MINISTERE DE L'ENSEIGNEMENT SUPERIEUR
ET DE LA RECHERCHE SCIENTIFIQUE

Felix Houphouët-Boigny University

UNITE DE FORMATION ET DE RECHERCHE
SCIENCES DES STRUCTURES DE LA
MATIERE ET DE TECHNOLOGIE

RÉPUBLIQUE DE CÔTE D'IVOIRE
UNION - DISCIPLINE - TRAVAIL

SPONSORED BY THE
Federal Ministry of Education and Research

Nº: 834

INTERNATIONAL MASTER PROGRAM

IN RENEWABLE ENERGY AND GREEN HYDROGEN

SPECIALITY: GEORESOURCES (WATER/WIND) AND GREEN HYDROGEN TECHNOLOGIES

Topic:

INFLUENCE OF CLIMATE MODEL SELECTION ON LONG-TERM GROUNDWATER RECHARGE FORECASTS ACROSS DIFFERENT AFRICAN REGIONS

Presented on the **25th September, 2025**.

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Academic year: 2024-2025

DEDICATION

I dedicate this work to my lovely parents, Mr and Mrs. Agbeme, whose love, prayers, and sacrifices have been my foundation, and to my dear siblings, whose encouragement and support have inspired me throughout this journey.

ACKNOWLEDGEMENTS

First and foremost, I express my deepest gratitude to Almighty God for granting me the strength, knowledge, and abilities to embark and complete this research journey.

I deeply appreciate the German Federal Ministry of Education and Research (BMBF) and the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), together with all other partners, for the scholarship opportunity that made this academic pursuit possible.

Special thanks to the President of the University Félix Houphouët-Boigny, Prof. Ballo ZIE, for hosting our specialty studies. I also extend my appreciation to Prof Komla Dodzi KOKOROKO, President of Université de Lomé, and Prof. Moussa BARAGE, President of Université de Abdou Moumouni, for their generous hospitality and institutional support during the first and second semesters, respectively. I am sincerely grateful to the Director of IBG-3 for granting me the opportunity to develop and improve my skills during my internship period in the institute.

To the WASCAL directors, Dr. Konan Edouard KOUASSI (Côte D'Ivoire), Prof. Adamou RABANI (Niger) and Prof. Komi AGOKA (Togo), thank you for your unwavering support throughout the master's program. Your endless encouragement and assistance, fatherly mentorship played a pivotal role in the successful completion of my studies. I also appreciate the support of Dr. Wanignon Ferdinand FASSINOU (Côte D'Ivoire), the specialty coordinators, and the scientific coordinators for their assistance to the directors and ensuring smooth academic studies.

My sincere appreciation goes to my supervisors, Prof. Harrie-Jan Hendricks Franssen, Dr. Adamu Bamba and my daily supervisors, Bamidele Oloruntoba (Ph.D.) and Dr. Bagher Bayat for their consistent guidance, encouragement and insightful feedback throughout the entire research process.

I am also thankful to the esteemed jury members for their time and valuable insights during the evaluation of this thesis.

Finally, I express my heartfelt thanks to my family and loved ones for their support, encouragement, patience and belief in me. Your confidence in my abilities has been a constant source of strength. I am equally grateful to all my colleagues, most especially team Ghana and everyone I encountered along this journey for their kindness and care.

ABSTRACT

The continuous availability and renewability of groundwater rely on the process of groundwater recharge. Therefore, recharge forecasting is essential for effective groundwater resource management, particularly in the context of climate change. In this study, we employ the Community Land Model version 5 to forecast recharge across Africa for the period 2071-2100 at 10km spatial resolution. The land module was forced with outputs from three regional climate model outputs (CCLM5, RegCM4 and REMO2015), each driven by two global climate models (MPI_ESM and NorESM) under two climate scenarios (RCP2.6 and RCP8.5), and recharge estimated using the water balance approach at both continental and regional scales. Based on the long-term recharge forecast, continental average recharge potential of 119 mm/year (with standard deviation of 68 mm/year) and 92 mm/year (with standard deviation of 59 mm/year) for RCP2.6 and RCP8.5 were recorded respectively. The standard deviation serves as an indicator of spatial variability across the models' ensemble.

Further analysis, including correlation, coefficient of variation and bias were used to assess regional recharge reliability and sensitivity, respectively. Model performance was found to be region specific, with significant differences in biases between CCLM5 and REMO2015, while REGCM4 demonstrated consistent pattern across most regions and both climate scenarios.

The results indicate recharge projections are more influenced by model structures and the choice of driving GCM than emission scenarios. These structural differences and uncertainties highlight the complex interactions between global and regional climate processes that influence recharge projections. Such uncertainties present challenges for regional development and climate adaptation strategies. Therefore, this study recommends evaluating the performance of individual models within ensemble frameworks and highlights the importance of local and regional calibrations to enhance the reliability of groundwater recharge projections.

Keywords: Groundwater recharge; climate models; climate scenarios; long-term forecast; regional sensitivity; African regions.

RÉSUME

La disponibilité et la renouvelabilité continues des eaux souterraines dépendent du processus de recharge des nappes phréatiques. Par conséquent, la prévision de la recharge est essentielle pour une gestion efficace des ressources en eaux souterraines, en particulier dans le contexte du changement climatique. Dans cette étude, nous utilisons le modèle Community Land Model version 5 pour prévoir la recharge à travers l'Afrique pour la période 2071-2100 avec une résolution spatiale de 10 km. Le module terrestre a été alimenté par les résultats de trois modèles climatiques régionaux (CCLM5, RegCM4 et REMO2015), chacun piloté par deux modèles climatiques mondiaux (MPI_ESM et NorESM) dans le cadre de deux scénarios climatiques (RCP2.6 et RCP8.5), et la recharge a été estimée à l'aide de l'approche du bilan hydrique à l'échelle continentale et régionale. Sur la base des prévisions de recharge à long terme, le potentiel de recharge moyen continental de 119 mm/an (avec un écart type de 68 mm/an) et de 92 mm/an (avec un écart type de 59 mm/an) a été enregistré respectivement pour les scénarios RCP2.6 et RCP8.5. L'écart type sert d'indicateur de la variabilité spatiale dans l'ensemble des modèles.

Une analyse plus approfondie, incluant la corrélation, le coefficient de variation et le biais, a été utilisée pour évaluer respectivement la fiabilité et la sensibilité de la recharge régionale. Les performances des modèles se sont avérées spécifiques à chaque région, avec des différences significatives entre les biais du CCLM5 et du REMO2015, tandis que le REGCM4 a montré un schéma cohérent dans la plupart des régions et pour les deux scénarios climatiques.

Les résultats indiquent que les projections relatives à la recharge sont davantage influencées par les structures des modèles et le choix du MCG utilisé que par les scénarios d'émissions. Ces différences structurelles et ces incertitudes mettent en évidence les interactions complexes entre les processus climatiques mondiaux et régionaux qui influencent les projections relatives à la recharge. Ces incertitudes posent des défis pour les stratégies de développement régional et d'adaptation au climat. Par conséquent, cette étude recommande d'évaluer les performances des modèles individuels dans le cadre d'ensembles et souligne l'importance des calibrages locaux et régionaux pour améliorer la fiabilité des projections relatives à la recharge des eaux souterraines.

Mots-clés : Recharge des eaux souterraines ; modèles climatiques ; scénarios climatiques ; prévisions à long terme ; sensibilité régionale ; régions africaines.

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ACRONYMS AND ABBREVIATIONS

BMBF:	German Federal Ministry of Education and Research
CAF:	Central Africa Region
CCLM:	Consortium for Small-Scale Modelling Regional Model
CEAF:	Central East Africa Region
CLM5:	Community Land Model version 5
CMIP5:	Coupled Model Intercomparison Project 5
CORDEX:	Coordinated Regional Climate Downscaling Experiment
Corr:	Correlation
CRU	Climate Research Unit
CV:	Coefficient of Variation
FZG:	Forschungszentrum Julich
GCM(s):	General Circulation Model(s)
GHG:	Greenhouse Gases
GWR:	Groundwater recharge
IBG-3:	Institute of Biological and Geosciences
ITCZ:	Inter-tropical Convergence Zone
MED:	Mediterranean Region
MPI:	Max Planck Institute Earth System Model
NEAF:	North East Africa Region
NOR:	Norwegian Earth System Model
P-Bias:	Percentage Bias
RCM(s):	Regional Climate Model(s)
RCP:	Representative Concentration Pathways
REGCM:	Regional Climate Modelling System

REMO: Max Planck Regional Climate Model

SAH: Sahara Region

SEAF: South East Africa Region

SST: Sea Surface Temperature

Std: Standard Deviation

SWAF: South West Africa Region

UFHB University Félix Houphouët-Boigny

WAF: West Africa Region

WASCAL: West African Science Service Centre on Climate Change and Adapted Land Use

GENERAL INTRODUCTION

GENERAL INTRODUCTION

Background

Groundwater makes up a significant portion of available freshwater and is a major source of water for domestic and agricultural uses (Dari et al., 2025). It forms the fundamental of water supply throughout most of African communities as demand for quality and secure water rises (MacDonald et al., 2021). Groundwater is the most abundant freshwater resource in Africa based on storage volume, which has led to intense competition among various water users, such as the food and energy production sectors (Bayat et al., 2023). Across the African continent, groundwater resources are widely distributed and characterised by two aquifer systems: low recharge/high storage regional sedimentary aquifers and high recharge/low storage weathered crystalline rock aquifers (MacDonald et al., 2021; Pazola et al., 2023). Continuous supply of groundwater relies on the recharge process, which restores the aquifers from the surface. Groundwater recharge is the amount of water that infiltrates into the subsurface, reaching the groundwater table by means of various mechanisms, which include rainfall infiltration (both diffuse and preferential pathways), return flow from irrigation and leaking pipes (Crosbie et al., 2011).

Groundwater recharge rate estimation is primarily important to assessing current trends in water security and forecasting future changes (Gleeson et al., 2020; MacDonald et al., 2021). Its rates are influenced by a range of climatic conditions, hydrological and hydrogeological variables (Moeck et al., 2016; Pazola et al., 2023). Due to complexities influencing the recharge rates, parameters and factors are identified both at regional and global scales (Pazola et al., 2023). Seasonal variability of precipitation and potential evapotranspiration directly influence the amount of water available for recharge. Vegetation influences the processes involved in infiltration rates and deep drainage, and land cover changes lead to considerable variation in groundwater recharge. Direct measurement of groundwater recharge is difficult and almost impossible due to the nature of recharge quantity, complexity and varying nature of hydrogeological setting (Jayakody et al., 2014). Commonly known procedures used for recharge estimation are chloride mass balance, soil physics methods, environmental and isotopic tracers, groundwater-level fluctuation methods, water balance (WB) methods and estimation of baseflow to rivers (MacDonald et al., 2021). These methods provide valuable insight, but are constrained by site-specific applicability, limited spatial or temporal resolution and challenges in representing long-term climatic variability. To address these limitations, hydrological modelling has become an essential tool for groundwater recharge estimation. By integrating watershed characteristics, soil hydraulic properties, land cover and topographic data, hydrological models present hydrological processes more holistically. They also offer the capacity to assess the influence of climate variability on recharge, making them essential for groundwater dynamics to environmental and climatic changes (Jayakody et al., 2014). Performance of hydrological models depend on the availability and quality of climatic inputs such as precipitation, temperature, insolation and humidity (Nitcheva, 2018). Since recharge is driven by these variables, reliable projections are required to ensure robust assessment. Climate models, therefore, serve as indispensable tools that provide the necessary boundary conditions and large-scale climatic information that drives hydrological processes for accurate recharge simulations.

Climate models, ranging from global circulation models (GCMs) to more detailed regional climate models (RCMs), simulate atmospheric variables such as temperature, precipitation, wind patterns, and carbon emissions to simulate and predict future climatic conditions (McGuffie & Henderson-Sellers, 2001;Allen et al., 2010). GCMs project significant changes to both regional and globally averaged precipitation and temperature, with significant implications for groundwater recharge (Kurylyk & MacQuarrie, 2013). Hydrological and land surface models are therefore coupled with climate model outputs to estimate recharge under different emission scenarios. Consequently, projections are highly sensitive to the choice of climate models due to varying capabilities and inherent uncertainties to simulate rainfall patterns and intensities, temperature changes and extreme weather events (Crosbie et al., 2011).

Although historical and present-day estimates of groundwater recharge can be validated with measured water balance components and observational datasets, long-term groundwater recharge forecast remain uncertain due to climate variation, the complex nature of recharge processes, climate model structural differences, emission scenarios and further limitations. Studies conducted by Xu & Beekman, (2019); Ashaolu et al. (2020); Barbosa et al. (2022), adopted hydrological and climate models to estimate and predict recharge across various African regions. Additionally, MacDonald et al. (2021) provided groundwater recharge estimates maps through ground-based observations for Africa. These studies offer valuable insights into groundwater recharge but often focus on methodological development while neglecting the variability introduced by different GCM-RCM configurations, particularly in Africa's diverse hydroclimatic regions.

Addressing this gap, the present study investigates how the choice of model influences recharge projections by uncovering model-specific nuances that highlight regional differences, uncertainties, and areas of consistent agreement in projected groundwater recharge. The research is important as it improves the reliability of water resource projections, which are crucial for sustainable management, policy formulation and climate adaptation planning. Robust recharge estimates will support long-term initiatives such as long-term planning of green hydrogen production in Africa and ensure water security for both ecosystems and communities under changing climate conditions.

Objectives

This study aims to assess the extent and nature of model-driven variability in projected groundwater recharge over Africa using multiple climate model data

The specific objectives of the study are;

- Simulate future GWR using CLM5 forced by six GCM–RCM combinations.
- Quantify model-driven spread and identify regions of spatial recharge agreement.
- Diagnose regional recharge sensitivity to climate model configuration.
- Provide insights for water planners on the spatial reliability of model-based recharge forecasts.

This work is divided into several sections. The first chapter provides a literature review on groundwater and recharge systems, an overview of climate models and uncertainty, and the second chapter presents the materials and methods used in the study. The third chapter presents the results and discussions. Lastly, conclusions and recommendations.

CHAPTER ONE:

LITERATURE REVIEW

CHAPTER ONE: LITERATURE REVIEW

Introduction

This chapter highlights a comprehensive study of research works concerning groundwater, recharge, climate models, the contribution of models in hydrological studies, and uncertainty sources and assessment.

1.1 Groundwater and Recharge System

1.1.1 Groundwater

Groundwater is a primary source of high-quality freshwater worldwide (Mileham et al., 2009) and the largest reserve of unfrozen freshwater (96%) on Earth (Taylor et al., 2013), providing vital and climate-resilient access to water (Müller Schmied et al., 2021). It is stored within pore spaces, fractures, and cavities in subsurface materials. The storage within geological structures defines the groundwater systems as either unconfined or confined aquifers. Unconfined groundwater systems are associated with exposed water surface through permeable soil layers, while confined aquifers lie between impermeable layers and are subjected to high pressure (Atangana, 2018). The occurrence of groundwater is mainly influenced by geology, geomorphology, and precipitation (Lei et al., 2010). Major hydrogeological environments existing in Sub-Saharan Africa include Precambrian basement rocks, consolidated sedimentary rocks, unconsolidated sediments and volcanic rocks (Adelana et al., 2008).

Across Africa, particularly in the arid and semi-arid regions, most rural and urban communities strongly depend on groundwater due to its perennial presence, capacity to buffer short-term climate variability and affordability of abstraction infrastructure as compared to other water sources (Döll & Fiedler, 2008; MacDonald et al., 2021). The African population's dependence on groundwater varies from ~ 50% to 75% (Carter & Parker, 2009). In the face of rapid population growth and climate change, groundwater plays a crucial role in sustainability and ensuring human adaptation to extreme and global environmental conditions. Groundwater forms an essential component of the climate system as illustrated in figure 1, influencing the study of the climate change influence on groundwater resources (Amanambu et al., 2020).

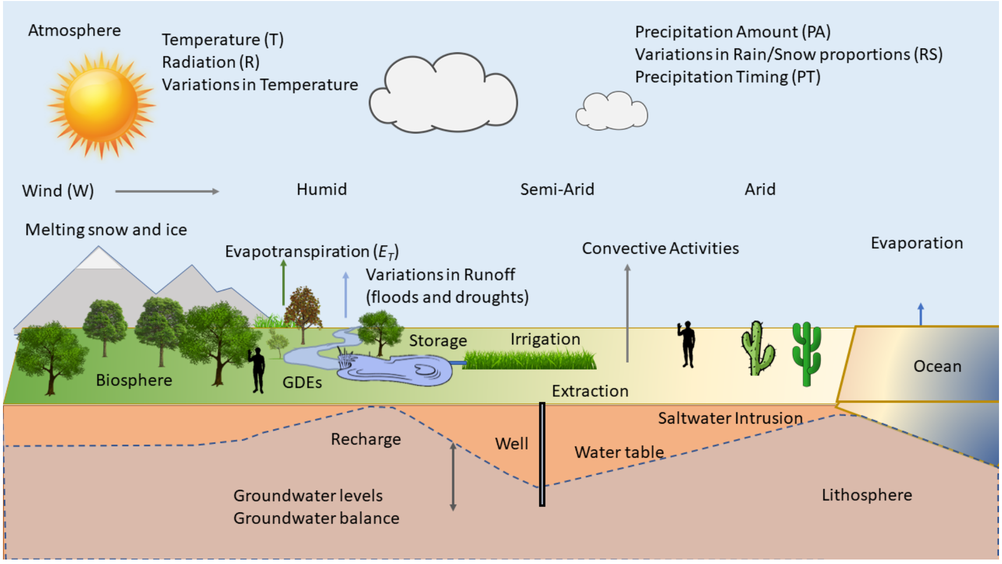

Figure 1: Groundwater interaction with Earth's climate system. Source: (Amanambu et al., 2020).

1.1.2 Groundwater Recharge

Groundwater recharge is a key driver of the hydrogeological system, and its estimation forms a fundamental part of groundwater renewability and resource management (Pazola et al., 2023). It is the downward movement of water from the surface of the soil through the unsaturated zone to the saturated zone beneath the water table. Net infiltration, drainage, percolation, and residual flux are terminologies used in literature to equate recharge (Scanlon et al., 2002). Recharge sources are classified as direct recharge, localised recharge, and indirect recharge as shown in figure 2. The figure provide visual explanation of the recharge mechanism associated the various recharge types. Direct recharge is the portion of rainfall or irrigation that contributes to the groundwater by direct percolation through the unsaturated zone after partitioning from surface runoff and evaporation. Recharge that results from surface depressions is known as localised recharge. Whereas the quantity of water that percolates into the aquifer through canals, river beds, or other waterbodies is referred to as indirect recharge (Mahmud et al., 2023). MacDonald et al. (2009) delineated three primary rainfall recharge zones in Africa, namely: negligible groundwater recharge in areas receiving less than 200 mm/year of rainfall, approximately 50 mm/year recharge in regions with rainfall between 200-500 mm/year, and over 50 mm/year recharge in zones where rainfall surpasses 500 mm/year.

Groundwater recharge is influenced by factors such as climate, land use, land or vegetation cover, geology, topography, soil texture and structure, irrigation water use, depth of water table and existence of nearby water bodies (Acharya et al., 2018; Ali & Mubarak, 2017). These factors, individually or as combined efforts affect the rate of recharge. Precipitation is the key climatic factor that regulate the recharge and abundance of water on the land surface (Scanlon et al., 2002). According to Jobbágy & Jackson (2004), the distribution of pore sizes and soil porosity have an impact on transpiration, infiltration, water holding capacity, and overall recharge. Sandy soils possess more porosity and have greater hydraulic conductivity, leading to higher recharge and clayey soils, on the contrary, have tiny pores with greater surface tension and lower recharge. Runoff components of rain and irrigation, including soil evaporation, are largely governed by the type of soil cover and density, and thus lead to variable groundwater recharge (Ali & Mubarak, 2017).

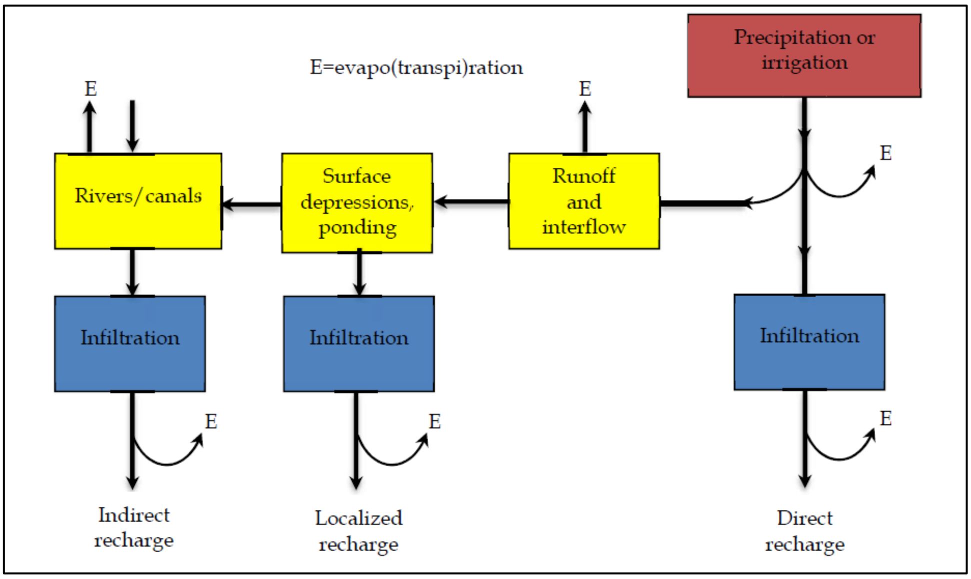

Figure 2: Types of groundwater recharge mechanisms. Source: (Mahmud et al., 2023)

1.1.3 Groundwater Recharge Estimation Methods

Direct and accurate quantification of the volume of water that reaches the water table is challenging. Consequently, a variety of methods and techniques have been developed for the estimation and prediction of groundwater recharge. The methods include direct measurements, water balance methods, Darcian approaches, tracer techniques and empirical methods (Lei et al., 2010). Mahmud et al. (2023) classified methods primarily as direct and indirect methods. The direct physical method is the lysimeter method, and the direct chemical method is the tracer technique (applied or historical). Indirect physical methods are the soil water balance, water budget method, and groundwater table fluctuation methods. Recharge estimations can also be classified based on regions where arid, semi-arid and humid climates exist. Water budget method, isotopic tracers, lysimeters, Darcy's law and other numerical methods are used in arid and semi-arid climatic zones (Mahmud et al., 2023). For humid zones, soil water balance, water budgets, lysimeters, Darcy's law, applied tracers, and numerical models are most appropriate

(Scanlon et al., 2002). Mahmud et al. (2023) outlined a detailed review on the estimation methods for natural groundwater recharge, equations and problems associated with recharge estimation using the lysimeter method, water balance methods, water budget method, water table fluctuations, applied tracer techniques, and use of Darcy's equation.

