Evaluating the Feasibility of Hydrologic Parameter Transferability to Ungauged Domains Under Data-Sparse Conditions in Nigeria

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ABSTRACT

Hydrologic modelling has become a vital tool for formulating policies to plan and manage water resources sustainably. However, inadequate or non-available hydro-meteorological datasets significantly hinder its application in ungauged basins. This issue has highlighted critical research gaps and deprived such regions of the advantages of continuous hydrologic modelling for understanding and mitigating hydrologic extremes and developing and managing water resources infrastructure. The major objectives of this study are to: (1) evaluate the ability of remotely-sensed precipitation products to capture rainfall dynamics across different locations in Nigeria, (2) assess the mesoscale hydrologic model (mHM) streamflow simulation within a multi/uni-variable calibration framework, driven by gridded precipitation datasets, (3) evaluate the regionalization of mHM parameters from donor to ungauged basins for streamflow predictions, and (4) model actual evapotranspiration and soil moisture across Nigeria using mHM parameters acquired when constrained using only streamflow data.

The ability of several gridded precipitation products (CHIRPS, PERSIANN-CDR and TAMSAT) to replicate rainfall characteristics at 24 climatic stations distributed across Nigeria was evaluated against in-situ measurements. The results indicate that all products well captured the observed annual cycle and spatial trends across selected locations. Statistical assessment reveals that the CHIRPS dataset was consistent with observations across most climatic stations, accurately reproducing local rainfall characteristics. Next, various gridded precipitation products within a uni- and multi-variable calibration framework were employed to evaluate the performance of the mHM across four different data-scarce basins in Nigeria. This model utilizing CHIRPS and ERA5 rainfall datasets as input, consistently generated acceptable Kling-Gupta efficiency (KGE) values (0.5 < KGE < 0.75) for streamflow simulation during model validation under both calibration frameworks. However, constraining model parameters in both calibration schemes did not significantly improve model simulations in all selected study domains. Furthermore, the transferability of optimized mHM parameter sets from gauged to ungauged domains was assessed under a multi-domain modelling configuration. Optimized mHM streamflow simulations, driven by CHIRPS, ERA5 and MSWEP precipitation datasets, demonstrated significant improvement (KGE > 0.5) across all modelling domains compared to using mHM default parameters. Subsequently, the optimized model parameters were transferred to three independent basins for streamflow prediction. Acceptable streamflow simulation using regionalized mHM parameter sets was shown only in one basin, presenting a KGE of 0.54. Lastly, optimized mHM parameter sets derived from distinct basin-precipitation configurations were utilized to simulate actual evapotranspiration (aET) and soil moisture across three agro-climatic zones in Nigeria. Spatial patterns of mean annual aET for all mHM configurations exhibited similar trends with observations (GLEAM and FLUXNET). CHIRPSdriven aET simulations demonstrated satisfactory correlation scores (r > 0.5) with the GLEAM datasets. Similarly, all mHM setups showcased comparable trends in the annual aET cycle, with acceptable model fits (KGE > 0.7) observed in the Sahel region. The monthly temporal variation of soil moisture anomaly exhibited acceptable agreements (r > 0.8) across all agroclimatic zones. This study represents the first evaluation of mHM under sparse input data constraints in Nigeria. The results of this study not only align with the objectives of the International Association of Hydrological Sciences initiative on prediction in ungauged basins but also address the challenges of hydrologic modelling in Nigeria (and in regions with similar climatic conditions).

Bewertung der Übertragbarkeit hydrologischer Parameter auf Einzugsgebiete mit eingeschränkter Mess- und Datenverfügbarkeit in Nigeria

KURZFASSUNG

Die hydrologische Modellierung ist ein wichtiges Instrument für die Erarbeitung von Strategien zur nachhaltigen Bewirtschaftung von Wasserressourcen. Defizite der Datenverfügbarkeit behindern jedoch die Anwendung hydrologischer Modelle in Einzugsgebieten ohne meteo-hydrologische Messsysteme. Dieses Problem hat kritische Forschungslücken aufgezeigt, die darin bestehen, dass in diesen Gebieten die Vorteile hydrologischer Modellierung nicht genutzt werden können, um ein Verständnis für das Entstehen hydrologischer Extremsituationen zu gewinnen und um Konzepte für die Entwicklung von Wasserinfrastruktur zu erarbeiten. Wesentliche Ziele dieser Studie sind: (1) die Eignung von Produkten der Fernerkundungs-basierten Quantifizierung des Niederschlags für die Erfassung der räumlich-zeitlichen Dynamik des Niederschlags in verschiedenen Regionen Nigerias einzuschätzen, (2) die Qualität der Abflusssimulation mit dem mesoskaligen Hydrologischen Modell mHM bei Nutzung Fernerkundungs-basierter Niederschlagsprodukte und Anwendung uni- sowie multivariabler Kalibrierungsansätze zu bewerten, (3) die Übertragbarkeit von mHM-Parametern von Einzugsgebieten mit Messsystemen auf solche ohne Monitoring zu beurteilen (im Hinblick auf Abflussvorhersagen), und (4) die aktuelle Evapotranspiration und Bodenfeuchte für Nigeria zu modellieren unter Nutzung von mHM-Parametern, die aus der Kalibrierung des Modells nur unter Verwendung von Abflussdaten ermittelt wurden.

Die Eignung raster-basierter Niederschlagsprodukte (CHIRPS, PERSIANN-CDR, TAMSAT), um die Niederschlagseigenschaften von 24 über Nigeria verteilten Klimastationen wiederzugeben, wurde anhand von In-situ-Messungen bewertet. Die Ergebnisse zeigen, dass alle Produkte den beobachteten Jahresverlauf und die räumlichen Trends des Niederschlags an den Stationen gut erfassen. Die statistische Auswertung belegt, dass der CHIRPS-Datensatz mit den Beobachtungen an den meisten Klimastationen übereinstimmt und die lokalen Niederschlagsverhältnisse genau wiedergibt. Als Nächstes wurden verschiedene raster-basierte Niederschlagsprodukte mit ein- und mehrvariablen Kalibrierungsansatz verwendet, um die Leistungsfähigkeit des mHM-Modells in vier Einzugsgebieten mit eingeschränkter Datenlage zu bewerten. Dieses Modell mit CHIRPS- und ERA5-Niederschlagsdaten als Input, erzeugte bei der Modellvalidierung (Abflusssimulation) in beiden Kalibrierungsansätzen durchweg akzeptable Werte der Kling-Gupta-Effizienz KGE (0,5 < KGE < 0,75). Die Einschränkung der Modellparameter in beiden Kalibrierungsschemata führte nicht zu einer signifikanten Verbesserung der Modellsimulationen in allen Untersuchungsgebieten. Weiterhin wurde die Übertragbarkeit der optimierten mHM-Parametersätze von Gebieten mit Messwerten auf solche Multi-Domain-Modellierungskonfiguration untersucht. ohne in einer Optimierte mHM-Abflusssimulationen, die CHIRPS-, ERA5- und MSWEP-Niederschlagsdaten nutzten, ermöglichten in allen Modellierungsbereichen signifikante Verbesserungen (KGE > 0,5) im Vergleich zur Verwendung der mHM-Standardparameter. Anschließend wurden die optimierten Modellparameter auf drei unabhängige Einzugsgebiete zur Simulation des Abflusses übertragen. Allerdings konnte lediglich in einem Einzugsgebiet mit regionalisierten mHM-Parametersätzen der Abfluss mit akzeptabler Zuverlässigkeit simuliert werden (KGE von 0,54). Schließlich wurden optimierte mHM-Parametersätze, die aus verschiedenen Einzugsgebiet-Niederschlags-Konfigurationen abgeleitet wurden, zur Simulation der aktuellen Evapotranspiration (aET) und der Bodenfeuchte in drei agroklimatischen Zonen Nigerias verwendet. Die räumlichen Muster der mittleren jährlichen aET für alle mHM-Konfigurationen wiesen ähnliche Trends wie die Beobachtungen auf (GLEAM und FLUXNET). AET-Simulationen mit CHIRPS zeigten zufriedenstellende Korrelationswerte (r > 0,5) mit den GLEAM-Datensätzen. Alle mHM-Setups zeigten vergleichbare Trends im jährlichen aET-Verlauf, wobei in der Sahelzone akzeptable Modellanpassungen (KGE > 0,7) beobachtet wurden. Die zeitliche Variation der Bodenfeuchteanomalie (monatliche Auflösung) wies in allen agro-klimatischen Zonen akzeptable Übereinstimmungen (r > 0.8) auf. Die Studie stellt die erste Einschätzung der Eignung des

mHM bei knappen Eingangsdaten in Nigeria dar. Die Ergebnisse dieser Studie stehen im Einklang mit den Zielen der Initiative der International Association of Hydrological Sciences zur Modellierung von Einzugsgebieten ohne Messsysteme und stellen eine Antwort auf die Herausforderungen der hydrologischen Modellierung in Nigeria (und Regionen mit ähnlichen klimatischen Bedingungen) dar.

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LIST OF ACRONYMS AND ABBREVIATIONS

aET	Actual evapotranspiration
ARC	African Rainfall Climatology
CDF	Cumulative Distribution Frequency
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CPC	Climate Prediction Centre
DEM	Digital Elevation Map
ECDF	Empirical Cumulative Distribution Function
ECMWF	European Center for Medium-Range Weather Forecast
ERA5	5 th ECMWF Re-Analysis
ESA CCI	European Space Agency Climate Change Initiative
FLUXNET	Flux Network
GLEAM	Global Land Evaporation Amsterdam Model
GPCC	Global Precipitation Climatology Centre
GRDC	Global Runoff Data Centre
HBV	Hydrologiska Byråns Vattenbalansavdelning
IAHS	International Association of Hydrological Sciences
IPCC	Intergovernmental Panel on Climate Change
IR	InfraRed
ITD	InterTropical Discontinuity
JAXA	Japan Aerospace Exploration Agency
KGE	Kling-Gupta Efficiency
mHM	mesoscale Hydrologic Model
MPR	Multiscale Parameter Regionalization
MSWEP	Multi-Source Weighted-Ensemble Precipitation
MW	Microwave
NOAA	National Oceanic and Atmospheric Administration
NASA	National Aeronautics Space Administration
PBIAS	Percent Bias
PERSIANN CDR	Precipitation Estimation from Remotely Sensed Information using an
	Artificial Neural Network-Climate Data Record
PUB	Prediction in Ungauged Basins
RFE	RainFall Estimate
RMSE	Root Means Square Error
SM	Soil moisture
SPI	Standardized Precipitation Index
TAMSAT	Tropical Applications of Meteorology using SATellite and ground-
	based observations
TRMM	Tropical Rainfall Measuring Rainfall
USGS	United States Geological Survey
VIC	Variable Infiltration Capacity
WMO	World Meteorological Organization

1 General Introduction

1.1 Background

This chapter presents a general introduction, beginning with the underlying background and a brief overview of critical studies that motivate the research.

Nigeria, the most populated nation in Africa, is highly vulnerable to the adverse impacts of climate variability because of its high exposure and low adaptive capacity (Akinsanola et al., 2018; Almazroui et al., 2020). Pervasive poverty, a weak economy, and dependence on rainfed farming exacerbate this vulnerability, resulting in a reliance on food imports to feed its two hundred million people (Ogungbenro & Morakinyo, 2014). The fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC AR5) predicts a temperature rise of about 1.5 – 2.5 °C by 2025 over West Africa for the different carbon emissions representative pathways (Almazroui et al., 2020; Epule et al., 2021). Such an increase in the earth's surface temperature will lead to an increase in evapotranspiration and rainfall variability, resulting in significant altercations in the hydrologic cycle (Awotwi et al., 2021; Todzo et al., 2020). Knowledge of a region's water resource availability is vital for policy-makers in the context of effective water resource management (Choi et al., 2023). Flooding is considered one of the most devastating environmental threats in the world and has continued to occur more frequently in recent years (Echendu, 2023; Umar & Gray, 2023). Between 1998 and 2017, floods accounted for 43.4% of natural disasters globally, causing the second-highest economic damage, valued at about US\$656 billion and affecting approximately 2 billion people (Belvederesi et al., 2022). Persistent rainfall events have wreaked havoc in many parts of Nigeria, resulting in severe physical, environmental and economic consequences, and most importantly causing loss of human lives (Gbode et al., 2019). Usman et al. (2018) reported that annual flood occurrence in Nigeria over the last two decades has resulted in the loss of about 1,763 human lives and damages to properties worth billions of US\$. Specifically, the 2012 floods led to the loss of about 363 human lives, displaced over 2.3 million persons, and caused the loss of properties, which is estimated to cost about US\$16.9 billion (Echendu, 2023). Nigeria is also prone to droughts due to the high variability of rainfall occasioned by the latitudinal movement of the intertropical convergence zone. However, significant droughts have not occurred in the Sahel since the 1970 Great Sahelian drought, which left millions of persons starving (Hassan et al., 2019). Nevertheless, there is a tendency for its occurrence in the future due to observed climate variability (Shiru et al., 2018, 2020). The northern region (Sahel) of Nigeria is characterized by a short wet season, thereby exposing this region to droughts and desertification (Hassan et al., 2019). Overall, the observed and projected variability in the dynamics of climatic variables (rainfall and temperature) over Nigeria poses grave consequences for a population that is solely dependent on rain-fed farming. The situation is further exacerbated by the existing weak governance structures and economic conditions. These factors have led to a downsizing of commercial farming to a subsistence scale, resulting in substantial adverse effects on the national economy (Poméon et al., 2018a). Global agriculture is rain-fed-dominated and practised on about 80% of global cropland, resulting in about 60% of global food production (Ringler et al., 2022). This pattern of predominantly rainred agriculture is also reflected in the Nigerian agricultural production system but the low adaptive capacity and dearth of water resources infrastructure have resulted in severe impacts on national food security.

Accurate modelling of major hydrologic processes is crucial for water resources management, planning, development, flood prediction, drought warnings and operational hydrology (Chathuranika et al., 2022; Guo et al., 2021). In the face of a growing threat from rising global air temperature, hydrologic modelling and predictions are poised to play a major role, exerting significant influence on deriving sound and evidence-based management decisions and enabling the development of resilient adaptative strategies for potential future scenarios (Taia et al., 2023). However, issues related to the unavailability/poor quality of hydrological modelling data requirements and hydro-meteorological observations limit model applications, especially in ungauged basins (Dembélé et al., 2020a; Tarek et al., 2021). Ungauged regions, characterized by poor observation system networks, vandalized gauging instruments, inaccessible terrains, and a shortage of skilled human resources, suffer from a lack/incomplete time series of hydrological data (Fasipe & Izinyon, 2021). This challenge of hydrologic system modelling in ungauged basins is identified as a significant problem in the field of hydrology and has become an important research area in eco-hydrology (Golian et al., 2021; Guo et al., 2021). The possibilities of hydrological instrumentation in many regions, especially developing countries (e.g., Nigeria) and remote terrains for accurate estimation of hydrological variables resulted in the launch of the International Association of Hydrologic Sciences (IAHS) Scientific Initiative for Predictions in Ungauged Basins (PUB) (Sivapalan et al., 2003). The PUB initiatives mobilized the scientific community towards gaining improved knowledge on the components of the hydrologic system (hydrologic processes, model parameters, and climatic datasets) for a gauged basin and utilizing this knowledge to make predictions in ungauged basins. Hydrological regionalization methods have been widely adopted to solve problems of prediction in ungauged basins (Farfán & Cea, 2023; Golian et al., 2021; Guo et al., 2021; Pool et al., 2021; Qi et al., 2022; Singh et al., 2022; Tarek et al., 2021). However, the transferability of hydrologic model parameters calibrated in gauged basins to simulate hydrologic processes in ungauged basins has in some cases yielded unacceptable results and accuracies (Guo et al., 2021). Simulation results are affected mainly by hydrological model structure, hydrological data availability, climate characteristics and choice of regionalization methods (Pool et al., 2021; Yang et al., 2023). The choice of regionalization method (e.g., similarity-based, hydrological signature-based or regression-based) plays a significant role in producing acceptable hydrological predictions in ungauged basins (Song et al., 2022).

Performance Evaluation of Gridded Precipitation Products

The advancements in information and computing technologies (ICT) have led to the development of satellite-based, gauge-based interpolations, and reanalysis precipitation products, which provide extensive spatial coverage of continuous climate observations even over rugged or uninhabited landscapes (Le Coz & Van De Giesen, 2020; Li et al., 2021). Their popularity is attributed to their free availability, particularly in developing regions that face challenges of non-existent, poor quality or sparse ground-based climate observation networks (Akinyemi et al., 2019; Irvem & Ozbuldu, 2019). However, its performance in most cases has been deemed unacceptable, especially in complex landscapes characterized by high spatiotemporal variability in precipitation and poor gauge networks (An et al., 2020; Dembélé et al., 2020a; Satgé et al., 2019). While satellite precipitation products are affected by retrieval algorithms, faulty sensors, and systemic bias, uncertainties in reanalysis products result from model forcing parameters and model physics (Dembélé et al., 2020a; Le Coz & Van De Giesen, 2020). These inherent uncertainties have necessitated the evaluation of these datasets using in-

situ gauge-based observations before utilizing them for climate research. Many studies have evaluated gridded precipitation products over different regions of the world with substantial differences in accuracies of the temporal dynamics of precipitation events. In regions where quality stream discharge observations can be obtained, gridded precipitation products can be evaluated through the hydrological modelling method, as presented by Nhi et al. (2019), Musie et al. (2019), Alemayehu et al. (2018), Tarek et al. (2020), Raimonet et al. (2017), Dembélé et al. (2020b) and Oyerinde et al. (2017). However, this approach is not feasible in basins challenged by scarcity or poor-quality discharge observations. In the absence of gauged streamflow records, in-situ or gauged-based precipitation products have also proven successful in evaluating gridded precipitation products for scientific studies (An et al., 2020; Belay et al., 2019; Camberlin et al., 2019; Hassan et al., 2020; Satgé et al., 2020; Trinh-Tuan et al., 2019; Zandler et al., 2019). These studies demonstrated varying magnitudes of performances for all these selected precipitation products. It has been shown that discrepancies in replicating hydroclimatic observations were observed more in complex terrains or regions with poor hydroclimatic gauge networks (Zandler et al., 2019).

Improving Hydrologic Simulations Through Multi-Variate Calibration

Hydrological model calibration is a widely accepted process performed to achieve a representative model, often conducted at the outlet of a basin (Desai et al., 2021; Taia et al., 2023). This involves constraining the model parameter range to identify the best parameter set which represents the basin hydrological processes (Rajib et al., 2018). In many instances, hydrological models are constrained by relying only upon streamflow observations, often ignoring other crucial hydrologic variables (e.g., evapotranspiration, soil moisture, total water storage) (Budhathoki et al., 2020; Koppa et al., 2019). However, utilizing only streamflow observations for hydrological model parameterization does not reflect information about a basin spatial heterogeneity, which exists naturally in every hydrologic system (Dembélé et al., 2020b). It is worth noting that acceptable basin-streamflow simulation may be obtained using only a streamflow-constrained hydrologic model but this approach might result in a misrepresentation of other internal basin's hydrological processes (e.g., evapotranspiration, soil moisture) (Rajib et al., 2018). Knowledge of other major hydrologic processes rather than solely streamflow is required for integrated water resources management. Studies have shown that constraining a model with datasets from multiple components of the hydrologic system in a multivariable framework has the potential to improve hydrologic simulation performance (Golian et al., 2021; Shah et al., 2021). However, this can result in overparameterization/equifinality and produce similar hydrologic responses through a combination of different parameter sets (Guo et al., 2021; Koppa et al., 2019; Rakovec et al., 2016a; Shah et al., 2021). Problems of model equifinality have been noted as one of the biggest challenges facing hydrological modelling (Beven, 2001; Golian et al., 2021; Loritz et al., 2021; Shah et al., 2021). Multi-variable calibration can be a daunting task, especially in data-limited regions characterized by sparse gauge networks (Taia et al., 2023). In this regard, freely available and fine-resolution remotely sensed products may be employed as an alternative. Notwithstanding that these satellite products offer free and cost-effective hydro-meteorologic measurements, their use is greatly associated with high uncertainties which impact simulation results.

Parameter Regionalization for Hydrologic Prediction in Ungauged Basins

Achieving reliable prediction of streamflow in ungauged basins has been a significant challenge in hydrology, given its importance in applied hydrology (e.g., for water resources infrastructures) and water resources development and management (Golian et al., 2021; Yang et al., 2023). Recent advancements in process and physically-based hydrologic models to cope with the availability of fine-resolution model-input datasets (DEM, soil and land use maps) have resulted in more computational requirements and model complexity but have not improved hydrologic process representations (Beven, 2001, 2002). This author also noted that despite the existence of complex hydrologic models, the issue of model over-parameterization, particularly at the mesoscale, remains unresolved. This is even more daunting in ungauged basins characterized by complex heterogeneous landscapes, where parameter values are unknown. In many developing regions, the decreasing efforts to instrument basins pose a significant challenge for hydrologic model calibration, a trend more likely to persist even in the future (Qi et al., 2022; Yang et al., 2023). Scientific reports from the IAHS PUB initiative acknowledged that parameter regionalization is best suited to make hydrologic predictions in data-sparse basins (Arsenault et al., 2019; Farfán & Cea, 2023; Pool et al., 2021; Singh et al., 2022; Song et al., 2022; Tarek et al., 2021). Several studies (Golian et al., 2021; Qi et al., 2022; Samaniego et al., 2019) have shown the feasibility of parameter transfer from gauged to ungauged basins, although with varying magnitude of performances. To date, researchers are still experimenting with different regionalization schemes, such as physical similarity, spatial proximity, and regression-based, in a bid to find a suitable method (Song et al., 2022). Furthermore, most regionalization methods assume lumped parameter values, such as the hydrologic response unit of the SWAT model (Arnold et al., 1998; Bieger et al., 2017; Wagner et al., 2022) without explicitly accounting for subbasin heterogeneity/variability necessary for capturing land surface characteristics (Samaniego et al., 2011; Song et al., 2022). The effectiveness of any regionalization scheme in hydrology relies on factors such as the choice of hydrological model, the approach to linking model parameters and the basin's physical descriptors, and the selection of objective functions for parameter optimization (Golian et al., 2021). A regionalization method which incorporates these factors will have the potential to produce satisfactory simulations across scales, locations and hydrological variables other than that used for parameter value estimation (Mizukami et al., 2017; Rakovec et al., 2019; Rakovec et al., 2016a; Samaniego et al., 2017). The Multiscale Parameter Regionalization (MPR) (Samaniego et al 2010), incorporated within the mesoscale Hydrologic Model (mHM) (Kumar et al., 2013; Samaniego et al., 2010) structure explicitly addresses these issues (Rakovec et al., 2019). Few studies (Dembélé et al., 2022; Dembélé et al., 2020a; Dembélé et al., 2020b; Poméon et al., 2018a) have tested the mHM-MPR within sub-Saharan Africa (SSA) with successful results. On the other hand, the mHM has been applied successfully in over 400 European basins (Rakovec et al., 2016b), across the continental United States (Rakovec et al., 2019) and global scale (Shrestha et al., 2024). Considering the limitations associated with the paucity of hydro-meteorologic data in Nigeria, the fully distributed hydrologic mHM tool is well suited for its dynamic climate and complex terrain.

1.2 Research Questions

This section addresses the fundamental research questions that will drive this study. They are described as follows:

1. How well do certain selected gridded precipitation products perform at the synoptic-station level in Nigeria?

Studies have shown that gridded precipitation products exhibit varying performances over complex landscapes. In this study, the performances of several gridded products (CHIRPS, PERSIANN-CDR and TAMSAT) against in-situ rain gauge records obtained at different synoptic stations across three agro-climatic regions of Nigeria were evaluated at a point-to-pixel basis. This research question is addressed in Chapter 2:

2. To what extent does the mesoscale Hydrologic Model (mHM) accurately replicate the temporal variability of observed streamflow under data-limited conditions?

mHM, which initially incorporated the MPR scheme, is gaining popularity because of its capability to perform spatially distributed hydrologic simulations at the mesoscale. The MPR technique ensures the generation of consistent parameter sets, permitting their transferability across different scales and locations. Additionally, the mHM offers compatibility with remotely sensed gridded datasets as model inputs, a valuable advantage in regions characterized by a paucity of hydro-climatic datasets. In this stage, several other gridded precipitation products were introduced to expand the range of products and provide a comprehensive performance evaluation in hydrological modelling. The inclusion of ERA5 (reanalysis data), GPCC (gauge-based), CPC (multi-source) and MSWEP (multi-source), alongside CHIRPS, allows for the evaluation of products characterized by a variety of data sources and spatio-temporal resolutions. Incorporating state-of-the-art datasets such as ERA5 and MSWEP ensures that this evaluation leverages the most advanced and accurate datasets. Using these products complements earlier assessments and helps validate the robustness and reliability of mHM across a diverse range of precipitation inputs. The mHM was set up across diverse basins, utilizing different gridded rainfall products (CHIRPS, CPC, ERA5, GPCC, MSWEP) and employing a multi-calibration and single-variable calibration approach. Streamflow simulation performance for both calibration approaches was evaluated. This research question is addressed in Chapter 3.

3. How reliable is the MPR technique for parameter transferability to ungauged basins?

Nigeria is characterized by sparse hydro-meteorological gauge networks, which have impacted hydrological model calibrations and water resources management. The MPR regionalization scheme, incorporated within the mHM structure, retains sub-grid variability of model parameters and facilitates parameter transfer from gauged to ungauged basins. A hydrological evaluation of the satellite and re-analysis products on different basins was performed. Next, mHM was constrained over multi-domain (i.e., two basins), and streamflow records were utilized during mHM calibration. The model parameter set from this stage was transferred to independent basins that were not used during calibration and assessed for streamflow simulation. This research question is addressed in Chapter 4:

4. How effectively does mHM simulate evapotranspiration and soil moisture on a regional scale when utilizing calibrated parameters obtained at the basin level?

