Appendix B: Published article 2

water

MDPI

Article

Multi-Site Validation of the SWAT Model on the Bani Catchment: Model Performance and Predictive Uncertainty

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Abstract: The objective of this study was to assess the performance and predictive uncertainty of the Soil and Water Assessment Tool (SWAT) model on the Bani River Basin, at catchment and subcatchment levels. The SWAT model was calibrated using the Generalized Likelihood Uncertainty Estimation (GLUE) approach. Potential Evapotranspiration (PET) and biomass were considered in the verification of model outputs accuracy. Global Sensitivity Analysis (GSA) was used for identifying important model parameters. Results indicated a good performance of the global model at daily as well as monthly time steps with adequate predictive uncertainty. PET was found to be overestimated but biomass was better predicted in agricultural land and forest. Surface runoff represents the dominant process on streamflow generation in that region. Individual calibration at subcatchment scale yielded better performance than when the global parameter sets were applied. These results are very useful and provide a support to further studies on regionalization to make prediction in ungauged basins.

Keywords: SWAT; Bani catchment; West Africa; discharge; daily calibration; performance and predictive uncertainty

1. Introduction

Water resources managers are facing challenges in many river basins across the world due to limited data availability. Anthropogenic activities add more uncertainties to this task by inducing changes to land and climate at different scales [1,2]. This situation is more pronounced in developing countries, where in many river basins no runoff data are available [3–7] and the existing ones are of questionable quality or, at best, short or incomplete.

The Niger River basin is not an exception to that rule. The general situation of insufficient data is exacerbated by a deterioration of measurement networks. In the 80s and 90s, for instance, hydrometric stations were reduced to a minimum and many have been abandoned (e.g., [8]). To prevent the hydrologic observing system from more degradation, the Niger Basin Authority (NBA) has set the Niger-HYCOS project, which one of its specific objectives is to improve data quality of the Niger Basin.

For this purpose, the project identified and brings assistance in the installation and the management of 105 hydrometric stations shared by nine countries drained by the River, and contributes to the capacity building of national hydrological services.

In its fifth assessment report on regional aspects of climate change, the Inter-Governmental Panel on Climate Change [9] has shown that adaptation to climate change in Africa is confronted with a number of challenges among which is a significant data gap. Too many basins lack reliable data necessary to assess, in details, impacts of climate change on different components of the hydrological cycle and to develop strategies of adaptation related to each specific impact. Thus, it is germane to predict hydrological variables in ungauged basins for building high adaptive capacity by improving: (i) water resources knowledge, planning, and management; (ii) identification and implementation of strategies of adaptation to climate change in the sector of water, and (iii) ecological studies for a sustainable development.

The application of rainfall-runoff models and then, transferring model parameters from gauged to ungauged catchments is a long-standing method [10] for flow prediction in ungauged basins and has been highlighted during the decade of Prediction in Ungauged Basins (PUB) launched in 2003 by the International Association of Hydrological Sciences (IAHS) and concluded by the PUB Symposium held in 2012. This is the framework of the present study, in which the Soil and Water Assessment Tool (SWAT) model was calibrated on the Bani catchment (Niger River basin) and the most sensitive model parameters were estimated.

Many studies have successfully applied the SWAT model in West Africa, on different river basins. Examples include, among others: calibration of the SWAT model on the Niger basin [11–16], the Volta basin [12–15,17–19] and the Oueme catchment in Benin [15,20–22]. However there are few published papers on the application of the SWAT model on the Bani catchment. For instance, Schuol and Abbaspour [12] and Schuol *et al.* [14] applied the SWAT model to selected watersheds in West Africa including the Niger basin and modeled monthly values of river discharges (blue water) as well as the soil water (green water), and clearly showed the uncertainty of the model results. They developed and applied a daily weather generator algorithm [13] that uses 0.5 degree monthly weather statistics from the Climatic Research Unit (CRU) to obtain time series of daily precipitation as well as minimum and maximum temperatures for each sub-basin. These generated weather data were then used as input for model setup and the authors concluded that "discharge simulations using generated data were superior to the simulations using available measured data from local climate stations". Reported Nash-coefficient values obtained vary largely between sub-basins and were principally presented as average intervals limiting thus, our understanding of model performance at finer spatial (subbasin) and temporal (daily) scales.

Laurent and Ruelland [23] successfully calibrated SWAT on the Bani catchment using daily measured climate data. They interpolated precipitation data on a regular grid by the Inverse Distance Weighted (IDW) method, which has proven to yield better results than kriging, Thiessen and spline methods, especially when a hydrological model is used [24]. To show the model performance, Laurent and Ruelland [23] reported both discharge and biomass calibration results on an average annual basis, but did not assess model calibration uncertainty. Moreover, both above-mentioned studies performed interpolation of input data out of the model framework to obtain a time series of daily weather data for each sub-basin. However, the results of interpolation methods are strongly influenced by the density and spatial distribution of the measurement stations used in the interpolation [25]. Such a density of data is not always available in developing countries.

Against this background, the objective of this study was to assess the performance of the SWAT model and its predictive uncertainty on the Bani at catchment and subcatchment levels. More specifically, this meant to: (i) set up a hydrological model for the Bani catchment using the SWAT program; (ii) calibrate the model at the catchment outlet at daily and monthly time steps and assess the predictive performance and uncertainty; (iii) evaluate the spatial performance of the watershed-wide model within the catchment by validating it at two internal stations; and (iv) calibrate the model at

the sub-catchments separately and provide a comparative assessment of the model performance at different spatial scales.

The originality of this study was the daily performance of the SWAT model at the whole catchment outlet and at two internal stations. Another important output of this paper was the involvement of evapotranspiration (the most important component of the water balance after rainfall especially under warm climate) in the verification of model outputs reasonability, a particular attention that has not been considered by any previous study in the region. In addition, we used in the current work point rain gauge data (as per SWAT's standard procedure) opposed to areal precipitation as used in previous studies [12–15,24,26,27] on the same basin in order to maintain the real data condition (limited in time and space) to the extent possible.

2. Material and Methods

2.1. The Study Area

The Bani is the major tributary of the Upper Niger River. Its drainage basin is principally located in Mali but spans in a lesser extent over Cote d'Ivoire and Burkina Faso and covers an area of about 100,000 km^2 at Douna gauging station (Figure 1). The Bani watershed was chosen for this study, on one hand, due to its relatively high-quality data availability compared to regional situation. It thus constitutes the appropriate gauged catchment in different hydro-climatic variables. On the other hand, this watershed has not been affected by important hydraulic structures able to significantly modify its flow regime, making the hydrological modeling of that catchment more convenient.

The catchment's topography (Figure 1) is characterized by a gentle elevation that ranges from 826 m in the South and the center-east to 249 m at the outlet in the North. According to FAO (2003) [28], major soil groups are mainly constituted by Luvisol, Acrisol, and Nitosol (Figure 2a). Based on the USGS Global Land Cover Characterization (GLCC) version 2.0 [29], agricultural land constitutes the dominant land use category followed by savannah and forest (Figure 2b). The Bani catchment is characterized by a Sudano-Sahelian climatic regime. The river flows from south to north along a high rainfall gradient. Annual precipitation varies from 1250 mm at Odienne to 615 mm at Segou (average of the period 1981–2000). The average annual discharge recorded at Douna gauging station between 1981 and 2000 was 184 m^3 s^{-1}, which is equivalent to 58 mm of surface runoff depth for an average annual precipitation of 1000 mm. The smallest runoff values were recorded during the years 1983, 1984, and 1987. Due to climate change, there was an abrupt decrease in rainfall in the period 1970–1971 and remained for two decades [27,30] with a more severe impact on water resources. A decrease of more than 60% in discharge at Douna [27,31] and lower contribution of baseflow to the annual flood [32,33] have been reported since the 70s. Concerning future climate change impacts, the Bani basin is projected to experience substantial decrease in rainfall and runoff especially in the long term behavior [27].

