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Simulation of Climate Change Impacts on Peanut Productivity in Bambey, Senegal, Using the DSSAT Model

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DEDICATION

This research work is dedicated to my beloved parents, family and friends for their support and assistance financially, morally and spiritually as well as their hard work in terms of prayer on my studies and my life in general, May Almighty reward them abundantly in this universe and hereafter, Ameen.

DECLARATION

I, Mor Kane DIOUF, hereby declare that this thesis titled "**Simulation of Climate Change Impacts on Peanut Productivity in Bambey, Senegal, Using the DSSAT Model**" represents my personal work and the result of my own research and it has not been presented in any form, anywhere for the award of a degree in any situation. I also declare that all information, materials and results from other works presented here, have been fully cited and referenced in accordance with the academic rules and ethics. Therefore, all shortcomings in this work are entirely my responsibility.

Mor Kane DIOUF

Reg. No: PAUWES/2023/MCCE12

Date : 25 March 2025

This thesis represents the original scholarly contribution of the candidate, developed under our supervision and guidance. It has been prepared in accordance with the academic standards required by our institution and is submitted for examination with our full endorsement as the candidate's appointed Supervisor.

Adama FAYE

Date : 25 March 2025

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ACRONYMES

ANSD : Agence Nationale de la Statistique et de la Démographie

APSIM: Agricultural Production Systems Simulator

CaO: calcium oxide

CEC: Cation-Exchange Capacity

CMhyd: Climate Model for hydrologic modelling

CMIP: Coupled Model Intercomparison Project

CMIP5: Coupled Model Intercomparison Phase Five

CMIP6: Coupled Model Intercomparison Phase Six

CMS : Cropping System Model

CNRA Centre National de Recherche Agronomique de Bambey

CO_2 : Carbon Dioxyde

CSE : Centre de Suivie Ecologique

DAPSA : Direction de l'Analyse, de la Prévision et des Statistiques Agricoles

DUL: Drained Upper Limit

DSSAT: Decision Support System for Agro-technology Transfer

FAO: Food and Agriculture Organization

GCM: General Circulation Model

GDP: Gross domestic product

GHG: Greenhouse Gases

GIS: Geographical Information System

IBSNAT: International Benchmark Sites Network for Agrotechnology Transfer

ISRA : Institut Sénégalais de Recherches Agricoles

IPCC: Intergovernmental Panel on Climate Change

LAI: Leaf Area Index

LL: Lower Limit

MES: Ministry of Environment of Senegal

N_2O: Nitrogen

RCM: Regional Climate Model

RCP: Representative Concentration Pathway

RMSE: Root Mean Square Error

SARRA-H : Système d'Analyse Régionale des Risques Agroclimatiques version « Habillé »

SIMPLACE: Scientific Impact assessment and Modeling PLatform for Advanced Crop and Ecosystem management

SRES: Special Report Emission Scenarios

SSP: Shared Socioeconomic Pathways

WMO: World Meteorological Organization

ABSTRACT

Climate change presents a major challenge to agriculture, particularly in rainfed systems such as Senegal’s peanut basin. This study evaluates the potential impacts of climate change on peanut productivity in Bambey, Senegal, using the DSSAT CROPGRO-Peanut model. A multi-model ensemble from two General Circulation Models (GCMs) was utilized to assess historical climate trends and project future conditions under SSP2-4.5 and SSP5-8.5 scenarios. The study further examines the effectiveness of various crop management strategies in mitigating climate change effects. The findings reveal a statistically significant annual and monthly increasing trend (Z-value > 1.96 at $\alpha = 0.05$) in both maximum and minimum temperatures across past and future periods, highlighting a consistent warming trend. In contrast, annual and monthly rainfall patterns demonstrate relative stability, with no significant trends toward decreasing precipitation (-1.96 < Z-value < 0). However, an exception is observed in August, the wettest month, which exhibits a statistically significant decline in rainfall (Z-value < -1.96) during the baseline period and across future climate scenarios. This deviation suggests a potential shift in the rainfall regime during a critical period of the growing season. Simulation results indicate that while biomass production may experience a marginal increase of approximately 2.5 to 3.2% in the near future, depending on the climate scenario and variety, a decline of 3.2 to 17.7% is projected in the mid-term future. Conversely, grain yields are expected to decrease across all future periods, with reductions intensifying over time. Specifically, yield losses are estimated at 1.9 to 5.6% in the near future and 23.3 to 48.9% in the mid-term future, depending on the climate scenario and variety. However, the adoption of crop management strategies, such as short-cycle varieties and optimal sowing date adjustments between July 11 and July 21, can help mitigate yield losses. These findings highlight the importance of climate-smart agricultural practices, including improved water and soil management, diversified cropping systems, and strengthened adaptation policies. The study provides critical insights for policymakers, researchers, and farmers in developing strategies to sustain peanut production in the face of climate change.

1. INTRODUCTION

1.1 Background

Climate change stands as one of the most pressing global challenges of our time. It refers to significant shifts in the average values of meteorological parameters, such as precipitation and temperature, observed over extended periods (WMO, 1992; Malhi et al., 2021). According to the Intergovernmental Panel on Climate Change (IPCC) (2021), the impacts of climate change are expected to be widespread and severe, affecting both human and natural systems. Alterations in rainfall patterns and increased evaporation rates are likely to exacerbate water scarcity, reducing freshwater availability and creating significant challenges for agriculture and water consumption supplies (Roberts, 2022).

Agriculture is particularly vulnerable to climate change, as it is heavily reliant on regional weather conditions. The selection of optimal crops, as well as planting and harvesting schedules, depends on local climatic factors. Consequently, the ongoing climate change driven by rising greenhouse gas emissions poses direct threats to agricultural production and productivity (Ahmed et al., 2021). The effects of climate change are anticipated to be more pronounced in developing countries, where agricultural systems are highly dependent on rainfall and lack the resilience to adapt to such shocks (Adger et al., 2003; Mendelsohn, 2008; Lybbert & Sumner, 2010). Among the most vulnerable regions globally is the Sudano-Sahelian zone, which includes Senegal (Ahmed et al., 2021).

In Senegal, where agriculture forms the backbone of the economy, climate change and variability pose significant risks to food security and livelihoods (Noba et al., 2014). Agriculture contributes 10–13% of the country's GDP and supports over 65% of the rural population, serving as the primary income source for 95% of rural households (ISRA, 2024). Predominantly rainfed, Senegalese agriculture relies on extensive farming systems (ANSD, 2017), making it particularly susceptible to climatic changes. Reports from the Ecological Monitoring Center (CSE) (2010), reveal that Senegal has experienced significant climatic variability, including a 1.6 °C increase in mean annual temperature since 1950, with northern regions observing increases of up to 3 °C. Furthermore, rainfall declined by 30% between 1950 and 2000, with notable variability across years and regions. While precipitation levels have shown increase since 2000, this does not necessarily mark the end of prolonged dry cycles. These climatic trends exacerbate Senegalese agriculture's vulnerability, with negative consequences expected for national food security. The sensitivity of Senegal's agricultural sector to changes in temperature and precipitation underscores the likely adverse impacts on crop yields and livestock. For instance, crop models predict a potential decline in groundnut yields by 5–25%, while maize and rainfed rice yields could increase by 5–25% in some areas (Jalloh et al., 2013).

Peanut (Arachis hypogaea L.), an essential oilseed and food crop, plays a critical role in Senegalese agriculture. It is widely cultivated across West Africa, a region characterized by high temperatures and low or erratic rainfall. In Senegal, peanut farming is primarily conducted by smallholder and resource-poor farmers, serving as a vital source of income for rural communities. The country ranks as Africa's second-largest peanut producer after Nigeria, with a reported production of 1,501,498 tonnes in the 2022–2023 agricultural season—a decrease of 11% from the previous year but a 6% increase compared to the five-year average (DAPSA, 2023). Peanut cultivation holds great economic and strategic importance for Senegal as it serves as a subsistence, commercial, industrial, fodder, and fertilizing crop (World Bank, 2015). Peanut is grown in all districts in the country but the central part named the “peanut basin” constitutes the core of production. Despite their importance, peanut cultivation faces significant challenges, particularly due to its reliance on rainfed agriculture and sensitivity to agro-climatic factors such as rainfall, temperature, sunlight, and wind. These factors exhibit considerable temporal and spatial variability (MES, 2006), further complicating cultivation efforts. The combination of climatic variability and systemic agricultural weaknesses highlights the urgent need for adaptive strategies to ensure sustainable peanut production.

Understanding the interplay between climate variability and agricultural performance across both spatial and temporal scales is critical for developing effective adaptation strategies (Araya et al., 2022). Given the intricate interconnections between climate, agricultural practices, and plant species/cropping systems, modelling become a valuable tool for investigating the impact of climate change on crops (Rezaei et al., 2014). Modelling allows for the exploration of numerous scenarios involving different climate conditions, agricultural practices, and crop responses within a relatively short time (Timlin et al., 2024).

1.2 Problem Statement

Since the 1970s and 1980s, the peanut basin of Senegal has experienced a significant decline in agronomic potential, primarily due to recurrent droughts (Garambois et al., 2019), agricultural expansion, and unsustainable farming practices (Civil, 2022). These factors have led to diminishing soil fertility and reduced agricultural productivity, particularly in peanut cultivation. Climate risks and hazards such as premature sowing, untimely cessation of the growing season, and water stress during critical growth stages have notably impacted crop production in the region's rainfed agricultural systems (MacCarthy et al., 2021). Additionally, the distribution of seasonal rainfall is expected to be adversely affected by climate warming, resulting in increased variability and frequency of extreme weather events, which may further compromise agricultural productivity (MacCarthy et al., 2021). Recent climate trends indicate worsening variability, characterized by irregular rainy season patterns and prolonged dry spells, contributing to food insecurity and decreased crop yields (Huang et al., 2015; Ilboudo et al., 2021). Moreover, the region is experiencing a warming trend, with maximum temperatures rising between 0.4 °C and 0.7 °C from south to north (Faye et al., 2024). These climatic changes intensify water stress during critical reproductive phases, such as flowering and pod formation, thereby shortening the reproductive cycle and leading to yield reductions (Ahmed et al., 2022). Changes in climate-related variables directly influence crop growth, yields, input availability, and broader farming system management practices (Knox et al., 2012).

Coupled with declining soil fertility, these climatic factors pose a significant threat to agricultural productivity unless appropriate adaptation measures are implemented (Roudier et al., 2011). This situation raises concerns about the future of peanut farming in Senegal’s peanut basin (Garcia, 2015). Therefore, characterizing climate change impacts in Senegal and assessing their effects on crop yields—particularly for groundnuts, the primary cash crop under various farming systems—are essential for developing more effective agricultural strategies. While numerous researchers have investigated the effects of climate change and crop management practices on peanut productivity in Bambey, few have employed crop modeling approaches, and none have addressed the recent CMIP6 Shared Socioeconomic Pathways (SSP) scenarios for future projections. Considering that the study area encompasses a significant proportion of smallholder farmers, it is imperative to incorporate socioeconomic pathways into these assessments.

1.3 Research Objectives

The main objective of this study is to assess the potential climate change impacts on peanut yields in Bambey, Senegal, and contribute to the development of sustainable adaptation strategies. To achieve this objective, the following specific objectives are investigated to:

- Calibrate and evaluate the DSSAT model for peanut to simulate peanut growth and yield in Bambey, Senegal.

- Analyze the impact of climate change on peanut growth and yields in Bambey, under SSP2 and SSP5 climate scenarios.
- Investigate how effective crop management practices may exacerbate the negative effects of climate change on peanut productivity in Bambey.

1.4 Research Questions

- How can the DSSAT model be calibrated and evaluated for simulating peanut growth and yields in Bambey, Senegal?
- What is the impact of climate change on peanut growth and yields in Bambey under SSP2 and SSP5 climate scenarios?
- How do specific crop management practices influence or exacerbate the negative effects of climate change on peanut productivity in Bambey, Senegal?

1.5 Significance of the Study

This study holds great relevance in the context agricultural sector of Senegal, particularly in peanut cultivation, due to its high sensitivity to climate change. The research questions and working hypotheses aim to understand the effects of climate change on peanut yields and develop strategies to mitigate these impacts. By evaluating peanut performance under current and future climatic conditions, this study seeks to provide valuable insights into the potential decline in production and assess the most effective adaptation strategies to mitigate the negative effects of climate change on peanut cultivation. Consequently, it contributes to enhancing long term sustainability. The expected outcomes of this study have the potential to provide valuable information for policymakers, researchers, and agricultural practitioners, enabling them to make informed decisions and develop strategies to mitigate the adverse effects of climate change on the peanut sector. Moreover, it highlights the importance of utilizing advanced modeling techniques to understand and address the complex interactions between climate change and agricultural practices.

2. LITERATURE REVIEW

2.1 Overview of Climate Change Trend in Senegal

Climate change in Senegal is marked by increasing temperatures, altered rainfall patterns, and heightened variability, posing challenges to agriculture and livelihoods (McSweeney et al., 2010; Funk et al., 2012; Sultan et al., 2013; IPCC, 2014; Garcia, 2015; Maidment et al., 2015; Serdeczny et al., 2017; Ahmed et al., 2021; Civil, 2022).

2.1.1 Realized Trends

The assessment of climate change in the Sahel, particularly concerning rainfall patterns, remains uncertain and contentious (Garcia, 2015; Civil, 2022). Climate change is anticipated to lead to increased temperatures and decreased average precipitation, resulting in recurrent droughts across West Africa (IPCC, 2014). Conversely, the region has experienced a recovery in precipitation following the catastrophic droughts of the 1970s and 1980s. Specifically, between 1983 and 2010, annual rainfall consistently increased, averaging 294.3 mm per year per decade (Maidment et al., 2015). However, this rise in annual rainfall has been accompanied by a greater frequency of short-term extreme droughts and intense rainy episodes, contributing to a more unpredictable rainy season (Maidment et al., 2015).

Additionally, studies have proved a delay of approximately one week in the optimal sowing dates for crops during the period from 1970 to 2008 when compared to the earlier period of 1950 to 1969. This shift has also been associated with a reduction in the overall length of the growing season (Garcia, 2015). Moreover, warming trends indicate that from 1975 to 2009, temperatures in Senegal during the June–September rainy season have increased by over 0.7°C. This transition to a warmer climate is likely to diminish crop yields and reduce pasture availability, further exacerbating the impacts of drought (Funk et al., 2012).

2.1.2 Future Projections

Future projections of average annual rainfall across Senegal, derived from various models, indicate a wide range of potential changes, with a general trend towards decreased precipitation, particularly during the wet season (July, August, and September) (Ahmed et al., 2021). Specifically, projected changes in rainfall range from -38% to +21% by the 2090s, with an ensemble mean of -18% (McSweeney et al., 2010). Similarly, for July, August, and September, the expected changes range from -41% to +48% by the 2090s. According to Alioune and Moctar (2018), these rainfall projections yield contradictory results, indicating both increases and decreases during the monsoon season (JJAS).

Consequently, rainfall patterns under RCP4.5 and RCP8.5 scenarios are characterized by significant variability. Projections for the Sahel, particularly in its western regions, suggest a notable decline in precipitation under high greenhouse gas forcing scenarios by the end of the 21st century (M. B. Sylla et al., 2016), although Serdeczny et al. (2017) predict an increase in rainfall in Senegal. Furthermore, simulations conducted by Sultan et al. (2013) project an average temperature rise of +2.8°C during the period from 2031 to 2060. These annual projections also indicate an increase in the number of hotter days, with estimates suggesting that 22-46% of days in the 2060s and 29-67% of days in the 2090s will be classified as hotter. Hotter nights are projected to occur on 27-51% of nights by the 2060s and 37-70% by the 2090s. Importantly, all projections indicate a decrease in the frequency of days and nights currently classified as 'cold' (A. Ahmed et al., 2021).

2.2 Impact of Climate Change on Agriculture

The Sudano-Sahelian region, which includes Senegal, is among the most vulnerable areas globally to climate change. This region is characterized by a monsoon season that spans from May to September, accounting for the majority of annual precipitation, which ranges from 200 to over 1200 mm (Defrance et al., 2020). Climate change affects all economic sectors, with agriculture being the most severely impacted due to its reliance on climatic conditions, particularly rainfall and temperature (Ahmed et al., 2021). In Senegal, where rainfed agriculture is predominant, agro-climatic risks are strongly associated with failed sowings, premature cessation of the growing season, and water stress during critical stages such as post-flowering and grain-filling (MacCarthy et al., 2021).

Changes in temperature and precipitation can significantly reduce crop productivity through various physiological mechanisms. Notably, both photosynthesis and respiration are nonlinear functions of temperature, while the relationship between crop development rates and temperature is approximately linear (Porter & Semenov, 2005). Thus, while warmer conditions may accelerate crop development, yields are likely to decline if temperatures exceed optimal thresholds (Porter & Semenov, 2005). In arid and semi-arid regions, water availability is a critical limiting factor for crop growth. A potential decrease in precipitation during the growing season can reduce soil moisture available to rain-fed crops, leading to increased water stress and diminished crop productivity.

Several studies employing various methodologies project a detrimental impact of climate change on crop yields across Sub-Saharan Africa (Ahmed et al., 2015). Crop models, including those developed by Sultan (SARRA-H, APSIM), indicate a decline in potential yields throughout the Sahel, even with increased precipitation. This decline is primarily attributed to rising temperatures, which shorten crop cycles. The introduction of photosensitive varieties may mitigate some disruptions caused by elevated temperatures (Sultan et al., 2013).