Nigeria's current model-input data limitation is expected to persist as a significant issue in the future. There is, hence, a critical need to further evaluate the transferability of mHM parameters from a smaller domain to a larger domain under data-sparse conditions. In this section, distinct mHM parameter sets obtained post-calibration at the basin scale, and considering various basin-rainfall combinations were determined. Subsequently, these parameter sets were utilized to configure mHM for actual evapotranspiration and soil moisture simulations across three agro-climatic regions in Nigeria. Temporal dynamics of mHM simulations were compared against their observed counterparts at seasonal, monthly and annual periods. This research question is addressed in Chapter 5.

1.3 Study Objectives

The main focus of this research is to explore the capability of mHM for hydrologic prediction in ungauged basins. Certain parts of this study have been disseminated as scientific articles in peer-reviewed open-access journals and presented at several academic conferences. The mHM codes (Samaniego et al., 2021) and input datasets used in this study can be obtained freely from their various repositories.

Specific objectives include:

- 1. To evaluate the performances of gridded precipitation products across synoptic station data in Nigeria.
- 2. To assess mHM streamflow simulation within a multi-calibration framework, utilizing gridded precipitation datasets in four (4) data-scarce basins.
- 3. To assess the transferability of optimized mHM parameters from gauged to ungauged basins for streamflow prediction.
- 4. To evaluate mHM actual evapotranspiration and soil moisture simulations on a larger domain utilizing parameter sets obtained post-calibration at a smaller domain.

1.4 Structure of the Study

This study is structured into various chapters. Chapter 1 discusses the general introduction and justifies the motivation for and the relevance of this research. Chapter 2 presents a performance evaluation of selected gridded precipitation products at various synoptic station levels in Nigeria. Chapter 3 evaluates the mHM ability for streamflow prediction in data-sparse basins. Chapter 4 focuses on assessing the MPR technique for parameter transfer across several basins in Nigeria. Chapter 5 presents a multi-variable evaluation of hydrologic simulations in diverse climatic and landscape conditions using a streamflow-calibrated mHM. In chapter 6, a general conclusion is given. Chapters 2, 3 and 4 have been published in peer-reviewed journals. A draft paper on Chapter 5 has been produced and is being prepared for submission. The publications are listed below, while this dissertation includes sightly modified versions as chapters.

Chapter 2: Ogbu, K. N., Hounguè, N. R., Gbode, I. E., and Tischbein, B. (2020). Performance evaluation of satellite-based rainfall products over Nigeria. *Climate*, 8(10). <u>https://doi.org/10.3390/cli8100103</u> **Chapter 3:** Ogbu, K.N., Rakovec, O., Samniego L., Okafor, G.C., Tischbein B, and Meresa, H. (2024). Evaluating the skill of the mesoscale Hydrologic Model (mHM) for discharge simulation in sparsely-gauged basins in Nigeria. *Proc. IAHS*, 385, 211-218, https://doi.org/10.5194/piahs-385-211-2024

Chapter 4: Ogbu, K. N., Rakovec, O., Shrestha, P. K., Samaniego, L., Tischbein, B. and Meresa, H. (2022). Testing the mHM Reliability for Parameter Transferability across Locations in North-Central Nigeria. *Hydrology*, 9(158), 1–23. https://doi.org/10.3390/hydrology9090158

2 Performance Evaluation of Satellite-Based Rainfall Products over Nigeria

This chapter is published as **Ogbu, K. N.**, Hounguè, N. R., Gbode, I. E., & Tischbein, B. (2020). Performance evaluation of satellite-based rainfall products over Nigeria. *Climate*, 8(10). <u>https://doi.org/10.3390/cli8100103</u>

Abstract: Understanding the variability of rainfall is important for sustaining rain-dependent agriculture and driving the local economy of Nigeria. The paucity and inadequate rain gauge networks across Nigeria make satellite-based rainfall products (SRPs), which offer a complete spatial and consistent temporal coverage, a promising option. However, the accuracy of these products must be ascertained before use in water resource development and planning. In this study, the performances of Climate Hazards Group Infrared Precipitation with Station data (CHIRPS), Precipitation estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR), and Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT) were evaluated to investigate their ability to reproduce long term (1983-2013) observed rainfall characteristics derived from twenty-four (24) gauges in Nigeria. Results show that all products captured the observed annual cycle and spatial trends in all selected stations well. Statistical evaluation of the SRPs performance shows that CHIRPS agree more with observations in all climatic zones by reproducing the local rainfall characteristics. However, the performance of PERSIANN and TAMSAT varies with season and across the climatic zones. Findings from this study highlight the benefits of using SRPs to augment or fill gaps in the distribution of local rainfall data, which is critical for water resources planning, agricultural development, and policy making.

Keywords: Gauge rainfall, Satellite rainfall Product; CHIRPS; PERSIANN; TAMSAT

2.1 Introduction

Over the last decades, occurrences of hydrologic extremes, such as flooding and droughts, have increased due to human-induced climate change in West Africa. These impacts have led to tremendous socio-economic losses in already vulnerable communities and, most often, resulted in the deaths of human beings and livestock (Dembélé & Zwart, 2016; Fall et al., 2021). The economies of local agrarian communities have been mainly affected because of their dependence on rain-fed agriculture (Pellarin et al., 2020; Usman et al., 2018). Sustaining water resources development for improved agricultural production under varying climatic conditions and extreme climatic events has proved more challenging due to the paucity of recorded climate data (Gebrechorkos et al., 2018). Consequently, sparse gauge networks do not allow for realistic temporal and spatial climate characteristics representation, as is evident in the scientific literature from this region. Funding issues and lack of serious efforts have limited installations and maintenance of adequate gauge networks below the standard recommended by the World Meteorological Organization (Le Coz & Van De Giesen, 2020).

The advent of satellite and remote sensing technologies has resulted in the availability of highquality satellite-based rainfall products. Its use and application are beginning to gain popularity in Africa due to the scarcity of ground-based climate stations (Akinyemi et al., 2019). These authors noted several inherent limitations in using rain gauge data, including incomplete datasets and lack of spatial and temporal representation have made satellite-based rainfall data more attractive, especially in ungauged regions. Previous studies (Akinyemi et al., 2019; Dinku et al., 2018; Usman et al., 2018) in many parts of Africa have shown that these products can reproduce local rainfall characteristics and could be an alternative in areas with a paucity of observed weather records. However, there is still a need to properly evaluate these products across different climatic situations to ascertain their accuracy and to provide valuable results to end-users and model developers.

In 1997, the Tropical Rainfall Measuring Mission (TRMM), developed by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA), became the first-generation satellite rainfall product (Satgé et al., 2019). The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) (Ashouri et al., 2015) and Tropical Applications of Meteorology Using SATellite and ground-based observations (TAMSAT) (Maidment et al., 2014, 2017; Tarnavsky et al., 2014) were modified from the TRMM and other satellite rainfall missions to deliver rainfall estimates with high spatial and temporal resolution and quality. The recent rainfall estimates from CHIRPS, PERSIANN, and TAMSAT consist of rainfall datasets from the early 1980s to the present; covering a larger period than the first-generation satellite rainfall products. Satellite-based rainfall estimates are obtained through indirect measurements from microwave (MW) or infrared (IR) radiation, from low-orbiting and geostationary satellites, respectively (Ayehu et al., 2018). The MW approach uses an empirical relationship to directly detect atmospheric liquid water content by penetrating clouds, while the IR method utilize an indirect relationship to estimate atmospheric liquid water content from the top of the cloud temperature (Ayehu et al., 2018; Romilly & Gebremichael, 2011). These authors noted that most satellite-based rainfall products combine MW and IR approaches in others to reduce their inherent limitations and to produce representative results, which are highly acceptable for applications in hydrologic modelling and drought simulations. The satellite rainfall products considered in this study produce rainfall estimates using a combination of both MW and IR approaches.

Recently, there has been an increase in the assessment of the quality of gridded rainfall datasets in Africa. Larbi et al. (2018) evaluated the ability of the CHIRPS gridded rainfall data to reproduce the climatology of the Vea Catchment in Ghana. In Burkina Faso, a study by Dembélé & Zwart (2016) investigated the performance of CHIPRS, PERSIANN, TAMSAT, TRMM, Africa Rainfall estimate Climatology (ARC 2.0), African Rainfall Estimation (RFE 2.0), and African Rainfall Climatology, and time-series using synoptic station data for the period 2001-2014. Due to the high uncertainty associated with these interpolated datasets, it is essential to evaluate the characteristics and pattern of the satellite rainfall datasets at the local scale (Hassan et al., 2020). The mean annual and seasonal rain cycle is necessary to check the performance of gridded datasets in estimating the amount of rainfall (Dembélé & Zwart, 2016). Information on the standardized precipitation index (SPI) is used to assess the frequency of wet and dry days and is essential for water resources management (Hassan et al., 2020; Larbi et al., 2018). The trend analysis of rainfall is essential to understand its pattern in the past and to be able to infer future patterns. Over the years, there has been a reduction in the number of groundbased meteorological stations in Sub-Saharan Africa due to political and financial instability (Poméon et al., 2018a; Usman et al., 2018). In Nigeria, 70% of the total number of rain gauges within the River Niger basin became non-functional between 1985 and 2004 (Oyerinde et al., 2017). This deterioration of existing gauge networks also occurs in other parts of the country. It poses a severe challenge to water resources development and climate change research in Africa's most populous nation. The use of remotely sensed rainfall data is gaining popularity to supplement existing (or replace missing) climate data and support solving water resourcerelated problems and policy making. However, studies showing which satellite-based rainfall products best suit Nigeria's heterogeneous topography and multi-climate regions are still lacking in the literature. Local evaluation of remotely sensed data is necessary before utilization by government agencies because of their inherent uncertainties and limitations, especially in developing countries bedevilled with a paucity of ground-truth data for adequate calibration and bias reductions (Akinyemi et al., 2019; Ayehu et al., 2018). Few studies (Akinyemi et al., 2019; Hassan et al., 2020; Usman et al., 2018) have attempted to validate the capability of some satellite-based rainfall products in Nigeria. However, these studies are region-specific, with no study in the literature showcasing satellite rainfall evaluation over Nigeria stretching over different climatic settings. In the northeastern part of Nigeria, the ability of satellite rainfall products to reproduce rainfall trends from 1981-2015 showed satisfactory results at decadal, monthly, and seasonal time scales (Usman et al., 2018). In southwestern Nigeria, a comparison of satellite and observed rainfall datasets from 1998 to 2016 also showed encouraging results (Akinyemi et al., 2019). However, owing to the poor state of climate gauge networks in Nigeria, assessing the performances of many of the existing satellite rainfall products for Nigerian conditions is lacking in the literature.

This study attempts to complement the aforementioned few studies on satellite rainfall product evaluation in Nigeria by evaluating the performance of three products using twenty-four (24) ground-based stations located all over Nigeria. The selected products were based on rainfall datasets, which use a combination of MW and IR methods and are bias-corrected with rain gauge data. This study aims to evaluate the capability of three satellite rainfall products (CHIRPS, PERSIANN–CDR, and TAMSAT) to reproduce local rainfall characteristics (seasonal and annual climatology) in Nigeria. We also aim to assess the gridded datasets' utility in reproducing inter-annual rainfall variability for the period 1983–2013. The Pearson coefficient of correlation (r), root mean square error (RMSE), and percent bias (PBIAS) were used to evaluate the performance of these satellite products over Nigeria. The remaining part of this study is structured as follows: Section 2.2 describes the data and methods, the findings are presented and discussed in Section 2.3, and the conclusions are made in Section 2.4.

2.2 Materials and Methods

Nigeria, the most populous country in West Africa, has a land area of about 923,770 km² and is situated between Latitudes 4°–14° N and Longitudes 2°–14° E, as shown in Figure 2.1. The widely varying climatic pattern experienced in Nigeria is partly influenced by the presence of the Atlantic Ocean to the southern part and the Sahara Desert to the northern part (Akande et al., 2017). The climate pattern is also affected by distinct relief systems, such as lowlands, highlands, and plateaus, as depicted in Figure 2.1. The major climatic zones divided latitudinally are Guinea (4°–8° N), Savannah (8°–11° N), and Sahel (11°–14° N) (Ogungbenro & Morakinyo, 2014). The spatial variability of Nigeria's climate is greatly influenced by the movement of the Inter-tropical Discontinuity (ITD), a narrow zone of trade-wind confluence between the southwest trade wind from the Atlantic Ocean and northeast trade wind from the Sahara Desert (Abatan et al., 2016).

The Guinea region experiences a mean annual rainfall of about 1575–2533 mm, and the Savannah region is characterized by a mean annual rainfall of about 897–1535 mm, while the

Sahel region receives a mean annual rainfall of about 434–969 mm (Gbode et al., 2019). These authors noted that the Guinea and Savannah regions are characterized by a bimodal rainy season due to the abrupt non-linear latitudinal shift of the rainfall band from a quasi-stationary position of 5° N to about 10° N. This process paves the way for the unimodal rainy season in Sahel from June to October, with the climatological peak in August. The Guinea and Savannah regions experience rainy seasons during March to May (MAM), June–August (JJA), and September–November (SON) seasons, while the Sahel is majorly characterized by a peak rainfall during the July–August (JAS) season. However, all regions experience widespread rainfall events from June to September (JJAS) due to more active convective activities accompanying the deep monsoon flow defined by the northward migration and surface position of the ITD.



Figure 2.1: Digital Elevation Map of Nigeria (in m.a.s.l) showing synoptic station locations within Guinea Coast, Savannah, and Sahel climatic zones (Gbode et al., 2019)

2.2.1 Rainfall Data Description

Gauge Rainfall

This study used twenty-four synoptic rainfall stations distributed across Nigeria, as shown in Figure 2.1 and Table 2.1. Daily observed rainfall data for the period 1983-2013 for these synoptic stations, located across the three climatic regions, were obtained from the Nigeria Meteorological Agency (NiMet) database and used for evaluating the performance of the satellite rainfall products. However, the climatic stations are not evenly distributed within the three climatic zones. Five stations are found within the Sahel, eight are within the savannah, and eleven are located within the Guinea climatic zone. The altitudes of the stations vary from about 40 m to 1160 m above sea level.

Station	Region	Longitude (N)	Latitude (E)	Elevation (m)
Asaba	Guinea coast	6.73	6.18	60
Awka		7.07	6.22	100
Benin		5.63	6.33	80
Calabar		8.32	4.95	80
Enugu		7.48	6.43	300
Ibadan		3.90	7.39	200
Ijebu		3.93	6.82	60
Ikeja		3.33	6.58	40
Ikom		8.70	5.97	40
Iseyin		3.60	7.97	300
Lokoja		6.73	7.80	180
Bauchi	Savannah	9.82	10.28	600
Bida		6.01	9.08	140
Gombe		11.17	10.29	440
Ibi		9.75	8.18	120
Ilorin		4.57	8.53	280
Jos		8.90	9.92	1,160
Kaduna		7.44	10.52	580
Minna		6.55	9.62	280
Gusau	Sahel	6.67	12.17	420
Kano		8.52	12.00	460
Katsina		7.53	13.00	440
Maiduguri		13.27	11.88	280
Nguru		10.45	12.88	340

 Table 2.1: Meteorological Stations

Satellite Rainfall

The advent of satellite observing platforms in the late twentieth century has brought many benefits by providing more spatially complete datasets that help advance our knowledge in atmospheric science and other environmental-related disciplines. Improved spatiotemporal resolution of satellite rainfall products is helpful as input in hydrologic modelling, especially in developing nations and data-scarce regions such as Nigeria. Table 2.2 shows an overview of the three gridded satellite rainfall products, freely available on the internet and assessed against gauged rainfall data in this study. These three products under consideration in this study showed satisfactory results out of a total of ten products, which were evaluated in a large-scale regional study in West Africa (Poméon et al., 2017).

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Satellite product	Temporal coverage	Spatial coverage	Instrument	Spatial Resolution	Temporal resolution	
CHIRPS	1981-present	50° N $- 50^\circ$ S	MW, IR, RG	0.05°	Daily	
PERSIANN– CDR	1983–present	60° N $- 60^\circ$ S	MW, IR, RG	0.25°	Daily	
TAMSAT	1983–present	Africa	IR. RG	0.0375°	Daily	

Table 2.2Overview of Satellite Rainfall Products.

MW = microwave imager, IR = infrared, RG = rain gauge, CHIRPS = Climate Hazards Group InfraRed Precipitation with Station data; PERSIANN-CDR = Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record, TAMSAT = Tropical Applications of Meteorology using SATellite data and ground-based observations.

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) data (Funk et al., 2015) was developed by scientists from the Climate Hazard Group at the University of California, Santa Barbara, in conjunction with the United States Geological Survey (USGS), specifically for monitoring droughts and to analyze shifts in rainfall in the data-sparse African continent. Information on the data inputs used in developing CHIRPS is extensively reported in the literature (Funk et al., 2015).

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks– Climate Data Record (PERSIANN–CDR; hereafter PERSIANN) was developed by the Center for Hydrometeorology and Remote Sensing group of the University of California, Irvine, in conjunction with the National Oceanic and Atmospheric Administration (NOAA) (Dembélé & Zwart, 2016).

Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT) was developed at the University of Reading and integrates about four thousand stations across Africa (Poméon et al., 2017). Information on its development is well documented in several studies (Maidment et al., 2014; Tarnavsky et al., 2014).

2.2.2 Quality Control

Quality control and homogeneity tests were performed on all observed datasets using RClimDex and RHtests software packages in a previous study by Gbode et al. (2019). Quality control was performed to remove erroneous values in the data series, such as negative rainfall values or days with daily rainfall values greater than 200 mm, and replaced with -99. A homogeneity test is essential to correct anomalies that might result from a change in station location and faulty gauging equipment (Wang et al., 2010; Wang & Feng, 2013). Quality control checks were also performed on all of the satellite rainfall datasets using RClimDex software. The permission to use this software package was obtained upon request from the model developers (http://:www.etccdi.pacificclimate.org). Before use in this study, missing and/or erroneous values within these datasets were replaced with -99.

2.2.3 Methodology

Daily rainfall data (1983–2013) were extracted from three satellite rainfall products using geographic coordinates of the twenty-four synoptic stations (Table 2.1) and processed for comparison with observed data. The satellite data were all extracted at grid points closest to the location of each synoptic station. The rainfall amounts were characterized into mean

seasonal, annual, and inter-annual variations to evaluate how well the selected remotely sensed rainfall datasets reproduced observed rainfall characteristics from 1983 to 2013. Daily values were aggregated to monthly values for all datasets under study. Aggregated rainfall values for March to May (early rainfall season), June to August (mid-rainfall season), and September to November (late rainfall season) were processed, and their mean was determined to represent mean seasonal rainfall for the different seasons. Consequently, rainfall amounts for June–September were also aggregated, and the mean for this period was obtained to represent the JJAS season. The JJAS season is the only period in Nigeria when all climatic zones receive rainfall, and it is highly influenced by the Intertropical Convergence Zone (ITCZ) oscillations.

Climatological and statistical evaluations of CHIRPS, PERSIANN, and TAMSAT were conducted against observed datasets. Spatial rainfall patterns representing seasonal climatology (MAM, JJA, and SON) of satellite products were assessed against observed datasets. Annual cycle and inter-annual variability for all locations (Figure 2.1) were evaluated against observed (gauged) data. The ability of the satellite rainfall products to reproduce observed extreme events (wet and dry spells) at the selected twenty-four climate stations was evaluated using the standardized precipitation index (SPI) (McKee et al., 1993). The SPI is based on the probability of rainfall for a given period and is applied in hydro-meteorological studies to monitor drought conditions. The SPI is calculated by fitting a rainfall time series to a probability distribution, which is then normalized so that the mean SPI for that location is zero (McKee et al., 1993). These authors further stated that positive SPI values imply greater than median rainfall while negative values signify lower than median rainfall.

A comparison of monthly rainfall cumulative distribution frequency (CDF) for all satellite product datasets against gauged datasets was performed at all stations to evaluate their deviations from observed/gauged patterns. Furthermore, trend analysis was conducted using the Mann–Kendall (MK) test statistic (Kendall, 1975) to detect monotonic changes in the rainfall time series at a 5% significance level. This statistic tests whether to accept that there is a monotonic trend (alternative hypothesis, Ha) or to reject the null hypothesis (Ho), which states that no trend is present in the time series data (Adeyeri et al., 2019). The MK statistic has been used extensively in hydro-meteorological studies (Adeyeri et al., 2019; Akinsanola et al., 2018; Okafor & Ogbu, 2018) for analyzing monotonic changes in time series data. The MK statistic is stated as:

$$S = \sum_{n=1}^{n} \sum_{j=i+1}^{n} Sgn\left(x_j - x_i\right)$$
(2.1)

Where, x_j and x_i are sequential data values; n is length of datasets. The Signum (Sgn) function is given as:

$$Sgn(x_{j} - x_{i}) = \begin{cases} 1 \text{ if } x_{j} > x_{i} \\ 0 \text{ if } x_{j} = x_{i} \\ -1 \text{ if } x_{j} < x_{i} \end{cases}$$
(2.2)

The statistics (S), the mean E(S), and the variance V(S) can be estimated as (Adeyeri et al., 2019):

$$E(S) = 0 \tag{2.3}$$

$$V(S) = \frac{1}{18} \{ n(n-1)(2n-1) - \sum_{i=1}^{n} t_i \left[(t_i - 1)(2t_i + 5) \right] \}$$
(2.4)

Where, t_i is the extent of any given tie. The standardized test statistic, Z is stated as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{V(S)}} & \text{if } S > 0\\ 0 & \text{if } S = 0\\ \frac{S+1}{\sqrt{V(S)}} & \text{if } S < 0 \end{cases}$$
(2.5)

The remotely sensed rainfall datasets were validated for mean seasonal (for JJAS season) and annual rainfall using the Pearson correlation coefficient (r), root mean square error (RMSE), and percent bias (PBIAS) and were presented by showing their spatial patterns. The equations representing these statistical models are shown below, as reported in other studies (Ayugi et al., 2020; Dembélé & Zwart, 2016; Knoben et al., 2019; Poméon et al., 2017; Pool et al., 2018).

$$r = \frac{\sum_{i=1}^{n} (O_i - \bar{O})(M_i - \bar{M})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^{n} (M_i - \overline{M})^2}}$$
(2.6)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (M_i - O_i)^2}$$
(2.7)

$$PBIAS = \frac{\sum_{i=1}^{n} (O_i - M_i) \times (100)}{\sum_{i=1}^{n} (O_i)}$$
(2.8)

Where, O and M are rain gauge and model values, respectively, \bar{o} and \overline{M} are mean rain gauge and model values respectively, n = number of data pairs, α = measure of flow variability error, β = bias term.

The spatial distribution of climate variables is vital for understanding hydrological processes (Hofstra et al., 2008). This study used the inverse weighting distance (IDW) interpolation method to present the spatial distribution of rainfall characteristics. This method was adopted due to its popularity and wide applications in hydrology (Chen et al., 2017; Yang et al., 2015). The IDW interpolation technique assumes that the weight between an observed and unobserved point decreases exponentially as their distance increases. The characteristics of the interpolated cells were controlled by applying the variable search radius and adopting the default number of input points in the ArcMap window. The IDW function in ArcMap version 10.3 was used in this study and is implemented as follows (Chen et al., 2017):

$$Y(X_o) = \sum_{i=1}^n \lambda_i Y(X_i)$$
(2.9)

$$\lambda_{i} = \frac{d_{io^{-P}}}{\sum_{i=1}^{n} d_{io^{-P}}}, \sum_{i=1}^{n} \lambda_{i} = 1$$
(2.10)

Where, $Y(X_0)$ = interpolated value at point X_0 ; $Y(X_i)$ = observed value at point X_i ; n = number of observations; λ = weight; P = power; d_{io} = distance between unknown point and known point.

2.3 Results and Discussion

2.3.1 Seasonal Climatology

The mean seasonal climatology results for March to May (MAM), June to August (JJA), and from September to November (SON), as well as the June to September (JJAS) period, during which the monsoon and associated rainfall widely dominate the West African region, are

presented in this section. Evaluation of the JJAS period is critical because about 60% of the West African population depends on rain-fed agriculture for their source of livelihood (Poméon et al., 2018a). These classifications were computed using data from 1983 to 2013 compared to in-situ datasets, as shown in Figure 2.1. These comparisons assessed the difference between observed and remotely sensed rainfall datasets.

The spatial distribution of mean MAM, JJA, and SON seasons for observed (gauged), CHIRPS, PERSIANN, and TAMSAT data are presented in Figure 2 (a) - (c). As depicted in Figure 2.2(a) (MAM season), all products captured the high rainfall in the south and the low rainfall in northeast Nigeria. The lowest gauged seasonal rainfall for this period was about 5 mm at Nguru, while the highest amount of 232 mm was in Calabar, as expected, as the latter station is located on the Guinea coast, closer to the Atlantic Ocean. At the same time, the former is situated in the Sahel. Though the products performed reasonably well in capturing the seasonal rainfall within the Savannah and Sahel regions, they poorly reproduced observed amounts in the Guinea coast (Ikom), Savannah (Bida and Kaduna), and Sahel (Nguru) while underestimations occurred within the range of 2 - 52 mm in Guinea (Benin, Calabar, Enugu, Ibadan, Iseyin), Savannah (Bauchi), and Sahel (Kano, Katsina, Lokoja).



Figure 2.2(a) Spatial distribution of March-May (MAM) mean rainfall (mm/month) over Nigeria



Figure 2.2(b): Spatial distribution of June–August (JJA) mean rainfall (mm/month) over Nigeria.



Figure 2.2(c): Spatial distribution of September–November (SON) mean rainfall (mm/month) over Nigeria.

During the JJA (Figure 2.2b), the seasonal spatial pattern of rainfall amount for all products was consistent with observed datasets. All products recorded low seasonal rainfall amounts in Nguru and high amounts in Calabar. Specifically, all of the models showed underestimations

in Guinea (Asaba, Awka, Benin, Ibadan, and Ijebu), Savannah (Bauchi and Bida), and Sahel (Gombe and Kano). The CHIRPS product agrees more with the observed data than the PERSIANN and TAMSAT datasets in capturing the spatial distribution pattern during the JJA season.

During the SON season (Figure 2.2c), all products could also reproduce the spatial and seasonal rainfall pattern over Nigeria, with the highest rainfall recorded in the south and the lowest in the north. The observed seasonal amount was overestimated in many locations across the three climatic zones.