Recharge equations based on the lysimeter method (eq. 1.1) and the water balance (eq. 1.2) are:

$$R = P + I - ET \pm \Delta S \qquad (1.1)$$

$$R = P + I - ET - R_o \pm \Delta S \qquad (1.2)$$

Where R = recharge, P = precipitation, I = Irrigations, ET = Evapotranspiration, R_o = runoff, $\pm \Delta S$ = changes in soil water storage (calculated as differences in initial to final water content in the lysimeter zone or basin/site). Estimates based on the lysimeter method and water balance are dependent on the reliability and accuracy of the water flux data. Problems associated with the lysimeter are the high expense of constructing and maintaining the lysimeter. Also, flow along the sidewalls of the lysimeter can lead to overestimation of the actual recharge. Furthermore, estimation of surface runoff is the main source of uncertainty in the water balance approach, especially in humid regions (Ali & Mubarak, 2017).

Numerical modelling provides essential tools needed for continuous understanding of groundwater processes. They help in understanding the past, present and future states of geophysical (including groundwater processes) and earth systems. A widely used numerical groundwater model is the Modular Groundwater Flow Model (MODFLOW), developed by the United States Geological Survey (USGS). It's a three-dimensional finite model with enhanced capabilities to simulate flow, solute transport, and coupled surface-groundwater flow (Amanambu et al., 2020). Amanambu et al. (2020) enlisted numerical models (groundwater and surface/subsurface coupled) and their characteristics used in groundwater recharge studies.

Hydrological models are simplified computational representations of water cycles within a region or basin (Kour et al., 2016), that simulate the dynamic processes involved in transforming precipitation into surface runoff, groundwater recharge, and streamflow through mechanisms such as infiltration, interception, evaporation, transpiration, snowmelt, and subsurface flows (Chokkavarapu & Mandla, 2019). These models range from simple empirical relationships between precipitation and recharge, soil-water-balance models (HELP Model, SMBM, etc.), embedded soil water balance models within coupled hydrological modelling framework and models based on Richards' equation (HydroGeosphere, ParFLOW, HYDRUS, FEFLOW, Mike SHE, etc.) (Moeck et al., 2016). The effectiveness of these models relies on how well the equations approximate the physical system being modelled. Use of geographical information systems (GIS) and remote sensing are also tools that aid in groundwater recharge estimation and simulation. It can be used singly for gathering and manipulating large, high-quality databases or fully integrated with other numerical models. Visualisation capabilities of GIS help recalibrate numerical models by showing differences between modelled, interpolated and measured water levels (Amanambu et al., 2020). A globally known hydrological model for groundwater recharge studies is the WaterGAP Global Hydrology Model (WGHM) (Döll et al., 2002; Alcamo et al., 2003). The model was used to provide a global groundwater recharge map by Döll et al. (2002) at a grid scale of 0.5 degree × 0.5 degree and an updated simulation using the WGHM2 model by Döll & Fiedler (2008). The first global-scale study on groundwater recharge was conducted by L'vovich (1979); the estimation was based on the baseflow components of observed river discharge.

1.2 Climate Models and Their Role in Hydrological Modelling

1.2.1 The need for climate models

Climate models are computer-based representations of the Earth's climate system, including atmosphere, ocean, land, and ice. They solve mathematical equations that describe the planet's energy budget and vary from simple to complex depending on the feedback mechanisms involved as shown in figure 3. Models are based on fundamental physics laws: energy and mass conservation, fluid motion and ideal gas laws (Philander, 2012). Climate models are used to quantitatively measure climate sensitivity, radioactive forcings and climate feedbacks (Kour et al., 2016). Climate sensitivity was defined as the equilibrium change in surface temperature that results from given radiative forcings by Schwartz (2004).

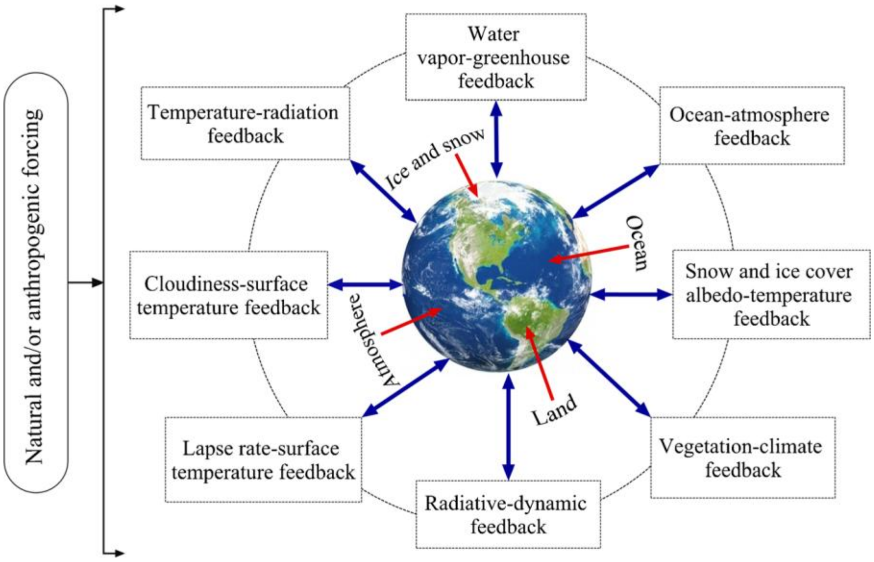

Figure 3: Types of feedback mechanisms in the Earth's climate system. Source: (Kour et al., 2016).

Climate models are essential tools needed for investigating, understanding, and predicting the climate system efficiently. They provide meteorological input data such as rainfall, and temperature for simulating the water cycles at various scales. In combination with hydrological models, they help evaluate how future climatic scenarios may alter hydrological regimes, informing water resource management and adaptation strategies (Kour et al., 2016).

1.2.2 Overview of climate models

Climate models differ in complexity, purpose, and spatial resolutions. EBMs are the simplest climate models used to simulate the Earth's temperature by balancing incoming solar radiation with outgoing infrared radiation. They are used to study fundamental climate processes and sensitivities (Kour et al., 2016). Global Circulation Models (GCMs) are the most sophisticated models, which simulate the climate system components in three dimensions, including atmosphere, ocean, land surface, and ice. They are used for detailed climate projections and understanding the interconnections within the Earth's climate system at a large spatial scale, approximately 100 – 250 km resolution (Teutschbein & Seibert, 2010; McGuffie and Henderson-Sellers 2001). GCMs are primary tools for climate simulations under a range of future GHG emissions (Nikulin et al., 2012). Due to the coarse resolution of GCMS, regional models are developed to dynamically downscale them (nesting RCMs in GCMs) to produce high-resolution climate data outputs (Kour et al., 2016). Regional Climate Models (RCMs) are advanced models designed to simulate the climate system at meso- and regional scales compared to GCMs. RCMs usually operate at a resolution of approximately 2km for convection permitting RCMs (very high resolutions) to the CORDEX spatial resolution (Akinsanola et al.,

2025) which allows finer representation of land features, coastlines, and elevation for more accurate local climate variations.

1.2.3 The value of CORDEX Africa simulations for understanding African climate

Regional climate models (RCMs) are key components of regional climate change vulnerability, impacts, and adaptation studies. Coordinated Regional Climate Downscaling Experiment (CORDEX) is a regional modelling project that carries out a set of experiment where reanalysis data such as ERA-INTERIM and the Coupled Model Intercomparison Project Phase 5 (CMIP5) GCMs are dynamically downscaled to produce historical and future simulations at horizontal resolution of 0.44° × 0.44° and improved to 0.22° × 0.22° in 2019 (Ilori & Balogun, 2022; Nikulin et al., 2018; Giorgi et al., 2009). Africa has been the priority and essential domain for CORDEX due to inadequate quality observation datasets, climate change vulnerability and low adaptive capacity (Ilori & Balogun, 2022). CORDEX Africa (CORDEX Region 5) simulations provide high-resolution, homogenous ensembles of regional climate projections that are crucial for understanding African Climate dynamics. The higher spatial resolution, multi-model approach and specific focus on the continent's unique climate challenges enable assessment of climate variables such as solar irradiance, temperature, cloud cover, precipitation, and wind speed by approximate estimation and reproducing the observed spatio-temporal pattern despite some biases. The simulations also allow robust projection of future climate variables under different emission scenarios and evaluation of future risks related to droughts, floods, groundwater recharge, food security and health. CORDEX Africa simulations also developed a new set of metrics for model validations tailored for the different African regions, which help boost confidence in both present-day and future climate projections (Gnitou et al., 2021). The high-resolution (~25 km) CORDEX-CORE framework provides models valuable for identifying regional vulnerabilities and informing adaptation strategies tailored to specific African sub-regions (Sawadogo et al., 2021). According to the results of CORDEX simulations, CORDEX Africa and CORDEX-CORE products are potentially suitable for a variety of high-resolution precipitation data applications throughout Africa. Several studies investigated the performance of CORDEX RCMs in simulating past and present precipitation, temperature trends and variability, projections and climate change studies over African regions (Demissie, 2023; Ilori & Balogun, 2022; Gibba et al., 2019; Akinsanola & Ogunjobi, 2017; Dosio, 2017; Dosio & Panitz, 2016; Pinto et al., 2016; Nikulin et al., 2012, 2018). These studies highlighted the performance of CORDEX RCMs in simulating well precipitation and temperature at seasonal, annual, and diurnal timescales and highlighted the superior performance of multi-model ensembles compared to individual models. Despite adequate performance of CORDEX Africa simulations in understanding the African climate, variations exist in model performance. RCMs' agreement with GCMs' projections varies across regions because of several GCMs downscaled by the same RCM, poor representation of topography and small-scale processes (such as convection) resolved differently by GCMs and RCMs. Differential climate signals stemming from different GCM and RCM physics and parameterisation also contribute to uncertainties and less confidence in simulations.

1.2.4 Contributions of CORDEX Africa simulations to Hydrological modelling

For better investigation, simulation, and representation of hydrological variables for modelling at regional scales, high-resolution datasets are required. CORDEX Africa aids in the provision of fine-scale climate parameters, such as precipitation, radiation, and temperature datasets of resolution (~25 to 50km), which accurately capture the spatial variability and extremes important for hydrological processes compared to coarser global datasets (Giorgi & Gutowski, 2015). By downscaling global models, CORDEX RCMs allow hydrological modellers to reflect basin-scale climate variations, enhancing the reliability of projected changes in streamflow, groundwater recharge, and drought frequency assessment (Mathewos et al., 2023). Integration of CORDEX Africa data into hydrological modelling frameworks helps to study major river basins and headwaters, supporting assessment of future water security and planning of irrigation and hydropower projects (Musie et al., 2020). CORDEX-Africa enhanced data also allow researchers to assess climate change impact on water resources across different regions. Simulations are used to project changes in precipitation and other climate variables under different emission scenarios and help provide vital information for understanding potential river flow changes, water availability and flood risk (Banda et al., 2022; Bojer et al., 2024) and assessment of potential impacts of climate change on hydropower production in different watersheds (Kouadio et al., 2024). An ensemble of CORDEX RCMs further improves uncertainty reductions in hydrological models' inputs and forecasts (Gyamfi et al., 2021; Kalognomou et al., 2013).

1.3 Regional Disparities in Responses to Climate Models

1.3.1 Selected CMIP5 GCM Performance across African Regions

Africa’s regional climatic patterns are affected by large climate variability, rapid topographical variations, inland waterbodies, and land-sea contrasts with the adjacent Atlantic and Indian

Oceans. The results of such climate variability affect the livelihood, food productivity and water availability across the region, putting the continent among the most vulnerable to the potential climate changes induced by 21st-century greenhouse gas (GHG) forcing (Mariotti et al., 2014). Max Planck Institute Earth System (MPI-ESM-LR), Hadley Centre Global Environment Model by UK MetOffice (HadGEM-ES) and Norwegian Earth System Models (NCC-NorESM1-M) constitute CMIP5 GCM models used for climate studies in Africa. Taylor et al. (2012) provide a detailed description of the models' experimental design and parameters. The climate response and scenario estimates of NorESM1-M were emphasised by Iversen et al. (2013). In comparison to other models in CMIP5, the model's predicted equilibrium climate sensitivity is 2.9 K. Giorgetta et al. (2013) examined the climate and carbon cycle of MPI-ESM simulations used in CMIP5, stating that MPI-ESM-LR has an equilibrium climate sensitivity of 3.6 K. The study further highlighted the model's structure and revealed that climate feedback depends on the level of global warming and possible forcing history. Description of HadGEM-ES development and evaluation used in CMIP5 is also detailed in Collins et al. (2011). It has a notably lower cloud cover compared to other GCMs. HadGEM-ES is a robust climate model with significant improvement in ocean temperature and tropical variability for representing climate dynamics, especially over Mediterranean regions (Dosio & Panitz, 2016).

Mehran et al. (2014) evaluated CMIP5 continental precipitation simulations relative to satellite-based gauge-adjusted observations. CMIP5 simulations, including MPI-ESM, NorESM, and HadGEM-ES simulations, were cross-validated against Global Precipitation Climatology Project (GPCP) data. Results of the volumetric analysis hit index (VHI) of total monthly precipitation prove the models' simulations are in good agreement with GPCP patterns in most regions but show less skill in simulating precipitation at high quantiles of the reference data (75th and 90th percentiles) except in regions such as Central Africa. Analysis of total bias also revealed models overestimate precipitation over regions with complex topography (for example, Southern Africa) while underestimating in arid regions. A study by McSweeney et al. (2015) to aid selecting CMIP5 GCMs for downscaling over multiple regions indicated the ability of MPI-ESM-LR, HadGEM-ES and NorESM1-M to capture 29, 27 and 25 out of 36 key teleconnection relationships in Africa, respectively. Africa's climate conditions are strongly influenced by the seasonal migration of the Inter-tropical Convergence Zone (ITCZ) and associated seasonal rainfalls. Teleconnections with major modes of variability in sea-surface temperatures (SST) such as ENSO and IOD are factors that influence the strong interannual climate variability across Africa (McSweeney et al., 2015). MPI-ESM-LR and HadGEM-ES were used in a study by Dosio & Panitz (2016) to assess climate change projections for the CORDEX-Africa domain. The results showed GCMs overestimated present climate precipitation and overestimated seasonal mean precipitation across Central African regions, whereas present-day mean temperature is also largely overestimated across the Sahel region. Both models also show a decrease in mean precipitation and an increase in consecutive dry days over West Africa (Dosio & Panitz, 2016). Agyekum et al. (2018) also evaluated CMIP5 GCMs precipitation simulation over the Volta Basin. The evaluation of a limited number of GCMs revealed that NOR-ESM-LR could accurately replicate the observed climatological mean of the total annual precipitation and the peak observed rainy season in the Sudano-Sahel, the Sahel, and the entire Volta basin. However, it struggled to replicate the Guinea Coast's bimodal pattern.

1.3.2 Regional Climate Model Performance across African Regions

Regional climate models (RCMs) play an important role in improving African's diverse climate zones representation, yet their performance is influenced by methodological approaches and inherent data limitation. The spatial accuracy of RCMs varies across regions and seasons as they capture localised climate phenomena such as monsoons, elevation gradients and land cover, introducing model challenges (Wu et al., 2020). Compared to GCMs, RCMs generally better simulate finer-scale rainfall features and seasonal cycles; however, persistent biases remain in simulation of regional rainfall intensities, annual cycles, the onset and cessation of rainy seasons (Gerasu et al., 2024). As part of the CORDEX project, the consortium for small-scale modelling (COSMO), the regional model (CCLM), the Regional Climate Model (REMO) and the Regional Climate Modelling System (RegCM) are widely used models for evaluation in the Africa domain. The models are developed by KIT, Karlsruhe, Germany, in collaboration with the CLM-community; Climate Service Center, Germany and Abdus Salam International Centre for Theoretical Physics, Italy, respectively. REMO and REGCM4 are hydrostatic models, while CCLM is a non-hydrostatic model. Details on the models' dynamic and physical parameterisation are provided by Giorgi et al. (2012) and Nikulin et al. (2012).

Focusing on individual model performances, CCLM5 demonstrated considerable skills in reproducing key African climate, specifically the seasonal pattern of precipitation and temperature, but exhibited quantitative biases (Fotso-Kamga et al., 2020). It improves simulations of both mean seasonal and daily precipitation, capturing features such as the West African monsoon and the rainfall regime in the Sahel region (Panitz et al., 2013). To assess climate change projections, Dosio & Panitz (2016) employed CCLM to assess CORDEX-

Africa output relative to GCMs, revealing projected increase in seasonal temperature similar to projections of GCMs. In contrast, over regions such as Central Africa, precipitation trends simulated are in opposite directions to GCMs, with significant reduction in precipitation. Similarly, over Southern Africa, CCLM simulates warmer temperature than GCMs during the both January-February-March (JFM) and July-August-September (JAS) periods over 1981-2010 (Dosio & Panitz, 2016).

REMO2015 is recognised for capturing temperature cycles and broad precipitation patterns well over subtropical and tropical regions, often outperforming other models in daily and seasonal temperature metrics (Vondou & Haensler, 2017). It also produces a realistic annual precipitation cycle and magnitude, but present regional biases; underestimation or overestimation depending on the subregions or domain (Safari et al., 2023). The study by Jacob et al. (2012) assessed the transferability of REMO to different CORDEX regions with a standard setup. Using boundary conditions from the ERA-Interim global reanalysis dataset over the period 1989 to 2008, evaluating via the Koppen-Trewartha climate classification and probability density function (PDF) skill score compared to the CRU dataset, REMO was found capable of well simulating the mean annual climatic features across all domains, including Africa, despite some dry biases in East Africa. Importantly, REMO captures the inter- and intra-annual seasonal variability for most climate across the Koppen-Trewartha climate classes.

Similarly, RegCM4 with improved land surface schemes and convection parameters (such as Emmanuel convection scheme) show acceptable simulation of temperature and precipitation typical of earlier versions, though it underestimate rainfall during peak rainy seasons (Koné et al., 2018). Comparisons with CRU observational data highlights RegCM4's skill in capturing mean precipitation and low-level wind circulations. Representation of the Intertropical Convergence Zone (ITCZ) over the Atlantic is narrower in the model, but the regional features of both seasonal precipitation fields are well reproduced. The model also captures well the Tropical Easterly Jet and the African Easterly Jet (Giorgi et al., 2012). In West Africa and the Sahel region, RegCM4 simulates a forward shift in the monsoon onset as produced in MPI-ESM-LR, with widespread decrease of monsoon precipitation associated with decreased easterly wave activity and soil moisture precipitation interaction (Mariotti et al., 2014; Saini et al., 2015).

Akinsanola & Ogunjobi (2017) used CCLM, REMO and an earlier version of RegCM (RegCM3) in combination with other CORDEX regional models to evaluate present-day precipitation of West Africa. Despite CCLM and REMO overestimating rainfall during preand post-monsoon seasons, all models captured the geographical extent and the three distinct phases of the West African monsoon. RegCM3 was found to outperform all other models and recommended for use in West Africa rainfall assessment (Akinsanola & Ogunjobi, 2017). Ilori & Balogun's (2022) further support the performance of RegCM in simulating the mean seasonal rainfall over West Africa. The study evaluated the performance of three RCMs (CCLM, REMO and RegCM) by downscaling three CMIP5 GCMs (HadGEM, MPI-ESM-LR and NORESM1-M) at a resolution of 0.22° × 0.22°. Their analysis spanning the period 1970 to 2005, highlighted RegCM's ability to replicate West African rainfall pattern.

Overall, studies have confirmed the RCM's abilities to capture the African climate patterns and dynamics, including adding value to driven GCM simulations. However, unavoidable biases persist and vary according to season, sub-area and GCM-RCM chain (Gnitou et al., 2021). To address this, multi-model ensembles are widely adopted due to better performance than individual models. Multi-model ensemble outperforms individual RCMs as a result of the cancellation of opposite-signal biases found in the different RCMs (Wu et al., 2020). Ensemble based approaches including CCLM5, RegCM, and REMO have been used in other studies to investigate the effect of global warming increase across the different regions for climate adaptation and resource management (Dosio, 2017; Klutse et al., 2018; Mba et al., 2018; Nikulin et al., 2018; Fotso-Kamga et al., 2020; Dosio et al., 2021).

1.4 Variability and Uncertainty in Groundwater Recharge Forecasts

1.4.1 Known Sources of Uncertainty in Groundwater Recharge Simulations

Uncertainties from water resources modelling perspective stem from differences in spatial and temporal resolution of climate models compared to the finer resolution of hydrological models (Goderniaux et al., 2015; Banda et al., 2022). Banda et al. (2022) classified sources of uncertainties from climate model projections as (i) scenario uncertainty; uncertainty related to emission or concentration scenario (ii) Global circulation models (GCM) uncertainty; uncertainty related to how global models respond to specific emission scenario (iii) Regional climate models (RCM) uncertainty or downscaling uncertainty; uncertainty from the use of several RCMs and downscaling techniques from a specific GCM projection (iv) uncertainty caused by internal variability of the climate system. Choices of GCM and RCM are the principal sources of uncertainty, particularly GCM, with the most significant uncertainty in future recharge estimations (Crosbie et al., 2011). RCM errors are related to process parameterisations such as cloud representation, convection, horizontal diffusions and microphysics (Solman et al., 2013). Hydrological model uncertainties originate from parameter uncertainty (Reinecke et al., 2021), model structure (Döll et al., 2016) and process (inability to simulate real-world processes thoroughly), groundwater table dynamics, input and observed data (Moges et al., 2021). Known sources of hydrological data uncertainties are measurement or point uncertainty, for example, rainfall, uncertainty from data interpolated in space and time, scaling uncertainty, and uncertainties in data management (McMillan et al., 2018).

1.4.2 Uncertainties in recharge forecast across Africa

The long-term forecast of groundwater recharge in Africa is prone to uncertainty due to a combination of environmental, methodological, and data-driven factors. The primary sources of uncertainty include;

- Model structure and parameterisation: Climate and hydrological models vary in simulating rainfall, evapotranspiration, soil moisture and subsurface flow. Model selection, spatial resolution and internal assumptions result in significant variations in recharge forecasts even when applied over similar areas (Reinecke et al., 2021).
- Observational Data Limitations: Observed data are needed for validation of model outputs, but are sparse with no functioning measuring stations across many African regions, especially in arid and remote landscapes (Beyene et al., 2024). Remote sensing for large-scale monitoring and the provision of data adds to uncertainty due to limitations in satellite data resolution and interpretation (Richey et al., 2015).
- Estimation Method Uncertainty: Different ways of estimation (water table fluctuations, soil moisture, remote sensing, etc.), model simplification, and assumptions often lead to different outcomes and biases (Reinecke et al., 2024).
- Diverse landscapes and environmental controls: Rainfall conversion into groundwater recharge is influenced by features such land cover, soil type, geological formations, and topography. This diverse distribution of features across Africa causes difficulties in generalising findings across regions (West et al., 2023).

1.5 Review of Recharge Studies across Africa.

Considerable studies have been conducted to estimate groundwater recharge using different methods and to characterise uncertainties in recharge estimation across several areas in Africa. Chung et al. (2016) investigated groundwater recharge studies in the humid and semi-arid African region. In their study, recharge estimation methods were assessed. Water-balance fluctuations (WTF) and chloride methods can be used with better certainty for recharge estimation in arid and semi-arid regions. The accuracy of these methods can be compromised by factors such as localised inputs data and water vapour transport. However, the lack of basic data remains a major challenge in these regions. MacDonald et al. (2021) helped bridge the gap in historical data by mapping recharge across Africa. The study quantified long-term average recharge rates across Africa for the period 1979-2019 from 134 ground-based estimates. Recharge mechanisms included natural diffuse and local focused recharge, excluding discrete leakage from large lakes and irrigation. Based on the use of a linear mixed model at the African continental scale, long-term average rainfall and long-term annual recharge are correlated with other factors important at the local scale. Building on the continental estimates of MacDonald et al. (2021), Pazola et al. (2023) employed random forest regression at a finer resolution (0.1° resolution) enhancing spatial detail and improving the representation of recharge variability. However, the random forest model is constrained by its representation of focused recharge and limited study in humid and equatorial African regions.

