Scholars Academic Journal of Biosciences
Abbreviated Key Title: Sch Acad J Biosci
ISSN 2347-9515 (Print) | ISSN 2321-6883 (Online)
Journal homepage: https://saspublishers.com
National Library of Medicine
NLM ID:101629416
OPEN ACCESS
Zoology

Impact of Climate Change on Water Requirements and Maize Yields to 2050 in Northwest Côte d'Ivoire (Bagoué Region)

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DOI: https://doi.org/10.36347/sajb.2025.v13i06.010 | **Received:** 05.05.2025 | **Accepted:** 11.06.2025 | **Published:** 19.06.2025

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Abstract **Original Research Article**

Climate change is having an impact on agricultural ecosystems, and can significantly alter the conditions required to grow many crops, including maize. To assess the impact of these changes, the use of crop models coupled with remote sensing represents a promising approach to help forecast water requirements and crop yields. In this study, vegetation indices (NDVI) derived from the Copernicus-Sentinel 2 satellite were coupled to future climate data (2026-2050) in the AQUACROP model to simulate the yield and water requirement of maize crops under the RCP (Representative Concentration Pathway) 4.5 and RCP 8.5 scenarios on silty-clay, silty-sandy and silty-clay-sandy soils. The results show that water requirements increase by 11.10% under RCP 4.5 and 13.92% under RCP 8.5, over the future period. As for yields, they will fall by 13% under the RCP 4.5 scenario and by 17% under the RCP 8.5 scenario. As a result, maize yields are set to fall significantly by 2050, particularly in the most pessimistic scenario, RCP 8.5.
Keywords: Climate change, Water requirements, Yields, Maize, Bagoué region.

1. INTRODUCTION

The main biophysique processus involved in agricultural crop production, such as soil evaporation, plant transpiration, nutrient cycles and plant growth, are being altered by climate change (Rahman *et al*., 2019). Due to the importance of rain-fed agriculture and the low institutional and economic capacity to manage and adapt to climate change, Africa is highly vulnerable to the impacts of climate change (Baarsch, *et al*., 2020 and Sylla, *et al*.,2016). Indeed, agricultural production remains low, with crop yields below potential. Several factors are at the center of the low yield obtained, including reduced rainfall, soil erosion, and the absence of adequate agricultural practices (Bangata *et al*.,2013; Kasongo *et al*., 2013; Banza *et al*., 2019; Ilunga *et al*., 2015; Mulimbi *et al*., 2019).

Forecasting agricultural production on a local or regional scale is a very important geostrategic, economic and humanitarian asset today, and a guarantee of food security. One way of examining these impacts is to use crop models coupled with future climate projections and remote sensing. Given the threats posed by climate change to agricultural water use and other demanding uses, simulation models such as AquaCrop, developed by the Food and Agriculture Organization of the United Nations (FAO, 2009), have proved to be important tools for assessing water requirements and crop yields (Durodola and Mourad 2020). he effectiveness of the AquaCrop model has been proven on several crops and in several regions of the world (Iqbal *et al*., 2014; Vanuytrecht *et al.,* 2014; Pereira *et al*., 2015; Abi Saab *et al*., 2015; Benabdelouahab *et al*., 2016; Xu *et al*., 2019; Tsakmakis *et al*., 2019; Banza and John, 2020). It is a simple but robust model (Steduto *et al*.,2007; Vanuytrecht *et al*., 2014; Pawar *et al*., 2017; Sandhu and Irmak, 2019). It has been developed to estimate crop growth, development, yield, water use efficiency, water consumption and irrigation schedules under different climatic conditions, based on soil texture, field management, conservation practices and soil fertility.

As rainfed maize production is predominant in the region, it is important to examine the future water requirements and yields of this crop. Studies have shown that climate change will affect crop productivity differently depending on soil type, crop and climatic zone (Rahman *et al*.,2019 and Roudier *et al*., 2011). In Côte d'Ivoire in general and particularly in the Bagoué region very few studies have used crop models and remote sensing to simulate agricultural yields and water requirements. Yet simulation approaches are often proposed as effective tools to assist farmers in making decisions to increase their yields and water requirements rendements agricoles. Also, the use of remote sensing enables better spatial calibration of growth models through local re-estimation of missing model parameter information throughout the growing season (Batchelor *et al*., 2002). In order to provide greater clarity, it is imperative to conduct studies to examine how maize will respond in different locations, since the impact of climate change differs from one growing location to another. The aim of this study is to characterize these impacts on water requirements and maize yields by 2050.