Generally, all the rainfall products' spatial and seasonal patterns were consistent with the gauged (observed) dataset for all considered seasons. This revealed that all the products captured the seasonal south-north rainfall oscillations tightly coupled with the ITCZ latitudinal migration.

2.3.2 Annual Cycle of Mean Monthly Rainfall

The annual cycles (1983 - 2013) of mean monthly rainfall at twenty-four (24) point-based synoptic station scales were compared to corresponding point-based datasets for the satellite-based products in the Sahel, Savannah, and Guinea coast climate zones as shown in Figure 2.3(a-c), respectively. The magnitude of the errors of the satellite-based products from observed data for all locations is presented in Table 2.3. Results showed that satellite product datasets could capture trends and peaks at all synoptic locations, with error deviations ranging from 3 to 60 mm. This shows that the latitudinal oscillations of the ITCZ from southern latitudes to northern latitudes, which results in convective processes, were well captured by all satellite-based products.

In the Sahel region (e.g., Nguru station, Figure 2.3a), the products underestimated observed rainfall peak at Gusau and Kano synoptic stations, with CHIRPS producing the lowest RMSE (Table 2.3) values of 13.5 mm and 35.6 mm, respectively. All gridded products produced a good model fit with minimal residuals ranging from 3 mm to 11 mm for Maiduguri and Nguru synoptic stations. At Katsina, the rainfall peak was over-predicted by all products with RMSE values of 12 mm, 15 mm, and 17 mm for TAMSAT, CHIRPS, and PERSIANN, respectively.

The seasonal cycle was reasonably captured by all the entire products in the Savanna zone. The mean seasonal cycle at the Jos climate station is depicted in Figure 2.3b. CHIRPS and TAMSAT datasets represent the peaks better than PERSIANN, especially in Ilorin and Minna. Overestimations of rainfall peaks by all satellite products were observed at Bida, Ibi, Ilorin, Kaduna, and Jos, with RMSE values ranging from 7-26 mm. Generally, CHIRPS and TAMSAT presented lower RMSE values ranging from 7.2-20.8 mm compared to higher values by the PERSIANN, which ranges from 12.3-23.2 mm.

Contrary to results from the Sahel and Savannah regions, more significant biases were detected for all of the products in all the locations within the Guinea region, except at Iseyin (Figure 2.3c) and Lokoja, as shown in Table 2.3. This notable difference can be partly explained by the region's heterogeneous land use and land cover, as well as the Atlantic Ocean's presence at the country's south border, which significantly influences rainfall processes. The satellite rainfall datasets showed a wide range of error magnitudes from 9.2 to 60.1 mm. All products recorded RMSE > 10 mm values at all synoptic stations, except for minimal RMSE <10 mm values

recorded by CHIRPS at Lokoja. All satellite products overestimated (underestimated) rainfall peak at Ikom (Benin), showing a significant RMSE value > 29 mm.

It is also important to note that all the satellite-based products showed strong agreement (r > r0.9) with gauged datasets at all locations for mean monthly data in Figure 2.3. Generally, the CHIRPS and TAMSAT datasets performed better in capturing the unimodal and bimodal annual rainfall patterns as influenced by the ITCZ for all locations studied. Unimodal and bimodal rainfall patterns as a result of oscillations of the ITCZ from 15° S to 15° N (Ayugi et al., 2020) were well represented by all satellite products in all climatic zones of Nigeria. In a previous study (Akinyemi et al., 2019), the performance of CHIRPS rainfall estimates compared to gauge records for six stations in southwest Nigeria showed strong relationships with high correlation (r) values greater than 0.70. The CHIRPS also showed strong relationships with gauge data at monthly and seasonal time resolutions in a study (Usman et al., 2018) conducted in the Sudano-Sahelian zone of Nigeria. In another study (Gebrechorkos et al., 2018) in East Africa (Ethiopia, Kenya, and Tanzania), CHIRPS was reported as the preferential data source for climate change and hydrological studies in ungauged locations. These authors noted that CHIRPS was more accurate than African Rainfall Climatology, version 2.0, (ARC), Observational-Reanalysis Hybrid (ORH), and Regional Climate Models (RCMs) in reproducing mean monthly rainfall amounts over East Africa. Dinku et al. (2018) across East Africa (Ethiopia, Kenya, Somalia, Uganda, Rwanda, and Tanzania) reported a strong relationship with CHIRPS, TAMSAT, and gauge data with correlation values greater than 0.9 at monthly time steps.



Figure 2.3a: Mean Monthly Rainfall Data at Nguru Climatic Station in the Sahel Zone.



Figure 2.3b: Mean Monthly Rainfall Data at Jos Climatic Station in the Savannah Zone.



Figure 2.3c: Mean Monthly Rainfall Data at Iseyin Climatic Station in the Guinea Coast Zone.

Station	Region	CHIRPS	PERSIANN-CDR	TAMSAT
Asaba	Guinea coast	28.3	28.3	23.6
Awka		19.1	22.8	22.8
Benin		29.4	49.1	35.5
Calabar		22.1	45.9	30.8
Enugu		12.9	24.2	11.8
Ibadan		21.1	18.1	11.7
Ijebu		20.4	34.1	14.8
Ikeja		21.2	27.0	20.6
Ikom		60.1	31.2	50.2
Iseyin		9.6	10.0	11.2
Lokoja		9.2	12.4	12.7
Bauchi	Savannah	15.9	20.7	17.7
Bida		8.1	14.7	7.2
Gombe		15.8	12.3	20.8
Ibi		13.8	15.1	12.1
Ilorin		11.2	23.2	7.7
Jos		9.5	20.3	10.4
Kaduna		13.3	18.9	16.2
Minna		8.7	26.0	7.5
Gusau	Sahel	13.5	15.2	37.7
Kano		35.6	45.7	48.5
Katsina		15.7	16.5	11.7
Maiduguri		6.8	4.8	11.4
Nguru		3.0	8.7	3.9

Table 2.3 Root mean square error (RMSE) values (in mm) for all products with respect to gauged datasets.

2.3.3 Inter-Annual Rainfall Anomaly

The capabilities of CHIRPS, PERSIANN, and TAMSAT products to reproduce observed yearto-year rainfall anomalies using standardized precipitation index (SPI) within the three climatic zones are shown in Figures 2.4(a-c) by using a single station in each zone for illustrations. The SPI at annual resolutions were estimated differently using rainfall records for gauge and satellite-based rainfall products at point-based location scale for the period 1983-2013. Table 2.4 presents the correlation scores between each satellite product and gauge data for all locations within the study area at the annual time step. All products exhibited moderate agreement with gauged datasets with correlation values greater than 0.5 (r > 0.5), except at locations within the Sahel region (Katsina; TAMSAT in Gusau), Savannah region (Bida, Ilorin, Jos and Kaduna; PERSIANN at Bauchi; PERSIANN and TAMSAT at Ibi and Gombe), and the Guinea coast region (Calabar and Ikom; CHIRPS at Benin; PERSIANN at Asaba and Ibadan), as shown in Table 2.4.

Station	Region	CHIRPS	PERSIANN-	TAMSAT
			CDR	
Asaba	Guinea coast	0.56	0.38	0.49
Awka		0.54	0.47	0.56
Benin		0.37	0.66	0.56
Calabar		0.44	0.40	0.41
Enugu		0.77	0.61	0.75
Ibadan		0.67	0.41	0.68
Ijebu		0.61	0.63	0.69
Ikeja		0.62	0.60	0.63
Ikom		0.24	0.36	0.25
Iseyin		0.67	0.57	0.48
Lokoja		0.65	0.50	0.46
Bauchi	Savannah	0.68	0.43	0.55
Bida		0.28	0.11	0.23
Gombe		0.55	0.42	0.44
Ibi		0.56	0.10	0.05
Ilorin		0.43	0.11	0.23
Jos		0.36	0.43	0.29
Kaduna		0.31	0.13	0.40
Minna		0.56	0.69	0.50
Gusau	Sahel	0.48	0.48	0.02
Kano		0.76	0.83	0.76
Katsina		0.37	0.36	0.32
Maiduguri		0.74	0.71	0.64
Nguru		0.75	0.64	0.59

Table 2.4 Correlation of Annual Rainfall Anomalies for Satellite Products with Respect to Gauge Data.

SPI results for Kastina, Bida, and Ikom stations are shown in Figures 2.4a, 2.4b, and 2.4c, respectively. For the period of rainfall time series considered, and in many locations, the CHIRPS dataset exhibited satisfactory performance over PERSIANN and TAMSAT in reproducing the year-year variations of rainfall anomalies. The unsatisfactory correlation found in most of the locations may be attributed to the presence of large-scale forcings on local climatic conditions (Akinsanola et al., 2018).



Figure 2.4a: Inter-annual variations of SPI at Kastina in the Sahel climatic zone.



Figure 2.4b: Inter-annual variations of SPI at Bida in the Savannah climatic zone.



Figure 2.4c: Inter-annual variations of standardized precipitation index (SPI) at Ikom in the Guinea coast climatic zone.

2.3.4 Empirical Cumulative Distribution Frequency

The ability of satellite-based rainfall products to reproduce the frequency of gauged monthly rainfall amounts from 1983 to 2013 is evaluated using the empirical cumulative distribution function (ECDF) plots. Comparisons of the ECDFs of mean monthly rainfall at a point-based scale for gauged and satellite products within Sahel, Savannah, and Guinea Coast climatic zones are shown in Figures 2.5(a-c) using one station in each climatic zone. Generally, similar patterns of gauged monthly rainfall distributions in all locations were captured by the satellite products. The frequency of monthly rainfall within the Sahel climatic zone was significantly overestimated by all products at the Kano synoptic station (Figure 2.5a) in the range of 200 - 400 mm/month. TAMSAT and PERSIANN exhibited overestimation (100-200 mm/month) at Gusau and Katsina, respectively. However, all products showed close monthly rainfall probabilities to gauged datasets at Maiduguri and Nguru.



Figure 2.5a: Empirical cumulative distribution function (ECDF) of mean monthly rainfall in Kano within the Sahel climatic zone.

In the Savannah region, both CHIRPS and TAMSAT captured overall frequencies of observed values at all locations, although with slight margins, as shown in Figure 2.5b. The PERSIANN showed consistent frequencies with gauged datasets but underestimated the mean monthly rainfall frequency at Ibi, Ilorin, Jos, Kaduna, and Minna by 150 - 300 mm/month.



Figure 2.5b: ECDF of mean monthly rainfall in Bauchi within the Savannah climatic zone.

In the Guinea coast climatic zone, the entire product showed consistent frequencies, except at Ikom (Figure 2.5c), where CHIRPS and TAMSAT significantly underestimated rainfall frequency in the 200 - 400 mm/month range. Conversely, all products overestimated rainfall at more than 200 mm/month (at Asaba, Benin, Awka, Ibadan, Ijebu, and Iseyin) and more than 400 mm/month (at Calabar).



Figure 2.5c: ECDF of mean monthly rainfall in Ikom within the Guinea coast climatic zone.

2.3.5 Trend Analysis

Table 2.5 shows the p-values result of the non-parametric Mann-Kendall method used to assess significant trends at annual and seasonal (MAM, JJAS, and SON) time scales. The test was performed for all datasets at all synoptic stations under consideration in this study. In the Sahel, all the satellite products and gauged datasets exhibited significant positive trends in the annual rainfall series, except for Gusau, where only TAMSAT and PERSIANN showed similar consistency. MAM in-situ rainfall features a positive significant trend in Katsina, which is accurately replicated by the PERSIANN dataset. This significant positive trend was also observed at Gusau (PERSIANN and TAMSAT), Maiduguri (CHIRPS), and Nguru (CHIRPS and PERSIANN). The JJAS observed rainfall showed an increasingly significant trend, which aligns with all satellite product datasets in this zone, except for Gusau (gauge, CHIRPS, and TAMSAT were insignificant). During the SON season, observed data from Kano and Maiduguri exhibited a significant trend replicated by PERSIANN and TAMSAT, as seen in Table 2.5.

All satellite-based products and local rainfall annual series in Savannah showed a significant positive trend at Bauchi. TAMSAT exhibited a significant increasing trend at all locations within this zone. The same was observed for PERSIANN at Bida, Jos, Kaduna, and Minna, while CHIRPS showed the same trend in Jos. Both CHIRPS and TAMSAT indicated a significant increasing trend at the seasonal scale, as seen in the gauged rainfall at Bauchi during the JJAS period. During the SON period, significant positive trends exhibited by the gauge time series at Ibi and Ilorin were reproduced by all satellite products, while in Minna, only PERSIANN and TAMSAT could successfully replicate the gauged increasing significant trend. Many of the products replicated seasonal observed trends in most locations but with different levels of accuracy, as presented in Table 2.5.

Over the Guinea coast, TAMSAT consistently exhibited significant positive trends in all locations at the annual time step (Table 2.5), and it was consistent with gauged data recorded at Benin, Calabar, Enugu, and Ijebu. From Table 5, significant positive trends shown in the

gauge time series were also replicated by PERSIANN (at Ijebu) and CHIRPS (at Calabar). At the seasonal scale during the MAM period (Table 2.5), TAMSAT exhibited significant positive trends in all stations within the Guinea coast, except in Iseyin. This significant trend was only exhibited in the gauged time series at Benin. For the high monsoon period (JJAS season), gauged data at Calabar exhibited the same significant positive trends as CHIRPS and TAMSAT. Moreover, observed data at Ibadan, Ijebu, and Iseyin showed the same significant positive trends with all satellite products during the SON season. Similar significant positive trends were also exhibited between gauge, PERSIANN, and TAMSAT datasets in Enugu and Ikeja and between gauged data and TAMSAT at Benin in the same season.

Station	Data	Annual	MAM	JJAS	SON	Climatic Zone
Gusau	Observed	0.20	0.92	-0.95	-0.82	Sahel
	CHIRPS	0.82	-0.31	0.82	0.71	
	PERSIANN	2.65	2.26	2.14	2.69	
	TAMSAT	2.51	2.60	1.39	2.53	
Kano	Observed	3.81	1.56	3.74	2.86	
	CHIRPS	2.35	0.92	2.41	1.33	
	PERSIANN	3.09	1.94	3.37	2.35	
	TAMSAT	3.03	1.14	3.03	2.46	
Katsina	Observed	3.06	2.67	2.58	1.36	
	CHIRPS	2.31	0.74	2.34	1.22	
	PERSIANN	3.71	2.58	2.43	2.04	
	TAMSAT	3.16	1.43	0.00	1.58	
Maiduguri	Observed	3.64	0.73	3.26	1.97	
	CHIRPS	2.11	2.11	2.07	1.22	
	PERSIANN	3.26	1.73	3.26	2.44	
	TAMSAT	3.60	1.04	3.37	2.87	
Nguru	Observed	2.58	0.48	2.75	0.89	
	CHIRPS	2.45	2.14	2.28	1.29	
	PERSIANN	3.74	2.14	3.77	2.58	
	TAMSAT	3.88	1.34	3.88	2.21	
Bauchi	Observed	3.94	-0.64	4.08	1.87	Savannah
	CHIRPS	2.11	-0.95	2.18	0.44	
	PERSIANN	2.01	1.33	1.94	2.31	
	TAMSAT	2.94	1.16	3.03	2.35	
Bida	Observed	0.48	-0.88	0.17	1.05	
	CHIRPS	0.03	-0.41	-0.85	0.61	
	PERSIANN	2.55	2.58	0.75	2.79	

Table 2.5. Mann-Kendall Statistic (Z) at Annual and mean Seasonal Time Series. JJAS = June - September.

	TAMSAT	2.51	2.60	1.39	2.53	
Gombe	Observed	0.65	-1.63	0.58	0.85	
	CHIRPS	1.33	0.17	1.29	1.87	
	PERSIANN	1.39	0.51	1.67	3.20	
	TAMSAT	4.22	1.19	3.74	3.06	
Ibi	Observed	0.00	-0.54	-0.85	2.11	
	CHIRPS	0.99	-0.30	0.07	2.11	
	PERSIANN	1.33	2.17	-0.48	3.23	
	TAMSAT	1.71	2.62	2.38	2.84	
Ilorin	Observed	0.41	-0.10	0.00	2.24	
	CHIRPS	1.33	-0.75	0.51	3.63	
	PERSIANN	1.67	1.46	-0.17	3.23	
	TAMSAT	2.71	1.63	1.16	2.75	
Jos	Observed	1.50	0.37	0.08	1.73	
	CHIRPS	1.97	-0.20	2.35	0.00	
	PERSIANN	2.45	2.52	1.43	1.84	
	TAMSAT	3.84	2.65	3.60	2.28	
Kaduna	Observed	1.60	0.71	0.92	1.80	
	CHIRPS	0.92	-0.03	0.20	0.14	
	PERSIANN	3.43	1.70	2.75	2.72	
	TAMSAT	4.01	2.69	3.06	2.33	
Minna	Observed	1.53	0.31	1.56	2.65	
	CHIRPS	0.75	0.37	-0.34	1.77	
	PERSIANN	3.09	2.62	0.82	2.86	
	TAMSAT	3.20	2.99	1.92	3.33	
Asaba	Observed	0.31	0.75	-0.73	0.27	Guinea
	CHIRPS	1.60	1.29	0.10	1.70	
	PERSIANN	0.24	1.16	-2.28	1.02	
	TAMSAT	3.30	3.16	1.80	3.03	
Awka	Observed	1.73	1.80	-0.92	0.88	
	CHIRPS	1.09	0.74	-0.17	2.24	
	PERSIANN	0.51	1.90	-2.41	2.10	
	TAMSAT	3.81	3.71	1.87	3.16	
Benin	Observed	2.31	2.86	1.12	2.67	
	CHIRPS	0.17	0.92	-0.31	1.12	
	PERSIANN	0.37	1.12	-1.67	1.50	
	TAMSAT	3.09	3.21	1.63	3.06	
Calabar	Observed	2.65	0.88	2.11	0.54	
	CHIRPS	2.41	0.10	2.44	-0.24	

	PERSIANN	1.09	1.77	-1.94	-1.70
	TAMSAT	3.94	3.23	0.03	2.41
Enugu	Observed	2.28	1.12	1.19	4.39
	CHIRPS	1.12	1.70	0.51	1.84
	PERSIANN	1.05	2.28	-1.53	2.62
	TAMSAT	3.57	3.94	1.94	3.23
Ibadan	Observed	1.09	0.20	1.36	2.31
	CHIRPS	0.54	-0.99	0.00	2.31
	PERSIANN	1.16	0.48	-0.10	3.16
	TAMSAT	2.78	2.18	0.61	3.23
Ijebu	Observed	3.17	0.25	2.45	2.57
	CHIRPS	1.77	0.14	0.54	2.24
	PERSIANN	2.04	0.446	-0.24	3.06
	TAMSAT	3.47	2.58	0.88	2.82
Ikeja	Observed	1.83	0.84	0.81	2.78
	CHIRPS	1.05	0.41	0.07	0.20
	PERSIANN	1.35	0.24	-0.24	2.21
	TAMSAT	3.91	2.55	1.53	2.69
Ikom	Observed	1.67	0.65	-0.17	1.73
	CHIRPS	-0.03	0.20	-1.56	0.85
	PERSIANN	0.88	2.35	-2.75	2.41
	TAMSAT	3.40	2.41	1.70	2.86
Iseyin	Observed	1.05	0.10	0.03	2.04
	CHIRPS	1.90	-0.20	0.00	2.79
	PERSIANN	2.04	0.71	0.37	3.54
	TAMSAT	3.16	1.56	0.53	3.30
Lokoja	Observed	0.68	1.46	-0.48	0.99
	CHIRPS	0.85	-0.27	0.34	1.60
	PERSIANN	0.37	1.63	-1.43	2.21
	TAMSAT	2.48	2.99	1.05	2.48

A positive (negative) Z-value indicates an increasing (decreasing) trend. Bold values indicate a significant trend at a 95% confidence interval

2.3.6 Seasonal Evaluation of Satellite Rainfall Products

The capability of the satellite products to reproduce local rainfall characteristics at the synoptic station level was assessed using statistical methods. Results of these statistics at mean seasonal and annual time resolution for 1985 - 2013 are presented as spatial plots produced using the IDW interpolation method. The suitability of satellite products is dependent not only on low RMSE and PBIAS values but also on a strong correlation coefficient between gauge and model values (Akinsanola et al., 2018).
Inter-Annual Variation of Mean Seasonal Rainfall

The JJAS period was selected for evaluating the performance of the satellite products because, during this period, all three climatic zones in Nigeria experienced rainfall (Adeniyi & Dilau, 2015). Each satellite product was compared against gauge datasets using statistics: r, RMSE, and PBIAS, and are presented in Figures 2.6, 2.7, and 2.8, respectively. Within the Sahel (Figure 2.6), CHIRPS and PERSIANN performed satisfactorily, exhibiting good correlations (r > 0.5) against gauge data, except in Kastina (where r < 0.4). However, TAMSAT presented weak correlations (in Kastina and Gusau), with an r-value of -0.01 at Gusau. Results also indicate statistical significance at a 95% confidence level for all products except in Kastina. The spatial plot of the satellite product bias (Figure 2.7) exhibits low bias in the range of -33.6 to 23.1% and RMSE (Figure 2.8) of 86 to 104 mm in Kano.

Results within the Savannah zone (Figure 2.6) show that the gridded products generally were unsuitable for simulating seasonal JJAS rainfall. Only the CHIRPS product reliably showed a strong correlation (r > 0.5) in Bauchi, Gusau, Ilorin, and Ibi but was not suitable (r < 0.5) at Bida, Kaduna, and Minna. PERSIAN and TAMSAT exhibited weak correlations (r < 0.4) at all locations, except that TAMSAT performed well at Bauchi (r = 0.6). However, low bias (Figure 2.7) and RMSE (Figure 2.8) were mainly prevalent over the Savanna zone.

In the Guinea coast zone (Figure 2.6), CHIRPS was more suitable and showed reasonable correlation with gauge datasets except at Ikom, where it exhibited a weak correlation (r = 0.07) in comparison to PERSIANN (r = 0.3) and TAMSAT (0.1). Consequently, the correlation between CHIRPS and gauge was significant at a 95% confidence level, except at Ikom and Calabar. Furthermore, CHIRPS and TAMSAT exhibit bias of 26.3% and 20.3%, respectively. The RMSE values above 78 mm were observed in Benin, Calabar, and Ikom and were consistent for all products. Generally, the CHIRPS products showed good results during the JJAS rainfall season compared to other products under study.



Figure 2.6. Correlation Coefficient of Mean JJAS Rainfall.



Figure 2.7. Percent bias (PBIAS) of mean JJAS rainfall.



Figure 2.8. Root mean square error (RMSE) of mean JJAS rainfall.

Inter-Annual Variation of Mean Annual Rainfall

The results in this section reveal the inter-annual variation of annual rainfall (mm/year) of all products. Findings from Figure 2.9 show that CHIRPS can reproduce observed annual rainfall with good correlation values (r > 0.4) at Bida, Ikom, Kaduna, and Katsina. The PERSIANN and TAMSAT data did not well capture a more significant portion of the Savannah zone. The northwest region of the Sahel zone was also poorly represented by the TAMSAT product, exhibiting a low correlation of less than 0.4.



Figure 2.9. Correlation coefficient of annual rainfall (mm/year) over Nigeria.

Figure 2.10 depicts the spatial plot of satellite product bias from gauge datasets. Both CHIRPS and TAMSAT show the same pattern of bias, with model overestimations of gauge datasets visible in southwestern and northeastern Nigeria. Both products overestimated gauge records in Savannah and the northwestern region of Nigeria.



Figure 2.10. Percent bias (PBIAS) of annual rainfall (mm/year) over Nigeria.

The RMSE pattern (Figure 2.11) for all satellite products shows a gradient from south to north, with RMSE values above 300 mm within the Guinea zone (Benin, Calabar, Ikom) and Sahel (Kano).



Figure 2.11: Root mean square error (RMSE) of annual rainfall (mm/year) over Nigeria.

2.4 Conclusion

Recently, the easy accessibility of high-quality satellite rainfall products over Africa has stirred up research activities in rainfall-dependent sectors. Most applications at regional scales showed promising results and underscored the utility of these products in data-scarce regions. In this study, the capabilities of the CHIRPS, PERSIANN, and TAMSAT to reproduce local rainfall characteristics in Nigeria from 1983 to 2013 were evaluated at a point-pixel scale. Using statistical approaches, satellite product performances were analyzed at seasonal, inter-seasonal, and inter-annual time scales.

Findings from the spatial distribution of seasonal rainfall showed that all of the products followed the same pattern, depicting the south (high) to north (low) gradient of rainfall amount. All products visibly captured this trend during the early (MAM) and late (SON) seasons, but poorly reproduced it during the wet rainfall period (JJA and JJAS). The satellite products captured the unimodal and bimodal trend of rainfall peaks, with high RMSE values observed in locations within the Guinea Coast climatic zone. The products with varying magnitude of accuracy simulated the inter-annual variations of local rainfall anomaly. The pattern of frequency of monthly rainfall occurrence was also in agreement with gauge datasets, but with varying accuracy. It is noting that CHIRPS performed better than other products in reproducing local rainfall climatology in most locations.

Within the Sahel, a significant increasing trend was accurately reproduced by all products at the annual time series except at Gusau, where only CHIRPS and gauge datasets exhibited a similar trend. At the seasonal time series, variations in capturing significant trends exist at different locations and for different products. Generally, product evaluation statistics show that CHIRPS scored high correlations (r > 0.5) in many of the locations within all zones. However, poor agreements between all products against observed data are seen around the southern and northwestern axis of Nigeria.

3 Evaluating the skill of the mesoscale Hydrologic Model (mHM) for discharge simulation in sparsely-gauged basins in Nigeria

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Abstract: Predictive hydrologic modelling to understand and support agricultural water resources management and food security policies in Nigeria is demanding due to the paucity of hydro-meteorological measurements. This study assessed the skill of using different remotely sensed rainfall products in a multi-calibration framework for evaluating the mesoscale hydrologic Model (mHM) performance across four different data-scarce basins in Nigeria. Grid-based rainfall estimates obtained from several sources were used to drive the mHM in different basins in Nigeria. Model calibration was first performed using only discharge records and a combination of discharge and actual evapotranspiration forced with different gridded rainfall products. The mHM forced with CHIRPS produced reasonable Kling-Gupta efficiency KGE) results (0.5 > KGE < 0.85) under both calibration frameworks. However, constraining model parameters under a multi-calibration arrangement showed no significant discharge simulation improvement in this study. Results show the utility of the mHM for discharge simulation in data-sparse basins in Nigeria.