2.2. Model Description

SWAT is a river basin, or watershed, scale model developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time [34]. The model is semi-distributed, physically based and computationally efficient, uses readily available inputs and enables users to study long-term impacts [35]. For a detailed description of SWAT, see Soil and Water Assessment Tool input/output version 2012 [36] and the Theoretical Documentation, Version 2009 [37].

The ArcSWAT (ArcGIS extension) is a graphical user interface for the SWAT model. In the present study, the recent version, ArcSWAT2012, was used for building the hydrological model of the Bani catchment.

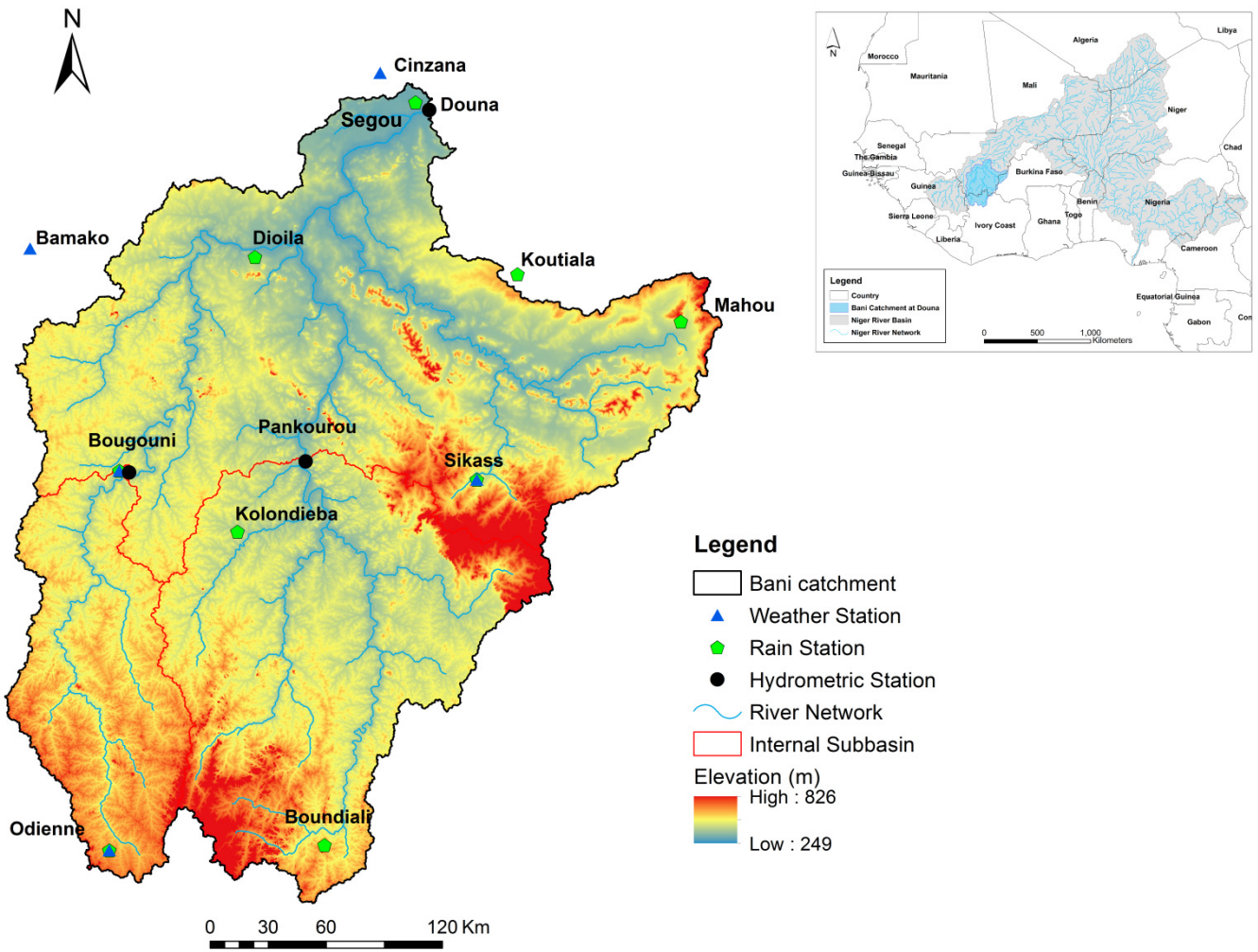

Figure 1. Localization of the Bani catchment at the Douna outlet. The altitude and the monitoring network of the catchment are also given.

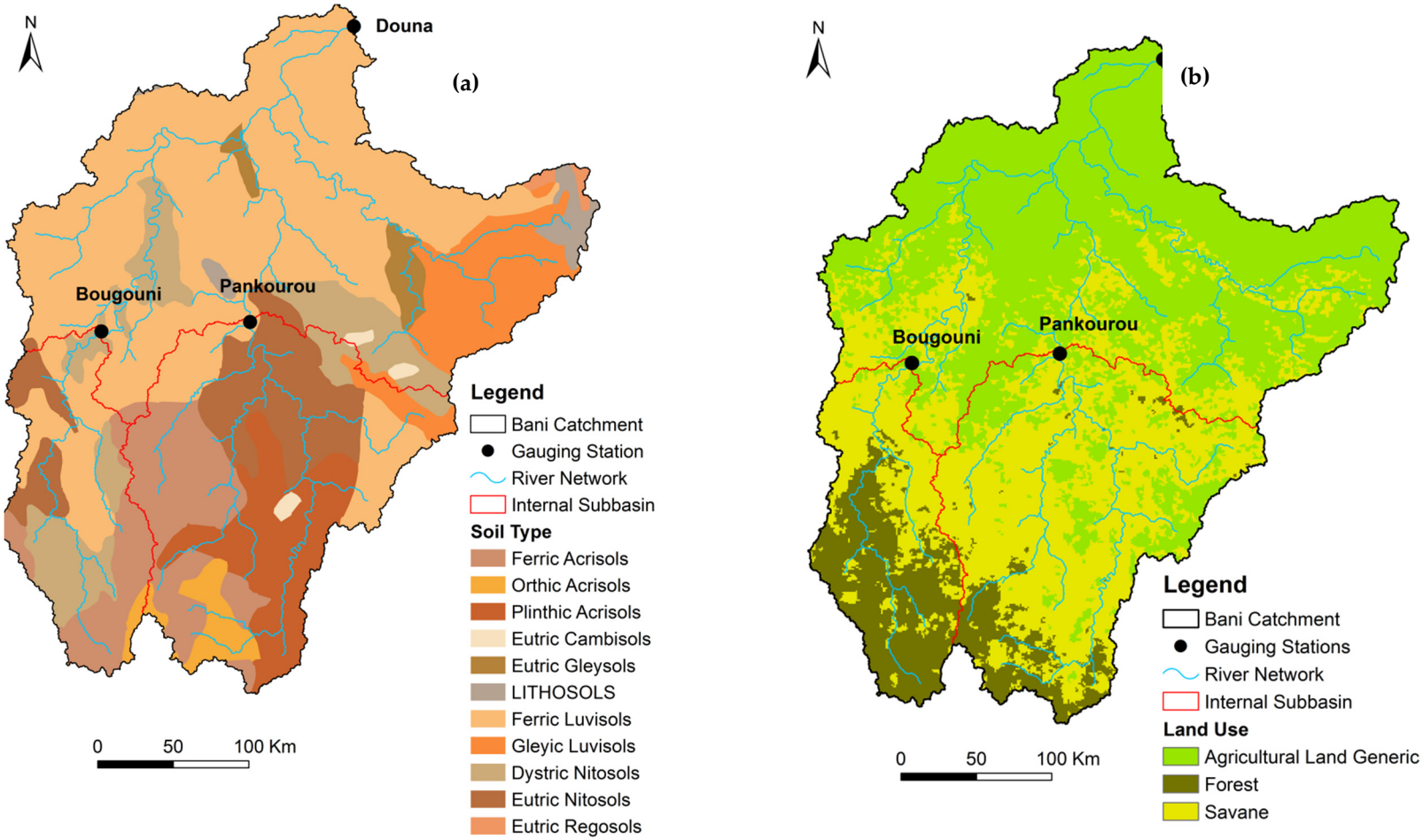

Figure 2. (**a**) Soil attributes and (**b**) land use categories of the Bani catchment.

