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DEDICATION

I dedicate this humble work to my family, especially my mother, Haoua OUEDRAOGO, and father, Piga TIEMTORE, as well as to all those who believe in me and support me throughout this journey.

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ABSTRACTS

This study focuses on a comparative analysis of groundwater recharge over Africa using atmospheric data from the reanalysis dataset originating from GSWP3 project and projections dataset originating from the CORDEX covering the common period from 2006 to 2014. The aim is to understand the reasons for the discrepancies between the recharge estimates obtained from these two types of datasets based on the output of the CLM5 and examine their implications for water resource assessment. The first step in the analysis was to estimate groundwater recharge using reanalysis data and projected data separately. This comparison revealed significant differences between the two sources. In order to better understand the origin of these differences, a study of the components of the water balance was conducted. This showed that precipitation and evapotranspiration are the main determinants of groundwater recharge. The differences observed between the results are therefore largely due to differences in these two hydrological components between the datasets considered. The variability in precipitation can be explained by the intrinsic nature of the data, as it was directly incorporated into the recharge calculation without first being used by CLM5. This characteristic contributes to accentuating the differences between reanalyses and projections. Furthermore, examination of the meteorological variables used as model inputs revealed significant differences between the data from reanalyses and those from climate projections. These discrepancies raise questions about the reliability of reanalysis data and highlight the high degree of uncertainty associated with them. A further analysis of the characteristics of the two datasets also showed that they differ in terms of spatial and temporal resolution. As the model was run without harmonising these resolutions, this methodological difference is likely to be an additional factor explaining the extent of the discrepancies observed. From this study, further recommendations are observed. Firstly, a detailed verification process and validation of the weather atmospheric dataset, to further continue the investigation related to meteorological variables influencing the evapotranspiration, and secondly, to analyse the impact of using the same resolution datasets for the input of the CLM5.

Keywords: Groundwater recharge Estimation; Projected dataset; Reanalysis dataset; Uncertainties;

RESUME

Cette étude porte sur l'analyse comparative de la recharge en eau souterraine sur l'Afrique à partir de données atmosphériques issues de données réanalysées originaire du projet GSWP3 et de données de projections climatiques originaire du CORDEX, couvrant la période commune de 2006 à 2014. L'objectif est de comprendre les raisons des divergences constatées entre les estimations obtenues à partir de ces deux types de données basées sur les variables de sortie du CLM5 et d'en examiner les implications pour l'évaluation des ressources en eau. La première étape de l'analyse a consisté à estimer la recharge en eau souterraine en utilisant séparément les données de réanalyse et les données projetées. Cette comparaison a permis de mettre en évidence des écarts notables entre les deux sources. Afin de mieux cerner l'origine de ces différences, une étude des composantes du bilan hydrique a été menée. Celle-ci a montré que les précipitations et l'évapotranspiration sont les principaux déterminants de la recharge en eau souterraine. Les écarts observés entre les résultats proviennent ainsi, en grande partie, des différences existant dans ces deux composantes hydrologiques entre les jeux de données considérés. La variation observée au niveau des précipitations peut être expliquée par la nature inhérente des données, vu que celles-ci ont été insérées directement dans le processus de calcul de la recharge en eau souterraine sans être préalablement utilisées par CLM5. Cette caractéristique contribue à l'accentuation des différences entre données issues des réanalyses et celles projetées. De plus, l'analyse des variables météorologiques utilisés comme entrée du model révèles d'important différence entre les deux jeux de données. Ces divergences soulèvent des questions quant à la fiabilité des données de réanalyse et mettent en évidence le degré élevé d'incertitude qui leur est associé. Une analyse plus approfondie des caractéristiques des deux jeux de données a également montré qu'ils diffèrent en termes de résolution spatiale et temporelle. Comme le modèle a été exécuté sans harmonisation préalable de ces résolutions, cette différence méthodologique constitue probablement un facteur supplémentaire expliquant l'ampleur des écarts observés. De cette étude, plusieurs recommandations peuvent être formulées. Premièrement, la mise en place d'un processus rigoureux de vérification et de validation des données atmosphériques utilisées, pour mieux continuer l'investigation concernant les variables météorologiques influençant l'évapotranspiration, et deuxièmement, d'analyser l'impact de l'utilisation des mêmes résolutions des jeux de données d'entrée du CLM5.

<u>Mots-clés :</u> Estimation de la recharge en eau souterraine ; Jeux de données projetés ; Jeux de données réanalysés, Incertitudes.

ACRONYMS AND ABREVIATIONS

20CR: 20^{th} Century Reanalysis.

AR: Assessment Report

BAU; Business As Usual

BMBF: German Federal Ministry of Education and Research

CAF: Central Africa

C3S: Copernicus Climate Change Service

CDO: Climate Data Operators

CEAF: Central-East Africa

CESM: Community Earth System Model

CLM: Community Land Model

CLM5: Community Land Model version 5

CMIP6: Coupled Model Intercomparison Project Phase 6

CMB: Chloride Mass Balance

COP21: 21st Conference of the Parties

CORDEX: Coordinated Regional Climate Downscaling Experiment

CRU TS: Climate Research Unit Times Series

ECMWF: European Centre for Medium-Range Weather Forecasts

ECOWAS: economic Community of west African States

Eq.: Equation

ERA5-Land: European Reanalysis dataset version 5 (Land)

ET: Evapotranspiration

EU : European Union

Fig. : Figure

GERICS: Climate service Center Germany

GCMs: Global Climate Models

GHG: Greenhouse Gas

GPCC: Global Precipitation Climatology Centre

GRIB: Gridded Binary.

GSWP3: Third Global Soil Wetness Project

GWR: Groundwater Recharge

HDF5: Hierarchical Data Format Version 5

IBG-3: Institute of Biology and Geosciences 3

ICTP: International Centre for Theoretical Physics

IMP-EGH: International Master Programme in Energy and Green Hydrogen Production

IPCC: Intergovernmental Panel on Climate Change

IRENA: International Renewable Energy Agency

LTA: Long-Term Average

MED: Mediterranean

MPI: Max Planck Institute

MPI-ESM-LR: Max Planck Institute Earth System Model, low resolution

NCAR: National Center for atmospheric Research.

NCEP: National Center for Environmental Prediction

NEAF: North-East Africa

NetCDF: Network Common Data Form.

NorESM / NorESM1-M: Norwegian Earth System Model (version 1-M)

PT: Precipitation

Q: Surface runoff

RCMs: Regional Climate Models

RCPs: Representative Concentration Pathways

RegCM4: Regional Climate Model version 4 (ICTP)

REMO2015: Regional Model 2015 (GERICS)

SADC: Southern African Development Community

SAH: Sahara

SASCAL: Southern African Science Service Centre for Climate Change and Adaptive Land Management

SEAF: South-East Africa

SRB: Surface Radiation Budget

SRES: Special Report on Emissions Scenarios

SWAF: South-West Africa

SWAT+: Soil Water Assessment Tool Plus

UFHB : Université Félix Houphouët-Boigny

UN : United Nations

UNEP: United Nations Environment Programme

UNFCCC: United Nations Framework Convention on Climate Change

WAF: West Africa

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

WBC: Water Balance Components

WCRP: World Climate Research Programme

WTF: Water Table Fluctuation

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GENERAL INTRODUCTION

GENERAL INTRODUCTION

Climate change is regarded as one of the significant challenges of the 21st century (Wright, 2008). The International Panel on Climate Change (IPCC) defined it as a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer (IPCC, 2007). Climate change may result from natural internal processes or external forcing such as solar cycle variations, volcanic eruptions, and long-term shifts in land use or atmospheric composition. According to the United Nations Framework Convention on Climate Change (UNFCCC), it specifically refers to changes in the climate that are directly or indirectly caused by human activities altering the global atmosphere, beyond natural climate variability observed over comparable periods (UNFCC,2015). This places significant emphasis on the notion of human responsibility in regard to the alteration of the Earth's climate system. Scientists working under the IPCC have shown that the rise in global warming is mainly driven by the increase in greenhouse gas (GHG) emissions (IPCC, 2021). These include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), chlorofluorocarbons, and water vapour (H_2O) as well. Such emissions come from human activities like the burning of fossil fuels (coal, oil, etc.), agriculture, deforestation, and industrial processes. Once released into the atmosphere, they form a barrier that traps the heat emitted by the Earth, preventing it from escaping into space. This mechanism reduces the loss of heat and leads to a gradual increase in the planet’s temperature. The impacts of this warming are already visible through indicators such as rising sea levels, more frequent extreme weather events, growing water scarcity, and loss of biodiversity (IPCC, 2021). Climate change is therefore a serious threat to human health, food security, and ecosystems worldwide. Its effects are not limited to the present but also compromise future generations' lives. To face these challenges, the international community has taken action through major conferences and agreements. One key milestone was the Paris Agreement, adopted by 196 countries during the UN Climate Change Conference under the Conference of the Parties 21 (COP21) in Paris on 12 December 2015. This treaty aims to keep the rise in global average temperature “well below 2°C above pre-industrial levels” and to continue efforts to limit it to 1.5°C (Barston, 2019), as recommended by the IPCC. Since 2020, Nationally Determined Contributions, known as NDCs, have been submitted by countries to assess their national efforts and long-term decarbonization strategies (UNFCCC, 2015). A key element of the mitigation strategies is the transition from fossil fuels to renewable energy sources, such as solar, wind, and clean hydrogen (IRENA, 2022). In this regard, regional initiatives have been undertaken. For instance, the project H_2 ATLAS constitutes the initial phase of a joint initiative by the German Federal Ministry of Education and Research (BMBF) and African partners in the Sub-Saharan region (SADC and ECOWAS countries). The project is led by the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), the Southern African Science Service Centre for Climate Change and Adaptive Land Management (SASCAL), and the Forschungszentrum Julich Center based in Germany. The objective of the project is to explore the potential of green hydrogen production from the substantial renewable energy sources within the sub-regions. The project's findings are presented in the form of an interactive atlas map, which serves as a decision-support tool for policymakers, investors, researchers, and all stakeholders in both Germany and Africa (https://www.h2atlas.de/en/).

Green Hydrogen is produced through water electrolysis, whereby an electric current is used to split water into hydrogen and oxygen. This process does not emit greenhouse gas, provided the electricity used to power the process is entirely from renewables (Oliveira et al., 2021). The use of green hydrogen is versatile, spanning various sectors. It can serve as a chemical feedstock, be burned for heat, used as a reagent for fuel production, or converted back to electricity through fuel cells (Oliveira et al., 2021). Green hydrogen's role extends to long-term energy storage, with tanks or underground caverns serving as storage capacity. This makes it a sustainable technology for energy storage across seasons (Oliveira et al., 2021). The reaction stoichiometry indicates that the production of 1kg of Hydrogen (H_2) requires approximately 9 liters of water (H_2O) (Beswick et al., 2021). Ensuring a sustainable and reliable water supply within the region is imperative for the sustainable green hydrogen production in Africa. It is estimated that the underground water resources of Africa are 20 times larger than surface water resources, including lakes, rivers, and reservoirs (Cuthbert, 2019). Due to its capacity to respond more slowly to weather changes, groundwater serves as a natural reserve during extreme conditions, such as droughts (Calow et al., 2010; MacDonald et al., 2012). Consequently, groundwater commonly represents the only year-round freshwater source and is generally more reliable than other types of water resources (Cuthbert, 2019). These characteristics make groundwater an attractive and essential source for the sustainable production of green hydrogen in Africa, as well as for other applications, including drinking water, irrigation, and industry.

Groundwater recharge is widely regarded as a pivotal indicator of groundwater availability and renewability, both of which are deemed to be critical factors in supporting sustainable green hydrogen production (Ferreira et al., 2024). It is defined as the replenishment of an aquifer by the infiltration of water from precipitation, surface water bodies, or other sources. However, the assessment of groundwater recharge remains a complex task, especially in regions like Africa, where hydrological diversity is high. This complexity arises from limited data availability, intricate subsurface dynamics, and the significant influence of localised factors such as climate variability, land use, and soil composition (MacDonald et al., 2021). Climate and hydrological models often produce widely varying recharge estimates, driven by differences in spatial resolution, input data, and assumptions about surface–subsurface interactions (Allen et al., 2010). Moreover, several methods can be used to determine the groundwater recharge, and according to Wang et *al.* (2010a), groundwater can be quantified using several methods such as direct measurement, water balance methods, Darcian approaches, tracer techniques, and empirical methods (Wang et al., 2010a). This study will focus on the water balance approach, which is based on the mass conservation law.

The use of land surface models, such as the Community Land Model version 5 (CLM5), relies strongly on his input dataset which are the soil texture, the land cover and the availability of atmospheric forcing data, which itself is influenced by climate change. In this context, Bayat et al. (2023) conducted a study entitled “Implications for sustainable water consumption in Africa by simulating five decades (1965–2014) of groundwater recharge”, where before calculating the groundwater sustainable yield, they used the output of CLM5 simulations, and applied the water balance approach to estimate the long-term average (LTA) of groundwater recharge across the African continent, based on the reanalysis atmospheric dataset covering the period from 1965 to 2014.

Similarly, the Project H_2 ATLAS employed the water balance approach to estimate future groundwater recharge for a prospective green hydrogen project or any associated project utilising groundwater under an optimistic scenario (RCP 2.6) and a pessimistic scenario (RCP 8.5) from 2015 to 2100. These estimates are derived from atmospheric scenario forcing data originating from the Coordinated Regional Downscaled Experiment (CORDEX) and serve as inputs to the CLM5.

To date, no study has explored the difference between the two simulated recharge origins from the two atmospheric forcings (i.e., reanalysis and projected). Therefore, to ensure the long-term viability of green hydrogen production in Africa, as well as providing sustainable irrigation for agriculture to secure food security, promoting a sustainable water supply for drinking, improving Africa's resilience to climate change and energy crisis; it is crucial to compare the groundwater recharge during the overlapping periods (i.e. from 2006 to 2014) between these two datasets, and then understand how projected recharge patterns can differ from historical or reanalysis conditions and what would be the possible reasons for this are.

The main objective of our study is to understand how projected groundwater recharge estimates differ from estimates driven by the reanalysis dataset, over a common period from 2006 to 2014, and find the possible reasons behind such discrepancies. The outcomes of this work can enhance the comprehension of the influence of datasets on groundwater recharge simulations, thereby improving the accuracy of the estimation process, which is essential for water resources management, as well as future projects based on water availability, like green hydrogen in Africa. This will contribute to Africa's resilience to Climate change.

The structure of this study is outlined as follows: Chapter 1 introduces the concept of groundwater and previous research, which encompasses the various studies carried out. Chapter 2 describes the materials and methods employed. Chapter 3 presents and discusses the study's results. Finally, we give some limitations, recommendations, and future work as a general conclusion.

CHAPTER 1: LITERATURE REVIEW

CHAPTER 1: LITERATURE REVIEW

Introduction

The present chapter offers a comprehensive overview of the subject of groundwater recharge, in conjunction with a survey of extant studies on the estimation of groundwater recharge within the African domain, employing a range of recharge estimation methodologies, whether as a standalone approach or in a mixed configuration.

1.1 Overview of Groundwater Recharge

This part provides a comprehensive overview of GWR, encompassing its definition to the types of groundwater and their significance, and finally explores the current challenges it faces.

According to MacDonald et *al*(2012), GWR can be understood as the process through which underground aquifers are replenished, either naturally or artificially. Natural recharge occurs when precipitation or surface water slowly infiltrates the soil and permeable rock layers until it reaches the groundwater table. This process is often linked to rainfall or snowmelt gradually filtering through the subsurface. In contrast, artificial recharge refers to the deliberate introduction of surface water, treated wastewater, or rainwater into aquifers. This is achieved through carefully designed civil and hydraulic infrastructures that guide and control the flow of water underground, sustaining aquifer sustainability.

Groundwater is a vital resource for human societies, and human daily activities like agriculture, industry, as well as the ecosystems, particularly in regions with limited rainfall. Studies indicate that it provides at least part of the drinking water for nearly half of the world's population and contributes to about 43% of irrigation needs globally (Adhikari et al., 2022a; Gebreslassie et al., 2025). Furthermore, around 2.5 billion people depend entirely on groundwater to meet their daily water demands (Gebreslassie et al., 2025). Overall, groundwater represents one of the most important freshwater reserves, accounting for approximately 33% of global water withdrawals (Ochwo et al., 2025). It is essential not just for practical uses, but also for maintaining environmental balance and helping societies adapt to changes in climate (Ochwo et al., 2025). As a key water resource in Africa, groundwater is a strategic resource due to its stability under variable climate conditions and its relatively high quality (Wang et al., 2010b).