2. MATERIALS AND METHODS

2.1 Presentation of the study area

The Bagoué region covers an area of 10150 km2 or 3.3% of the total area of Côte d'Ivoire. It lies between longitude 5°40′ and 7°10′ West and latitude 9°15′ and 10°50′ North. The region delimits a geographical unit made up of 03 departments Boundiali, Kouto, Tengrela (Figure 1). Two distinct seasons characterize the climate of the study area: a dry season from November to April and a rainy season from May to October. Average interannual rainfall is less than 1200 mm (Brou, 2005). The pedology is characterized by 5 soil types: Ferric Acrisols, Orthic Acrisols, Plinthic Acrisols, Eutric Cambisols and Eutric Nitosols (FAO, 2007). Agriculture is the main activity of the region's population. The main food crops are maize, rice, millet, yams, groundnuts and sorghum. Cotton, cashew nuts and mangoes are the region's main cash crops.

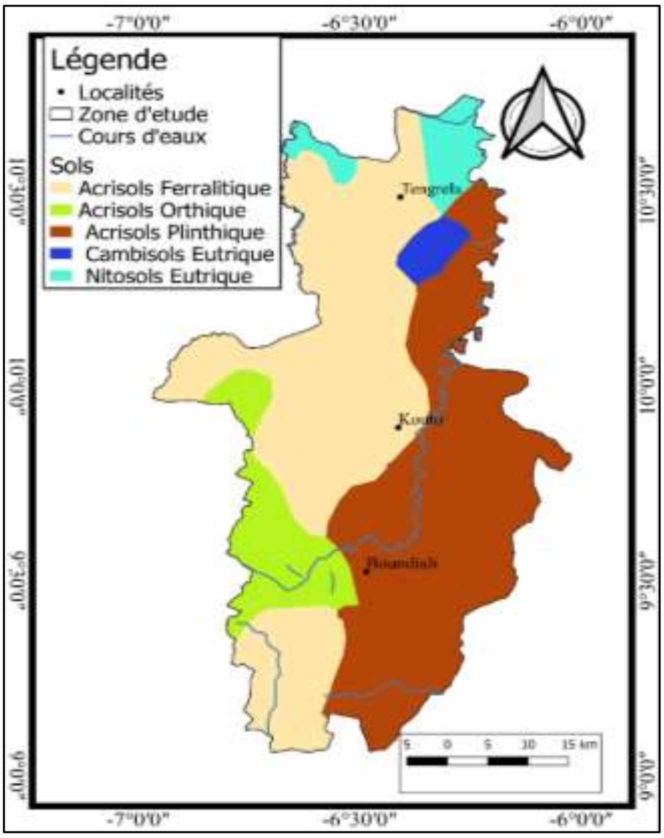


Figure 1: Location of study area

2.2 DATA

2.2.1. Historical climatic and agronomic data

Climate data from 1981 to 2020 were obtained from the Naza Power aerospace agency website (https://power.larc.naza.org). Data sets included maximum and minimum temperatures, wind speed and daily solar radiation. Climate data from the CHIRPS (Climate Hazards Group Infrared Precipitation with Station) satellite were also used for the period 1981-2020. CHIRPS data are gridded precipitation time series with a horizontal resolution of 0.05° (Ogega *et al*., 2021). These datasets have been widely used for studies in West Africa (Basse *et al*.,2021; Boluwade, 2020) and Côte d'Ivoire by Koffi (2022). In addition, rainfall, maximum and minimum temperatures, wind speed and solar radiation have been used for historical simulations of maize yield and water requirements (1981-2020). Daily maximum, minimum temperature and precipitation data were used for future climate simulations (2026-2050). The future climate data used in this study were obtained from the Coordinated Regional Downscaling Experiment (CORDEX) project, downloaded (https://esgf-index1.ceda.ac. fr/recherche/cordex-ceda/). CORDEX-Africa datasets are available on the following scales daily, decadal and monthly time series at a spatial resolution of 0.44° × 0.44°, i.e. around 50 km × 50 km for the period 1981-2005 (historical) and (2026-2050) (future). In the CORDEX project, several global climate models (GCMs) were downscaled using different regional climate models (RCMs) to regional levels, including Africa. Based on an extensive literature review, the Rossby Centre Regional Climate Model (RCA4) and CNRM-CM5-LR, which are RCMs developed by the Swedish Meteorological and Hydrological Institute (SMHI) and France as part of the nine GCMs in the CORDEX-Africa project, were selected for this study. ACR4 has been evaluated with very satisfactory results in numerous studies (Ayugi *et al*.,2020; Nikulin *et al*.,2018, Akinsanola *et al*.,2018). In order to definitively select the presented CNRM, CM5-LR and ICHEC-EC-EARTH were evaluated using the historical dataset. Data concerning crop parameters were collected in the field. Data from the 2018-2019 growing season was used for calibration, while validation was carried out using data from the 2018-2019 growing season while validation was carried out using data from the 2020 growing seasons.