The hydrologic cycle simulated by SWAT is based on the water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw} \right) \quad (1)$$

where, SW_t is the final soil water content (mm H_2O), SW_0 is the initial soil water content on day i (mm H_2O), t is the time (days), R_{day} is the amount of precipitation on day i (mm H_2O), Q_{surf} is the amount of surface runoff on day i (mm H_2O), E_a is the amount of evapotranspiration on day i (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm H_2O) and Q_{gw} is the amount of groundwater exfiltration on day i (mm H_2O).

SWAT divides a basin into sub-basins which are further discretized into hydrologic response units (HRUs), based on unique soil-land use-slope combinations. The subdivision of the watershed enables the model to reflect differences in evapotranspiration for various crops and soils. Runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed. This increases accuracy and gives a much better physical description of the water balance [37].

Various hydrological models exist and there is no strict guideline on the selection of the model. The SWAT model uses a modified version of the Curve Number method, which was developed in the US for specifically calculating surface runoff generation. Therefore the model is especially suitable for regions with a high share of overland flow on total runoff. Other advantages of the SWAT model are that it allows a number of different physical processes (hydrologic, sediment, pollutants) to be simulated in a watershed. It has been previously validated for several large-scale watersheds throughout different climate contexts across the globe and has performed satisfactorily even in data poor and complex catchments (e.g., [38,39]). SWAT is also very flexible in terms of using specific and appropriate soil and land use information's of the watershed to be modeled by adding them to its database. However in this context, it is worth using a low cost or free model, which West African National Hydrological services could afford due to economic constraints.

2.3. Input Data and Databases

The SWAT model for the Bani was constructed using weather data and globally and freely available spatial information described in Table 1. Daily precipitation data from 11 rain gauges as well as daily maximum and minimum temperature from five weather stations located mainly on the catchment were used as input. The location and spatial distribution of input precipitation and temperature stations are represented in Figure 1.

It is worth noting the weak spatial density of the measuring network that is characterized by a rain gauge for more than 9000 km^2. Precipitation data are complete at the majority of the sites except for a few numbers of them, where the maximum missing data percentage varies between 8.5% and 100% in a year. Many more missing values are recorded in the temperature data. Collected climate data time series were of varying lengths. Thus, a common period of observation from 1981 to 2000 was first determined. Retained data then underwent a thorough quality control as recommended by the World Meteorological Organization (WMO) in the guide to climatological practices, third edition [40]. Three procedures were applied: (1) completeness check; (2) plausible value check; and (3) consistency check. The aim of the check is to detect erroneous data in order to correct and, if not possible, to delete it. Missing values were filled by the weather generator during the running time. For this purpose, the excel macro WGNmaker4 [41] was used to calculate weather stations statistics needed to generate representative daily climatic data.

Two different databases were used to set up the model. The SWAT database is composed by the crop database and the user soils database, both included in swat2012.mdb. They are named crop1 and soil1, respectively. Crop1 was kept default whereas soil1 was filled with soils transferred from mwswat2009.mdb (the database of the MapWindow interface for SWAT). The second database is composed by crop2 and soil2. Four land use categories define crop2: forest, savannah-bush, savannah,

and steppe whereas six major soil groups are added to soil2: Acrisol, Cambisol, Gleysol, Lithosol, Luvisol ferrique, and Nitosol. Detailed description of this database can be found in [23].

Table 1. Input data of the SWAT model for the Bani catchment.

Data Type	Description	Resolution/Period	Source
		Simulation Data	
Topography	Conditioned DEM	90 m	USGS hydrosheds [42]
Land use/land cover	GLCC version 2	1 km	Waterbase [43]
Soil	FAO Soil Map	Scale 1:5000000	FAO [44]
River	River network map	500 m	USGS Hydrosheds [42]
Weather data	Rainfall, maximum and minimum temperature	Daily (1981-2000)	AGRHYMET
		Calibration/Verification Data	
Discharge	Discharge	Daily (1983–1997)	AGRHYMET/National hydrological service of Mali
PET	Potential evapotranspiration	10-day (1983–1998)	National Meteorological Agency of Mali
Epan	Pan evaporation	Monthly (1983–1997)	AGRHYMET

For calibration purpose, we used daily river discharge data at Douna, Bougouni and Pankourou stations covering the period 1981–2000, obtained from AGRHYMET and the National Hydraulic Direction of Mali. The period 1981–1997 was kept for calibration and validation processes as it exhibits few gaps. Small existing gaps were thus filled by a simple linear interpolation.

2.4. Model Setup

The catchment was delineated and divided into sub-catchments based on the DEM. A stream network was superimposed on the DEM in order to accurately delineate the location of the streams. The threshold drainage area was kept as default and additional outlets were considered at the location of stream gauging stations to enable comparison of measured discharge with SWAT results. The whole catchment was so discretized into 28 sub-catchments, which were further subdivided into 181 HRUs based on soil, land use, and slope combinations. Further parameters have been edited through the general watershed parameters and SWAT simulation menus and are reported in Table 2. Four simulations were performed based on land use and soil databases combinations: crop1soil1, crop1soil2, crop2soil1, and crop2soil2. A Nash-Sutcliffe Efficiency (*NSE*) [45] was thereafter calculated at Douna by comparing measured discharges against each default simulation and the one which will yield the highest *NSE* value will be kept for calibration and validation processes.

Table 2. Input methods for SWAT model simulation on the Bani catchment.

Code	Description	Method
	General Watershed Parameters	
IPET	Potential Evapotranspiration method	Hargreaves
IEVENT	Rainfall/runoff/routing option	Daily Rainfall/CN runoff/Daily routing
ICN	Daily Curve Number calculation method	Soil moisture (Plant ET at Bougouni)
IRTE	Channel water routing method	Variable storage
	SWAT Simulation	
Period of simulation	-	1981–2000
NYSKIP	Warm-up period	Two years (1981 and 1982)

2.5. Calibration and Validation Procedures

It is commonly accepted in hydrology to split the measured data either temporally or spatially for calibration and validation [36]. In addition to the split-sample method, a split-location calibration and validation approach has been performed because the global parameter set is not expected to be

optimal for sub-catchments processes in view of the high heterogeneity in terms of climate, topography, soil, and land use characterizing such a large-area watershed. This approach is especially needed when prediction at data sparse sites is foreseen [46,47]. In the split-sample approach, the model was calibrated using discharge data solely measured at the catchment outlet by splitting the homogenous period mentioned in Section 2.3 into two datasets: two-thirds for calibration (1983–1992), and the other one for validation (1993–1997). To implement the split-location method, the model was calibrated at Douna and then validated at intermediate gauging stations (Bougouni and Pankourou) by turning the model on the same period (1983–1992), using the same behavioral parameter sets determined at the outlet.

Calibration was thereafter performed at Bougouni and Pankourou stations individually, and both modeling frameworks facilitated a comparative analysis of model performance and predictive uncertainty through scales. At this step, the calibration at Bougouni did not succeed within realistic range of the Curve Number (*CN*). Then, the daily *CN* calculation method was changed to Plant ET for simulation at Bougouni because soil moisture method is found to predict too much runoff in shallow soils [36]. An additional parameter (*CNCOEF*) was then necessary as required by the plant ET method and fixed to 0.5 in the Edit SWAT input menu.