Keywords: UPH20, MPR, discharge, CHIRPS

3.1 Introduction

Modelling of hydrologic systems is crucial to understanding how climatic variables drive hydrologic responses, which are highly sensitive to land use/cover changes and population dynamics. Model-based quantifying the components of the water balance provides strategic information to policymakers and water resources managers for developing key water resources management projects (Nesru et al., 2020). In Nigeria, in-situ measurement of hydrologic variables is primarily constrained by financial instability, weak institutions and political instability, resulting in a steady decline and uneven distributions of existing hydrometeorological networks (Adeoti, 2020; Poméon et al., 2018a). Precipitation is a critical driver in the hydrologic system, affecting other hydrologic processes' spatial and temporal variability. Gridded rainfall products provide continuous and spatially homogenous estimates and have become an alternative, especially in data-scarce regions (Ayehu et al., 2018). However, their ability to reproduce observed hydrologic processes is a pre-condition for use in water resources modelling (Dembélé et al., 2020a).

The availability of remotely sensed datasets (elevation, soil, land use/cover, climatic variables) led to the development of complex hydrologic models. However, these efforts did not impact model results (Poméon et al., 2018a). This is because the traditional model calibration method involving determining the best model parameter set could reproduce observed hydrologic variables but misrepresent critical watershed processes (Rajib et al., 2018). The importance of understanding hydrologic processes and improving their mathematical representation is well highlighted during the International Association of Hydrologic Sciences (IAHS) scientific decade (2003 - 2012) (Hrachowitz et al., 2013). To overcome the problems of over-

parameterization and equifinality, the Mesoscale Parameter Regionalization (MPR) proposed by Samaniego et al. (2010) presents a technique which links model parameters at a coarser scale with their counterparts at a finer resolution using pedotransfer functions, whereby only the global parameters that define these relationships are obtained through calibration. Compared with other regionalization methods (e.g. standard regionalization), MPR showed superiority in preserving the spatial variability of state variables and overall performance of model hydrologic processes simulation (Kumar et al., 2010; Samaniego et al., 2010). The MPR technique reduces the number of free mHM calibration parameters and seeks to address Question 20 (reducing model uncertainty) of the Unsolved Problems in Hydrology (UPH 20) (Blöschl et al., 2019). In this study, the critical research question is: What is the performance of the mHM-MPR technique in reproducing the temporal variation of the streamflow process under a paucity of input-data conditions? This is the second attempt to apply the mHM for hydrologic modelling in data-scarce basins and the first time within Nigeria. This study assessed the suitability of using gridded-rainfall products in a multi-calibration framework for evaluating the performance of mHM for river discharge simulations across four different datascarce basins in Nigeria.

3.2 Methodology

3.2.1 Study area

The study area consists of four river basins located in the northern part of Nigeria (Lat $4^{\circ} - 14^{\circ}$ N, Lon $2^{\circ} - 14^{\circ}$ E), which were selected based on the availability of discharge data: Jamaare (13929.711 km²), Hadejia (16820.336 km²), Kaduna (64848.594 km²) and Oroo (4500.174 km²) as shown in Figure 3.1. Rainfall in this region is unimodal and is impacted by the latitudinal movement of the Inter-Tropical Discontinuity (ITD). Jamaare, Hadejia, and Kaduna basins receive an annual mean rainfall of about 434 – 969 mm, while the Oroo basin is characterized by an annual mean of 897 – 1535 mm (Gbode et al., 2019; Ogbu et al., 2020).



Figure 3.1: Study locations - Jamaare, Hadejia, Kaduna and Oroo River Basins

3.2.2 The Mesoscale Hydrologic Model (mHM)

mHM is a grid-based, process-based and fully distributed hydrologic model which simulates various hydrologic processes (evapotranspiration, infiltration, surface and subsurface runoff, etc.) that are formulated based on the HBV and VIC models (Kumar et al., 2013; Samaniego et al., 2010). Spatial-temporal simulations of hydrologic processes in the mHM are processed at the grid/cell scale. Three levels of gridded information are required for mHM set-up: Level-0 (basin characteristics), Level-1 (dominant hydrological processes) and Level-2 (meteorological datasets), to account for sub-grid variability (Kumar et al., 2013). The MPR proposed by Samaniego et al. (2010) is the main feature in the mHM model and serves to bridge the gap between observations and the basin scale (Rakovec et al., 2019). The MPR involves a two-step parameterization procedure (Figure 3.2); (1) model parameters at Level-0 are regionalized by linking them with their corresponding basin characteristics through linear or non-linear transfer functions; (2) In this stage, effective parameters are obtained by linking the regionalized parameters with their corresponding one at Level-0 through an upscaling operator. The primary goal of the MPR is to derive global model parameters that are spatially seamless, scale-independent and transferable across locations (Rakovec et al., 2019).



Figure 3.2: Schematic diagram of MPR (Samaniego et al., 2010)

3.2.3 Data

In this study, mHM was set up using grid-based meteorological, soil, land use and morphological datasets. Rainfall estimates were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Climate Prediction Center (CPC), European Center for Medium-Range Weather Forecast (ECMWF) Reanalysis 5th Generation (ERA5), Global Precipitation Climatological Center (GPCC) and Multi-Source Weighted Ensemble Precipitation (MSWEP) and used as model forcing. Potential evapotranspiration was computed with the Hargreaves method using daily temperature data obtained from the ERA5

product. These climatic products were selected based on their performances in previous studies (Dembélé et al., 2020b; Hounguè et al., 2021; Ogbu et al., 2020; Poméon et al., 2017) within the West African region. Soil attributes for six different soil layers were extracted from the Harmonized World Soil Database, version 1.2, while Land use and cover information were obtained from the Globecover product. Slope, aspect, flow accumulation and flow direction were derived from a 90 m resolution digital elevation model obtained from the Shuttle Radar Topographic Mission database. mHM calibration and validation were performed using discharge (Q) and actual evapotranspiration information obtained from the German-developed Global Runoff Data Center (GRDC) and Global Land Evaporation Amsterdam Model (GLEAM) databases, respectively.

3.2.4 Model Set-up

mHM version 5.11 (Samaniego et al., 2021) was set up in four data-scarce basins with varying rainfall inputs for each setup. In the first case, calibration and validation were performed using only Qobs. In the second case, they were performed using Qobs and AET. Simulation and calibration periods vary for all basins due to the paucity of data and significant gaps in existing discharge time series. Discharge (Q) optimization was performed using the Dynamically Dimensioned Search (DDS) (Tolson & Shoemaker, 2007) algorithm (4,000 iterations), based on the Kling-Gupta Efficiency (KGE) (Gupta et al., 2009; Kling et al., 2012) metric at a daily time step. Best model parameter sets are obtained with the DDS algorithm by using about 10 - 20% of the number of iterations required by the Shuffle Complex Evolution optimization method (Rakovec et al., 2019). The KGE is an improved version of Nash Sutcliffe Efficiency (NSE) and constitutes correlation (r), variability and mean bias, as shown in Equation 3.1.

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$$
(3.1)

Where, r = linear correlation, $\alpha = measure$ of flow variability error, $\beta = bias$

The multivariable calibration, using Q and domain average AET (Equation 3.2), was used to complement Qobs and assess if a more realistic result would be achieved.

$$SO_{30} = [1 - KGE(Q)] \times RMSE(\overline{\text{basin ETA}})$$
(3.2)

Where, $SO_{30} = mHM$ objective function Number 30,

KGE = Kling-Gupta Efficiency,

RMSE $(\overline{basinETA})$ = root mean square error sof the basin average actual ET simulation.

3.3 Results and Discussion

3.3.1 Model Performance for Discharge

Generally, model results varied across rainfall datasets for all domains during calibration and validation periods for Qobs simulation (Figure 3.3). Daily discharge simulations showed reasonable results (KGE > 0.5) in all domains except for MSWEP (in Hadejia), GPCC (in Oroo) and CPC (in Kaduna) during model calibration. On the other hand, validation results showed KGE > 0.5 in Jamaare Basin (for ERA5, CHIRPS and CPC) and Oroo Basin (for CHIRPS).



Figure 3.3: Qobs calibration and validation for gridded products in each basin

An example of daily mHM simulated hydrographs for the Jamaare River Basin during model calibration (Figure 3.4) and validation (Figure 3.5) showed an acceptable fit with the Qobs time series. However, the KGE value decreased from 0.85 (during model calibration) to 0.61 (during model validation) (see Figures 3.4 and 3.5).



Figure 3.4: Daily hydrograph simulation when calibration is performed using only Qobs for Jamaare



Figure 3.5: Daily hydrograph simulation when validation is performed using only Qobs for Jamaare

3.3.2 Model Performance for Qobs and AET Model Calibration Scheme

In the Qobs/AET model calibration setup, daily streamflow simulations exhibited the same trend, if not slightly worse, as in the Qobs model calibration scheme (see Figure 3.6). This result is similar to a previous mHM study (Poméon et al., 2018a) in West Africa, with the Qobs model calibration scheme showing improved discharge predictions. Unsatisfactory KGE

results (< 0.5) were obtained in Oroo Basin (driven by GPCC) and Kaduna Basin (forced with GPCC) during model calibration. For the validation period, discharge simulations showed acceptable results (SO₃₀ > 0.5) in Oroo (driven by CHIRPS), Hadejia (CPC and MSWEP) and Jamaare (ERA5, CHIRPS, 0.51). We showed example hydrographs for the Jamaare River Basin produced using Qobs/AET model calibration setup (Figure 3.7) and for model validation (Figure 3.8). For this example, the SO₃₀ value decreased from 0.85 (calibration) to 0.64 (validation), while correlation followed the same trend from 0.85 – 0.78.



Figure 3.6: Calibration and validation results for gridded products using Qobs/AET calibration setup





Figure 3.7: Optimized daily hydrograph simulation using Qobs/AET mHM model setup for Jamaare



Figure 3.8: Daily hydrograph validation using Qobs/AET mHM model setup for Jamaare

3.3.3 Discussion

The flow simulation performances driven by the different gridded rainfall products under the different optimization frameworks vary across the different domains, which are modelled in

this study. Overall, the simulated streamflow exhibited acceptable KGE values (KGE > 0.50) during calibration periods compared to model validation for most rainfall products. These poor performances could be attributed to gaps in discharge observations, which exist more within validation periods. Minor KGE improvements were achieved when mHM was calibrated with both Qobs and AET, yet only evident in Hadejia and Jamaare basins and do not reflect mHM robustness for this study. This poor performance in discharge simulation displayed when model parameters are constrained under a multivariable calibration scheme was also reported in another study (Poméon et al., 2018a) conducted within the West Africa region. Visual inspection of simulated and observed hydrographs showed that the CHIRPS outperformed other rainfall products in mimicking observed discharge trends, as shown in Figures 3.4, 3.5, 3.7 and 3.8. The performances of the CHIRPS dataset in most of the domains are in line with its ability to reproduce observed rainfall at a point-to-pixel scale in the West African region, as shown in several studies (Dembélé & Zwart, 2016; Ogbu et al., 2020; Poméon et al., 2017). In this study, satisfactory KGE scores obtained in most domains while using remotely sensed rainfall datasets, especially during model calibration, could be attributed to implementing the MPR technique within the mHM structure, which reduced the number of free calibration parameters while preserving its spatial variability.

3.4 Conclusion

In this study, the discharge simulation skill of the mHM was evaluated in four data-limited basins located in Nigeria under multivariable optimization setups. The MPR technique, which integrates the spatial heterogeneity of a domain's physiographic characteristics and overcomes the problem of model over-parameterization, is well suited for application in this data-scarce region. Notwithstanding the significant gaps in Qobs, the reanalysis product (ERA5) and the satellite rainfall dataset (CHIRPS) were consistent in satisfactory discharge simulations in most domains. However, significant improvements in discharge simulations were not observed when mHM was calibrated using Qobs and AET. Currently, the mHM lacks a reservoir component and several dams within the study domains were not included during model setups. Furthermore, mHM accepts only three land use and land cover classes (impervious, pervious, and forest), which do not sufficiently represent the existing classes. This study presents the utility of different gridded-rainfall datasets for discharge simulation in data-scarce regions in Nigeria. However, the government should prioritise investments in hydro-climatic instrumentations at all levels in Nigeria, as remote-sensing rainfall products can only complement in-situ records.

4 Testing the mHM-MPR Reliability for Parameter Transferability across Locations in North-Central Nigeria

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Abstract: Hydrologic modelling in Nigeria is plagued by non-existent or paucity of hydrometeorological/morphological records, which has detrimental impacts on sustainable water resource management and agricultural production. Nowadays, freely accessible remotely sensed products are used as inputs in hydrologic modelling, especially in regions with deficient observed records. Therefore, utilizing the fine-resolution spatial coverage offered by these products in a parameter regionalization method that supports sub-grid variability is appropriate. This study assessed the transferability of optimized model parameters from a gauged to an ungauged basin using the mesoscale Hydrologic Model-Multiscale Parameter Regionalization (mHM-MPR) technique. The ability of the fifth generation European Centre for Medium-Range Weather Forecasts Reanalysis product (ERA5), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), Global Precipitation Climatology Centre (GPCC), and Multi-Source Weighted-Ensemble Precipitation (MSWEP) gridded rainfall products to simulate observed discharge in three basins was first assessed. After that, the CHIRPS rainfall product was used in three multi-basin mHM setups. Optimized model parameters were then transferred to independent basins, and the reproduction of observed discharges was assessed. Kling-Gupta Efficiency (KGE) scores improved when mHM runs were performed using optimized parameters compared to default parameters for discharge simulations. Optimized mHM runs performed reasonably (KGE > 0.4) for all basins and rainfall products. However, only one basin showed a satisfactory KGE value (KGE = 0.54) when optimized parameters were transferred to an ungauged basin. This study underscores the utility of the mHM-MPR tool for parameter transferability during discharge simulation in data-scarce regions.

Keywords: CHIRPS; streamflow; mHM; MPR

4.1 Introduction

The declining economic conditions in many sub-Saharan African (SSA) countries have resulted in about 50 - 60% of their workforce depending on agriculture (subsistence farming) as a source of livelihood (Poméon et al., 2018a). A nation's agricultural sector is essential for ensuring food security, mental health, the health of its population, economic stability, and national development. In Sub-Saharan Africa (SSA), the agriculture production per capita trend has declined since 1960, resulting in 30% of its population being food insecure (Bjornlund et al., 2020). Farming is characterised mainly by rain-fed agriculture and is practised at the subsistence level. Sub-Saharan African countries import considerable wheat, vegetable oil, and fertilizer from Ukraine and Russia. Unfortunately, the ongoing Ukraine-Russian war has disrupted food importation, thereby increasing already high food prices and worsening food security for millions of the population. In the era of increasing global warming, rainfall variability, and more frequent hydrologic extremes (flood and drought), the source of livelihood of a great majority of the population in this region is threatened (Dembélé & Zwart, 2016). Based on a study analyzing rainfall observations over West Africa, these authors noted that the average annual rainfall during 1970 - 2009 was below the annual average recorded from 1900-1970. Other studies (Chapman et al., 2020; Emediegwu et al., 2022; Ofori et al., 2021) projected significant and extensive impacts of climate change on agriculture due to

reductions in the length of farming seasons, shifts in seasonality, more severe dry spells, heat stress, and an increase in water-stress risks.

The availability of high-quality rainfall data is essential for water-related research and to support policy-making in designing and managing water infrastructure (Akinsanola et al., 2018; Caldera et al., 2016; Dembélé & Zwart, 2016; Hounguè et al., 2021; Ogbu et al., 2020). An analysis of annual rainfall data in Nigeria for a period of 72 years (1916–1987) showed a decreasing trend over southern, middle belt, and northern Nigeria (Anyadike, 1993). Many studies (Adeyeri et al., 2019; Akande et al., 2017; Animashaun et al., 2020; Okafor & Ogbu, 2018; Usman et al., 2018) reported significant variability in rainfall trends in different regions in Nigeria. In recent decades, economic instability, weak government institutions, and inadequate infrastructure have led to a decline in rainfall-monitoring networks across this region, posing great insecurity to water resource planning and management (Poméon et al., 2018a). Additionally, the growing Nigerian population, expansion of urban areas, insufficient water governance, and lack of adequate water laws have hindered the effective implementation of integrated water resources management (IWRM), resulting in more water-related issues (Ezenwaji et al., 2015; Ngene et al., 2021). Furthermore, the unavailability of observational hydro-meteorological data has impeded hydrologic-related research efforts and consequently is increasingly exposing the population to risks of extreme hydrologic events, hunger, and economic instability (Shiru et al., 2021).

The emergence of gridded rainfall products at high spatio-temporal resolution and the development of distributed hydrological modelling procedures have created possibilities for water resource modelling in ungauged basins (Camici et al., 2020; Dembélé et al., 2020a; Ogbu et al., 2020). Spatial rainfall data provide homogenous spatial coverage over inaccessible locations and has an advantage over in situ gauged data. However, the application of remotely sensed rainfall data for research and operational hydrology in Nigeria is scarce in published works of literature to date. Many studies (Camberlin et al., 2019; Contractor et al., 2015; Dembélé et al., 2020b; Hassan et al., 2020; Mbaye et al., 2016; Nhi et al., 2019; Raimonet et al., 2017; Trinh-Tuan et al., 2019) have shown that gridded rainfall datasets can satisfactorily replicate observed spatio-temporal characteristics of gauged in situ records, although with reported inconsistencies. Detailed reviews of the characteristics and performance of gridded rainfall data are found in the literature (Dinku et al., 2018; Hersbach et al., 2020; Sun et al., 2018). However, notwithstanding the advances in the development of gridded rainfall products, they are rarely applied in operational hydrology due to inherent biases (Bitew & Gebremichael, 2011; Dembélé et al., 2020a), hence the need for validation to identify which product suits a specific region or locality.

Realistic hydrologic simulations and forecasting are constrained mainly by hydrologic model complexity and input-data requirements (Samaniego et al., 2011). The paucity of hydrometeorological records in data-scarce regions has hindered hydrologic modelling applications. However, many studies (Fujihara et al., 2014; Poméon et al., 2018b; Schuol et al., 2008; Xie et al., 2012) have shown success in utilizing global meteorological datasets for water balance analysis in SSA. These freely available datasets have proven to be suitable alternatives and have aided realistic hydrologic process simulation and a better understanding of hydrologic systems (Poméon et al., 2017). However, the utilization of remotely sensed data has increased model complexity and, consequently, the need for higher computational power (Kumar et al., 2010), which is not always available in developing countries (Tegegne et al., 2017). Furthermore, fully distributed hydrologic models exist to cope with available high-resolution inputs, but the issue of realistic process representation persists (Beven, 2001). Many authors (Beven, 2001, 2002; Kumar et al., 2010) noted that problems of model nonlinearity, scale, uniqueness, uncertainty, and equifinality had not been satisfactorily addressed by the development of these complex distributed hydrologic models and their application at the mesoscale. Issues of over-parameterization and equifinality of feasible solutions aid the production of unreliable hydrologic outputs even when a good fit between observed and simulated discharge is achieved, creating uncertainties (Schoups et al., 2008). Even when model parameters can be deduced through optimization these values cannot be transferred to ungauged basins or to other scales other than that used during model calibration (Kumar et al., 2013; Ocio et al., 2019; Samaniego et al., 2010). It is against this background that the International Association of Hydrologic Sciences (IAHS) in 2012 initiated the Scientific Decade of Prediction in Ungauged Basins (PUB) in their efforts to encourage more hydrologic research aimed toward the understanding of hydrologic processes, especially in data-scarce basins (Hrachowitz et al., 2013).

Parameterization techniques that are geared toward reducing the number of free parameters and model complexity have been developed in the past (Golian et al., 2021; Kumar et al., 2013; Samaniego et al., 2010). For example, the soil and water assessment tool (SWAT) (Arnold et al., 1998) the model employs the hydrologic response unit (HRU) technique, where a unique land use, soil, and slope area is homogeneously grouped before model calibration. The hydrologic water balance is then modelled at the HRU level, as shown in many studies (Bizuneh et al., 2021; Guug et al., 2020; Ndulue et al., 2018; Odusanya et al., 2019; Xie et al., 2012; Zettam et al., 2020). However, a significant drawback of this approach is that those model parameters are not directly linked to physical basin properties (Kumar et al., 2013). Alternatively, distributed hydrologic models can also be parameterized using the multiscale parameter regionalization (MPR) method (Samaniego et al., 2010). In this technique, a distributed hydrologic model can be calibrated by connecting the model parameters to the basin's physical characteristics by assuming a priori-defined relationship, e.g., pedotransfer function (Hundecha & Bárdossy, 2004; Rakovec et al., 2016a). Several studies (Kumar et al., 2013; Samaniego et al., 2010) reported that the strength of the MPR method lies in its ability to account for sub-grid variability of soil, land use, and elevation characteristics to support the transfer of model parameters to other scales or ungauged basins other than those used during model calibration.

The mesoscale Hydrologic Model (mHM) (Kumar et al., 2013; Samaniego et al., 2010) employs the MPR technique to aid the transferability of parameters to other scales and ungauged basins. Detailed information on the MPR-mHM is explicitly explained by Kumar et al. (2013) and Samaniego et al. (2010). The mHM model has been successfully applied in over 220 basins in Germany (Zink et al., 2017), 300 pan-European Union basins (Samaniego et al., 2019), the continental United States (Rakovec et al., 2019), as well as in South East Asia (Saha et al., 2021). In contrast, there were only a few applications of the mHM on the African continent at the time of writing this paper. In a study (Poméon et al., 2018a) in a few West African basins, mHM produced satisfactory results. Additionally, mHM was used to model hydrological processes in the Volta River Basin, Ghana (Dembélé et al., 2022; Dembélé et al., 2020b). Applying mHM in any basin within Nigeria has not been undertaken before or is not evident in scientific published literature. In light of this information and given the sparse network of hydro-meteorological facilities that exist in Nigeria at present, this study employs the mHM-MPR technique for hydrologic simulation under data-scarce conditions. This approach is appropriate considering the challenges to water resources development in Nigeria due to recent modifications in the climate system and its impact on rain-fed agriculture. Furthermore, the unavailability of in situ input datasets for realistic hydrologic modelling in Nigeria and the need to apply distributed hydrologic models to take advantage of existing highresolution spatial datasets will support reliable simulation of hydrologic extremes (flood and droughts). We believe that the ability of the MPR method to support sub-grid variability and effective landscape representation can address the challenge of estimating reliable hydrologic model parameters at the mesoscale in Nigeria. This study addresses the following research questions:

- 1. What is the performance of gridded rainfall datasets over Nigeria?
- 2. How does mHM perform across selected basins when forced with different gridded rainfall datasets?
- 3. What is the performance of mHM when parameters are transferred from gauged to ungauged basins?

4.2 Methods

4.2.1 Study Area

Nigeria is located between latitude 4° -14° N and longitude 2° -14° E (Figure 4.1). It is bordered in the north by the Sahara Desert and south by the Atlantic Ocean. Its geographical position gave rise to InterTropical Discontinuity (ITD), which controls the weather throughout the year. The ITD is the region of lowest atmospheric pressure, which separates the dry northeast trade winds from the Sahara Desert from the wet southwest monsoon from the Atlantic Ocean (Akande et al., 2017). Three major climatic zones are subdivided latitudinally, as presented by Omotosho & Abiodun (2007) exist in Nigeria: Guinea coast (Latitude 4 - 8° N), Savannah (8 -11° N), and Sahel (11 - 14° N). Distinct climate characteristics over these regions are described in an earlier study (Gbode et al., 2019; Ogbu et al., 2020).





The study basins are the Kaduna (64,848 km²), Hadejia (16,820 km²), and Jamaare (13,929 km²) River Basin systems, which are located in the semi-arid north-central region of Nigeria (Figure 4.2). This region is characterized by sparse vegetation with scattered shrubs occasioned by frequent droughts and high rainfall variability (Adeyeri et al., 2019; Odunuga et al., 2011). Most inhabitants dwelling in the Hadejia–Jamaare river basin are involved in cattle rearing, irrigated agriculture, cropland farming, and trading as sources of income (Adeyeri et al., 2019). During monsoon periods (April - September), farmers cultivate major crops, including sorghum, maize, millet, yams, soybean, and irrigated rice in the dry season (October - March).

The Kaduna River is a critical water supply to the metropolis's inhabitants and for irrigated agriculture (Okafor & Ogbu, 2018). Both the Hadejia and Jamaare rivers discharge into Lake Chad but take their sources from both the Kano highlands and Jos Plateau, respectively (Odunuga et al., 2011). Constructions of large-scale projects (e.g., dams) on these rivers (Shiroro dam on the Kaduna River; Tiga and Challawa Gorge dams on the Hadejia-Jamaare river system) (Adeyeri et al., 2019; Odunuga et al., 2011; Okafor & Ogbu, 2018) have impacted water flows and subsequently affected the micro-climate within the region. These dams were not represented during the modelling process due to the lack of a dam/reservoir component in mHM. The mean annual rainfall cycle over the north-central region of Nigeria is about 700 - 800 mm, with uni-modal peak in August. All study basins are located within the same agro-climatic region and are characterized by karstic geological formations and sparse vegetation as a result of long periods of dry season and short periods of monsoon season. The major differences between these basins are varied topography (Figure 4.2) and anthropogenic activities on the landscape. Large urban centers characterized by high human population and economic activities exist majorly within the Kaduna and Hadejia basins.



Figure 4.2. DEM for Kaduna (Basin No. 572), Hadejia (GRDC No. 1837410), and Jamaare river basins (GRDC No. 1837250) (U.S Geological Survey, 2010).