However, the excessive extraction of water and the unsustainable exploitation of aquifers to satisfy water demands, in conjunction with the repercussions of climate change, are driving widespread declines in groundwater levels. This depletion leads to multiple consequences, including falling water tables, reduced streamflow and lake levels, land subsidence, rising extraction costs, deteriorating water quality, and ecological damage. The rate of groundwater depletion is accelerating on a global scale, and its impacts are becoming increasingly pronounced, underscoring the imperative need for impartial analysis and the exploration of sustainable solutions. Consequently, groundwater depletion has emerged as a matter of global concern (Gebreslassie et al., 2025). Moreover, groundwater is increasingly threatened by pollution, climate change, and inadequate management. Over the past three decades, global average temperatures have risen by approximately 1°C, with some regions experiencing increases of up to 3°C in minimum temperatures. Concurrently, precipitation patterns have become highly variable across both space and time. These climatic shifts exert significant pressure on the hydrological cycle, with direct implications for groundwater availability and sustainability (Ochwo et al., 2025).

In response to these growing challenges, it is imperative to develop a comprehensive understanding and quantification of GWR to facilitate the formulation of sustainable groundwater management strategies. Consequently, a plethora of methodologies have been employed globally to estimate recharge rates under a wide range of climatic and geological conditions.

GWR estimation refers to the process of measuring how much water seeps into underground reservoirs from various origins, such as direct recharge from precipitation, localised recharge from depressions (e.g. ponds) and rivulets, indirect recharge from rivers, irrigation losses, and urban recharge (Bennett et al., 2024; Ferreira et al., 2024; Kumar et al., 2021; Rath & Hinge, 2024). However, quantifying groundwater recharge at a larger scale remains a significant challenge due to the scarcity of in situ observations, the complexity of recharge processes, and the influence of climate variability and human activities on groundwater dynamics (Belay et al., 2024; Ferreira et al., 2024). Despite these challenges, many methods have been used over time to estimate it. A variety of methods used to estimate both natural and artificial recharge are documented in the literature (Gebreslassie et al., 2025; Wang et al., 2010b). The selection of an appropriate method depends on several factors, including: (1) data availability, (2) local geographic and topographic conditions, (3) spatial and temporal scales required for the analysis, and (4) reliability of results for the specific context (Bennett et al., 2024; Gebreslassie et al., 2025). A recent study published in 2025 reviewed 76 articles selected among 166 articles to bring out the main methods used for groundwater recharge estimation, in addition to those presented in the literature (Gebreslassie et al., 2025).

The following techniques are utilised in order to estimate GWR:

a) water table fluctuation (WTF),
b) water budget,
c) Darcy's law,
d) empirical relationships,
e) tracer techniques, and
f) groundwater models.

In the subsequent section of the thesis, we will explore the recent studies conducted regarding GWR worldwide, and especially in Africa.

1.2 Previous Studies on Groundwater Recharge (GWR) estimation.

GWR is an important and determining factor in sustainable water management, especially in dry areas or areas with limited rainfall. However, its estimation raises significant challenges due to hydro-climatic conditions and a lack of data. Despite those challenges, scientists across the world have made important progress concerning the recharge estimation, encompassing various spatial resolutions as well as various study areas, either catchment, countries or at the continental scale. This was done by using numerous methodological approaches.

Kumar et al. (2021) review the widely used methods for recharge estimation, and then highlight that recharge estimates are often subject to important uncertainties, which may come from incorrect assumptions, measurement errors, unreliable or limited data, and challenges linked to the parameterisation. Such uncertainties can strongly influence the results. They emphasise that choosing an appropriate method depends on factors including temporal and spatial resolution, its objectives, the hydrogeological characteristics of the area, and data availability and reliability. Then, they suggest the WTF and water balance methods as the suitable choice regarding Indian conditions.

Rath and Hinge (2024) utilised the WetSpass model to assess the viability of Managed Aquifer Recharge (MAR) in the semi-arid Dwarkeswar River basin of India, with the objective of supporting groundwater sustainability. The analysis revealed substantial spatial variation in runoff and recharge potential across the basin. Through the integration of hydrological modelling with spatial decision-making tools, the study identified areas exhibiting varying degrees of suitability for MAR, ranging from unsuitable to highly suitable zones. Key factors influencing recharge potential included geological conditions, soil thickness, slope, and runoff availability. The findings underscore the significance of employing integrated modelling approaches to guide sustainable groundwater management, particularly in drought-prone regions where water security is critical for achieving long-term development objectives.

Belay et al. (2024) work on evaluating remote sensing based on hydro-meteorological data for estimating groundwater recharge in areas with limited data. They study compared spatially distributed recharge estimates obtained from the WetSpass model with point-based estimates derived from the WTF and Chloride Mass Balance (CMB) methods.The results showed average annual recharge values of 420 mm/year using the WTF method, 308 mm/year using the CMB method, and 365 mm/year using WetSpass. A strong correlation of 72% between the WTF and WetSpass estimates highlighted the reliability of remote sensing data in capturing groundwater recharge dynamics.

Similarly, Noori et al. (2023) evaluated groundwater recharge across Iran using a dataset of groundwater abstractions collected between the period ranging from 2002 to 2017. With more than 80 million people relying on aquifers sustained by recharge, Iran is experiencing severe groundwater depletion. Their findings indicate a significant decline in recharge of approximately 3.8 mm per year, primarily due to unsustainable water and environmental resource management and the impacts of climate change. From the water balance analysis, the average annual groundwater recharge, around 40 mm/year, exceeds the average annual surface runoff of roughly 32 mm/year, underscoring the vital role of surface water in maintaining groundwater levels.

Hepach et al. (2024) examine GWR in the Western Mountain Aquifer (WMA), which is a vulnerable karst aquifer spanning Israel and the West Bank. Recharge was estimated using three approaches: SWAT (Soil and Water Assessment Tool), PIM (Process-Based Infiltration Model), and empirical regression models. The findings exhibit consistent results between 32 to 36% of annual precipitation. Simulations encompassed the period 1981–2001 as the baseline and 2051–2070 for future climate projections. Under climate change scenarios, SWAT predicted a 23% decline in recharge, while PIM estimates a 9% decrease, reflecting key differences in how infiltration and surface runoff are modelled. All recharge outputs were integrated into the MODFLOW model to evaluate impacts on groundwater storage. The findings emphasise the importance of ensemble modelling for reducing uncertainty and guiding sustainable groundwater management in climate-sensitive karst environments.

Over numerous approaches to groundwater recharge estimation, some tools have been developed to facilitate and support the water balance models. It is the case of the waterpyBal based on Python and developed by Assanzadeh et al. (2024). This tool can be used for groundwater recharge assessment, urban hydrology, and water resources planning.

With respect to the climate change impact affecting GWR, Adhikari et al.(2022b) mainly focused on reviewing studies that focus both on qualitative and quantitative aspects of groundwater, which allows for taking climate change into consideration.

After examining GWR studies at the global level, it is now essential to focus on the African domain, a vulnerable continent, and the central focus of our study.

Larbi et al. (2020) used the SWAT model, along with daily climate data, soil data, as well as land cover maps to assess the impact of land use change on water balance components of a WASCAL key site located in Ghana. This was done under two scenarios: Afforestation and Business as usual. They found out that the land cover is changing rapidly. Under the Business As Usual (BAU) scenario, the mean annual water yield is projected to increase by 9.1%, while evapotranspiration decreases and groundwater recharge rises. Conversely, the afforestation scenario results in a 2.7% decrease in water yield, an increase in evapotranspiration, and a more pronounced rise in groundwater recharge compared to BAU. These findings underscore the substantial influence of land-use dynamics on water resource availability and highlight the critical need to integrate land-use planning into sustainable catchment management strategies.

Hamma et al. (2024) work on the hydro-chemical characteristics and the quality of underground water in the arid Ain Sefra region of southwest Algeria and used a multivariate statistical technique, geochemical modelling, and water quality indices. Their study revealed that a high proportion of the groundwater is suitable to meet human consumption; in fact, 97.68% of groundwater samples are suitable, while 2.32% are not. The groundwater was also found to be appropriate for agricultural use, even though it emphasises about the salinity control.

Cook et al. (2022) employed high-resolution climate models combined with land surface simulations to investigate the impacts of climate change and rising atmospheric CO_2 concentrations under the RCP8.5 scenario on the West African monsoon, rainfall patterns, evapotranspiration, and groundwater recharge. As a result, there is an enhanced summertime Saharan heat low, leading to an overall increase in monsoon rainfall. The eastern Sahel experiences a significant increase in precipitation (+12.2%), whereas the western Sahel becomes drier (−13.5%). Evapotranspiration decreases across much of West Africa due to the CO_2 fertilisation effect, which reduces plant transpiration. We retain from this work that groundwater recharge increases, mainly driven by higher soil moisture resulting from increased rainfall and reduced transpiration.

West et al. (2023) examined global-scale groundwater recharge compared to 100 field-based estimates and revealed that there is a disagreement in recharge estimates among the models across the majority of Africa. Models incorporating strong climatic controls tend to perform better and align more closely with observed data, yet there remains considerable variability in how well each model matches ground-based measurements.

MacDonald et al. (2012) present the first continent-wide quantitative maps of groundwater storage and potential borehole yields across Africa. Groundwater storage was estimated by combining the saturated thickness and effective porosity of aquifers throughout the continent. The total volume of groundwater is estimated at 0.66 million km^3 (range: 0.36–1.75 million km^3), which is more than 100 times the annual renewable freshwater resources and approximately 20 times the volume of freshwater stored in African lakes. However, groundwater is unevenly distributed across the continent. The largest reserves are concentrated in the sedimentary aquifers of North Africa, particularly in Libya, Algeria, Egypt, and Sudan. (MacDonald et al., 2012)

MacDonald et al. (2021) also present the first ground-based, continent-wide map of LTA groundwater recharge rates across Africa for the period 1970–2019, derived from 134 field-based estimates and statistical upscaling. The analysis includes natural diffuse and local focused recharge, while excluding recharge from large rivers, lakes, and irrigation leakage. The results show that measurable recharge occurs across most African environments:

- In arid regions, average decadal recharge is approximately 60 mm/decade (range: 30–140 mm)
- In semi-arid regions, it is around 200 mm (range: 90–430 mm)

The average decadal recharge across Africa is estimated at 15,000 km^3 (range: 4,900–45,000 km^3), which accounts for about 2% of the continent's total estimated groundwater storage. A linear mixed model indicates that, at the continental scale, LTA rainfall is the only significant predictor of recharge. The inclusion of other climatic or terrestrial variables does not improve the model. However, kriging analysis reveals spatial dependency up to 900 km, suggesting that large-scale factors influence recharge patterns. The study highlights a stark contrast between:

- High-storage, low-recharge sedimentary aquifers in North Africa
- Low-storage, high-recharge weathered crystalline aquifers in tropical Africa

This complementary distribution enhances water security across the continent, as countries with low recharge often possess large groundwater reserves, while those with limited storage benefit from frequent and regular recharge.

Bennett et al. (2024) used two methods to estimate the groundwater recharge over the northern and southern slopes of Mount Meru, in Tanzania. with WTF, he finds that the GWR estimate is 544mm/year, representing 53% of the annual rainfall over the southern part and 90 mm/year for northern slope, accounting for 13 % of the annual rainfall; with the Baseflow separation technique, it shows that GWR is 88mm/year and 54 mm/year, representing respectively 12% and 7% of the annual rainfall. Overall, the WTF suggests a higher recharge rate compared to the baseflow approach, particularly in the southern slope.

Kisiki et al. (2023) conducted a study in the Makupuku catchment, Tanzania, and applied the WetSpass model to estimate GWR. Results revealed that annual recharge ranged from 0 to 120.88 mm/year, with a mean of 24.88 mm/year, accounting for 3.6% of total annual precipitation. The basin receives approximately 1041.4 million m^3 of rainfall annually, of which 650.85 million m^3 is lost to evapotranspiration, 353.25 million m^3 becomes surface runoff, and only 37.3 million m^3 contributes to groundwater recharge. Seasonal variation was pronounced: during the wet season (November–April), recharge averaged 24.65 mm/year, while the dry season yielded a negligible 0.24 mm/year. These findings underscore the limited recharge potential in semi-arid regions and highlight the importance of seasonal dynamics in water resource planning.

In the hydrological field, the Water Balance Methods represent one of the widely used methods to estimate recharge, especially in areas with a lack of direct data measurement, such as Africa. Many studies have applied this method for various hydroclimatic conditions zones.

Andualem et al. (2021) estimated the annual groundwater recharge in the Gumara and Ribb watersheds of Ethiopia to be about 253.70 mm/year. Their analysis was carried out using streamflow data provided by the Ministry of Water, Irrigation, and Electricity of Ethiopia, along with rainfall records from the Amhara National Meteorology Agency. To assess recharge, the authors combined empirical methods, including the water balance approach and several baseflow separation techniques. One of the significant findings of the study is that the recharge coefficient, which is derived from rainfall data, was 0.18. This value highlights the groundwater potential of the region and underlines its link to future groundwater development initiatives in the area.

Maswanganye et al. (2022) investigate the dynamics of surface water pools along the non-perennial Touws River in the Klein Karoo region of South Africa. By applying a water balance approach that integrates both in-situ and satellite-derived data, the research aims to quantify the water fluxes influencing pool behaviour and enhance the understanding of their hydrological functioning. The findings reveal that evaporation is the dominant mechanism of water loss, and that groundwater interactions vary with water levels, initially resulting in subsurface losses before transitioning to gains. The Wolverfontein 2 pool, when full, can retain water for up to 258 days without surface inflow. A water balance model developed for the study showed strong agreement with observed water levels, particularly in upstream pools, though performance declined in downstream areas. While remote sensing data provided useful baseline information, its lower resolution introduced uncertainties, reducing model accuracy. Overall, the study underscores the importance of combining multisource data with water balance modelling to support the effective management of non-perennial river systems.

Oloruntoba et al. (2025) evaluate how different sources and processing methods of soil texture data, combined with three different atmospheric forcing inputs: CRUNCEPv7 (6-hourly input resolution), GSWPv3 (3-hourly), and WFDE5 (hourly), impact land surface simulations over Africa using CLM5 at a 3 km resolution. One of the key points from the result is to emphasize the need to use higher temporal resolutions for atmospheric forcing data to capture more land surface heterogeneity, resulting in improving the accuracy of the results.

Land surface simulations using models like the CLM5 are considerably dependent on the quality and type of atmospheric forcing data, which is possibly affected by climate change. Bayat et al. (2023) employed CLM5 to simulate five decades (1965–2014) of groundwater recharge across Africa using the water balance approach and historical atmospheric data, generating LTA estimates. In parallel, the project H_2 ATLAS applied the same modelling and methodological framework to project future groundwater recharge between 2015 and 2100, targeting potential applications such as green hydrogen production, under two climate scenarios: RCP 2.6 (optimistic) and RCP 8.5 (pessimistic), using atmospheric inputs from the CORDEX downscaled dataset. Oloruntoba et al. (2025), as part of their study, compare different temporal resolutions of atmospheric forcing data from historical data originating from different sources.

Despite these valuable efforts, no study has yet compared groundwater recharge estimates derived from a historical-based reanalysis dataset and the projected past scenarios-based atmospheric forcing. This study, therefore, represents a key opportunity to better understand how projections diverge from observed patterns and to find the potential drivers of these differences. then, this research seeks to analyse the discrepancies between historical and projected groundwater recharge estimates over Africa during the overlapping period of 2006 to 2014. By identifying the underlying reasons behind variations in recharge simulations, the study will enhance comprehension of how atmospheric forcing datasets influence groundwater recharge estimation over Africa.

Partial Conclusion

Chapter one has provided the background to this research and reviewed existing studies on groundwater recharge. Globally and within Africa, recharge has been investigated using a wide range of approaches, whether applied independently or in combination, including field observations, modelling techniques, and remote sensing. These efforts have advanced understanding of recharge processes but also underline persistent uncertainties, particularly under changing climatic conditions. Building on this foundation, the present study aims to extend these insights by focusing on the specific challenges of comparing reanalysis and projected datasets in the assessment of groundwater recharge.