Calibration/validation, uncertainty analysis, and sensitivity analysis were performed within the SWAT Calibration and Uncertainty Programs SWAT-CUP version 2012 [48] using Generalized Likelihood Uncertainty Estimation (GLUE) procedure [49]. GLUE is a Monte Carlo based method for model calibration and uncertainty analysis. It was constructed to partly account for non-uniqueness of model parameters. GLUE requires a large number of model runs with different combinations of parameter values chosen randomly and independently from the prior distribution in the parameter space. The prior distributions of the selected parameters are assumed to follow a uniform distribution over their respective range since the real distribution of the parameter is unknown. By comparing predicted and observed responses, each set of parameter values is assigned a likelihood value. The likelihood functions selected here is principally the *NSE* as it is very commonly used and included in SWAT-CUP for GLUE performance assessment. In this study, the number of model runs was set to 10,000 and the total sample of simulations were split into "behavioral" and "non-behavioral" based on a threshold value of 0.5, a minimum threshold for *NSE* recommended by [50] for streamflow simulation to be judged as satisfactory on a monthly time step. In that case, only simulations which yielded a $NSE \geqslant 0.5$ are considered behavioral and kept for further analysis.

In the calibration procedure, we included 12 parameters that govern the surface runoff and baseflow processes. The real approached baseflow alpha factor (*ALPHA_BF*) value has been determined by applying the baseflow filter program developed by [51] and modified by [52] to streamflow data measured at the three outlets. One novelty in this study was to involve the Manning's roughness coefficient for overland flow (*OV_N*) and the average slope length (*SLSUBBSN*) parameters that are not commonly used in calibration. The reason behind this choice was to correct the tendency of the model to delay the runoff as detected by graphical analysis. The remaining parameters were chosen based on the literature [53–55] and their adjusting ranges from the SWAT Input/Output version 2012 document (e.g., [56]).

2.6. Model Performance and Uncertainty Evaluation

To evaluate model performance, both statistical and graphical techniques were used as recommended by [50] based on previous published studies. The following quantitative statistics were chosen: *NSE* to quantify the relative magnitude of the residual variance ("noise") compared to the measured data variance, *PBIAS* for water balance error, and R^2 to describe the degree of collinearity between simulated and measured data, and were given for the best simulation. The *NSE*, R^2 and *PBIAS* were determined using the following equations:

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)^2}, \tag{2}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)\left(Y_i^{sim} - \overline{Y^{sim}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - \overline{Y^{obs}}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} - \overline{Y^{sim}}\right)^2}}\right)^2, \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Y_i^{sim} - Y_i^{obs}\right) \times 100}{\sum_{i=1}^{n} Y_i^{obs}} \tag{4}$$

where Y_i^{sim} and Y_i^{obs} are the *i*th simulated and observed discharge, respectively, $\overline{Y^{sim}}$ and $\overline{Y^{obs}}$ the mean value of simulated and observed discharge, respectively and n the total number of observations.

The *NSE* varies between $-\infty$ and 1 (1 inclusive), with *NSE* = 1 being the optimal value. The optimal value of *PBIAS* is 0, with low *PBIAIS* in absolute values indicating accurate model simulation. Positive values indicate model overestimation bias, and negative values indicate model underestimation bias. R^2 ranges from 0 to 1, with higher values indicating less error variance, values greater than 0.5 are considered acceptable.

In the present study, model performance, for a monthly time step, will be judged as satisfactory if *NSE* > 0.50 and *PBIAS* < ± 25% for discharge [50] and if the graphical analysis reveals a good agreement between predicted and measured hydrographs.

The GLUE prediction uncertainty was then quantified by two indices referred to as *P-factor* and *R-factor* [57]. The *P-factor* represents the percentage of observed data bracketed by the 95% predictive uncertainty (95PPU) band of the model calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling. The *R-factor* is the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. For uncertainty assessment, a value of *P-factor* > 0.5 (*i.e.*, more than half of the observed data should be enclosed within the 95PPU band) and *R-factor* < 1 (*i.e.*, the average width of the 95PPU band should be less than the standard deviation of the measured data) should be adequate for this study, especially considering limited data availability.

2.7. Sensitivity Analysis

A Global Sensitivity Analysis (GSA) was performed after 10,000 simulations on the 12 parameters included in the calibration process. Only GSA is allowed with GLUE in SWAT-CUP and can be performed after one iteration. A *t*-test is then used to identify the relative significance of each parameter. *T*-stat provides a measure of sensitivity and *p*-value determines the significance of the sensitivity. A larger *t*-stat in absolute value is more sensitive and a *p*-value close to zero has more significance [48].

2.8. Verification of Model Outputs

To evaluate the accuracy of the SWAT model to predict PET, we considered the model average annual basin output which was computed by the Hargreaves method [58] and compared it to PET values calculated with two other methods: the FAO-Penman Monteith method and the pan evaporation method. The estimates from those three methods are hereinafter referred to as PET_{har} (for average annual PET estimated by the Hargreaves method), PET_{pen} (for average annual PET estimated by the Penman-Monteith method) and PET_{pan} (for average annual PET estimated by the pan evaporation method). The modified Penman method is taken herein as the standard because it was considered to offer the best results with minimum possible error [59]. Average observed 10-day PET_{pen} were collected and computed to obtain average annual value on the calibration-validation period. Monthly observed pan evaporation data were used to estimate PET_{pan}. Doorenbos and Pruitt [60] related pan

evaporation to reference evapotranspiration, ET_0 (or PET) using empirically derived coefficients. PET can be obtained by:

$$PET = K_p \times E_{pan} \quad (5)$$

where, PET is the potential evapotranspiration in mm· day^{-1}, Epan represents the pan evaporation in mm· day^{-1}, and K_p is the pan coefficient, which is the adjustment factor that depends on mean relative humidity, wind speed, and ground cover.

As the pan factor in the Bani catchment could not be exactly determined due to lack of information about the pan environment and the climate, the average value of 0.7 [61] was used in this study. The *PBAIS* was again used as the evaluation criterion representing the deviation of the predicted PET compared to the one considered as the baseline.

3. Results

3.1. The Catchment Scale Model

3.1.1. Global Model Performance

In the preliminary analyses, we tested different land use and soil databases and kept for subsequent analysis the simulation of databases combination crop2soil2, which yielded the highest default, *i.e.*, before calibration, performance (*NSE* = 0.09). The impact of land use database was not so significant, but the type of soil database used to setup the model was very decisive in obtaining a simulation with the smallest overall error. SWAT-CUP output results are presented as 95PPU as well as the best simulation (Table 3).

Table 3. Model performance statistics for the Bani catchment at Douna, Pankourou, and Bougouni discharge gauging stations.

Time Step		Calibration (1983–1992)			Validation (1993–1997)		
	Criterion	Douna	Pankourou	Bougouni	Douna	Pankourou	Bougouni
Daily	*NSE*	0.76	0.73	0.66	0.85	0.77	0.37
	R^2	0.79	0.74	0.68	0.87	0.83	0.57
	PBIAS (%)	−12.23	6.08	−15.01	−23.26	−19.57	−59.53
Monthly	*NSE*	0.79	0.78	0.72	0.85	0.81	0.47
	R^2	0.82	0.78	0.76	0.88	0.91	0.68
	PBIAS (%)	−15.78	5.93	−13.14	−26.91	−19.54	−58.40

Overall, calibration and validation of the hydrological model SWAT on the Bani catchment at the Douna outlet yielded good results in terms of *NSE* and R^2 for both daily and monthly timesteps. 364 simulations for daily calibration against 588 for monthly calibration returned a $NSE \geqslant 0.5$ and were thus considered as behavioral. Very good *NSE* and R^2 values were obtained and were greater than 0.75 for the best simulations. Moreover, it can be noticed that the performance is slightly lower for daily calibration compared to monthly calibration, but always higher for the validation period. Only one year (1984) over 10 showed very low performance with a *NSE* of 0.23.