Bayat et al. (2023) quantified groundwater recharge using the water balance approach. Land surface hydrology was simulated for the period 1965 – 2014 using the Community Land Model version (CLM5). In their study, irrigation was included in the computation. The results of this study offered the first model-based estimation of water availability across Africa. Ashaolu et al. (2020) employed the water balance model to estimate spatial and temporal recharge in the Osun drainage basin of Nigeria. The study confirmed the importance of the water balance model in understanding the spatial and temporal status of recharge. Through advancements in technologies and satellite data, GIS and remote sensing techniques are also employed in recharge estimation. Barbosa et al. (2022) used NASA Gravity Recovery and Climate Experiment (GRACE) data to evaluate groundwater storage change and recharge of aquifers in Niger. The water table fluctuation approach was used in the study to predict recharge rates between 2002 and 2021. The studies of Bayat et al. (2023) and MacDonald et al. (2021) provide valuable datasets for global and continental model calibration and a baseline for future changes; however, noticeable uncertainties exist in estimation methods, hydrological models and model forcings. West et al. (2023) compared global-scale model estimates of groundwater recharge across Africa. Long-term average recharge and recharge ratio from eight global models over 100 ground-based estimates in Africa were compared. Models' estimates were found to disagree significantly across most of the regions. Positive and negative biases exist in most landscapes, posing challenges to identifying areas requiring model improvement. Xu & Beekman (2019) also assessed groundwater recharge estimation in arid and semi-arid Southern

Africa. Methods of estimating recharge, including chloride mass balance (CMB) and water fluctuation methods, were investigated. Methods based on mass balance and the relationship between rainfall and water level fluctuation were proven to have the potential to simulate and forecast recharge. In the case of South Africa, CMB are highly recommended. However, uncertainties are known to be associated with error input and method propagation.

For a better understanding of process control on recharge variability across Africa, West et al. (2022) synthesize information on reported groundwater control. They developed 11 descriptors consisting of climatic, topographic, vegetation, soil and geological properties using global datasets. The study classified Africa into 15 recharge landscape units influenced by the descriptors. Annual precipitation, seasonal precipitation, and irrigation showed a positive relationship with recharge. Whereas radiation, slope, transpiration, and bedrock have a negative correlation with recharge.

Previous studies estimated recharge using several known methods and assessed their limitations across the different landscapes. However, research has not investigated the extent and atmospheric forcings variability in hydrological modelling. The work in this thesis aims to forecast recharge under two climate scenarios assessing recharge potential and reliability. It also identifies areas of model agreement and regional recharge sensitivity to the GCM-RCM choices, providing insights into uncertainty. Results of these assessments would help in the provision of valuable insights to water planners on the spatial reliability of model-based recharge forecasts.

Partial Conclusion

The literature review highlighted an overview of groundwater, recharge processes and the various estimation methods relied on. It has outlined the role of climate models and their contribution to advancing hydrological modelling, while examining the performance across different African regions. The review examined the uncertainties inherent in groundwater recharge projections arising from both climate and hydrological models. Finally, recharge-focused studies conducted across Africa were considered, drawing attention to existing gaps and diverse methodologies applied. These insights underscore the complexity of groundwater recharge assessment under changing climate conditions and indicate the necessity of our study in addressing model-driven variability and implications for water sustainability in Africa.

CHAPTER TWO:

MATERIALS AND METHODS

CHAPTER TWO: MATERIALS AND METHODS

Introduction

This section presents the study area, climate model combinations, simulation methods, data analysis, and tools used for assessing recharge potential, reliability, and regional sensitivity across various African regions under two climate scenarios.

2.1 Study Area

The study is conducted over the CORDEX Africa domain, which spans from longitude -24.59° to longitude 60.23° and latitude -45.71° to latitude 42.19°, covering an area of 30.3 million km^{2,} including adjacent islands. Continental Africa is bordered by the Mediterranean Sea to the North, the Indian Ocean to the East, and the Atlantic Ocean to the West. Africa is on both the equator and the prime meridian. Rainfall across the continent is highly variable, providing a basis for different climatic conditions and regional divisions (hot desert, semi-arid, tropical wet and dry, equatorial, Mediterranean, humid subtropical marine, warm temperature upland and mountain areas) (Lim Kam Sian et al., 2025). Mean annual precipitation varies from negligible across the Sahara to very high rates in the equatorial regions influenced by seasonal migration of the Inter-tropical Convergence Zone (ITCZ) and the associated seasonal rainfalls (Pazola et al., 2023). Africa's hydrogeology is also diverse, reflecting differences in geology and aquifer types. Crystalline basement covers about 40% of sub-Saharan Africa, especially West and Central Africa. The aquifers are typically weathered rocks with variable yields. High-yielding sedimentary aquifers are found in the Sahara (notably Libya, Egypt, and the West African coastal basins). Volcanic aquifers are mostly found in the East and Southern Africa regions (Macdonald et al., 2008).

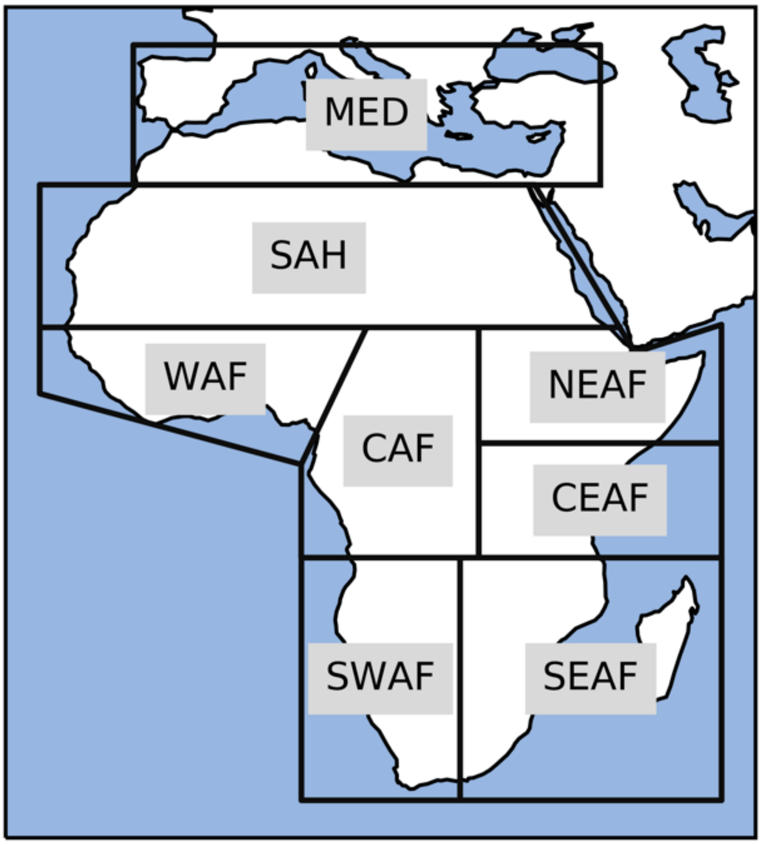

Figure 4: Modified climatic zones for regional assessment. Source: (Oloruntoba et al., 2025)

The study adopted the modified regional division by Oloruntoba et al. (2025) as shown in figure 4, which was based on the IPCC climate reference regions for subcontinental analysis developed by Iturbide et al. (2020). The new regions include the Mediterranean (MED), Sahara (SAH), West Africa (WAF), Central Africa (CAF), Central East Africa (CEAF), South West Africa (SWAF), and South East Africa with Madagascar combined (SEAF).

2.2 Climate Data

Future climate projections of precipitation, temperature, windspeed, humidity, air pressure, shortwave and longwave radiation datasets for the period (2071 – 2100) were obtained from CMIP5 GCM models: MPI_ESM_LR and NCC_NORESM_M (Taylor et al., 2012). Outputs from the global models were dynamically downscaled using CORDEX_Africa regional models (CCLM5, RegCM4 and REMO2015; Nikulin et al., 2012) at a resolution of 0.22° under two climate scenarios. Two representative concentration pathways (RCPs), namely RCP2.6 and RCP8.5 of the IPCC fifth assessment report (AR5), were scenarios considered for analysis. RCP2.6 assumes strong mitigation policies that result in low greenhouse gas forcing of 2.6 W/m^2. RCP8.5 assumes high population and slow income growth with a modest rate of technological advancement and energy intensity improvements, leading to long-term high energy demand and high greenhouse forcing of 8.5 W/m^2 (Moss et al., 2010).

Table 1: Global and Regional climate models (GCM/RCM) combinations

RCM	DRIVING GCM	
	MPI_ESM_LR	NOR_ESM_M
CCLM5	MPI-CCLM	NOR-CCLM
REGCM4	MPI-REG	NOR-REG
REMO2015	MPI-REMO	NOR-REMO

2.3 CLM5 Setup and Simulation

Community Land Model version 5 (CLM5) is a land surface model developed by the National Centre for Atmospheric Research (NCAR). It helps represent land surface heterogeneity, such as Africa, differently compared to other surface models. The model uses a multi-layered sub-grid hierarchy, with each grid representing multiple land units consisting of vegetated, lake, urban and glacier areas. Each land unit represents multiple columns, which could include different soil profiles of evolving soil moisture content and temperature. Multiple patches of plant functional type (PFT) or crop functional type (CFT) are included in each column (Lawrence et al., 2019). Detailed description and evaluation of the CLM5 model can be found in Lawrence et al. (2019).

The CLM5 land surface model was used in this study to simulate groundwater recharge forecasts across the different African regions at a half-hourly time step for a spatial resolution of 10km. The downscaled climate data output for the far-future (2071- 2100) was used as climate forcings in CLM5 to calculate surface evapotranspiration, runoff, and irrigation (considered as anthropocentric water supply) to calculate recharge for each model. Moderate Resolution Imaging Spectroradiometer land cover type product (MCD121QI), soil texture and properties information obtained from the International Geosphere-Biosphere Program Data and Information System (IGBP-DIS, GSD Task, 2014) were also used in the CLM5 model for simulation. Recharge was then calculated using the simple water balance approach (eq. 2.1) aggregated to monthly and annual timescales.

$$R = (P + I) - ET - Q \qquad (2.1)$$

Where R is groundwater recharge (mm/yr), P is the precipitation (mm/yr), I is the simulated irrigation by CLM to account for all anthropocentric water supply (mm/yr), ET is evapotranspiration (mm/yr), and Q is surface runoff (mm/yr). A detailed description of the method and approach using CLM5 for recharge simulation is provided by Bayat et al. (2023). Results of simulations are stored in a NetCDF file named after each model combination for both scenarios. Each file contained properties which include time (representing year), longitude, and latitude (for grid cell position) and recharge values.

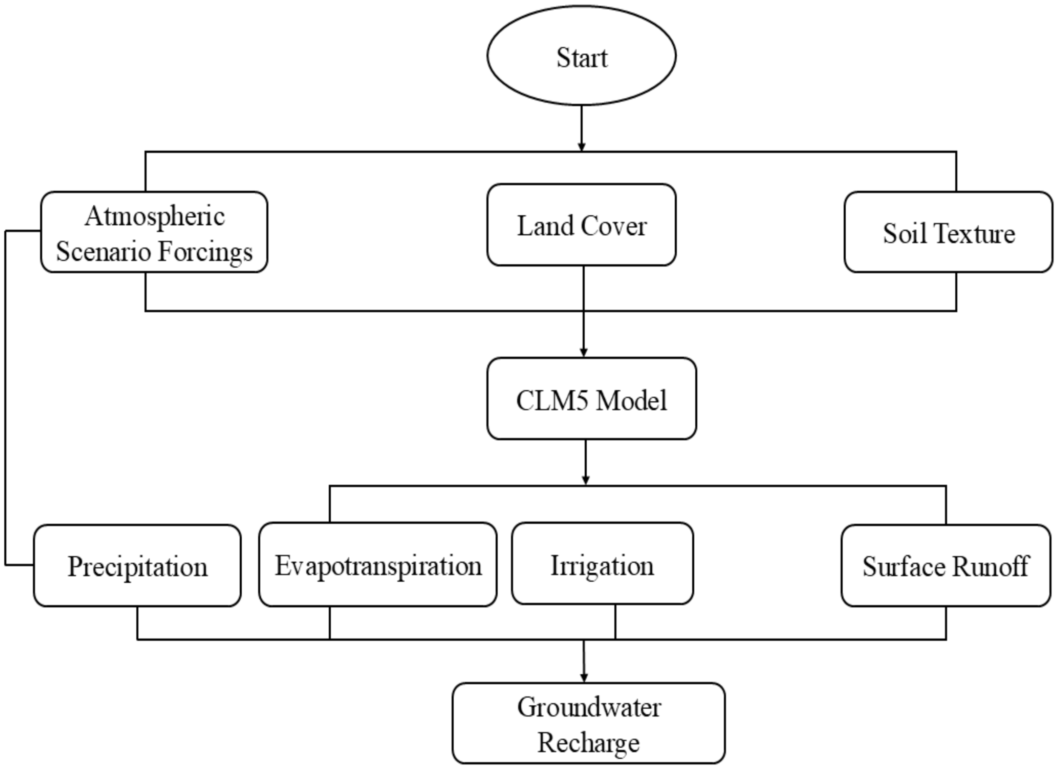

Figure 5: Adopted methodology for groundwater recharge simulation using CLM5

2.4 Statistical Analysis

2.4.1 Continental Recharge Trend and Spatial Pattern

To analyse continental-scale recharge trends, the yearly recharge was spatially averaged across the continent for each model combination under every climate scenario. The performance of individual model combinations, their respective recharge trends, were then compared against an ensemble mean derived from all other models, excluding the specific model under investigation. This comparison utilised metrics such as correlation and model percentage bias to assess trend performance relative to the ensemble.

Pearson Correlation = $\frac{\sum(R_{mi}-\overline{R_m})(R_{ensi}-\overline{R_{ens}})}{\sqrt{\sum(R_{mi}-\overline{R_m})^2\sum(R_{ensi}-\overline{R_{ens}})^2}}$ (2.2)

Percent Bias = $\frac{\sum_{i=1}^{n} R_{mi}-R_{ensi}}{\sum_{i=1}^{n} R_{ensi}} \times 100$ (2.3)

Where R_{mi} and R_{ensi} are the values of the variable at the ith grid cell point of the model and reference, respectively, with $\overline{R_m}$ *and* $\overline{R_{ens}}$ representing their mean values.

The long-term ensemble average of all six model combinations under each climate scenario was calculated to assess and observe the spatial recharge distribution across the continent. Similar procedures were carried out for the water balance components (precipitation, evapotranspiration and runoff).

2.4.2 Model Agreement and Disagreement

To assess regions where models agree and disagree, standard deviation (std) and coefficient of variation (CV) were used. Models were stacked together in one NetCDF file, with the standard deviation per grid cell across all models calculated and plotted. A mapped visualization of standard deviation highlighted regions of model consensus and areas of variation. The coefficient of variation was then calculated as the average standard deviation divided by the average spatial recharge value per region and scenario to help assess the recharge reliability.

2.4.3 Regional Sensitivity

To determine the regional sensitivity of individual climate models, the deviation of their output from the ensemble mean was calculated. For each grid cell in the region's domain, the difference between the individual model's value and the mean of all other models in the ensemble (excluding the model under consideration) was calculated. The disparity was then assigned to a specified scale, ranging from greater than 40mm/year to less than -40mm/year. Metrics used for assessment include mean bias (M-Bias) eq. 2.5 and percentage bias (P-Bias) eq. 2.3

Bias = $R_{mi} - R_{ri}$ (2.4)

Mean Bias = $\frac{\sum_{i=1}^{n} R_{mi}-R_{ensi}}{N}$ (2.5)

Where N is the total number of grid points, R_{mi} and R_{ensi} are the values of the variable at the ith grid point of the model and reference, respectively, with $\overline{R_m}$ *and* $\overline{R_{ens}}$ representing their mean values.

2.5 Tools

Analyses were carried out using Climate Data Operator (CDO), Python and QGIS. Installed python libraries used include matplotlib (visualisation), NetCDF and Xarray (for extracting data from files), Pandas and NumPy (for metrics computation). Regional files were generated using the Climate Data Operator (CDO) and Quantum GIS (QGIS) to split continental files with defined latitude and longitude values and shapefiles, respectively.

Partial Conclusion

This chapter outlined the methodological framework adopted in this study. We first described the study area and its relevance for understanding groundwater recharge dynamics across Africa. The analysis relied on atmospheric forcing data from CORDEX, while CLM5 was employed to simulate evapotranspiration and runoff, which formed the basis for recharge estimation using the water balance approach. Pearson correlation and percentage bias were used to analyse long-term recharge trends at the continental scale. The ensemble mean provided insights into spatial recharge potential. Recharge reliability was evaluated through the coefficient of variation, while ensemble standard deviation was used to identify areas of model agreement. Regional sensitivity was assessed using simple bias. CDO, Python and GIS are tools employed that enabled robust data processing, analysis, and visualisation. This methodological approach provides a solid foundation for the study and interpretation of groundwater recharge.

CHAPTER THREE:
RESULTS AND DISCUSSION

CHAPTER THREE: RESULTS AND DISCUSSION

Introduction

This chapter presents the results of the continental recharge forecast trends, spatial distribution, and regional sensitivity. It examines how the different regions respond to simulated recharge by the different GCM-RCM configurations under climate scenarios RCP2.6 and RCP8.5 for the period 2071-2100. Reasons for model performance across regions are discussed in relation to precipitation and other climatic conditions. Insights on the implications of model-driven uncertainties are further provided.

3.1 Projected Recharge Trend

The simulated recharge for each model combination and their comparison with the multi-model ensemble under both climate scenarios for the far-future (2071 – 2100) are presented in figures 6 and 7, respectively. Noticeable peaks and troughs are observed under both climate cases, but more pronounced under RCP8.5. RCMs exhibit different temporal patterns despite being driven by the same GCM. These observations highlight structural uncertainty even under low-emission scenarios. Under RCP2.6, REG models overestimate (~ 2.8 to 16.3 %), whereas REMO models underestimate (~ -5.3 to -14.4 %) the ensembles. CCLM model either underestimates (NOR-CCLM; ~ -5.5%) or overestimates (MPI-CCLM; ~ 6.6%). Models exhibit moderate positive correlation with the ensemble (~ 0.4 to 0.7), excluding MPI-REG with a weak correlation (0.13).

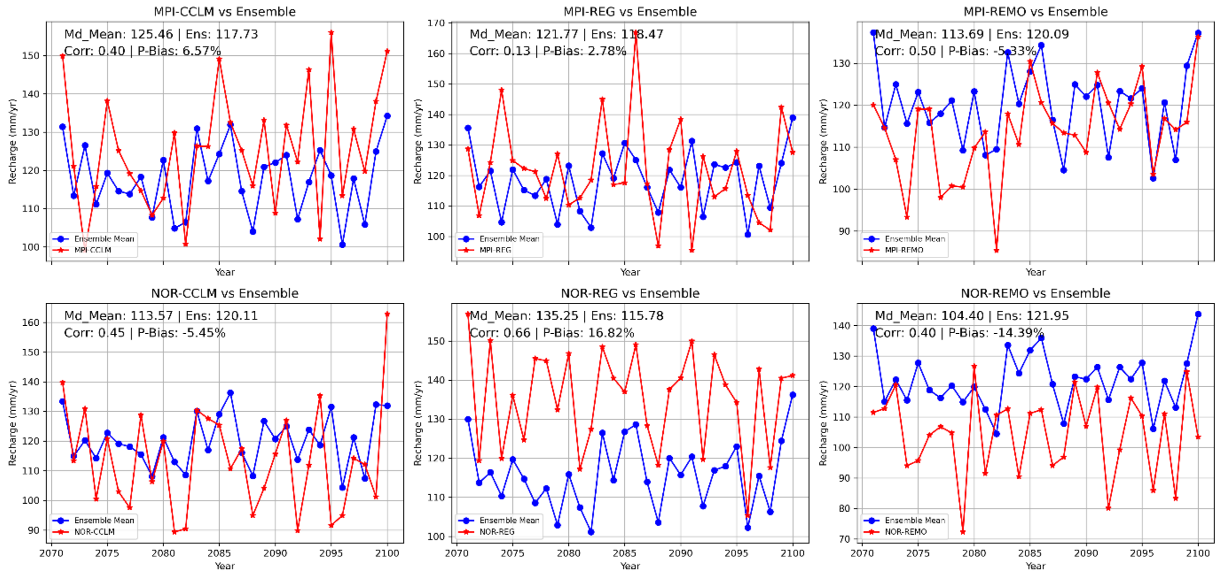

Figure 6: Continental recharge time series per model and comparison with ensemble under RCP2.6 climate scenario

Increased model uncertainties are more evident under RCP8.5 (Fig.3.2), consistent with the more intense and extreme climate forcing under this scenario. CCLM models show strong underestimation (~ -29.5 to -49.2 %) with weak positive correlation, while REG models show strong overestimation (~ 35.2 to 54.6 %), with no correlation (MPI-REG; 0.0) to moderate correlation (NOR-REG; 0.40) with the ensembles. REMO models simulate closest to the ensemble with weak to moderate correlation (~0.25 to 0.42).

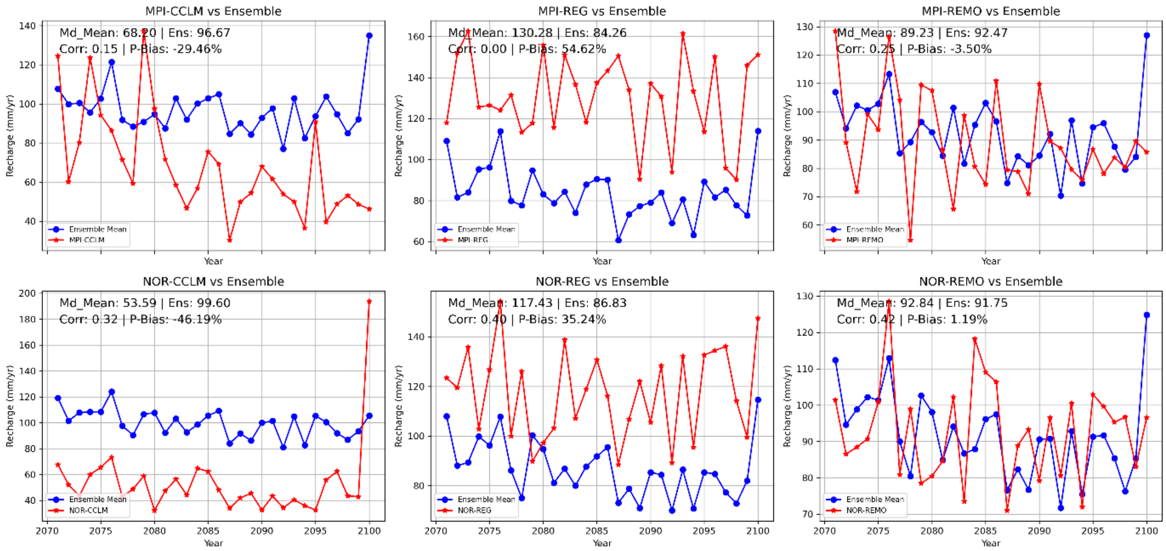

Figure 7: Continental recharge time series per model and comparison with ensemble under RCP8.5 climate scenario

This time series analysis provides valuable insight and highlights the temporal variations of groundwater recharge simulated by the different models. The different models' performance facilitates deeper analysis and understanding of regional response to model configurations across the continent on a spatial scale.