CHAPTER 2: MATERIALS AND METHODS

CHAPTER 2: MATERIALS AND METHODS.

Introduction

This chapter describes the study area and its regional partitioning and outlines the materials, datasets, and tools employed in the research. It also introduces the fundamental equation that underpins the analysis and explains the methodological approach adopted.

2.1 Study Area

The study focuses on Africa, and Africa's hydrogeology varies greatly across the continent, characterized by its diverse climate and long geological history. Aquifer systems of Africa range from limited-capacity crystalline rocks to expansive sedimentary deposits with high yields, influencing both the quantity and accessibility of groundwater resources. (MacDonald et al., 2012)

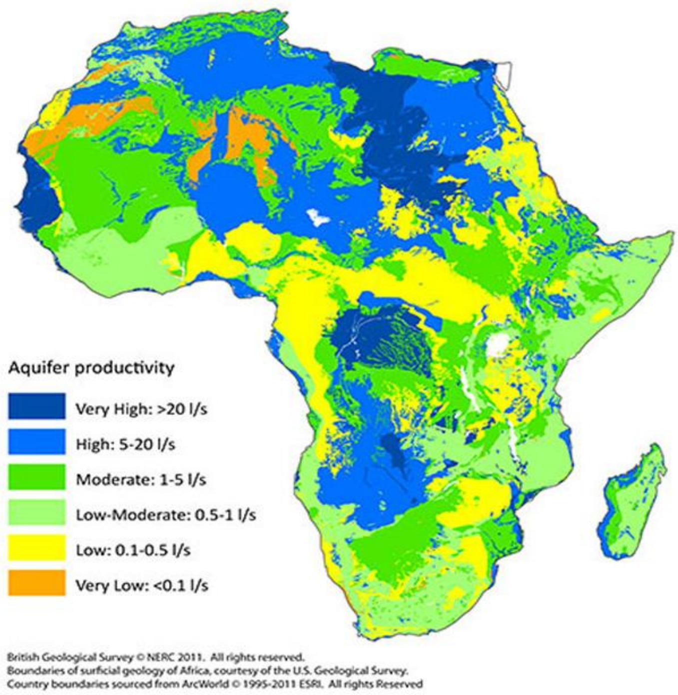

Figure 1: Africa Aquifer Productivity

Source: (MacDonald et al., 2012)

For this study, the partitioning is based on the updated IPCC climate reference regions defined by Iturbide et al. (2020). These regions were revised to capture coherent climatic regimes and physiographic settings at the subcontinental scale, while maintaining an appropriate size for climate model representation. Climatic homogeneity within the regions is characterized by the mean temperature and precipitation, as classified by the Köppen–Geiger system, as well as by the annual precipitation cycle (Iturbide et al., 2020)

In accordance with the approach adopted by Oloruntoba et *al.* (2025), we adopted a modified version of the approach by Iturbide et al. (2020), which combines south-eastern Africa and Madagascar into a single region. This results in a total of eight areas: the Mediterranean (MED), the Sahara (SAH), West Africa (WAF), North-East Africa (NEA), Central Africa (CAF), Central-East Africa (CEAF), South-West Africa (SWAF), and South-East Africa (SEAF).

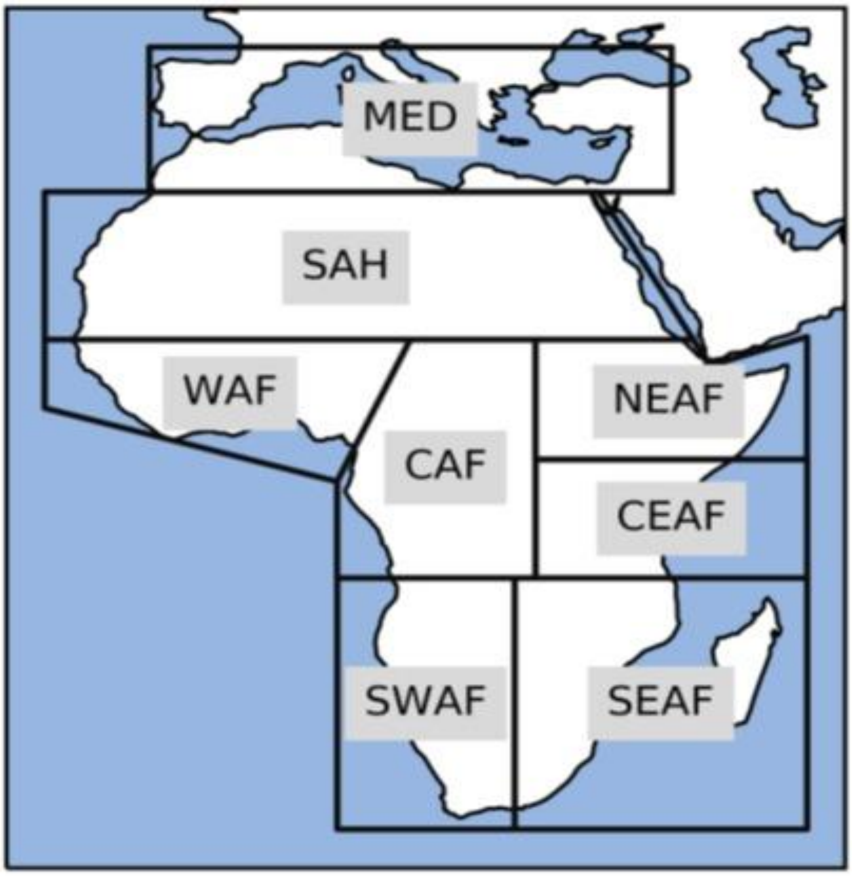

Figure 2: Africa partitioned into 8 regions.

Source: Oloruntoba et al. (2025)

2.2 Materials and Tools

2.2.1 Material

- **The Community Land Model 5 (CLM5)**

The Community Land Model (CLM), developed by the National Center for Atmospheric Research (NCAR), is a comprehensive land surface model. This study employs version 5.0 of the model, which is the latest version published in 2019 (Lawrence et al., 2019). CLM represents major biophysical and biogeochemical processes, including interactions between incoming solar radiation and both the canopy and soil, as well as the exchange of sensible heat, latent heat, and carbon between the land surface and the atmosphere. It also models key hydrological and physiological processes, including snow dynamics, water movement within soil layers, such as infiltration, surface runoff, deep percolation, and plant physiology related to stomatal function or regulations and photosynthesis (Bayat et al., 2023; Oleson et al., 2008). These capabilities enable the detailed estimation of evapotranspiration, irrigation, and surface runoff, which are critical variables in determining groundwater recharge and are therefore essential to this study. Moreover, CLM incorporates spatial variability through a structured subgrid hierarchy, enabling finer-scale representation of heterogeneous land surface features (Bayat et al., 2023; Oloruntoba et al., 2025a)

- **Atmospheric forcings: Input of the CLM5 model**

The CLM model relies on a comprehensive set of atmospheric forcing inputs to function effectively. These include precipitation, surface air temperature, incoming shortwave and longwave radiation, relative humidity, surface pressure, and wind velocity. Each variable plays a critical role in driving the land-atmosphere exchange processes modelled within CLM (Bayat et al., 2023). For this study, we used three (3) sets of data as weather input to the model: the historical forcing data, the projected atmospheric forcing data under optimistic and pessimistic scenarios, respectively, RCP 2.6 and 8.5.

❖ Historical Atmospheric Forcing Data

The historical atmospheric forcing data used in this study are derived from the Global Soil Wetness Project version 3 (GSWP3), a 3-hourly dataset at 0.5° horizontal resolution, available from 1900 to 2014. GSWP3 is originally based on the 20th Century Reanalysis Project by the National Centers for Environmental Prediction (NCEP) land atmosphere model, which originally provided data at a coarser 2° resolution. This original dataset has then been downscaled to 0.5° using a spectral-nudging technique, incorporating the Global Spectral Model (GSM) and data assimilation methods. To derive the GSWP3 dataset from 20CR, a bias correction has been performed on 4 out of 7 parameters, namely precipitation (using the Global Precipitation Climatology Centre GPCC v6 dataset), temperature (using Climate Research Unit CRU TS v3.21 dataset), longwave and shortwave incoming radiation (using Surface Radiation Budget SRB dataset). The GSWP3 dataset also serves as the default atmospheric forcing input for CLM5, and since it was pre-processed for compatibility with the model, no additional data manipulation was required (Bayat et al., 2023; Oloruntoba et al., 2025c). Moreover, for this study, we only use the data from our time period, which is from 2006 to 2014.

❖ Projected Atmospheric Forcing Data

The projected atmospheric forcing data used in this study are derived from the Coordinated Regional Climate Downscaling Experiment (CORDEX), which is an international initiative supported and coordinated by the World Climate Research Programme (WCRP). CORDEX aims to collaborate with global partners to provide a high-resolution climate data tailored to the local and regional levels, by downscaling Global climate models (GCM), supporting risk assessments, and policy decisions for adaptations and mitigations. The CMIP5-based simulations were widely used in the IPCC AR6 report, and there is ongoing work on the CMIP6 which is supposed to support the Assessment Report 7 (AR7) (Diez-Sierr et al., 2022; Lake & Bukovsky, 2024). Our data are based on the CMIP5, which is the latest available to date.

In fact, climate projections are generated using global climate models (GCMs), based on numerical hyper-computation to simulate how the Earth's climate responds to external influences, especially greenhouse gas emissions scenarios. The Coupled Model Intercomparison Project (CMIP) provides coordinated sets of long-term climate simulations from multiple GCMs at a coarse resolution ranging from 100 to 200 km. However, the coarse resolution does not adequately capture local-scale variability; therefore, regional climate models (RCMs) are used to overcome these challenges (Rampal et al., 2024), justifying the use of CORDEX data in our study.

In addition, the GCMs and RCMs are run based on different climate scenarios, which are hypothetical assumptions of how the future might look like for the years to come. It can be defined as the projected concentrations of greenhouse gases, aerosols, and other climate-sensitive pollutants released from both natural and anthropogenic sources, including assumptions also on change in land use and land cover (Jalota et al., 2018).

Over the years, a variety of approaches to emissions have been used in climate research, starting from SA90 in 1990, passing through IS92, SRES in 2000, and ending with RCP scenarios. The currently widely used are the Special Report on Emissions Scenarios (SRES) and the Representative Concentrations Pathways (RCPs). For this study, the focus will be on the most recent Representative Concentration Pathways (RCPs), which offer a good projection of radiative forcing (defined as the shift in the balance between incoming solar radiation and outgoing infrared radiation due to changes in atmospheric composition). These scenarios are essential inputs for climate modelling and are measured in watts per square meter (W/m^2), representing the additional heat retained in the lower atmosphere as a result of greenhouse gases and aerosols. Of the four pathways (RCP2.6, RCP4.5, RCP6.0, RCP8.5), the analysis will focus on the two extremes: RCP2.6 (low emissions) and RCP8.5 (high emissions), representing respectively optimistic and pessimistic scenarios.

For this study, we utilize three RCMs: RegCM4 (Regional Climate Model version 4, developed by the International Centre for Theoretical Physics, ICTP), REMO2015 (Regional Model 2015, maintained by the Climate Service Center Germany; GERICS), and CCLM5 (Climate version 5 of the Local Model, also known as COSMO-CLM, developed by the CLM Community); each driven by two GCMs: MPI-ESM-LR (Max Planck Institute Earth System Model) and NorESM1-M (Norwegian Earth System Model version). This results in a total of six GCM–RCM combinations, all simulated under the RCP 2.6 and 8.5. The data are from the CORDEX Africa domain (AFR-22), which has a horizontal resolution of 0.22° (~25 km). The variables used are the same as those used as historical forcing data, ensuring comparability and reliability in comparing the two datasets or their results from CLM5.

In the count of projected atmospheric forcing data, there are two datasets which serve as projected atmospheric forcing data:

- **Projected atmospheric forcing data under RCP2.6**
- **Projected atmospheric forcing data under RCP8.5**

- **Output of CLM5**

For this study, we used key water balance variables derived from CLM5 using the three datasets mentioned as atmospheric forcing used as input to the CLM5. These variables include **Surface runoff (Runoff)**, and **evapotranspiration (ET)**; all of which are fundamental components of the water balance.

Surface Runoff (Q): refers to the proportion of water, mainly precipitation, that flows over the land surface and which is not infiltrating into the soil. It represents the water loss and is directly affected by rainfall intensity, soil saturation, and land cover conditions. **Evapotranspiration (ET):** represents the combined process of water loss to the atmosphere through **evaporation** from soil and water surfaces, and **transpiration** from vegetation. It is a major component of the water balance and varies with temperature, humidity, wind, and vegetation type (https://www.usgs.gov/)

- **European Reanalysis Dataset-Land (ERA5-Land)**

For our study, we make use of the ERA-5 Land as a reference dataset to compare with our results. The ERA5 land is developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) within the Copernicus Climate Change Service (C3S), and provides data at high spatial resolution, i.e. 9km for variables such as precipitation, soil moisture, and so on. However, for this study, we only used the 3 water balance components and the recharge estimate from ERA5 land. The ERA5 land is finer than the ERA5 where it originates. It captures the evolution of water and energy cycles over land consistently. While some variables, such as snow depth, may have mixed performance depending on location, the dataset overall offers a reliable benchmark for assessing land-surface simulations and comparing modeled results with observations (Muñoz-Sabater et al., 2021)

2.2.2 Tools or software

- **CDO**

We employed Climate Data Operators (CDO), a comprehensive suite of command-line tools developed by the Max Planck Institute for Meteorology, in order to process, analyse, and transform climate datasets, particularly those in netCDF format. CDO is widely used in climate science for its efficiency, flexibility, and compatibility with large-scale numerical model outputs, and also supports a wide range of data formats, including netCDF, GRIB, and HDF5, and offers over 600 operators for tasks such as statistical analysis, interpolation, data transformation, spatial remapping, ensemble operations processing, and so on. Its flexibility and efficiency make it particularly suitable for handling large climate datasets and performing reproducible workflows in regional climate modelling. (Climate Data Operator (CDO), 2024)

Applying directly to this study, we use it for processing our dataset. We calculate the ensemble mean, the merging of different datasets, annual year mean, the remapping, to extract general information about the dataset, and so on, when needed. In general, the whole process of making our dataset ready enough to be used in Python.

- **Python**

In this study, we employed Python, an open and versatile open-source programming language, for comprehensive climate data processing, analysis, and visualization. Python's adoption in climate and Earth system sciences has expanded rapidly due to its robust scientific ecosystem and support for large and multidimensional datasets, making it suitable for all engineers (Millman & Aivazis, 2011). One of its key strengths is the use of the xarray library, which enables efficient manipulation of labeled multi-dimensional arrays common in climate model outputs, supporting essential operations for managing regional datasets such as those from CORDEX (Hoyer & Hamman, 2017). Furthermore, the interactive Jupyter Notebook environment enhances transparency and reproducibility by integrating code, results, and documentation within a single workflow, facilitating open and replicable climate research suitable for publication and direct use from its nice and friendly interface. (Kluyver et al., 2016)

2.3 Methods

2.3.1 Water balance approach

The water balance method is a widely used and comprehensive approach in hydrological modelling for estimating GWR. It is based on the principle of mass conservation, where the difference between inputs (precipitation, or/and irrigation) and outputs (evapotranspiration, runoff, and other losses) represents the portion of water available for infiltration and potential recharge to groundwater. The water balance method has been extensively used in large-scale and regional studies due to its relative simplicity and the fact that most of the parameters can be measured or estimated. It is particularly useful for data-scarce regions like Africa, or parts of Africa where direct groundwater measurements are limited (Gebreslassie et al., 2025; Islam et al., 2016; Scanlon et al., 2002; K. A. Wright & Xu, 2000)

The general water balance equation only holds over long time periods, and it is expressed as follows:

$$\boldsymbol{GWR = PT - ET - Q} \quad \text{(Equ.1)}$$

Where:

GWR: Groundwater recharge (mm/year)

PT: Precipitation (mm/year)

ET: Evapotranspiration (mm/year)

Q: Surface runoff (mm/year)

For this study, groundwater recharge was estimated using the General Water Balance Equation mentioned earlier (Equ.1), based on outputs from CLM5. Evapotranspiration and surface Runoff (Q) come from the output of CLM5, while the precipitation (PT) comes from the Input Atmospheric dataset. The calculation of groundwater is the same process for the three different cases: historical or reanalysis, projected under RCP2.6, and projected under RCP8.5.