2.2.2 Multi-spectral images and soil physical properties

Sentinel-2 multi-spectral images were acquired for the 2018, 2019 and 2020 growing seasons. The images used are those from the month of August, which corresponds to the period when the maize crop reaches its peak of development. The multi-spectral images (MSI) aboard Sentinel-2 capture data at spatial resolutions of 10, 20 and 60 m over 13 spectral bands with a very high revisit time of five days covering the area, were acquired from the Copernicus Open Access Hub (https://scihub.copernicus.eu/). The physical and chemical properties of the region's soils were obtained from the Harmonised World Soil Database (HWSD), which has a resolution of 1 km (30 arc seconds). The data were downloaded from the FAO website (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases) (Fischer *et al.,* 2008). The texture of the agricultural soil (0-100 cm) is sandy-loam, clayey-loam and sandy-clayey-loam. These data were validated with field data.

2.3 AquaCrop software

Version 6.1 of the AquaCrop (AC) software was used in this study. This model was developed by the Food and Agriculture Organization of the United Nations (FAO). Several improvements have been made to the model up to the current version. It is a decision-making tool for planning strategies to improve water productivity in agriculture (Hsiao *et al*., 2009; Steduto *et al*., 2009; Jin *et al*., 2020).

2.4 Pre-processing of future precipitation and temperature data

The choice of simulations lies not only in scientific interest, but also in the availability of data and the ability to process them (Muerth *et al*.,2013). Thus, because of the scope of this study, the entire RACMO22E and ALADIN63 regional climate model, at a daily time step, spatial resolution 0.44 (50 km x 50 km) dynamically scaled to the GCM (ICHEC-EC-EARTH and CNRM-CM5-LR) was used. All the Regional Climate Models (RCM) used are capable of simulating maize yields and future water requirements.

2.3 Performance and bias correction of climate models

Model evaluation is based on compassion between observed and simulated data, while making use of statistical indicators: coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). Observed and simulated daily climate data for the historical period 1981-2005 were used for evaluation. The coefficient of determination (R^2) criterion describes the combined dispersion of the observed and simulated series in comparison with the dispersions of each of the series. It lies between 0 and 1, and an increase in its value indicates a decrease in the error of variance. It is defined by equation1**:**

$$R^2 = \frac{\sum_{i=1}^{N}(Pi - \overline{P\iota})(Oi - \overline{O\iota})}{\sqrt{(Pi - \overline{P\iota})^2}\sqrt{(Oi - \overline{O\iota})^2}} \quad (E_1)$$

The mean difference between experimental data and simulation results is described by the root mean square error (RMSE) as follows:

$$RMSE = \left[\sum_{i=1}^{N} N(Pi - Oi)^2\right]^{0.5} \quad (E_2)$$

In addition, modeling efficiency (NSE) was defined as follows:

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left(O_i - O_p\right)^2}{\sum_{i=1}^{N}\left(O_i - O_p\right)} \quad (E_3)$$

- **Correcting bias in daily rainfall data**

The Bias Correction function in the downscaleR package of the R software allows us to apply a number of standard bias correction techniques in the climate context, ranging from the simplest local scale to the most sophisticated. Thus, before using the projected climate data for precipitation and temperature, which claim to be overestimated or underestimated in their evolution, appear to be tainted by errors (Ardoin, 2004; Kouakou, 2011). These were corrected before the actual hydrological modeling began, using the root-mean-square error approach proposed by (Iturbide and Herrera 2018). This method makes no assumptions about the statistical distribution of the variable and consists in calibrating the empirical predictions of the Cumulative Distribution Function (CDF) by adjusting the models and the observed quantiles (Déqué, 2007). The optional argument n.quantiles is used to specify the number of quantiles to be adjusted (by default, percentiles are used for correction). In addition, this method allows for a corrected constant factor (bias) which is estimated by the difference between the observed data and the raw data of the simulated model (Lenderink *et al*., 2007) in (Fang, 2015). Precipitation is generally adjusted using a multiplier, and temperature is corrected by the additive term on the basis of monthly mean values, as shown respectively in equations (4) and (5) :

$$P^{cor}_{(j.m.a)} = P^{futur}_{(j.m.a)} * \left(\frac{P_{(Obs)}}{P_{(réf)}}\right) m \ (4)$$

$$T^{cor}_{(j.m.a)} = T^{futur}_{(j.m.a)} + \overline{(T_{(Obs)}} - \overline{T_{(réf)}}\ )m\ (5)$$

Where precipitation and temperature, expressed in mm and °C respectively, are visualized by observed rainfall series, reference periods and future projections according to the pessimistic scenarios RCP 8.5 and RCP4.5.