The water balance prediction can be considered as accurate at a daily time-step but becomes hardly satisfactory for monthly calibration, which is characterized by higher *PBIAIS* values showing increasing errors in the prediction. For example, the *PBIAIS* values increased from daily to monthly time intervals: from −12% to −16% in the calibration period and from −23% to −27% in the validation period (Figure 3). With regard to high flow events, visual analysis of simulated and observed hydrographs represented in Figure 3 came out with the following results: timing of peak is well reproduced although the simulation tends to underestimate peak flows especially during dry years (e.g., 1983, 1984, and 1987).

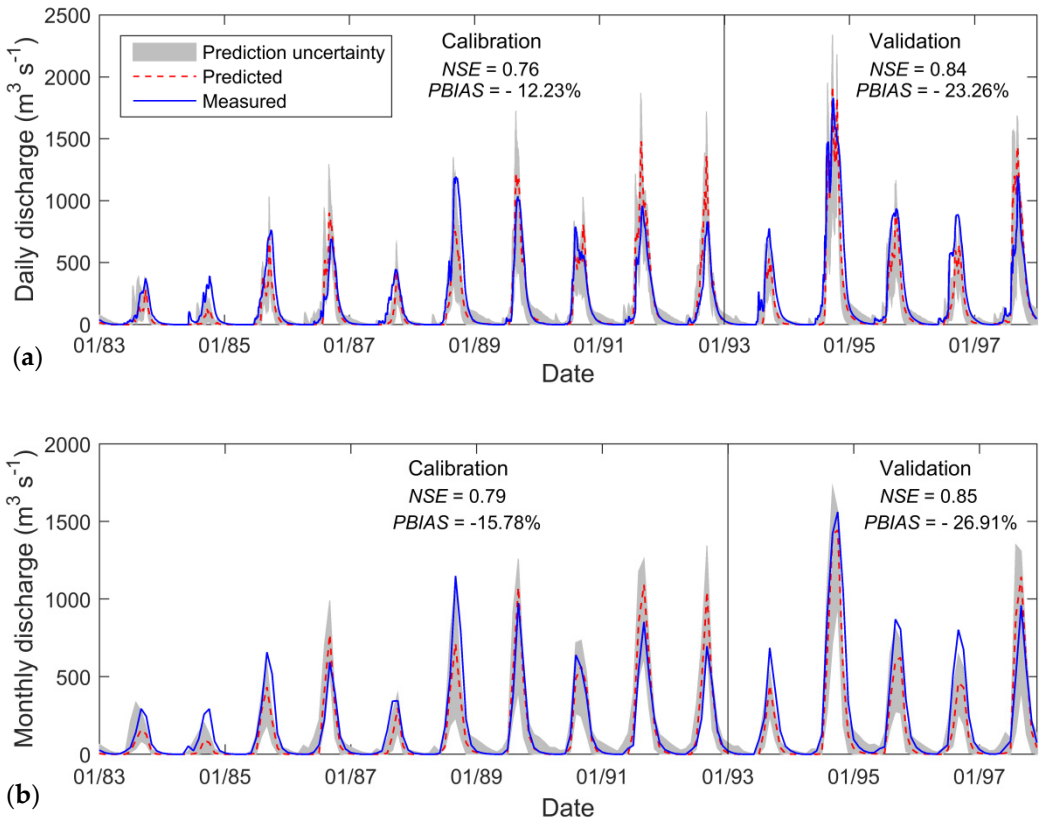

Figure 3. Simulated and observed hydrographs at Douna station at (**a**) daily and (**b**) monthly timesteps along with calculated statistics on calibration and validation periods.

3.1.2. Verification of Average Annual Basin Values

Table 4 reports the average annual values of the SWAT model simulated on the Bani catchment. However, there are not available data to enable a full verification of all model outputs at the watershed scale. In this case, we focused on available PET and biomass for which there exist regional values.

Table 4. Average annual basin values of precipitation (P), evapotranspiration (ET), potential evapotranspiration (PET), and biomass as SWAT outputs on the Bani catchment.

Period	P (mm)	ET (mm)	PET (mm) [a]	Biomass (ton ha^{-1})		
				Agricultural Land Generic	Savannah	Forest
Calibration (1983–1992)	960	895	1926	1.18	0.27	3.09
Validation (1993–1997)	1050	975	1925	1.72	0.53	5.51

[a] Average annual PET estimated by the Hargreaves method (herein used by SWAT).

Average annual basin values simulated by the model and described in Section 2.8 are shown in Table 4. The analysis of these values came out with several results. On average, PET_{har} presented a positive *PBIAS* of 11% compared with observed PET_{pen} herein equal to 1737 mm and the latter is very close to PET_{pan}, estimated to 1755 mm. These results give a clear indication of overestimation of PET by the SWAT model over the Bani catchment, an overestimation that can be attributed to the Hargreaves method used herein by the model to compute PET.

Table 5. Summary of the SWAT model parameters calibrated on the Bani catchment at Douna on a daily time interval.

Parameter	Description	Input Calibration Range	Calibrated Parameters: Best Parameter Value [Range]	Global Sensitivity Analysis	
				t-Stat	*p*-Value
CN2	SCS runoff curve number II (-)	±20%	−0.155 [−0.199; 0.102]	−54.03083	0.00000
OV_N	Manning's "*n*" value for overland flow (-)	0.01–30	23.153 [3.061; 29.915]	11.41603	0.00000
SLSUBBSN	Average slope length (m)	10–150	149.808 [12.677; 149.924]	8.87352	0.00000
ESCO	Soil evaporation compensation factor (-)	0.01–1	0.958 [0.768; 0.991]	−6.08880	0.00000
SOL_AWC	Available water capacity of the soil layer (mm H_2O/mm sol)	±20%	0.140 [−0.199; 0.197]	2.89864	0.00376
GW_DELAY	Groundwater delay (days)	0.0–50	4.938 [0.487; 49.823]	1.81341	0.06980
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	0.0–4000	3082.500 [0.043; 3995.710]	−1.51853	0.12891
REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm H_2O)	0–500	173.709 [0.636; 499.845]	−0.64939	0.51610
RCHRG_DP	Deep aquifer percolation fraction (-)	0–1	0.346 [0.001; 0.999]	0.46408	0.64260
GW_REVAP	Groundwater "revap" coefficient (-)	0.02–0.2	0.190 [0.021; 0.199]	−0.12613	0.89963
SURLAG	Surface runoff lag coefficient (-)	0.05–24	20.219 [0.076; 23.878]	−0.07433	0.94075
*ALPHA_BF**	Baseflow alpha factor (d^{-1})	0.034	0.034	ND	ND

* Determined on observed discharges by applying the baseflow filter program. ND: Not Determined.

To further investigate the model's accuracy, we evaluated predicted biomass values over the calibration/validation period (Table 4) against reported values for the study area. Simulated biomass was on average 4.3 ton· ha^{-1} for forest and 1.45 ton· ha^{-1} for agricultural land and both are in the ranges of observed values in the region (the observed biomass ranges between 2–4 and 2–3 ton· ha^{-1} for forest and cultivated land, respectively [23,62]). Nevertheless, this component is far underestimated for savannah with a simulated value of 0.4 ton ha^{-1} compared to the observed value which varies between 0.8 and 2 ton· ha^{-1} [62].

3.1.3. Sensitivity Analysis

There is a wide range of uses for which sensitivity analysis is performed. Based on the 12 selected SWAT parameters (*ALPHA_BF* being fixed), a GSA was used herein for identifying sensitive and important model parameters in order to better understand which hydrological processes are dominating the streamflow generation in the Bani catchment.

Sensitivity analysis results of 10,000 simulations are summarized in Table 5. The three most sensitive parameters (*CN2*, *OV_N*, and *SLSUBBSN*) are directly related to surface runoff, reflecting therefore the dominance of this process on the streamflow generation in the Bani catchment. Processes occurring at soil level followed at the second position as pointed out by the sensitivity of *ESCO* and *SOL_AWC*. Groundwater parameters happened in the last position demonstrating the low contribution of the latter to flows measured at the Douna outlet. The same sensitive parameters were identified by daily and monthly calibrations with only different ranks for soils parameters (*ESCO* and *SOL_AWC*).