In addition to groundwater recharge, each of the water balance components (PT, ET, Q) was individually analysed across both the projected and reanalysis datasets. This was done to explore the potential causes of variation in simulated recharge under our different cases. Moreover, an investigation of the weather characteristic was also carried out to collect key information, and finally the seven atmospheric input variables used as atmospheric forcing in

CLM5 were also examined, including: incoming shortwave radiation (SWR), incoming longwave radiation (LWR), precipitation (PT), surface air temperature (tas), specific humidity (huss), wind speed (Wind), and surface pressure (ps). The path of the investigation is illustrated in Figure *3*. The process of our investigation follows the reverse process of the water balance methods, starting with the results obtained from the initial input of the model.

Figure 3: Process of investigation of the possible discrepancies.

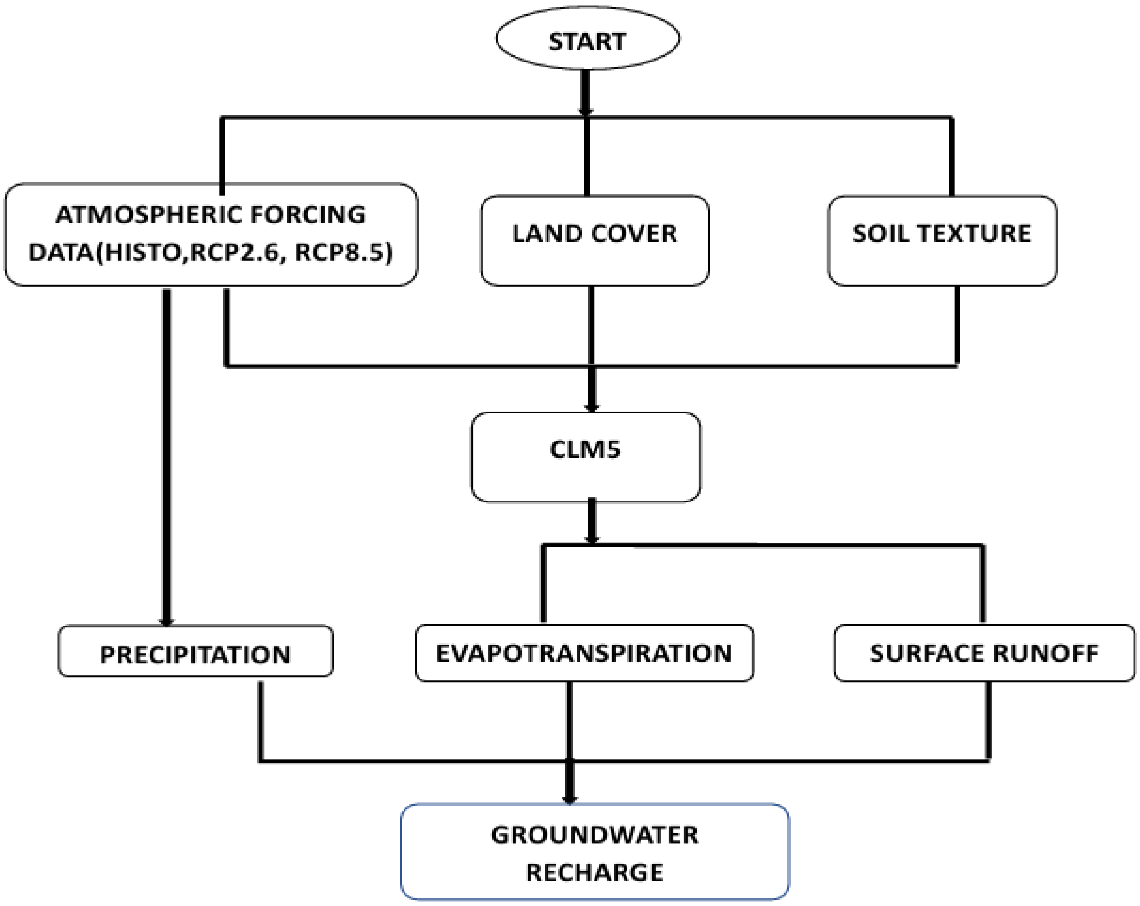

Figure 4: Methodology adapted for GWR estimation.

2.3.2 Statistical Analysis

To examine the temporal and spatial variability of groundwater recharge and its controlling factors across the different cases of the study, a series of statistical analyses was performed, including the computation of mean values, standard deviation, inter-model standard deviation, percentage differences, spatial mean maps, and annual time series plots. Each of these metrics is presented and discussed in detail in the following sections to provide a comprehensive assessment of both spatial patterns and temporal trends:

- **Mean**

The global mean was calculated for each variable by averaging values across the entire study area and over the full period from 2006 to 2014 (9 years). This spatio-temporal mean provides an overall benchmark for comparing water balance components and assessing potential changes.

- **Global Standard Deviation**

The global standard deviation for each variable was computed to quantify the degree of spatial variability across the entire study area over the full period from 2006 to 2014. This measure provides insight into the heterogeneity of water balance components within the region and complements the global mean by highlighting the extent of variability across space.

- **Percentage difference**

The percentage difference was calculated for each variable to quantify the extent to which the two projected datasets deviate from the historical baseline. This metric provides a normalized measure of change, allowing differences to be expressed in relative rather than absolute terms, which facilitates comparison across variables with different units and magnitudes. The calculation was performed using the following formula:

$$\Delta\ (\%) = \frac{X\ scenario - X\ historical}{Xhistorical} \times 100 \quad \text{(Equ.2)}$$

With Δ : Percentage difference.

Note: Positive values indicate an increase relative to the historical period, while negative values reflect a decrease

- **Nine-year mean Map**

Single maps were produced for each variable, representing the mean values over the entire 2006–2014 period. These provide a clear overview of the spatial distribution of long-term conditions under the three different cases.

- **Annual Time series plot (2006-2014)**

Time series plots showing the mean annual values of each variable across the study area from 2006 to 2014 were also generated. This visualization highlights interannual variability and potential trends for different cases, essential for comparison.

Partial Conclusion

Chapter 2 provides an overview of the study area, describes the methodology, and reviews the materials and tools used in the analysis. It also presents the statistical approaches applied to compare groundwater recharge across different datasets and to identify the key factors driving differences between projected and historical recharge. In doing so, it establishes the necessary conditions and framework for conducting this study.

CHAPTER 3: RESULTS AND DISCUSSION

CHAPTER 3: RESULTS AND DISCUSSIONS

Introduction

In this chapter, we present and discuss the results obtained from our study. We begin with a comparison of groundwater recharge estimated using reanalysis as forcing and projected atmospheric forcing under the optimistic scenario (RCP2.6) and the pessimistic scenario (RCP8.5), over the same period range (2006-2014), to highlight the relevance of our comparative approach. Next, we examine the water balance components for each of the three cases to assess their influence on groundwater recharge. We then investigate the characteristics of the weather input data used in the CLM5 model, particularly their resolution and nature. Furthermore, a detailed analysis of the datasets affecting these water balance components is conducted to identify the fundamental reasons behind differences in recharge estimates across Africa, as well as on the regional scale. Finally, a comparison with a reference dataset (ERA-5) is performed, followed by recommendations and implications related to renewable energy development, particularly green hydrogen.

3.1 Groundwater Recharge Comparison.

Figure *5* and Figure *6* present, respectively, the spatial and temporal distribution of GWR across Africa during the overlapping period from 2006 to 2014. The average annual mean GWR derived from the reanalysis dataset is 63.25 mm/yr, whereas the values using the past projected dataset under RCP2.6 and RCP8.5 are 125.96 mm/yr and 125.89 mm/yr, respectively. These represent an approximate 99% increase compared to the reanalysis estimate. Such a large discrepancy between the datasets raises important questions and highlights the need for further investigation into the possible causes. Understanding these differences is crucial for water resource planning and the implementation of projects that rely on groundwater use, particularly the development of green hydrogen, which is increasingly seen as a strategic opportunity for Africa given its vast natural resource potential. In addition, Figure 5 reveals significant regional variability, as indicated by the large spatial standard deviations, highlighting the importance of regional-scale studies in capturing local realities more accurately. In addition, Figure 6 illustrates the annual mean evolution of groundwater recharge over the study period. It shows a relatively similar trend from 2006 to 2014, but with a high magnitude difference. This difference in GWR using the reanalysis dataset and the projected dataset formed the motivation of this research. Therefore, our next step is to investigate the water balance components used in the calculation of the GWR for different cases and explain the difference.

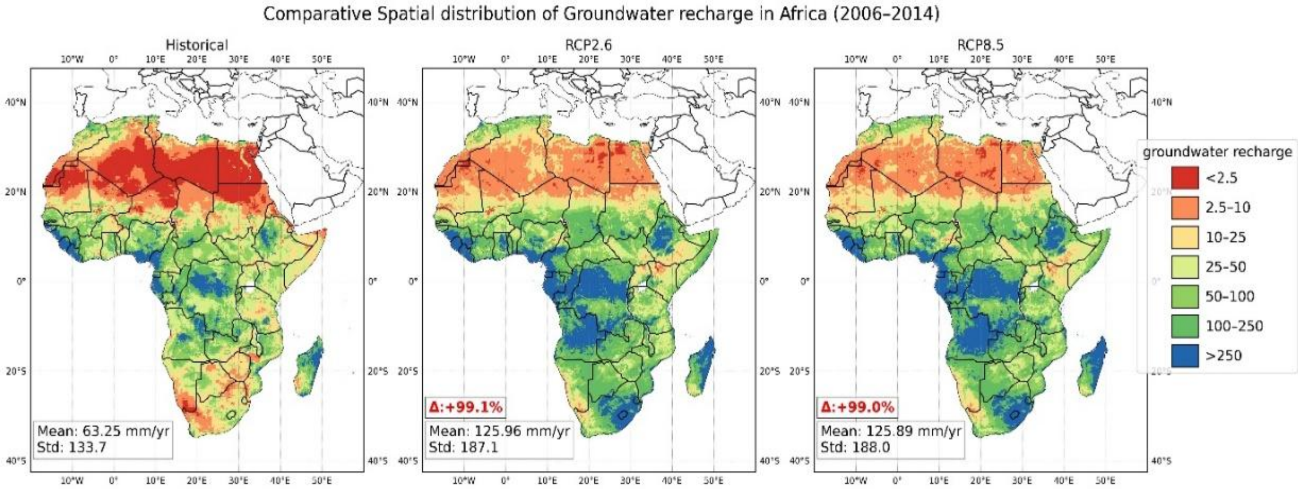

Figure 5: Comparative spatial distribution of GWR using reanalysis and projected dataset over Africa (2006-2014).

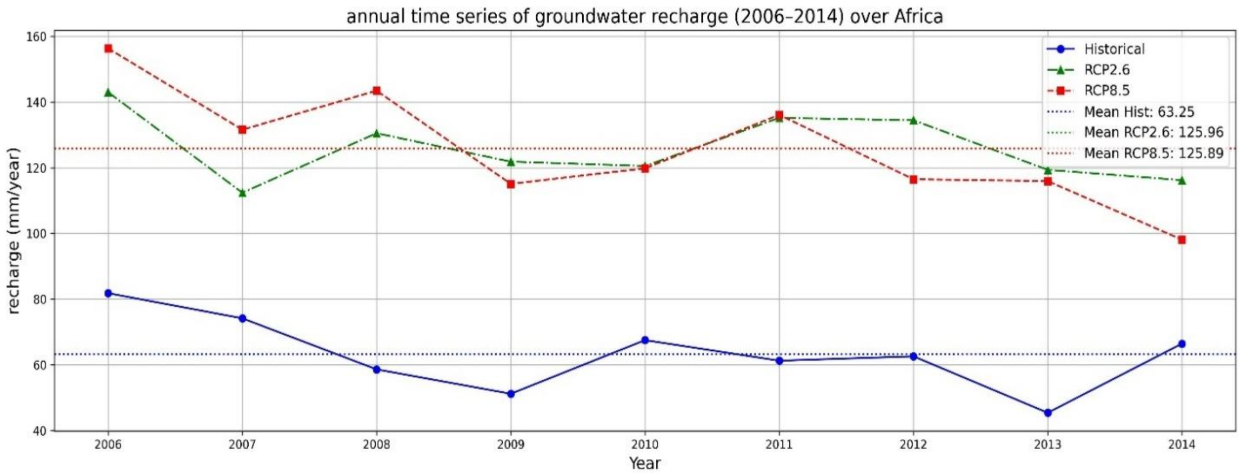

Figure 6: Annual mean comparison of groundwater recharge using the reanalysis dataset and projected data over Africa. (2006-2014)

3.2 Water Balance Components examination.

In order to identify the possible reasons for these differences, a comparative analysis of the water balance components used in the calculation of GWR was conducted. this approach allows us to determine which variables show the largest discrepancies and how they directly influence the estimation of GWR. Accordingly, Figure 7 presents an overview of the water balance components for the three cases, as well as the variation of the projected values compared to the reanalysis dataset.

As demonstrated in Figure 7, it is evident that past projected precipitation values are 696.7 mm/yr (RCP2.6) and 688.9 mm/yr (RCP8.5), which are marginally higher than the reanalysis mean of 658.1 mm/yr, representing approximately 40 mm/year differences. This difference arises from the inherent characteristics of the data, since precipitation is not derived from CLM5 simulations nor subjected to any pre-processing within the model; it is taken directly from the raw input datasets. This is corroborated by Wiebe et al. (2025), which highlights that a large portion of the uncertainty in groundwater recharge estimates arises from variability in rainfall.

For evapotranspiration and surface runoff, which are computed within CLM5, different trends are observed. Past projected ET values are 449.2 mm/yr (RCP2.6) and 444.2 mm/yr (RCP8.5), both lower than the reanalysis value of 487.4 mm/yr, representing approximately 40 mm/year differences; this in addition to the precipitation difference of 40 mm/years, lead then to 80 mm/year more available GWR in projections, compared to the reanalysis. However, projected runoff values are larger compared to the reanalysis estimate: 144.1 mm/yr (RCP2.6) and 141.8 mm/yr (RCP8.5), against 125.3 mm/yr in the reanalysis data. this corresponds to approximately 20 mm/yr differences, which is going to reduce the 80 mm/yr more available groundwater recharge of 20 mm/year making an estimation of around 60 mm/yr in terms of groundwater recharge differences. Exactly what is observed in the GWR map differences.

According to (Equ 1) for the calculation of GWR via the water balance approach, an increase in precipitation leads to a higher water input into the system, thereby increasing recharge. Similarly, a reduction in ET decreases water loss to the atmosphere, which also enhances recharge. Conversely, an increase in runoff leads to greater water loss through surface flow, thereby reducing recharge. These results from Figure *7* indicate that precipitation is the most influential water balance component in determining GWR, followed by evapotranspiration, which also plays a significant role. Runoff, while less influential under moderate variations, cannot be entirely neglected, particularly in cases of very large increases, for instance, greater than 50%.

These points align closely with a wide range of research in hydrology, including studies such as MacDonald et *al*(2021) and Liu et *al*(2022), which consistently show that precipitation is the main factor driving groundwater recharge. By considering both the positive contribution of rainfall and the limiting effect of evapotranspiration, these studies help paint a clearer picture of the complex processes that control groundwater recharge, highlighting how climate and environmental conditions together shape the availability of this vital resource.

We can therefore understand that the difference in GWR is mainly because the projections simulate higher precipitation values compared to the reanalysis data, while at the same time simulating lower ET values compared to the historical case. Since both precipitation and ET are the most influential variables in the water balance, each contributes, at its level, to the increase in recharge. By contrast, the effect of runoff does not significantly influence recharge, but has an effect to reduce the recharge.

To further investigate the causes of these differences, a detailed examination of precipitation and ET is recommended. The possible reasons behind the changes in precipitation have already been discussed earlier. The next step, therefore, is to conduct an in-depth analysis of the factors influencing ET, namely the input variables used in CLM5: shortwave radiation (SWR), longwave radiation (LWR), temperature, wind speed, pressure, and specific humidity.