2.6. Etalonnage et validation du modèle

In this study, the canopy cover (CC) indicator was replaced by the normalized vegetation index (NDVI), estimated from Sentinel-2 imagery. The NDVI for the 2018-2019 season was used to calibrate the model under rainfed cultivation. It was then validated with data from the 2020 seasons. Calibration was carried out by manually entering the most important crop-related data: sowing date, crop cycle, density and germination rate. For parameters related to field and soil management, field observations, soil analysis data and water retention results obtained by pedo-transfer functions were used. Model validation is based on the comparison of observed and simulated data for all treatments, using data sets different from those used for treatment model calibration. To assess the performance of the AquaCrop model, the four years of experimental data obtained were evaluated by R2, RMSE, MAE and NSE. The results show that simulated yields correspond well to observed yields. Average simulated and observed maize yields are 2.8 t/ha and 2.95 t/ha respectively, as shown in the table. The results obtained are satisfactory, making the model reliable and suitable for future climatic conditions in the region.

2.7 Water requirements and crop yields

- **Evaluation of evapotranspiration**

Reference evapotranspiration (ETo) is estimated in AquaCrop from input climate data using the Penman-Monteith equation (Allen, R.*et al*., 1998), which is considered the most efficient method for estimating evapotranspiration (Fisher and (Pringle 2013). Water requirement is estimated in the model as shown in equation (6).

$$\mathbf{ETc = Kc * ET0}\ (\mathbf{E_6})$$

$$ETo = \frac{0{,}408*\Delta*(R_n - G) + \gamma\frac{900}{\tau+273}\mu_2(e_S - e_a)}{\Delta+\gamma(1+0{,}34\mu_2)} \quad (E_7)$$

- **Estimating corn yields**

Converting biomass to yield

Crop yield (Y) is the product of biomass (B) and harvest index (HI), equation(3). The harvest index (HI) increases progressively to reach its reference value (HIo) at the crop's physiological maturity (Raes *et al*., 2012; Vanuytrecht *et al*., 2014). Following daily variation in water stress and/or temperature, the harvest index is regularly adjusted during yield formation (equation(3)). The crop yield, AquaCrop uses the multiplication of biomass and harvest index as shown in equation (2)(Raes *et al.,*2008 and FAO, 2007):

$$\mathbf{Y = HI \times B} \quad (E_8)$$

Where: Y = Crop yield (kg/ha or t/ha), HI = Harvest index (fraction or percentage), B = Biomass (t/ha or kg/ha).

Simulation of crop transpiration

In the model, daily transpiration is calculated by multiplying the crop coefficient with ETo and the soil coefficient as indicated by (Vanuytrecht, *et al*., 2014) in equation (9) :

$$\mathbf{Tr\ = Ks(Kc\ Tr.x *\ CC *)ET0} \quad (E_9)$$

Where Tr = crop transpiration (mm/day), Ks = stress factor (Kssto or Ksaer) (fraction), CC* = adjusted canopy green cover (fraction), Kc*Tr.x * CC= crop coefficient.

- **Simulation of above-ground biomass**

The water productivity (WP) of a crop translates the dry matter (g or kg) produced per unit of soil surface (m² or ha) and per unit of transpired water (mm) (equation 5). To account for variability in climatic conditions, the AquaCrop model uses normalized water productivity (WP*) to simulate above-ground biomass. This normalization aims to make water productivity applicable across regions and seasons while considering different climate change scenarios (Steduto *et al*., 2009; Raes *et al*., 2012 and Raes *et al*., 2018). In the yield estimation, the model automatically adjusts the harvest index to respond to temperature changes and water stress conditions, which is very cru-cial for this study. Daily biomass production in the model is estimated as given by (Vanuytrecht *et al*.,2014) in equation (10).

$$\mathbf{B\ = Ksb *\ WP *\ Tr} * \sum \boldsymbol{ET_0} \quad (E_{10})$$

Where B = daily above-ground biomass (t/ha or kg/m²), Tr = daily crop transpiration (mm/day), ET0 = daily reference evapotranspiration (mm/day), WP* = crop variety water productivity normalized for atmospheric CO2 concentration levels and evaporation (kg/m3), Ksb = cold temperature stress factor for biomass (fraction).

In AquaCrop, the coefficient of modification of atmospheric CO2 concentration is estimated by equation (21) for normalization of CO2 concentration, which is essential for normalizing water productivity (Raes *et al*.,2009; Heo, *et al*.,2019).

$$f_{CO2} = \frac{\frac{Ca}{Ca,0}}{1 + 0,000318 * (Ca - Ca,0)} \quad (E_{11})$$

where fCO2 = modification coefficient for CO2 (dimensionless), Ca = atmospheric CO2 (µL/L), Ca,0 = reference CO2 recorded in 2000 at the Mauna Loa observatory, Hawaii, which is 369.47 µL/L.