3.1.4. Spatial Validation

The results of the spatial validation were divergent according to the location (Figure 4). For instance, at Pankourou, the same parameter sets determined at Douna produced a good simulation on a monthly basis (satisfactory for daily validation) whereas predictive uncertainty remained adequate and all met our requirements (*NSE* > 0.5, *P-factor* > 0.5 and *R-factor* < 1). In addition, the water balance was reasonably predicted at both time steps. In contrast, it has been recorded a complete loss of model performance at Bougouni with unsatisfactory *NSE* values and more uncertainty related to input discharge as expressed by a lower percentage of observed data (*P-factor* = 0.55 et 0.57 for daily and monthly validation) inside the 95PPU band (Figure 4). Accordingly, important uncertainty could be attributed to observed discharge at Bougouni.

3.2. The Subcatchment Model

Statistical evaluation results of the subcatchment calibration are presented in Table 3 and time series of observed and simulated hydrographs are shown in Figures 5 and 6. Good to very good performance was obtained at Pankourou with accurate predictive uncertainty. However, the validation period remained unsatisfactorily simulated at Bougouni. A comparative analysis of the catchment and subcatchment calibration performances came out with the following results:

- When calibrated separately, the prediction at Pankourou was slightly better, but greatly improved at Bougouni compared to when the catchment wide model was applied.
- The total uncertainty of the model is smaller at Pankourou (smaller *R-factor* and larger *P-factor*) than at the whole catchment, but larger at Bougouni.
- The water balance is better simulated at both internal stations compared to the watershed-wide water balance as depicted by smaller *PBIAIS* values, except always in the validation period at Bougouni.
- The model performance in terms of *NSE* and R^2 was higher at the watershed-wide level than at the sub-watershed level.

Overall, these results revealed that further calibration at the internal gauging stations was synonymous with gain of performance at the subcatchment level.

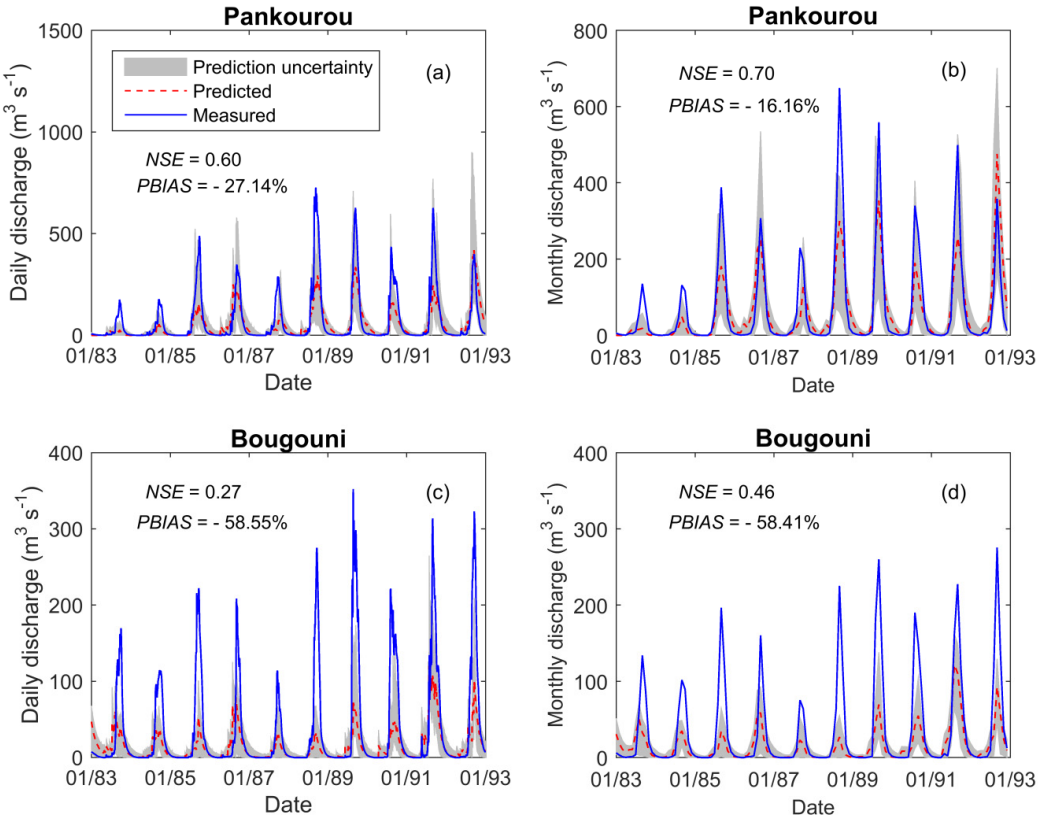

Figure 4. Spatial validation of the SWAT model on the Bani catchment. The model was turned at Pankourou ((**a**) daily and (**b**) monthly time steps) and at Bougouni ((**c**) daily and (**d**) monthly timesteps) by using the same behavioral parameter sets determined at the Douna outlet on the period 1983–1992.

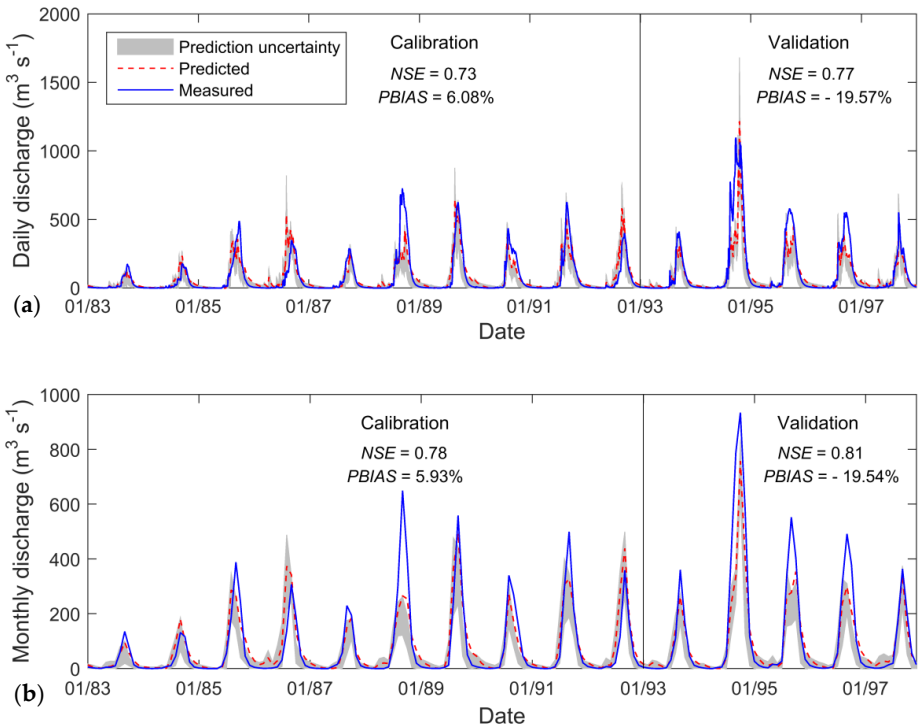

Figure 5. Simulated and observed hydrographs at Pankourou station at (**a**) daily and (**b**) monthly time steps along with calculated statistics on calibration and validation periods.