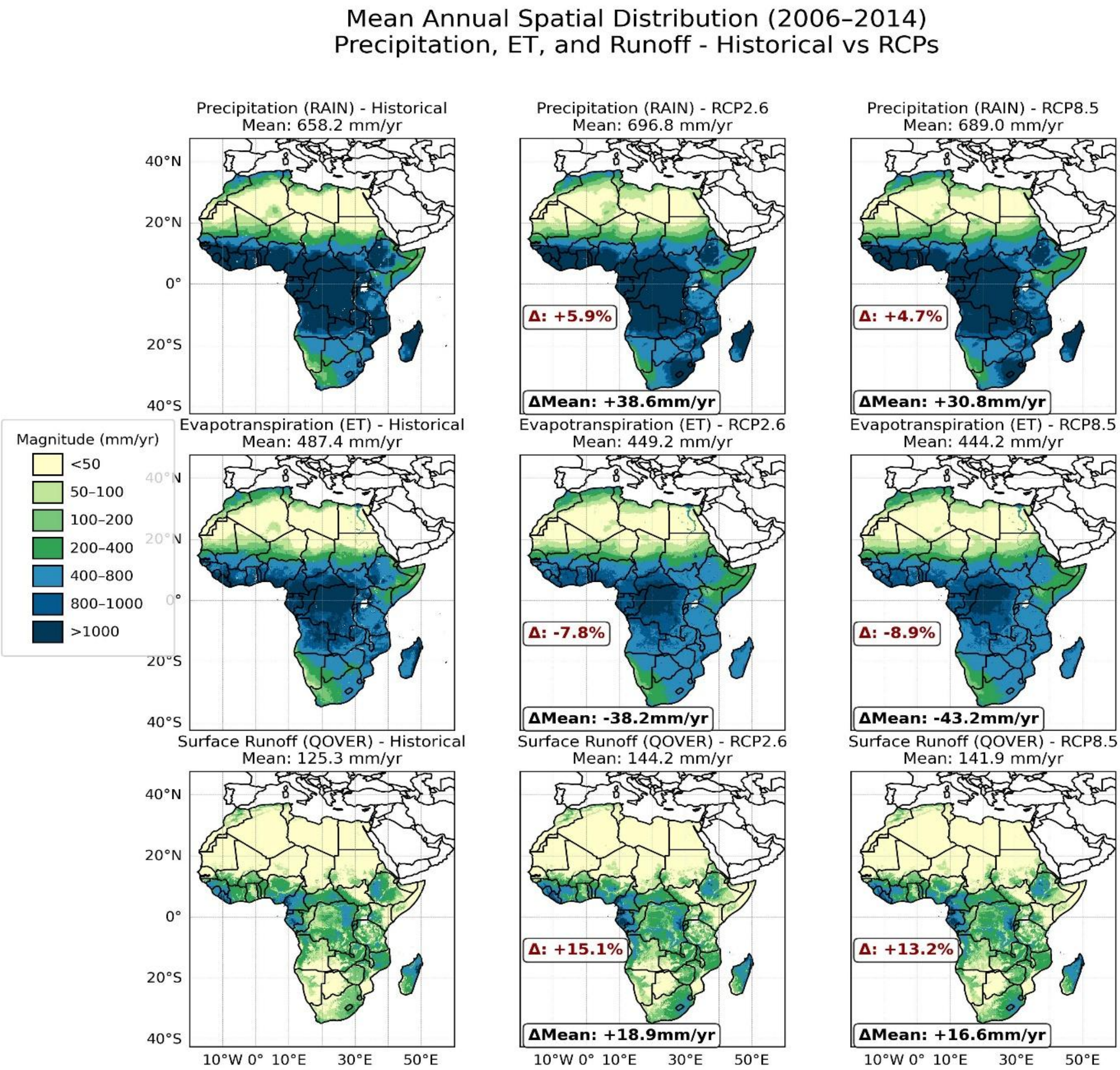

Figure 7: Comparative mean map of the water balance components using reanalysis and projected data for precipitation, evapotranspiration, and runoff over Africa(2006-2014).

3.3 Comparison of the weather input characteristics dataset.

This part of the study aims to gather some useful information related to the two types of datasets we are using, specifically their spatial and temporal resolution, the sources of the datasets, as well as the CLM5 settings. The reanalysis simulations are based on the Global Soil Wetness Project version 3 (GSWP3), which is 3-hourly data at 0.5° spatial resolution and comes from the 20th Century reanalysis project (20CR), with 25°, and the projected simulations originate from the CORDEX. More explanation has been given in the chapter under the Material section. A summary of key information is collected and presented.

Dynamical downscaling involves using RCM to simulate regional climate processes while being driven at the boundaries by GCM outputs, ensuring consistency with large-scale climate features. It should be noted that these data, with the same spatial and temporal resolutions, were used as inputs for the CLM5 model, which subsequently enabled the calculation of GWR. A summary of this information is presented in Table *1*; the observed differences may be partly attributed to the inherent characteristics of the data generation process. However, this alone does not fully account for the magnitude of the discrepancy. The CLM5 model configuration, particularly the differences in spatial and temporal resolution between historical and projected datasets, may also contribute to the variations in GWR derived from the model outputs. Therefore, a thorough investigation of the CLM5 setup is recommended for more detailed future studies.

Table 1: Table of the weather input characteristics of the different datasets used in this study.

	Reanalysis Dataset	**Projected Dataset**	
Temporal Resolution	3-hourly	Daily	Daily
Spatial Resolution	0.5°	0.22°	0.22°
Sources and Methods	GSWP3, reanalysis Data, downscaled by GSM, Bias corrected	CORDEX, Dynamical Downscaling Method using GCMs as forcing	CORDEX, Dynamical Downscaling Method using GCMs as forcing

3.5 Weather input dataset comparison.

In this section, we analyse the different variables by comparing the three scenarios for each input parameter influencing ET in the CLM5 model. Figure 8 presents the annual variations of each scenario for the respective variables. The results show that for temperature, longwave radiation, wind speed, pressure, and specific humidity, the projected values are lower than those of the historical dataset, which is consistent with the trend observed for ET. In contrast, shortwave radiation exhibits the opposite behaviour, with projected values being higher than the reanalysis ones. However, a deep analysis reveals some large differences between the different variables. In fact, the annual differences in temperature observed are between 1K (in 2014) and 1.75K (in 2006), which is too large and unrealistic, for the period 2006-2014, knowing that RCPs represent around 1,5° differences in the projections to 2100 if nothing is done to tackle climate change. In addition, there is an average difference of 43% in specific humidity, and 72 hPa differences in pressure, which are also large for the short-period study. There seem to be altitude standardization issues due to the values observed. These result reveals, therefore, some high uncertainties in the reanalysis dataset used, reflecting a need to double-check and validate the data used.

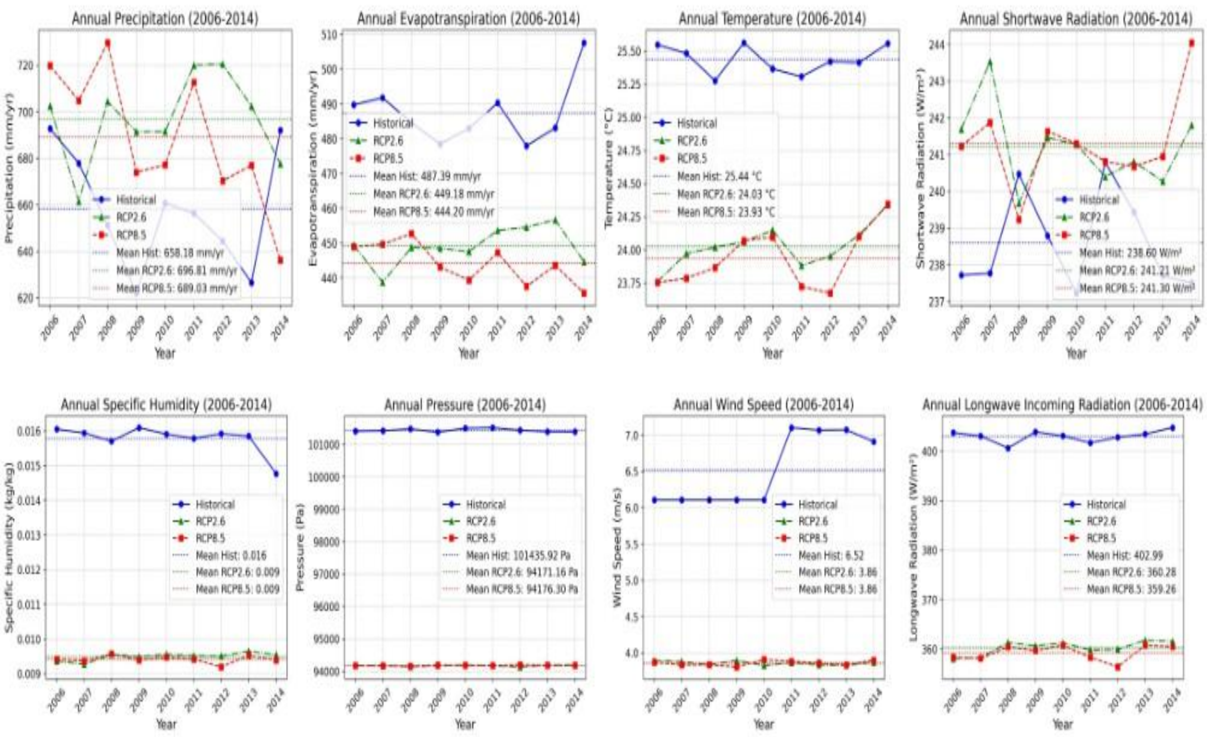

Figure 8: Annual comparison of meteorological parameters used as input for CLM5 and influencing evapotranspiration over Africa from 2006 to 2014.

3.6 Regional Case Study:

After comparing the different input datasets used in the CLM5 across Africa, we now turn to a regional comparison of the eight subregions. This approach will help identify the key factors driving regional differences and provide an understanding of the variations in groundwater recharge between reanalysis and projection datasets.

3.6.1 NORTH EAST AFRICA (NEAF)

As observed over Africa as a whole, GWR in Northeast Africa is higher using the projected dataset compared to the historical or reanalysis dataset (see Figure 9). However, the percentage variations are considerably larger in this region. Under RCP2.6, GWR reaches 109.0 mm/yr (102.04% increase), while under RCP8.5 it goes to 119.38 mm/yr (121.10% increase). These differences are substantial, with increases exceeding 100%. Figure 10 shows the annual trends over the overlapping period; different trends are observed with a large difference.

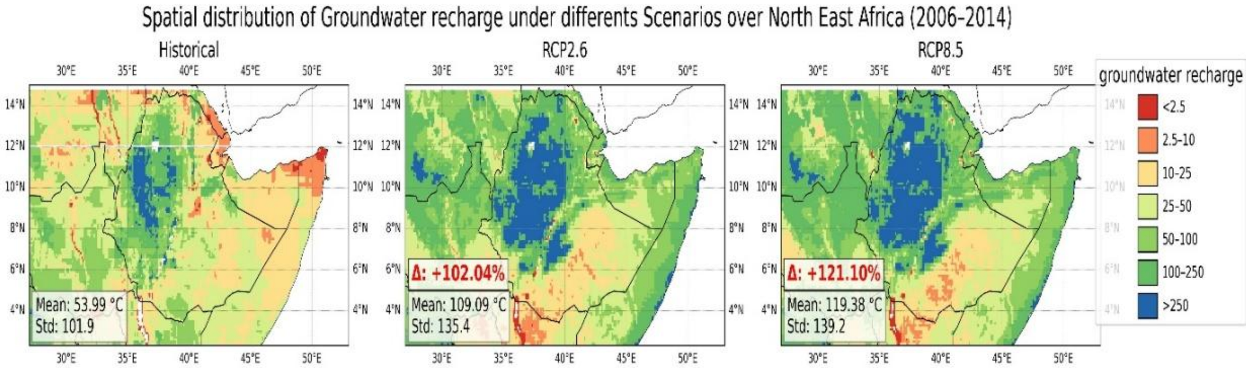

Figure 9: Comparative spatial distribution of groundwater recharge over NEAF using historical and projected data (2006-2014)

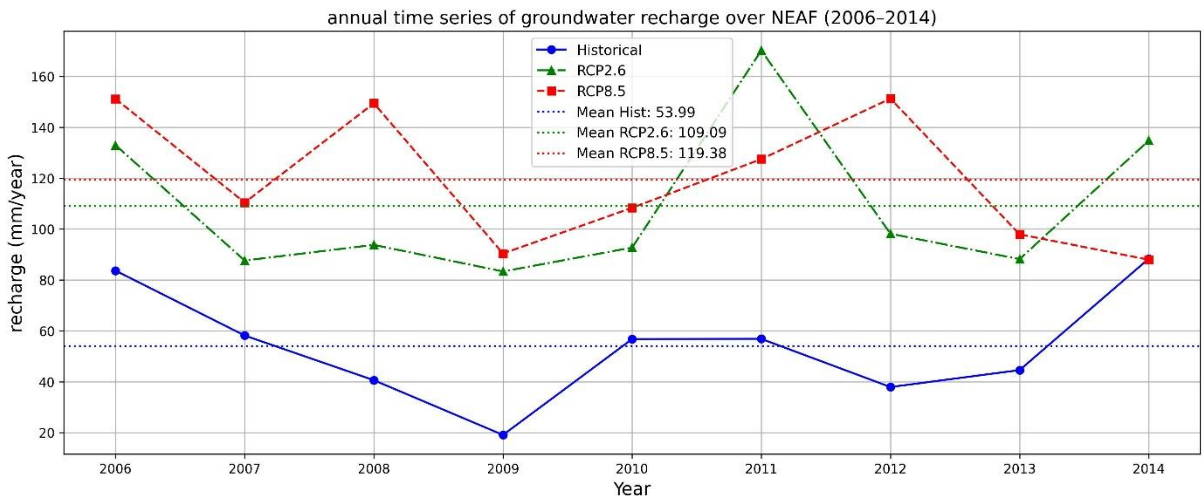

Figure 10:Annual mean comparison of groundwater recharge over NEAF using historical and projected data. (2006-2014)

We now examine the water balance components associated with recharge. Figure *11* presents the mean map of precipitation, ET, and runoff. For all three variables, the projected datasets reveal lower values compared to the reanalysis dataset. In fact, precipitation exhibits about 73 mm/year differences under RCP2.6 and about 56 mm/year differences under RCP8.5. ET shows a much stronger difference, with 106 mm/year (RCP2.6) and 102 mm/year (RCP8.5). Runoff differences are comparatively smaller, with about 10 mm/year (RCP2.6) and 5 mm/year (RCP8.5). In terms of directions, the values of the projected are all lower than the reanalysis. In fact, the ET difference of 106 mm/year and the runoff difference of 10 mm/year leads to a high recharge difference of 116 mm/year, while the precipitation difference of around 70 mm/year leads to a reduction in the recharge. This is the result of what is seen in the GWR differences.

According to the GWR equation, or water balance (Eq. 1), the increase in recharge over Northeast Africa is mainly driven by the reduced ET values in the projections compared with the reanalysis dataset. Both precipitation and ET are the most influential variables, but the difference in ET is substantially larger than that of precipitation. Runoff, on the other hand, plays a minor role, with a relatively small influence and difference across scenarios.