3. RESULTS

3.1 Analysis of projected climate parameters

Evaluation of the table highlights the performance and ability of the climate model to capture observed data. Three statistical indicators have been used: the coefficient of determination (R^2), the root mean square error (RMSE) and the mean absolute error (MAE). R^2 ranges from 0 to 1, with a value of 1 indicating a perfect match between observed and simulated values. RMSE is a measure of the mean difference between simulated and observed values. MAE gives the mean of the deviation between simulated and observed values, and takes the simulated parameter as its unit. The closer the MAE value is to zero, the better the model's performance. The results in the table show that all the models scaled up by CNRM-CM5-LR and EC-EARTH give satisfactory results.

Table 1: Statistical evaluation of climate models on historical data (1981-2005)

	Precipitation (mm)			Maximum temperature (°C)			Minimum temperature (°C)		
Statistical parameters	**R²**	**RMSE**	**MAE**	**R²**	**RMSE**	**MAE**	**R²**	**RMSE**	**MAE**
CNRM-CM5-LR	0,98	0.97	0,79	0,97	0.10	0,99	0,95	0,99	0,5
EC-EARTH	0.99	0.92	3,58	0,98	0.92	0,99	0,99	0,99	1,26
ENSEMBLE	0.98	0.98	1,79	0,97	0.4	0,99	0,97	0,99	0,6

Future changes in precipitation, minimum and maximum temperatures for the periods in the near future (2026 -2050), according to the RCP 4.5 and RCP 8.5 scenarios compared with the average for the reference period (1981-2020), have been estimated on the basis of the ensemble projections of the models (CNRM-CM5-LR and EC-EARTH). Analysis of the results in the table shows that a reduction in annual precipitation is possible in the region for all scenarios for the future period. According to Table 4, for the RCP 4.5 scenario, annual precipitation will decrease by 24% by 2050 compared to the reference period average. In addition, maximum temperature is expected to rise by 2.03°C and 3.14°C by the end of 2050 under the RCP 4.5 and RCP 8.5 scenarios, respectively, compared with the reference period average. Similarly, minimum temperatures will rise by 2.25°C and 2.29°C by 2050, according to the RCP 4.5 and RCP 8.5 scenarios, respectively, compared with the reference period averag

Table 2: Changes in precipitation, minimum and maximum temperatures for future periods under RCP 4.5 and 8.5 scenarios, compared with the average for the reference period (1981-2005)

Climate parameters	Observed	Relative change	
	(1981-2005)	**RCP 4,5**	**RCP 8,5**
		(2026-2050)	**(2026-2050)**
Rainfall (mm)	1221,46	923,14 (-24%)	887,93 (+27,30%)
Minimum temperature (°C)	20,2	22,45 (+11%)	22,49 (+11,33%)
Maximum temperature (°C)	31,8	33,83 (-3,04%)	34,93 (+4,83%)

3. 2 Calibration and statistical evaluation of AquaCrop performance

AquaCrop parameters for simulating yields and water requirements are presented in Table 5, values are from calibration (c), field measurements (m) and estimates from 2018-2019 season data under rainfed crop.

Table 3: Crop parameters used for AquaCrop corn simulations

Non-conservative parameters	Calibration	Determination method
Plant population Plants/ha	20000	e
Initial canopy cover (%)	28	m
Maximum canopy cover (%)	67	e
Days from planting to GDD emergence (days)	7	e
Days from planting to maximum cover GDD (days)	99	e
Days from planting to senescence GDD (days)	115	e
Days from planting to maturity GDD (day)	120	m

Non-conservative parameters	Calibration	Determination method
Days from planting to flowering GDD (Days)	66	e
Duration of flowering GDD (day)	(55)	e
Maximum effective rooting depth (m)	1	m
Water productivity normalized for climate and CO2 (g/m2)	17	e
Soil fertility stress -	modéré	-
Reference harvest index (%)	50	50