Furthermore, research indicates that a temperature increases of 2°C could significantly enhance crop water demand and irrigation requirements, thereby reducing irrigation availability (Sylla et al., 2018). Although elevated carbon dioxide (CO_2) levels may have beneficial effects on yields due to enhanced photosynthesis and transpiration efficiency, the associated increases in temperature and decreases in rainfall will likely counteract these benefits (Defrance et al., 2020). Notably, the positive impact of elevated CO_2 levels is expected to be more significant in C3 crops compared to C4 crops (Ahmed et al., 2015). Crop production in Senegal is constrained by a combination of factors, including climate change and variability, water stress, poor soil fertility (Akponikpe, 2008; Ganyo et al., 2019). Therefore, comprehensive investigations are essential to develop effective agronomic management strategies that address the challenges posed by current and future climate scenarios.

2.3 PEANUT CULTIVATION IN SENEGAL

2.3.1 Phyto-technical Aspects of Peanut Cultivation

Peanut (*Arachis hypogaea L.*) is an annual legume that typically grows to a height of 30 to 70 centimeters, exhibiting either an erect or creeping growth habit. The aerial part of the plant is supported by a central stem that remains upright, along with two primary lateral branches that emerge from the plant's collar. The base of the fertilized ovary elongates to form a stalk called the gynophore, which penetrates the soil where the fruit (the pod) develops. Each pod, characterized by an indehiscent shell, contains one to four seeds. The peanut plant possesses a taproot system that enables it to explore a significant volume of soil. This root system is equipped with nitrogen-fixing nodules, a characteristic feature of legumes, allowing the plant to enrich the soil with nitrogen under favorable conditions. In Senegal, peanut cultivation typically spans from June to November-December, reflecting the spatial and temporal variability of rainfall (Kouadio, 2007).

2.3.1.1 Soil Requirements

Peanuts can be cultivated in various soil types; however, productivity is enhanced in well-drained plots. Sandy soils are particularly advantageous as they facilitate the penetration of gynophores and the development of pods. The physical properties of the soil play a crucial role in the adaptation of peanuts to their environment, especially concerning water and nutrient availability, as well as root penetration and development (Patrick, 2008). Peanuts are sensitive to soil salinity and acidity. Highly acidic soils (pH below 5) or those deficient in calcium oxide

(CaO) can lead to aluminum or iron toxicity; such acidity inhibits the development of nitrogen-fixing bacteria, which is evident in the chlorotic appearance of the foliage and the lack of red coloration in the nodules, indicating active bacterial presence.

2.3.1.2 Temperature and Sunlight

Temperatures below 15°C and above 45°C can hinder or completely block growth, with the optimal range being between 25°C and 35°C. Although peanuts are relatively insensitive to photoperiod, longer daylight hours positively influence productivity; therefore, early sowing (when rainfall or irrigation permits) is preferred. Imbalances in environmental conditions often result in an unfavorable ratio of foliage to pods, a phenomenon also observed in equatorial regions and under shrub-based cropping systems when sunlight becomes limiting (Kouadio, 2007).

2.3.1.3 Water Regime

Peanuts exhibit varying sensitivities to drought at different growth stages. Water requirements are particularly high during seed imbibition, but once germination begins, excess water can be detrimental. The period of flowering and pod formation (30 to 70 days post-sowing) is critical for drought sensitivity, whereas the final maturation phase benefits from relative dryness; excessive rainfall during this stage can induce premature germination in non-dormant varieties. Generally, a rainfall range of 500 to 1,000 mm during the growing season is conducive to good yields, but the timely distribution of rainfall relative to the variety's growth cycle is more critical than total precipitation. According to Schilling (1997), yields exceeding 1 tonne/ha have been achieved in northern Senegal with only 350 mm of rain concentrated over three months, using the early-maturing drought-tolerant variety 55-437. During periods of water stress, supplementary irrigation can often lead to substantial improvements in yield and quality with minimal investment. However, in traditional agricultural practices prevalent in Senegal, the preference tends to lean towards late-maturing, high-yielding varieties.

2.3.2 Importance and Challenges of Peanut Cultivation

Peanut cultivation holds significant importance in Senegal. It is an essential oil seed and food crop grown across West Africa, a region characterized by high temperature and low or erratic rainfall. Peanut cultivation is predominantly carried by small-holder and resource-poor farmers, serving as the main source of income in rural areas. Senegal ranks as the second-largest peanut producer in Africa following Nigeria (Faye, 2018), with a reported production of 1,501,498 tonnes in the 2022-2023 agricultural season, reflecting an 11% decrease from the previous season. Notably, this production level represents a 6% increase compared to the average over the past five years (DAPSA, 2023).

The cultivation period for peanuts in Senegal extends from June to November-December, influenced by spatial and temporal variability in rainfall. Peanut are grown throughout Senegal, with major growing areas located in the Groundnut Basin including Kaolack, Fatick, Thiés, Diourbel and Louga (Diagana and al., 2008). Peanut cultivation holds great economic and strategic importance for Senegal as it serves as a subsistence, commercial, industrial, fodder, and fertilizing crop (World Bank, 2015). Historically, the peanut sector has been the cornerstone of Senegal's economy, with exports of peanuts and their by-products, such as oil and shelled peanuts, contributing significantly to the country's monoculture prestige.

However, since the 1970s and 1980s, the peanut basin, which accounts for the largest proportion of peanut cultivation, has experienced a substantial deterioration of its agronomic potential. This deterioration can be attributed to a combination of climate events such as recurrent droughts (Garambois et al., 2019), expansion of cultivated land and inappropriate agricultural practices (Pierre et al., al., 2018 ,Civil, 2022). Consequently, there has been a persistent decline in soil fertility, which has adversely affected agricultural productivity in the region. Peanuts are particularly sensitive to climatic variables, as any fluctuations in weather conditions from sowing to harvesting can significantly impact crop productivity. For instance, exposure to high temperatures can lead to considerable yield losses. The increase in temperature affects critical stages of crop development, making it essential to study the influence of temperature changes in terms of thermal and photo-thermal time (Ahmed et al., 2022).

While peanut plants can thrive within a broad temperature range, flowering and pod filling occur within a narrow temperature window. If temperatures exceed this optimal range, the plants may suffer from heat stress, which can stunt growth and deteriorate peanut quality. One of the main effects of high temperature in this region have effect to accelerate the development of peanut and shorten the reproductive duration which have effect on reducing yield. Other negative effects of hot temperature above the optimum are known to be the reduction in radiation use efficiency (Prasad, 1999) on peanut as respiration increases more than photosynthesis as temperature rises above. Additionally, during critical growth phases, peanuts require substantial water, but excessive moisture can be detrimental. The challenges posed by climate change are multifaceted. Some researchers argue that rising temperatures represent the most significant threat, while others contend that increased rainfall poses a greater risk (Caitlin

& Sonya, 2023). Although farmers can adopt irrigation strategies during dry periods, they have limited options for mitigating the effects of excessively high temperatures (Caitlin & Sonya, 2023).

While field evidences indicate that increased CO_2 concentrations have a beneficial effect on C3 crops, such as wheat, rice, and groundnut, resulting in productivity enhancements of 15-20% under optimal growing conditions (Tubiello et al., 2008). Elevated CO_2 levels stimulate growth and photosynthesis in C3 plants; however, in C4 plants, the net leaf photosynthetic carbon dioxide exchange rate becomes nearly saturated at current ambient CO_2 concentrations (Vanaja et al., 2013). Consequently, pod and seed yields may increase by approximately 30% due to a rise in the total number of pods or seeds associated with enhanced photosynthesis. Nonetheless, when temperature thresholds are surpassed, crop yields for both C3 and C4 plants are likely to decline despite the advantages of elevated CO_2 (Singh et al., 2014). Therefore, future CO_2 levels are expected to favor C3 plants, providing limited benefits to C4 crops, particularly when water is not a limiting factor (Tubiello et al., 2007). While the opposite will be expected under water limited and temperature increases and the net effects remain uncertain (Tubiello et al., 2007). Furthermore, studies indicate that the soils in the peanut basin, having been depleted by decades of monoculture practices initiated during French colonialism, yield low outputs even under conditions of abundant rainfall. Despite the ongoing crisis affecting the peanut sector, it continues to serve as a vital source of income for rural populations in Senegal (Kouadio, 2007). Thus, addressing these agronomic and climatic challenges is essential for ensuring the sustainability and productivity of peanut cultivation in the region.

2.4 Adapting Crop Management Strategies

Adapting crop management practices is a crucial strategy for mitigating the negative impacts of climate change on agricultural systems in the Sahel region. Climate change exacerbates the challenges faced by rural populations, including extreme heat, reduced access to water resources, and limited adaptive capacity (Assane & Waoundé, 2023). The Intergovernmental Panel on Climate Change (IPCC) (2014), defines adaptation as making adjustments in natural or human systems in response to actual or anticipated climate change effects, with the aim of minimizing harm or capitalizing on potential opportunities.

In agriculture, adaptation to climate change involves changes in management practices in response to the changing climate conditions. Farmers in the Sahel region commonly employ agricultural adaptation strategies such as using of drought resistant varieties, diversifying crops cultivations, adjusting cropping patterns and planting calendars, adopting appropriate tillage methods to conserve soil moisture, improving irrigation efficiency, and implementing afforestation and agroforestry practices (Akinnagbe & Irohibe, 2015). Moreover, as noted by Khosravi et al. (2010), selecting the optimal sowing time and crop variety is crucial for maximizing yields. The timing of planting and the choice of genotypes significantly affect phenological phases and overall plant growth (Damahe, 2018). Adopting drought-resistant crop varieties, as highlighted by the significant yield gaps in traditional Senegalese agriculture, can increase adaptability to shifting climate patterns (Goundan et al., 2020). Furthermore, timely planting facilitated by accurate climate forecasts, as noted in the Ecocrop models findings on suitable planting months, can directly influence crop yields by aligning growth cycles with favorable weather conditions (Crespo et al., 2020). Additionally, with rising soil temperatures, there is an acceleration in soil organic matter turnover and respiration, which increases the demand for fertilizers to maintain soil stability. However, reducing fertilizer application can mitigate the negative effects of high-temperature stress on dry matter accumulation in plants and prevent phytotoxicity; such damage often results from heat stress impairing nitrogen uptake, altering N2O flux, and affecting denitrification processes (Quan et al., 2024).

However, it is important to note that some of these techniques may need to be adjusted to address additional risks associated with climate change. One of the main challenges in implementing agricultural adaptation strategies in Africa, including the Sahel, is the limited knowledge, expertise, and data on climate change issue (Asseng et al., 2015). Crop modeling can play an important role in assisting agricultural activity to adapt to climate change (Ewert, 2012) by providing an understanding of the impacts of climate change factors on the growing seasons and assessing management practices at spatial and temporal scales to develop adaptation strategies in Senegal (Ganyo et al., 2021).

2.5 Crop Modeling

Improving our understanding of the potential impacts of climate change on crop yields is fundamental for devising timely and appropriate responses. Analysts seeking to anticipate these effects must rely on conceptual or numerical models that elucidate how crop yields respond to climatic variables (Lobell & Burke, 2010). Crop models are widely utilized in the development of sustainable crop management strategies, particularly in the context of changing climatic conditions (Ahmed et al., 2022). Prospective studies in agronomy necessitate a combined examination of climate change, potential adaptations in agricultural practices, and the responses of various plant species across different cropping systems (Garcia, 2015). Given the intricate interactions among climate, practices, and species-systems of cultivation, modeling becomes an invaluable tool for assessing the impacts of climate change on crops (Eyshi Rezaei et al., 2014). This approach allows researchers to explore a vast array of scenarios (including climate, crop, and management practices) within a constrained timeframe. The outputs generated by these models can inform farmers, scientists, and policymakers regarding water allocation, optimal planting dates, and field management strategies.

2.5.1 Types of Crop Model

Two primary types of models are often employed, depending on their complexity: empirical (or statistical) models and process-based (or dynamic) models (Civil, 2022). Statistical models are frequently utilized in climate change impact studies or to analyze crop responses to management practices (Civil, 2022). These models are simplified and focus on establishing mathematical relationships between a dependent variable and explanatory variables (Wallach et al., 2018). They do not aim to represent the entire system but instead seek to quantify the relationship between the variables involved, with linear regression models serving as a typical example (Wallach et al., 2018). Furthermore, when statistical crop models are integrated with economic models, it becomes feasible to project future crop prices based on simulated crop parameters, climate change scenarios, and agronomic conditions (Roudier et al., 2011). The primary advantages of statistical models include their minimal reliance on field calibration data and their transparent assessment of model uncertainties. However, they are not without significant limitations. Issues such as collinearity among predictor variables (e.g., temperature and precipitation), assumptions of stationarity (i.e., the expectation that past relationships will persist in the future, despite potential changes in management systems), and low signal-to-noise ratios in yield or weather records present challenges (Lobell & Burke, 2010).

In contrast, process-based models are grounded in equations that represent the physical and physiological processes of crop growth and development in response to external environmental factors (Sultan et al., 2015). These models are typically developed and validated through experimental trials, allowing them to leverage decades of research across disciplines such as crop physiology, agronomy, and soil science. However, they require extensive input data regarding cultivar characteristics, management practices, and soil conditions, which can be lacking in many regions (Lobell & Burke, 2010). Process-based models aim to accurately reflect system functioning and are predominantly utilized for agricultural impact studies due to their capacity to capture intra-seasonal and nonlinear climatic effects on crops (Sultan et al., 2015). The complexity of these models necessitates a greater degree of parameterization and data input such as soil properties and cultivar information compared to empirical models, leading to their more common application at the plot scale where such data are available (Sultan et al., 2015; Civil, 2022). Notable examples of these models include AquaCrop, Agricultural Production Systems Simulator (APSIM), Decision Support System for Agro-technology Transfer (DSSAT), and others. These models adopt two distinct approaches: specific agronomic models designed for particular crops under defined conditions, such as CROPGRO-peanut (Naab et al., 2004), and generic models like APSIM (Robertson et al., 2002), which can be adapted for multiple crops through parameterization. However, process-based models also face challenges related to data input requirements. Fine-scale data series, often difficult to obtain or generate, are necessary for optimal performance (Basso et al., 2015). This issue is especially pronounced in developing countries, where challenges in physical instrumentation, measurement, and long-term data collection persist. Despite these limitations, research has demonstrated that process-based crop models generally outperform statistical models in the context of climate change studies (Adeboye et al., 2019).

2.5.2 Crop Model Selection Criteria

There is no single crop model that is universally appropriate for all research, planning, or policy formulation efforts. The selection of crop models is contingent upon the specific objectives and scope of the study, the researcher's expertise, the desired outputs, and the availability of input data.

In our study area (Bambey), many researchers have examined the effects of climate change and crop management practices on peanut productivity; however, few have utilized crop modeling approaches. For instance, Garcia (2015) investigated the limitations of nitrogen and water on peanut yield through virtual experimentation on peanut using the CELSIUS model. Conversely, Faye (2018) employed the SIMPLACE model to simulate canopy temperature, thereby calculating heat stress and assessing the impacts of fertilizer application and water availability on peanut development, growth, and yield. Notably, none of these studies have addressed the recent CMIP6 Shared Socioeconomic Pathways (SSP) scenarios for future projections. Given that the study area comprises a significant proportion of smallholder farmers, it is crucial to consider socioeconomic pathways. This consideration will enable decision-makers to better understand the root causes of the challenges faced by these farmers and to recommend the adoption of new, climate-smart agricultural techniques essential for enhancing food production. In this context, our study employs the DSSAT model (CROPGRO-Peanut model), a key component of the DSSAT framework, which, according to existing literature, is the most widely used crop model in West Africa (Faye, 2018). This model will be calibrated using data from CMIP6 under the SSP scenarios to investigate the potential impacts of climate change on peanuts under various crop management practices.

The DSSAT model is capable of estimating various parameters and dynamically responds to daily weather inputs, soil moisture levels, cultivar selection, and management practices. The CROPGRO-Peanut model effectively predicts phenology, development, and yield, influenced by climatic conditions, cultivar traits, and management practices, thus offering a practical means to enhance peanut production while addressing environmental and management-related challenges. For example, Halder et al. (2017) utilized the DSSAT model to investigate peanut growth, development, and yield, finding the calibrated model to be quite accurate in simulating peanut yield. Similarly, Guled et al. (2012) concluded that the model's predictions closely aligned with observed phenology and pod yield of peanut cultivars. Yadav et al. (2012) reported that the CROPGRO-Peanut model can simulate yield, days to anthesis, and shelling percentage. They also suggested that the model could be used to enhance current peanut management practices, ultimately leading to increased peanut production.

2.6 DSSAT Model

2.6.1 Overview of DSSAT model

Crop simulation models have great significance in transferring new technologies to the farmers and decision-makers and Decision Support Systems for Agrotechnology Transfer (DSSAT) have been one of the most important of them. Ten years of endeavor in developing DSSAT by scientists of the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) has turned DSSAT as a really useful tool for researchers and policy-makers for decision-making and to answer what - if questions related to a cropping system. Since its first release it has been customized and modified as a better suite of models to represent a system or simulate one or more crops with a system approach based on the soil and climate condition (Sarkar, 2009). DSSAT is a software application program that can be used for the simulation of more than 40 crops, including peanut. The DSSAT is a collection of independent programs that operate together; crop simulation models are at its center. In this software package, there is a specialized model for each crop. CERES-Maize and CROPGRO-Peanut are examples of these models (Moroozeh et al., 2023). Attachment of weather generators, genetic coefficients, GIS, databases and different decision support tools made DSSAT even more supportive to farmers for taking the right decision at the right time while keeping future scenario updated. DSSAT have been widely used to simulate crop yield of a system under different management strategies, select management practices for optimum resource use and sustainable crop production with minimum malefic effect on environment, take right decision based on economic return of a system and alter management options based on weather changing (Sarkar, 2009).