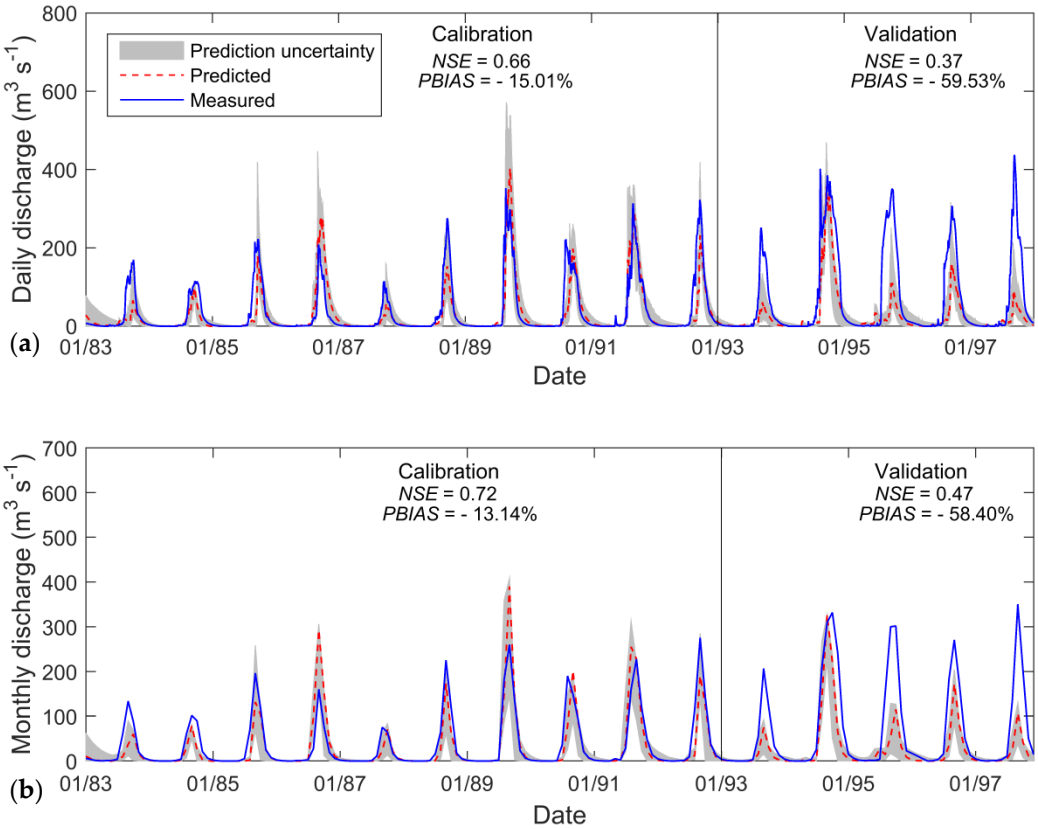

Figure 6. Predicted and measured discharges at Bougouni station at (**a**) daily and (**b**) monthly intervals during the calibration and validation periods with their corresponding statistics.

3.3. Model Predictive Uncertainty

In the global model, the predictive uncertainty, as indicated by the *P-factor* and *R-factor*, is adequate, though being larger during peak flow and recession periods (reflected by larger 95PPU band). On a daily basis, for instance, 61% of the observed discharge data are bracketed by a narrow 95PPU band depicted by the *R-factor* < 1 (Table 6). It has been noted that the entire uncertainty band is, however, very large during the year 1984 (Figure 3).

Table 6. Predictive uncertainty indices of the SWAT model for the Bani catchment at Douna, Pankourou, and Bougouni discharge gauging stations.

Time Step		Calibration (1983–1992)			Validation (1993–1997)		
	Criterion	Douna	Pankourou	Bougouni	Douna	Pankourou	Bougouni
Daily	*P-factor*	0.61	0.68	0.60	0.62	0.63	0.51
	R-factor	0.59	0.41	0.57	0.51	0.29	0.35
Monthly	*P-factor*	0.65	0.71	0.58	0.70	0.67	0.55
	R-factor	0.65	0.45	0.54	0.55	0.31	0.32

It is important to note the decrease of predictive uncertainty from Douna to Pankourou. In fact, the percentage of observed discharge bracket by 95PPU band has increased to 68%, while the width of the uncertainty band itself has decrease to 0.41 for the daily calibration (Table 6).

The same trend has been observed for the monthly calibration. At Bougouni, results showed a clear decrease of the uncertainty band (for daily and monthly calibration), but at the expense of bracketing less observed data. For instance, the *P-factor* and *R-factor* decreased from 0.65 to 0.58 and from 0.65 to 0.54, respectively, when moving from Douna to Bougouni during the monthly calibration.

Moreover, an increase of the uncertainty band with increasing time step (daily to monthly) has been recorded as depicted by higher *R-factor* values at Douna and Pankourou (from 0.59 to 0.65 and from 0.41 to 0.45, respectively). However, the uncertainty band was reduced during the validation period compared to the calibration period for all the stations (Table 6).

4. Discussion

4.1. Model Performance

In an effort to assess the performance of the SWAT model on the Bani catchment, we calibrated and validated the model at multiple sites on daily and monthly time steps by using measured climate data. There was no statistically significant difference in model performance among time intervals. Using guidelines given in Moriasi *et al.* [50], the overall performance of the SWAT model in terms of *NSE* and R^2 can be judged as very good, especially considering limited data conditions in the studied area. On a monthly basis, we obtained at the Douna outlet a *NSE* value equal to 0.79 for the calibration period (0.85 for the validation period). These results are greater than the ones of the studies by Schuol and Abbaspour [12], and Schuol *et al.* [14] at the same outlet. Schuol and Abbaspour [12] reported indeed a negative *NSE* (between −1 and 0) for the monthly calibration and a value ranging between 0 and 0.7 for monthly validation, while Schuol *et al.* [14] obtained a *NSE* between 0 and 0.70 for both monthly calibration and validation. However, Laurent and Ruelland [23] reported a greater performance (*NSE* values varying between 0.81 and 0.91 for calibration and validation period, respectively) but on a coarser time step (average annual basis). The water balance is less well simulated, especially for monthly time step with a *PBIAIS* greater than 25% in absolute value.

The quantified prediction uncertainty is surprisingly satisfactory (Table 6). At the end of the daily calibration, the model was able to account for 61% of observed discharge data (65% for monthly calibration) in a narrow uncertainty band. These results are close to the result of Schuol *et al.* [14] who estimated the observed discharge data bracketed by the 95PPU between 60% and 80% for monthly calibration (40% and 60% for monthly validation). However, one explanation that could be attributed to the small uncertainty band we obtained is that model predictive uncertainty derived by GLUE depends largely on the threshold value to separate "behavioral" from "non-behavioral" parameter sets [63,64].

This means, a high threshold value (as in this case) will generally lead to a narrower uncertainty band [65–67] but this will be achieved at the cost of bracketing less observed data within the 95PPU band. In addition, GLUE accounts partly for uncertainty due to the possible non-uniqueness (or equifinality) of parameter sets during calibration and could therefore underestimate total model uncertainty [68]. For instance, Sellami *et al.* [69] showed that the GLUE predictive uncertainty band was larger and surrounded more observation data when uncertainty in the discharge data was explicitly considered. Engeland and Gottschalk [70] demonstrated that the conceptual water balance model structural uncertainty was larger than parameter uncertainty. In spite of all the aforementioned limitations of GLUE, we succeeded in enclosing interestingly most of the observed data within a narrow uncertainty band (the sought adequate balance between the two indices) hence increasing confidence in model results. These are encouraging results showing, on one hand, the good performance of the SWAT model on a large Soudano-Sahelian catchment under limited data and varying climate conditions and, on the other hand, the capability of observed climate and hydrological input data of this catchment, even though contested, to provide reliable information about hydro-meteorological systems prevailing in the region.