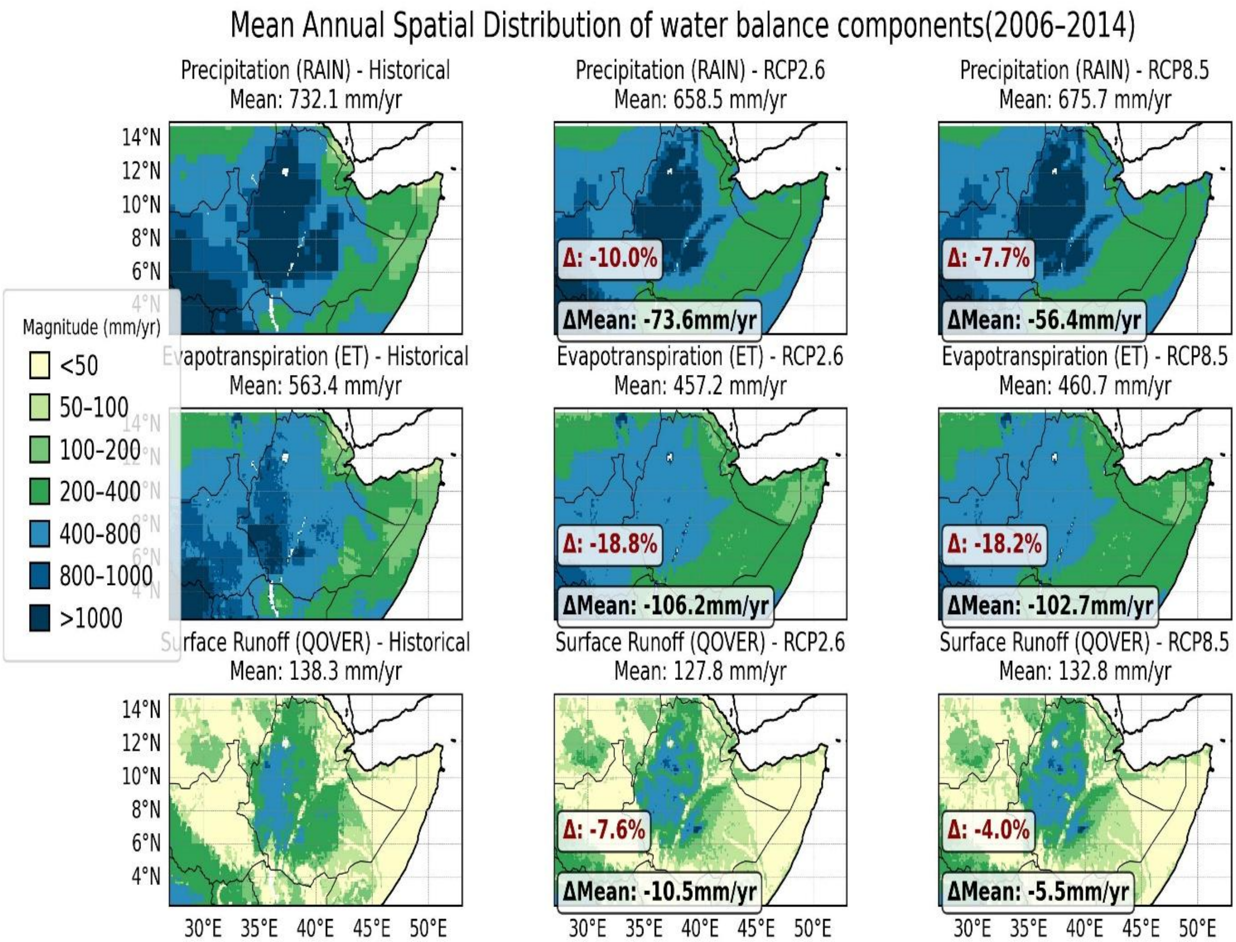

Figure 11: Comparative mean map of the water balance components using reanalysis and projected data for precipitation, evapotranspiration, and runoff over NEAF(2006-2014)

To investigate the reasons behind the decrease in ET, we apply the same approach used for Africa as a whole by comparing the other input variables of CLM5 over Northeast Africa. Figure 12 shows trends consistent with those observed at the continental scale. The results indicate that projected values for temperature, longwave radiation, wind speed, pressure, and specific humidity are all lower than those using the historical or reanalysis dataset, which aligns with the decline in ET. In contrast, shortwave radiation shows the opposite pattern, with projected values exceeding those of the reanalysis case. However, a deep analysis reveals some large differences between the different variables. In fact, the maximum annual differences in temperature observed are around 1K (in 2006), which is slightly better than the one observed over Africa. In addition, there is an average difference of 35% in specific humidity and 91 hPa differences in pressure, which are also large for the short-period study. There seem to be altitude standardization issues due to the values observed. These result reveals, therefore, some high uncertainties in the reanalysis dataset used, reflecting a need to double-check and validate the data used.

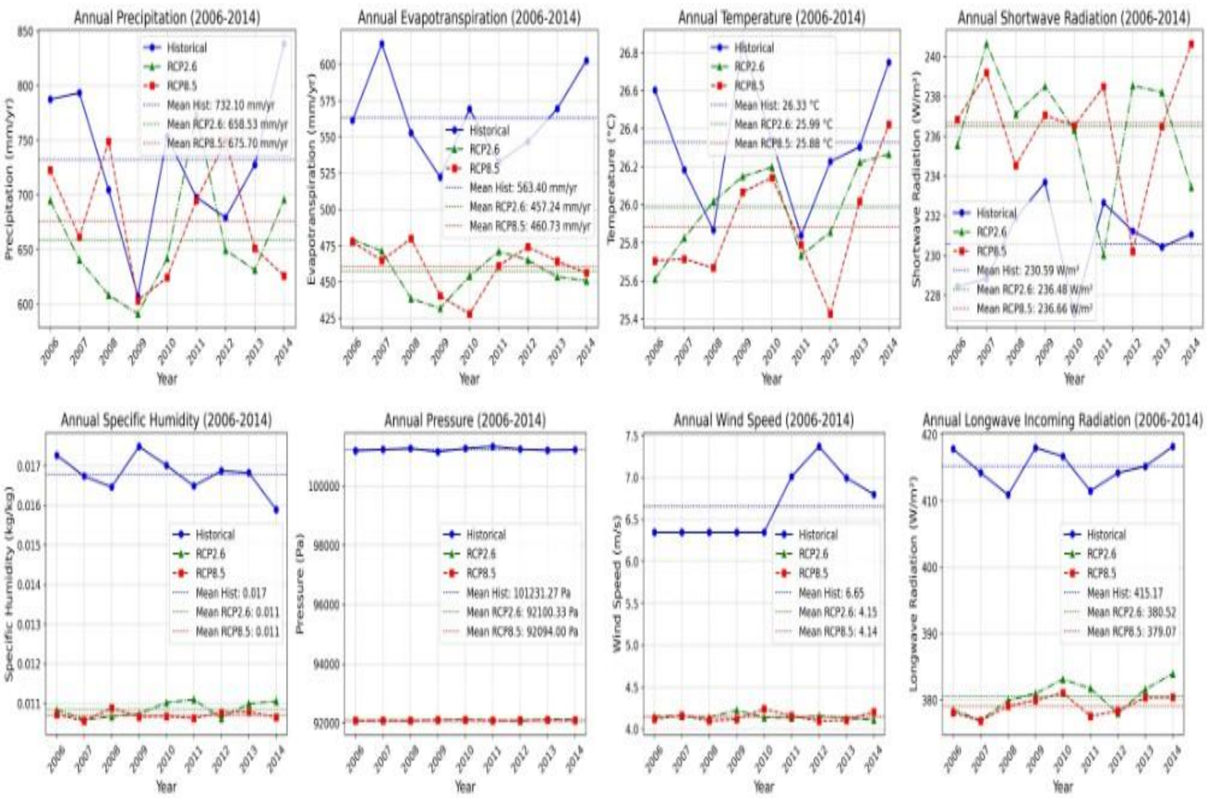

Figure 12: Annual comparison of meteorological parameters used as input for CLM5 and influencing evapotranspiration over NEAF from 2006 to 2014.

3.6.2 WEST AFRICAN (WAF)

Over West Africa, GWR under the projection scenarios is higher than under the reanalysis dataset. Similar to the continental-scale results, reanalysis GWR is 147.17 mm/year, while projected GWR is 204.63 mm/year (39.04% higher) under RCP2.6 and 190.35 mm/year (29.34% higher) under RCP8.5 (Figure 13)

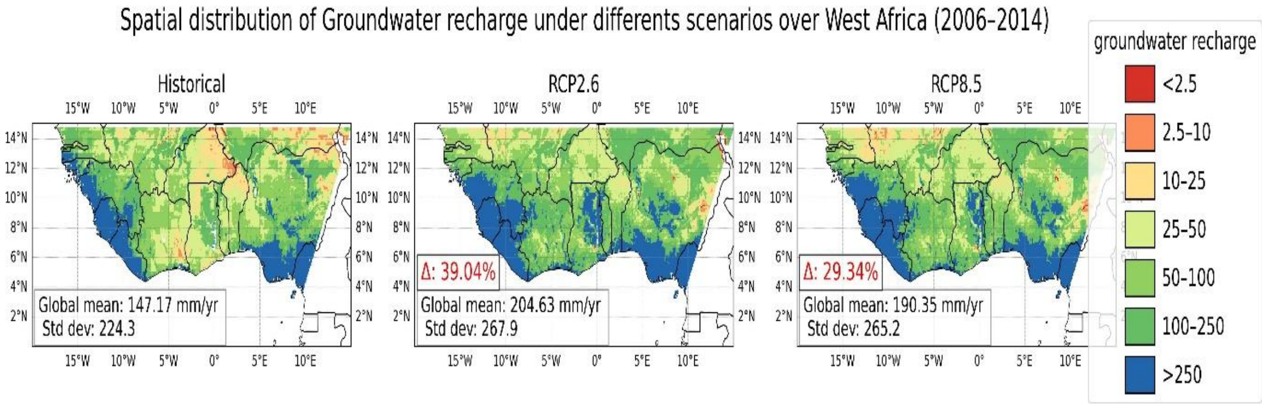

Figure 13: Comparative spatial distribution of groundwater recharge over WAF using historical and projected data (2006-2014)

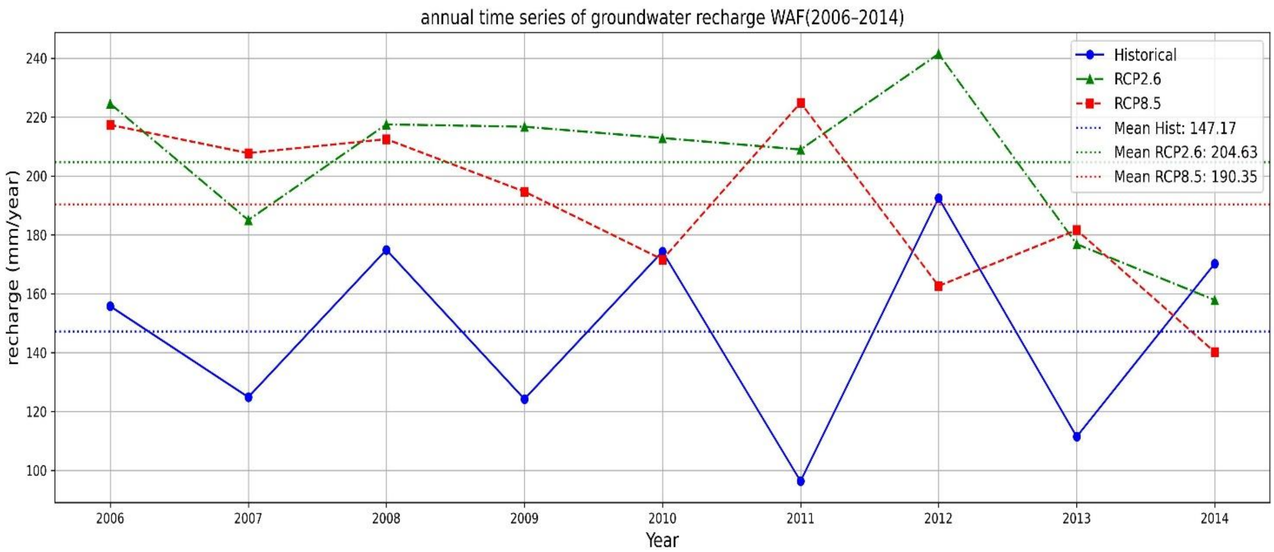

Figure 14:annual mean comparison of groundwater recharge over WAF using historical and projected data (2006-2014).

The next step is to compare the water balance components. Figure 15 presents the spatial mean of precipitation, evapotranspiration (ET), and runoff for the three cases. The results show that, relative to the historical dataset, precipitation and runoff are higher in the projections, whereas ET is lower. Specifically, under RCP2.6, precipitation differences of about 10 mm/year, ET differences of 70 mm/year, and runoff differences of about 30 mm/year. Under RCP8.5, precipitation difference of 30 mm/year, ET difference of 85 mm/year, and runoff increases by 12 mm/year. Since precipitation and ET are the most influential components in the water balance approach, the higher GWR values in the projections can be explained by the combined effect of high projected precipitation and low projected ET compared to the historical case. Runoff, on the other hand, has only a minor contribution to recharge differences. In terms of mm/year, there is a 9.7mm/yr addition in RCP2.6 precipitation, while a 34.3 mm/yr reduction in precipitation under RCP8.5 compared to the reanalysis. Also 72.3 mm/yr reduction in RCP2.6 and an 85.2mm/yr reduction in RCP8.5 for ET, finally, an addition of 28.3 mm/yr under RCP2.6, and 12.7mm/yr under RCP8.5 for surface runoff.

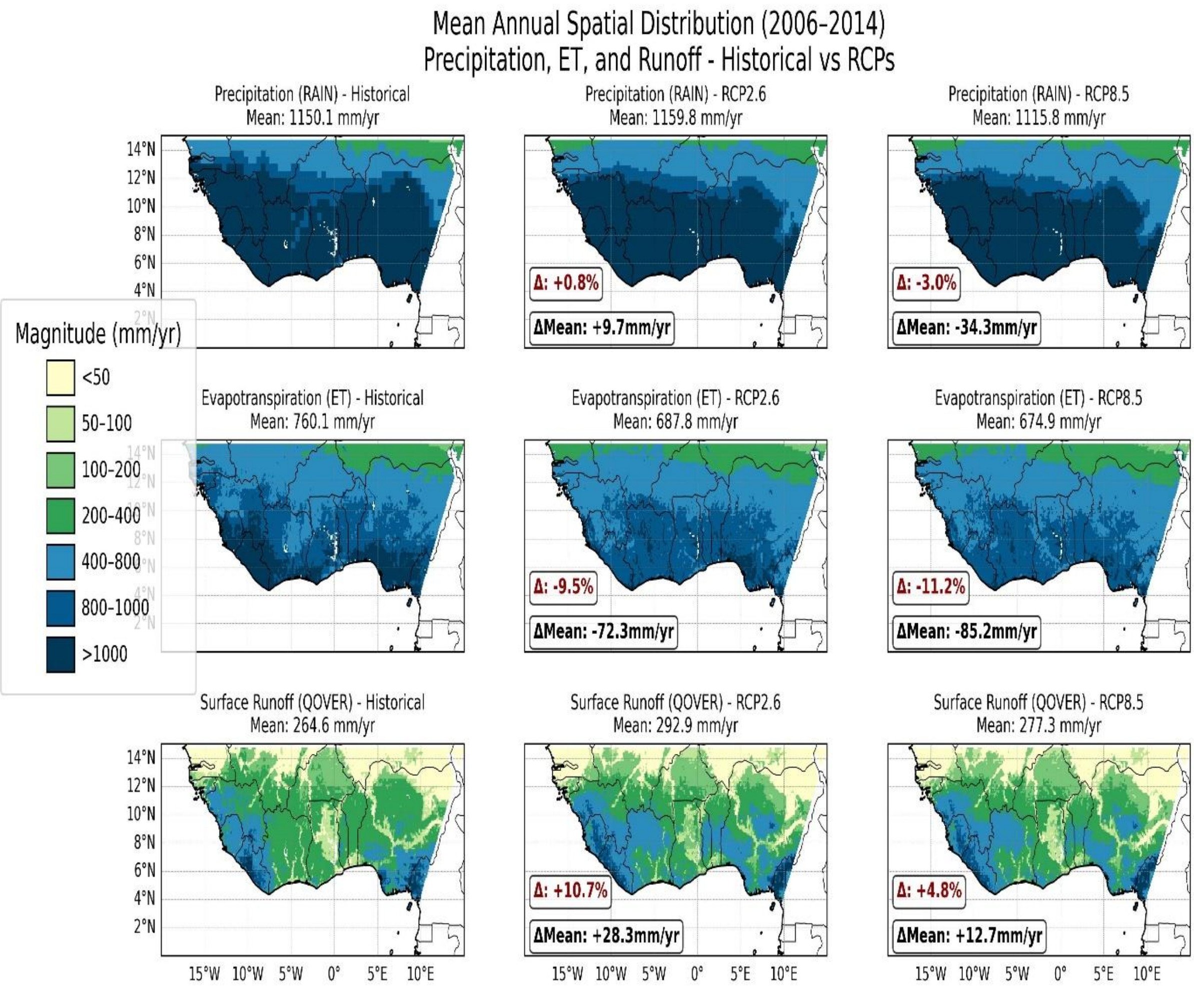

Figure 15: Comparative mean map of the water balance components using reanalysis and projected data for precipitation, evapotranspiration, and runoff over WAF(2006-2014)

Considering now the variables of the atmospheric dataset used as input to the CLM5, over the West African regions, the result (Figure *16*) shows that temperature, shortwave radiation (SWR), longwave radiation (LWR), wind speed, pressure, humidity, and ET have higher values in the historical dataset compared to the projections. However, a deep analysis reveals some large differences between the different variables. In fact, the maximum annual differences in temperature observed are around 1K (in 2006), which is slightly better than the one observed over Africa. In addition, there is an average difference of 35% in specific humidity and 36 hPa differences in pressure, which are also large for the short-period study. There seem to be altitude standardization issues due to the values observed. These result reveals, therefore, some high uncertainties in the reanalysis dataset used, reflecting a need to double-check and validate the data used.