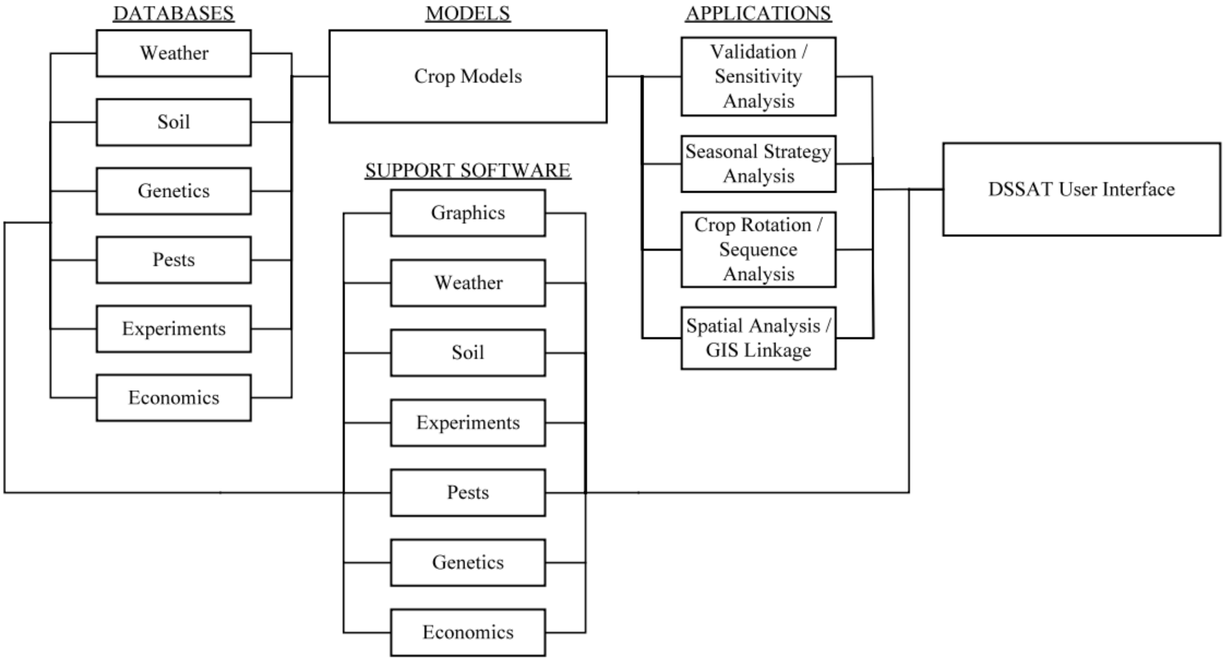


Figure 1: Diagram of database, application, and support software components and their use with crop models for applications in DSSAT v3.5 (Jones et al., 2003).

2.6.2 The Cropping System Model (CSM)

The main engine of the DSSAT ecosystem is the Cropping System Model (CSM; Fig. 2) For most users, the model is run through the DSSAT Interface, but for power users, it can also be run through a command line interface on iOS, Linux, and Unix platforms. The original crop models in the first version of DSSAT were CERES-Maize, CERES-Wheat, SOYGRO, and PNUTGRO. These original models morphed over time from many independent models to a single agricultural systems model that encompasses all the original crop models as individual crop modules (Jones et al., 2003). Development of models for new crops was initially based on creating new, stand-alone models, such as the model for dry beans BEANGRO, which was developed based on SOYGRO (Hoogenboom et al., 1994). In the early 1990s, the DSSAT developers realized that code modifications were often made redundantly for the separate

SOYGRO (Jones et al., 1987), PNUTGRO (Boote et al., 1987), and BEANGRO (Hoogenboom et al., 1990) models. Therefore, we pulled all crop-specific parameters and relationships out of the FORTRAN code and placed them into external species files (per crop), thus allowing a single generic executable CROPGRO code to represent three crop species (Hoogenboom et al., 2019).

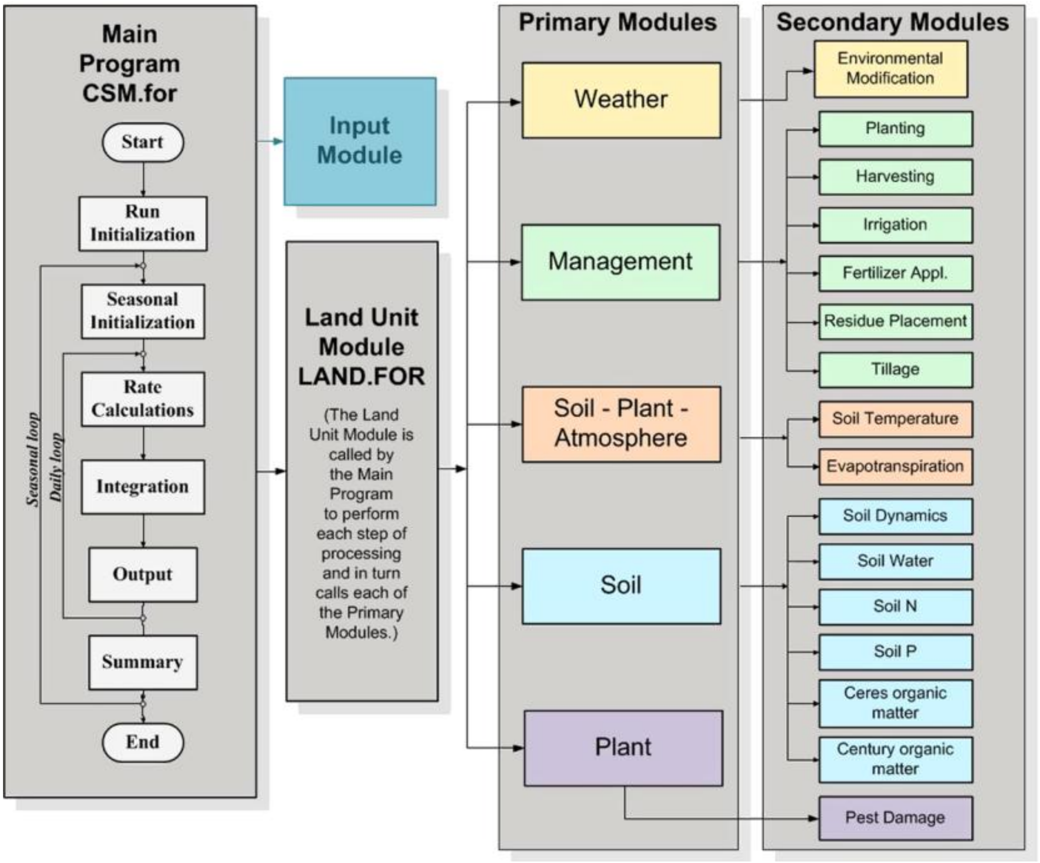


Figure 2: The structure of the Cropping System Model (Hoogenboom et al., 2019)

During the 1990s, code improvements were made to the CROPGRO model to add mechanistic leaf-level photosynthesis coupled with hedgerow light interception to simulate leaf-to-canopy assimilation running on an hourly basis for sunlit and shaded leaf classes (Boote et al., 1998). In the decade from 2000 to 2010, the DSSAT-CSM was created (Jones et al., 2003). This single executable program was able to simulate all the crop models, including the CROPGRO models (Boote et al., 1998), that until this point were available only as individual models. With CSM, each crop module shares the same routines for the simulation of soil water dynamics, soil N dynamics, soil C dynamics, management operations, and daily weather processes.

2.7 Climate Change Modeling

2.7.1 Climate Models and Coupled Model Intercomparison Project Phase 6 (CMIP6)

Climate models have undergone significant evolution over the past few decades, reflecting a sophisticated approach to comprehending the intricate interactions within the Earth's climate system (Laprise, 2008). These models, which include Global Climate Models (GCMs) and Regional Climate Models (RCMs), enable researchers to examine both historical climate changes and future projections (Faye et al., 2022). Specifically, GCMs simulate the Earth's physical processes and atmospheric dynamics, allowing for the assessment of climate responses to greenhouse gas (GHG) emissions and land-use changes (Lin et al., 2021; Magdy Hamed et al., 2021).

One notable advantage of GCMs is their capacity to project long-term climate scenarios based on various anticipated atmospheric GHG concentration trajectories. Consequently, these projections are instrumental in climate change mitigation strategies and in preparing for potential extreme weather events. However, it is important to recognize the limitations of these models, particularly their challenges in accurately capturing small-scale processes, such as cloud dynamics (Onyutha et al., 2016).

Despite these limitations, the integration of scientific principles, sophisticated simulations, and ongoing refinements in climate modeling provides a comprehensive toolkit for enhancing our understanding of climate complexities (Laprise, 2008). The models are released in phases through the Coupled Model Intercomparison Project (CMIP), an inter-comparison framework developed by the Intergovernmental Panel on Climate Change (IPCC). The phases of CMIP include CMIP1, CMIP2, CMIP3, CMIP5, and the latest, CMIP6. Notably, CMIP6 distinguishes itself from previous phases by offering an improved representation of the Earth's physical processes and providing projections based on new scenarios known as Shared Socioeconomic Pathways (SSPs) (Moss et al., 2010; Schlund et al., 2020).

Recently, several dozen CMIP6 GCM simulations have been made publicly available. However, utilizing all GCMs for climate projections is often impractical due to the considerable uncertainties associated with them (McSweeney et al., 2015). While CMIP6 GCMs exhibit technical improvements over earlier versions, studies indicate that their data still contain substantial biases and uncertainties (Song et al., 2021). Therefore, the adoption of a multi-model ensemble comprising the better-performing GCMs is recommended to enhance the reliability of climate projections (Magdy Hamed et al., 2021).

2.7.2 Climate Change Scenarios

Climate change scenarios are crucial for understanding potential future impacts of climate change. These scenarios provide credible projections of anticipated environmental conditions, including factors such as temperature, precipitation, and various climatic patterns. The evolution of climate change scenarios has undergone significant refinement and expansion over time. Initially, storylines based on demographic, technological, and land use factors led to the development of the Special Report on Emissions Scenarios (SRES), which enhanced our ability to model climate impacts (Gebremeskel et al., 2015). However, the introduction of Representative Concentration Pathways (RCPs) marked a paradigm shift, offering more comprehensive insights into greenhouse gas concentrations and radiative forcing, thus overcoming the limitations of earlier models (Basalirwa, 2014). RCPs not only replaced SRES but also expanded our understanding of the complex interactions between climate dynamics and socio-economic factors (Birara et al., 2020).

Subsequently, Shared Socioeconomic Pathways (SSPs) emerged as the next frontier, reflecting a dynamic socio-economic landscape and society's ability to guide mitigation and adaptation efforts (Jiang et al., 2022). The Intergovernmental Panel on Climate Change (IPCC) released its Sixth Assessment Report on August 9, 2021, which outlines five SSPs: SSP1 (Sustainability), SSP2 (Middle of the Road), SSP3 (Regional Rivalry), SSP4 (Inequality), and SSP5 (Fossil-Fuelled Development) (Januta, 2021). These SSPs depict alternative visions for how society and climate may evolve over the coming decades, providing a framework for integrating these pathways in various studies. Importantly, the SSPs consider socioeconomic trends, technological advancements, and other environmental changes, such as land use, to project future climate (Moss et al., 2010).

The five SSPs were designed to cover a range of outcomes concerning two key societal characteristics: the challenges each pathway presents for adapting to climate change and the challenges it poses for mitigation efforts. Notably, the SSPs do not include specific mitigation and adaptation responses or the impacts of climate change itself. This design choice enables integrated studies to assess the effects of specific policies and the magnitude of impacts by comparing their outcomes to those outlined in the SSPs. Consequently, the SSPs serve as a valuable reference framework for a wide range of studies investigating various policies and projected risks (O’Neill et al., 2020).

2.7.3 Downscaling of Climate Change Data

Downscaling techniques are pivotal in refining climate projections and bridging the resolution gap between GCMs and the intricate demands of local and regional climate assessments. Given the limitations of GCMs in accurately capturing precipitation dynamics and their inherently larger spatial scales compared to hydrological needs, downscaling strategies have been embraced to transition from global to local contexts seamlessly (Manatsa et al., 2008). Downscaling of future climate data can be categorized in two methods which are the statistical downscaling method and dynamical downscaling method which is also known as Regional Climate Models (RCMs).

The statistical downscaling method is employed to project finer-scale data for various variables by developing mathematical functions known as transfer functions and regression equations from large-scale data obtained from Global Climate Models (GCMs). Another approach to statistical downscaling involves the use of stochastic weather generators, which are commonly used to temporally downscale annual or monthly data into daily data for a specific location (Irwin et al., 2012). These weather generators operate by adding the differences between 40 GCM data points and observed data to create a regression equation that generates a new dataset. This dataset is then utilized in a weather generator to estimate future daily data for the specified location.

However, a dynamical downscaling method known as Regional Climate Models (RCMs) simulates future climate data using GCMs as boundary conditions to achieve finer scales, typically within a resolution range of 10 to 50 km. RCMs are capable of depicting climate change trends observed in the parent GCM. While statistical downscaling is cost-effective and saves computational time, one of its drawbacks is its inability to estimate weather variables across multiple locations simultaneously without altering the spatial relationships within the observed data. In contrast, RCMs have been designed to reduce the biases inherent in GCM data (Klutse et al., 2018). However, questions remain regarding the accuracy of RCM data, as RCMs simulate climate change trends along with the biases and uncertainties embedded in the parent GCM.

2.7.4 Bias Correction Techniques

Future climate data are usually characterized with errors known as bias. Biases are methodical errors from climate models as a result of algorithms used in projection and large spatial resolution. In order to correct these anomalies, some bias correction techniques have been established. Bias correction techniques are crucial in the context of climate and meteorological modeling. Bias correction refers to the mathematical or statistical adjustments made to the output data from GCMs or other climate models. These adjustments aim to mitigate systemic biases or inaccuracies in the model simulations (Ghimire et al., 2019). These techniques can be broadly categorized into three main types: mean-based, distribution based, and distribution and persistence-based methods (Chen et al., 2013).

Mean-Based Bias Correction: This method, also known as delta change, is a straightforward approach that involves adjusting the mean values of model outputs to align them with observed data. However, it has limitations as it does not account for variability in time series data, making it less suitable for analyzing extreme events and assessing the impacts of climate change (Nguyen et al., 2016).

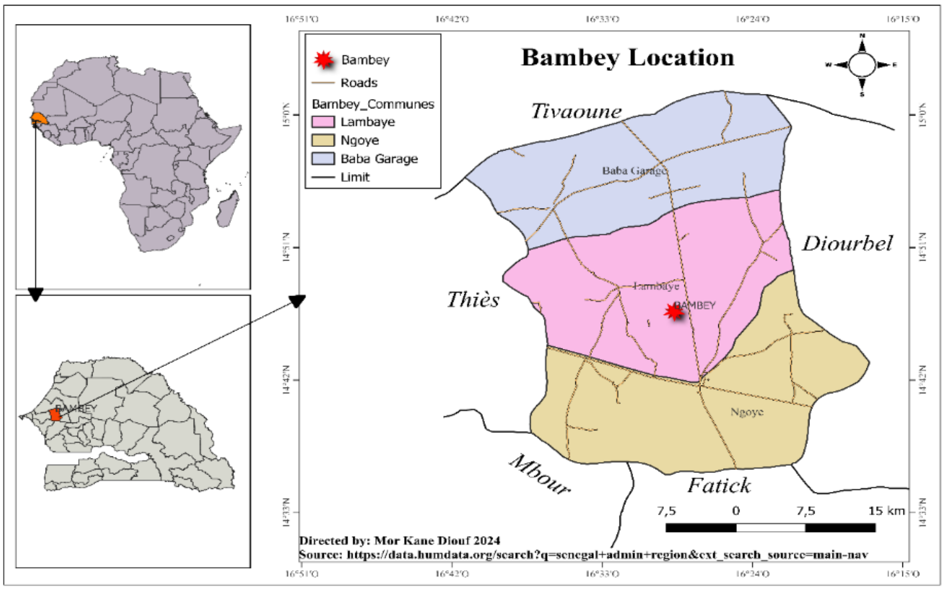
Distribution-Based Bias Correction: Distribution-based approaches, such as quantile mapping, focus on adjusting the entire distribution of model output data to match that of observed data at a specific time scale. While this method addresses distribution properties, it may only consider a single specified time scale, potentially overlooking changes over time (Nguyen et al., 2016).

Distribution and Persistence-Based Bias Correction: Techniques like nesting bias correction (NBC) and Recursive Nested Bias Correction (RNBC) fall under this category. They aim to simultaneously correct biases at multiple time scales while considering distributional and persistence characteristics in the data. This approach provides a more comprehensive way to correct biases and can capture variations over time (Nguyen et al., 2016). These bias correction techniques come in a variety, and they exhibit different performances when adjusting the biases in the GCM simulation and the observed data.

3. METHODOLOGY

3.1 Study Area

The study was carried out in Bambey department located at 120 km from Dakar, the Senegal capital city, at 14°42 latitude North and 16°28 longitude West, at an altitude of 17m. Bambey is at the heart of the former Groundnut Basin and covers an area of 1,357 km2. It is bordered to the north by the Tivaouane department, the east by Diourbel, the west by Thies, the south-west by Mbour and the south by the Fatick department.