It has been also noted that the model did not perform well during the year 1984 particularly (lower performance and larger uncertainty). This loss of performance can be attributed to the disruption in rainfall-runoff relationship consequence of consecutive years of drought, which has prevailed in the beginning of the 80s. The over-predicted PET on the Bani catchment could be attributed to the Hargreaves method, which could give a greater estimate of PET than it actually is. Ruelland *et al.* [28]

applied a temperature-based method given by Oudin *et al.* [71] and provided a similar estimate of PET (1723 mm) than the values calculated herein by the Penman and pan evaporation methods hence corroborating our results. These results demonstrated the valuable of pan evaporation measurements for estimating PET and that the simple pan evaporation method appears to be suited for application in the study area and can be used when all the climatic data required by the Penman method are missing.

As far as biomass is concerned, the underestimation of this component in savannah could be explained by inappropriate specification of all categories in the land use map grid to be modeled by SWAT as savannah or inaccurate savannah characteristics added in the SWAT database, directly affecting biomass production such as *BIO_E* and *LAI* parameters, among others.

4.2. Impact of Spatial and Temporal Scales on the Model Uncertainty

Results showed that transferring the model parameters from the catchment outlet (Douna) to the internal gauging stations performs reasonably well only in the case of similarity between donor and target catchments. The case of catchments controlled by Douna and Pankourou gives a clear example of such physical proximity where precipitation, soil and land use vary smoothly between both catchments. However, the SWAT model parameters determined at the outlet could not reproduce well the measured discharge at Bougouni mainly due to more significant spatial dissimilarities. Bougouni is indeed situated in a more humid zone and dominated by forest whereas Douna is more arid. Moreover, it has been demonstrated that the individual calibration at subcatchment scale has led to a narrower uncertainty band and more observed discharge data enclosed in it, which is the sought adequate balance between the two indices. Hence, predictive uncertainty was found to decrease with decreasing spatial scale. This finding can be attributed to the presence of less heterogeneity in hydrological variables in smaller catchments. These results showed the importance of the calibration of hydrological models at finer spatial scale to ensure that predominant processes in each subcatchment are captured, and this is particularly relevant in case of large-area global catchments. Concerning the effect of temporal scale, we demonstrated that the validation period is characterized by less predictive uncertainty as opposed to the calibration period. One explanation that can be given is the fact that 1993-1997 constitutes a more humid period than 1983-1992 and is characterized, therefore, by less variability in precipitation. In contrast, when moving from daily to monthly calibration, the uncertainty of the model, in terms of uncertainty band width, increased. This could be attributed to the cumulative effect of uncertainty in daily discharge data used to compute monthly discharge, resulting therefore in larger monthly uncertainty. Overall, due to decreasing prediction uncertainty with decreasing spatial and temporal scales, it is germane to develop on the basin a more efficient system of hydro-meteorological data collection to account for spatial and temporal variabilities in hydro-meteorological systems prevailing in the region, especially under changing climate and land use conditions.

4.3. Advance in Understanding of Hydrological Processes

The GSA confirms what has already been reported on and around the Bani catchment about the contribution of hydrological processes to streamflow generation. In order to better understand the origin of flows at Kolondieba (a tributary of the Bani River), Dao *et al.* [72] showed that Groundwater contribution to the hydrodynamic equilibrium at the outlet of watershed Kolondieba is small and the direct flow from the soil surface governs the runoff process. This fact can be explained by the double impact of a general impoverishment of shallow aquifers due to reduction in precipitation in West Africa in general since the great drought of the 70s as well as a concurrent increase of the recession coefficient of the Bani river as demonstrated by Bamba *et al.* [32] and Mahé [73] with a decrease of baseflow contribution to total flow in absolute and relative values as corollary.

4.4. Spatial Performance

The results of different calibration and validation techniques showed varying predictive abilities of the SWAT model through scales. Firstly, it can be derived from these findings that model performance in terms of *NSE* and R^2 was higher on the watershed-wide level than on the sub-watershed level. However, this could be attributed to compensation between positive and negative errors of processes occurring at a larger scale [74,75]. This suggests that calibrating a model only at the basin outlet leads to an overconfidence in its performance than at the sub-basin scale. Secondly, individual calibration of subcatchment processes expectedly improved model accuracy in predicting flows at the internal gauging stations, due to reducing heterogeneities with downsizing space [76], and is especially beneficent while the donor and receiver catchments are substantially different. Finally, predictive uncertainty appears to decrease with reducing spatial scale, but increases with humidity as shown by the lower performance recorded at Bougouni. The inability of the model to perform during the validation period at Bougouni could be attributed to the structure of the validation period which is substantially different to that of calibration, and is solely composed by average to wet years while in contrast, the occurrence of dry, average, and wet years during the calibration period is noted.

These results have an important role to play in the calibration and validation approaches of large-area watershed models and constitutes a first step to model parameter regionalization for prediction in ungauged basins.

Generally speaking, it is well known that in recent decades the Niger River basin has suffered from a serious degradation of its natural resources, which in turn lead to severe environmental issues. To this end, different agreements and collaborations on water and climate data sharing have been established between the 9 countries sharing the basin through different national and international programs. Thus, the need to reinforce the existing framework of integrated, coordinated, and sustainable water management strategies in the Bani basin and therefore the Niger River Basin become more urgent than ever.

Therefore, this study is a step in that long-term direction, where an integrated water management tool has been developed and validated spatially on the Bani catchment, which allows investigation of future effects of land use and climate change scenarios on water resources.

5. Conclusions

In this study, the performance of the widely-used SWAT model was evaluated on the Bani catchment using both split-sample and split-location calibration and validation techniques on daily and monthly intervals. The model was calibrated at the Douna outlet and at two internal stations. Freely available global data and daily observed climate and discharge data were used as inputs for model simulation and calibration. Calibration, validation, uncertainty, and sensitivity analyses were performed with GLUE within SWAT-CUP. Both graphical and statistical techniques were used for hydrologic calibration results evaluation. Evapotranspiration and biomass production outputs were verified and compared to regional values to make sure these components were reasonably predicted. Sensitivity analysis contributed to a better understanding of the hydrological processes occurring at the study area.

Final results showed a good SWAT model performance to predict daily as well as monthly discharge at Douna with acceptable predictive uncertainty despite the poor data density and the high gradient of climate and land use characterizing the study catchment. However, the daily calibration resulted in less predictive uncertainty than the monthly calibration. The performance of the model is somehow lower at an internal sub-catchments level when the global parameter sets are applied, especially at the one with higher humidity and dominated by forest. However, subcatchment calibration induced an increase of model performance at intermediate gauging stations as well as a decrease of total uncertainty. With regard to predicted PET, this component is overestimated by the model when the Hargreaves method is applied in that specific region while biomass production

remained low in the savannah land use category. The GSA revealed the predominance of surface and subsurface processes in the streamflow generation of the Bani River.

Overall, this study has shown the validity of the SWAT model for representing globally hydrological processes of a large-scale Soudano-Sahelian catchment in West Africa. Given the high spatial variability of climate, soil, and land use characterizing the catchment, additional calibration is however needed at subcatchment level to ensure that predominant processes are captured in each subcatchment. Accordingly, the importance of spatially distributed hydrological measurements is demonstrated and constitutes the backbone of any type of progress in hydrological process understanding and modeling. The calibrated SWAT model for the Bani can be used to assess the current and future impacts of climate and land use change on water resources of the catchment, increasingly necessary information awaited by water resources managers. Knowing this information, a strategy of adaptation in response to the current and future impacts can be clearly proposed and the vulnerability of the population can therefore be reduced. More widely, this impact study can increase the transferability of the model parameters from the Bani subcatchment to another ungauged basin with some similarities, and then predicting discharge without the need of any measurement. These findings are very useful, especially in West Africa, where many river basins are ungauged or poorly gauged.

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Author Contributions: All authors designed the objectives and methods of the study. J. C. Begou, P. Bazie, and A. Afouda collected the climatological and hydrological datasets required for the model. J. C. Begou, S. Jomaa, S. Benabdallah, and M. Rode conducted the model setup and performed the simulations. All authors analyzed the obtained data. J. C. Begou prepared the manuscript with contributions from all co-authors. All authors read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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