3.2 Spatial Recharge Pattern

Long-term ensemble groundwater recharge averages for Africa (2071–2100) under RCP2.6 (Fig. 8) and RCP8.5 (Fig. 9) scenarios show remarkably similar spatial distributions. Compared to RCP2.6 a significant decrease (~27.09 mm/year) under the higher-emission (RCP8.5) scenario was recorded. Increased concentration of GHG emissions leads to the occurrence of chaotic events such as drought, flood, and elevated temperature (high evapotranspiration rates). Higher recharge rates (>300 mm/year) are observed in the tropical rainforest areas, specifically parts of Sierra Leone, Liberia, the southeastern coast of Nigeria, Congo, Madagascar, and Lesotho. In contrast, arid regions, most especially the Sahel and Kalahari Desert areas, record much lower recharge rates (< 50 mm/year). The tropical wet and dry climatic zones record moderate recharge averages (100–250 mm/year).

Continental and regional recharge rates are mainly influenced by hydrological variables (precipitation and evapotranspiration) including topographic, vegetation and geological formations as emphasised by West et al. (2022) . Spatial distribution of projected water balance components are shown in Fig. A9 and Fig. A11 for RCP2.6 and RCP8.5, respectively. Regions with higher rainfall record higher rates, whereas regions with lower precipitation records show low recharge potential. These observations confirm the direct influence of long-term precipitation average on groundwater recharge, as highlighted by Bayat et al. (2023) and MacDonald et al. (2021). Additionally, simulated evapotranspiration and surface runoff show positive spatial correlation with precipitation. Regions with higher precipitation levels, such as WAF and CAF, experienced the higher ET values with values above 400 mm/year. SAH and MED regions record the lowest ET values (< 200 mm/year). However, it is important to note that models project differently the spatio-temporal distribution of the water balance components as shown in Fig A1 to A8 for the two climate scenarios.

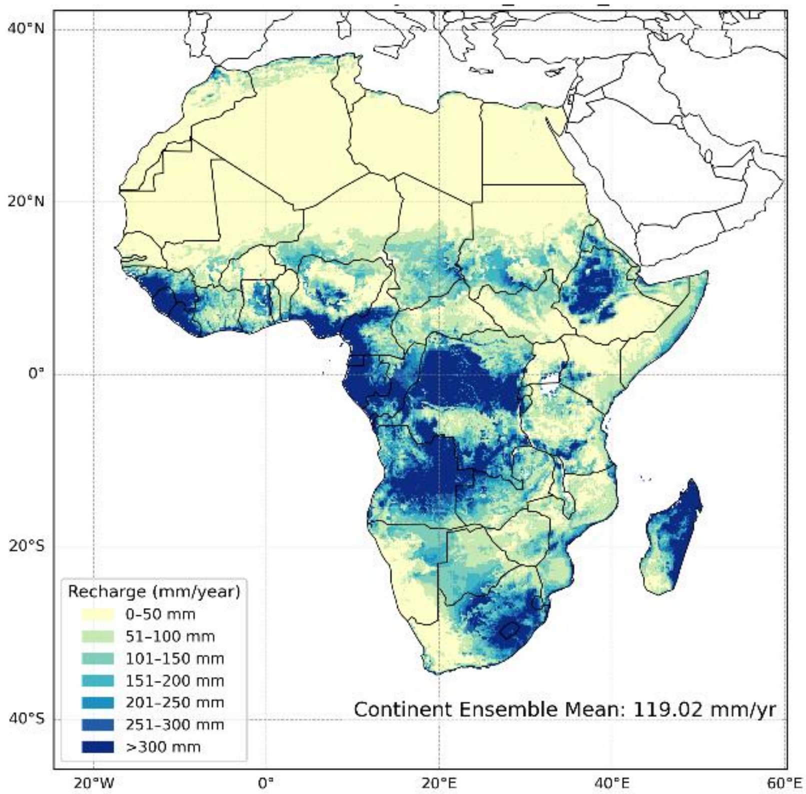

Figure 8: Continental spatial recharge distribution under RCP2.6 climate scenario

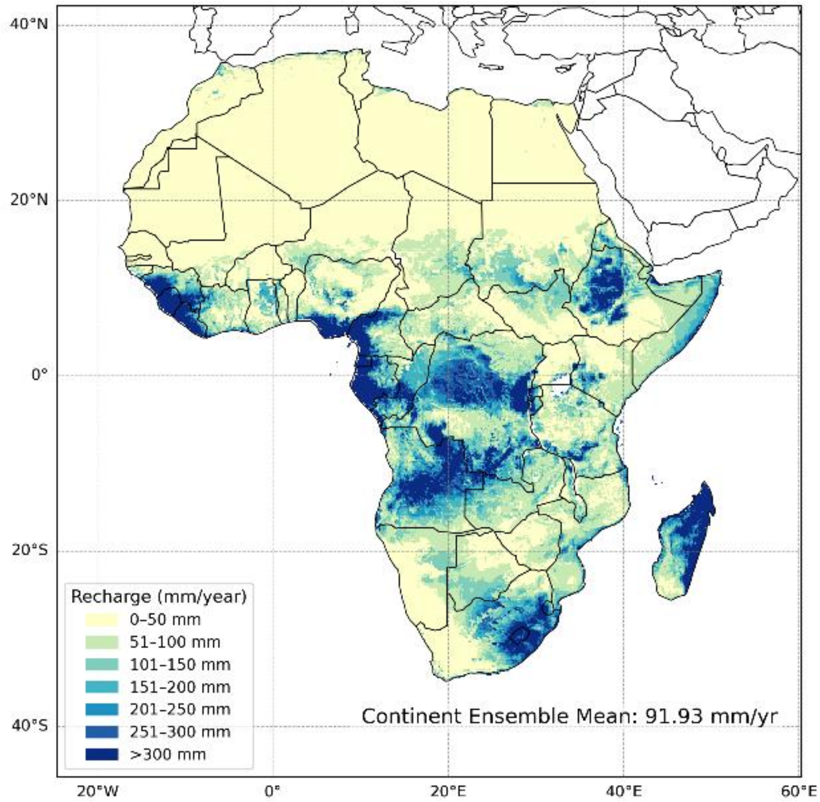

Figure 9: Continental spatial recharge distribution under RCP8.5 climate scenario

3.3 Recharge Potential and Reliability

Spatial ensemble standard deviation (Fig. 10 & 11) shows a similar distribution pattern as observed in the spatial recharge maps. Humid and tropical wet areas show high std (> 100 mm/year), whereas semi-arid and arid areas show lower std (<75 mm/year). Regional-based average recharge, average std and coefficient of variation (CV) under both climate scenarios are displayed in Table 3.1. Results of the CV highlight the reliability in recharge projection across regions. The Sahel region, despite having the lowest recharge and std, records the highest CV (~0.73 to 0.84), indicating high relative uncertainty. Central Africa, with the highest average and std under both climate cases, records the lowest CV (0.5) under RCP2.6, whereas Central-East Africa records the lowest CV (0.59) under RCP8.5. All other regions record low to moderate CV (~0.53 to 0.68) under both emission forcings, with a general decrease in std (~8.95 mm/year).

Recharge projections are reliable in the tropical regions (Central and West Africa) despite having a high model spread. Arid zones and the Mediterranean stand out as vulnerable zones, indicating that even small fluctuations in recharge can have substantial impacts on water availability and pose significant challenges for water security in such regions. Variation in recharge values are due to differences in model simulation of regional climatic conditions. Precipitation exhibits significant variation as compared to other components used in recharge calculations (Fig. A10 & A12). The spatial distribution of model consensus and spread agrees with the findings of West et al. (2023). The study highlights that models diverge most in wetter regions, and dry regions significantly record high CV. Differences in recharge estimates are caused by precipitation-recharge conversion rates, attributed to varying model structure and parameterisations. Discrepancies in model simulation of precipitation characteristics align with findings of Dosio et al. (2021).

Table 2: Regional recharge potential and reliability under both RCP2.6 and RCP8.5 climate scenarios

	RCP2.6			**RCP8.5**		
Regions	**Mean (mm/year)**	**Std (mm/year)**	**CV**	**Mean (mm/year)**	**Std (mm/year)**	**CV**
Mediterranean	31.48	18.84	0.60	21.92	14.55	0.66
Sahel	16.93	14.29	0.84	11.79	8.61	0.73
West Africa	179.12	94.76	0.53	134.16	80.26	0.60
Central Africa	232.05	115.24	0.50	158.76	105.89	0.67
North East Africa	115.4	78.96	0.68	110.3	68.54	0.62
Central East Africa	146.77	89.93	0.61	128.21	75.41	0.59
South East Africa	188.86	116.1	0.61	161.95	101.98	0.63
South West Africa	165.04	89.3	0.54	118.66	80.26	0.68

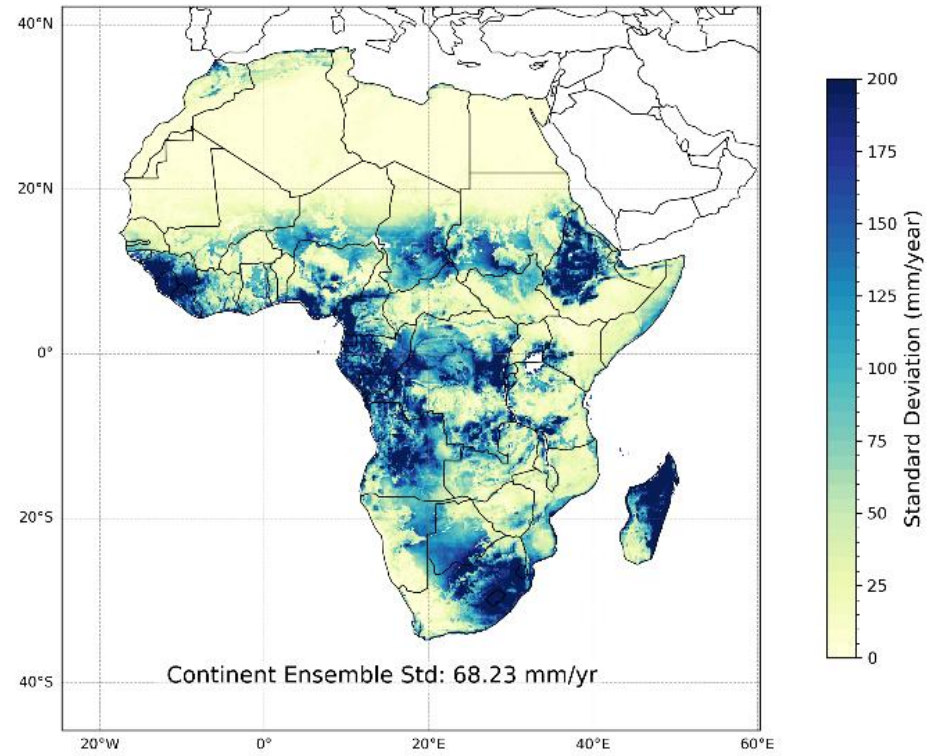

Figure 10: Continental spatial models' variation under RCP2.6 climate scenario

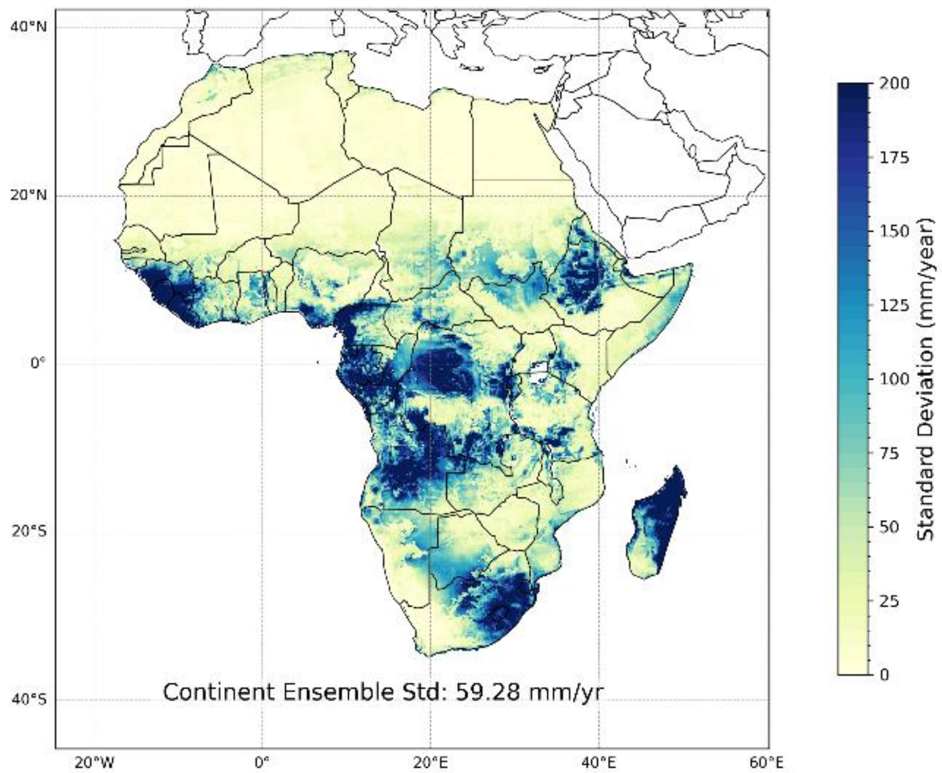

Figure 11: Continental spatial models' variation under RCP8.5 climate scenario

3.4 Regional Sensitivity

I. Mediterranean

The Mediterranean Region is found between latitudes 30° and 45° north with a dry summer climate type. Long-term average recharge of ~ 31.48 (21.92) mm/year under RCP2.6 (RCP8.5) are simulated, yielding low deviation within >±30 mm/year across the region. Figures 12 and 13 illustrate the spatial sensitivity pattern of the MED regions under RCP2.6 and RCP8.5, respectively. Overestimation (positive bias) is seen across REG models, whereas CCLM and REMO models underestimate (negative bias). MPI-REG overestimates (15.85 mm/year) under RCP2.6, with an increase (23.37 mm/year) under RCP8.5. NOR-CCLM shows the highest underestimation (~12 mm/year) under both scenarios. The Atlas region, consisting of Morocco, North of Algeria (Algiers) and Tunisia, stands out as the region with the most sensitivity to model configurations. These findings highlight model challenges in simulating complex climatic conditions in coastal and highland zones.

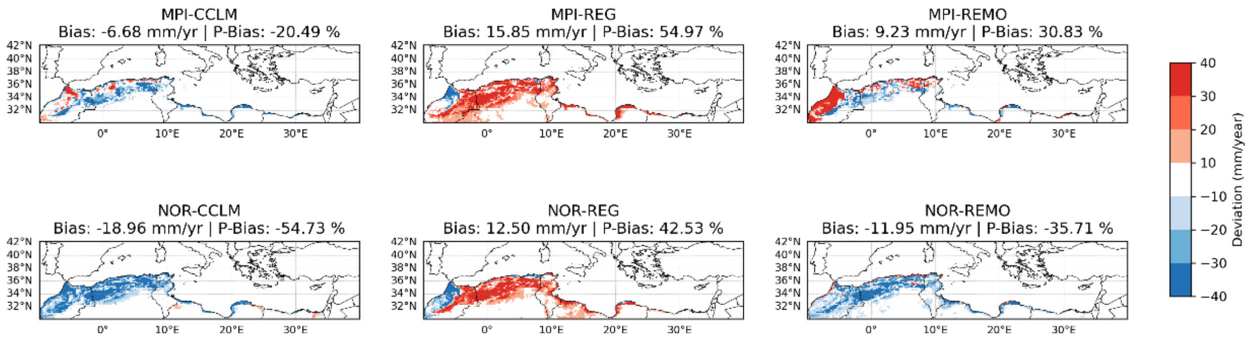

Figure 12: Mediterranean region spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

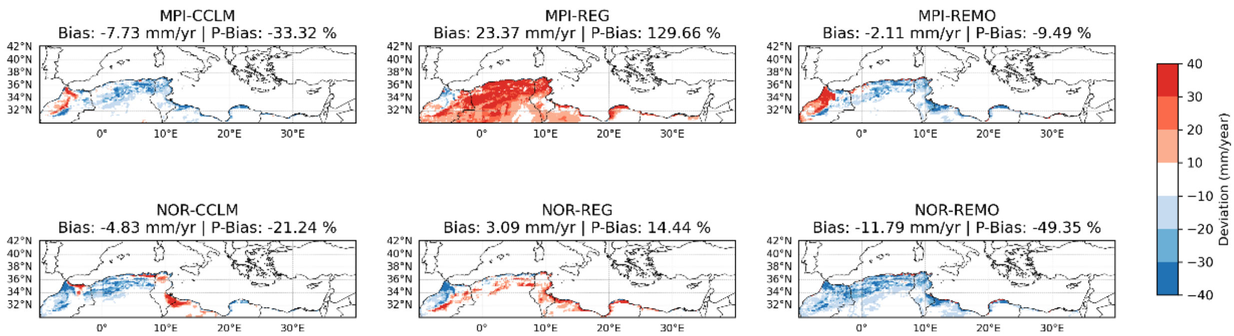

Figure 13: Mediterranean region spatial models' variation in comparison with the ensembles under RCP8.5 climate scenario

II. Sahara

The Sahel region remains the driest zone under both scenarios, with low average recharge (~12 to 17 mm/year). Figures 14 and 15 present the regional sensitivity over the Sahara under RCP 2.6 and 8.5. The region records high model agreement within ±10 mm/year. Systematic model deviations are observed across the region. CCLM models overestimate (~13 to 22 mm/year) recharge, while REMO models tend to underestimate (~-13 to -18 mm/year) recharge. CCLM records a significant decrease (~11 to 20 mm/year), while REG models show an increase in positive deviations (~5.30 to 11 mm/year) under RCP8.5. However, variations are more evident towards the South of the region, which constitutes the north of the Savanna zone. RCMs' structure uncertainty is noticed to be more influential as compared to GCM and emission scenario.

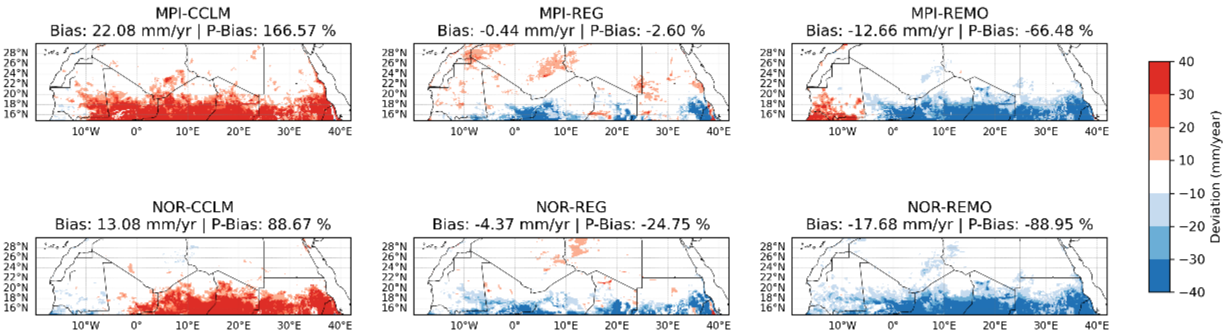

Figure 14: Sahara region spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

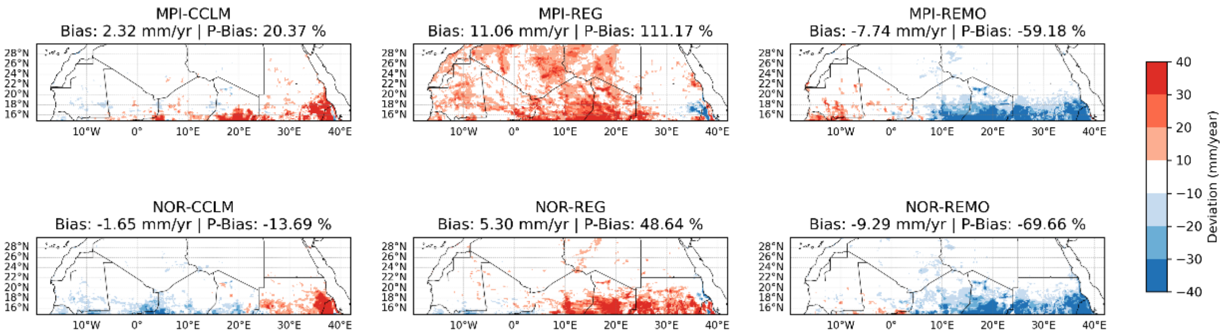

Figure 15: Sahara region spatial models' variation in comparison with the ensembles under RCP8.5 climate scenario

III. West Africa

In this study, West Africa comprises the Guinea coast and the Savanna region. Precipitation across the region decreases from the Guinea coast toward the Sahara, with diverse landscapes including coastal plains, inland plateaus, and mountain ranges. The region records a high recharge average (~134 – 180 mm/year), with moderate CV (~0.53 – 0.60). Figures 16 and 17 illustrate the regional sensitivity under both climate scenarios. Noticeable model disagreement spread across the region, with MPI-driven models deviating most on the positive (overestimation), while NOR-driven models deviate mostly on the negative (underestimation). MPI-REMO show extreme overestimation (~ 77 to 81 mm/year), and NOR-CCLM show extreme underestimation (~53 to 94 mm/year). Models diverge within >±30 mm/year, with less agreement within the ±10 mm/year recharge range. Findings across this region highlight the influence of driven GCM uncertainties on RCM.