4.2.2 The mHM Structure: Description

The mesoscale Hydrologic Model (mHM) is a grid-based, spatially explicit process-based hydrologic model forced with hourly or daily precipitation, temperature, and potential evapotranspiration datasets (Kumar et al., 2013; Samaniego et al., 2010). Its mathematical formulations are based on numerical approximations of dominant hydrologic processes as found in Hydrologiska Byrans Vattenbalansavdelning (HBV) (Lindström et al., 1997) and Variable Infiltration Capacity (VIC) (Liang et al., 1994) models. The major components modelled in mHM include canopy interception, snow accumulation, soil moisture dynamics, infiltration, surface runoff, evapotranspiration, deep percolation, baseflow and flow routing, and groundwater storage (Samaniego et al., 2011). This study estimated potential evapotranspiration (PET) using temperature information obtained from ERA5 and read into mHM with aspect correction. A six-layer (50 mm, 150 mm, 300 mm, 500 mm, 1000 mm, and 2000 mm) infiltration capacity approach was used to calculate soil moisture in the root zone. Runoff routing from upper to lower grids through river networks was generated using the Muskingum-Cunge method or the kinematic wave equation. The next version of mHM will also have a full Richard's and soil-temperature module for better integration with a fully distributed groundwater model. mHM currently has several modules for PET estimation and a forward operator to assimilate CRNS observations. Interested readers can find a detailed mHM description in the previously published literature (Kumar et al., 2013; Samaniego et al., 2010). mHM code is open source and is published in an online repository - sgit.ufz.de/mHM. Version 5.11.0, accessed on 06.10.2020 was used for this research.

To describe the spatial dynamics of hydrologic processes per grid cell during hydrologic simulation, mHM requires at most 28 parameters (see Appendix A). Three mHM levels (Level-0, Level-1 and Level-2) represent the spatial variability of state and input variables. Level-0 has the finest resolution and comprises morphological data such as elevation, land use, and slope, while Level-2 has the coarsest resolution and contains meteorological forcing data of precipitation, temperature, and evapotranspiration. Level-1 represents the dominant hydrologic processes and model outputs. Few mHM parameters (e.g., β_2 , β_4 , β_9 , β_{11} , β_{12} , and β_{14} are assumed as global parameters because they do not exhibit spatial variability and, as such, are not regionalized (Samaniego et al., 2010).

Estimating each of the 28 mHM parameters for each grid modelling cell through calibration will result in over-parameterization (Kumar et al., 2010). To reduce the number of free calibrated parameters vis à vis the prediction uncertainty, MPR was employed to translate high-resolution input data variables into model parameters using transfer functions and upscaling operators (Samaniego et al., 2010). This is performed in two steps, as reported in Kumar et al. (2013). In the first stage, mHM parameters evaluated at the input data scale (Level-0) are coupled with basin physical properties (e.g., terrain, soil texture, land cover, geology, etc.) through a priori established linear or non-linear transfer functions and a set of global parameters. In the final stage, these high-resolution parameters are upscaled to produce fields of effective parameters at the required hydrologic modelling spatial scale (Level-1) using upscaling operators such as arithmetic mean, geometric mean, or harmonic mean. Kumar et al. (2010) summarized these two steps as follows:

$$\beta_{pi}(t) = O_p \langle \beta_{pj}(t) \quad \forall j \in i \rangle_i$$
(4.1)

$$\beta_{pj}(t) = f_p(u(t)_j()) \tag{4.2}$$

where p = number of model parameters; $u_j = v$ -dimensional predictor vector for cell j at Level-0, which is contained by cell i at Level-1; $O_p \langle \beta_{pj}(t) \quad \forall j \in i \rangle_i =$ upscaling operator applied for regionalization of the parameter, p; $\gamma =$ s-dimensional vector of global parameters to be calibrated; v and s denote the total number of basin predictors and the total number of free parameters to be calibrated, respectively.

This procedure generates quasi-scale independent parameters which characterize sub-grid variability. In the end, approximately 64 global parameters were established over the whole modelling domain instead of independently estimating parameters at each grid cell. The advantage of this approach lies in the reduction of model complexity and overparameterization, allowing transferability of model parameters across catchments and improving model sub-grid variability and overall hydrologic simulation performance (Samaniego et al., 2010). A calibration technique was then performed to adjust these parameters to simulate realistic historical hydrologic variables. Interested readers can find a detailed description of mHM in previous studies (Kumar et al., 2013; Rakovec et al., 2019; Samaniego et al., 2017). The mHM regionalization technique is superior to other regionalization schemes by reducing the dimensionality of parameter space while maintaining sub-grid variability. In a study (Samaniego et al., 2010) to assess the performance of the MPR and the Standard Regionalization (SR) methods using a distributed hydrologic model, MPR results showed superiority in many aspects. Furthermore, the MPR method was also tested with other hydrologic models over large continental domains with satisfactory results (Imhoff et al., 2020; Mizukami et al., 2017; Samaniego et al., 2017).

4.2.3 Data and Inputs

Morphological Datasets

Digital elevation model (DEM) data at a resolution of 0.002° was obtained from the Global Multi-resolution Terrain Elevation Data (GMTED2010) (U.S Geological Survey, 2010). ArcMap geographical information system (GIS) was used to process the study basins' slope, flow direction, aspect, and flow accumulation. Geological properties at 0.5° were obtained from the Global Lithological Map (GliM) version 1.0 database (Hartmann & Moosdorf, 2012).

Soil information related to physical properties, including soil depth, bulk density, sand, and clay content, was obtained from SoilGrids database (Hengl et al., 2017) at a resolution of 250 m for different soil layers and used during the model setup.

In the mHM, land use data is aggregated and restricted to three (3) major classes: coniferous and mixed forest (class 1); impervious areas such as settlements, highways, and industrial parks (class 2); pervious areas representing fallow lands, agricultural lands, and pastures (class 3), using information obtained from the European Space Agency (ESA) at 300 m spatial resolution (Bontemps et al., 2011). The monthly gridded leaf area index (LAI) was obtained from the Global Inventory Modeling and Mapping Studies (GIMMS) at 8 km spatial resolution (Zhu et al., 2013).

Meteorological Data

Four gridded precipitation products (ERA5, CHIRPS, GPCC, and MSWEP) (Table 4.1) comprising satellite, reanalysis, and gauge datasets were evaluated at the synoptic station scale (grid-to-point analysis) and over three distinct climatic regions in Nigeria. These products were selected based on their performance in previous studies (Dembélé & Zwart, 2016; Ogbu et al., 2020; Poméon et al., 2017) in the West African sub-region. These studies further noted that the GPCC, for example, satisfactorily captures the high variability that characterizes West African rainfall events. This robustness by the GPCC is unsurprising as its development incorporates gauge records obtained from national meteorological agencies. Thermal infrared imagery and in situ station data are incorporated to develop CHIRPS gridded observations. MSWEP was produced by merging in situ gauge, satellite, and reanalysis rainfall estimates, while ERA5 was developed from historical records using advanced modelling and data assimilation systems. Daily rainfall data (1983 - 2013) from 24 synoptic stations (see Figure 4.1) were obtained from the Nigeria Meteorological (NiMet) Agency and used as references to evaluate these gridded datasets at the climatic region scale. The selection of this period (1983–2013) is a consequence of missing data for many locations. Statistical metrics such as the Kling-Gupta efficiency (KGE) (Gupta et al., 2009), Pearson correlation coefficient (r), per cent bias (PBIAS), and root mean square error (RMSE) (Moriasi et al., 2015) were used to assess model performance against in situ gauge observations. The KGE addresses several limitations of the NSE and is based on the decomposition of NSE into three components (correlation, variability (α), and bias (β)). KGE values range from - ∞ to 1, and KGE = 1 designate perfect agreement between predictions and observations. Beta (β) is the ratio of the mean of the predicted values to the observed values. It has an ideal value of 1 (i.e., ideal $\beta = 1$), while alpha (α) is the ratio between the standard deviation of the predicted value and observed values. The ideal value for $\alpha = 1$. Pearson's correlation coefficient describes the degree of collinearity between model-simulated and observed time series records and ranges from -1 to 1. No relationship exists between predicted and observed data when r = 0. On the other hand, a perfect positive or negative relationship exists when r = 1 or -1, respectively. PBIAS quantify the likelihood of predicted values deviating from their observed counterparts. In this case, PBIAS = 0 indicates accurate model prediction, while negative and positive values signify model overestimation and underestimation biases, respectively. RMSE measures the standard deviations of the prediction errors. A smaller RMSE value designates better model performance.

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$$
(4.3)

where r is the linear correlation between simulation and observation, α is the flow variability, and β is the bias ratio.

$$r = \frac{\sum_{1}^{n} (o_i - \overline{o})(s_i - \overline{s})}{\sqrt{\sum_{1}^{n} (o_i - \overline{o})^2 \sum_{1}^{n} (s_i - \overline{s})^2}}$$
(4.4)

$$PBIAS = \frac{\sum_{i=1}^{n} o_i - S_i}{\sum_{i=1}^{n} o_i} \times 100$$
(4.5)

where O and S are observed and simulated values, respectively, and i is time steps.

Precipitation Product	Data Sources	Spatial Coverage	Spatial Resolution
ERA5	Reanalysis	Global	0.25°
CHIRPS	Satellite, gauge, reanalysis	50° N - 50° S	0.05°
GPCC	Gauge	90° N - 90° S	1.0°
MSWEPv2.2	Satellite, gauge, reanalysis	Global	0.1°

Table 4.1 Precipitation products evaluated in this study

Discharge Data

Daily discharge data for study basins obtained from the database of the World Meteorological Organization German Global Runoff Data Center (GRDC) and Nigerian Hydrological Services Agency (NHISA) were used for mHM calibrations and validation (Table 4.2). GRDC documents river discharge data on behalf of the World Meteorological Organization and with the permission of national governments. The problem of missing data necessitated the use of different periods for each study basin during model calibration. The GRDC station No. 1837250 is hereafter named Basin 250, while GRDC Station No. 1837410 is hereafter named Basin 410 to correspond with the 3-digit Basin 572. We acknowledge the policy guiding the documented dissemination of GRDC data as https://www.bafg.de/GRDC/EN/01 GRDC/12 plcy/data policy node.html;jsessionid=D0D2 E24F2991D2AE1C9FA4BEF25C995A.live11311/ accessed on 6 October 2020.

Basin Name	GRDC Station No	Period of Coverage	Station Name	Source
Jamaare	1837250 (250)	1983 - 1997	Kotagum	GRDC
Hadejia	1837410 (410)	1987 - 1991	Wudil	GRDC
Kaduna *	572	1989 - 1995	Wuya	NHISA, Nigeria

Table 4.2. Daily discharge data.

*Obtained from Nigeria Hydrological Services Agency (NHISA).

Hydrological Modeling Framework

To guarantee some level of trust in the mHM results in this study, a modelling experiment was developed where the model output (discharge) was assessed for 12 different simulation runs while varying precipitation datasets (CHIRPS, ERA5, GPCC, and MSWEP) across 3 river basins and using default model parameters. Due to limited climate data availability, potential evapotranspiration was computed by applying the Hargreaves–Samani method (Hargreaves & Samani, 1985) driven with ERA5 daily mean temperature and daily temperature ranges for all model setups. Firstly, hydrologic simulations for each river basin were performed, forced separately with each gridded precipitation product while using default model parameter values. Secondly, all model setups were calibrated for discharge simulation using each gridded precipitation dataset. Performance in discharge simulations for different model setups (i.e.,

different precipitation datasets) was assessed using the Kling–Gupta efficiency (Kling et al., 2012) metric (Equation (4.3). The choice of the KGE method stems from the fact that it addresses the limitations of NSE and is now the preferred choice for model calibration and evaluation (Knoben et al., 2019). Popular optimization algorithms which produce optimal solutions include shuffled complex evolution (Duan et al., 1993), adaptive simulation annealing (Ingber, 1993), particle swarm optimization (Eberhart & Kennedy, 1995), covariance matrix adaptation evolution strategy (Hansen, 2007), and dynamically dimensioned search (DDS) (Tolson & Shoemaker, 2007), algorithm. The DDS algorithm is more effective and well-suited for computationally intensive hydrologic modelling than the shuffled complex evolution (SCE) optimization method. The DDS provides an automatic and faster stochastic neighbourhood search method for finding the best parameter combinations within a user-set number of iterations during distributed hydrologic modelling (Tolson & Shoemaker, 2007). Once the best-performed gridded dataset is established, it is used in the next stage of modelling experimentation. Thirdly, a multi-basin mHM setup was developed by setting up the mHM for three different basin combinations (Basins 250 + 410, Basins 572 + 410, Basins 250 + 572) using only CHIRPS datasets to infer unique model parameter sets for every basin combination. Optimized parameter sets obtained from the two-basin combinations were used to simulate discharge in an independent third basin. This approach is necessary to assess the feasibility of transferring mHM-optimized parameters to a different basin for stream discharge simulation.

4.3 Results and Discussion

4.3.1 Gridded Precipitation Rainfall Product Performance

Daily gridded precipitation estimates (1983 - 2013) were obtained on a grid-to-point scale using the location of synoptic weather stations, as shown in Figure 4.1. Taylor diagrams depicting time series of daily gauge rainfall compared to grid-based products for stations within the Sahel, Savannah, and Guinea coast regions are presented in Figures 4.3 - 4.5, respectively.



Figure 4.3: Taylor diagram of synoptic stations within the Sahel climatic zone.



Figure 4.4: Taylor diagram of synoptic stations within Savannah climatic region.



Figure 4.5: Taylor Diagram of Synoptic Stations within Guinea coast region.

Correlation and RMSE values for some selected synoptic stations within each of the three climatic zones, as presented in Figure 4.3 (Sahel), Figure 4.4 (Savannah) and Figure 4.5 (Guinea), show varying results without any particular order at daily temporal resolution. In the Sahel, only GPCC was able to record satisfactory correlation (r > 0.5) and RMSE (RMSE > 12) for all locations under consideration. This trend was also the same in the Savannah region, with correlation values above 0.6 (i.e., r > 0.6) and lower RMSE values (RMSE > 9). In the Guinea coast region, an acceptable result (r > 0.9, RMSE > 5) was only obtained in Lokoja (Figure 4.5).

GPCC showed consistently satisfactory performances compared to in situ station data, mainly in the Sahel (Figure 4.3) and Savannah (Figure 4.4) regions. Similar studies (Ogunjo et al., 2022; Salaudeen et al., 2021) exhibited the same performance when the GPCC dataset was evaluated against synoptic stations in Nigeria. These authors attributed the GPCC performances to integrating in situ gauge rainfall records in its algorithm during development.

The general performances of the GPCC in many of the locations agree with the results of (Ogunjo et al., 2022) in their study to evaluate the performances of three gridded rainfall products over Nigeria. This performance is attributed mainly to incorporating in situ rainfall observations within the GPCC computational algorithm. Other studies (Poméon et al., 2017; Zandler et al., 2019) showed similar trends concerning the GPCC's ability to reproduce station records.

The mean annual cycle of all precipitation datasets over each climatic zone was evaluated for gauge and gridded rainfall data records. Results over the Sahel, Savannah, and Guinea coast regions are presented in Figure 4.6, and the error indices are shown in Figure 4.7.



Figure 4.6. Mean annual cycle over the Sahel, Savannah, and Guinea coast region.



Figure 4.7: Error Indices for rainfall products.

The annual precipitation cycle of mean monthly rainfall for each of the three climatic regions implies that all grid-based products could reproduce observed rainfall trends and peaks, though with a varying magnitude of errors, as seen in Figure 4.7. This also signifies that these grid-based products captured the latitudinal oscillations of convective processes from southern latitudes to northern latitudes well, which characterize the West African monsoon. Furthermore, rainfall seasonality in all regions was well-reproduced by grid products under

consideration in this study; the unimodal rainfall peak was reproduced in the Sahel and Savannah regions, while all grid-based products in the Guinea Coast region showed bimodal peaks. All gridded datasets recorded high KGE (KGE ≥ 0.8) and NSE values (NSE ≥ 0.8) in all climatic regions but were not presented in this study. Low RMSE (<10 mm) and bias ($\pm 6\%$) values were recorded by the CHIRPS gridded data in all locations and showed its ability to reproduce the West African monsoon with low error margins. The acceptable performance of the CHIRPS dataset in this study is in agreement with other studies (Akinyemi et al., 2019; Dembélé et al., 2020a; Satgé et al., 2019) carried out over the SSA region.

All precipitation products in the Savannah and Guinea coast regions (Figure 4.6) showed a nearly similar trend compared to in situ observations to those presented for the Sahel region. Satgé et al. (2020) suggested that mismatches between satellite rainfall datasets and observations, as is evident in the Sahel and Guinea coast regions (Figure 4.6), could be attributed to differences in reporting times for all datasets. In their study (Satgé et al., 2019, 2020), satellite-based rainfall products (e.g., CHIRPS, MSWEP) showed overall better performance over reanalysis products which is in agreement with our findings in this study. In the Sahel, ERA5 gave RMSE > 25 and PBIAS > 20% (Figure 7) against lower values obtained for other products.

4.3.2 Default and Optimized Model Results

During mHM exploratory runs, discharge simulations were performed using default model parameters while varying precipitation inputs across the three study basins. Twelve default model runs were conducted to evaluate simulated discharge results against observed discharge. The result of exploratory mHM simulations using default parameter values is shown in Table 4.3. To assess which gridded precipitation input reproduced gauged discharge time series, mHM was calibrated for each river basin while varying precipitation inputs. KGE values during optimized mHM runs are also shown in Table 4.3.

Simulation Using Default mHM Parameters		Simulation Using Optimized mHM Parameters			Forcing	
Jamaare (Basin 250)	Hadejia (Basin 410)	Kaduna (Basin 572)	Jamaare (Basin 250)	Hadejia (Basin 410)	Kaduna (Basin 572)	
0.68	-1.18	-2.22	0.79	0.66	0.51	CHIRPS
0.06	0.68	-1.78	0.75	0.64	0.44	ERA5
0.65	-0.53	-1.78	0.76	0.74	0.52	MSWEP
0.42	-1.34	-1.50	0.45	0.63	0.49	GPCC

Table 4.3 KGE results for default and optimized mHM discharge simulations.

Discharge simulations in the Jamaare (Basin 250), Hadejia (Basin 410), and Kaduna (Basin 572) basins using default mHM parameters while varying precipitation inputs, as presented in Table 4.3, generally show poor KGE results. Acceptable KGE values, as recommended by Knoben et al. (2019), were obtained for discharge simulation in the Jamaare River basin when

forced with CHIRPS (KGE = 0.68) and MSWEP (KGE = 0.65). In the Hadejia and Kaduna River basins, none of the gridded rainfall products showed satisfactory results except ERA5 in the Hadejia basin (KGE = 0.68). Using KGE = 0 as a threshold between good and bad model simulation in this study, negative KGE scores (KGE < 0) obtained mainly in the Hadejia and Kaduna basins designate poor model performance. Additionally, none of the poor-performing basins provided a KGE value greater than -0.41, and, as such, this signifies that the result did not improve upon using the mean, as reported by Knoben et al. (2019). Overall, the results of the mHM exploratory (using default parameter values) indicate unacceptable performance in almost all modelled basins. These poor KGE results obtained using default parameters are similar to those obtained in another mHM application (Poméon et al., 2018a) in West African Basins. The study of Poméon et al. (2018a) and our research share similarities; both applied mHM in West African Basins, and potential evapotranspiration data were read with an aspectdriven correction. Both studies produced poor KGE values when mHM was driven with GPCC product in all basins using the default model setup. In this study, default mHM simulation results forced with each meteo forcing are vague and unclear. Stream discharge dynamics were mostly captured in the Jamaare basin. Poor results in the Hadejia and Kaduna basins could be attributed to the misrepresentation of dams/reservoirs in these locations.

On the other hand, optimized mHM discharge simulations showed significant improvements when compared with results from the default mHM parameter simulations. Satisfactory calibrated discharge results were produced by CHIRPS (KGE > 0.5) in all three basins, with ERA5 in Jamaare (KGE = 0.75) and Hadejia (KGE = 0.64). MSWEP produced a KGE > 0.5in the three basins, while GPCC provided a KGE value of = 0.63 in the Hadejia River basin. Compared with default mHM parameter simulation, optimized discharge simulation results (KGE values) showed an increase of 15.85% in Jamaare, 155.62% for Hadejia, and 123.11% in the Kaduna basin when forced with CHIRPS. For ERA5, a decrease of 6.43% was obtained in Hadejia, while an increase of 1155.44% and 124.98% were observed in the Jamaare and Kaduna basins, respectively. These improvements in discharge results, when compared to those from default mHM runs, were also obtained when optimizations were performed with MSWEP (17.31 - 241.1%) and GPCC (4.57 - 132.64%) forcings in the three basins. Optimized KGE results for all meteorologic products indicate agreement between simulations and observations. It is clear from this study that the calibrated mHM model performed well for discharge simulations. This performance is consistent with the studies of Poméon et al. (2018a) and Dembélé et al. (2020b), which showed acceptable discharge simulations in West African basins using optimized model parameter values. There was no clear pattern concerning highperforming rainfall products across all basins under consideration. As presented in Table 4.3 (for optimized mHM parameters), CHIRPS exhibited the highest KGE in the Jamaare basin, while MSWEP was best at performing in the Hadejia and Kaduna basins. Therefore, no particular rainfall products performed best across all locations. This finding aligns with the studies of Beck et al. (2017) and Dembélé et al. (2020a). These authors recommend rainfall product performance evaluation to select the most suitable dataset for a specific location.

Daily hydrographs of simulated discharge against observations at Jamaare (Basin 250), Hadejia (Basin 410), and Kaduna (Basin 572) forced with the CHIRPS dataset are shown in Figure 4.8, respectively. Model performances for the three basins revealed acceptable values, but simulated peak flows in the Hadejia and Kaduna basins were not successfully captured. These

variations could be attributed to the quality of gauged station observations and the high uncertainties inherent in gridded precipitation records.



Figure 4.8: Hydrographs for Jamaare, Hadejia, and Kaduna basins forced with CHIRPS dataset.

Generally, daily hydrographs obtained using optimized parameters forced with the CHIRPS dataset for Jamaare (Basin 250), Hadejia (Basin 410), and Kaduna (Basin 572) show acceptable fits between observed and simulated discharge. High correlation values (r > 0.5) were recorded across the three hydrographs, with Basin 250 showing high KGE (KGE = 0.79) and correlation (r = 0.86) scores. Peak and low simulated flow followed the observed trend recorded in the Jamaare Basin more satisfactorily than displayed in the Kaduna and Hadejia Basins. The study by Poméon et al. (2018a) also showed poor trend and peak flow representations in some of the West African basins under their consideration. These authors further observed discrepancies in mHM flow simulations in basins located within the same region. In this study, our hydrographs (Figure 4.8) also showed that optimized mHM performs acceptably in the Jamaare basin and poorly in the Hadejia and Kaduna basins. We agree with Poméon et al. (2018a) that several

factors could be responsible: (1) several dams/reservoirs which exist within the Hadejia and Kaduna basins were not represented in mHM. The Shiroro dam, located in the Kaduna basin, has a total reservoir capacity of 7,000,000 m³. The Challawa Gorge and Tiga Dams in the Hadejia basin contain reservoirs that have a total volume of 930,000,000 m³ and 1,968,000,000 m³, respectively. In addition to these large dams located in these two basins, many other medium-sized dams are also existing in this region. Consequently, mHM lacks a reservoir component and does not simulate reservoirs and water abstracted for irrigation or domestic water supply purposes. (2) Secondly, data gaps and insufficient discharge time series impact model performance. Generally, improvements in KGE values from uncalibrated to optimized mHM runs underscore the benefit of the MPR technique for discharge simulation in the study region.

4.3.3 Multi-Basin Optimization

A multi-basin mHM, comprising two basins (Basin 1 and Basin 2) each, was set up. A total of three different multi-basin combinations (Basins 250 + 410, Basins 572 + 410, and Basins 250 + 572) were created and forced with the CHIRPS precipitation product. Each of these model setups was calibrated using KGE as the objective function. Optimized model parameters were transferred to a different basin, which was not considered during model parameterization. Model evaluation was performed by assessing mHM capability in reproducing observed discharge in an independent basin using optimized model values from the multi-basin setup which is shown in Table 4.4. KGE values for each of the multi-basins (Basin 1 and Basin 2) combinations are presented in Table 4.4.

Basin	Multi-Basin Combinations			Meteo
	Basin 250 + Basin 410	Basin 572 + Basin 410	Basin 250 + Basin 572	
1	0.33	0.51	-0.03	CHIRPS
2	0.64	0.51	0.58	

Table 4.4. Optimized mHM results (KGE) from multi-basin combinations.

Having calibrated each of the multi-basin mHM setups for discharge simulation, optimized parameter values from Basin 250 + 410 were transferred to Basins 572 for discharge simulation. Additionally, calibrated mHM parameters from Basins 572 + 410 were used for flow simulation in Basin 250, while optimized parameters from Basin 250 + 572 were transferred to Basin 410. KGE results of these discharge simulations are provided in Table 4.5. Optimized model parameters from basin combination comprising of Basins 250 + 572 produced accepted KGE values (see Table 4.5).

Table 4.5 mHM	validation	results on	indepe	ndent basins.
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Metric	Single	Meteo		
	Basin 572	Basin 250	Basin 410	CHIDDS
KGE	0.024519	-0.12124	0.54387	CHIKPS

Hydrographs of daily, monthly and annual flow cycles for Basin 410 (Hadejia River Basin) are shown in Figure 4.9. Hydrographs for Basin 572 and Basin 250 are not presented because they exhibited unsatisfactory KGE scores. The final values of optimized global parameters for all three basin setups are presented in Appendix B.



Figure 4.9. Hydrograph for Discharge Validation using mHM parameters from the independent model setup.

Optimized mHM parameters from different multi-basins were transferred to an independent basin to evaluate the predictive skill of mHM for discharge simulation in ungauged basins. KGE values obtained during optimization of multi-basin mHM runs forced with CHIRPS are shown in Table 4.3. Results from Table 4.5 for Basin 410 revealed an acceptable KGE (KGE = 0.54) when mHM was evaluated using optimized parameters which were obtained after calibration in Basin 250 + Basin 572. The daily discharge (Figure 4.9) shows a slight underestimation of observed discharge but with acceptable performance (KGE = 0.66, r = 0.78). The more desirable agreement exhibited at the monthly temporal resolution is a result of averaging the daily time series over the simulation period. This is comparable to a study by Zink et al. (2017) at a daily time step, observed and simulated discharge exhibited a similar trend but with clear peak flow mismatches.