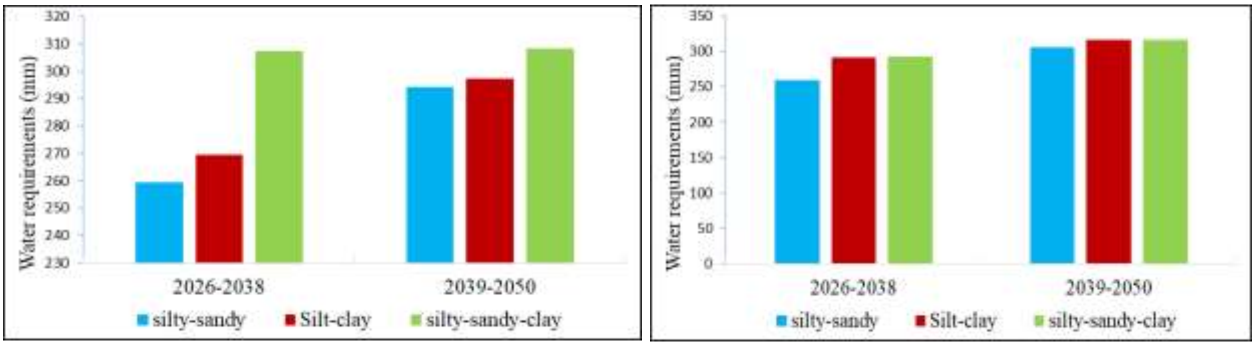
Analysis of the results in Table 3 shows the model's performance in simulating maize yields in different soil textures for three growing seasons. These results show that simulated yields correspond well to observed yields. The average observed and simulated maize yields were 2.8 t/ha and 2.95 t/ha, respectively. Table 1 show that the R^2, RMSE and MAE of simulated maize yields range from 0.95 to 0.99, from 0.04 t/ha to 0.3 t/ha and from 0.03 t/ha to 0.27 t/ha, respectively. The model is validated with an NSE performance of 0.96%.

Table 4: Evaluation of model performance for simulating maize yield in different soil textures for three growing seasons

Year	Soil texture	Observed yield (t/ha))	Simulated yield (t/ha)	R^2	RNSE (t/ha)	MAE (t/ha)
2018	silty-sandy	2,65	2,704	0,99	0,04	0.06
	Silt-clay	2.56	2.615			
	silty-sandy-clay	1,47	1,49			
2019	sandy loam	2,6	2,83	0,95	0.3	0.27
	Silt-clay	2,72	2,3			
	silty-sandy clay	1,3	2,4			
2020	sandy loam	4,1	4,17			0,03
	Silt-clay	4	4,15	0,99	0,1	
	silty-sandy-clay	3,93	3,96			

3.3. Future seasonal water requirements of crops

The results of the analysis in Figure 2 show an increase in the water requirements of maize by 2050 compared with the results of the analysis of historical data, which were 236.76; 228.73; 269.3 mm respectively during the periods (1981 -2020), on sandy-loam, clayey-loam and sandy-loam soils. Under the RCP 4.5 scenario, average water requirements for maize are expected to be 259.33; 269.30 and 307.36 mm respectively over the period (2026 -2038) and 294.33; 297.42; 308.36 mm over the period (2039 -2050). However, under RCP 8.5, the average water requirements of maize on silty-clay, silty-sandy and silty-clay-sandy soils will be 282.3; 291.65 and 292.62 mm respectively over the period (2026 -2038) and 306.1; 315.70 and 315.79 mm over the period (2039 -2050). Under the RCP 8.5 scenario, water requirements for maize will increase compared with the results obtained under the RCP 4.5 scenario for all future periods.



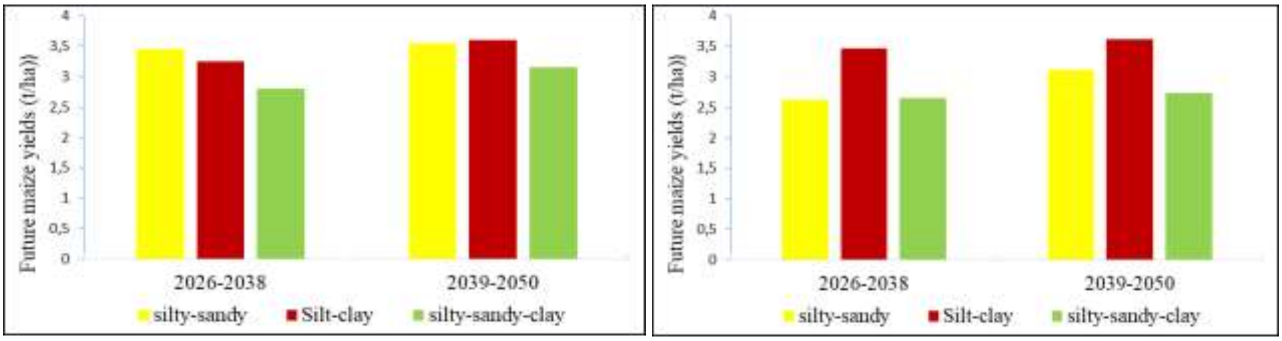
RCP 4,5 (2026-2050) RCP 8,5 (2026-2050)

Figure 2: Future water requirements for maize under RCP4.5 scenarios

3.4. Future corn yields

The analysis results in Figure 3 show a decline in average maize yields over the period (2026 to 2050) compared with the historical period (1981-2020). Average yields over the historical period were 3.90; 3.89; 3.65 t/ha on sandy loam, clay loam and sandy clay loam soils respectively. Under the RCP 4.5 scenario, average maize yields are expected to be 3.45; 3.25 and 2.83 t/ha in the period (2026 -2038) and 3.55; 3.60; 3.15 t/ha in the period (2039 -2050). For the RCP 8.5 scenario, analyses show that average maize yields should be 2.63, 3.37 and 2.65 t/ha respectively in sandy loam, clayey loam and sandy clay loam soils for the period (2026- 2038) and

3.14, 3.61 and 2.27 in the period (2039- 2050). According to figure 3, maize yields will.