Directed by: Mor Kane Diouf 2024
Source: https://data.humdata.org/search?q=senegal+admin+region&ext_search_source=main-nav

Figure 3: location map of Bambey (source: DIOUF, 2025)

The area's climate is of the Sudano-Sahelian type, hot and dry. The department of Bambey is located between the 300 and 600 mm isohyets, the distribution of rainfall is generally uneven and irregularly characterized by a long alternating dry season from October to June and a rainy season from July to October (Mane et al., 2021). The rainy season in the area is uni-modal, mainly occurring over a duration of three to four months from June to September, with August receiving the highest amounts of rainfall. Following a prolonged period of drought, precipitation has become more abundant, with average levels ranging between 400 mm and 500 mm. However, the rainy season is still characterized by late onset, occasional early arrivals, and uneven distribution across the region.

Temperatures vary annually from an average of 21 to 38 °C. During the cold season (November-February), temperatures are relatively low, ranging from 18 to 24 °C. In contrast, during the dry and hot season (March-May), maximum temperatures range from 34 to 40 °C. Furthermore, maximum solar radiation happens from March to April, reaching up to 25 MJ m^2 per day, while the minimum solar radiation values are found from November to December, with a low of 14 MJ m^2 per day. Additionally, the average relative humidity of the atmosphere is low during the dry season; however, it rises during the rainy season, fluctuating between 70 to 80% (Faye, 2018; Civil, 2022). The area is also influenced by strong prevailing winds, such as the continental trade winds, the harmattan, and the monsoon.

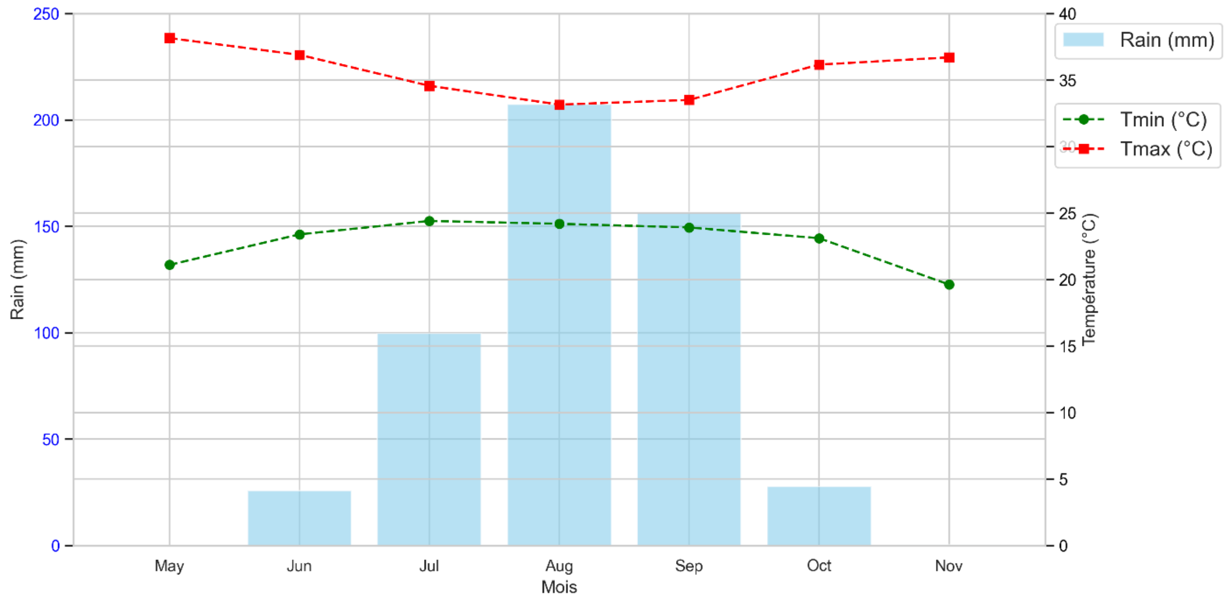


Figure 4: Monthly Averages of Precipitation and Temperature (May to November, 1981-2023) (source: DIOUF, 2025)

Regarding soil composition, Bambey contains three main types based on the average percentages of silt and clay present in the upper 40 cm layers. These comprise tropical ferruginous soils, often called "Dior soils," which are very sandy (with clay and silt representing less than 12%), as well as leached tropical ferruginous soils referred to as "Deck-Dior soils," which incorporate slightly more clay (with clay and silt varying from 12% to 15%) (Faye, 2018).

3.2 Data Collection and Preparation

3.2.1 Observed Climate Data

The historical climate data, which includes rainfall, temperature, and solar radiation, was collected from the meteorological stations of the Senegalese Institute of Agricultural Research (ISRA) covering the years from 1984 to 2023. This dataset plays a crucial role in calibrating and validating the Decision Support System for Agrotechnology Transfer (DSSAT) crop model, guaranteeing compatibility with recorded environmental conditions.

3.2.2 Soil Data

Soil data were collected from the Senegalese Institute of Agricultural Research (ISRA) and were complemented by soil analyses performed by Faye (2018) (figure2). This data consists of laboratory analyses of the soil's physicochemical properties, which were used to estimate values at different depths relevant to the effective rooting zone of peanuts some parameters such as Lower Limit (LL), Drained Upper Limit (DUL), and Saturated (SAT) moisture content that are critical for properly simulating peanut growth within the DSSAT framework.

3.2.3 Crop Experimental Data

Experimental data from the rainy and dry seasons of 2014 and 2015, collected in two (2) experimental sites (Bambey and Nioro), were obtained from the Senegalese Agricultural Research Institute (ISRA) and from Faye in 2018. This dataset contains all relevant information regarding management practices, such as sowing dates, harvesting dates, quantities and dates of fertilizers application, dates and amounts of irrigation, and planting density. These specifics are vital for comprehending crop management strategies and their influence on yield results.

3.2.4 Future and Projected Climate Data

Daily future weather information was obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) to evaluate the dynamics of peanut production in the future, considering various management practices. After a thorough review of the current literature, we have chosen four (4) Global Circulation Models (GCMs) that showed the strongest correlation with historical data pertinent to our research area. These models have been used in previous studies conducted by researchers in the area (Fall et al., 2023). The selected GCMs, include prominent models such as MRI-ESM2-0, MRI-JAPON, IPSL and CBRM-CM6-1. For projections concerning climate change and crop yield assessments, we investigated two different Shared Socioeconomic Pathways (SSPs): SSP2 and SSP5.

3.3 Methodology

3.3.1 Data Processing and Analysis

3.3.1.1 Downscaling and Bias Correction Methods

Global Circulation Models (GCMs) have limitations in their ability to accurately represent sub-grid scale climate because of their coarse grid resolutions. For local scale agronomic studies, climate data with finer resolutions is crucial. To resolve the scale mismatch between GCM outputs and localized data needs, we applied downscaling techniques. This research used statistical downscaling because of its benefits, including high spatial resolution, a broad range of emission scenarios, and cost efficiency (Klutse et al., 2018). Specifically, the CMhyd tool was used to downscale extensive climate variables produced from the CMIP6 model for historical times, as well as for SSP2-4. 5 and SSP5-8. 5 scenarios (Hordofa et al., 2022).

To further improve the accuracy of GCM outputs prior to their incorporation into the crop model, bias correction techniques were applied to reduce any biases or inaccuracies. The CMhyd tool offers eight bias correction methods, which include linear scaling, delta change correction, precipitation local intensity scaling, power transformation of precipitation, variance scaling of temperature, and distribution mapping of precipitation and temperature. In this investigation, distribution mapping was chosen because of its superior performance compared to other techniques in prior studies (Hordofa et al., 2022). The main aim of bias correction is to enhance the reliability and accuracy of GCM data, thus making it more appropriate for crop modeling and impact assessment.

3.3.1.2 Multi-Model Ensemble Climate Projection

The multi-model ensemble technique utilized the arithmetic mean method to compute the ensemble mean more than one GCM. This method was chosen due to its ease of use and established effectiveness in previous climate change research (Garcia, 2015). Before proceeding with the multi-model mean ensemble, a rigorous evaluation process was conducted involving four general circulation models (GCMs) used by Fall et al (2023) in a study on climate change in Senegal. For this study, two of these 4 models namely CNRM-ESM2-1 and CBRM-CM6-1were selected based on their demonstrated ability to correlate with the climate of the study area. The bias correction results for these models, as well as their performance measures, in particular their correlation with observed data in Bambey according to the Pearson coefficient, are shown in appendices 1.

$$r = \frac{\sum(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(X_I - \overline{X})^2} \cdot \sqrt{\sum(Y_I - \overline{Y})^2}}$$

Where:

X_i and Y_i are the observed and simulated values of rainfall, respectively.

$\overline{X}$ and $\overline{Y}$ are the averages of the observed and simulated values, respectively

3.3.1.3 Rainfall and Temperature Trend Analysis

The main methods for analyzing time series data, especially concerning climate change, involve trend analysis. Previous research has shown that the non-parametric Mann-Kendall test is among the most commonly used techniques for evaluating trends in temperature and precipitation data (Kamal and Pachauri, 2018; Aswad et al., 2020). In this research, the Mann-Kendall test was used to determine if there are upward, downward, or no trends in temperature and rainfall for both historical and future periods in the study area. The formula used for this dataset is provided by the following equation:

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

Where:

n: numbers of data points

x_j and x_i are annual values in years j and i , $j > 1$

And Sign ($x_j – x_i$) calculated using the equation:

$$\mathrm{sign}\ (\mathrm{xj} - \mathrm{xi}) = \begin{cases} -1 \ \text{if} \left(\mathrm{x}_j - \mathrm{x}_i\right) < 0 \\ 0 \ \text{if} \left(x_j - x_i\right) = 0 \\ 1 \ \text{if} \left(x_j - \mathrm{x}_i\right) > 0 \end{cases}$$

3.3.2 DSSAT Model Setup, Calibration and Validation

3.3.2.1 Experimental data

Crop management information gathered from field trials carried out in Bambey and Nioro, in the dry season of 2015 and the rainy season of 2014, was used for the parameterization, calibration, and validation of the DSSAT model. The experimental information is described in details by (Faye, 2018). A total of four (4) field trials were implemented across these two locations, consisting of one trial in the dry season and another in the rainy season for each site (see Table 1). Each experimental plot had an area of 16 m² (4 m x 4 m), with a spacing of 50 cm between rows (inter-row) and 15 cm between plants in rows (intra-row). Sowing was conducted manually at a depth of approximately 4 cm. The peanut cultivars selected for this study included Fleur 11 (V1), a Spanish-type variety known for early maturity (90 days), and 73-33 (V2), a Virginia-type variety recognized for medium maturity (110 days). Composite fertilizer (6-20-10) was applied immediately after planting at a rate of 150 kg/ha, following the guidelines set by the National Agricultural Research Institute of Senegal (see Table 1). During the dry season, irrigation was managed at a level where field capacity was maintained, ensuring that the plants experienced no water stress. The Bambey dataset from the rainy season of 2014 and the dry season of 2015 was utilized for model calibration, while the Nioro dataset from the same seasons served for model evaluation. Consequently, a total of 24 simulation units (USMs) were developed, each capable of being executed independently. Each USM integrates all necessary input data related to plant, soil, climate, and cultivation techniques for the model.

Table 1 :Summary of the treatments in the seven field experiments

Sites	Seasons	Irrigation Level	Fertilizer levels	varieties
Bambey	Rainy season 2014	no irrigation	T0, T1, T2 and T3	V1 and V2
Nioro				
Bambey	Dry season 2015	E	T0 and T1	V1 and V2
Nioro				

3.3.2.2 Climate data

Daily records of solar radiation, minimum and maximum temperature, precipitation and wind speed collected were prepared in Microsoft Excel 2021, transformed into a text file and subsequently input into DSST for model simulation.

Future projections of daily rainfall, along with minimum and maximum temperatures for the basin, were obtained from the mean ensemble models for the period of 2021 to 2080 under SSP2 and SSP5 scenarios. These datasets were previously processed in Python and Microsoft Excel before being input into DSSAT. The climate datasets were categorized into two timeframes: near future (2021–2050) and mid-term future (2051–2080).

3.3.2.3 Soil

A comprehensive soil file was prepared to detail various soil characteristics. This file includes key parameters such as texture information, bulk density, organic carbon percentage, and nitrogen percentage, as illustrated in (Figure 1 and 2). These values were derived from laboratory analyses of the soil's physicochemical properties, conducted at multiple depths to encompass all layers accessible to peanut roots. The initial input of this soil file into DSSAT facilitated the estimation of critical soil water-holding characteristics required by the model, including drained upper limit (DUL), lower limit (LL), saturation (SAT), and runoff etc. Following this, the estimated characteristics were further refined to enhance their specificity to the experimental site, in accordance with the methodology outlined by Singh et al. (1994).

Table 2 : Soil analysis in 2014 (Faye, 2018)

Localities	horizon	pH	C	N	K	P	CEC	A	L	S	bd
Bambey	0-10	6.3	0.16	0.015	0.139	45.08	3.39	2.82	1.53	94.95	1.48
	20-Oct	5.8	0.144	0.024	0.119	40.71	2.67	3.77	1.7	92.7	1.48
	20-30	5.8	0.128	0.024	0.112	39.83	2.9	5.07	1.63	91.8	1.47
	30-40	5.8	0.152	0.02	0.119	36.33	3.36	6.15	1.72	91.15	1.57
	40-50	5.8	0.256	0.039	0.125	26.26	3.59	6.95	1.77	89.85	1.44
	50-60	5.7	0.088	0.015	0.119	24.95	3.36	7.17	1.65	89.7	1.44
	60-70	5.6	0.128	0.015	0.134	20.13	4.3	6.45	2.22	91.5	1.35
	70-80	5.7	0.056	0.01	0.115	18.82	4.79	6.22	2.63	91.05	1.38
	80-90	5.8	0.08	0.015	0.108	18.38	4.45	6.07	2.03	90.35	1.31
	90-100	5.9	0.088	0.015	0.112	18.82	4.41	5.92	1.25	87.6	1.44
Niorro	0-10	6.2	0.487	0.049	0.183	37.2	3.51	4.45	4.32	92.8	1.4
	20-Oct	5.1	0.447	0.029	0.139	23.64	5.3	3.24	9.73	88.65	1.4
	20-30	5.1	0.383	0.024	0.104	16.19	4.76	3.43	10.3	86.45	1.47
	30-40	5.6	0.359	0.02	0.113	10.94	3.31	3.06	9.21	86.6	1.43
	40-50	5.6	0.335	0.015	0.114	10.07	2.67	4.01	12	84.25	1.41
	50-60	5.6	0.211	0.01	0.125	7.44	3.59	4.63	13.9	80.7	1.35
	60-70	5.7	0.208	0.015	0.125	6.13	4.05	18.4	3.58	77.55	1.24
	70-80	5.8	0.192	0.015	0.147	5.25	4.51	21.4	4.12	74	1.2
	80-90	5.9	0.207	0.01	0.135	7	4.55	14.8	11	73.05	1.17
	90-100	6	0.168	0.029	0.154	5.25	4.88	23.9	4.25	72.5	1.15

Table 3: Soil analysis in 2015 (Faye, 2018)

Localities	horizon	pH	C	N	K	P	CEC	A	L	S
Bambey	0-10	7.9	0.156	0.269	0.014	0.012	0.04	8	4	17.14
	20-Oct	7.8	0.293	0.504	0.028	0.02	0.04	9	5.75	15.07
	20-30	7.7	0.215	0.37	0.014	0.016	0.13	9	7	15
	30-40	6.9	0.312	0.538	0.028	0.02	7.68	10	6.25	19.74
	40-50	6.6	0.273	0.471	0.028	0.012	6.53	18	9.25	20.72
	50-60	6.6	0.351	0.605	0.028	0.008	3.33	19	10.3	48.26
	60-70	6.3	0.234	0.403	0.028	0.04	2.99	20	11	32.43
	70-80	6.1	0.176	0.303	0.014	0.02	1.79	22	10.5	34.56
	80-90	6.3	0.195	0.336	0.014	0.016	1.75	20	14.5	27.11
	90-100	6.2	0.195	0.336	0.014	0.012	1.92	21	15.8	26.21
Nioro	0-10	5.8	0.488	0.84	0.042	0.016	15	24	5.5	25.545
	20-Oct	5	0.371	0.639	0.028	0.02	10	33	8.5	28.58
	20-30	4.8	0.234	0.403	0.014	0.02	11	34	10.3	31.705
	30-40	4.9	0.429	0.74	0.042	0.016	5	34	11	24.915
	40-50	5.1	0.215	0.37	0.014	0.012	2	31	9.5	29.585
	50-60	5	0.234	0.403	0.028	0.008	2	34	9.25	26.51
	60-70	5.4	0.244	0.42	0.028	0.04	2	30	12	29.905
	70-80	5.5	0.254	0.437	0.028	0.02	1	29	19.3	14.11
	80-90	5.8	0.215	0.37	0.014	0.016	1	27	15	28.36
	90-100	6	0.205	0.353	0.014	0.012	1	26	16.5	27.12

3.3.2.4 Calibration of Genetic Coefficients for CROPGRO-Peanut Model

The CROPGRO-peanut model requires specific genetic coefficients that define the duration of various phases in the crop life cycle, as well as vegetative and reproductive traits unique to each cultivar (Boote et al., 1998). In this study, the peanut cultivars Fleur 11 (V1) and 73-33 (V2) had not been previously calibrated within the DSSAT framework, to the best of our knowledge. Due to the absence of genetic coefficients for these specific cultivars, the calibration process commenced with the reference cultivars Spanish and Virginia 897, which served as benchmarks for Fleur 11 and 73-33, respectively.