Overall, the feasibility of transferring mHM-optimized parameters across different locations exhibited promising results only in the Hadejia basin. However, our study could not fully demonstrate the effectiveness of transferring optimized parameter sets to ungauged basins although these basins exist in the same agro-climatic region. This observation is also reported by Zelelew & Alfredsen (2014). These authors attributed this inconsistency to input data uncertainties, parameters interactions and model structure. In our case, integrating model parameter sets from two basins, which increased the parameter search space, failed to improve simulation results in the Jamaare and Kaduna basins. The acceptable KGE score obtained in the Hadejia basin by using an optimized parameter set from Kaduna and Jamaare could also be attributed to their domain size. The area of Kaduna Basin is about four times the size of either Jamaare or Hadejia Basin. Therefore, changes in soil, elevation and land use may have also led to inconsistencies in model performance. mHM does not incorporate a dynamic crop growth component and recognizes only three land use classes (forest, pervious and impervious). These factors could have contributed to the mismatch in peak flow simulations. Furthermore, the poor-performing basins could be attributed to uncertainties inherent in the individual basins that constitute the multi-basin setups.

4.4 Conclusion

Sparse and non-existent hydro-meteorological gauging networks have hindered hydrologic modelling in Nigeria. This has major implications for water and agricultural management at the mesoscale and at a period when hydrologic extremes (flood and drought) occasioned by climate variability occur annually in Nigeria. This study evaluates the skill of mHM for the transferability of model parameters from gauged to ungauged regions. After evaluating four grid-based precipitation products, the CHIRPS precipitation dataset was selected as model forcing to evaluate the robustness of the mHM regionalization scheme in data-sparse basins located in Northern Nigeria. Our results showed acceptable discharge simulations by using optimized parameters in contrast to default model parameters. The CHIRPS datasets produced satisfactory results during default and optimized mHM discharge simulations. For optimized mHM runs, CHIRPS and MSWEP products exhibited acceptable performance with KGE > 0.6 across all basins under consideration. The sub-grid variability at the level in morphological input datasets, which characterizes the MPR technique is a major factor for satisfactory flow simulation in all basins. However, this result was not achieved when optimized parameter sets were obtained in a multi-basin configuration and transferred to an independent basin. Only the Hadejia river basin showed acceptable results when mHM was evaluated using optimized model parameter values from another location. This inconsistency in model performance can be caused by poor representation of dam/reservoirs, lack of a plant module within the mHM structure and uncertainties inherent in model inputs.

There is a need for further mHM studies in Nigeria to exhaustively investigate the performance of model parameter transferability to ungauged basins. The paucity of discharge records limited such applicability in this aspect. It will be interesting to assess mHM hydrologic simulation performance in the same region driven by ground-measured rainfall data. This approach will reinforce the scientific understanding of the utility of the model robustness for discharge simulation in Nigeria. In addition, a multi-variable calibration scheme should be incorporated to constrain the model's internal state. This research seeks to encourage and stir interest within the Nigerian scientific community, watershed managers and government institutions or policymakers on the feasibility and applicability of the mHM scheme to support water resources management and policy-making in the light of the hydro-meteorological deficits.

5 Multivariate Assessment of Hydrologic Simulations in Diverse Climatic Regions Using a Streamflow-Calibrated Mesoscale Hydrologic Model

Abstract: The sparse and unavailability of hydro-meteorological observations in Nigeria has hindered hydrologic model calibration and significantly impacted applied hydrology. The goal of this study was to evaluate the feasibility of using model parameters obtained by constraining the mesoscale hydrologic model (mHM) with solely streamflow records for the simulation of actual evapotranspiration (aET) and soil moisture (SM). For this purpose, six (6) distinct calibrated model parameter sets were employed, derived during the calibration of mHM for various basins and driven by different gridded rainfall datasets (CHIRPS and ERA5). Model simulations were compared to gridded aET (GLEAM and FLUXNET) and ESA CCI soil moisture observations at various temporal resolutions spanning 1982 to 2011. Seasonal aET trends and magnitudes over three climatic regions in Nigeria were evaluated using the nonparametric Mann-Kendall test and Sens Slope estimator. The Pearson correlation coefficient was utilized to measure the agreement between standardized soil moisture simulation and the ESA CCI dataset. The spatial pattern of mean annual aET climatology for all simulations agrees with observations, presenting an increasing trend from northern to southern Nigeria. While mHM configurations forced with ERA5 demonstrated weak correlation (r < 0.5) when compared with FLUXNET, satisfactory agreements (r > 0.5) were exhibited by all CHIRPSdriven models in comparison to the GLEAM datasets. All mHM setups replicated similar trends of observed annual aET cycles over the modelled domains. However, higher KGE scores in the Sahel region of northern Nigeria signify a robust agreement between aET simulations and observations in this region, than in the southern (Guinea savannah) part of Nigeria. Simulated monthly soil moisture anomaly captured the temporal variability (r > 0.8) of surface soil moisture across the distinct climatic regions and the entire Nigeria domain. Results underscore the feasibility of using mHM parameters calibrated using streamflow for hydrologic simulations in Nigeria.

Keywords: mHM, soil moisture, actual evapotranspiration, CHIRPS, ERA5

5.1 Introduction

The importance of hydrologic modelling application as a tool to support decision and policymaking for sustainable water resources management and planning, environmental pollution control, the reduction of hydro-meteorological risks, food security, and climate change adaptation scenarios cannot be overemphasized today (Holmes et al., 2023; Ricard et al., 2013). However, the adaptability of complex hydrologic models vis-à-vis limited data availability poses a significant challenge to the production of high-performance predictions, especially in developing countries (Odusanya et al., 2021). This is a result of such regions being largely characterized by limited/sparse hydro-meteorological monitoring networks, heterogeneous landscapes with significant variations in climate systems and unavailability of spatio-temporal hydro-meteorological observation systems (Odusanya et al., 2019; Poméon et al., 2018a). However, the advancements in the field of remote sensing resulted in sophisticated space-borne sensors for the production of hydrologic input datasets at high spatial-temporal resolutions (He et al., 2023). Notwithstanding the utility and availability of these spatial-temporal datasets, their use for water resource development, especially in sub-Saharan Africa (SSA), is grossly under-utilized to model water resource variability and support policy decisions in this sector. The rapidly developing SSA region grapples with challenges in water resources sustainability

and availability, impacting hydropower generation, and rain-fed/irrigated agriculture, with significant negative economic implications for the entire region (Kwakye & Bárdossy, 2020).

Evapotranspiration and soil moisture are major components of the land phase of the hydrologic budget (Lai et al., 2023). These variables play significant roles in hydrologic studies such as groundwater recharge, agricultural water management, flood forecasting, and climate modelling, and are crucial for predicting other hydrologic processes (Fatima et al., 2023; Taia et al., 2023). In semi-arid regions such as the savannah-sahel region of SSA, evapotranspiration and soil moisture studies are critical for vegetation growth/crop growth modelling and play an important role towards food security. Accurate estimation of these hydrologic variables is important for the determination of crop water requirements, resulting in efficient irrigation practices and improved crop yields (Ajjur & Al-Ghamdi, 2021). Nigeria is the most populous nation in Africa but faces threats of unsustainable agricultural production with a score of below 50% on the Global Food Security Index (Wudil et al., 2023). Information on water variability in this region is important for developing critical reservoirs and irrigation projects to achieve food sustainability and overall economic development.

The availability and application of fully distributed, physically-based hydrologic models have not necessarily translated to improved simulation results due to the difficulty of model parameter estimation (Golian et al., 2021; Qi et al., 2022). This is even more challenging in sparsely instrumented regions (e.g., Nigeria), where limited or unavailability of observational data presents a bottleneck for hydrologic model parameter calibration and poses a challenge to applied hydrology. Many basins exist in Nigeria where the construction of hydrologic structures and irrigation facilities are proposed, but no gauging stations exist. In this situation, model applications can employ regionalization methods, aiming to transfer model parameter sets from gauged to ungauged domains (Arsenault et al., 2019; Qi et al., 2022; Singh et al., 2022; Tarek et al., 2021).

Realistic hydrologic model application stems from the proper representation of hydrologic inputs within the modelling framework and the accurate estimation of model parameters. The utility of a hydrologic model is not only evaluated in its ability to reproduce observed state and flux variables but also in its ability to simulate observed events using parameters obtained from hydrologically similar domains (Qi et al., 2022; Smith et al., 2016). This procedure is important for verifying a model's suitability to reproduce dominant hydrologic processes in a hydrologic domain (Holmes et al., 2023). Qi et al. (2022) proposed parameter regionalization as the most common technique to facilitate hydrologic simulations in ungauged basins. Several reviews summarized regionalization methods for continuous hydrologic simulation (Parajka et al., 2013; Pool et al., 2021; Qi et al., 2022; Farfán & Cea, 2023).

The mesoscale hydrologic model (mHM) has emerged as a powerful tool for simulating state and flux water variables and has been successfully applied in different regions, i.e., North America (Rakovec et al., 2019), Europe (Kumar et al., 2010, 2013; Samaniego et al., 2017, 2019; Zink et al., 2017), West Africa (Dembélé et al., 2022; Dembélé et al., 2020a; Dembélé et al., 2020b; Ogbu et al., 2022; Poméon et al., 2018a), and Asia (Saha et al., 2021; Samaniego et al., 2011). A regionalization method, the multiscale parameter regionalization (MPR) is implemented within the mHM structure to decrease the dimensionality of model parameter space. A hydrologic assessment conducted by Kumar et al. (2013) across 45 German basins to evaluate the transferability of model parameters to ungauged basins revealed that the MPR technique demonstrated reliability and effectiveness in replicating observed hydrologic states and fluxes across various temporal and spatial resolutions. In some West Africa basins characterized by sparse hydro-climatic networks, Poméon et al. (2018a) showed the efficacy of the MPR technique in transferring model parameters across various scales, achieving acceptable replication of hydrologic observations. Given the persistent challenges with the availability of hydroclimatic datasets in Nigeria and anticipating this trend to continue into the near future, there is a need to test the MPR scheme for hydrologic simulations in Nigeria. In a pioneering effort employing this technique, this study evaluated the performance of simulated hydrologic variables across distinct agro-climatic zones in Nigeria, using mHM parameters calibrated with streamflow at the basin scale.

This study aims to evaluate the simulation of actual evapotranspiration (aET) and surface soil moisture (SM), using calibrated mHM parameters across the entire Nigeria domain, and employing remotely sensed precipitation records. These parameters were calibrated based on only runoff data from three different basins, which exhibit divergent physical and climatic characteristics. Six different model parameter sets based on different basin-rainfall combinations were used to set up the mHM for the Nigeria domain. Comparisons of simulated aET and SM were assessed at different agro-climatic zones within the country against observed datasets. The transferability of calibrated model parameters between domains with divergent physical, climatic and topographic characteristics was also evaluated. The goal is to contribute to the International Association of Hydrologic Sciences (IAHS) scientific initiative, Prediction in Ungauged Basins (PUB) (Hrachowitz et al., 2013), by investigating the feasibility of model parameter transferability to support hydrologic modelling studies in data-limited regions like Nigeria.

5.2 Methods

5.2.1 Study Area and Datasets

Nigeria, located in SSA, is bounded by Cameroun in the east, the Republic of Benin in the west, the Niger Republic in the north and the Atlantic Ocean in the south (refer to Fig. 5.1). The spatio-temporal variation of climatic changes in Nigeria results in two (2) climate seasons (wet and dry seasons) influenced by the cool air from the Atlantic Ocean and the tropical continental air mass from the Sahara Desert (Ogunjo et al., 2022). The impact of the West African Monsoons over Nigeria is largely witnessed in the variability of rainfall patterns from the southern to the northern part of the country. For this study, the distinct agro-climatic zones as reported by Gbode et al. (2019), Omotosho and Abiodun (2007) and (Abiye et al., 2019) were adopted and used for evaluating mHM simulation performances. These zones are Guinea (latitude $4^{\circ} - 8^{\circ}$ N), Savannah (latitude $8 - 11^{\circ}$ N) and Sahel (latitude $11^{\circ} - 14^{\circ}$ N), and characterize the distinct land use and climate of each region. The Guinea zone lies in the southern part of Nigeria and experiences a bi-modal rainy season with a mean annual rainfall of 1,575 – 2,533 mm (Gbode et al., 2019). The two other regions experience a unimodal rainy season trend, with the semi-arid region of the Savannah zone characterized by a reduction in mean annual rainfall in comparison to the Guinea zone with an average annual amount ranging from 897 - 1,533 mm. The Sahel area experiences a further reduction in rainfall amount resulting in an average annual amount of 434 – 969 mm (Gbode et al., 2019; Oguntunde et al., 2011).

Observed discharge records from three basins located within the Savannah-Sahel region (see Fig. 5.1) were used for mHM calibration (Ogbu et al., 2022). These basins are the Jamaare, Hadejia and Kaduna River Basins with a total land area of 13,929 km², 16,820 km² and 64,848 km², respectively. Rainfall in the Savannah-Sahel region exhibits a unimodal pattern with a peak around August (Ogbu et al., 2020). Agricultural activities, including crop farming, animal husbandry, etc., are more widespread in this zone and support the economic viability of the region. The average annual rainfall within the region (Savannah-Sahel) ranges from 434 to 1,533 mm, and the vast arable land makes it a very important food-producing area in Nigeria, boasting more than half of the wheat, maize and sorghum produced in the country. Communities within these basins depend on the numerous existing river systems for domestic water supplies, transportation, irrigation, industrial uses, fishing, etc. (Ogbu et al., 2022; Okafor & Ogbu, 2018).



Figure 5.1: Map of Nigeria showing hydrologic basins used for mHM calibrations

Morphological (elevation, land use, leaf area index, soil, and slope) and climatic (rainfall and temperature) datasets were used to set up the fully distributed mHM. Stream discharge data obtained from the Global Runoff Data Centre (GRDC) database were used for model calibration at the basin scale. A previous study by Ogbu et al. (2022) described mHM data requirements (refer to Table 5.1) for the Jamaare, Hedejia and Kaduna River basins. Model parameters obtained post-calibration for these basins were used to parameterize mHM over the entire Nigeria domain for actual evapotranspiration and surface soil moisture simulations.

Variable	Product	Spatial Resolution	Temporal Resolution	References
Climate Data				
Rainfall	CHIRPS v2.0	0.05°	Daily	(Dinku et al., 2018; Funk et al., 2015)
Temperature	ERA5	0.25°	Daily	(Hersbach et al., 2020)
Morphological				
Data				
Elevation	GMTED	0.002°	Static	(U.S Geological Survey, 2010)
Soil	SoilGrid	0.002°	Static	(Hengl et al., 2017)
Landuse	Globcover 2009	0.002°	Static	(Bontemps et al., 2011)
Geology	GLIM v1.0	0.5°	Static	(Hartmann & Moosdorf, 2012)
Leaf area index	GIMMS	0.08°	Static	(Zhu et al., 2013)
In-situ data				
Streamflow	-	Point	Daily	GRDC database
Remotely sensed			-	
dataset				
Actual	GLEAM v3.2a	0.25°	Monthly	(Jung et al., 2011; Martens et
Evapotranspiration	FLUXNET		-	al., 2017)
Surface soil	ESA CCI SM	0.25°	Monthly	(Gruber et al., 2019)

 Table 5.1: Datasets for mesoscale Hydrologic Model (mHM) setup

*CHIRPS – Climate Hazards Group InfraRed Precipitation with Station data; ERA5 – 5th generation of ECMWF (European Centre for Medium-Range Weather Forecasts) Reanalysis; GLEAM – Global Land Evaporation Amsterdam Model: GLIM, Global Lithological Map; GMTED – Global Multi-resolution Terrain Elevation Data; ESA CCI SM – European Space Agency Climate Change Initiative Soil Moisture.

Actual evapotranspiration (aET) data, which includes water evaporation from the soil surface, vegetation surfaces, water bodies, and vegetation transpiration, was obtained from the Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al., 2017) and Flux Network (FLUXNET) observations (Jung et al., 2011). Evapotranspiration represents about 60% of terrestrial precipitation and constitutes the second-largest flux of the hydrologic cycle (Rakovec et al., 2016b). GLEAM relies on remote sensing data incorporating measurements from meteorological data, satellites, and land surface models. In contrast, the gridded FLUXNET data are typically collected at the site level, with measurements coming from flux towers located in specific ecosystems. These datasets were obtained at a spatial resolution of 0.25° and processed for the period 1982 – 2011 at monthly temporal resolution. Interested readers can refer to Jung et al. (2011) for a detailed description of the algorithm used to process the FLUXNET dataset.

In this study, the European Space Agency Climate Change Initiative (ESA CCI) soil moisture data (Gruber et al., 2019) is used to represent soil moisture at depths ranging from 50 - 2,000 mm, covering six (6) soil horizons for a period of 1982 - 2011. Accurate hydrological modelling of soil moisture is important for portioning rainfall into evapotranspiration and runoff. Soil moisture is a major hydrologic process and determines the vegetation characteristics of a region (Rakovec et al., 2019). The ESA CCI dataset is derived from satellite retrievals using two active sensors (advanced scatterometer and ERS active microwave

instrument) and four (4) passive sensors (SMMR, SSM/I, TMI and AMSR-E) (Gruber et al., 2019).

5.2.2 mHM: Overview

The mHM is a spatially explicit, process-based and fully distributed grid-based hydrologic model (Kumar et al., 2010; Samaniego et al., 2010). It is based on the numerical approximations of dominant hydrologic processes as represented in the Hydrologiska Byråns Vattenbalansavdelning (HBV) (Lindström et al., 1997) and Variable Infiltration Capacity (VIC) (Liang et al., 1994) models. The mHM can simulate the following hydrologic processes: canopy interception, infiltration, surface runoff, soil moisture, evapotranspiration, subsurface flow, soil moisture and flood routing (Rakovec et al., 2019). Net rainfall is determined by partitioning rainfall into soil moisture and percolation using a non-linear separation scheme. A six-layer (50 mm, 150 mm, 300 mm, 500 mm, 1,000 mm, 2,000 mm) soil infiltration capacity scheme was used to calculate the daily dynamics of soil moisture considering rainfall, evapotranspiration and percolation. Runoff is routed from upstream cells to downstream cells following river networks using the multiscale Routing Model (mRM) (Thober et al., 2019), based on the Muskingum-Cunge (Cunge, 1969) formula. The Muskingum-Cunge method is the most popular method for calculating hydrologic river routing and is known to reflect natural basin conditions (Tu et al., 2020). The computation of its parameters depends on the mean physical characteristics of the flow wave and the river channel. This is expressed as:

$$K = \frac{\Delta x}{c_k} = \frac{\Delta x}{\partial Q_{\partial A}}$$
(5.1)

$$X = \frac{1}{2} \left(1 - \frac{Q}{BC_k S_0 \Delta x} \right) \tag{5.2}$$

Where, K = storage constant (hr); Δx = increment in space (m); C_k = flow celerity (m/s); Q = flow discharge (m³/s); A = cross-sectional area of the channel (m²); X = weighting factor (dimensionless); B = width of the water surface (m); S₀ = bed slope (dimensionless)

The Hargreaves and Samani (Hargreaves & Samani, 1985) method was used for computing reference evapotranspiration in this study due to the extensive data requirements of the Food and Agricultural Organization (FAO) Penman-Monteith method. Evapotranspiration was computed using daily temperature observations obtained from ERA5 datasets. This is computed as:

$$ET_0 = 0.0023 \times 0.408 \times R_a \times (T_{av} + 17.8) \times (T_{mx} - T_{mn})^{0.5}$$
(5.3)

Where, $ET_o = Reference$ evapotranspiration (mm/day); $R_a = extraterrestrial radiation (MJ.m².d⁻¹); T_{av} = mean daily temperature (°C); T_{mx} = daily maximum temperature (°C); T_{mn} = daily minimum temperature (°C); 0.0023 = empirical temperature Hargreaves constant; 17.8 = empirical temperature Hargreaves constant; 0.5 = empirical Hargreaves exponent.$

The spatial-temporal dynamics of hydrologic processes are simulated at the grid-scale level and require about twenty-eight parameters at each grid, which are inferred during calibration. Calibrating these parameters for each cell during simulation would result in overparameterization problems and significant predictive uncertainty. A regionalization scheme the multiscale parameter regionalization (MPR) was incorporated within the mHM framework aimed at overcoming model over-parameterization, accounting for sub-grid variability and transfer of global parameters to ungauged domains (Kumar et al., 2013; Samaniego et al., 2010;
Schweppe et al., 2022). The primary aim of the MPR technique is to enable the estimation of effective model parameters that reflect basin characteristics influencing dominant hydrologic processes (Samaniego et al., 2010). Three levels of gridded observations are needed during mHM setup to represent the spatial variability of state and input variables: Level-0 represents basin characteristics (elevation, slope, land use, soil, etc.), Level-1 describes the dominant hydrological processes and the geological formation of the study domain, and Level-2 represents climatic forcing (evapotranspiration, rainfall and temperature) (Kumar et al., 2010). Detailed information about the mHM scheme can be found in Samaniego et al. (2010).

5.2.3 Modelling Experimental Design

The mHM (v5.11, https://mhm.pages.ufz.de/mhm/stable/index.html) was previously set up independently for three basins - Jamaare (hereafter referred to as #250), Hadejia (hereafter referred to as #410) and Kaduna basins (hereafter referred to as #572) (Ogbu et al., 2022), located within the Savannah-Sahel region of Nigeria (see Figure 5.1), to simulate daily observed stream discharge at their different outlets. Daily meteorological datasets of rainfall and temperature were obtained from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) data and the 5th Generation ECMWF Re-Analysis (ERA5) global database and used separately as model forcing for each mHM setup. mHM runs were independently performed over three basins using two gridded rainfall datasets (CHIRPS and ERA5) as model forcing. A spin-up period of one year was used to establish an initial period of state variables. Model calibrations for only streamflow were performed using the Dynamically Dimensioned Search (DDS) (Tolson & Shoemaker, 2007) algorithm. According to these authors, the DDS method is well suited to computationally expensive and highly parameterized hydrologic models and was designed to establish practical solutions to model calibration issues rather than providing a globally optimal solution. Calibrated model parameter sets for each basin-rainfall data mHM setup were obtained using the framework presented in Figure 5.2. Detailed information on model setup and calibration for these basins can be found in Ogbu et al. (2022). Initial model parameter ranges were based on the default mHM configuration. Large gaps (missing values) in observed historical streamflow records for the different basins did not allow for a uniform calibration period.



Figure 5.2: mesoscale Hydrologic Model (mHM) Rainfall-Basin Parameter Combination (from Stage 1)

The workflow for this study consists of two stages – Stage 1 and Stage 2 (see Figure 5.3). In the first stage (Stage 1), the mHM model was calibrated for different basins and driven by CHIRPS and ERA5 gridded rainfall datasets, as described in the previous section and reported extensively in Ogbu et al. (2022). Stage 2 (see Figure 5.3) is an extension of a previous study (Ogbu et al., 2022) depicted by Stage 1 (see Figure 5.3). In Stage 2, model parameter sets obtained after calibration in Stage 1 were used to set up a new model for the entire Nigeria domain to simulate soil moisture and actual evapotranspiration at a monthly timescale from 1982 - 2011. A description of model input datasets, hydrological variables of soil moisture, and actual evapotranspiration are shown in Table 5.1. Comparative performance between model-simulated and observed datasets of soil moisture and actual evapotranspiration are shown in Table 5.1. actual evapotranspiration was evaluated over three different agro-climatic regions of Nigeria, at annual, monthly and seasonal temporal resolutions.



Figure 5.3: Schematic diagram of study workflow

5.2.4 Model Performance Evaluation

In this study, the predictive ability of mHM was assessed by evaluating the transferability of parameterized values across spatial and temporal scales. This involves examining its performance over a period and within a modelling domain larger than that used during calibration. mHM-simulated actual evapotranspiration (aET) was evaluated against observations obtained from GLEAM v3.2a (referred to hereafter as GLEAM) and FLUXNET products. Additionally, we compared surface soil moisture, representing the first soil layer of mHM-simulated soil moisture (SM), to the observed ESA CCI soil moisture dataset. These remotely sensed datasets have been utilized in various hydro-climatic studies (Adeyeri & Ishola, 2021; Dembélé et al., 2020a; Odusanya et al., 2019; Poméon et al 2018a; 2018b) in West Africa, they contribute to a better understanding of the variability of hydrological variables and its potential impacts on water resource availability in the region. Model simulations, derived from six unique mHM configurations obtained through different rainfall data-basin mHM combinations, were compared to observations (aET and SM) at various temporal scales.

The mHM's performance in reproducing observed aET and soil moisture across the entire domain and in three agro-climatic regions was evaluated. In the initial step, the annual climatology of simulated and observed aET over 30 years (1982 - 2011) was determined by

obtaining mean estimates over the entire modelling domain and at each agro-climatic region. Additionally, simulated aET results over the entire domain were assessed for the monsoon (June – September) and dry (January – March) seasons. These periods were selected as they align with the period when Nigeria experience wet and dry seasons, justifying their selection. This seasonal period agrees with a recent aET study over the West Africa region (Adeyeri & Ishola, 2021).

Several studies (Ayugi et al., 2020; Holmes et al., 2023; Moriasi et al., 2015) have proposed various statistical metrics to assess the comparison of hydrologic simulations to observations. In this study, various performance metrics such as the modified Kling Gupta Efficiency (KGE), root mean square error (RMSE), and percent bias (PBIAS) were employed to assess the performance of mHM simulations. The agreement between simulated and observed datasets was assessed using the Kling and Gupta efficiency (KGE) (Gupta et al., 2009; Kling et al., 2012) statistic:

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (\gamma - 1)^2}$$
(5.4)

$$\beta = \frac{\mu_s}{\mu_o} \tag{5.5}$$

$$\gamma = \frac{CV_s}{CV_0} = \frac{\sigma_s/\mu_s}{\sigma_o/\mu_o} \tag{5.6}$$

$$r = \frac{\sum_{i=1}^{n} (o_i - \bar{o})(s_i - \bar{s})}{\sqrt{\sum_{i=1}^{n} (o_i - \bar{o})^2 \sqrt{\sum_{n=1}^{n} (s_i - \bar{s})^2}}}$$
(5.7)

Where, KGE is the modified KGE statistic (dimensionless), r is the correlation coefficient between the simulated and observed variable, β is the bias ratio (dimensionless), γ is the variability ratio (dimensionless), CV is the coefficient of variation (dimensionless), μ is the mean of the variable of interest, and s and o represent simulated and observed variables, σ is the standard deviation of the variable of interest.