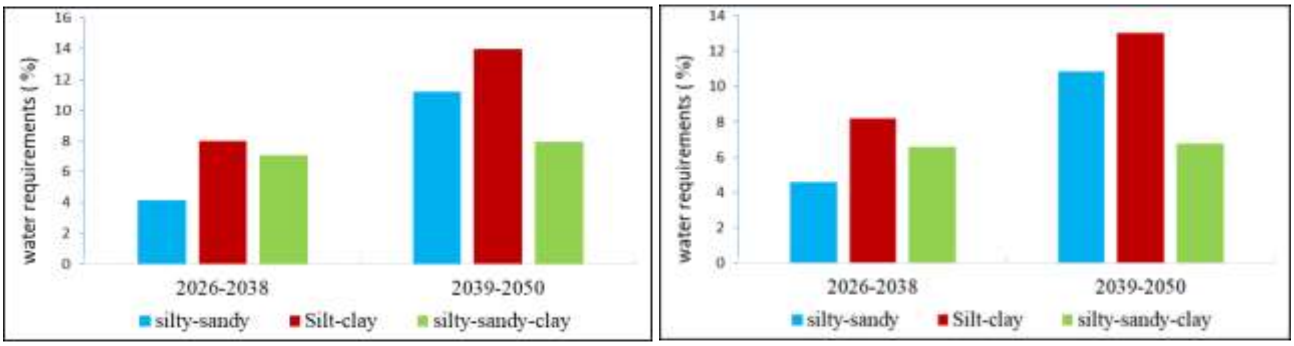


RCP 4,5 (2026-2050) RCP 8,5 (2026-2050)

Figure 3: Future corn yields under RCP 4.5 and RCP 8.5 scenarios

3.5 Changes in future seasonal water requirements for maize crops

Future changes in water requirements for maize crops are expected to fluctuate from the historical period average. Analyses according to Figure 4, under RCP 4.5, changes from 4.56 to 8.18% are expected over the period (2026 - 2038) and from 4.13 to 12.09 over the period (2039 - 2050). In addition, under RCP 4.8, an increase is predicted in changes, these changes could reach 16% depending on soil textures in the period (2026-2050). In the RCP 8.5 scenario, increases ranging from 7.94 to 15.97% over the period (2026 - 2038) and from 6.76 to 13.05% over the period (2039 - 2050).

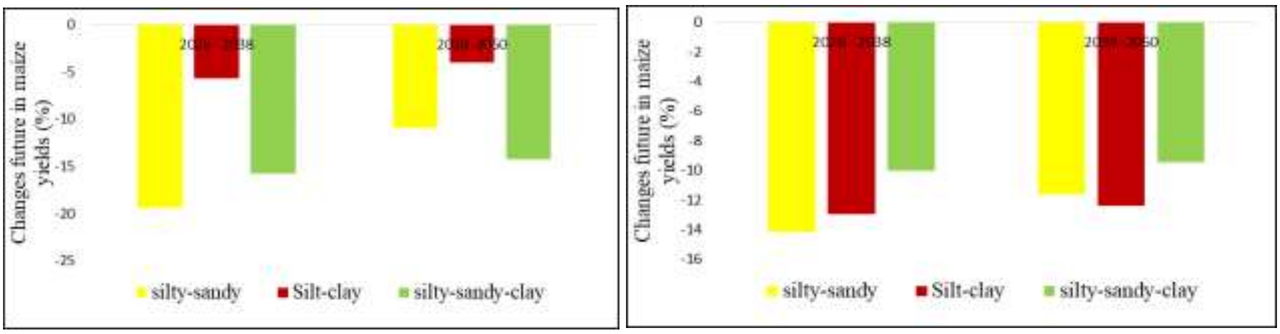


RCP 4,5 (2026-2050) RCP 8,5 (2026-2050)

Figure 4: Temporal changes in future water requirements for maize under the RCP4.5 and RCP8.5 scenarios

3.6 Changes in future seasonal maize yields

Negative changes are predicted in maize yields for future periods under the RCP4.5 and RCP8.5 scenarios. Analyses of the results show that under the RCP 4.5 scenario, changes range from (-1.5 to -7.5%) and (-4 to -13%) respectively in the period (2026 -2038) and (2039 - 2050). Under the RCP 8.5 scenario, the change ranges from (-2.53 to -10%) and (-2.05 to -17.45%) respectively in the period (2026 -2038) and (2039 -2050).