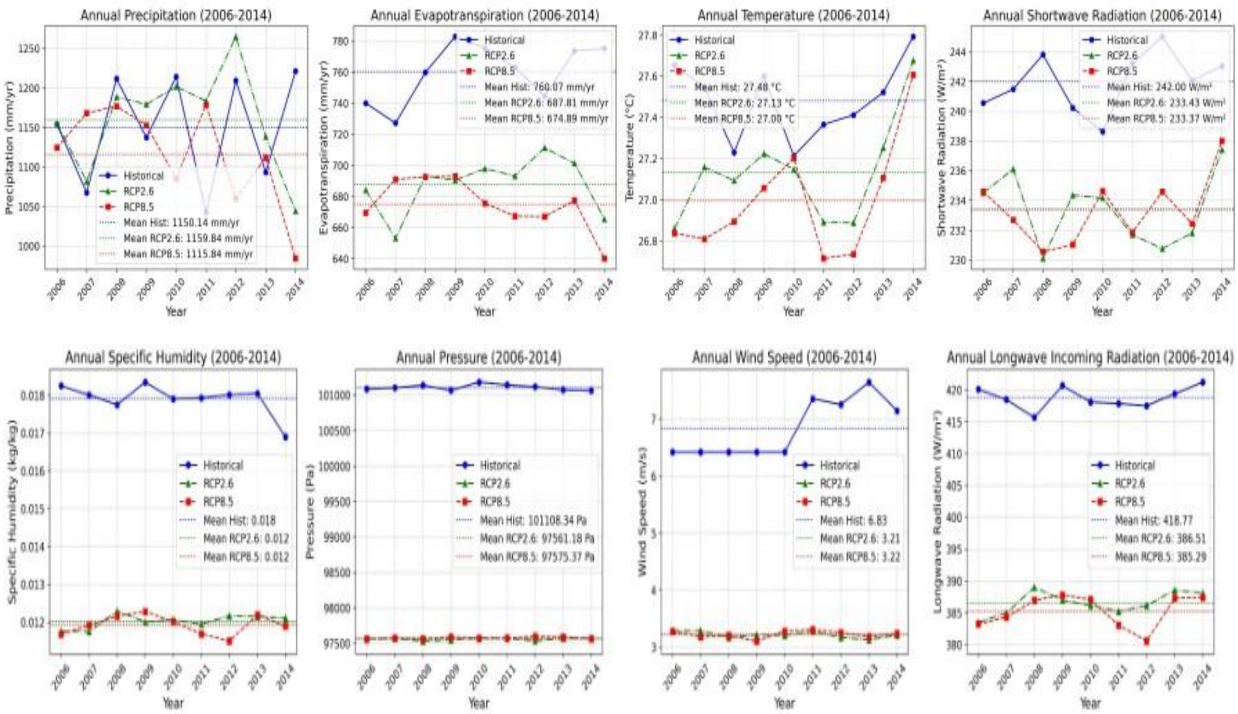

Figure 16:Annual comparison of meteorological parameters used as input for CLM5 and influencing evapotranspiration over WAF from 2006 to 2014.

3.6.3 SAHARA(SAH)

In the Sahara region, GWR under the projection scenarios follows the same trend observed for Africa as a whole, with values higher than in the historical dataset (Figure 17 and Figure 18). However, the variations relative to the historical case are even greater, because the overall magnitudes of GWR being very small. As shown in Figure *17*, historical GWR is 8.17 mm/yr, while it rises to 17.2 mm/yr under RCP2.6 (110% increase) and 19.0 mm/yr under RCP8.5 (132.51% increase). Both projection scenarios show a decreasing trend in the later years of the overlapping period, although RCP2.6 remains higher than RCP8.5

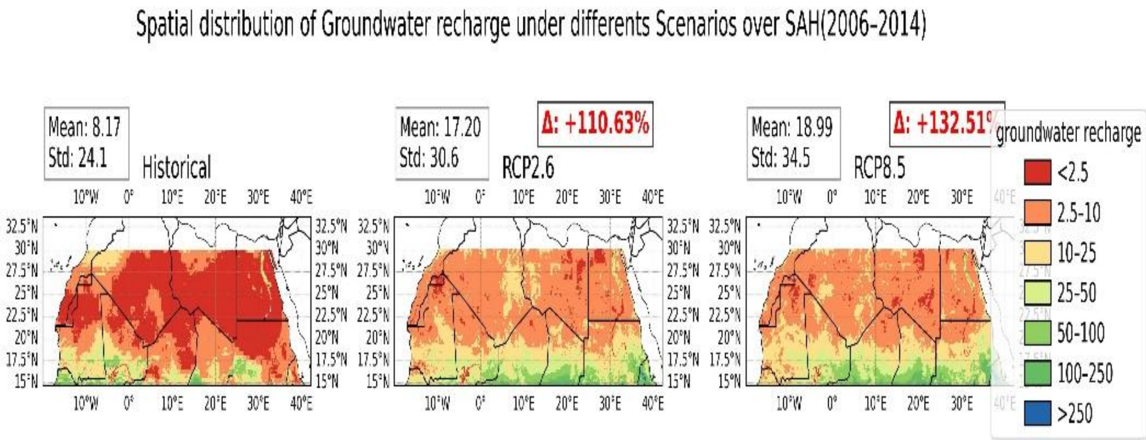

Figure 17: Comparative spatial distribution of groundwater recharge over SAH using historical and projected data (2006-2014)

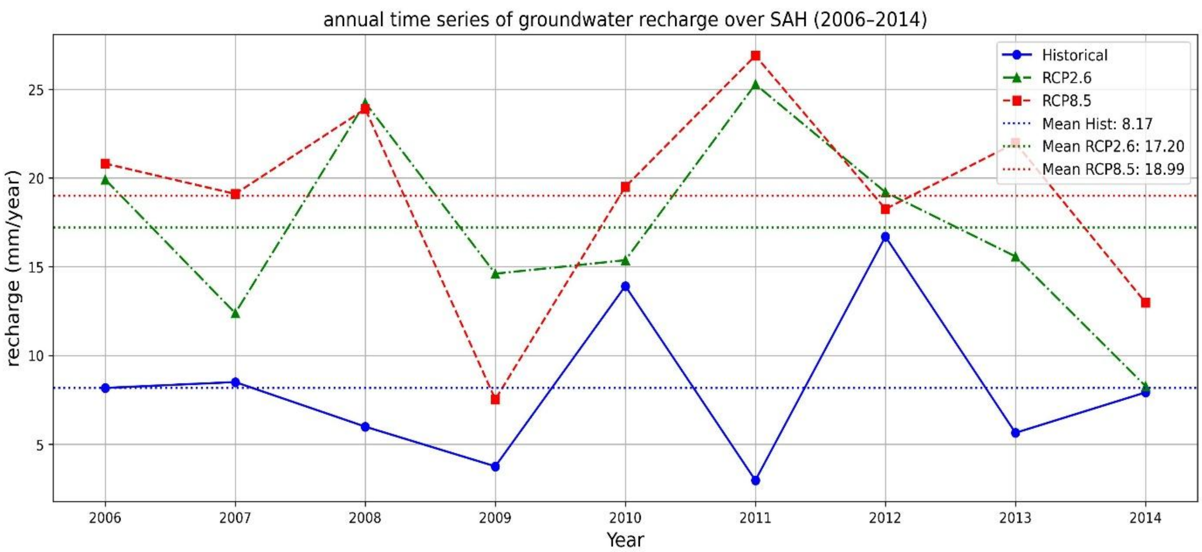

Figure 18:Annual comparison of meteorological parameters used as input for CLM5 and influencing evapotranspiration over SAH from 2006 to 2014.

Next, we examine the water balance components associated with groundwater recharge. Figure 19 presents the mean map of precipitation, ET, and runoff. For all three variables, the projection datasets' values are higher compared to the reanalysis dataset. Specifically, precipitation difference of about 9 mm/year under RCP2.6 and 12 mm/year under RCP8.5. ET also exhibits slight differences, about 2 mm/year under RCP2.6 and RCP8.5. Runoff shows a comparatively larger difference of 28.5% under RCP2.6 and 35.7% under RCP8.5. In terms of differences in mm/year, there is a 9.0mm/year addition under RCP2.6, 12.4 mm/yr under RCP8.5 for projected precipitation compared to the reanalysis. Respectively 2mm/yr and 2.5 mm/yr for RCP2.6 and RCP8.5 for ET, and finally, 2.4mm/year and 3mm/year addition for surface runoff. Referring to the GWR calculation (Equ 1), the increase in recharge over the Sahara is primarily driven by the higher precipitation values in the projections relative to the historical dataset. While both precipitation and ET are key influencing factors, the difference in precipitation is substantially larger than that of ET. Runoff, on the other hand, plays a minor role, with a relatively small influence and differences across scenarios.

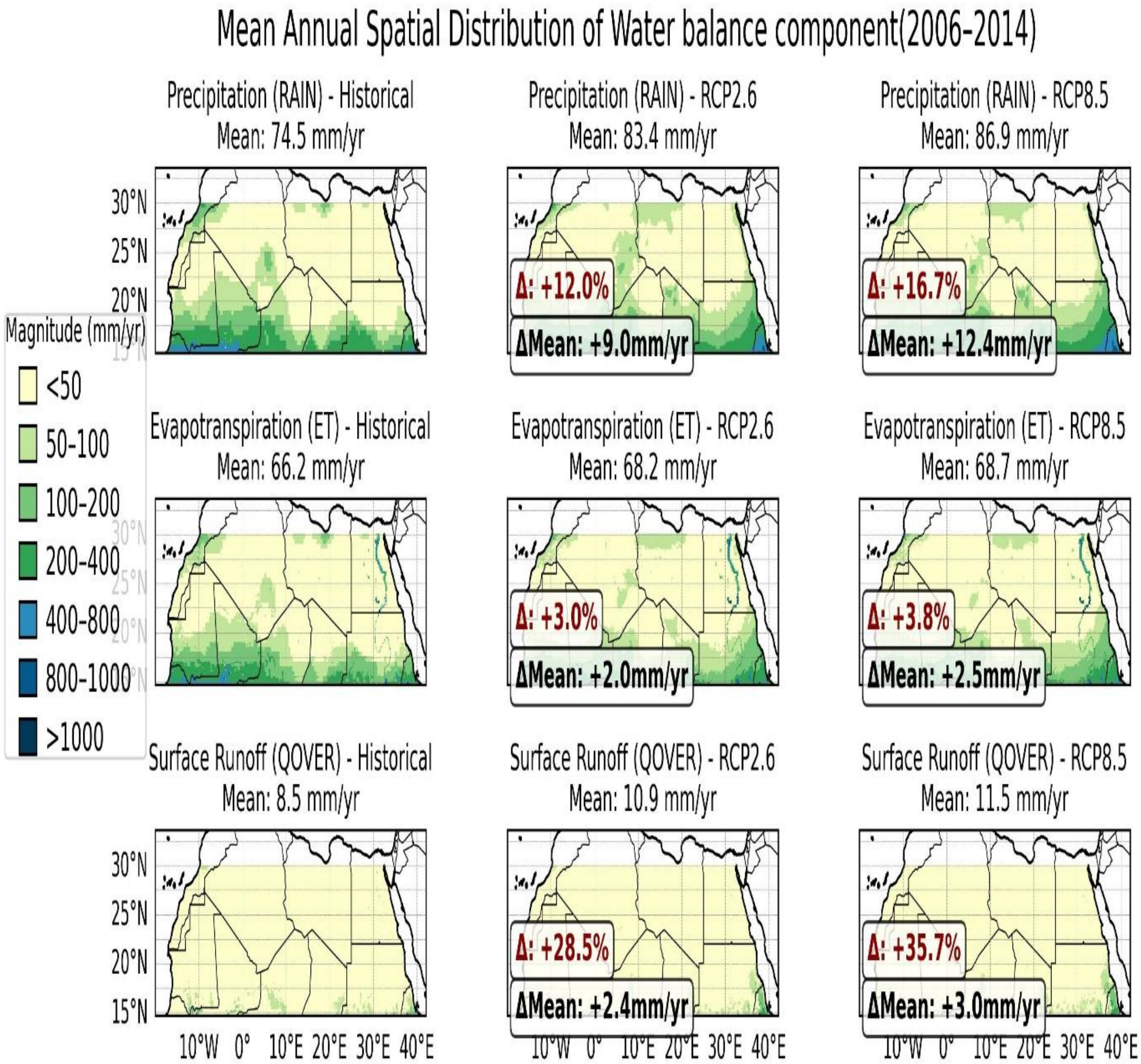

Figure 19:Comparative mean map of the water balance components using reanalysis and projected data for precipitation, evapotranspiration, and runoff over SAH(2006-2014)

In this part, we analyse the variables used as inputs for the CLM5 model over the Sahara zone. We observe that ET in the projection datasets is slightly higher compared to the historical dataset, which differs from the trend seen over Africa as a whole. Furthermore, temperature, wind speed, specific humidity, and pressure in the projections are lower than in the historical dataset, whereas shortwave radiation (SWR) shows the opposite behaviour, with projected values higher than historical ones, similar to ET. However, there is a large difference observed in meteorological variables between the reanalysis and the projections dataset. In fact, around 54 hPa annual differences in Pressure are observed, and around 60% differences in specific humidity are also observed. For temperature, it is more comprehensible with annual differences less than 0.8K. These large differences highlight the uncertainties of the reanalysis dataset used in the study.

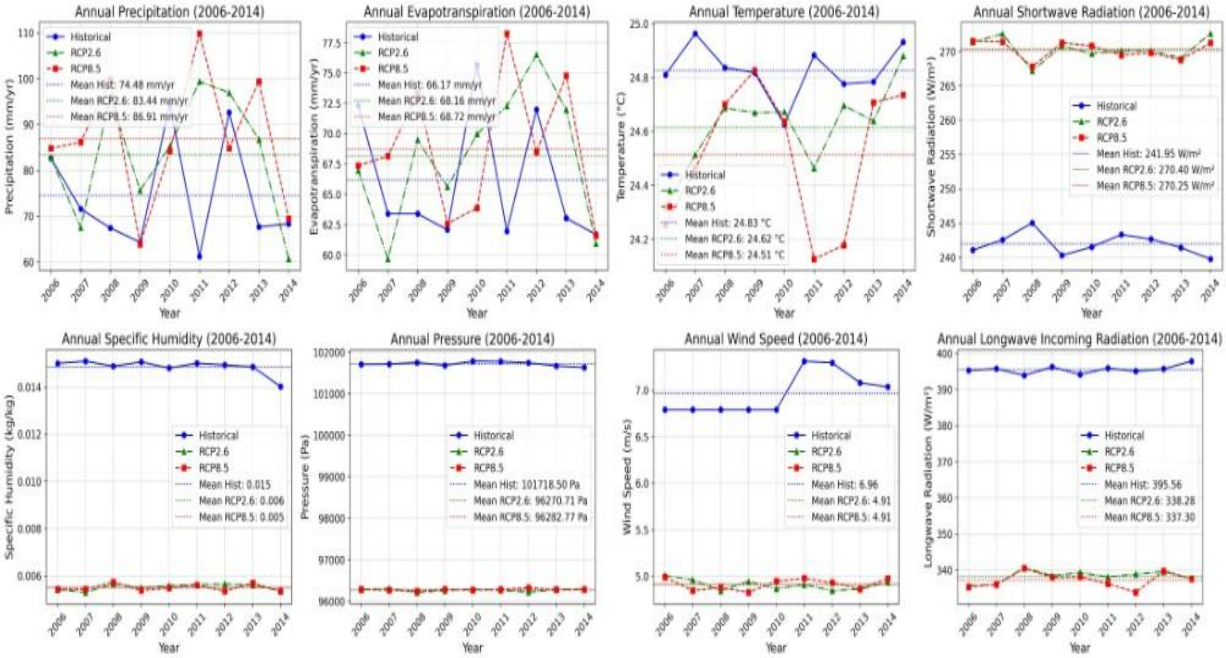

Figure 20: Annual comparison of meteorological parameters used as input for CLM5 and influencing evapotranspiration over SAH from 2006 to 2014.