The determination of genetic coefficients (Table 2) was accomplished through an iterative model simulation process, utilizing data collected from Bambey in 2014 and 2015, as described by Boote et al. (1999) and Naab et al. (2004). This approach facilitated the refinement of model parameters to accurately reflect the specific traits of the cultivars under investigation. The process involved the careful selection of a limited number of coefficients that significantly influence the necessary adjustments for estimating target variables (Ahmed et al., 2020).

As outlined by Ahmed et al. (2020), the calibration process was executed through a multi-step simulation. The initial step involved running the model with reference crop parameters and comparing the simulation results with the observed dataset, particularly focusing on potential yield. Subsequently, crop parameters were adjusted using the Generalized Likelihood Uncertainty Estimation (GLUE) coefficient estimator and sensitivity analysis tools integrated within DSSAT version 4.8.2. This methodology ensured a robust alignment between the simulated and observed values, enhancing the accuracy of the model. Therefore, parameters such as LAI, Tops weight and grains yield was used for model calibration

Table 4 : Genetic coefficient of peanut cultivars calibrated in DSSAT (Fleur 11 and 73-33).

Coefficients	Definition	Value Fleur 11	Value 73-33
CSDL	Critical short-day length below which reproductive development progresses with no day length effect (h)	11.84	11.84
PP-SEN	Slope of the relative response of development to photoperiod with time Phenology (h-1)	0	0
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	23.31	22
FL-SH	Time between first flower and first peg (R2) (photothermal days)	7	6.6
FL-SD	Time between first flower and first seed (R5) (photothermal days)	15	20

SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	55.65	60
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	65	80
LFMAX	Maximum leaf photosynthesic rate at 30°C, 350 vpm CO2, and high light (mg CO2/m-2s-1)	1.22	1.2
SLAVR	Specific leaf area under standard growth conditions (cm2g-1)	250.6	250
SIZLF	Maximum size of full leaf (three leaflets) (cm2)	20	15
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.996	0.96
WTPSD	Maximum weight per seed (g)	0.76	0.86
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	29.56	26
SDPDV	Average seed per pod under standard growing conditions (Numbers per pod)	1.906	1.65
PODUR	Time required to reach final pod load under optimal conditions Growth (photothermal days)	11	10
THRSH	The maximum ratio of (seed/(seed+shell)) at maturity	82	82
SDPRO	Fraction protein in seeds (g(protein)/g(seed))	0.27	0.27
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.51	0.51

3.3.3 Model evaluation

The calibrated model was assessed by comparing the measured and predicted data to evaluate the reliability and accuracy of calibrated genetic coefficients. The model was run with dataset from Nioro to test the performance of genetic coefficients. The performance of the model, once calibrated by the Bambey data, was assessed on the Nioro dataset using the following statistical indicators:

Root Mean Square Error (RMSE) is used to estimate the magnitude of the model error and its relative value (rRMSE) in %. A low rRMSE value is a good indicator of the model's ability to predict the measured values (Faye, 2018, civil, 2022).

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} (Y_I - X_i)^{\ 2}}$$

$$\mathrm{rRMSE} = \frac{\mathrm{RMSE}}{\overline{\mathrm{X}}} \times 100$$

The Index of Agreement (d) measures the accuracy of model predictions by comparing observed and simulated values. It ranges from 0 to 1, where 1 indicates perfect agreement.

$$\mathrm{d} = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} (Y_i - P_i)^2}{\sum_{\mathrm{i}=1}^{\mathrm{n}}(|P_i - \overline{\mathrm{Y}}| + |Y_i - \overline{\mathrm{Y}}|)^2}$$

where n is the number of observations, Y_i is the observed value for the measurement; P_i is the corresponding predicted value and $\overline{Y}$ is the mean of the observed values.

3.3.4 Simulation Setup

Model Simulations for Climate Change Analysis under Different Crop Management Practices

To assess the effects of climate change on peanut cultivation under different crop management strategies, this study utilized historical meteorological data and downscaled future climate projections to analyze yield variations under different climate scenarios.

a. Yield Changes of Two Peanut Varieties under Different Climate Scenarios

Simulations for this section were performed under rainfed conditions in Bambey, utilizing the recommended fertilizer application rate (T3) for the two peanut varieties: Fleur 11, a medium-cycle variety, and 73-33, a long-cycle variety. Atmospheric CO_2 concentrations were set in accordance with the Mauna Loa records. A comparative analysis was performed by contrasting the average yields of the two peanut varieties during the reference period (1981–2010) with the simulated yields under the SSP2 and SSP5 scenarios for the near future (2021–2050) and the mid-term future (2051–2080). Yield variations were quantified by calculating the differences between the simulated future potential yields and those of the reference period. The reference period yields served as the baseline for estimating future yield deviations. The percentage change in yield relative to the reference period was computed using the following formula:

$$\text{Percentage Change in Yield} = \left(\frac{\text{Future Yield} - \text{Reference Yield}}{\text{Reference Yield}}\right) \times 100$$

This methodology facilitated a comprehensive assessment of the potential impacts of climate change on peanut yields, offering insights into the adaptability of different peanut varieties under evolving climatic conditions.

b. Yield Changes Based on Optimal Sowing Dates under Future Climate Scenarios

Following the FAO (1980) guidelines, the onset of the planting season was determined as the week when long-term weekly rainfall equals or exceeds 50% of the weekly reference evapotranspiration. The optimal planting date was identified using a simulation model that evaluated yield and yield variability across seven planting date treatments (01-Jun, 10-Jun, 20-Jun, 30-Jun, 10-Jul, 20-Jul, 30-Jul, and 10-Aug) under future climate scenarios. The optimal planting date was defined as the date that maximizes long-term average yield while minimizing yield variability (Araya et al., 2021).

After identifying the optimal sowing date, the peanut grain yield based on this optimal date was compared with the yield based on the current planting date used in the study (06-Aug) to quantify the yield changes. This adaptation strategy was tested exclusively for the medium-cycle variety (Fleur 11) under rainfed conditions. This approach aimed to assess the potential benefits of adjusting sowing dates as a climate adaptation strategy for peanut cultivation.

4. RESULTS AND DISCUSSION

4.1 RESULTS

4.1.1 Model evaluation

4.1.1.1 Comparison Between Simulated and Observed Leaf Area Index Values

The dataset from Bambey during the rainy season of 2014 and the dry season of 2015 was utilized for calibration, while data from Nioro during the same period were employed for validation. Figure 5 illustrates the performance of the CROPGRO-Peanut model in simulating times series of the Leaf Area Index (LAI) for the peanut varieties Fleur 11 and 73-33 during both calibration and validation phases. The results demonstrate that the model exhibited a slight overestimation of LAI during the calibration phase and maintained a reasonable alignment with the observed LAI dynamics. In contrast, during the validation phase, the tendency of the model to overestimate LAI values became more pronounced, however, it continued to reflect the observed dynamics adequately.

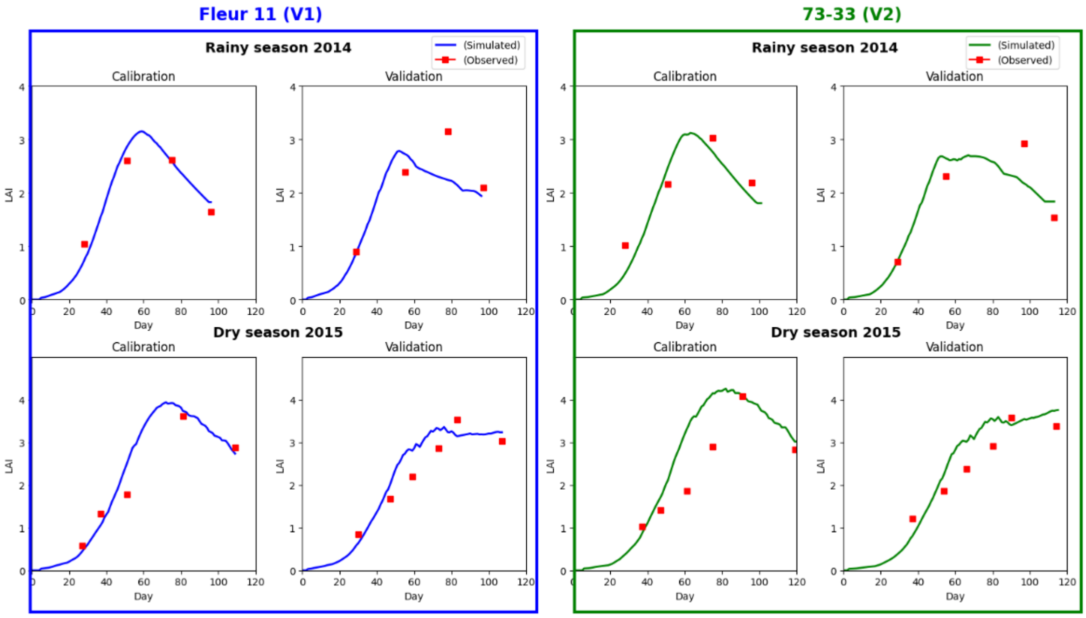


Figure 5: Comparison of simulated LAI with observed values during calibration and validation

4.1.1.2 Comparison Between Simulated and Observed Grains yield

Figure 6 illustrates the model's performance in simulating grain yield during both the calibration and validation phases. During calibration, the model accurately reproduces grain yield values for both the Fleur 11 and 73-33 varieties, with (rRMSE) of 17.08% and 15.59% respectively and a high degree of agreement (d-index) of 0.96 for Fleur 11 and 0.98 for 73-33. Additionally, the model effectively captures the notable differences between rainfed and irrigated yields within the study area of Bambey. The difference is likely attributable to the early cessation of the rainy season in 2014 at Bambey, highlighting the strong predictive capability of the model under Sahelian conditions using an independent dataset. Similarly, the outputs of the model during validation show a strong agreement with observed values, with rRMSE of 4.27% for Fleur 11 and 7.60% for 73-33. The model also achieved a high degree of agreement (d = 0.97) for Fleur 11, while demonstrating a moderate degree of agreement (d-index = 0.60) for 73-33. These results underscore the robustness of the model in predicting grain yields.

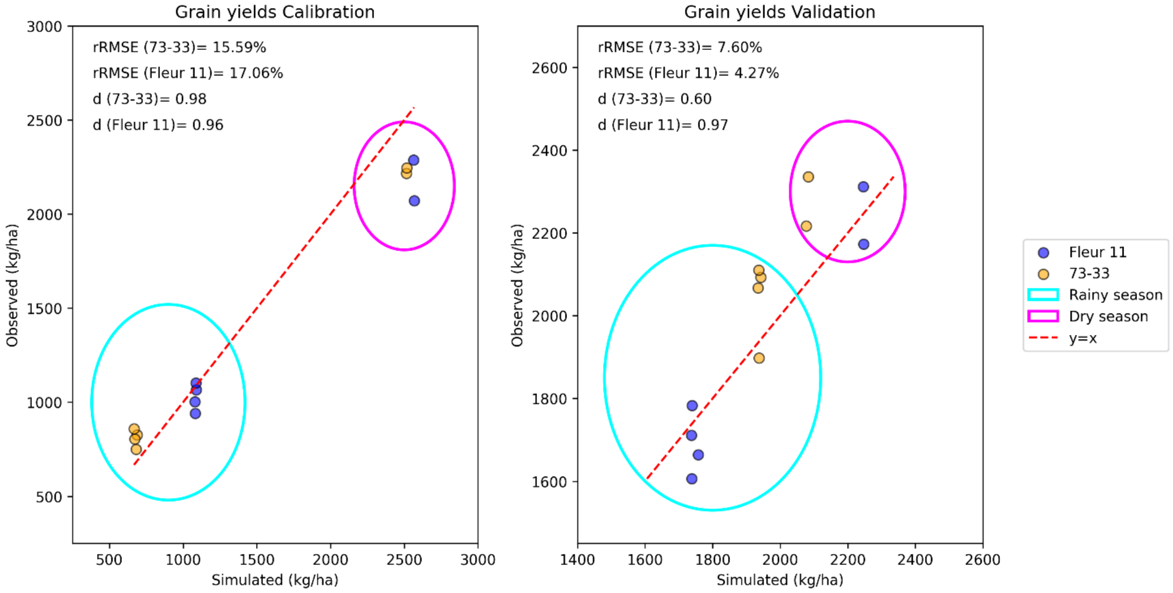


Figure 6: Model performance for simulating grain yield during calibration and validation

4.1.1.3 Comparison Between Simulated and Observed Biomass

The performance of the DSSAT model in simulating biomass for the peanut varieties Fleur 11 and 73-33 during both calibration and validation phases is depicted in Figure 7. For the variety 73-33, the model exhibited moderate performance during both calibration and validation phases, as indicated by the rRMSE values of 29.10% and 29.93%, respectively. Additionally, a high level of agreement was observed, with the index of agreement (d) values of 0.94 for calibration and 0.90 for validation, suggesting that the simulations are reliable. In contrast, the calibration results for Fleur 11 showed a higher rRMSE (47.40%) and moderate agreement (d = 0.85). During the validation phase, the model performed better in simulating biomass for the Fleur 11 variety, with an rRMSE of 29.41% and an agreement index (d) of 0.84, indicating the reliability of the model. However, a notable overestimation of the biomass for both varieties was highlighted by the results in the both calibration and validation during rainy season.

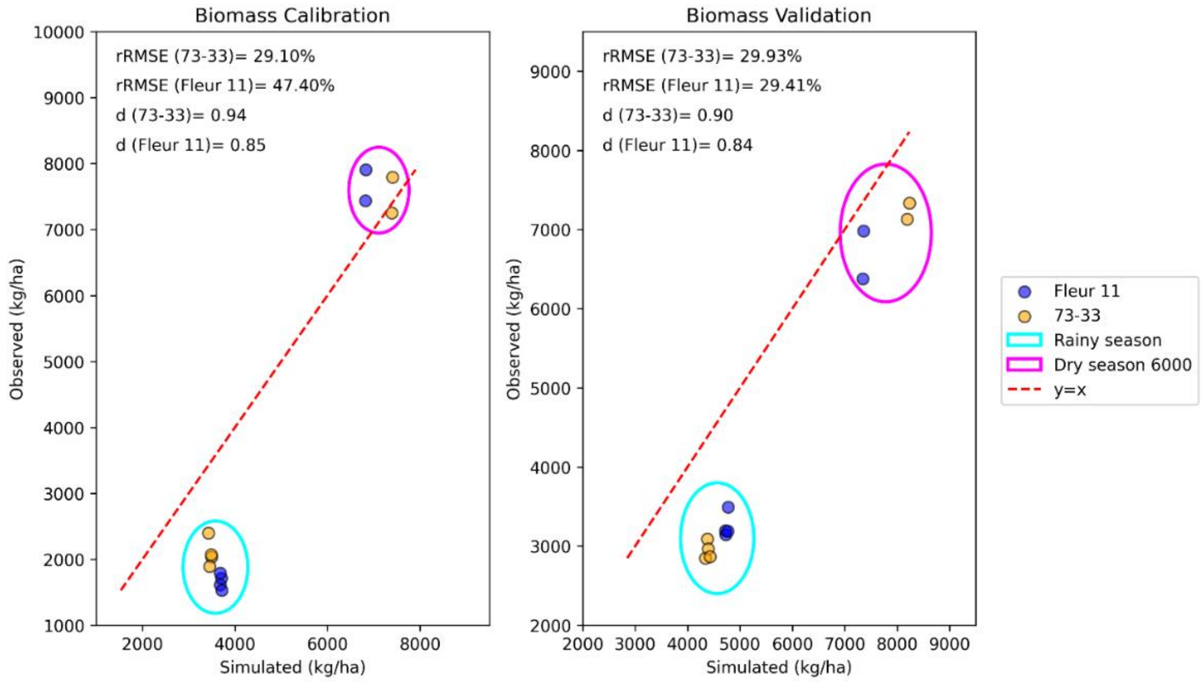


Figure 7: Model performance for simulating biomass yield during calibration and validation

4.1.2 Climate change analysis

4.1.2.1 Multi-Model Ensemble Climate projection

Figure 8 illustrates a comparative analysis of simulated and observed historical data for mean monthly rainfall, maximum temperature (Tmax), and minimum temperature (Tmin) in Bambey region, covering the period from 1981 to 2014. The results reveal a significant correlation between simulated and observed historical climate data. While the ensemble model occasionally overestimates and underestimates specific peaks in rainfall, maximal temperature, and minimal temperature for certain years, it effectively captures the overall dynamics of precipitation and temperature trends. This is evidenced by high Pearson correlation coefficients: 0.83 for rainfall, 0.80 for minimal temperature, and 0.94 for maximal temperature. These findings underscore the robustness of the multi-model ensemble approach in accurately representing the climatic patterns of the region. The bias-corrected data from the mean ensemble were subsequently employed for climate trend analysis and integrated into the DSSAT crop model to simulate peanut yields under projected climate change scenarios.