RCP 4,5 (2026-2050) RCP 8,5 (2026-2050

Figure 4: Temporal changes in future corn yields under RCP 4.5 and RCP 8.5 scenarios

4. DISCUSSION

In the context of climate change, the regional climate model assessment shows that projected annual precipitation will record a negative change of 24% under the RCP 4.5 scenario and 27.30% under the RCP 8.5 scenario. These decreases in precipitation are due to the lack of forest and the intersection of entropic activities in the area. Our results are in line with those of (Kouassi *et al*. 2023), who predict a 19.2% decrease in precipitation in western Côte d'Ivoire over the N'zo Sassandra by 2071-20100. On the other hand, minimum and maximum temperature projections for the RCP 4.5 scenario show increases of 2.25°C and 2.29°C respectively. For the RCP 8.5 scenario, temperatures will rise by 2.03°C for minimum values and 3.14°C for maximum values by 2050. These results show that the effects of climate change on the region are certain, with an increase in temperature by 2050 compared with the reference period. Our results are similar to those of the sixth report of the Intergovernmental Panel on Climate Change (IPCC, 2022), which forecasts a temperature rise of 1.3°C to 1.9°C over the period 2021-2040 and 1.9°C to 3°C over the period 2041-2060. These temperature rises are thought to be due to the intensification of human activities on the environment. In the Bagoué region, vast areas of land are used to grow food crops and export crops. Analysis of the results indicates an increase in future period water requirements of 3.93 to 13.94% under the RCP4.5 scenario and 9.31 to 32.28% under the RCP 8.5 scenario for the region's sandy loam, clayey loam and sandy clay loam textured soils. Oludare *et al*. (2020) assessed soybean water requirements for different soil textures in the Gun-Ona basin of Nigeria and found results in line with our own. This could be explained by the existence of a delayed rainfall probability relative to baseline coupled with higher transpiration, meaning that maize production will require more rainfall relative to baseline for optimum production. A delay in the arrival of rains can be a challenge for farmers, and planting dates. Analysis of vegetation indices (NDVI) obtained from sentinel-2 image data during the maize growing seasons has enabled us to simulate future production yields. These yields show a decline of 1.5 to 13% in the RCP4.5 scenario by 2050, while the RCP8.5 scenario shows a decline of 2.05 to 17.45% over the 2026-2050 period. These yields show a decline of 1.5 to 13% in the RCP4.5 scenario by 2050, while the RCP8.5 scenario shows a decline of 2.05 to 17.45% over the 2026-2050 period. However, decreases in maize yields are likely to be linked to increased entropic activity, which will have a greater influence on temperature increase and precipitation decrease. The results obtained are in line with those of Corbeels *et al*. (2018), who obtain a decrease in future maize yields in Southern Africa simulated with the process-based model (ASPIM) coupled with 17 GCMs. Similarly, in Cameroon, a 14.6% reduction in maize yield is predicted in future periods by Tingem *et al*. (2009) simulated with GCMs based on global climate models. According to Roudier *et al.* (2011) future maize yields in West Africa are expected to decrease by 5% according to simulations carried out as part of climate change projections that take into account an induced increase in CO2. This also confirms that maize yields in sub-Saharan Africa will decrease in the event of an increase in CO2 concentration and temperature in the RCP 4.5 and RCP 8.5 scenarios for all species.

5. CONCLUSION

The objective of this study was to simulate the seasonal seasonal water requirements and yields of rainfed maize crops in the Bagoué Bagoué region, based on future climate data from 2026-2050. The AquaCrop model developed by the FAO was used for its robustness, simplicity and reduced input data. Historical weather data were obtained from the NASA and CHS satellite NASA and CHIRPS (Climate Hazards Group Infrared Precipitation with Station) for the years (1981- 2020). For the simulation of future yields and requirements, all the climate models (CNRM-CM5-LR and EC-EARTH) were used. These models able to simulate the region's future climate satisfactorily. satisfactory. According to climate projections, the region should be drier and warmer drier and warmer in the future, particularly during the crop growing seasons. In addition, future scenarios show that water requirements 13% under the RCP8.5 scenario. In corn yields are expected to decrease significantly in both scenarios both scenarios, up to 17% under RCP8.5. We can therefore conclude that maize maize will be negatively affected by climate change in the region. By Moreover, this study shows that maize yields (C4 crop) are strongly influenced by changes in precipitation and increased temperature.

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