The advantage of the KGE as an improvement over the Nash Sutcliffe efficiency (NSE) is underscored by its decomposition into correlation (r), bias (β) and variability (γ) components (Kling et al., 2012; Knoben et al., 2019; Pool et al., 2018; Qi et al., 2022). KGE values close to 1 indicate a perfect match between simulated and observed datasets.

The percent bias (PBIAS) assesses the average inclination of the simulated values to either exceed or fall short of their observed counterparts (Zettam et al., 2020). Negative values indicate an underestimation in simulated values, whereas positive values signify an overestimation. The PBIAS is estimated as:

$$PBIAS = \frac{\sum_{i=1}^{n} o_i - S_i}{\sum_{i=1}^{n} o_i} \times 100$$
(5.8)

RMSE measures how dispersed simulation errors are on the regression line. Lower RMSE values reflect high performance. The RMSE is calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - S_i)^2}{n}}$$
(5.9)

Where, O_i is the observed data; S_i is the simulated data; n is the number of data points

Trends in the seasonal aET over the entire domain and the three climatic regions were also computed using the Mann-Kendall (MK) test (Kendall, 1975; Mann, 1945). The MK test, a widely utilized non-parametric approach for identifying significant trends in hydroclimatological observations, offers the advantage of being insensitive to extreme values and not necessitating adherence to any specific statistical distribution of the data (Aschale et al., 2023). Investigations for trends in hydro-climatic variables have been investigated in different studies within the West African subregion (Adeyeri & Ishola, 2021; Akinsanola et al., 2018; Gbode et al., 2019; Ogbu et al., 2020). Statistically significant trends between simulated and observed mean seasonal time series were compared to evaluate mHM ability to capture and reproduce observed temporal patterns. Significant discrepancies highlight biases in mHM simulation and the need for improvement. The Mann-Kendall test statistics (S) is calculated as (Frimpong et al., 2022):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i)$$
(5.10)

Where, n = total number of data points; x_i and $x_j = data$ values at time j and i; and sgn function, given as:

$$sgn(x_j - x_i) = \begin{cases} +1. if x_j - x_i > 0\\ 0, if x_j - x_i = 0\\ -1, if x_j - x_i < 0 \end{cases}$$
(5.11)

The variance of the MK statistics is computed as follows:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(t_1 - 1)(2t_1 + 5)}{18}$$
(5.12)

Where, m = number of tied groups; $t_i =$ number of data points in the ith group. A tied group is a collection of sample data points that share identical values. Therefore, the summation term in the numerator is applicable only when the time series includes tied values.

$$Z_{s} = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & \text{if } S > 0\\ 0, & \text{if } S = 0\\ \frac{S+1}{\sqrt{Var(S)}}, & \text{if } S < 0 \end{cases}$$
(5.13)

The null hypothesis, indicating no significant trend, is accepted when the test statistics Z_s is not statistically significant. Increasing trends signify positive Z_s values, whereas negative Zs values indicate decreasing trends. This study evaluated trend results at the 95% confidence level (5% significant level).

The slope of the trend line was determined using the non-parametric Theil-Sen estimator (Sen, 1968). This is obtained by calculating the median of all possible slopes between pairs of data points in a time series record. This estimator is given by (Aschale et al., 2023):

$$\beta = Median\left(\frac{x_i - x_j}{i - j}\right) for all i > j$$
(5.14)

Where, xi and xj = data points at times i and j, respectively. $\beta > 0$ indicates an increasing trend.

Spatial estimates of mHM simulated surface soil moisture were aggregated at all distinct agroclimatic regions and the whole domain and compared to the ESA CCI datasets at monthly temporal resolutions. The soil moisture anomaly (expressed as a z-score) was determined by subtracting the long-term mean and then dividing by the standard deviation as demonstrated in the study by Suribabu & Sujatha (2019).

$$z - score = \frac{x - \bar{x}}{\sigma} \tag{5.15}$$

Where, x = monthly soil moisture data; \bar{x} = mean soil moisture: σ = standard deviation of monthly data.

The Standardized anomaly values indicate how many standard deviations the soil moisture values deviate from the historical mean soil moisture (Suribabu & Sujatha, 2019; Xu et al., 2018). Negative values signify values lower than the historical mean, while positive values indicate values higher than the soil moisture mean during the period under study. Correlation scores between mHM-surface soil moisture simulation and observations were used to evaluate the performance of mHM in replicating temporal patterns of historical observations, providing insights into the model's ability to reproduce soil moisture dynamics across different climatic regions and for the entire domain.

5.3 Results and Discussion

In this section, aET and surface soil moisture simulations are presented. These simulations used unique mHM-calibrated parameters derived from various rainfall data-basin mHM configurations. The assessment covers the entire domain and three distinct agro-climatic regions, with evaluations carried out on both annual, monthly and seasonal timescales for aET. However, the evaluation for soil moisture simulation was conducted only on a monthly temporal resolution.

5.3.1 Annual Climatology

The spatial climatology of mean annual total aET simulations for all mHM configurations is presented in Figure 5.4. The overall increase in mean annual aET was most prominent in the southward direction across all simulations, demonstrating strong agreement with both observations (GLEAM and FLUXNET). This same trend was reported by Adeyeri and Ishola (2021) and (Jung et al., 2019) in an assessment study of various aET products over West Africa. However, upon visual inspection of Figure 5.4, it is evident that all aET simulations exhibit a strong similar pattern to the observed datasets only in northern Nigeria (Fig. 4). The spatial mean of annual aET for GLEAM was overestimated by 151.65 mm, 15.16 mm, 150.04 mm, 84.74 mm, 57.41 mm, and 138.86 for CHIRPS 250, CHIRPS 410, CHIRPS 572, ERA5 250, ERA5 410, and ERA5 572, respectively. For the FLUXNET dataset, the mean spatial annual aET was underestimated by CHIRPS 410 (86.26 mm), ERA5 250 (16.79 mm), and ERA5 410 (44.12 mm). Additionally, it was overestimated by 50.12 mm, 48.51 mm and 37.33 mm for CHIRPS 250, CHIRPS 572 and ERA5 572, respectively. Although there are similarities in the spatial aET pattern compared to observations, significant biases are primarily found in the Guinea region (southern part), indicating poor simulation performances in this region for all mHM configurations.



Figure 5.4: Spatial fields of mean annual annual total actual evapotranspiration (aET) across Nigeria (1982 – 2011)

Since evaporation processes are linked with rainfall process, differences in replicating aET pattern in the Guinea region were also displayed when performances of gridded precipitation products were evaluated across Nigeria (Ogbu et al., 2020). Weak agreement of aET simulations in the southern part of Nigeria can also be attributed to the potential evapotranspiration (PET) method employed. The PET was estimated using the Hargreaves and Samani method (Hargreaves & Samani, 1985), which utilizes only temperature records for calculating evapotranspiration. An mHM study (Rakovec et al., 2019) across the continental USA show that leaf area index, stomatal conductance, and root dept models employed within the mHM structure are significant factors that may affect mHM-aET simulations, especially in regions characterized by high rainfall events. These factors could also have contributed to the model's poor performance in the highly vegetated areas of southern Nigeria, i.e., the Guinea region.

In Figure 5.5, Pearson correlation coefficients (r) are depicted, originating from the assessment of the mean annual total aET across the entire modelling domain, in comparison to both GLEAM and FLUXNET products. All aET simulations from various mHM setups demonstrated satisfactory correlation (0.5 > r < 0.7) compared to the GLEAM product. However, when compared to FLUXNET aET observations, all mHM setups forced with ERA5 (ERA5_250, ERA5_410 and ERA5_572) exhibited poor correlation results (r < 0.3), while those driven by the CHIRPS rainfall dataset demonstrated satisfactory outcomes (0.7 > r < 0.8).



Figure 5.5: Taylor diagram showing the correlation of all mesoscale hydrologic model (mHM) simulations against observations (GLEAM and FLUXNET)

All mHM-aET simulations exhibited more acceptable correlations with GLEAM datasets than against the FLUXNET product (Fig. 5.5). This satisfactory agreement with the GLEAM dataset is consistent with results from another mHM application in the Volta River region of West Africa (Poméon et al., 2018a). The reanalysis precipitation (ERA5) driven-mHM aET simulation indicated poor agreement with the FLUXNET. The limited presence of aET flux towers in Africa may have impacted its use for the evaluation of evapotranspiration simulation (Weerasinghe et al., 2020). Notwithstanding the use of FLUXNET for aET simulation in this study, none of the flux tower sites are located in Nigeria (Weerasinghe et al., 2020). Its choice of use in this study is based on its popularity as a reference variable for assessing the performance of remotely-sensed evapotranspiration models, as shown in various studies (Adeyeri & Ishola, 2021; Dzikiti et al., 2019; Liu et al., 2023; Weerasinghe et al., 2020; Xie et al., 2023; Zhu et al., 2022).

5.3.2 Annual Cycle of Monthly aET

Figure 5.6 depicts how the various mHM setups demonstrate their ability to reproduce the bimodal actual evapotranspiration pattern over the Guinea region and the unimodal pattern over the Savannah, Sahel, and the entire domain of Nigeria. Our results show that all the simulations driven by unique model parameter sets could capture the mean monthly temporal pattern of aET, including peaks, compared to the GLEAM and FLUXNET datasets. The bimodal aET peaks exhibited by all mHM configurations in the Guinea region (Figure 5.6) agree with the temporal aET pattern simulated by the Soil and Water Assessment Tool (SWAT) employed in the study by Odusanya et al. (2019) for the Ogun River basin of southwestern Nigeria (Guinea region). The single aET peak observed in the Sahel and Savannah regions reflects their seasonal rainfall patterns in these regions and agrees with a report by Ogbu et al. (2020). The annual rainfall cycle in Nigeria is impacted by the West African Monsoon, exhibiting latitudinal shifts of peak rainfall periods. This North-South oscillation of the Inter Tropical Convergence Zone (ITCZ), which characterizes the rainfall peaks in the distinct climatic zones of Nigeria is reflected in the temporal aET patterns in these regions. Compared to reference aET observations (GLEAM and FLUXNET), all mHM configurations replicated low aET rates in the north and higher rates in the southern region of Nigeria. mHM aET peaks in the Guinea and Savannah regions of Nigeria are consistent with the mean monthly climatology over the West African regional climatic zones (Jung et al., 2019). Overall, all mHM configurations demonstrated a strong seasonality across all climatic regions and the whole domain of Nigeria, with a close match between mHM aET simulations and observations in the Sahel region, in comparison to the two other regions (Fig. 5.6).



Figure 5.6: Annual cycle of monthly actual evapotranspiration (aET) in three different climatic regions of Nigeria (1982 – 2011)

The statistical evaluation for all mHM-setup simulations compared to observations at mean monthly temporal resolutions (1982 – 2011) is presented in Table 5.2. These results are shown for various climatic regions, the Nigeria domain and aET observations obtained from GLEAM and FLUXNET products. The temporal dynamics of simulated aET replicated the pattern of both GLEAM and FLUXNET, presenting correlation coefficients of above 0.5 (i.e., r > 0.5) for most mHM aET simulation configurations (see Table 5.2). Low correlation coefficients ($r \le 0.5$) were observed in the Guinea region for CHIRPS_572 and ERA5_572 mHM setups compared to GLEAM and FLUXNET.

		GLEAM				FLUXNET					
		KGE	r	Beta	Gamma	RMSE	KGE	r	Beta	Gamma	RMSE
Guinea	CHIRPS-250	0.46	0.79	1.11	0.52	11	0.41	0.62	0.95	0.55	10.37
	CHIRPS-410	-0.75	0.68	0.94	2.72	22.11	-0.86	0.96	0.81	2.85	23.88
	CHIRPS-572	0.24	0.47	1.12	0.46	13.31	0.25	0.46	0.96	0.49	11.16
	ERA5-250	0.71	0.81	1.13	0.83	12.33	0.84	0.9	0.97	0.87	5.67
	ERA5-410	0.19	0.75	1.09	1.78	16.27	0.13	0.97	0.94	1.87	11.15
	ERA5-572	0.10	0.38	1.19	0.37	18.14	0.2	0.48	1.02	0.39	10.67
Savannah	CHIRPS-250	0.46	0.96	1.31	0.56	20.99	0.46	0.82	1.13	0.51	22.08
	CHIRPS-410	0.39	0.82	1.03	1.58	25.34	0.54	0.99	0.9	1.44	13.36
	CHIRPS-572	0.36	0.96	1.32	0.45	22.83	0.37	0.83	1.15	0.41	23.42
	ERA5-250	0.85	0.92	1.12	1.02	13.8	0.93	0.98	0.97	0.93	7.29
	ERA5-410	0.54	0.87	1.05	1.44	21.02	0.67	0.99	0.91	1.32	9.73
	ERA5-572	0.4	0.87	1.23	0.46	20.38	0.37	0.82	1.07	0.42	22.35
Sahel	CHIRPS-250	0.86	0.98	1.13	0.94	8.46	0.94	0.98	1.06	1	6.36
	CHIRPS-410	0.71	0.93	1.01	1.23	14.84	0.64	0.98	0.95	1.36	11.07
	CHIRPS-572	0.88	0.95	1.08	0.94	10.16	0.96	0.97	1.02	0.99	7.37
	ERA5-250	0.89	0.98	1.01	1.11	7.5	0.81	0.99	0.95	1.18	5.17
	ERA5-410	0.73	0.96	1.01	1.27	12.39	0.65	0.99	0.95	1.35	9.39
	ERA5-572	0.7	0.95	1.06	0.71	11.03	0.74	0.92	1	0.75	12.45
Whole domain	CHIRPS-250	0.58	0.97	1.22	0.65	14.34	0.66	0.93	1.06	0.67	11.52
	CHIRPS-410	0.49	0.89	1.02	1.5	17.94	0.45	0.99	0.89	1.54	12.37
	CHIRPS-572	0.51	0.95	1.22	0.56	15.55	0.57	0.96	1.06	0.58	11.92
	ERA5-250	0.86	0.95	1.12	0.95	10.33	0.97	0.99	0.98	0.98	4.16
	ERA5-410	0.68	0.92	1.08	1.3	14.79	0.66	0.99	0.94	1.34	7.78
	ERA5-572	0.44	0.93	1.2	0.48	16.23	0.48	0.87	1.05	0.5	15.55

Table 5.2: Performance metrics of actual evapotranspiration (aET) simulations compared with GLEAM and FLUXNET

r, beta, and gamma are components of the KGE model

In the Guinea region, only the aET results from the ERA5_250 mHM setup yielded satisfactory KGE values (KGE > 0.70) in comparison to observations from the GLEAM and FLUXNET products (Table 5.2). This signifies that the temporal pattern was captured, exhibiting a low RMSE value (RMSE = 12.33) when compared against aET from the GLEAM dataset and RMSE = 5.67 against that from the FLUXNET dataset. However, simulations obtained from other mHM setups within this region showed poor performance. However, a high correlation (r > 0.5) between simulations and observations across most of the poor-performing models (for KGE) indicates the existence of model bias and the inability to capture the spread of observed datasets, thereby resulting in unacceptable KGE scores. The temporal dynamics of simulated aET exhibit about 2.5 times larger variability than both GLEAM and FLUXNET observations for CHIRPS_410 mHM configuration in this region. Other mHM configurations presented the same patterns in reproducing temporal variabilities of observations.

For the Savannah region, acceptable KGE scores (KGE > 0.5) were exhibited by ERA5_250 and ERA5_410 mHM configurations against observations from the GLEAM and FLUXNET aET products (Table 5.2). These results also showed acceptable correlations (r > 0.8) with reasonable error margins (RMSE < 21 mm). Also, the annual cycle of aET obtained using

CHIRPS_410 mHM setup also gave KGE = 0.54 and exhibited high correlation (r = 0.99) and RMSE = 13.36 mm compared with the FLUXNET dataset. KGE scores across all mHM setups in this region showed a slight improvement compared to the Guinea region.

Model performance in the Sahel for all mHM simulations compared to both observed datasets (GLEAM and FLUXNET) showed acceptable results across all performance metrics employed in this study (Table 5.2). In comparison to the GLEAM datasets, KGE values range from 0.70 - 0.89 and 0.65 - 9.94 in relation to the FLUXNET observations.

For the whole domain of aET simulations, the performance of the model followed no particular order. mHM setups parameterized using CHIRPS_410 and ERA5_572 resulted in a KGE < 0.5 in comparison to aET observations from the GLEAM and FLUXNET products (Tab. 5.2).

Generally, aET simulation results in the Sahel replicated the temporal annual cycle of measured aET in terms of acceptable KGE and correlation scores. Model performance values in the Guinea region were lower than that in the Sahel as the former is characterized by a more humid climate with mean annual rainfall > 1500 mm compared to the drier climate in the latter (with annual precipitation between 434 mm to 969 mm) (Gbode et al., 2019). Biases in rainfall pattern representation over this region are reflected in most gridded precipitation products evaluated over this area, thereby translating to unacceptable aET simulations. Previous studies on gridded precipitation assessment over Nigeria revealed the inability of CHIRPS and ERA5 precipitation products to reasonably capture the temporal dynamics of precipitation over the Guinea region (Ogbu et al., 2020, 2022). However, all mHM configurations presented satisfactory RMSE values (< 25 mm) values across all modelled domains, which align with acceptable thresholds recommended by Moriasi et al. (2015). Yet, lower RMSE values (RMSE < 15 mm) were mainly observed across all mHM configurations applied in the Sahel region. Compared to the GLEAM datasets, all simulated aET values across all modelled domains exhibit model overestimations (beta > 1.0), except for the CHIRPS 410 mHM configuration.

5.3.3 Seasonal Trend Analysis of aET

The Mann-Kendall (MK) test was employed to analyze aET trends in the dry (January – March) and rainy seasons (June - September) across the entire domain of Nigeria and the three distinct regions (Guinea, Savannah and Sahel). The MK test results were assessed at a 95% confidence interval and a significance level (α) of 0.05 (Table 5.3).

			JFM		JJAS			
Region	Observation	Z-value	p-value	Sen's slope	Z-value	p-value	Sen's	
							slope	
Guinea	GLEAM	-1.00	0.32	-0.58	1.39	0.16	0.44	
	FLUXNET	1.57	0.12	0.44	3.78	0.0002	0.24	
	CHIRPS-250	3.03	0.002	0.46	-0.25	0.80	-0.06	
	CHIRPS-410	1.00	0.32	0.40	0.50	0.62	0.20	
	CHIRPS -572	3.35	0.001	0.73	-0.14	0.89	-0.03	
	ERA5-250	-2.36	0.02	-0.90	-0.64	0.52	-0.14	
	ERA5-410	-2.07	0.04	-1.49	-0.04	0.97	-0.01	
	ERA5-572	-2.00	0.05	-0.32	-1.82	0.07	-0.23	
Savannah	GLEAM	-2.07	0.04	-0.63	2.0	0.05	0.61	
	FLUXNET	0.68	0.5	0.06	2.28	0.02	0.28	
	CHIRPS-250	2.57	0.01	0.58	0.46	0.64	0.13	
	CHIRPS-410	-0.46	0.64	-0.08	1.25	0.21	0.36	
	CHIRPS-572	3.28	0.001	0.74	0.79	0.43	0.15	
	ERA5-250	-2.60	0.01	-0.67	-3.18	0.001	-0.79	
	ERA5-410	-3.43	0.001	-0.92	-2.93	0.003	-0.71	
	EAR5-572	-1.18	0.24	-0.64	-2.64	0.01	-0.99	
Sahel	GLEAM	1.96	0.05	0.26	2.39	0.02	0.51	
	FLUXNET	0.14	0.89	0.007	0.57	0.57	0.23	
	CHIRPS-250	2.43	0.02	0.43	3.39	0.001	1.16	
	CHIRPS-410	2.53	0.01	0.14	3.18	0.001	1.29	
	CHIRPS-572	2.93	0.003	0.43	3.35	0.001	1.22	
	ERA5-250	0.25	0.80	0.07	-1.86	0.06	-1.03	
	ERA5-410	-0.18	0.86	-0.03	-1.25	0.21	-0.98	
	EAR5-572	0.32	0.75	0.16	-1.75	0.08	-0.87	
Whole	GLEAM	-1.25	0.21	-0.30	2.14	0.03	0.49	
Nigeria	FLUXNET	0.75	0.45	0.09	2.0	0.05	0.27	
	CHIRPS-250	3.60	0.0003	0.53	2.18	0.02	0.48	
	CHIRPS-410	1.00	0.32	0.11	2.71	0.01	0.72	
	CHIRPS-572	3.82	0.0001	0.62	2.57	0.01	0.52	
	ERA5-250	-2.21	0.03	-0.50	-2.28	0.02	-0.65	
	ERA5-410	-2.82	0.01	-0.77	-1.93	0.05	-0.60	
	EAR5-572	-0.75	0.45	-0.27	-2.78	0.01	-0.75	

 Table 5.3: Mann-Kendall test for Dry and Rainy Seasons in Nigeria (1982 – 2011)

*Bold p-value = significant trend.

In the Sahel, the positive significant trend shown by the aET observations obtained from the GLEAM product was replicated by all CHIRPS-driven mHM setups in both seasons under consideration (Tab 5.3). The GLEAM dataset revealed a statistically significant increase in dry season aET at a confidence level of 95.1%, with a magnitude of 0.26 mm. This observed trend was reproduced by CHIRPS_250 (0.43 mm), CHIRPS_410 (0.14 mm), and CHIRPS_572 (0.43 mm) during the same season. In the rainy season, the GLEAM aET observations also showed a statistically significant increase, supported by a 98% confidence level and a magnitude of 0.13 mm. This upward trend during the rainy season was also corroborated by simulations from the CHIRPS_250 (1.16 mm), CHIRPS_410 (1.29 mm), CHIRPS_572 (1.22 mm), signifying consistent patterns across the datasets in this region.

In the Savannah region, GLEAM observations showed a statistically significant decrease (at a 96% confidence level) in dry season aET, registering a magnitude of 0.63 mm observed from 1982 - 2011 (Tab. 5.3). This trend was exhibited by simulations from ERA5_250 (magnitude of 0.67 mm) and ERA5_410 (magnitude of 0.92 mm) mHM setups during the same season. However, during the rainy season, the statistically significant increases indicated by the

GLEAM (95% confidence level) and FLUXNET (98% confidence level) datasets were not observed in any of the mHM aET-simulation setups. All mHM setups forced with ERA5 showed a statistically significant decrease, with various magnitudes ranging from 0.71 - 0.99 mm.

In the Guinea region, the statistically significant increase (99.98% confidence level) observed in the FLUXNET aET data (JJAS season) was not replicated in any of the various mHM setups considered in this study (Table 5.3). These results imply a poor replication of seasonal aET trend for all mHM configurations in this region.

Across the entire domain, both GLEAM and FLUXNET revealed a statistically significant increase during the rainy season (Table 5.3). GLEAM exhibited a positive increase of 0.49 mm at a 97% confidence level. Similarly, FLUXNET demonstrated a positive increase at a 95% confidence level, with a magnitude of 0.27 mm. Notably, only the aET results from CHIRPS_250 (with a magnitude of 0.48 mm), CHIRPS_410 (with a magnitude of 0.72 mm), and CHIRPS_572 (magnitude of 0.52) mHM setups were able to reproduce a comparable increasing trend. Conversely, all mHM setups driven by ERA5 rainfall datasets simulated statistically negative trends in seasonal (JJAS) aET observations.

5.3.4 Temporal Seasonal Pattern

Figure 5.7 presents the ability of all mHM setups to simulate temporal seasonal annual totals of aET over the three regions and the entire domain as Taylor diagrams. Results are shown for both the dry season (January to March, Fig. 5.7a & 5.7b) and the wet season (June to September, Fig. 5.7c & 5.7d).

The correlation performance scores of all mHM setups varied across the modelled domains during the dry season (JFM) (Fig 5.7a – b). Temporal correlations with the GLEAM dataset were less than 0.40 for CHIRPS_572 in Guinea, Savannah and the entire domain (Fig 5.7a). This trend of low correlation (r = 0.38) was also observed for ERA5_572 in the Guinea region. The mHM setups also showed unacceptable correlation performance with FLUXNET aET observations in the same season (JFM). Low correlation (r < 0.40) was observed in the Guinea region (CHIRPS_572, ERA5_250, ERA5_410, ERA5_572), Savannah (CHIRPS_572, CHIRPS_572, ERA5_250, ERA5_410, ERA5_572), and the entire domain (CHIRPS_250, CHIRPS_572, ERA5_250, ERA5_410, ERA5_572). However, all mHM setups showed an acceptable correlation ($r \ge 0.5$) in the Sahel region with both GLEAM and FLUXNET aET-observations.



Figure 5.7: Correlation coefficients of seasonal annual total actual evapotranspiration (aET) for the three climatic regions of Nigeria and the whole modelling domain: (a) January – March(JFM) season in comparison to GLEAM; (b) JFM season in comparison to FLUXNET; (c) June – September (JJAS) season in comparison to GLEAM; (d) JJAS season in comparison to FLUXNET.

During the wet season (JJAS, Fig. 5.7c & d), total aET simulations in various regions showed correlations of 0.50 and above in comparison to reference observations. When compared with aET-GLEAM (Figure 5.7c), acceptable correlations (r > 0.50) were observed in the Guinea (ERA5_250, ERA5_410) and Savannah regions (CHIRPS_250, CHIRPS_410, CHIRPS_572) as well as in the entire domain (CHIRPS_250 and CHIRPS_572). In contrast to the FLUXNET product, only CHIRPS_250 and CHIRPS_410 demonstrated correlations of 0.52 and 0.51, respectively. In the simulations of rainy season aET (Figure 5.7c & d), weak negative

correlations (r < 0) were identified when compared to GLEAM data (in the Savannah and Sahel regions and the entire domain), and FLUXNET data (Guinea, Savannah and Sahel). These findings indicate a moderate correlation with observed datasets but highlight the challenge of simulating total wet season aET, particularly with the ERA5-driven mHM.