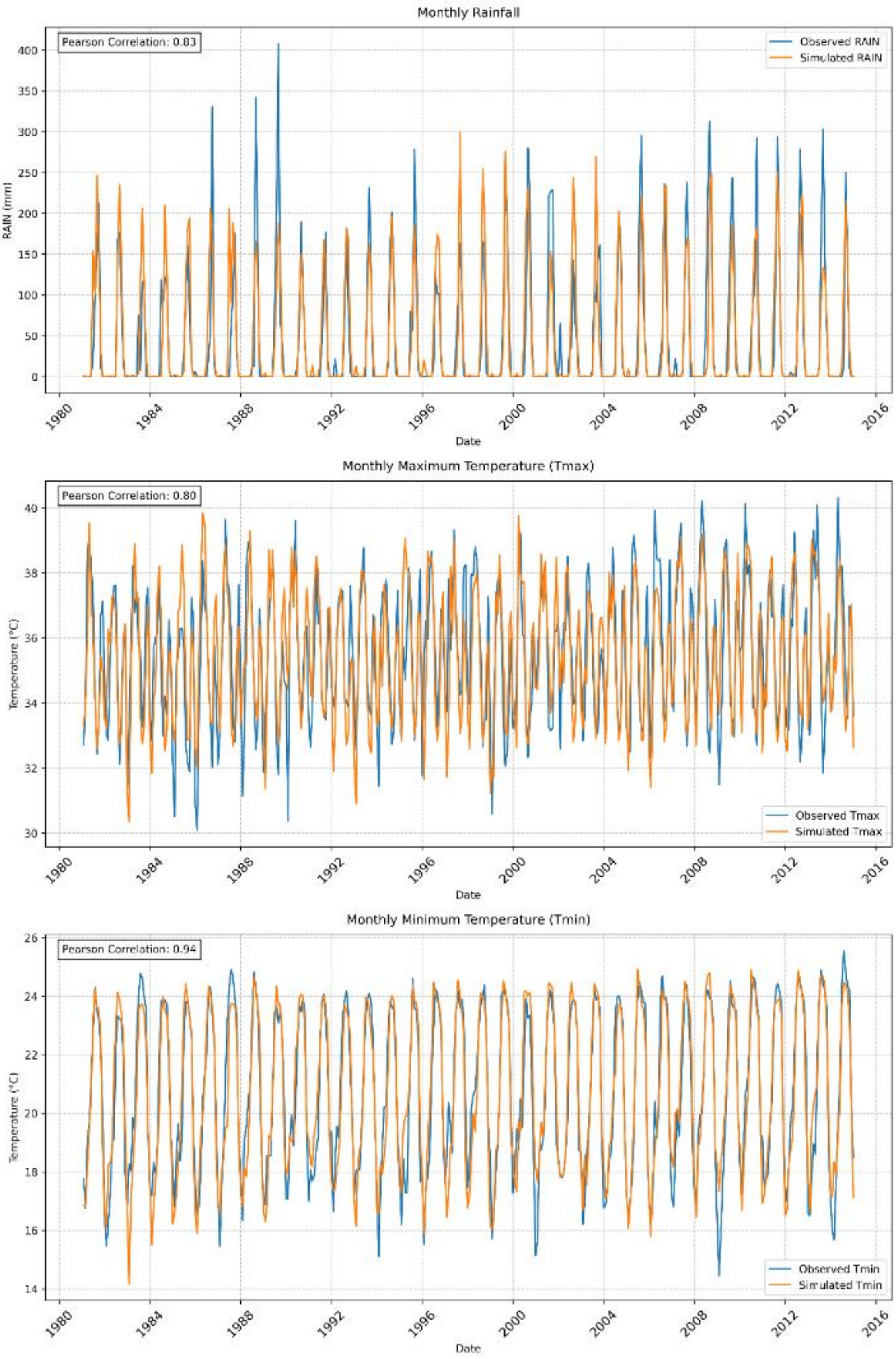


Figure 8: Comparison of the multi-model ensemble mean with observed historical rainfall, Tmax, and Tmin data in Bambey

4.1.2.2 Analysis of past and future climatic trends in Bambey, Senegal

4.1.2.2.1 Historical monthly temperature and rainfall trends

The figure 9 present the results of the Mann-Kendall test (Z-value), applied to analyze the historical average annual and monthly trends in rainfall, maximum temperature, and minimum temperature. These results provide insights into the temporal changes in these climatic variables.

The Mann-Kendall trend analysis reveals significant upward annual trends in both maximum temperature (Tmax) and minimum temperature (Tmin), with Z-values exceeding 1.96 (at $\alpha = 0.05$), underscoring a clear trend toward climatic warming. In contrast, annual rainfall exhibits no statistically significant trend, indicating relative stability in total precipitation over time. At the monthly scale, the trend analysis reveals considerable variability across different months. For both maximum temperature (Tmax) and minimum temperature (Tmin), a statistically significant upward trend is observed throughout the rainy season. However, an exception is noted for Tmax in June, which coincides with the onset of the rainy period in Bambey and does not show a significant trend. In terms of rainfall, monthly trends indicate that August, the wettest month, is the only period showing a statistically significant decreasing trend in precipitation (Z-value < -1.96 at $\alpha = 0.05$). For the remaining months of the rainy season, no statistically significant decrease in rainfall trends is detected, as indicated by Z-values ranging between -1.96 and 0. This suggests a relative consistency in precipitation patterns during these months, reflecting a stable and predictable rainfall regime.

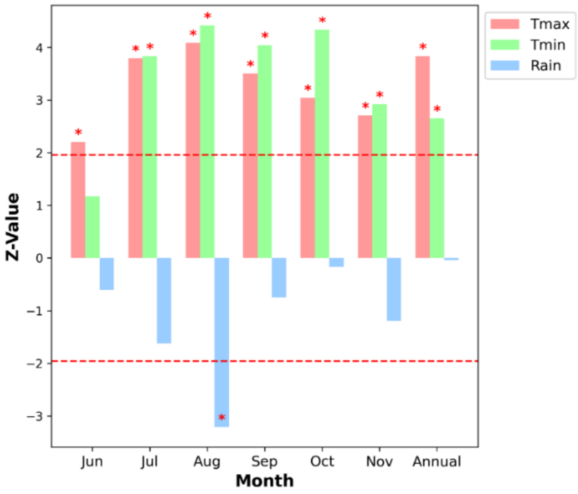


Figure 9: Trends in Precipitation and Temperature (Maximum and Minimum) According to the Mann-Kendall Test for The Baseline Period (1981-2024)

4.1.2.2.2 Future monthly temperature and rainfall trends

The results of the Mann-Kendall test applied to analyze of average annual and monthly trends of in rainfall, maximum temperature, and minimum temperature under the SSP2-4.5 scenario for both the near future (2025-2050) and the far future (2051-2090) are shown in Figure 10.

In terms of minimum temperature and maximum temperature, the trend analysis shows a significant increasing trend during the near future, both annually and throughout the rainy season months except for June, in respect with the baseline period. However, the far future presents a more complex scenario. While the annual maximum temperature trend continues to increase significantly (Z-value >1.96), the annual average minimum temperature shows no significant trend. On a monthly scale, a notable shift is observed during certain months of the rainy season, where both maximum and minimum temperatures show a slower rate of increase compared to the near future. This shift in trends is especially more pronounced for the monthly maximum temperature, suggesting potential seasonal changes in climate dynamics. Regarding rainfall, the analysis reveals a relative stabilization in precipitation trends, as evidenced by the absence of statistically significant trends over time, both on an annual and monthly basis, across the near and far future periods. This conclusion is supported by Z-values ranging between 0 and -1.96. However, an exception to this trend is observed in August during the near future, which exhibits a statistically significant decreasing trend in rainfall (Z-value < -1.96).

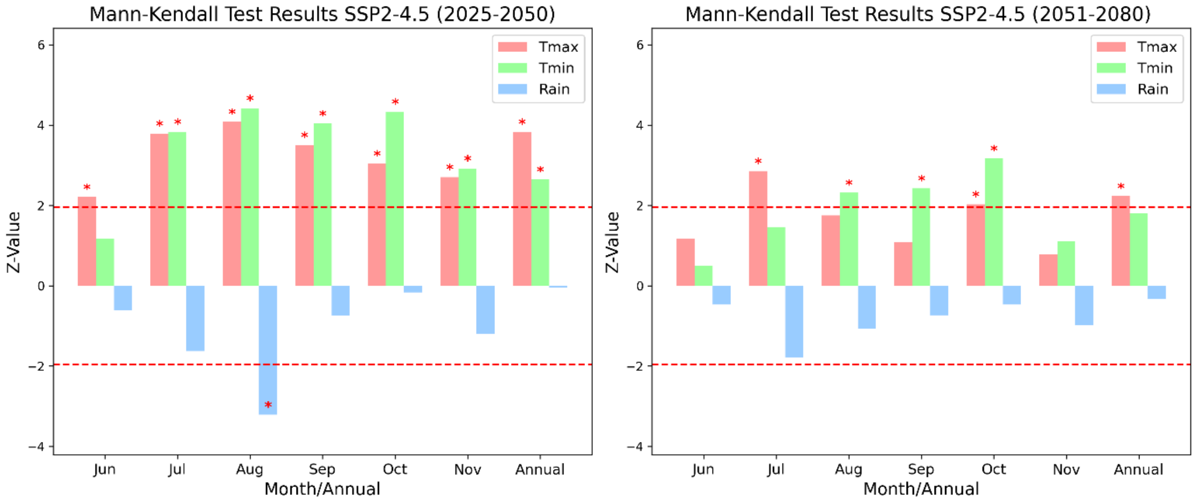


Figure 10: Trends in Precipitation and Temperature (Maximum and Minimum) According to the Mann-Kendall Test for Near future (2025-2050) and Mid-Term Future (2051-2090) (SSP2-4.5 scenario)

4.1.2.2.3 Future monthly temperature and rainfall trends

The results of the Mann-Kendall test applied to analyze of average annual and monthly trends of in rainfall, maximum temperature, and minimum temperature under the SSP5-8.5 scenario for both the near future (2025-2050) and the far future (2051-2090) are illustrated in Figure 11. The Mann-Kendall analysis of maximum and minimum temperatures reveals a significant increasing trend, observed annually and monthly throughout the rainy season for both the near future and the mid-term future under the high-emission scenario. In the mid-term future, this warming trend will be more pronounced, suggesting an ongoing rise in temperatures. The results of the Mann-Kendall test, applied to analyze trends in average annual and monthly rainfall, maximum temperature, and minimum temperature under the SSP5-8.5 scenario for both the near future (2025–2050) and the far future (2051–2090), are presented in Figure 11. The analysis reveals a statistically significant increasing trend in both maximum and minimum temperatures, observed on an annual basis as well as monthly throughout the rainy season, for both the near and far future periods under this high-emission scenario. This warming trend is projected to intensify further in the far future, indicating a continued rise in temperatures over time. In contrast, precipitation trends show a non-significant decrease across both future periods. However, August, emerges as an exception, exhibiting a statistically significant decline in rainfall, particularly in the far future. This deviation highlights a notable shift in precipitation patterns during a critical period of the rainy season.

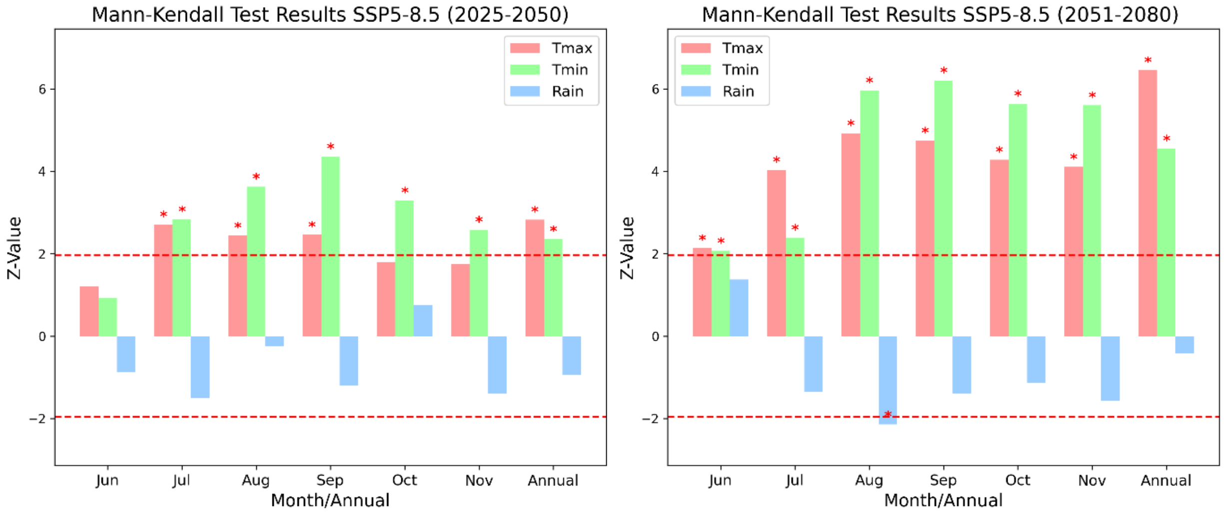


Figure 11: Trends in Precipitation and Temperature (Maximum and Minimum) According to the Mann-Kendall Test for Near future (2025-2050) and Mid-Term Future (2051-2090) (SSP5-8.5 Scenario)

4.1.3 Yield Change of Two Peanut Varieties under Different Climate Scenarios

4.1.3.1 Biomass Yield Change

The projected average biomass yield of peanut varieties Fleur 11 and 73-33 in the near future under SSP2 and SSP5 scenarios shows a slight increase compared to the historical average for both varieties, as illustrated in Figure 12. Specifically, the biomass yield of the Fleur 11 variety is expected to increase by 3.2% and 3.4% under SSP2 and SSP5, respectively. Similarly, the yield of the 73-33 variety is projected to rise by 2.5% and 2.6% under SSP2 and SSP5, respectively. However, the rate of increase varies between varieties and across scenarios. The results indicate that Fleur 11, a medium-cycle variety, will achieve a higher biomass yield than the long-cycle variety, 73-33. Additionally, biomass yield under SSP5 is expected to be slightly higher than under SSP2.

Conversely, in the mid-term future, the average biomass yield of both peanut varieties is projected to decline under both scenarios (Figure 12). More specifically, the biomass yield of the Fleur 11 variety is expected to decrease by 3.2% and 5.3% under SSP2 and SSP5, respectively. Similarly, the yield of the 73-33 variety is projected to decline by 15.2% and 17.7% under SSP2 and SSP5, respectively. This reduction is expected to be more significant under the high-emission scenario (SSP5) compared to the sustainable emission scenario (SSP2). Furthermore, the early-maturing variety, Fleur 11, will continue to exhibit better performance than the long-cycle variety, 73-33, which is expected to experience a greater reduction in yield under both scenarios.

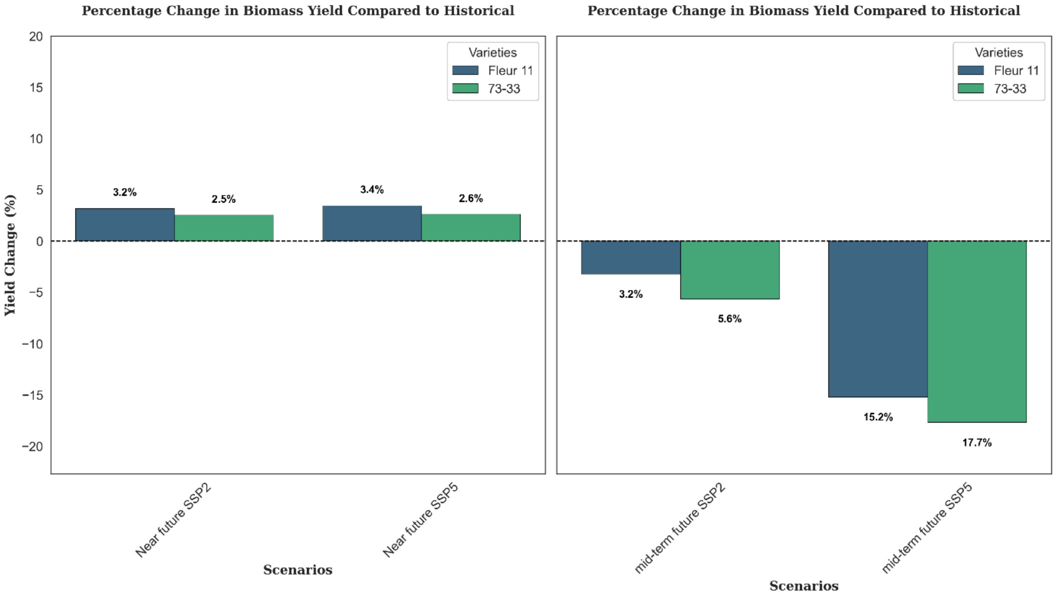


Figure 12: Projected Biomass Yield Change of Peanut from the Baseline Under SSP2 and SSP5 Scenarios for the Near and Mid-Term Future

4.1.3.2 Grain yields changes

Figure 13 presents the projected grain yield of two peanut varieties (Fleur 11 and 73-33) for the near and mid-term future under SSP2 and SSP5 scenarios. The projections indicate a decline in grain yield for both varieties, regardless of the scenario or time period considered. However, the long-cycle variety, 73-33, is expected to experience a more pronounced reduction than the medium-cycle variety, Fleur 11.

Furthermore, the decline is more significant in the far future than in the near future under both scenarios. Specifically, under SSP5, grain yield is projected to decrease by 44.3% for Fleur 11 and 48.9% for 73-33, while under SSP2, the reductions are 23.3% and 29.8%, respectively. In contrast, in the near future, the decrease remains relatively minor, with reductions across all scenarios and both varieties not exceeding 6%.