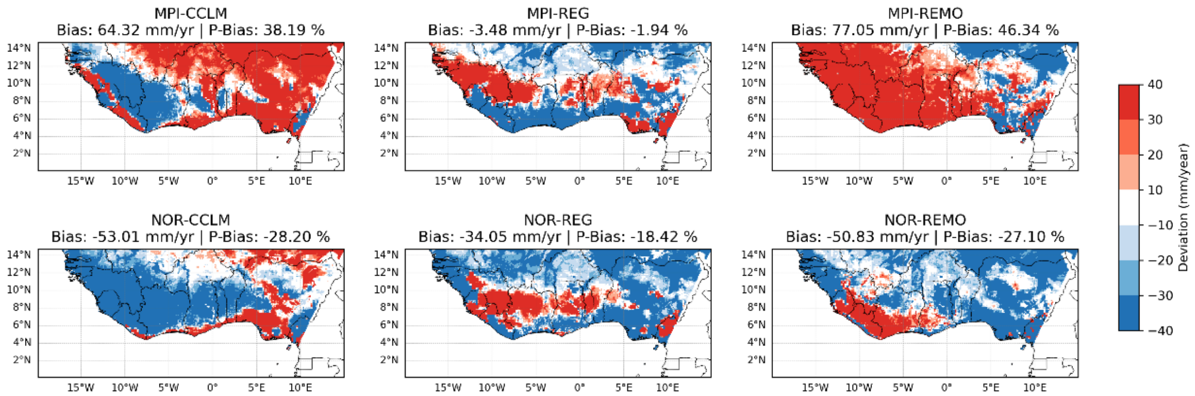

Figure 16: West Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

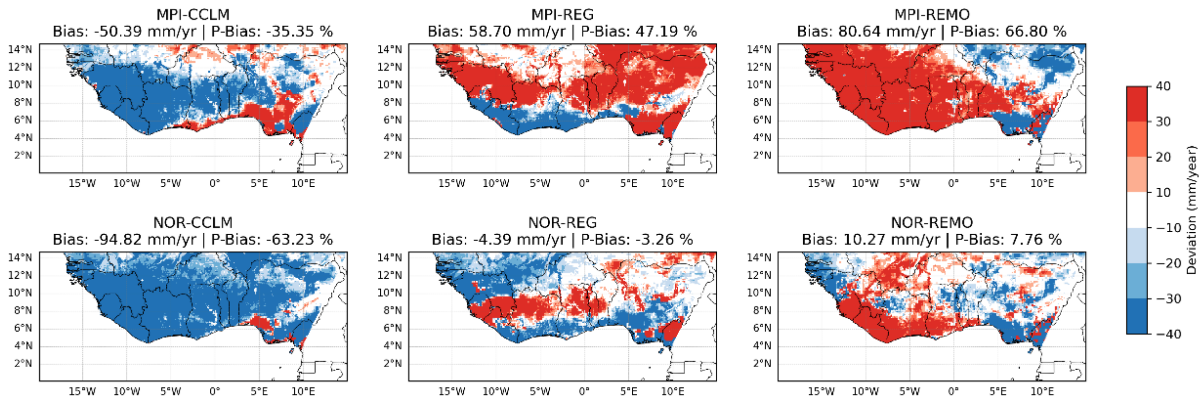

Figure 17: West Africa spatial models' variation in comparison with the ensembles under RCP8.5 climate scenario

IV. Central-Africa

Central Africa includes the Congo rainforest, which is among the most convectively active regions on the planet. As one of the moisture-rich regions in Africa, the mean rainfall ranges from 50 to 200 mm per month. Central Africa stands out as the region with the highest long-term simulated average recharge (~ 158 to 232 mm/year), with low to moderate CV (~0.50 to 0.67), indicating higher reliability. Higher std (~106 to 115 mm/year) indicates strong model disagreement. Spatial distribution of regional sensitivity to model configurations are shown in figures 18 and 19 for RCP2.6 and 8.5, respectively. Models exhibit a spatially mixed pattern across the region under both climate scenarios. Increased sensitivity values are recorded under RCP8.5. CCLM models show underestimation (~ -80 to -102 mm/year), whereas REG models show overestimation (~51 to 79 mm/year). REMO-based models show consistent spread in deviation under both climate cases. RCM variations are observed to be more influential than emission scenario across the regions.

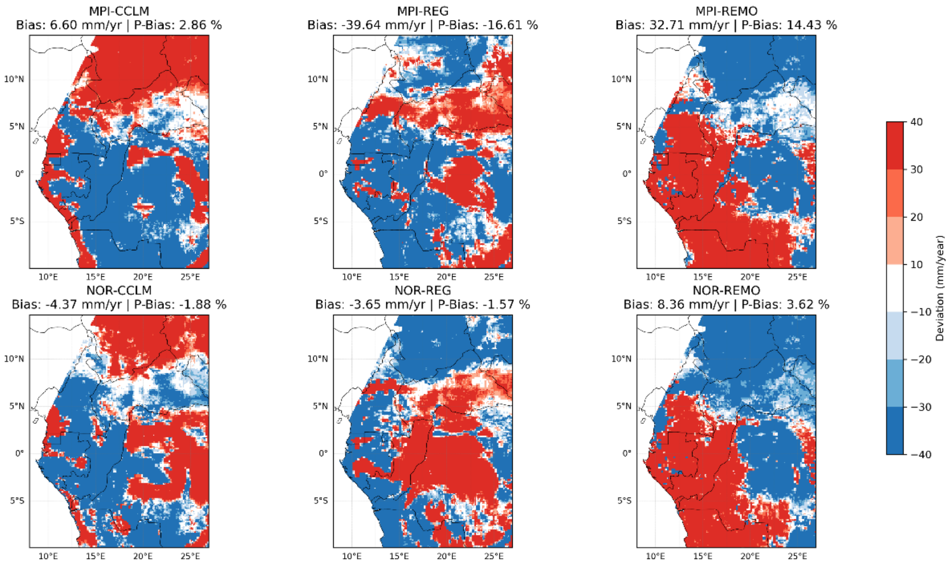

Figure 18: Central Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

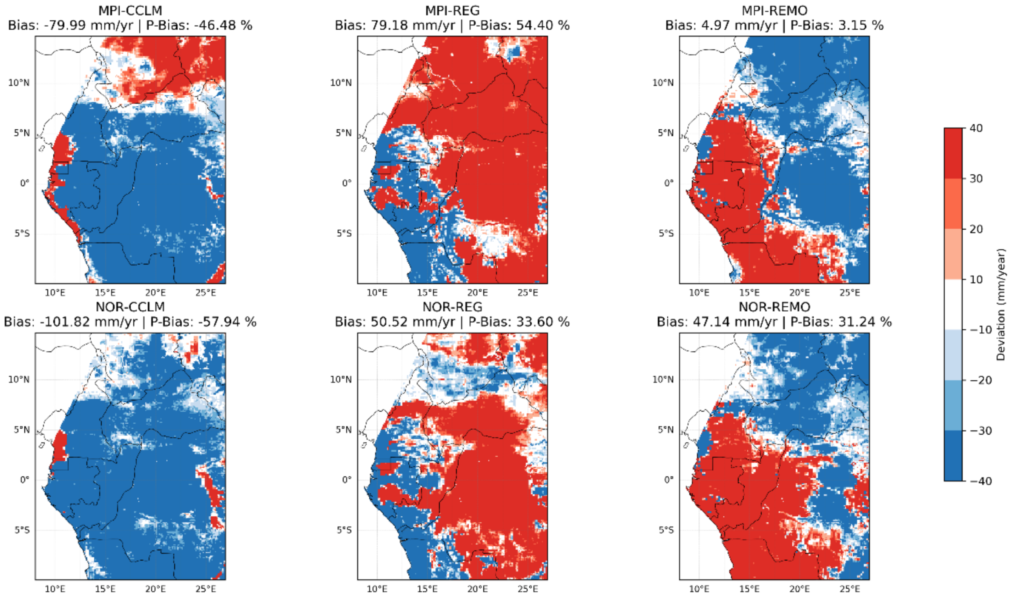

Figure 19: Central Africa spatial models' variation in comparison with the ensembles under RCP8.5 climate scenario

V. North East Africa

North East Africa, comprising Somalia, Djibouti, Ethiopia, and parts of Kenya, has a diverse climate ranging from arid and semi-arid in the North to humid conditions in the south and mountainous areas. Rainfall patterns vary significantly, with some areas experiencing a unimodal rainy season and others a bimodal rainy season. Moderate average recharge (~110 to 115 mm/year) is simulated across the region. However, with high std (~ 68.54 to 79 mm/year) and moderate CV (~0.62 to 0.68), there are uncertainties, making the region one of the least reliable regions for projections. CCLM and REG models mostly overestimate recharge, while REMO models underestimate, as shown in figures 20 and 21 for both climate cases. Comparing GCMs, MPI-driven models exhibit extreme deviations compared to NOR models. MPI-CCLM shows the highest overestimation (70 mm/year) under RCP2.6, MPI-REG (65.74 mm/year) under RCP8.5. MPI-REMO shows the highest underestimation (-80 to -91 mm/year) in both cases. Findings across this region highlight regional sensitivity to RCMs over GCMs.

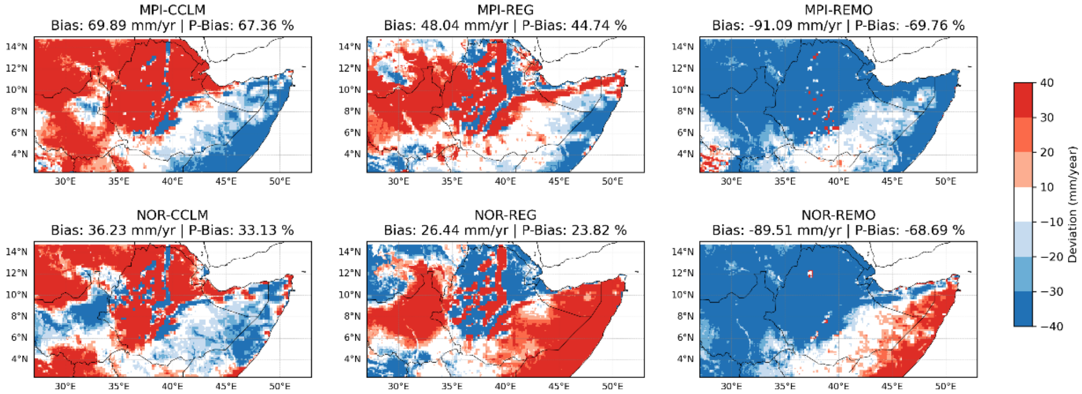

Figure 20: North-east Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

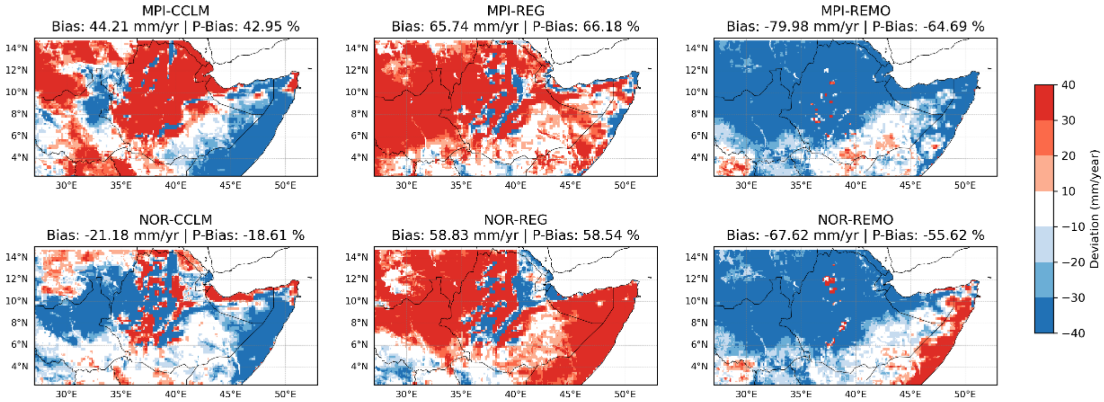

Figure 21: North-east Africa spatial models' variation in comparison with the ensembles under RCP8.5 climate scenario

VI. Central East Africa

The region of Central East Africa is dominated by complex topography, contributing to the factors responsible for the climate. The region experiences a bi-modal annual cycle of precipitation principally driven by the movement of the ITCZ. The region has moderate recharge potential (~ 128 – 147mm/year) comparable to North East Africa, the Mediterranean and the Sahara region. With moderate std (~ 75 to 90 mm/year) and CV (~0.59 to 0.61), significant disagreement exists between models, indicating low confidence in mean projections. Figures 22 and 23 present the regional sensitivity under RCP2.6 and RCP8.5, respectively. CCLM models overestimate (~40 to 87 mm/year), while REMO models underestimate (~ -56 to -78 mm/year) under RCP2.6. REG models exhibit a moderate spread in deviations across the region. In the extreme case (RCP8.5), REG models show a strong increase in bias (~17 to 49 mm/year). Deviations across this region are also geographically focused, especially lake zones (Lake Victoria), coastlines, and transition zones.

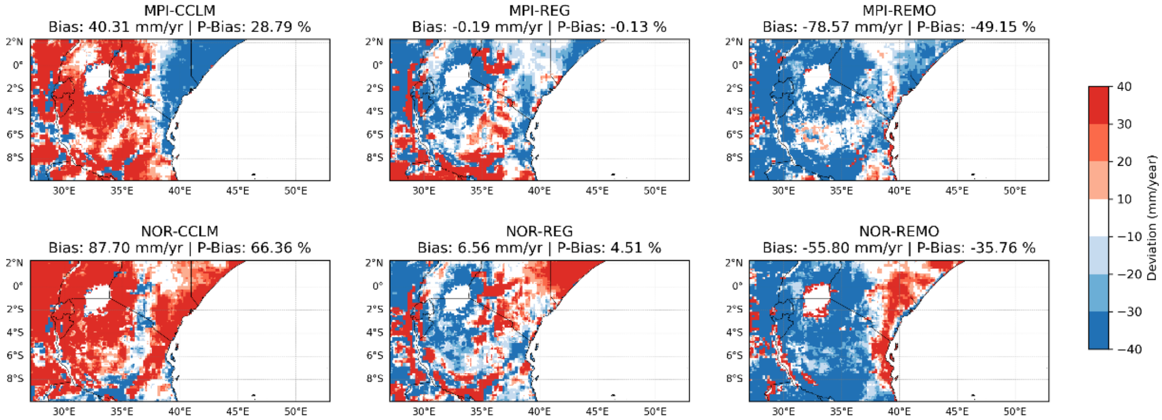

Figure 22: Central-east Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

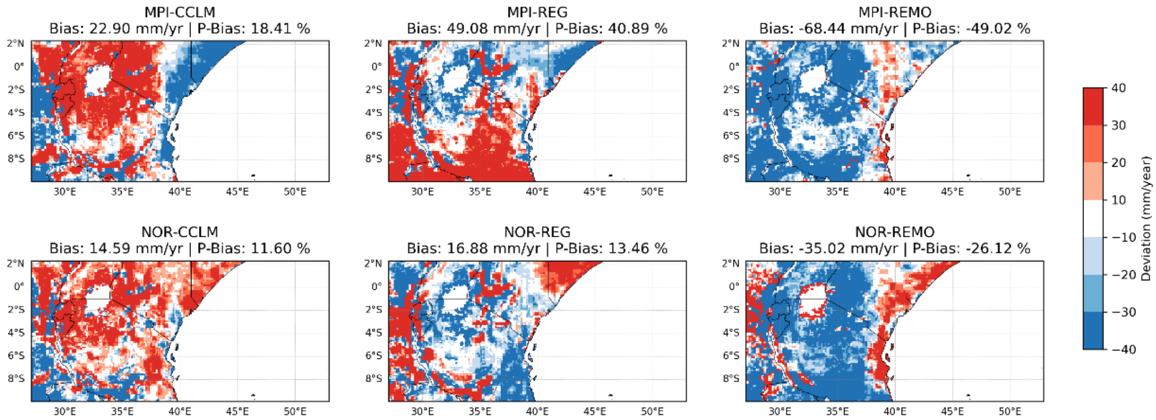

Figure 23: Central-east Africa spatial models' variation in comparison with the ensembles under RCP8.5 climate scenario

VII. South East Africa

South East Africa, including Madagascar, stands out among the regions with high recharge potential (~ 161 to 189 mm/year). The region has diverse climate conditions (semi-arid, tropical wet and dry, humid subtropical and tropical rainforest in the east of Madagascar), which influence model performance. Despite high recharge potential, the region shows high std (~ 102 to 116 mm/year) and low CV (~ 0.61 – 0.63), indicating high spread between models and significant uncertainty. MPI-driven models (REG & REMO) show strong positive deviations (overestimation), while NOR-driven models (REMO) show strong negative deviations (underestimation), with reverse trend over the same locations. Results are presented in figures

24 and 25 for RCP2.6 and 8.5, respectively. NOR-REG exhibits the highest overestimation 40.56 (74.49) mm/year under RCP2.6 (RCP8.5), while NOR-CCLM exhibits the highest underestimation -88.29 (-92.40) mm/year. GCMs are also observed to be more influential than RCMs and emission scenarios across this region.

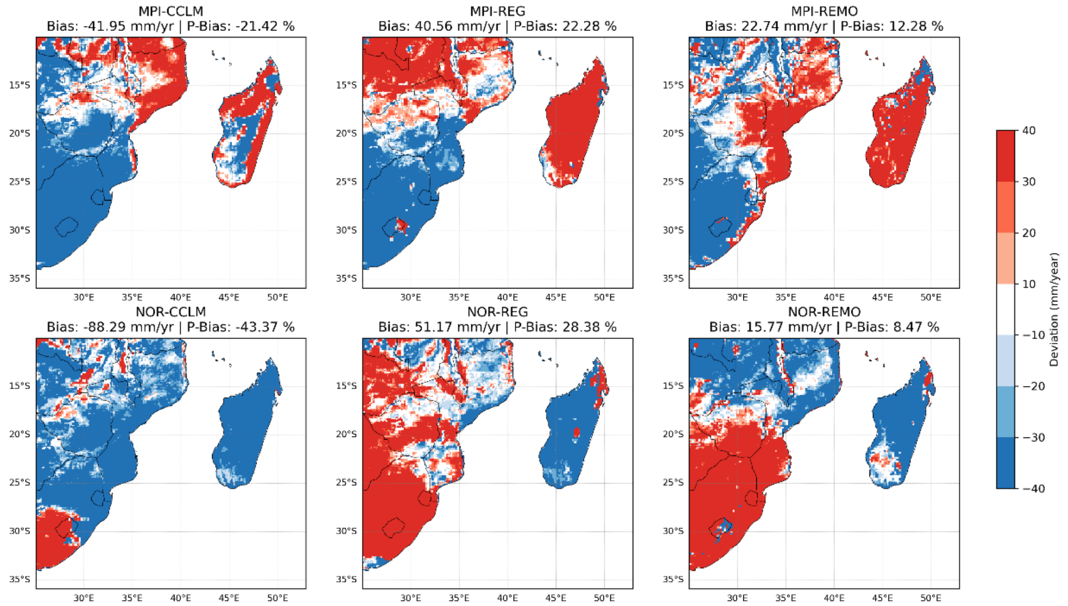

Figure 24: South-east Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

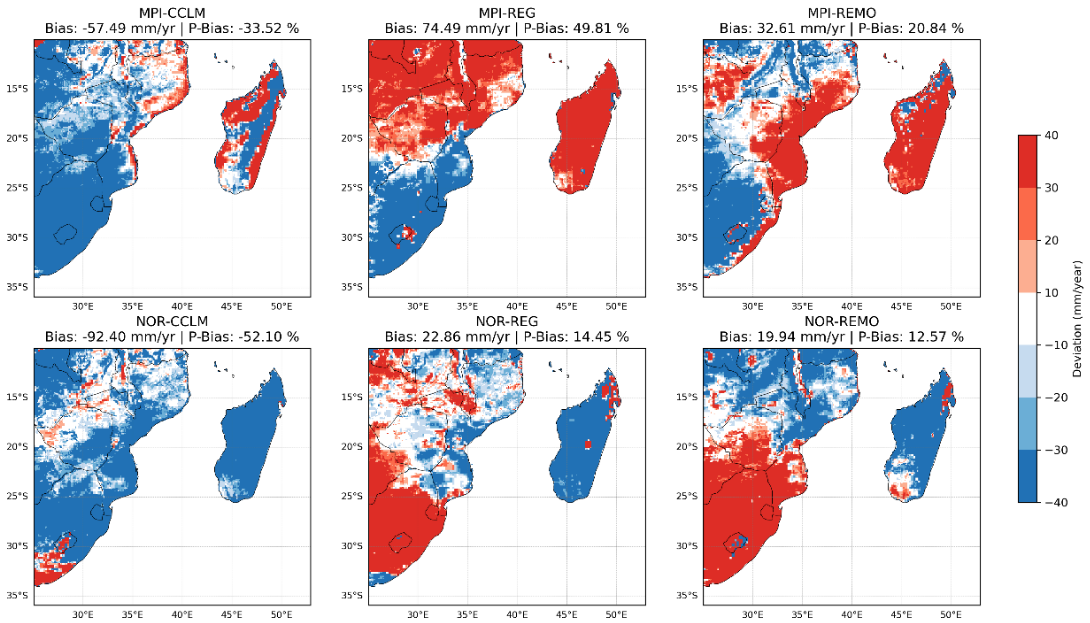

Figure 25: South-east Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

VIII. South West Africa

The region is characterised by semi-arid and arid (Kalahari desert) climates. Despite being an arid zone, the region has substantial recharge potential (~119 to 165 mm/year). However, the moderate to high std (~84 to 89 mm/year) and CV (~0.54 – 0.68) indicate large absolute differences between models. CCLM models show strong underestimation, whereas REG models show strong overestimation, as shown in figures 26 and 27. In comparison with RCP2.6, NOR-CCLM (-89.26 mm/year) and MPI-REG (51.95 mm/year) show an extreme increase in deviation, while MPI-REMO (-43.47 mm/year). NOR-REG shows the strongest positive bias (~ 122 to 151 mm/year), MPI-CCLM shows the extreme negative bias (~107 to 108 mm/year) in both climate scenarios. Agreement within the ± 10 mm/year is mostly observed across the Kalahari Desert, and due to the aquifer type.