3.6.4 SUMMARY OVER THE EIGHT REGIONS

Table *2* presents a summary of the behaviour of the different variables considered in this study, both across the eight regions and for Africa as a whole. It includes GWR, its water balance components, and the model input variables for different datasets. The sign '+' indicates that the projected values are higher than those of the historical dataset, while the sign '–' indicates the opposite, i.e., projected values are lower than historical ones.

From this synthesis, it is evident that GWR for the projected dataset is consistently higher than under historical conditions across all regions. For temperature, pressure, humidity, wind speed, and longwave radiation (LWR), projected values are lower compared to the reanalysis data. Precipitation, on the other hand, shows variable behaviour and is not predictable across regions. The large uncertainties observed in the analysis of the weather input dataset draw particular attention to the process by which the dataset is obtained, and therefore, need a validation of the dataset before further studies.

In terms of variation in GWR, the largest relative difference addition is observed over SWAF, with 209.34%, while the difference reduction is found over the MED region, with only 18%. Based on the historical dataset, the highest absolute GWR value is 147.17 mm/yr in WAF, while the lowest is 8.17 mm/yr in SAH.

Table 2: Table of comparison over the 8 regions between the projected data and reanalysis data on the meteorological variables.

	GWR	PT	ET	Q	SWR	LWR	Temp	Wind	Hum	Ps
Africa	+	+	-	+	+	-	-	-	-	-
MED	+	-	-	-	+	-	-	-	-	-
SAH	+	+	+	+	+	-	-	-	-	-
WAF	+	+-	-	+	-	-	-	-	-	-
CAF	+	+	-	+	-	-	-	-	-	-
CEAF	+	-	-	-	-	-	-	-	-	-
SWAF	+	+	+	+	+	-	-	-	-	-
SEAF	+	+	-	+	-	-	-	-	-	-
NEAF	+	-	-	-	+	-	-	-	-	-

3.7 Comparison with ERA5

In order to refine our study, it is necessary to compare our results against a reference dataset that is more closely aligned with reality. For this purpose, we compared our previous results with ERA5. Figure 22 shows the spatial mean of the historical dataset, the projections, and ERA5 over the overlapping period 2006–2014. The results indicate that precipitation and ET from ERA5 are closer to the reanalysis dataset. Specifically, ERA5 precipitation (646.86 mm/yr) is about 1.7% lower than the historical value (658.18 mm/yr), while ERA5 ET (517.84 mm/yr) is about 6.2% higher than the historical estimate (487.39 mm/yr). However, runoff shows a much larger discrepancy: historical runoff (125.28 mm/yr) is more than 50% higher than ERA5 runoff (48.61 mm/yr), representing a difference of 61.2%. This highlights a significant mismatch between the two datasets. Therefore, GWR estimated using ERA5 is 98.09 mm/yr, which is 55.08% higher compared to the historical value of 63.25 mm/yr. Although this discrepancy is substantial, it is still considerably smaller than the nearly 99% difference observed between the historical dataset and the projections. This could be explained by the fact that runoff depends strongly on parameterisations, and ERA5 will not have a particular good representation of runoff.

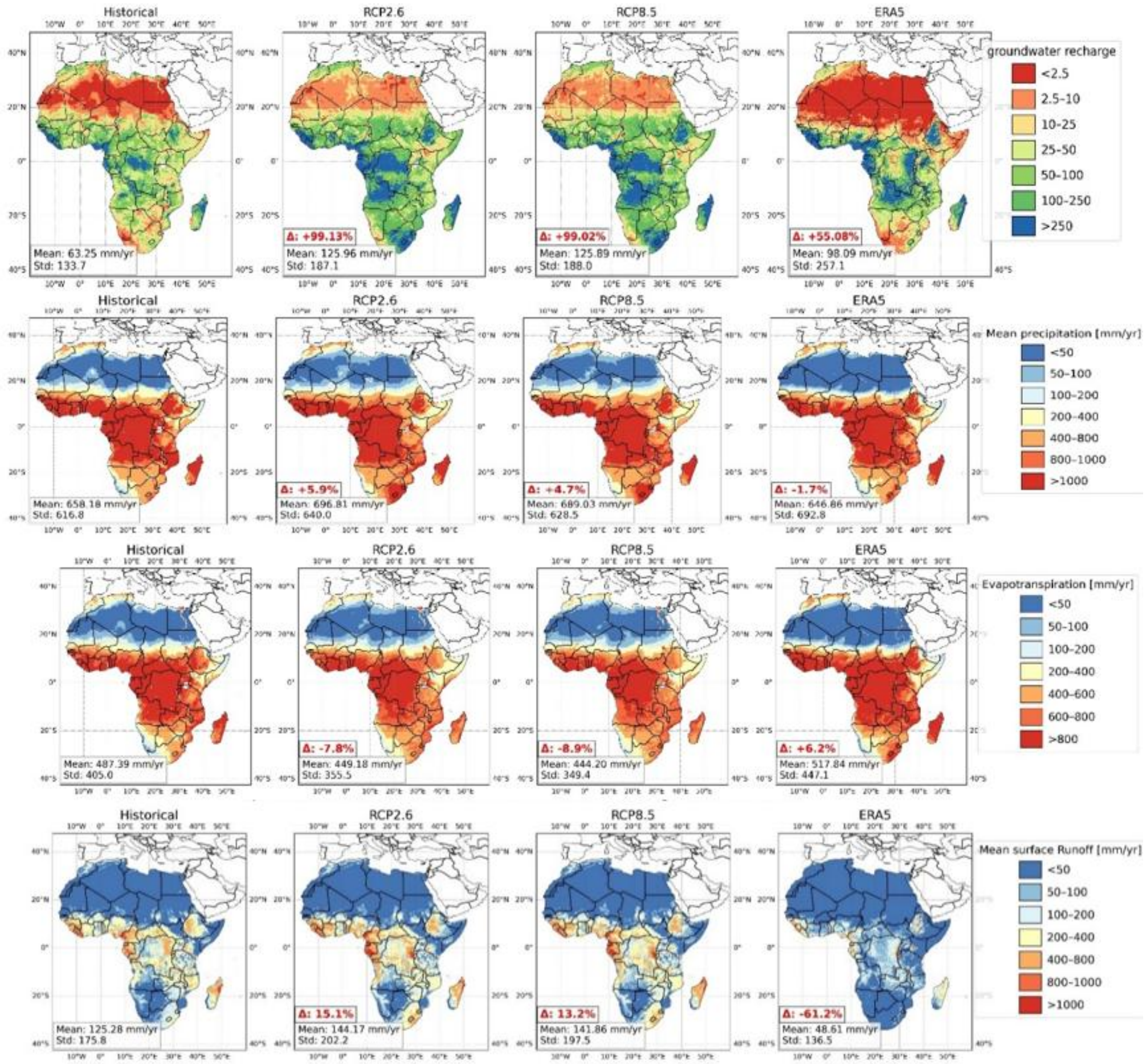

Figure 21:Spatial distribution of mean GWR, PT, ET, and Runoff including ERA-5 over Africa(2006-2014).

Figure *22* presents the annual trends of the projections, the historical dataset, and ERA5. A similar annual trend is observed between the historical dataset and ERA-5 for both GWR and surface runoff, although their magnitudes differ, highlighting uncertainties in the absolute values. For evapotranspiration and precipitation, ERA-5 and the reanalysis dataset show a closer alignment, indicating stronger consistency and robustness in the representation of these variables across datasets. Overall, comparison with ERA5 provides a useful reference to assess the accuracy of the projections, particularly for surface runoff, and highlight the associated uncertainties. The reason why surface Runoff is lower could be that CLM5 assumes 16 plant functional types (PFTs) for Africa. However, this standard setup does not fully capture the diversity of vegetation found across the continent (Oloruntoba et al., 2025).

Moreover, a comparison of these results aligns closely with the study of Mutna (2023); we can observe a high level of consistency across all variables. For precipitation (PT), Antonio reported mean values of 643.06 mm/yr (ERA5) and 653.11 mm/yr (CLM5), whereas our analysis yielded 646.86 mm/yr (ERA5) and 658.18 mm/yr (CLM5 reanalysis). Similarly, for evapotranspiration (ET), Antonio obtained 516.96 mm/yr (ERA5) and 485.84 mm/yr (CLM5), compared with 517.84 mm/yr and 487.39 mm/yr, respectively, in this study. Runoff estimates were also of the same order of magnitude, with Antonio reporting 48.13 mm/yr (ERA5) and 123.98 mm/yr (CLM5), while our results showed 48.61 mm/yr and 125.28 mm/yr, respectively. Finally, groundwater recharge (GWR) was estimated at 96.09 mm/yr (ERA5) and 48.48 mm/yr (CLM5) in Antonio's work, compared with 98.09 mm/yr and 63.25 mm/yr, respectively, in our analysis. Overall, the close agreement between the two sets of results confirms the robustness and reliability of the methodology. At the same time, the minor differences could be due to the difference in averaging periods (2005–2014 vs. 2006–2014) (Mutna, 2023); but also from other factors.

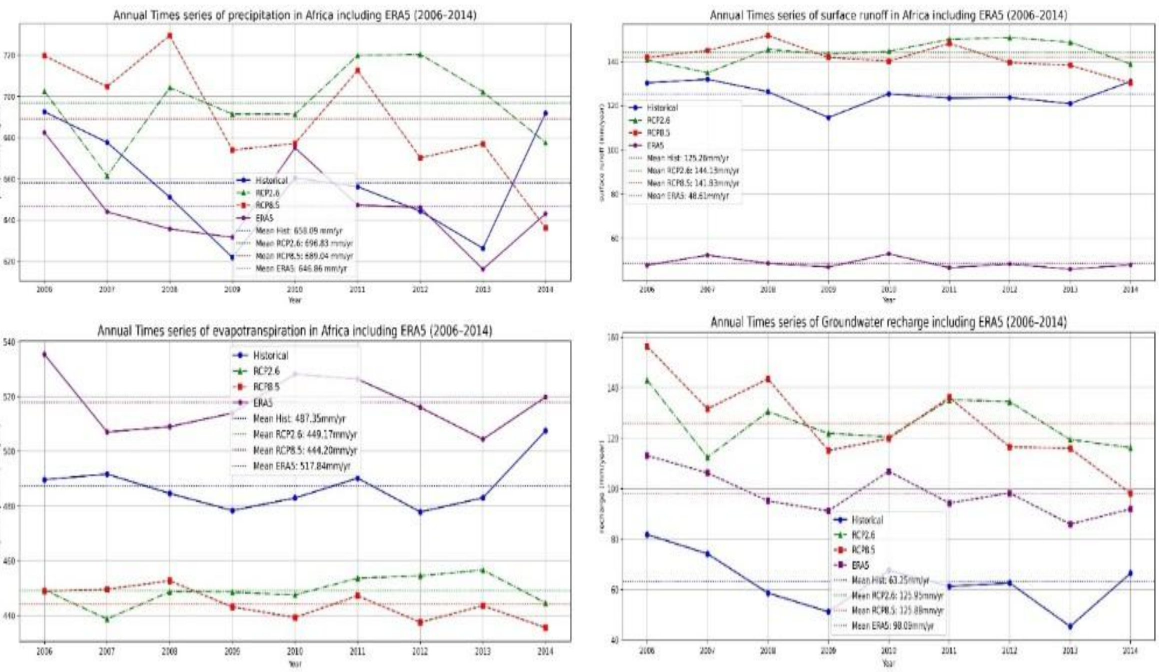

Figure 22:annual trend of GWR, PT, ET, and Runoff including ERA-5 over Africa (2006-2014)

3.8 Limitations of the approach

The estimation of GWR remains a highly challenging and complex task, subject to several uncertainties and methodological constrains. It is important to note that this study relies on model-based datasets, which are inherently dependent on assumptions and parameterizations. Consequently, the results are influenced by the structure, inputs, and limitations of the models themselves. In addition, irrigation, which can influence local water balances, was neglected in this analysis due to its relatively minor impact at the continental scale. However, in localized agricultural regions, its role may be more significant and should not be overlooked in future studies.

Furthermore, time limitations have been a limiting factor in this study; therefore, a double-check of data, a careful process of making the data ready enough, before the atmospheric comparison as well a code simulations, is also recommended to confirm and continue with this interesting topic.

Partial Conclusion

This chapter presented and discussed the results obtained, allowing us to identify the potential factors driving differences in GWR between the projection datasets (RCP2.6 and RCP8.5) and the reanalysis dataset. Before drawing any conclusions from the study, it is essential to acknowledge the fundamental differences in the characteristics of the datasets: the historical dataset is based on reanalysis products, whereas the projection datasets are generated through downscaling techniques and simulations. Moreover, they were produced at different spatial and temporal resolutions, which were subsequently used as inputs to CLM5.

The difference in recharge estimates is particularly observed with the variations in the hydrological balance. Among those variables, precipitation and evapotranspiration appear as the most determining variables, while runoff, which plays a minor role, still contributes. To better understand ET variability, an analysis of the CLM5 input dataset has been conducted and exhibits some large differences among the meteorological variables, highlighting the sensitivity of the reanalysis dataset. As for precipitation, the observed differences are largely attributed to the intrinsic nature of the forcing datasets.

To strengthen our evaluation, we compared the results with a reference dataset, which is ERA5. This comparison revealed strong consistency between precipitation and ET (with only minor differences), but a marked discrepancy for runoff, where reanalysis values were significantly higher than those of ERA5. This highlights persistent uncertainties in the representation of runoff, which must be carefully considered when interpreting GWR estimates. But this difference in surface runoff is explained by the fact that Runoff depend strongly on parametizations and also to the Plant functional type considered in CLM5 over Africa.

GENERAL CONCLUSION

GENERAL CONCLUSION AND PERSPECTIVES

This study demonstrates that the discrepancies observed between groundwater recharge estimates derived from reanalysis datasets and those based on projected datasets are primarily attributable to differences in their respective water balance components, with precipitation and evapotranspiration emerging as the dominant drivers. The divergence in precipitation reflects the intrinsic characteristic of the datasets, as precipitation is incorporated directly into the groundwater calculation without being mediated by the CLM5 model. By contrast, the differences in evapotranspiration required a more detailed assessment of the meteorological forcing datasets used as inputs to CLM5, since these inputs strongly regulate evapotranspiration. The substantial discrepancies observed, therefore, highlight the need to consider not only the inherent properties of the datasets but also potential internal inconsistencies in their generation and processing. Moreover, key information collected about the dataset reveals that the two datasets were run at different spatial and temporal resolutions. This might also influence the dataset.

In conclusion, this study reveals that evapotranspiration and precipitation are the major drivers of these differences, but requires further examination of the meteorological variables influencing evapotranspiration, and also draws attention to the importance of a critical approach to the selection of climate data for any water resource assessment, either for human consumption or for a potential hydrogen project. It emphasises that the differences observed are not only due to the simulated climatic conditions, but also to the nature of the datasets and the methodological choices made when integrating them into the models.

From this study, our recommendation is to further continue the study by investigating properly the meteorological variables influencing evapotranspiration, which requires a detailed verification process and validation of the weather atmospheric dataset, and to analyze the impact of using the same resolution datasets on the CLM5.

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