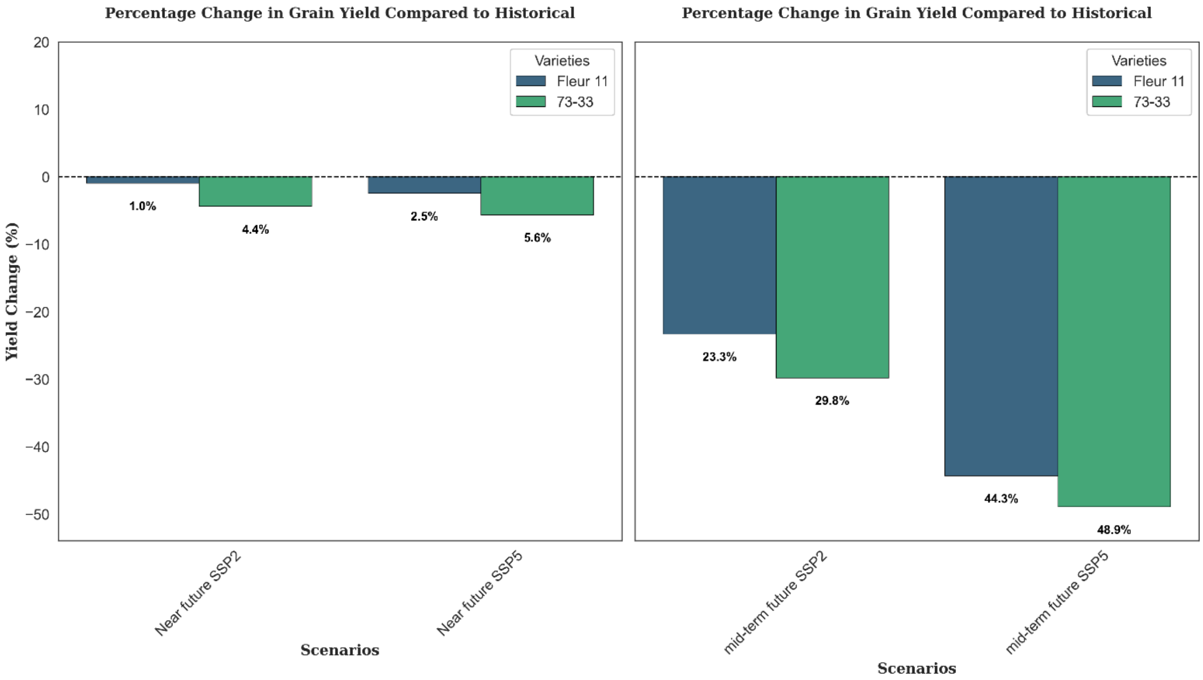


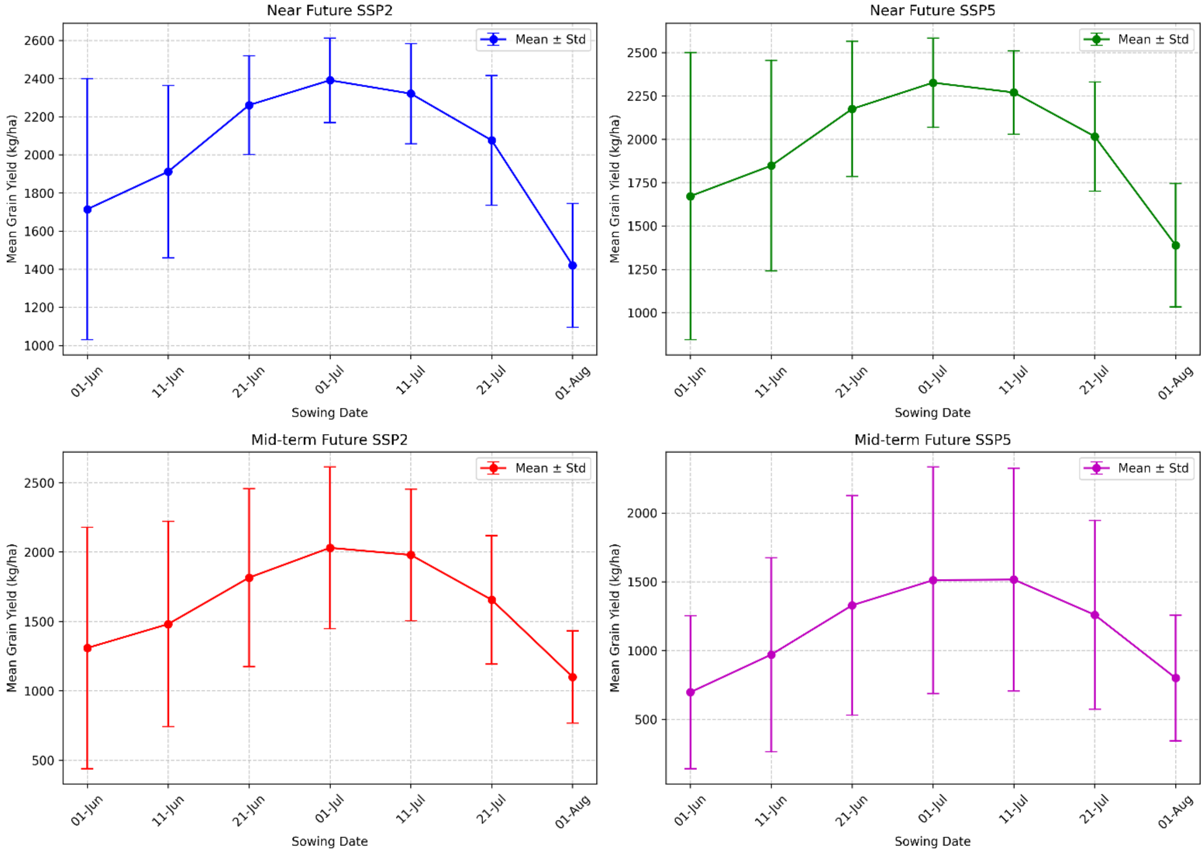
Figure 13: Projected Grain Yield Change of Peanut from the Baseline Under SSP2 and SSP5 Scenarios for the Near and Mid-Term Future

4.1.4 Yield Changes Based on Optimal Sowing Dates under Future Climate Scenarios

4.1.4.1 Screening optimal sowing date

Figure 14 illustrates the variation in average peanut yield across different future climate scenarios as a function of sowing dates. The results demonstrate that, for the near future, peanut yield is highest when the sowing date is set at the beginning of the second decade of July (11-July) for both the SSP2 and SSP5 scenarios. Furthermore, yield variability is significantly lower for this sowing date compared to others, indicating greater stability in production.

Similarly, in the mid-term future, this sowing date also displays higher yields. However, the beginning of the third decade of July shows even higher yields with less variability compared to other dates. Therefore, for the far future, the optimal sowing window lies between July 11 and July 21, providing the highest yields under both SSP2 and SSP5 scenarios.



Near Future SSP2

Near Future SSP5

Mid-term Future SSP2

Mid-term Future SSP5

Figure 14: Optimal Sowing Dates for Peanut Cultivation Under Future Climate Scenarios: Analysis of Mean Yield and Standard Deviation

4.1.4.2 Biomass and Grain yield change based on optimal sowing date

The figure 15 illustrates the changes in biomass and grain yield for future scenarios compared to the baseline period. For the future scenarios, the optimal sowing date identified in the previous section was applied, while the current sowing date (based on the 2014 experimental data during the rainy season) was used for the baseline period. The results indicate a notable increase in both biomass and grain yield across all future scenarios. However, the high-emission scenario in the mid-term future demonstrates a comparatively lower yield increase among all climate scenarios.

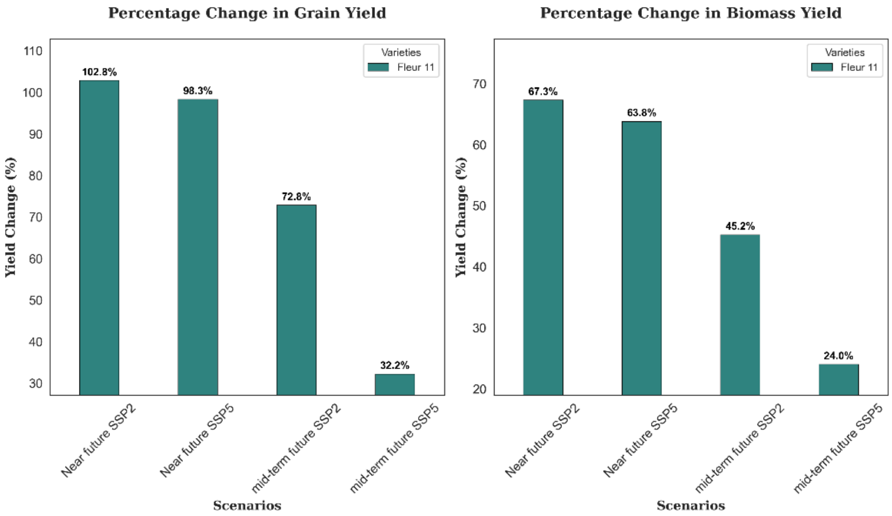


Figure 15: Projected Changes in Biomass and Grain Yields Using Optimal Sowing Dates Under Future Climate Scenarios

4.2 DISCUSSION

The first specific objective of this study was to calibrate the DSSAT model to simulate the growth and development of peanut varieties in Senegal. The process of the model evaluation showed the performance of the model to reproduce the observed values of the parameters used in the calibration and validation process, such as leaf area index (LAI), grain yield and biomass. Regarding LAI, although the model slightly underestimated the values for certain points at the end of the cycle, it adequately reproduced the growth dynamics. LAI is a difficult parameter to capture accurately by most of the crop models used in our study area, as demonstrated by the studies of Garcia (2015), Faye (2018) and Civil (2021), who used different types of models and recognized limitations in their performance to simulate accurately LAI values. Faye (2018) attempted to explain this by the fact that LAI is also related to leaf defoliation and the percentage of leaf area affected by diseases, aspects that are not simulated by the model. Garcia (2015), on the other hand, attributed these discrepancies not only to the limitations of the crop models, but also to measurement errors in the observed data, which can occur when conducting experiments. In contrast to LAI, the model simulated grain yield and biomass with a high agreement index (d-index) and low relative error (rRMSE). However, an overestimation of the model was noted during the 2014 rainy season in the Bambey experiment, which was part of the datasets used for calibration, resulting in a high rRMSE for the biomass simulation of the Fleur 11 variety. This overestimation was attributed to the late sowing and early cessation of rains observed during the 2014 experiment in Bambey. Naab et al (2015) attempted to explain the model's tendency to overestimate biomass by the late harvest, resulting in leaf and pod losses that are not accounted for by the model. Overall, the DSSAT model demonstrated a strong ability to predict grain yield and a moderate ability to simulate biomass, as shown by the rRMSE and d-index values presented in Figures 4 and 5. These results underline the effectiveness of the model for predicting groundnut crop performance under similar conditions, while highlighting areas where improvements are required for more accurate simulation of certain parameters, notably biomass and LAI.

As demonstrated by the Pearson correlation coefficient in Figure 8, the downscaling of data from General Circulation Models (GCMs), followed by bias correction and the application of a multi-model ensemble approach, have resulted in strong correlations between historical observations and projected historical climate data, particularly for rainfall patterns and temperature. These techniques, including statistical downscaling and multi-model ensemble methods, are crucial as they significantly reduce the discrepancies between model simulations and observed data. This finding is supported by Hosseinzadehtalaei et al. (2021) whose results indicate that the statistical downscaling approach effectively reduces bias in model simulations and provides robust scaling relationships. Furthermore, the importance of using multi-model ensembles for accurate climate projections and trend analysis has been emphasized by Samuel et al. (2023), highlighting their critical role in enhancing the reliability of climate models.

The annual and monthly historical trend analysis of Bambey, conducted using the Mann-Kendall trend test, offers a detailed perspective on climatic changes over the period 1983–2020. The Mann-Kendall test, a nonparametric method widely used for detecting trends in climatic time series data, revealed a general stability in annual rainfall, consistent with the recovery in precipitation observed in the Sahel region following the severe droughts of the 1970s and 1980s, as documented by Maidment et al. (2015). However, this stability in annual rainfall patterns was accompanied by a significant increasing trend in both minimum and maximum temperatures in Bambey, as illustrated in Figure 9. These findings highlight the constraints imposed by climate change on agriculture during the past period (1981–2024). Despite the relative stability of seasonal rainfall, the rising rates of evapotranspiration driven by progressively increasing minimum and maximum temperatures pose significant challenges to crop development, particularly for peanuts. On a monthly scale, the analysis revealed a decreasing trend in rainfall during the wettest month of the rainy season in Bambey, accompanied by an increase in minimum and maximum temperatures throughout the season. These changes could explain the observed decrease in crop yields in the region. These results are consistent with those of Funk et al (2012), who reported an increase in temperatures in Senegal of more than 0.7°C between 1975 and 2009 during the rainy season. Funk et al (2012) also pointed out that this warming trend is likely to reduce crop yields, exacerbate the effects of drought and pose additional challenges to agricultural productivity in the region.

When examining future climate scenarios, the results of the non-parametric Mann-Kendall test reveal patterns that are largely consistent with the baseline period in terms of rainfall, minimum temperature, and maximum temperature for the near future under both the SSP2 and SSP5 scenarios. These findings indicate a persistent warming trend, coupled with relatively stable annual rainfall and consistent patterns throughout the rainy season. However, in the far future, significant divergences emerge between the scenarios. Under the high-emission scenario (SSP5), the warming trend is projected to intensify further, with pronounced increases in both annual and monthly temperatures. In contrast, the SSP2 scenario suggests a notable shift in the region's climate patterns. Specifically, the annual minimum temperature is expected to decrease significantly, although a rising trend persists during certain months of the rainy season. Meanwhile, the maximum temperature is projected to decrease throughout the rainy season months but continue to rise on an annual basis. These results highlight the contrasting climate trajectories under different emission scenarios, particularly in the far future.

The unequivocal trend toward increased temperatures in most future scenarios is expected to have far-reaching effects on agricultural productivity and ecosystem stability. These findings underscore the importance of developing targeted adaptation strategies to address the evolving climatic conditions and their potential impacts on agriculture and ecosystems. As noted by Ouali et al. (2023), these trends necessitate a reevaluation of current management and conservation strategies to mitigate the adverse effects of climate change and enhance resilience in vulnerable regions.

To analyze the effects of climate change on peanut cultivation, the yield change between future periods under different scenarios and the baseline period was assessed using the DSSAT model, which had been previously calibrated and validated in this study. For biomass yield, a modest increase was observed for both scenarios in the near future, while a notable decrease was noted in the far future for both scenarios. The increase in biomass yield observed in the near future for both scenarios is likely attributable to the CO_2 fertilization effect, which benefits C3 plants, including peanuts. Elevated CO_2 levels can enhance the development of C3 plants when agroclimatic conditions are favorable. These findings are supported by the study of Bannayan et al. (2009) which indicates that elevated CO_2 concentrations alone resulted in a significant increase in total biomass at final harvest across a range of temperatures, except when temperatures exceed the optimal range. This also explains the decline in biomass yield observed in the far future for both scenarios, as the expected elevated CO_2 concentrations will be accompanied by rising temperatures, ultimately offsetting the CO_2 fertilization benefits. These results align with the findings of Faye (2018), who reported that the positive effects of increased CO_2 were influenced by temperature variations, leading to reduced yields in conditions where temperatures increased significantly. This suggests that the relative response of total biomass to CO_2 is diminished under pronounced warming conditions, highlighting the complex interaction between CO_2 levels, temperature, and crop productivity.

Regarding grain yields, a decrease compared to historical yields was observed across all scenarios examined in this study. However, the magnitude of the decline varied between scenarios, reflecting the influence of the Shared Socioeconomic Pathways (SSPs) and the temporal period, as climatic conditions worsen over time under both SSP2 and SSP5. The decline in seed yield could be associated with the projected increases in temperature and variability in rainfall under future climate scenarios, as these factors can severely affect the seed filling rate, duration, and timing, ultimately resulting in reduced seed mass. Jagadish et al. (2016) argue that a marginal rise in temperature during the peak seed development stage can significantly reduce seed yield, as it lowers photosynthate accumulation in the seeds. Similarly, Singh et al. (2013) highlight that seed yield can decrease in both C3 and C4 plants under water stress conditions due to a reduction in the number of fully developed seeds. The variations in seed and biomass yields, as demonstrated in the results above, were noted to vary depending on the varieties used. Specifically, the medium-cycle variety Fleur 11 experienced a greater increase and a smaller decrease in yield compared to the long-cycle variety under the future scenarios studied. These findings are consistent with those of Faye (2018), who reported that short-season varieties experienced greater relative yield changes and could therefore be recommended in Bambey to mitigate the effects of early rainfall cessation. This highlights the importance of adopting early-maturing varieties to mitigate the effects of climate change, particularly those related to rainfall variability and rising temperatures.

The use of crop model can allow to assess agricultural practices such identifying optimal sowing dates. In this context, a wide range of sowing dates was tested to determine the optimal sowing dates for the future climate scenarios. It was found that sowing between July 11 and July 21 allowed for higher yields with less variability across future scenarios.

The comparison of yield changes between future climate scenarios, using the optimal planting date the baseline period, using the current sowing date, and, revealed a significant increase in both grain yields and biomass for all future scenarios. This underscores the importance of adjusting sowing dates as a key adaptation strategy to mitigate the impacts of climate change and enhance agricultural productivity.

5. CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

This study highlights the significant impact of climate change on peanut productivity in Bambey, Senegal emphasizing the vulnerability of rain-fed agriculture in this region. A combined approach was adopted to analyze climate evolution in Bambey and assess its impact on peanut cultivation, integrating ensemble averages from two GCMs. This approach was preceded by bias correction and performance evaluation of these models.

The study also included an analysis of historical climate trends using the Mann-Kendall test, applied to annual precipitation as well as maximum and minimum temperatures, and examined future projections according to SSP2-4.5 and SSP5-8.5 scenarios. Following this trend analysis, the application of the DSSAT model, particularly the CROPGRO-Peanut module, allowed for the evaluation of the effects of climatic variability on peanut cultivation under different socio-economic scenarios and the exploration of suitable agricultural management strategies.

Results indicate a significant increase in both maximum and minimum temperatures, observed annually and across all months of the rainy season during the reference period (1981-2023). This temperature rise is expected to be even more pronounced in the future, depending on the scenario and period studied, except for the SSP2 scenario at the intermediate horizon (2023-2050), which shows a less pronounced warming. Regarding precipitation, Z-values indicate relative stability during the reference period and in future projections for the rainy season, except for August, which shows a significant decrease. The increase in temperatures and irregularity in precipitation reveal a potential major impact on peanut cultivation, threatening both yields and production stability.

Furthermore, this study demonstrated that the DSSAT model can be effectively calibrated for peanut cultivation and shows promising performance in analyzing crop dynamics under various Sahelian pedoclimatic conditions. The model exhibited good agreement with observed data during the calibration and validation phases, particularly for parameters such as grain yield and total biomass, as confirmed by performance indicators. However, while the model satisfactorily reproduces the dynamics of the leaf area index, it tends to overestimate this index at certain growth stages, particularly toward the end of the crop cycle.

Future climate projections indicate variable impacts on peanut cultivation. Biomass is expected to increase in the near future under both scenarios, before experiencing a notable decline in the mid-term future. In terms of grain yield, a decrease is anticipated in the near future across all scenarios, and this trend is expected to worsen in the mid-term future. However, the use of short-cycle varieties could mitigate this yield decline, and an optimal planting date, identified between July 11 and July 21, could significantly improve yields. Therefore, it is necessary to adopt adaptation strategies to address the effects of climate change, such as selecting more resilient and early maturing varieties, improving water and nutrient management, selecting optimal planting day and diversifying production systems.

5.2 RECOMMENDATION

To mitigate the adverse effects of climate change on peanut production and enhance agricultural resilience, a combination of adaptive strategies must be implemented. First, the adoption of early-maturing, heat-tolerant, and drought-resistant peanut varieties is crucial, as these cultivars can better withstand climatic uncertainties and sustain yields under changing environmental conditions. Additionally, improving water conservation techniques and optimizing soil nutrient management are essential to enhance crop growth and productivity while ensuring efficient resource utilization. Moreover, adjusting sowing dates, particularly between July 11 and July 21, can maximize yields by synchronizing crop development with optimal climatic conditions. Furthermore, diversifying production systems through crop rotation and intercropping can reduce vulnerability to climate-induced risks while promoting sustainable agricultural practices. Lastly, the integration of climate-smart agricultural strategies, including the strengthening of adaptation policies, farmer training programs, improved weather forecasting systems, and increased investment in agricultural research, will be fundamental in ensuring long-term resilience and sustainability in peanut farming. In addition to these adaptation measures, further research on the impacts of climate change on other key crops in the region and across the country is strongly recommended to support the formulation of more comprehensive and targeted agricultural policies. Moreover, a deeper investigation into the interaction between temperature, rainfall, and CO_2 variations is essential. Future studies should initially focus on controlled environments to isolate and quantify these interactions, followed by field-based research within actual farming systems to assess their real-world implications. Given that elevated CO_2 levels may exacerbate heat stress in plants, understanding these complex interactions will be critical for developing effective mitigation and adaptation strategies.

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APPENDICES

Appendix 1: Rainfall Simulation Performance Across Different Climate Models: A Comparative Analysis


Comparison of Observed vs Simulated Rainfall Across Models
CNRM-ESM2-1
Simulated RAIN (mm)
Observed RAIN (mm)
Pearson: 0.79
1:1 Line
CNRM-ESM2-1
Pearson Correlation: 0.79
Observed
Simulated
RAIN (mm)
Date
CNRM-CM6-1
Pearson: 0.77
1:1 Line
CNRM-CM6-1
Pearson Correlation: 0.77
MRI-ESM2-0
Pearson: 0.52
1:1 Line
MRI-ESM2-0
Pearson Correlation: 0.52
IPSL-CM6A-LR
Pearson: 0.36
1:1 Line
IPSL-CM6A-LR
Pearson Correlation: 0.36
0
50
100
150
200
250
300
350
400
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
200
400
600
800
1000
1200
250
500
750
1000
1250
1500
1750

Appendix 2: Seasonal analysis grain yields:

Scenario	Varieties	Mean	St Dev.	Min	Max
mid-term future SSP2	Fleur 11	877.7	262.3	325	1390
mid-term future SSP2	73-33	582.8	211.4	198	1061
mid-term future SSP5	Fleur 11	637.2	360.8	101	1297
mid-term future SSP5	73-33	424	267	55	1004
Near future SSP2	Fleur 11	1133.3	269.3	358	1573
Near future SSP2	73-33	793.5	223.9	216	1277
Near future SSP5	Fleur 11	1116	322	590	2024
Near future SSP5	73-33	783.3	261	377	1492
Historical	Fleur 11	1144.2	427.2	447	2457
Historical	73-33	830	389	288	2068

Appendix 3: Seasonal analysis biomass yields

Scenario	Varieties	Mean	St Dev.	Min	Max
mid-term future SSP2	Fleur 11	3271.3	430.6	2043	3972
mid-term future SSP2	73-33	3083.3	419.7	1856	3840
mid-term future SSP5	Fleur 11	2866	719.7	1406	3930
mid-term future SSP5	73-33	2689.2	678.5	1371	3804
Near future SSP2	Fleur 11	3488	403.3	2143	4051
Near future SSP2	73-33	3349.7	444.5	1978	4010
Near future SSP5	Fleur 11	3496.1	470.5	2670	4749
Near future SSP5	73-33	3352.2	497.4	2464	4718
Historical	Fleur 11	3379.8	606.1	2401	5217
Historical	73-33	3266.7	680	2148	5532

Appendix 4 : Mann kendall test results for the baseline periode

Period	Tmax Trend	Tmax Significant	Tmax P-Value	Tmax Tau	Tmax Z-Value	Tmax Slope
Jun	increasing	Yes	0.027120958	0.3048433	2.20977246	0.0302632
Jul	increasing	Yes	0.000148157	0.5213675	3.79413761	0.0667944
Aug	increasing	Yes	4.39E-05	0.5612536	4.08599435	0.0826882
Sep	increasing	Yes	0.000461293	0.4814815	3.50228087	0.0477083
Oct	increasing	Yes	0.002337278	0.4188034	3.04364885	0.0454677
Nov	increasing	Yes	0.006726327	0.3732194	2.71009829	0.0748981
Annual	increasing	Yes	0.000126534	0.137094	3.83310801	0.0041611
	Tmin Trend	Tmin Significant	Tmin P-Value	Tmin Tau	Tmin Z-Value	Tmin Slope
Jun	no trend	No	0.24303799	0.1623932	1.16742696	0.0256389
Jul	increasing	Yes	0.00012514	0.5270655	3.83583143	0.0432796
Aug	increasing	Yes	9.89E-06	0.6068376	4.41954491	0.0491935
Sep	increasing	Yes	5.25E-05	0.5555556	4.04430053	0.039625
Oct	increasing	Yes	1.45E-05	0.5954416	4.33615727	0.0414747
Nov	increasing	Yes	0.003516439	0.4017094	2.91856739	0.0423958
Annual	increasing	Yes	0.008083132	0.0947334	2.64857748	0.0031894
	Rain Trend	Rain Significant	Rain P-Value	Rain Tau	Rain Z-Value	Rain Slope
Jun	no trend	No	0.545383797	-0.08547	-0.6046918	-0.0265
Jul	no trend	No	0.10393711	-0.225071	-1.626059	-2.095417
Aug	decreasing	Yes	0.001325392	-0.441595	-3.2104241	-3.939286
Sep	no trend	No	0.452960392	-0.105413	-0.7504888	-0.7935
Oct	no trend	No	0.86754687	-0.025641	-0.1667753	-0.031389
Nov	no trend	No	0.234148695	-0.165242	-1.1897398	-0.010833
Annual	no trend	No	0.966566124	-0.001514	-0.0419154	0

Appendix 5 : Mann kendall test results in both near future under SSP2

	Tmax Z-value	Tmax p-value	Tmax Trend	Tmax Tau	Tmax Slope	Tmax Significant
Jun	2.209772456	0.02712096	increasing	0.3048433	0.0302632	Yes
Jul	3.794137613	0.00014816	increasing	0.5213675	0.0667944	Yes
Aug	4.085994352	4.39E-05	increasing	0.5612536	0.0826882	Yes
Sep	3.502280873	0.00046129	increasing	0.4814815	0.0477083	Yes
Oct	3.043648854	0.00233728	increasing	0.4188034	0.0454677	Yes
Nov	2.710098295	0.00672633	increasing	0.3732194	0.0748981	Yes
Annual	3.833108007	0.00012653	increasing	0.137094	0.0041611	Yes
	Tmin Z-value	Tmin p-value	Tmin Trend	Tmin Tau	Tmin Slope	Tmin Significant
Jun	1.167426958	0.24303799	no trend	0.1623932	0.0256389	No
Jul	3.835831433	0.00012514	increasing	0.5270655	0.0432796	Yes
Aug	4.419544912	9.89E-06	increasing	0.6068376	0.0491935	Yes
Sep	4.044300532	5.25E-05	increasing	0.5555556	0.039625	Yes
Oct	4.336157272	1.45E-05	increasing	0.5954416	0.0414747	Yes
Nov	2.918567395	0.00351644	increasing	0.4017094	0.0423958	Yes
Annual	2.648577481	0.00808313	increasing	0.0947334	0.0031894	Yes
	Rain Z-value	Rain p-value	Rain Trend	Rainfall Tau	Rain Slope	Rain Significant
Jun	-0.6046918	0.5453838	no trend	-0.08547	-0.0265	No
Jul	-1.62605898	0.10393711	no trend	-0.225071	-2.095417	No
Aug	-3.21042413	0.00132539	decreasing	-0.441595	-3.939286	Yes
Sep	-0.75048876	0.45296039	no trend	-0.105413	-0.7935	No
Oct	-0.16677528	0.86754687	no trend	-0.025641	-0.031389	No
Nov	-1.18973976	0.23414869	no trend	-0.165242	-0.010833	No
Annual	-0.04191542	0.96656612	no trend	-0.001514	0	No

Appendix 6 : Mann kendall test results in both mid-term future under SSP2

	Tmax Z-value	Tmax p-value	Tmax Trend	Tmax Tau	Tmax Slope	Tmax Significant
Jun	1.17750805	0.238992788	no trend	0.154023	0.0198889	No
Jul	2.85456496	0.004309582	increasing	0.3701149	0.048853	Yes
Aug	1.74842104	0.080391148	no trend	0.2275862	0.0414113	No
Sep	1.08847614	0.276384965	no trend	0.1425287	0.0189583	No
Oct	2.03387753	0.041963945	increasing	0.2643678	0.0505018	Yes
Nov	0.78500536	0.432450424	no trend	0.1034483	0.02	No
Annual	2.23232578	0.02559344	increasing	0.0757102	0.0022256	Yes
	Tmin Z-value	Tmin p-value	Tmin Trend	Tmin Tau	Tmin Slope	Tmin Significant
Jun	0.49954887	0.617392769	no trend	0.0666667	0.0115152	No
Jul	1.46296454	0.143477082	no trend	0.1908046	0.0208065	No
Aug	2.31933403	0.020376932	increasing	0.3011494	0.0258266	Yes
Sep	2.42638022	0.015250284	increasing	0.3149425	0.0202667	Yes
Oct	3.17570352	0.001494736	increasing	0.4114943	0.0397067	Yes
Nov	1.10614392	0.26866423	no trend	0.1448276	0.0164444	No
Annual	1.80623225	0.07088207	no trend	0.0612616	0.0019206	No
	Rain Z-value	Rain p-value	Rain Trend	Rain Tau	Rain Slope	Rain Significant
Jun	-0.4691166	0.638986265	no trend	-0.064039	-0.016708	No
Jul	-1.7820159	0.074746643	no trend	-0.236453	-1.515498	No
Aug	-1.0692095	0.284975268	no trend	-0.142857	-1.218162	No
Sep	-0.7315644	0.464434477	no trend	-0.098522	-0.752329	No
Oct	-0.4689515	0.639104271	no trend	-0.064039	-0.19856	No
Nov	-0.9834689	0.325376694	no trend	-0.130542	-0.003101	No
Annual	-0.3276234	0.743196404	no trend	-0.011301	0	No

Appendix 7 : Mann kendall test results in both near future under SSP5

Month	Tmax Z-value	Tmax p-value	Tmax Trend	Tmax Tau	Tmax Slope	Tmax Significant
Jun	1.209120778	0.226616448	no trend	0.1680912	0.012166666	No
Jul	2.710098295	0.006726327	increasing	0.3732194	0.043516128	Yes
Aug	2.439618644	0.014702774	increasing	0.3361823	0.046444282	Yes
Sep	2.459935375	0.013896204	increasing	0.3390313	0.043277778	Yes
Oct	1.792834257	0.07299943	no trend	0.2478632	0.044336918	No
Nov	1.751140437	0.079921722	no trend	0.2421652	0.048666667	No
Annual	2.824755065	0.004731677	increasing	0.1010338	0.002966107	Yes
	Tmin Z-value	Tmin p-value	Tmin Trend	Tmin Tau	Tmin Slope	Tmin Significant
Jun	0.917264038	0.359004297	no trend	0.1282051	0.023678571	No
Jul	2.835179755	0.004579991	increasing	0.3903134	0.041788856	Yes
Aug	3.627362333	0.000286331	increasing	0.4985755	0.040591398	Yes
Sep	4.357951254	1.31E-05	increasing	0.5982906	0.040233334	Yes
Oct	3.293811774	0.000988387	increasing	0.4529915	0.032827957	Yes
Nov	2.585016835	0.009737424	increasing	0.3561254	0.051366666	Yes
Annual	2.351306996	0.018707592	increasing	0.0841026	0.00276973	Yes
	Rain Z-value	Rain p-value	Rain Trend	Rain Tau	Rain Slope	Rain Significant
Jun	-0.87557022	0.381263722	no trend	-0.122507	-0.136333333	No
Jul	-1.50097752	0.133361377	no trend	-0.207977	-1.9575	No
Aug	-0.25016292	0.80246136	no trend	-0.037037	-0.43	No
Sep	-1.20912078	0.226616448	no trend	-0.168091	-1.605625	No
Oct	0.750488759	0.452960392	no trend	0.1054131	0.2746875	No
Nov	-1.40029741	0.161424275	no trend	-0.193732	-0.00375	No
Annual	-0.94532555	0.344492696	no trend	-0.033797	-6.62E-05	No

Appendix 8: Mann kendall test results in both far future under SSP5

Month	Tmax Z	Tmax p-value	Tmax Trend	Tmax Tau	Tmax Slope	Tmax Significant
Jun	2.14092372	0.03228019	increasing	0.2781609	0.03083333	Yes
Jul	4.03207301	5.53E-05	increasing	0.5218391	0.05194893	Yes
Aug	4.92412456	8.47E-07	increasing	0.6367816	0.0858871	Yes
Sep	4.74571425	2.08E-06	increasing	0.6137931	0.08685897	Yes
Oct	4.28184744	1.85E-05	increasing	0.554023	0.07947581	Yes
Nov	4.10343713	4.07E-05	increasing	0.5310345	0.12347619	Yes
Annual	6.45827164	1.06E-10	increasing	0.21901	0.00540072	Yes
	Tmin Z	Tmin p-value	Tmin Trend	Tmin Tau	Tmin Slope	Tmin Significant
Jun	2.0695596	0.0384936	increasing	0.2689655	0.03822917	Yes
Jul	2.39069815	0.01681637	increasing	0.3103448	0.03053763	Yes
Aug	5.95890436	2.54E-09	increasing	0.7701149	0.06032258	Yes
Sep	6.20867879	5.34E-10	increasing	0.8022989	0.06687778	Yes
Oct	5.6377658	1.72E-08	increasing	0.7287356	0.07095076	Yes
Nov	5.60208374	2.12E-08	increasing	0.7241379	0.09683333	Yes
Annual	4.5486255	5.40E-06	increasing	0.1542548	0.00494505	Yes
	Rainl Z-value	Rain p-value	Rain Trend	RainTau	Rain Slope	Rain Significant
Jun	1.37397807	0.16944849	no trend	0.1793103	0.03833333	No
Jul	-1.3559184	0.17512515	no trend	-0.177011	-0.765	No
Aug	-2.1409237	0.03228019	decreasing	-0.278161	-2.38075	Yes
Sep	-1.3916004	0.16404343	no trend	-0.181609	-1.56575	No
Oct	-1.141826	0.25352636	no trend	-0.149425	-0.2080556	No
Nov	-1.5710112	0.11618006	no trend	-0.204598	-0.0122222	No
Annual	-0.4244124	0.67126508	no trend	-0.014396	0	No