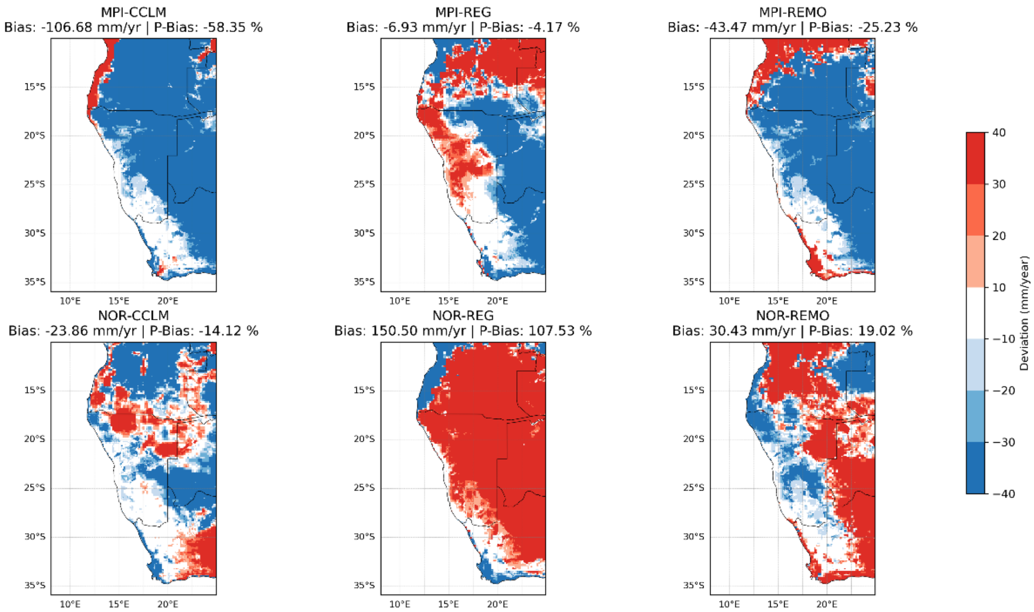

Figure 26:South-west Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

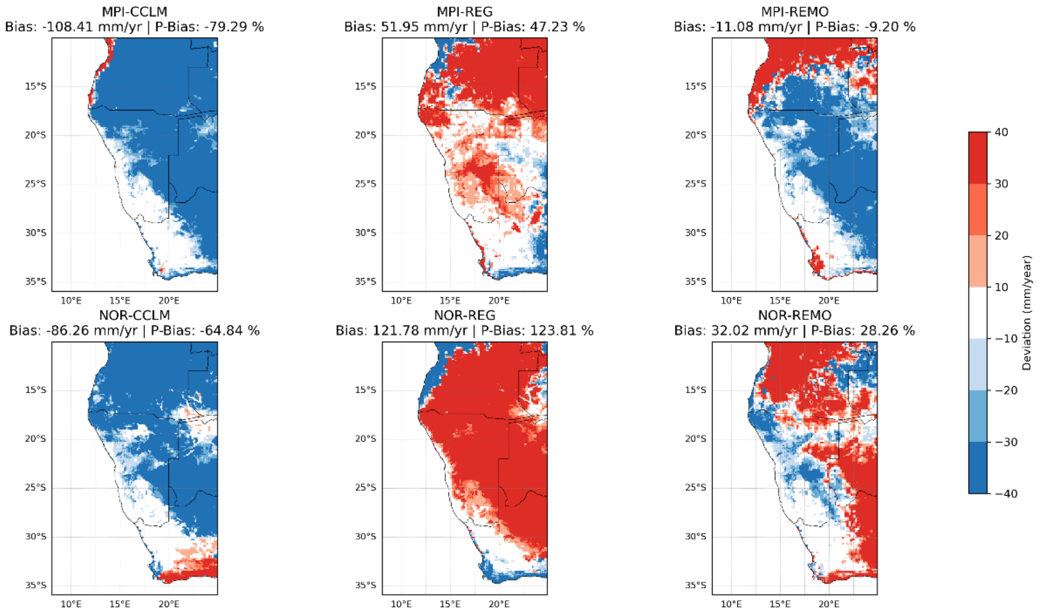

Figure 27: South-west Africa spatial models' variation in comparison with the ensembles under RCP2.6 climate scenario

The analysis of regional sensitivity to model configuration, as illustrated in figures 12 to 27, reveals important spatial patterns in model agreement and uncertainty. Regions with higher recharge average (Central, West, South Africa) show greater disagreement among models. Whereas arid regions like the Sahara show the greatest model agreement. This suggests that water-abundant areas face more uncertainty in projections, posing a significant risk to water resource planning and development. Model disagreement hotspots are region-specific, most especially areas with complex topography and diverse hydroclimatic zones, including convective rainfall and elevation-driven microclimates, as concluded by Akinsanola et al. (2015) and Klutse et al. (2016). WAF, SEAF and SWAF regions display strong sensitivities to the choice of driving GCMs, whereas MED, SAH, CAF, NEAF and CEAF show greater sensitivities to the RCM. These observation align with findings of Crosbie et al. (2011) stating the greater influence of model structure uncertainties than emission scenario uncertainties on recharge simulation. Considerable uncertainties among RCMs driven by the same GCM is also reported by Saini et al. (2015). These discrepancies and uncertainties reflect sensitivities to model physics, process parameterisations, and internal dynamics.

Considering the spatial patterns in model agreement and uncertainty, potential drivers for model performance are further discussed. Spatial agreement in the SAH and MED regions can be attributed to low precipitation and recharge records, simpler topography, and the model's abilities to simulate these climatic conditions. However, overestimation by CCLM4 and RegCM4 across some parts of the Sahel arises from the northward extension of high rainfall intensities and the overestimation of the daily rainfall index (Klutse et al., 2016). In West Africa, orography plays a significant role in rainfall patterns, but inadequate model resolution of topography leads to over- or underestimation of rainfall (Akinsanola & Ogunjobi, 2017). These challenges are evident across the orographic zones of MED, NEAF (including Ethiopian highlands), CEAF and Madagascar. Additionally, RCMs differ in the simulation of the magnitude, spatial extent, and development of the West African Monsoon (WAM) features (Sylla et al., 2010). The pre- and post-monsoon rainfall intensity is often overestimated by the CCLM and REMO models (Akinsanola & Ogunjobi, 2017). Klutse et al. (2016) also highlights the shift of higher rainfall intensities in regions equatorward, causing overestimation of rainfall intensity in the West Coast and dry biases in the Sahel. Variations among model simulations are also influenced by different sensitivities and responses to prescribed sea surface temperature (SST) patterns (Thorncroft et al., 2011).

Central Africa presents complex vegetation cover, water resources (such as the Congo Basin), and varied topography, which influence a diverse precipitation regime (Fotso-Kamga et al., 2020). Models show variability in the timing and intensity of the rainy season across the regions, partly due to a misconception of Central Africa demonstrating a bimodal pattern associated with migration of the ITCZ (Mba et al., 2018). CMIP5 models demonstrate disparities in the location of rainfall, correlated with the overestimation and underestimation of modelled moisture flux convergence in the region (Creese & Washington, 2016). Akinsanola et al. (2025) further attribute variability to models' misrepresentation of regional teleconnections (such as the Congo Basin Cell), land-sea thermal and pressure contrast. These variations induce biases in atmospheric circulation and land-atmosphere feedback, leading to errors in the regional hydrology.

In Southern Africa, mean precipitation and variability influencing recharge are driven by complex processes from global to local scales. The region is dominated by mid-latitude and tropical weather systems (Jury, 2013) with regional circulations features (such as Angola low, Kalahari heat low, Mozambique Channel Trough, Botswana High) (Akinsanola et al., 2025). Analysis of CMIP5 models shows overestimation of rainfall, whereas CORDEX RCMs show a decrease in rainfall bias (Pinto et al., 2018). Persistent biases relate to the inaccurate representation of the strength of Angola's low (Karypidou et al., 2022), tropical temperate trough orography and tropical convection dynamics (Munday & Washington, 2018). Models' projections of weaker (stronger) Mozambique Channel Trough lead to excess (deficient) rainfall simulation over Madagascar and parts of South Africa (Cook et al., 2004).

Eastern Africa lies within the tropics but is dominated by a semiarid and arid climate type. The rainfall season is driven by the migration of the ITCZ. Complex topography characterised by coastal plains to the east and interior highlands in the north-south direction is a major factor responsible for the climate in the region (Akinsanola et al., 2025). Variation in CMIP5 models stems from failure to properly simulate the annual rainfall cycle driven by sea surface temperature (SST) biases. Wet biases are due to models' inabilities to capture westerlies over the Indian Ocean, influencing rainfall (Hirons & Turner, 2018). Furthermore, CORDEX RCMs display wet bias related to the simulation of ITCZ rainfall belts, and difficulties capturing the dominant bimodal rainfall peak over the Eastern Horn (Endris et al., 2013).

In general, GCMs or RCMs inabilities to adequately capture processes such as orographically driven precipitation, convective systems, and effects of large water bodies contribute to model biases and diverse regional sensitivities across Africa. These limitations highlight the need for model improvements in regional climate projections, physical process representation and resolution to enhance reliability for water resource assessments.

3.3 Implications of Groundwater Recharge Uncertainty

The observed uncertainties in groundwater recharge forecasts across Africa pose significant challenges for water resource management, especially under changing climate scenarios. Development projects such as green hydrogen production in Africa hinge on the availability and sustainability of water resources, most especially in arid and semi-arid regions with scarce surface water. Green hydrogen production via electrolysis requires 9 –15 litres of purified water per kilogram of hydrogen produced (Scholz, 2024). The uncertainties in recharge forecast pose risks and challenges for large-scale initiatives and the underutilization of electrolysis infrastructure. In regions facing high uncertainty and vulnerable regions (e.g., the Sahara, Table A.1), the feasibility of hydrogen initiatives (operational reliability) can be jeopardised. High uncertainty complicates sustainable groundwater management, making it challenging to determine a safe abstraction limit and plan for future water security. This can lead to overexploitation and increased competition as population demand rises and reliance on irrigation increases. Investors and developers require confidence in long-term water availability. Areas with high inter-model uncertainties may lead to greater project risk of investment for environmental studies, monitoring of hydrogen project viability, water storage, and saltwater desalination. Moreover, in regions with high average and high reliability, such as Central Africa, there is potential for a stable foundation of water supply and sustainable development to meet growing demands, but it necessitates adaptive management strategies due to an increase in variability.

3.4 Limitations of the study

Groundwater recharge is a derived process influenced by the model representation of precipitation (P) and evapotranspiration (ET). Thus, uncertainties or biases in these forcing parameters directly propagate into the recharge estimates. Notable biases in CORDEX Africa precipitation data, such as over- or under-estimation in certain regions and seasons, annual variability and zonal misplacement of rainfall peaks (Gnitou et al., 2021) can significantly affect recharge simulations. Additionally, despite CLM5's advanced hydrological schemes, limited representation of African continent vegetation types, simplified conceptualisation of subsurface flow, complex aquifer recharge dynamics, and hard coding of irrigation into the surface dataset reduce the precision of recharge simulation. Absence of observational validation for predicted recharge values due to the inherent data limitations throughout the African continent is another critical limitation. This data scarcity constrains the ability to calibrate model outputs reliably. Consequently, instead of affirming the models' perfect real-world correctness, the main goal of this analysis was to quantify the disagreement and variability amongst the various model combinations within the ensemble. This method highlights the relative variations and dispersion in model projections as a helpful measure of confidence and spatial diversity in recharge estimates across Africa, while acknowledging the inherent uncertainties.

Partial Conclusion

The results and analysis show the recharge potential throughout Africa, with RCP2.6 estimates greater than RCP8.5 projections. Recharge was shown to be higher in tropical regions, though with higher model spread. In contrast, comparatively lower but more stable values seen in dry and semi-arid zones like the Sahel. High-recharge zones such as Central, West, and Southern Africa consistently show model disagreement while model agreement was highest in the Mediterranean and Sahel regions under both climate scenarios. These results show that model performance is primarily region-specific and that model structure is the primary driver of recharge projection uncertainty. Importantly, these uncertainties have direct impact on policy formulations, especially in developing water management plans and long-term energy projects such as green hydrogen production.

GENERAL CONCLUSION AND PERSPECTIVES

CONCLUSION AND PERSPECTIVES

Groundwater recharge estimation and forecast are essential for sustainable groundwater management and usage in the face of climate change. Numerous studies have used climate model outputs as forcings to hydrological and land surface models to estimate recharge. These studies highlight the performance of models but fail to highlight the sensitivity and reliability of the estimates across the different African regions. Hence, the objective of this study is to estimate recharge, define its reliability, quantify model-driven spread, identify places of model agreement, and diagnose regional sensitivities. To estimate and forecast recharge across Africa over the period 2071- 2100, the Community Land Model version 5 (CLM5) was employed. The land model was forced with three regional climate models (CCLM5, RegCM4 and REMO2015) driven by two general circulation models (MPI-ESM and NOR-ESM). Results of continental simulation under the two climate scenarios, RCP2.6 and RCP8.5, indicate enormous potential with long-term average recharge of 119.02 mm/year and 91.93 mm/year, respectively. RCP2.6 shows higher recharge potential than RCP8.5 across all regions. However, models show considerable spatial variation in forecast, particularly in regions with high recharge potential, with a continental average standard deviation of 68.23mm/year (59.23mm/year) under RCP2.6 (RCP8.5), respectively.

Spatial performance of model configurations are mostly region specific. Disagreements are most observed in tropical dense zones (Congo Basin, Guinea coast, Madagascar), highland (Guinea highlands, Ethiopian highlands) and transition zones posing risk to water resource development planning. In contrary, regions such as the Sahel and Mediterranean show the most model agreement due to lesser precipitation records and fewer diverse climate types. Model structural differences are observed to be more influential than emission scenarios. Opposing model biases mostly exist between CCLM and REMO models, with REG models showing a consistent pattern across most regions. CCLM models mostly overestimated in the Sahel, Northeast, and Central East regions and underestimated in the Mediterranean, West Africa, Central Africa, and South Africa regions. REG models exhibited overestimation across the Mediterranean, Sahel, Central Africa, Northeast, and Southwest Africa regions, with mixed patterns across the Southeast, Central East, and West Africa regions. REMO models dominate in underestimation in the Mediterranean, Sahara, and Eastern regions. Structural differences and uncertainties underscore the complex interplay of global and regional processes affecting climate projection. These necessitate improvement in model abilities at multiple scales. Model-driven uncertainties pose serious challenges to regional development and adaptation. Success of development projects (such as green hydrogen) rely not just on solar and wind but on water, which groundwater recharge either enables or constrains. Regions, such as West Africa (coastal and Guinea Highland zones), Central Africa, and Southern Africa (Madagascar, Lesotho), show moderate recharge potential crucial for long-term green hydrogen potential.

Findings from this study enhance scientific research and application-based projects by providing insights into regional sensitivities to model configuration and aid in the selection of models for hydrological and climate change studies. The study informs modelling centres of the need to enhance model parameterisation and convective schemes to better simulate region-specific climate dynamics. Furthermore, initiatives for green hydrogen production must integrate groundwater recharge forecasting, prioritise places with both resource abundance and model agreement, and invest in reducing uncertainty where stakes are highest. Uncertainties in projections could be reduced through the development of regionally tailored climate models, ensemble modelling, and local and regional-based calibrations. Attention should also be given to regions with high CV (Sahel, Mediterranean), as projections vary relative to their means. Regions with low CV but high std (Central Africa) also require much attention, though there is stability, but disagreement among models is large in absolute terms. Policy and decision makers are further encouraged to prioritise uncertainties and regional sensitivities to model outputs when planning developments and implementing water resource management strategies.

Further research is recommended to investigate and compare recharge forecasts by other hydrological, land models and reanalysis datasets (such as GLDAS) driven by the same climate models for further uncertainty assessment and validation. Advance provision of high-resolution datasets and observational stations across Africa are also encouraged to enhance further regional sensitivity studies.

BIBLIOGRAPHY REFERENCES

REFERENCES

Acharya, B. S., Kharel, G., Zou, C. B., Wilcox, B. P., & Halihan, T. (2018). Woody plant encroachment impacts on groundwater recharge: A review. *Water (Switzerland)*, *10*(10). https://doi.org/10.3390/w10101466

Adelana, S., MacDonald, A., Abiye, T. A., & Tindimugaya, C. (2008). Applied groundwater studies in Africa. In *Applied Groundwater Studies in Africa*. CRC Press. https://doi.org/10.1201/9780203889497

Agyekum, J., Annor, T., Lamptey, B., Quansah, E., & Agyeman, R. Y. K. (2018). Evaluation of CMIP5 Global Climate Models over the Volta Basin: Precipitation. *Advances in Meteorology*, *2018*(1), 4853681. https://doi.org/10.1155/2018/4853681

Akinsanola, A. A., & Ogunjobi, K. O. (2017). Evaluation of present-day rainfall simulations over West Africa in CORDEX regional climate models. *Environmental Earth Sciences*, *76*(10), 1–20. https://doi.org/10.1007/s12665-017-6691-9

Akinsanola, A. A., Ogunjobi, K. O., Gbode, I. E., & Ajayi, V. O. (2015). Assessing the Capabilities of Three Regional Climate Models over CORDEX Africa in Simulating West African Summer Monsoon Precipitation. *Advances in Meteorology*, *2015*. https://doi.org/10.1155/2015/935431

Akinsanola, A. A., Wenhaji, C. N., Barimalala, R., Monerie, P. A., Dixon, R. D., Tamoffo, A. T., Adeniyi, M. O., Ongoma, V., Diallo, I., Gudoshava, M., Wainwright, C. M., James, R., Silverio, K. C., Faye, A., Nangombe, S. S., Pokam, M. W., Vondou, D. A., Hart, N. C. G., Pinto, I., … Joseph, S. (2025). Modeling of Precipitation over Africa: Progress, Challenges, and Prospects. In *Advances in Atmospheric Sciences*. Science Press. https://doi.org/10.1007/s00376-024-4187-6

Alcamo, J., Döll, P., Henrichs, T., Kaspar, F., Lehner, B., Rösch, T., & Siebert, S. (2003). Development and testing of the WaterGAP 2 global model of water use and availability. *Hydrological Sciences Journal*, *48*(3), 317–337. https://doi.org/10.1623/hysj.48.3.317.45290

Ali, M., & Mubarak, S. (2017). Approaches and Methods of Quantifying Natural Groundwater Recharge – A Review. *Asian Journal of Environment & Ecology*, *5*(1), 1–27. https://doi.org/10.9734/AJEE/2017/36987

Allen, D. M., Cannon, A. J., Toews, M. W., & Scibek, J. (2010). Variability in simulated recharge using different GCMs. *Water Resources Research*, *46*(10), 1–18. https://doi.org/10.1029/2009WR008932

Amanambu, A. C., Obarein, O. A., Mossa, J., Li, L., Ayeni, S. S., Balogun, O., Oyebamiji, A., & Ochege, F. U. (2020). Groundwater system and climate change: Present status and future considerations. *Journal of Hydrology*, *589*, 125163. https://doi.org/10.1016/j.jhydrol.2020.125163

Ashaolu, E. D., Olorunfemi, J. F., PaulIfabiy, I., Abdollahi, K., & Batelaan, O. (2020). Spatial and temporal recharge estimation of the basement complex in Nigeria, West Africa. *Journal of Hydrology: Regional Studies*, *27*. https://doi.org/10.1016/j.ejrh.2019.100658

Atangana, A. (2018). Principle of Groundwater Flow. In *Fractional Operators with Constant and Variable Order with Application to Geo-Hydrology* (pp. 15–47). Elsevier. https://doi.org/10.1016/b978-0-12-809670-3.00002-3

Banda, V. D., Dzwairo, R. B., Singh, S. K., & Kanyerere, T. (2022). Hydrological Modelling and Climate Adaptation under Changing Climate: A Review with a Focus in Sub-Saharan Africa. In *Water (Switzerland)* (Vol. 14, Issue 24, p. 4031). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/w14244031

Barbosa, S. A., Pulla, S. T., Williams, G. P., Jones, N. L., Mamane, B., & Sanchez, J. L. (2022). Evaluating Groundwater Storage Change and Recharge Using GRACE Data: A Case Study of Aquifers in Niger, West Africa. *Remote Sensing*, *14*(7). https://doi.org/10.3390/rs14071532

Bayat, B., Oloruntoba, B., Montzka, C., Vereecken, H., & Hendricks Franssen, H. J. (2023). Implications for sustainable water consumption in Africa by simulating five decades (1965–2014) of groundwater recharge. *Journal of Hydrology*, *626*(October), 130288. https://doi.org/10.1016/j.jhydrol.2023.130288

Beyene, T. D., Zimale, F. A., & Gebrekristos, S. T. (2024). A review on sources of uncertainties for groundwater recharge estimates: insight into data scarce tropical, arid, and semiarid regions. *Hydrology Research*, *55*(1), 51–66. https://doi.org/10.2166/nh.2023.221

Bichet, A., Diedhiou, A., Hingray, B., Evin, G., Touré, N. E., Browne, K. N. A., & Kouadio, K. (2020). Assessing uncertainties in the regional projections of precipitation in CORDEX-AFRICA. *Climatic Change*, *162*(2), 583–601. https://doi.org/10.1007/s10584-020-02833-z

Bojer, A. K., Woldetsadik, M., & Biru, B. H. (2024). Machine learning and CORDEX-Africa regional model for assessing the impact of climate change on the Gilgel Gibe Watershed, Ethiopia. *Journal of Environmental Management*, *363*, 121394. https://doi.org/10.1016/j.jenvman.2024.121394

Carter, R. C., & Parker, A. (2009). Climate change, population trends and groundwater in Africa. *Hydrological Sciences Journal*, *54*(4), 676–689. https://doi.org/10.1623/hysj.54.4.676

Chokkavarapu, N., & Mandla, V. R. (2019). Comparative study of GCMs, RCMs, downscaling and hydrological models: a review toward future climate change impact estimation. *SN Applied Sciences*, *1*(12), 1–15. https://doi.org/10.1007/s42452-019-1764-x

Chung, I. M., Sophocleous, M. A., Mitiku, D. B., & Kim, N. W. (2016). Estimating groundwater recharge in the humid and semi-arid African regions: review. In *Geosciences Journal* (Vol. 20, Issue 5, pp. 731–744). Korean Association of Geoscience Societies. https://doi.org/10.1007/s12303-016-0001-5

Collins, W. J., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C. D., Joshi, M., Liddicoat, S., Martin, G., O'Connor, F., Rae, J., Senior, C., Sitch, S., Totterdell, I., Wiltshire, A., & Woodward, S. (2011). Development and evaluation of an Earth-System model - HadGEM2. *Geoscientific Model Development*, *4*(4), 1051–1075. https://doi.org/10.5194/gmd-4-1051-2011

Cook, C., Reason, C. J. C., & Hewitson, B. C. (2004). Wet and dry spells within particularly wet and dry summers in the South African summer rainfall region. *Climate Research*, *26*(1), 17–31. https://doi.org/10.3354/CR026017

Creese, A., & Washington, R. (2016). Using qflux to constrain modeled Congo Basin rainfall in the CMIP5 ensemble. *Journal of Geophysical Research*, *121*(22), 13,415-13,442. https://doi.org/10.1002/2016JD025596;WGROUP:STRING:PUBLICATION

Crosbie, R. S., Dawes, W. R., Charles, S. P., Mpelasoka, F. S., Aryal, S., Barron, O., & Summerell, G. K. (2011). Differences in future recharge estimates due to GCMs, downscaling methods and hydrological models. *Geophysical Research Letters*, *38*(11), 1–5. https://doi.org/10.1029/2011GL047657

Dari, J., Filippucci, P., Brocca, L., Quast, R., Vreugdenhil, M., Miralles, D. G., Morbidelli, R., Saltalippi, C., & Flammini, A. (2025). A novel approach for estimating groundwater recharge leveraging high-resolution satellite soil moisture. *Journal of Hydrology*, *652*, 132678. https://doi.org/10.1016/j.jhydrol.2025.132678

Demissie, T. A. (2023). Impact of climate change on hydrologic components using CORDEX Africa climate model in Gilgel Gibe 1 watershed Ethiopia. *Heliyon*, *9*(6), 2405–8440. https://doi.org/10.1016/j.heliyon.2023.e16701

Döll, P., Douville, H., Güntner, A., Müller Schmied, H., & Wada, Y. (2016). Modelling Freshwater Resources at the Global Scale: Challenges and Prospects. In *Surveys in Geophysics* (Vol. 37, Issue 2, pp. 195–221). Springer Netherlands. https://doi.org/10.1007/s10712-015-9343-1

Döll, P., & Fiedler, K. (2008). Global-scale modeling of groundwater recharge. *Hydrology and Earth System Sciences*, *12*(3), 863–885. https://doi.org/10.5194/hess-12-863-2008

Döll, P., Lehner, B., & Kaspar, F. (2002). Global Modeling of Groundwater Recharge. *Proceedings of Third International Conference on Water Resources and the Environment Research, Technical University of Dresden, Germany*, *I*(January 2002), 27–31.