5.3.5 Soil Moisture Anomaly

The simulated surface SM from the different mHM configurations (refer to Fig. 5.3) was also evaluated against SM observations obtained from the ESA CCI product for the three agroclimatic regions of Nigeria and the entire domain. Monthly spatial means of SM estimates for the different domains were estimated and standardized from 1982 to 2011. Figure 5.8 shows that all mHM configurations reasonably captured the monthly dynamics of observed SM anomalies in terms of the temporal pattern but with significant peak mismatches. This trend was observed in all modelled domains, with significant peak mismatch shown for CHIRPS_410 and ERA5_410 mHM configurations. Poor quality and insufficient stream gauge records used in constraining model parameters during calibration could have impacted estimated final parameter values. In addition, the ESA CCI SM observation was rescaled to align to the range of the Global Land Data Assimilation System SM field and does not represent absolute actual SM (Rakovec et al., 2016b).



Figure 5.8: Monthly soil moisture anomaly (z-score) in the three different climatic zones of Nigeria and the whole domain.

Figure 5.9 shows the model performance of SM across different climatic regions and the entire domain in terms of Pearson correlation values (r). In all mHM soil moisture simulations, correlation scores were high (r > 0.8) across all modelling domains (Fig. 5.9). The ERA5_572 model setup achieved the lowest correlation ($0.80 \ge r \ge 0.84$) across all the different climatic regions considered in this study. The coefficient of determination (R^2) showed a strong fit between mHM SM simulations and the ESA CCI dataset, ranging from 0.64 to 0.97 across all

different domains in this study. The ERA5_572 model setup yielded an R^2 value of 0.64. The range of low RMSE values (0.17 - 0.61) across the three different climatic regions and mHM configurations implies satisfactory overall model performance and an indication that the simulated soil moisture is close to the observed values and reflects the moisture conditions of the regions. Across all different agro-climatic regions of Nigeria, all calibrated mHM setups performed well in reproducing observed temporal trends of surface SM.



Figure 5.9: Correlation of mesoscale hydrologic model (mHM) surface soil moisture simulation against ESA CCI soil moisture

5.4 Conclusion

An evaluation of mHM simulations for aET and surface SM employing six unique mHMcalibrated parameter sets derived from various rainfall data-basin configurations was conducted across three agro-climatic regions in Nigeria. Calibrated mHM parameter sets obtained in a previous study (Ogbu et al., 2022) at the basin scale were used to assess mHM flux and state variables simulation on a much larger domain. The spatial annual total climatology of aET simulations across different mHM setups demonstrated a notable increase in the southward direction. They agreed with the spatially observed trends of the GLEAM and FLUXNET datasets. All mHM configurations were able to reproduce the bimodal (in the Guinea region) and unimodal (in the Savannah and Sahel regions) annual cycle of aET patterns in Nigeria, exhibiting reasonable performances of r > 0.8. The performance of annual total aET across the entire country shows satisfactory correlation scores (r > 0.5) for all mHM configurations with the GLEAM product. However, this ability deteriorates (r < 0.5) when mHM setups forced with ERA5 are compared against FLUXNET observations. The temporal variability trend of the annual aET cycle is well reproduced over all domains by all model configurations. This satisfactory mHM performance is well exhibited in the Sahel region (KGE > 0.7) but degenerates southward towards the Guinea region (0.1 > KGE > -0.7). Unsatisfactory aET-mHM performance in Guinea may be related to the inability mHM to capture the high temporal dynamics of precipitation in this region. The significant positive trend exhibited by the GLEAM-aET observations was replicated by all CHIRPS-driven mHM setups in wet and dry seasons in the Sahel region of Nigeria. This consistency was demonstrated by the ERA5driven mHM configurations in the Savannah region, but results deteriorated in the Guinea region. The simulated annual seasonal aET exhibits strong agreement with mostly the GLEAM observations during the dry season than in the wet season. The unavailability of flux tower sites in Nigeria may have increased uncertainties in using FLUXNET for aET evaluation. Evaluation of surface SM shows reasonable agreement (r > 0.9) across all domains. This reflects a reasonable replication of SM seasonality in the three distinct climatic regions of Nigeria.

This is the inaugural application of the fully distributed mHM constrained against only streamflow at the basin scale in Nigeria for the simulation of aET and SM on a larger domain and across distinct climatic regions of Nigeria. The multiscale parameter regionalization technique incorporated within the mHM structure allows for parameter transfer to ungauged regions without recalibration. Results reveal that acceptable agreement with observed data was predominantly observed in the Sahel region and aligns with the location of the basins used during parameter calibration. In this study, mHM constrained with only streamflow can produce reliable aET and SM simulation results in the Sahel. However, the unavailability of good-quality discharge records in the southern region of Nigeria did not allow for a robust model calibration process. Due to the lack of discharge data, especially in parts of the Savannah and Guinea regions, the incorporation of flux and state variables during mHM calibration is recommended to improve simulation results. This approach may further advance the hydrologic modelling results, and support applied hydrology in Nigeria and other data-scarce regions. Further investigations in this regard are essential for improving the accuracy and reliability of mHM simulations in capturing complex dynamics of hydrologic processes which exist under conditions in Nigeria and similar data-scarce regions.

6 Overall Conclusions

Dense and reliable hydro-meteorological monitoring networks are paramount for practical studies in hydrologic systems management. The unavailability of high-quality continuous hydro-meteorological datasets with adequate spatio-temporal resolution poses a significant challenge for hydrologic modelling, particularly in developing regions. Unfortunately, this trend of declining instrumentation in waterways and climate observation systems is expected to persist due to challenges such as poor government systems, vandalization, and discontinuation of government projects by subsequent administrations. This development has negatively affected the realistic application and calibration of hydrologic models to support decision-making in operational hydrology. Recently, the easy and free accessibility of highquality remote sensing datasets and the development of complex hydrologic models have ignited increased research activities in water resources modelling. However, these efforts have not contributed much to realistic hydro-meteorologic variables simulations owing to inherent biases in remote sensing products and hydrologic model structure. Conducting a regionspecific assessment of remotely sensed climatic variables is necessary to estimate the magnitude of bias and evaluate its overall quality. Furthermore, mathematical representations of complex hydrologic processes may result in model over-parameterization and consequently impact effective parameter calibrations, particularly in data-limited regions.

The effective utilization of high-performing satellite-gridded climatic datasets, along with a parameter regionalization technique that preserves a basin's heterogenous characteristics', holds great potential for hydrologic modelling in ungauged basins. In addition, hydrologic variables not considered during calibration can be independently used for model evaluation. The primary aim of this study is to evaluate the parameter transferability skill of the mesoscale Hydrologic Model (mHM) for hydrologic simulation under conditions of limited input datasets. This study contributes to the International Association of Hydrologic Sciences (IAHS) initiative of Prediction in Ungauged Basins (PUB).

The following paragraphs summarise major conclusions from each main chapter (2, 3, 4, and 5) according to the formulated research questions. The study's contributions and recommendations will also be presented.

1. How well do certain selected gridded precipitation products perform in Nigeria?

The performance of three different satellite-based precipitation products in replicating spatial and temporal dynamics of local rainfall characteristics was evaluated at the point-to-pixel scale. Data from CHIRPS, PERSIANN and TAMSAT were extracted and compared to in-situ records from 24 synoptic stations distributed across three agro-climatic regions in Nigeria. The selected products were assessed for performance at seasonal, monthly and annual scales. Findings show that seasonal rainfall patterns were similar, depicting an increasing gradient southward in the country. However, the wet seasons were poorly replicated. All products captured the temporal annual precipitation cycle but with significant biases in locations within the Guinea Coast region. All products could reproduce the monthly and inter-annual rainfall patterns, although with varying accuracy. Generally, performances were more successful in the Sahel region (northern Nigeria) than in the country's south. The CHIRPS rainfall products performed better than other satellite rainfall products in this study.

2. To what extent does the mesoscale Hydrologic Model (mHM) accurately replicate the temporal variability of observed streamflow under data-limited conditions?

Limited hydro-metrological data pose a significant challenge for hydrologic modelling in ungauged regions. To evaluate the mHM capability for streamflow calibration and validation, the mHM was set up across four distinct data-sparse basins. Five gridded precipitation products comprising satellite, gauge and reanalysis datasets were used as model forcings under a univariate (only streamflow) and multivariate (streamflow and actual evapotranspiration) calibration framework. All the precipitation products for both calibration frameworks presented acceptable streamflow simulation (KGE > 0.5) in the Jamaare River basin. Only the CHIRPS, CPC and ERA5 datasets maintained the same trend (KGE > 0.5) in the same basin during model validation. Data gaps in all streamflow observations limited effective calibration and evaluation of the mHM's robustness. About 50% of the missing data characterize the Jamaare River basin, while other basins feature worse situations. Using results from the Jamaare basin as a case study, the CHIRPS product exhibited the best results under both calibration frameworks. Overall, results from the multivariate calibration approach did not indicate significant superiority under this data-scare circumstance.

3. How reliable is the Multiscale Parameter Regionalization (MPR) technique for model parameter transfer to ungauged basins?

A significant strength of the mHM is its ability to utilize gridded datasets in netcdf file format as direct inputs. This is most suitable in ungauged regions where remote datasets can be an alternative for setting up a hydrologic model. The mHM incorporates a regionalization scheme, MPR, to address the model over-parameterisation problem and maintain sub-basin heterogeneity. The effectiveness of transferring mHM parameters across locations and scales has been evaluated in many developed regions with satisfactory results. The main aim was to assess the transferability of optimized mHM parameters from gauged to ungauged basins for streamflow simulation using gridded rainfall datasets. In a default mHM simulation, 12 mHM configurations comprised three different basins and four precipitation forcings. Model runs were performed using default mHM parameters and then constrained using each basin's streamflow records. Subsequently, the most performing precipitation product was utilized to optimize a multi-basin mHM. Calibrated parameters obtained from each mHM set-up were then used to simulate streamflow on an independent basin. Hydrological evaluation of the gridded precipitation products revealed that the CHIRPS products are the most performing datasets under existing conditions. mHM optimization results exhibited satisfactory streamflow simulation results when forced with MSWEP or CHIRPS. However, parameter transfer to an independent basin resulted in an acceptable simulation in one basin. Unacceptable performance was attributed to the unavailability of a reservoir component within the mHM structure. Significant gaps in streamflow observations could have impacted the parameter calibration process.

4. How effectively does mHM simulate evapotranspiration and soil moisture on a regional scale when utilizing calibrated parameters obtained at the basin level?

This study evaluated the feasibility of performing mHM simulation for independent variables using optimized parameters obtained by constraining mHM parameters with streamflow data. The mHM actual evapotranspiration and soil moisture simulations were evaluated using

parameters obtained when mHM was constrained with streamflow observations. Six distinct parameter sets were obtained when mHM was forced separately with CHIRPS and ERA5 precipitation products across three different basins. These parameters were used to set up mHM over the entire Nigeria domain for aET and SM simulation at monthly temporal resolutions. Simulations were compared against two aET (GLEAM and FLUXNET) and SM (ESA CCI) gridded products on different temporal resolutions across three distinct agro-climatic regions. Spatial annual patterns of aET presented an increasing trend from north to southern Nigeria, and agreed with observations. However, aET simulations agreed more with the GLEAM product than the FLUXNET. Sparse flux towers across the African continent, with none located in Nigeria, could be the reason for the poor representation of accurate aET datasets over this region. CHIRPS-driven mHM exhibited satisfactory aET performance in comparison to the ERA5-driven mHM. Improved aET simulations were observed more in the Sahel (northern Nigeria) than in the southern region. Simulated monthly surface soil moisture across Nigeria's agro-climatic regions agreed with observed counterparts.

Using station observations and a hydrologic modelling approach effectively assessed the performance of gridded rainfall products. Satisfactory simulation results obtained during univariate and multivariate calibration frameworks indicate the feasibility of the mHM-MPR technique for hydrologic predictions in data-sparse regions. The preservation of basin variability aided by the MPR was responsible for the model's performance under data-limited conditions.

7. Synthesis

The findings presented in this study underscore the critical role of gridded precipitation rainfall products as forcings for the mHM in addressing the challenges posed by the scarcity of hydrometeorological datasets in Nigeria. Each chapter complements and contributes to a greater understanding of the performances of these products over Nigeria as well as the utility of the mHM for continuous hydrological modelling in data-sparse regions. Adequate knowledge of rainfall variability is necessary for sustaining rain-dependent agriculture and driving the local economy of Nigeria. This information is critical for modelling hydrologic processes and monitoring the implications of water management scenarios. The unavailability of a comprehensive climatic gauge network necessitated the choice of gridded precipitation observations as a suitable alternative for modelling rainfall-runoff processes.

Realistic hydrologic modelling for understanding local and regional water resource variability depends significantly on the driving precipitation data and the structure of the hydrologic model. All gridded rainfall products evaluated showed great skill in capturing annual rainfall cycles and spatial trends of observations across different agro-climatic zones in Nigeria. However, the CHIRPS product displayed higher consistency in replicating the dynamics of rainfall patterns across selected locations in Nigeria. Other gridded rainfall products, such as the reanalysis ERA5, MSWEP and GPCC, also showed reliability, especially in Northern Nigeria. Gridded precipitation products do not entirely replace in-situ observations. Still, they have demonstrated the ability to effectively replicate the local rainfall cycle, especially in regions with limited climatic information. Information from these gridded datasets can likely be used to fill in missing gaps in station data. However, evaluations at a daily temporal resolution presented lower performance than results from monthly, seasonal and annual periods.

Significant efforts towards developing remotely sensed precipitation products were partly inspired by the need to fulfil the climatic data requirement for continuous hydrologic modelling, especially in regions plagued by inadequate instrumentation networks and inaccessible terrains. When evaluated within a hydrologic modelling framework in four Sahelian basins in Nigeria, the utility of these products demonstrated that they can be used as mHM forcings. Furthermore, product evaluations under uni and multi-calibration schemes presented nearly the same results and exhibited no significant change in stream discharge simulation. The CHIRPS product again proved to be reliable, producing reasonable KGE scores under both calibration frameworks, demonstrating its applicability in hydrologic modelling. Using both in-situ precipitation data and hydrologic modelling to evaluate the skill of gridded precipitation products provides a comprehensive evaluation framework. It ensures a robust assessment for selecting the most accurate and reliable dataset for the study domain. This ensures that the dataset can support studies involving water resources management, hydrologic extreme risks mitigations and climate change impact research.

The information from the comparative analysis of remotely sensed precipitation products provides valuable insights into their performance. Also, results contribute to the broader knowledge of how different data sources can impact their predictive skills. This is also necessary to guide the selection of appropriate datasets for rainfall-runoff process modelling. The regionalization method employed in the mHM model is an innovative methodology to overcome the problem of over-parameterization and facilitate the transfer of optimal model parameters from gauged to ungagued basins. This technique enhances the accuracy of hydrologic simulations and contributes to understanding parameter regionalization in hydrologic science. The improved KGE score (> 0.5) during streamflow prediction in one of the study basins further underscores its reliability in enhancing model simulation performance.

Results also showed that critical challenges of model calibration in ungauged regions can be overcome by transferring optimized parameters across scales. mHM parameters from different setups obtained when constrained with only streamflow at the basin scale successfully simulated actual evapotranspiration (aET) and surface soil moisture across Nigeria. Simulated spatial patterns of mean annual aET climatology present an increasing trend southwards from Northern (Sahel) Nigeria. This trend aligns with observations extracted from the GLEAM and FLUXNET aET products. However, CHIRPS-driven mHM showed a better correlation than ERA5-driven mHM. These improved scores were mainly observed across the Sahel region. The more humid Guinea region did not produce acceptable results due to the more variable and dynamic monsoon climate. Furthermore, the temporal variability of simulated monthly soil moisture across the three distinct agro-climatic regions agreed (r > 0.8) with observations. These results underscore the feasibility of reliable mHM hydrologic simulation in areas with similar data-limited characteristics.

Study results benefit sustainable water resources management and crop production planning in regions limited by hydro-climatic data, such as Nigeria. By providing a reliable framework for realistic hydrologic simulation, this research supports an informed decision-making process for stakeholders and policymakers in the water resources and agriculture sectors. The successful implementation of the mHM modelling tool in this region offers other hydrologic modellers awareness of the information needed to address the challenges of hydrologic predictions with limited observed data.

8. Outlook

This study evaluated the feasibility of mHM hydrologic parameter transferability to ungauged domains under data-limited conditions in Nigeria. The significant findings underscored the potential for setting up the mHM with gridded precipitation products for hydrologic process monitoring with sparse in-situ data. Overall, results contribute to the scientific understanding of rainfall variability and hydrological processes in regions characterized by sparse hydroclimatic variables. This effort is aimed to provide a basis for future studies on rainfall-runoff modelling and model transferability across multiple temporal and spatial scales. This chapter highlights the implications of the study findings suggests future research options, and study limitations.

Gridded precipitation datasets provide consistent and fine-resolution rainfall data that is useful for the timely detection and monitoring of droughts. This information is necessary to develop hydrologic extreme (drought and flood) warning systems for disaster mitigation. This proactive measure produces information needed to mitigate the impacts of climate change on agriculture and water resources. Effective agricultural management practices and realistic crop growth simulation can benefit from high-quality rainfall data. Such information is essential for optimizing crop planting schedules and efficient irrigation and fertiliser application, resulting in better food security. Driving the mHM model with gridded precipitation datasets can significantly enhance water management by providing reliable model inputs to support policymaking in regions without ground-based observations. The information gained through hydrologic modelling is essential for managing and sustaining watershed management practices, flood control and water supply structures. The ability to transfer optimized parameters to ungauged domains shows the robustness of the mHM model. Robust model configurations tend to improve hydrologic predictions and watershed management practices in regions characterized by sparse hydro-climatic station networks. Research results provide helpful information for decision-makers on the benefits of remotely sensed datasets for water resources management and agriculture. Insights on river dynamics, flood risks, soil moisture variabilities and drought conditions are helpful for decision-makers when formulating policies to mitigate the impacts of extreme hydrologic events. Decision-makers must leverage hydrologic results to ensure that water or agriculture-related policies are science-based and effective in sustaining and preserving ecosystems.

Future studies should focus on enhancing the quality and resolution of gridded precipitation products, especially across sub-Saharan Africa. National governments should contribute to this effort by increasing the density of hydro-climatic networks, which are critical for the calibrations and validations of these products. Refining hydrologic models to accurately represent land surface systems better is essential. This includes a feedback structure between human activities and hydrologic processes and integraton of critical model components (e.g., land/agricultural management practices, crop growth, lakes/wetlands, and reservoirs).

The hydrologic framework adopted in this study can help decision-makers formulate sciencebased water management decisions. Gridded datasets are a better alternative in regions with sparse or limited in-situ observations. This can improve the monitoring of water resources, preparedness for hydrologic extremes, and sustainable agricultural practices. Improving hydroclimatic data instrumentation and hydrologic model implementation and ensuring efficient and transparent collaboration between local communities, government agencies, and researchers is critical for the development and sustainability of hydrologic system balance.

Sensor limitations and data processing algorithms primarily impact the accuracies of remotely sensed precipitation products. Therefore, there is a need for continuous validation of these products to ensure their reliability. The unavailability of hydrometric data in other regions of Nigeria poses a significant challenge for mHM applications outside the Sahel region. Three major categories of land use cover (impervious, pervious and forest) are used in mHM to represent morphological datasets. These efforts could have lumped other land use classes that significantly impact hydrologic processes. Also, dams, reservoirs, and critical hydraulic structures that impact runoff and evaporation were not modelled by mHM when performing these simulations. Basins considered in this study contained various sizes of reservoir projects, which, if represented, could have improved simulation results. A functional crop growth module is also lacking in the mHM, which could have realistically simulated crop evapotranspiration and soil moisture. More studies are recommended to explore the transferability of mHM parameters to other regions with similar geographic conditions and explore its limitations under different hydrologic frameworks.

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Appendices

Appendix A: mHM Parameters

- β_1 Effective maximum canopy storage (mm).
- β_2 Threshold temperature for phase transition snow/rain (°C).
- β_3 Degree day factor during rainless days.
- β_4 Rate of increase of the degree day factor per unit of precipitation (d⁻¹ °C⁻¹).
- β_5 Maximum degree day factor reached during rainy days.
- $\beta^{k_{6}}$ Maximum soil moisture content.
- β_7 Parameter that determines the relative contribution of rain or snowmelt to runoff.
- β_8 Critical value of soil ice content above which the soil is practically impermeable.
- β_9 Shape factor of the distribution.
- β_{10} ATI threshold below which unfrozen water content reaches its minimum.
- β_{11} ATI threshold above which no frozen water exist.
- β_{12} Minimum fraction of unfrozen water content.
- β_{13} Weighing multiplier ranging from 0.1 to 1.
- β_{14} Maximum ponding retention in impervious areas.
- β_{15} Permanent wilting point.
- β_{16} Soil moisture limit above which the actual transpiration is equated with the PET.
- β^{k}_{17} Fraction of roots in the Kth horizon.
- β_{18} Maximum holding capacity of the second reservoir (unsaturated zone).
- β_{19} Fast-recession constant.
- β_{20} Slow recession constant.
- β_{21} Exponent that quantifies the degree of non-linearity of the cell response.
- β_{22} Effective percolation rate.
- β_{23} Baseflow recession rate.
- β_{24} Fraction of the groundwater recharge that might be gained or lost either as deep percolation or as inter-catchment groundwater flow in nonconservative catchments.
- β_{25} Duration of the TUH.
- β_{26} Muskingum travel time parameter.
- β_{27} Muskingum attenuation parameter.
- β_{28} Aspect correction factor of the PET.

Parameters	lower bound	upper bound	default	ERA 250	ERA 410	ERA 572	Chirps 250	Chirps 410	Chirps 572
Interception									
canopyInterceptionFactor	0.150	0.400	0.150	0.167	0.301	0.151	0.230	0.189	0.153
Soil Moisture									
orgMatterContent forest	0.000	20.000	5.030	8.334	17.660	1.480	10.230	14.178	1.188
orgMatterContent impervious	0.000	1.000	0.698	0.526	0.094	0.229	0.749	0.071	0.498
orgMatterContent pervious	0.000	4.000	3.815	0.059	2.225	0.494	2.337	3.986	0.098
PTF lower66 5 constant	0.646	0.951	0.800	0.866	0.683	0.950	0.861	0.947	0.929
PTF lower66 5 clay	0.0001	0.003	0.001	0.001	0.002	0.003	0.002	0.003	0.003
PTF lower66 5 Db	-0.373	-0.187	-0.250	-0.195	-0.197	-0.195	-0.320	-0.190	-0.240
PTF higher66 5 constant	0.536	1.123	0.804	0.885	1.086	0.635	0.724	1.120	0.569
PTF higher66 5 clay	-0.006	0.005	-0.001	-0.001	0.001	0.003	0.005	0.005	0.0002
PTF higher66 5 Db	-0.551	-0.091	-0.341	-0.546	-0.461	-0.282	-0.536	-0.134	-0.402
PTF Ks constant	-1.200	-0.285	-1.003	-0.566	-0.307	-0.332	-0.707	-0.828	-0.633
PTF Ks sand	0.006	0.026	0.016	0.008	0.009	0.014	0.007	0.026	0.0219
PTF Ks clay	0.003	0.013	0.003	0.004	0.01	0.012	0.012	0.009	0.007
rootFractionCoefficient forest	0.900	0.999	0.949	0.993	0.924	0.998	0.998	0.902	0.998
rootFractionCoefficient impervious	0.900	0.950	0.950	0.948	0.922	0.950	0.949	0.940	0.950
rootFractionCoefficient pervious	0.001	0.090	0.002	0.036	0.013	0.001	0.001	0.088	0.002
infiltrationShapeFactor	1.000	4.000	1.039	1.278	3.936	1.023	1.090	1.008	1.007
Direct sealed area runoff									
imperviousStorageCapacity	0.000	5.000	0.008	0.464	0.072	0.647	0.344	0.708	0.150
Potential evapotranspiration									
minCorrectionFactorPET	0.700	1.300	0.900	1.160	0.828	1.109	0.965	1.055	1.299
maxCorrectiobFactorPET	0.000	0.200	0.100	0.185	0.002	0.041	0.114	0.036	0.195
aspectTresholdPET	160.0	200.0	180.0	160.1	197.9	161.9	167.58	161.4	187.45
Interflow									
interflowStorageCapacityFactor	75.000	200.00	198.66	199.07	159.37	196.76	199.69	187.78	174.90
interflowRecession slope	0.000	10.000	8.257	8.23	7.278	7.284	6.563	7.522	2.491
fastInterflowRecession forest	1.000	3.000	2.963	2.936	2.944	2.997	2.970	2.926	2.237
slowInterflowRecession_Ks	1.000	30.000	1.534	1.317	9.501	8.286	7.295	4.158	2.072
exponentSlowInterflow	0.050	0.300	0.051	0.061	0.252	0.071	0.053	0.231	0.067
Percolation									
rechargeCoefficient	0.000	50.000	49.884	49.875	13.665	24.788	49.534	19.288	18.819
rechargeFactor_karstic	-5.000	5.000	-2.778	3.34	2.017	0.873	-2.856	3.640	2.302
Routing									
muskingumTravelTime_constant	0.310	0.350	0.350	0.348	0.314	0.332	0.349	0.341	0.338
muskingumTravelTime_riverLength	0.070	0.080	0.080	0.080	0.074	0.071	0.073	0.079	0.080
muskingumTravelTime_riverSlope	1.950	2.100	2.100	2.099	2.067	2.060	2.081	2.095	2.081
muskingumTravelTime_impervious	0.090	0.110	0.099	0.109	0.107	0.100	0.094	0.099	0.110
muskingumAttenuation_riverSlope	0.010	0.500	0.013	0.010	0.013	0.442	0.481	0.191	0.028
Geology									
GeoParam(1,:)	1.000	1000.0	986.47	913.22	759.06	52.974	943.57	974.02	436.87
GeoParam(2,:)	1.000	1000.0	977.00	894.22	999.88	599.25	934.24	988.70	543.13

Appendix B: Parameter for mHM Setups