Dosio, A. (2017). Projection of temperature and heat waves for Africa with an ensemble of CORDEX Regional Climate Models. *Climate Dynamics*, *49*(1–2), 493–519. https://doi.org/10.1007/s00382-016-3355-5

Dosio, A., Jury, M. W., Almazroui, M., Ashfaq, M., Diallo, I., Engelbrecht, F. A., Klutse, N. A. B. B., Lennard, C., Pinto, I., Sylla, M. B., & Tamoffo, A. T. (2021). Projected future daily characteristics of African precipitation based on global (CMIP5, CMIP6) and regional (CORDEX, CORDEX-CORE) climate models. *Climate Dynamics*, *57*(11–12), 3135–3158. https://doi.org/10.1007/s00382-021-05859-w

Dosio, A., & Panitz, H. J. (2016). Climate change projections for CORDEX-Africa with COSMO-CLM regional climate model and differences with the driving global climate models. *Climate Dynamics*, *46*(5–6), 1599–1625. https://doi.org/10.1007/s00382-015-2664-4

Endris, H. S., Omondi, P., Jain, S., Lennard, C., Hewitson, B., Chang'a, L., Awange, J. L., Dosio, A., Ketiem, P., Nikulin, G., Panitz, H. J., Büchner, M., Stordal, F., & Tazalika, L. (2013). Assessment of the Performance of CORDEX Regional Climate Models in Simulating East African Rainfall. *Journal of Climate*, *26*(21), 8453–8475. https://doi.org/10.1175/JCLI-D-12-00708.1

Fotso-Kamga, G., Fotso-Nguemo, T. C., Diallo, I., Yepdo, Z. D., Pokam, W. M., Vondou, D. A., & Lenouo, A. (2020). An evaluation of COSMO-CLM regional climate model in simulating precipitation over Central Africa. *International Journal of Climatology*, *40*(5), 2891–2912. https://doi.org/10.1002/joc.6372

Gerasu, T. S., Feyissa, T. A., Gudeta, B. G., Demissie, K., & Tesfahun, M. (2024). An evaluation of the Africa-CORDEX regional climate model's performance in simulating air temperatures and precipitation in the Melka-Wakena catchment, southeast Ethiopia. *Heliyon*, *10*(24), e40720. https://doi.org/10.1016/j.heliyon.2024.e40720

Gibba, P., Sylla, M. B., Okogbue, E. C., Gaye, A. T., Nikiema, M., & Kebe, I. (2019). State-of-the-art climate modeling of extreme precipitation over Africa: analysis of CORDEX added-value over CMIP5. *Theoretical and Applied Climatology*, *137*(1–2), 1041–1057. https://doi.org/10.1007/s00704-018-2650-y

Giorgetta, M. A., Jungclaus, J., Reick, C. H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Ilyina, T., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., … Stevens, B. (2013). Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the Coupled Model Intercomparison Project phase 5. *Journal of Advances in Modeling Earth Systems*, *5*(3), 572–597. https://doi.org/10.1002/jame.20038

Giorgi, F., Coppola, E., Solmon, F., Mariotti, L., Sylla, M. B., Bi, X., Elguindi, N., Diro, G. T., Nair, V., Giuliani, G., Turuncoglu, U. U., Cozzini, S., Güttler, I., O'Brien, T. A., Tawfik, A. B., Shalaby, A., Zakey, A. S., Steiner, A. L., Stordal, F., … Brankovic, C. (2012). RegCM4: Model description and preliminary tests over multiple CORDEX domains. *Climate Research*, *52*(1), 7–29. https://doi.org/10.3354/cr01018

Giorgi, F., & Gutowski, W. J. (2015). Regional Dynamical Downscaling and the CORDEX Initiative. In *Annual Review of Environment and Resources* (Vol. 40, Issue Volume 40, 2015, pp. 467–490). Annual Reviews Inc. https://doi.org/10.1146/annurev-environ-102014-021217

Giorgi, F., Jones, C., & Asrar, G. (2009). Addressing climate information needs at the regional level: the CORDEX framework. ... *Organization (WMO) Bulletin*, *58*(3). https://www.adaptation-changement-climatique.fr/sites/cracc/files/inline-files/CORDEX1.pdf

Gleeson, T., Cuthbert, M., Ferguson, G., & Perrone, D. (2020). Global Groundwater Sustainability, Resources, and Systems in the Anthropocene. *Annual Review of Earth and Planetary Sciences*, *48*, 431–463. https://doi.org/10.1146/annurev-earth-071719-055251

Gnitou, G. T., Tan, G., Niu, R., & Nooni, I. K. (2021). Assessing Past Climate Biases and the Added Value of CORDEX-CORE Precipitation Simulations over Africa. *Remote Sensing*, *13*(11), 2058. https://doi.org/10.3390/rs13112058

Goderniaux, P., Brouyère, S., Wildemeersch, S., Therrien, R., & Dassargues, A. (2015). Uncertainty of climate change impact on groundwater reserves - Application to a chalk aquifer. *Journal of Hydrology*, *528*, 108–121. https://doi.org/10.1016/j.jhydrol.2015.06.018

Gyamfi, C., Tindan, J. Z. O., & Kifanyi, G. E. (2021). Evaluation of CORDEX Africa multi-model precipitation simulations over the Pra River Basin, Ghana. *Journal of Hydrology: Regional Studies*, *35*, 100815. https://doi.org/10.1016/j.ejrh.2021.100815

Hirons, L., & Turner, A. (2018). The Impact of Indian Ocean Mean-State Biases in Climate Models on the Representation of the East African Short Rains. *Journal of Climate*, *31*(16), 6611–6631. https://doi.org/10.1175/JCLI-D-17-0804.1

Ilori, O. W., & Balogun, I. A. (2022). Evaluating the performance of new CORDEX-Africa regional climate models in simulating West African rainfall. *Modeling Earth Systems and Environment*, *8*(1), 665–688. https://doi.org/10.1007/s40808-021-01084-w

Iturbide, M., Gutiérrez, J. M., Alves, L. M., Bedia, J., Cerezo-Mota, R., Cimadevilla, E., Cofiño, A. S., Luca, A. Di, Faria, S. H., Gorodetskaya, I. V., Hauser, M., Herrera, S., Hennessy, K., Hewitt, H. T., Jones, R. G., Krakovska, S., Manzanas, R., Martínez-Castro, D., Narisma, G. T., … Vera, C. S. (2020). An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets. *Earth System Science Data*, *12*(4), 2959–2970. https://doi.org/10.5194/essd-12-2959-2020

Iversen, T., Bentsen, M., Bethke, I., Debernard, J. B., Kirkevåg, A., Seland, Ø., Drange, H., Kristjansson,

J. E., Medhaug, I., Sand, M., & Seierstad, I. A. (2013). The Norwegian Earth System Model, NorESM1-M – Part 2: Climate response and scenario projections. *Geoscientific Model Development*, *6*(2), 389–415. https://doi.org/10.5194/gmd-6-389-2013

Jacob, D., Elizalde, A., Haensler, A., Hagemann, S., Kumar, P., Podzun, R., Rechid, D., Remedio, A. R., Saeed, F., Sieck, K., Teichmann, C., & Wilhelm, C. (2012). Assessing the transferability of the regional climate model REMO to different coordinated regional climate downscaling experiment (CORDEX) regions. *Atmosphere*, *3*(1), 181–199. https://doi.org/10.3390/atmos3010181

Jayakody, P., Parajuli, P. B., Sassenrath, G. F., & Ouyang, Y. (2014). Relationships Between Water Table and Model Simulated ET. *Groundwater*, *52*(2), 303–310. https://doi.org/10.1111/gwat.12053

Jobbágy, E. G., & Jackson, R. B. (2004). Groundwater use and salinization with grassland afforestration. *Global Change Biology*, *10*(8), 1299–1312. https://doi.org/10.1111/j.1365-2486.2004.00806.x

Jury, M. R. (2013). A return to wet conditions over Africa: 1995-2010. *Theoretical and Applied Climatology*, *111*(3–4), 471–481. https://doi.org/10.1007/S00704-012-0677-Z/FIGURES/8

Kalognomou, E. A., Lennard, C., Shongwe, M., Pinto, I., Favre, A., Kent, M., Hewitson, B., Dosio, A., Nikulin, G., Panitz, H. J., & Büchner, M. (2013). A diagnostic evaluation of precipitation in CORDEX models over Southern Africa. *Journal of Climate*, *26*(23), 9477–9506. https://doi.org/10.1175/JCLI-D-12-00703.1

Karypidou, M. C., Katragkou, E., & Sobolowski, S. P. (2022). Precipitation over southern Africa: is there consensus among global climate models (GCMs), regional climate models (RCMs) and observational data? *Geoscientific Model Development*, *15*(8), 3387–3404. https://doi.org/10.5194/GMD-15-3387-2022,

Klutse, N. A. B., Ajayi, V. O., Gbobaniyi, E. O., Egbebiyi, T. S., Kouadio, K., Nkrumah, F., Quagraine, K. A., Olusegun, C., Diasso, U., Abiodun, B. J., Lawal, K., Nikulin, G., Lennard, C., & Dosio, A. (2018). Potential impact of 1.5 °c and 2 °c global warming on consecutive dry and wet days over West Africa. *Environmental Research Letters*, *13*(5). https://doi.org/10.1088/1748-9326/aab37b

Klutse, N. A. B., Sylla, M. B., Diallo, I., Sarr, A., Dosio, A., Diedhiou, A., Kamga, A., Lamptey, B., Ali, A., Gbobaniyi, E. O., Owusu, K., Lennard, C., Hewitson, B., Nikulin, G., Panitz, H. J., & Büchner, M. (2016). Daily characteristics of West African summer monsoon precipitation in CORDEX simulations. *Theoretical and Applied Climatology*, *123*(1–2), 369–386. https://doi.org/10.1007/s00704-014-1352-3

Koné, B., Diedhiou, A., Touré, N. E., Sylla, M. B., Giorgi, F., Anquetin, S., Bamba, A., Diawara, A., & Kobea, A. T. (2018). Sensitivity study of the regional climate model RegCM4 to different convective schemes over West Africa. *Earth System Dynamics*, *9*(4), 1261–1278. https://doi.org/10.5194/ESD-

9-1261-2018,

Kouadio, K. C. A., Silue, S., Amoussou, E., Kouassi, K. L., Diedhiou, A., Coulibaly, T. J. H., Obahoundje, S., Didi, S. R., & Coulibaly, H. S. J. (2024). Using of hydrological model and geospatial tool to assess climate change impact on the hydropower potential of the White Bandama watershed in Cote d'Ivoire (West Africa). *Proceedings of the International Association of Hydrological Sciences*, *385*, 39–45. https://doi.org/10.5194/piahs-385-39-2024

Kour, R., Patel, N., & Krishna, A. P. (2016). Climate and hydrological models to assess the impact of climate change on hydrological regime: a review. *Arabian Journal of Geosciences*, *9*(9). https://doi.org/10.1007/s12517-016-2561-0

Kurylyk, B. L., & MacQuarrie, K. T. B. (2013). The uncertainty associated with estimating future groundwater recharge: A summary of recent research and an example from a small unconfined aquifer in a northern humid-continental climate. *Journal of Hydrology*, *492*, 244–253. https://doi.org/10.1016/j.jhydrol.2013.03.043

Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bonan, G., Collier, N., Ghimire, B., van Kampenhout, L., Kennedy, D., Kluzek, E., Lawrence, P. J., Li, F., Li, H., Lombardozzi, D., Riley, W. J., Sacks, W. J., Shi, M., Vertenstein, M., … Zeng, X. (2019). The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty. *Journal of Advances in Modeling Earth Systems*, *11*(12), 4245–4287. https://doi.org/10.1029/2018MS001583

Lei, W., Brighid Ó, D., & David, M. (2010). A literature review of recharge estimation and groundwater resource assessment in Africa. *British Geological Survey Internal Report.*, *IR/10/051.*, 31pp.

Lim Kam Sian, K. T. C., Ayugi, B. O., Onyutha, C., Sagero, P., & Ait Brahim, Y. (2025). Rainfall variability across Africa. In *Climate Change and Rainfall Extremes in Africa: Occurrence, Impacts and Adaptation* (pp. 3–26). Elsevier. https://doi.org/10.1016/B978-0-443-28867-8.00001-0

MacDonald, A. M., Carlow, R. C., MacDonald, D. M. J., Darling, W. G., & Dochartaigh, B. É. Ó. (2009). What impact will climate change have on rural groundwater supplies in Africa? *Hydrological Sciences Journal*, *54*(4), 690–703. https://doi.org/10.1623/hysj.54.4.690

Macdonald, A. M., Davies, J., & Calow, R. C. (2008). African hydrogeology and rural water supply. *Applied Groundwater Studies in Africa*, 127–148. https://doi.org/10.1201/9780203889497-11

MacDonald, A. M., Lark, R. M., Taylor, R. G., Abiye, T., Fallas, H. C., Favreau, G., Goni, I. B., Kebede, S., Scanlon, B., Sorensen, J. P. R., Tijani, M., Upton, K. A., & West, C. (2021). Mapping groundwater recharge in Africa from ground observations and implications for water security. *Environmental Research Letters*, *16*(3). https://doi.org/10.1088/1748-9326/abd661

Mahmud, M. N. H., Roy, D., Paul, P. L. C., Hossain, M. B., Yesmin, M. S., Kundu, P. K., & Islam, M. T. (2023). Natural Groundwater Recharge: A Review on the Estimation Methods. *Bangladesh Rice Journal*, *25*(2), 45–56. https://doi.org/10.3329/brj.v25i2.62706

Mariotti, L., Diallo, I., Coppola, E., & Giorgi, F. (2014). Seasonal and intraseasonal changes of African monsoon climates in 21st century CORDEX projections. *Climatic Change*, *125*(1), 53–65. https://doi.org/10.1007/s10584-014-1097-0

Mathewos, Y., Abate, B., & Dadi, M. (2023). Characterization of the skill of the CORDEX-Africa regional climate models to simulate regional climate setting in the East African Transboundary Omo Gibe River Basin, Ethiopia. *Heliyon*, *9*(10), e20379. https://doi.org/10.1016/j.heliyon.2023.e20379

Maure, G., Pinto, I., Ndebele-Murisa, M., Muthige, M., Lennard, C., Nikulin, G., Dosio, A., & Meque, A. (2018). The southern African climate under 1.5 °c and 2 °c of global warming as simulated by CORDEX regional climate models. *Environmental Research Letters*, *13*(6). https://doi.org/10.1088/1748-9326/aab190

Mba, W. P., Longandjo, G. N. T., Moufouma-Okia, W., Bell, J. P., James, R., Vondou, D. A., Haensler, A., Fotso-Nguemo, T. C., Guenang, G. M., Tchotchou, A. L. D., Kamsu-Tamo, P. H., Takong, R. R., Nikulin, G., Lennard, C. J., & Dosio, A. (2018). Consequences of 1.5 °c and 2 °c global warming levels for temperature and precipitation changes over Central Africa. *Environmental Research Letters*, *13*(5), 055011. https://doi.org/10.1088/1748-9326/aab048

McGuffie, K., & Henderson-Sellers, A. (2001). Forty years of numerical climate modelling. *International Journal of Climatology*, *21*(9), 1067–1109. https://doi.org/10.1002/joc.632

McMillan, H. K., Westerberg, I. K., & Krueger, T. (2018). Hydrological data uncertainty and its implications. *Wiley Interdisciplinary Reviews: Water*, *5*(6), e1319. https://doi.org/10.1002/WAT2.1319

McSweeney, C. F., Jones, R. G., Lee, R. W., & Rowell, D. P. (2015). Selecting CMIP5 GCMs for downscaling over multiple regions. *Climate Dynamics*, *44*(11–12), 3237–3260. https://doi.org/10.1007/s00382-014-2418-8

Meehl, G. A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J. F. B., Stouffer, R. J., & Taylor, K. E. (2007). The WCRP CMIP3 multimodel dataset: A new era in climatic change research. *Bulletin of the American Meteorological Society*, *88*(9), 1383–1394. https://doi.org/10.1175/BAMS-88-9-1383

Mehran, A., Aghakouchak, A., & Phillips, T. J. (2014). Evaluation of cmip5 continental precipitation simulations relative to satellite-based gauge-adjusted observations. *Journal of Geophysical Research*, *119*(4), 1695–1707. https://doi.org/10.1002/2013JD021152

Mileham, L., Taylor, R. G., Todd, M., Tindimugaya, C., & Thompson, J. (2009). The impact of climate change on groundwater recharge and runoff in a humid, equatorial catchment: Sensitivity of projections to rainfall intensity. *Hydrological Sciences Journal*, *54*(4), 727–738. https://doi.org/10.1623/hysj.54.4.727

Moeck, C., Brunner, P., & Hunkeler, D. (2016). The influence ofmodel structure on groundwater recharge rates in climate-change impact studies. *Hydrogeology Journal*, *24*(5), 1171–1184. https://doi.org/10.1007/s10040-016-1367-1

Moges, E., Demissie, Y., Larsen, L., & Yassin, F. (2021). Review: Sources of hydrological model uncertainties and advances in their analysis. In *Water (Switzerland)* (Vol. 13, Issue 1, p. 28). Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/w13010028

Mohan, C., Western, A. W., Wei, Y., & Saft, M. (2018). Predicting groundwater recharge for varying land cover and climate conditions-a global meta-study. *Hydrology and Earth System Sciences*, *22*(5), 2689–2703. https://doi.org/10.5194/hess-22-2689-2018

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., Van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., & Wilbanks, T. J. (2010). The next generation of scenarios for climate change research and assessment. *Nature*, *463*(7282), 747–756. https://doi.org/10.1038/NATURE08823;SUBJMETA=106,159,689,694,704,706,843,844;KWRD=CLIMATE+CHANGE,ECONOMICS,ENVIRONMENTAL+ECONOMICS

Müller Schmied, H., Caceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., Asali Peiris, T., Popat, E., Theodor Portmann, F., Reinecke, R., Schumacher, M., Shadkam, S., Telteu, C. E., Trautmann, T., & Döll, P. (2021). The global water resources and use model WaterGAP v2.2d: Model description and evaluation. *Geoscientific Model Development*, *14*(2), 1037–1079. https://doi.org/10.5194/GMD-14-1037-2021

Munday, C., & Washington, R. (2018). Systematic Climate Model Rainfall Biases over Southern Africa: Links to Moisture Circulation and Topography. *Journal of Climate*, *31*(18), 7533–7548. https://doi.org/10.1175/JCLI-D-18-0008.1

Musie, M., Sen, S., & Srivastava, P. (2020). Application of CORDEX-AFRICA and NEX-GDDP datasets for hydrologic projections under climate change in Lake Ziway sub-basin, Ethiopia. *Journal of Hydrology: Regional Studies*, *31*, 100721. https://doi.org/10.1016/j.ejrh.2020.100721

Nemaxwi, P., Odiyo, J. O., & Makungo, R. (2019). Estimation of groundwater recharge response from rainfall events in a semi-arid fractured aquifer: Case study of quaternary catchment A91H, Limpopo Province, South Africa. *Cogent Engineering*, *6*(1). https://doi.org/10.1080/23311916.2019.1635815

Nikulin, G., Jones, C., Giorgi, F., Asrar, G., Büchner, M., Cerezo-Mota, R., Christensen, O. B., Déqué, M., Fernandez, J., Hänsler, A., van Meijgaard, E., Samuelsson, P., Sylla, M. B., & Sushama, L. (2012). Precipitation climatology in an ensemble of CORDEX-Africa regional climate simulations. *Journal of Climate*, *25*(18), 6057–6078. https://doi.org/10.1175/JCLI-D-11-00375.1

Nikulin, G., Lennard, C., Dosio, A., Kjellström, E., Chen, Y., Hansler, A., Kupiainen, M., Laprise, R., Mariotti, L., Maule, C. F., Van Meijgaard, E., Panitz, H. J., Scinocca, J. F., & Somot, S. (2018). The effects of 1.5 and 2 degrees of global warming on Africa in the CORDEX ensemble. *Environmental Research Letters*, *13*(6), 065003. https://doi.org/10.1088/1748-9326/aab1b1

Nitcheva, O. (2018). Hydrology models approach to estimation of the groundwater recharge: case study in the Bulgarian Danube watershed. *Environmental Earth Sciences*, *77*(12), 1–12. https://doi.org/10.1007/s12665-018-7605-1

Oloruntoba, B., Kollet, S., Montzka, C., Vereecken, H., & Hendricks Franssen, H.-J. (2025). High-resolution land surface modelling over Africa: the role of uncertain soil properties in combination with forcing temporal resolution. *Hydrology and Earth System Sciences*, *29*(6), 1659–1683. https://doi.org/10.5194/hess-29-1659-2025

Osima, S., Indasi, V. S., Zaroug, M., Endris, H. S., Gudoshava, M., Misiani, H. O., Nimusiima, A., Anyah, R. O., Otieno, G., Ogwang, B. A., Jain, S., Kondowe, A. L., Mwangi, E., Lennard, C., Nikulin, G., & Dosio, A. (2018). Projected climate over the Greater Horn of Africa under 1.5 °c and 2 °c global warming. *Environmental Research Letters*, *13*(6). https://doi.org/10.1088/1748-9326/aaba1b

Panitz, H. J., Fosser, G., Sasse, R., Sehlinger, A., Feldmann, H., & Schädler, G. (2013). Modelling near future regional climate change for Germany and Africa. In *High Performance Computing in Science and Engineering ’12: Transactions of the High Performance Computing Center, Stuttgart (HLRS) 2012* (Vol. 9783642333, pp. 375–390). Springer-Verlag Berlin Heidelberg. https://doi.org/10.1007/978-3-642-33374-3_28

Pazola, A., Taylor, R. G., Shamsudduha, M., French, J., Macdonald, A. M., Abiye, T., Goni, I. B., & Taylor, R. G. (2023). High-resolution long-term average groundwater recharge in Africa estimated using random forest regression and residual interpolation. *Hydrology and Earth System Sciences*, *2*(October), 2949–2967. https://doi.org/10.5194/egusphere-2023-1898

Philander, S. G. (2012). Encyclopedia of Global Warming & Climate Change. In *Encyclopedia of Global Warming & Climate Change*. SAGE Publications. https://doi.org/10.4135/9781452218564

Pinto, I., Jack, C., & Hewitson, B. (2018). Process-based model evaluation and projections over southern Africa from Coordinated Regional Climate Downscaling Experiment and Coupled Model Intercomparison Project Phase 5 models. *International Journal of Climatology*, *38*(11), 4251–4261.

https://doi.org/10.1002/joc.5666

Pinto, I., Lennard, C., Tadross, M., Hewitson, B., Dosio, A., Nikulin, G., Panitz, H. J., & Shongwe, M. E. (2016). Evaluation and projections of extreme precipitation over southern Africa from two CORDEX models. *Climatic Change*, *135*(3–4), 655–668. https://doi.org/10.1007/s10584-015-1573-1

Reinecke, R., Gnann, S., Stein, L., Bierkens, M., de Graaf, I., Gleeson, T., Essink, G. O., Sutanudjaja, E. H., Ruz Vargas, C., Verkaik, J., & Wagener, T. (2024). Uncertainty in model estimates of global groundwater depth. *Environmental Research Letters* , *19*(11). https://doi.org/10.1088/1748-9326/ad8587

Reinecke, R., Müller Schmied, H., Trautmann, T., Seaby Andersen, L., Burek, P., Flörke, M., Gosling, S. N., Grillakis, M., Hanasaki, N., Koutroulis, A., Pokhrel, Y., Thiery, W., Wada, Y., Yusuke, S., & Döll, P. (2021). Uncertainty of simulated groundwater recharge at different global warming levels: A global-scale multi-model ensemble study. *Hydrology and Earth System Sciences*, *25*(2), 787–810. https://doi.org/10.5194/hess-25-787-2021

Richey, A. S., Thomas, B. F., Lo, M. H., Famiglietti, J. S., Swenson, S., & Rodell, M. (2015). Uncertainty in global groundwater storage estimates in a Total Groundwater Stress framework. *Water Resources Research*, *51*(7), 5198. https://doi.org/10.1002/2015WR017351

Safari, B., Sebaziga, J. N., & Siebert, A. (2023). Evaluation of CORDEX-CORE regional climate models in simulating rainfall variability in Rwanda. *International Journal of Climatology*, *43*(2), 1112–1140. https://doi.org/10.1002/joc.7891

Saini, R., Wang, G., Yu, M., & Kim, J. (2015). Comparison of RCM and GCM projections of boreal summer precipitation over Africa. *Journal of Geophysical Research*, *120*(9), 3679–3699. https://doi.org/10.1002/2014JD022599

Sawadogo, W., Reboita, M. S., Faye, A., da Rocha, R. P., Odoulami, R. C., Olusegun, C. F., Adeniyi, M. O., Abiodun, B. J., Sylla, M. B., Diallo, I., Coppola, E., & Giorgi, F. (2021). Current and future potential of solar and wind energy over Africa using the RegCM4 CORDEX-CORE ensemble. *Climate Dynamics*, *57*(5–6), 1647–1672. https://doi.org/10.1007/s00382-020-05377-1

Scanlon, B. R., Healy, R. W., & Cook, P. G. (2002). Choosing appropriate techniques for quantifying groundwater recharge. *Hydrogeology Journal*, *10*(1), 18–39. https://doi.org/10.1007/s10040-001-0176-2

Scholz, M. (2024). New methodology for identifying sustainable freshwater resources for the production of green hydrogen. *International Journal of Sustainable Engineering*, *17*(1), 1–7. https://doi.org/10.1080/19397038.2024.2321612

Schwartz, S. E. (2004). Uncertainty requirements in radiative forcing of climate change. *Journal of the*

Air and Waste Management Association, *54*(11), 1351–1359. https://doi.org/10.1080/10473289.2004.10471006

Solman, S. A., Sanchez, E., Samuelsson, P., da Rocha, R. P., Li, L., Marengo, J., Pessacg, N. L., Remedio, A. R. C., Chou, S. C., Berbery, H., Le Treut, H., de Castro, M., & Jacob, D. (2013). Evaluation of an ensemble of regional climate model simulations over South America driven by the ERA-Interim reanalysis: Model performance and uncertainties. *Climate Dynamics*, *41*(5–6), 1139–1157. https://doi.org/10.1007/s00382-013-1667-2

Sylla, M. B., Coppola, E., Mariotti, L., Giorgi, F., Ruti, P. M., Dell'Aquila, A., & Bi, X. (2010). Multiyear simulation of the African climate using a regional climate model (RegCM3) with the high resolution ERA-interim reanalysis. *Climate Dynamics*, *35*(1), 231–247. https://doi.org/10.1007/s00382-009-0613-9

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Taylor, R. G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y., Longuevergne, L., Leblanc, M., Famiglietti, J. S., Edmunds, M., Konikow, L., Green, T. R., Chen, J., Taniguchi, M., Bierkens, M. F. P., Macdonald, A., Fan, Y., Maxwell, R. M., Yechieli, Y., … Treidel, H. (2013). Ground water and climate change. *Nature Climate Change*, *3*(4), 322–329. https://doi.org/10.1038/nclimate1744

Teutschbein, C., & Seibert, J. (2010). Regional climate models for hydrological impact studies at the catchment scale : a review of recent modeling strategies Regional Climate Models for Hydrological Impact Studies at the Catchment-Scale. *Geography Compass*, *4*(7), 834–860.

Thorncroft, C. D., Nguyen, H., Zhang, C., & Peyrille, P. (2011). Annual cycle of the West African monsoon: Regional circulations and associated water vapour transport. *Quarterly Journal of the Royal Meteorological Society*, *137*(654), 129–147. https://doi.org/10.1002/QJ.728

Vondou, D. A., & Haensler, A. (2017). Evaluation of simulations with the regional climate model REMO over Central Africa and the effect of increased spatial resolution. *International Journal of Climatology*, *37*, 741–760. https://doi.org/10.1002/joc.5035

Watson, A., Miller, J., Fleischer, M., & de Clercq, W. (2018). Estimation of groundwater recharge via percolation outputs from a rainfall/runoff model for the Verlorenvlei estuarine system, west coast, South Africa. *Journal of Hydrology*, *558*, 238–254. https://doi.org/10.1016/j.jhydrol.2018.01.028

West, C., Reinecke, R., Rosolem, R., MacDonald, A. M., Cuthbert, M. O., & Wagener, T. (2023). Ground truthing global-scale model estimates of groundwater recharge across Africa. *Science of the Total Environment*, *858*(October 2022), 159765. https://doi.org/10.1016/j.scitotenv.2022.159765

West, C., Rosolem, R., MacDonald, A. M., Cuthbert, M. O., & Wagener, T. (2022). Understanding process controls on groundwater recharge variability across Africa through recharge landscapes. *Journal of Hydrology*, *612*, 127967. https://doi.org/10.1016/j.jhydrol.2022.127967

Wu, M., Nikulin, G., Kjellström, E., Belušić, D., Jones, C., & Lindstedt, D. (2020). The impact of regional climate model formulation and resolution on simulated precipitation in Africa. *Earth System Dynamics*, *11*(2), 377–394. https://doi.org/10.5194/esd-11-377-2020

Xu, Y., & Beekman, H. E. (2019). Review: Groundwater recharge estimation in arid and semi-arid southern Africa. In *Hydrogeology Journal* (Vol. 27, Issue 3, pp. 929–943). Springer Verlag. https://doi.org/10.1007/s10040-018-1898-8

APPENDIX

Table A1: Summary of Recharge Potential, Reliability and Vulnerability

Regions	RCP2.6				RCP8.5			
	Mean (mm/year)	Std (mm/year)	CV	Reliability	Mean (mm/year)	Std (mm/year)	CV	Reliability
Mediterranean	31.48	18.84	0.60	Moderate	21.92	14.55	0.66	Vulnerable
Sahel	16.93	14.29	0.84	Vulnerable	11.79	8.61	0.73	Vulnerable
West Africa	179.12	94.76	0.53	Reliable	134.16	80.26	0.60	Moderate
Central Africa	232.05	115.24	0.50	Reliable	158.76	105.89	0.67	Moderate
North-East Africa	115.4	78.96	0.68	Moderate	110.3	68.54	0.62	Moderate
Central-East Africa	146.77	89.93	0.61	Moderate	128.21	75.41	0.59	Moderate
South-East Africa	188.86	116.1	0.61	Moderate	161.95	101.98	0.63	Moderate
South-West Africa	165.04	89.3	0.54	Reliable	118.66	80.26	0.68	Vulnerable

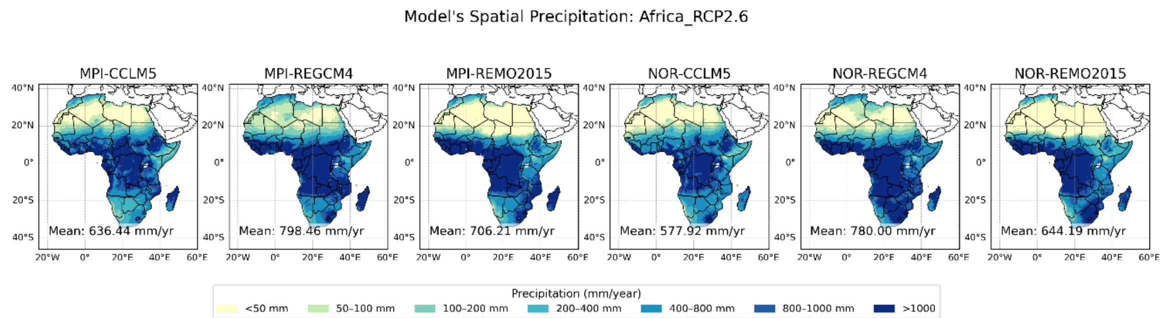

Figure A1: Models' Spatial Precipitation_Africa_RCP2.6

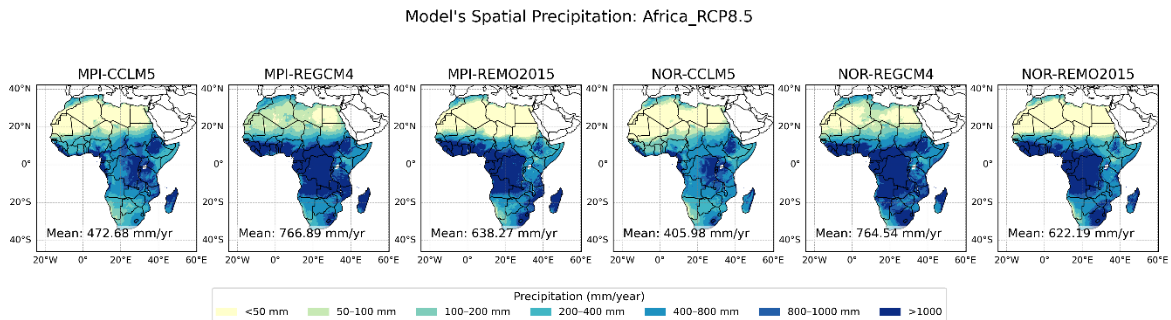

Figure A2: Models' Spatial Precipitation_Africa_RCP8.5

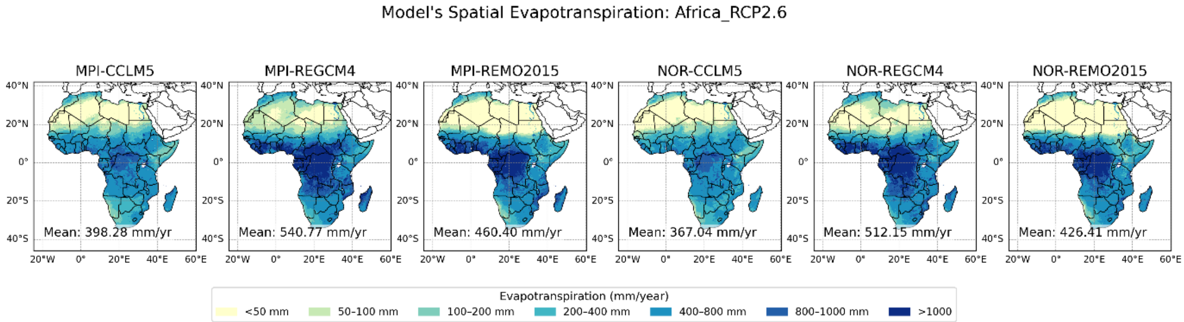

Figure A3: Models' Spatial Evapotranspiration_Africa_RCP2.6

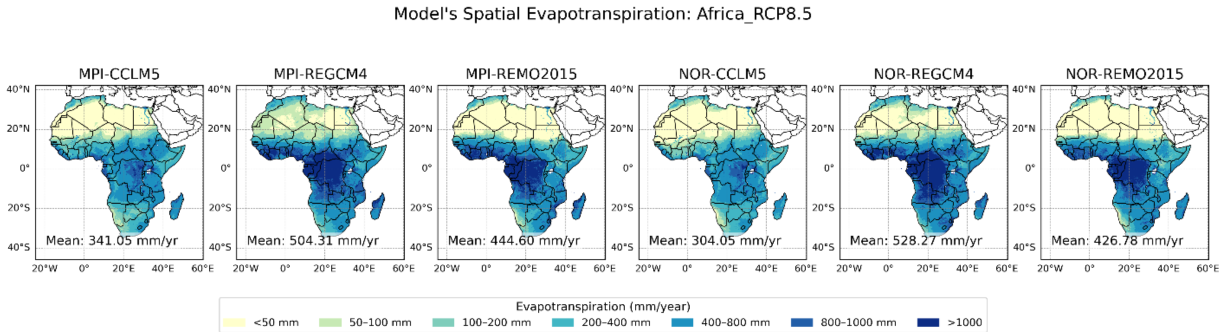

Figure A4:Models' Spatial Evapotranspiration_Africa_RCP8.5

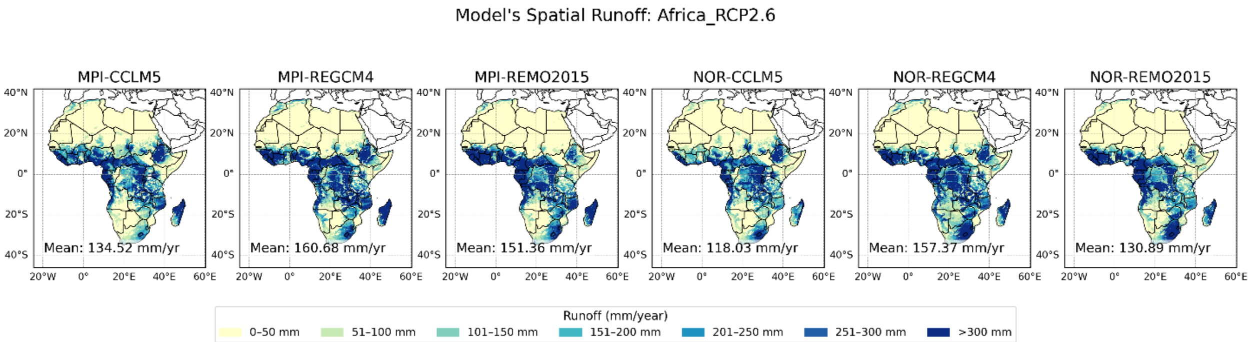

Figure A5:Models' Spatial Runoff_Africa_RCP2.6

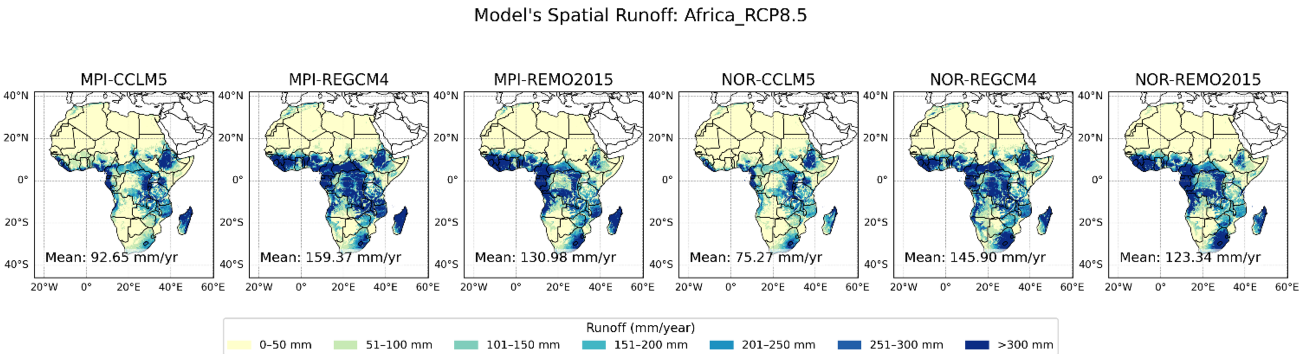

Figure A6: Models' Spatial Runoff_Africa_RCP8.5

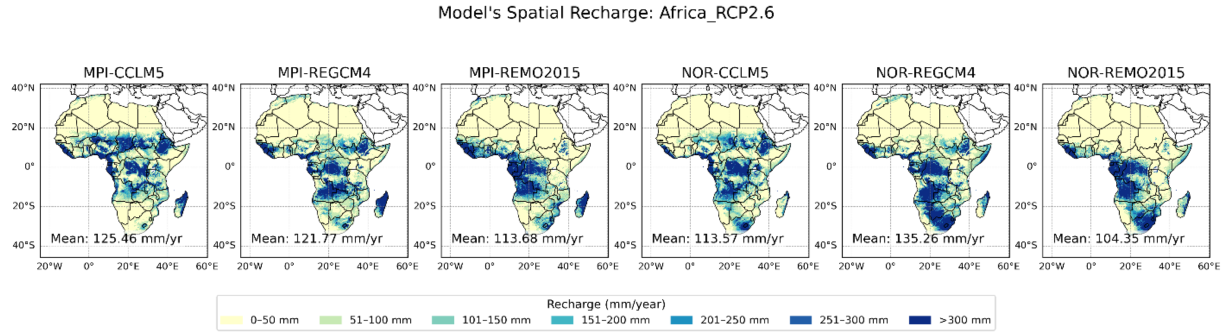

Figure A7: Models' Spatial Recharge_Africa_RCP2.6

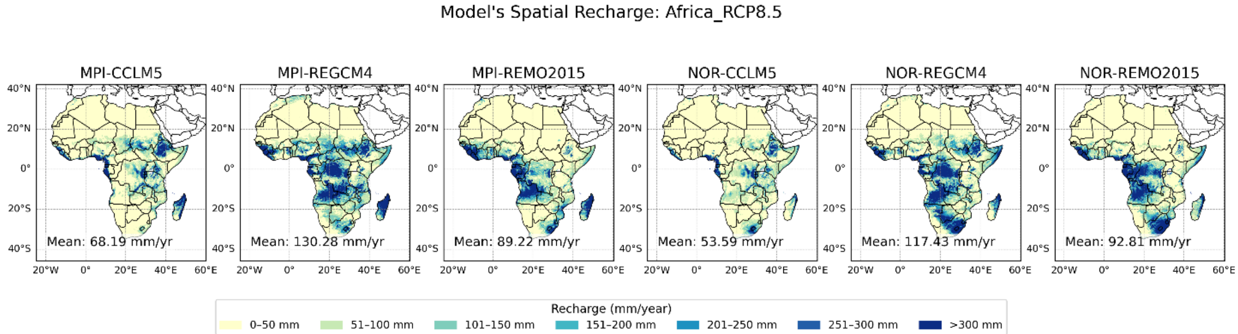

Figure A8: Models' Spatial Recharge_Africa_RCP8.5

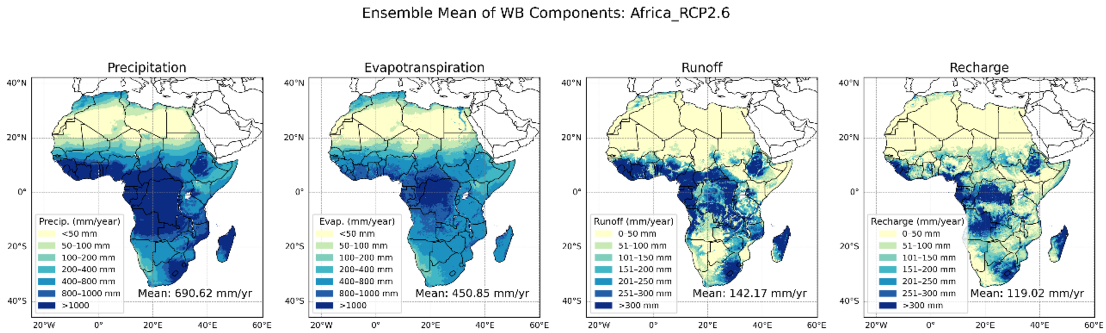

Figure A9: Spatial distribution of Water Balance Components_RCP2.6

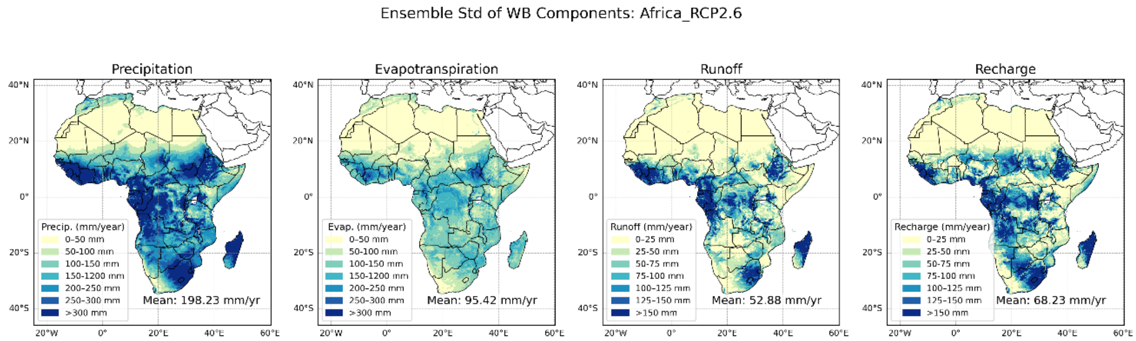

Figure A10: Models' spatial variation of Water Balance Components_RCP2.6

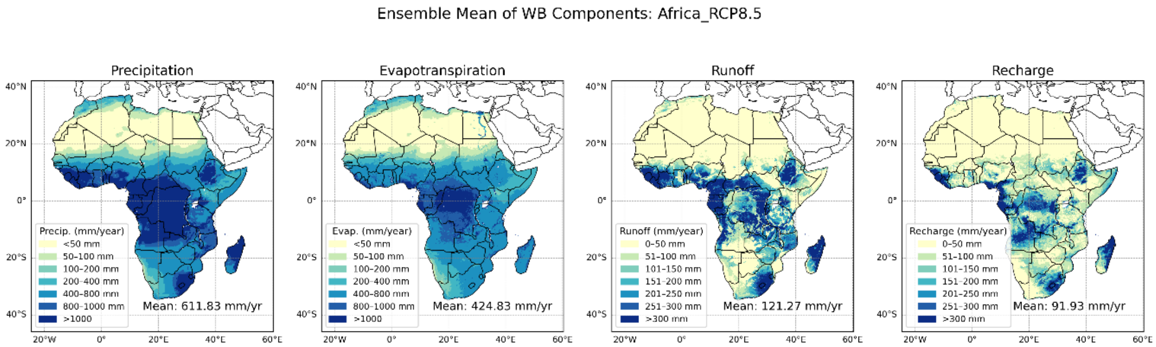

Figure A11:Spatial distribution of Water Balance Components_RCP8.5

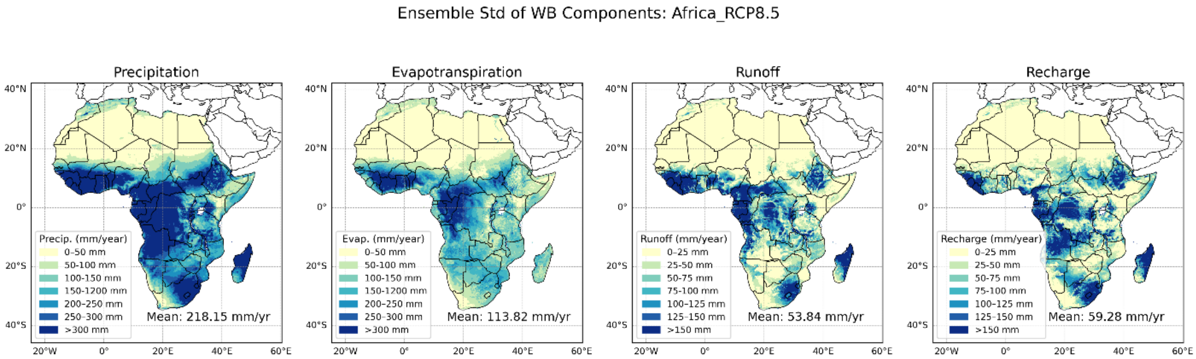

Figure A12: Models' spatial variation of Water Balance Components_RCP8.5