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Future Impact of Climate Change on Durum Wheat Growth and Productivity in Northern Tunisia

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Abstract: This study evaluates the projected impact of climate change on wheat production in Northwest Tunisia, specifically at Medjez El Beb (36.67 m, 9.74°) and Slougia (36.66 m, 9.6°), for the period 2041–2070. Using the CNRM-CM5.1 and GFDL-ESM2M climate models under RCP4.5 and RCP8.5 scenarios, coupled with the AquaCrop and SIMPLE crop growth models, we compared model outputs with observed data from 2016 to 2020 to assess model performance. The objective was to determine how different climate models and scenarios affect wheat yields, biomass, and growth duration. Under RCP4.5, projected average yields are 7.709 q/ha with AquaCrop and 7.703 q/ha with GFDL-ESM2M. Under RCP8.5, yields are 7.765 tons/ha with AquaCrop and 7.198 q/ha with SIMPLE Crop, indicating that reduced emissions could improve wheat growth conditions. Biomass predictions showed significant variation: in Medjez El Beb, average biomass is 17.99 tons/ha with AquaCrop and 18.73 tons/ha with SIMPLE Crop under RCP8.5. In Slougia, average biomass is 18.90 tons/ha with AquaCrop and 19.04 tons/ha with SIMPLE Crop under the same scenario. Growth duration varied, with AquaCrop predicting 175 days in Medjez El Beb and 178 days in Slougia, while SIMPLE Crop predicted 180 days in Medjez El Beb and 182 days in Slougia, with a standard deviation of ±12 days for both models. SIMPLE Crop demonstrated higher accuracy in predicting growth cycle duration and yield, particularly in Slougia, with mean bias errors of −3.6 days and 2.26 q/ha. Conversely, AquaCrop excelled in biomass prediction with an agreement index of 0.97 at Slougia. Statistical analysis revealed significant yield differences based on climate models and emission scenarios, with GFDL-ESM2M under RCP4.5 showing more favorable conditions. These findings emphasize the importance of model selection and calibration for accurately projecting the agricultural impacts of climate change, and they provide insights for enhancing prediction accuracy and informing adaptation strategies for sustainable wheat production in Northwest Tunisia.

Keywords: AquaCrop model; SIMPLE crop model; climate change; northwest Tunisia; CNRM-CM5.1 and FDL-ESM2M. models; RCP 4.5; RCP 8.5; wheat production

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1. Introduction

In the 21st century, climate change has become a major global concern, profoundly affecting livelihoods, agriculture, the environment, and public health [1,2]. Alarming forecasts indicate a potential increase in the Earth's average surface temperature by 2.6 to 4.8 °C by the end of the century, posing serious risks to global food security and ecosystem stability [3]. Concrete illustrations of disastrous consequences include excessive precipitation, extreme weather events, and glacier retreat [4,5]. In Tunisia, agriculture holds a critical role both economically and socially, with cereal cultivation forming a cornerstone of the national agricultural system. This sector is pivotal to the country's economy, significantly influencing the national economic balance [6]. Cereals, particularly durum wheat, are fundamental to the Tunisian diet, providing 54% of the population's caloric intake and 64% of their protein needs. On average, each Tunisian consumes 181 kg of cereals annually, with durum wheat accounting for 51% and soft wheat for 41% of this total, highlighting the vital importance of these crops not only for food security but also for the overall economy [7]. However, despite efforts to intensify agricultural practices, Tunisia's agriculture remains predominantly rain-fed, with 80% of agricultural land dependent on rainfall. This sector is also the largest consumer of water, using more than 80% of the country's water resources. Projections from General Circulation Models (GCMs) indicate a potential increase in average temperatures and a decrease in precipitation in the Mediterranean region [8], which could exacerbate the vulnerability of this crucial sector to climate change [6]. The Tunisian climate, characterized by rising temperatures and uneven intra- and inter-seasonal precipitation distribution, is undergoing significant transformations. These changes could have a considerable impact on the yield and quality of crops, particularly determinate-cycle plants like cereals [9,10]. Studies suggest that anticipated consequences of climate change could affect agricultural productivity, leading to fluctuations in prices of staple food products. This could jeopardize food balance and economic competitiveness against international counterparts [11,12]. Furthermore, climate change exacerbates regional inequalities and the vulnerability of disadvantaged rural populations [13,14]. The Tunisian revolution of January 2011 brought to light structural weaknesses in the agricultural sector, particularly prevalent in the country's inland sites, where agricultural activity is crucial. To address these challenges, it is imperative to ensure food security, promote sustainable agricultural development, and improve living conditions in rural areas in Tunisia. As a Mediterranean country in the Middle East and North Africa, Tunisia faces regular forecasts of increasing average temperatures and decreasing precipitation according to general circulation models [8,15]. Despite efforts to improve agricultural practices, the country relies heavily on extensive farming methods. Rain-fed crops, such as cereals and olives, dominate the agricultural landscape, significantly contributing to the national economy [6,16,17]. However, the resilience of these agricultural systems to increasing climate pressures remains a critical challenge. Crop models play a pivotal role in the context of climate change, particularly in tropical and subtropical sites, where the benefits of carbon dioxide can be counteracted by rising temperatures, leading to decreased yields and increased irrigation demand [18,19]. A thorough understanding of these impacts is essential for effectively advising farmers on crop management, including crop selection, planting dates, and irrigation optimization [20]. Farmers can adapt agricultural technologies to mitigate these adverse effects [21]. Simulation models like Decision Support System for Agrotechnology Transfer (DSSAT) and Crop Growth Model (DSSAT CROPGRO) are crucial for projecting the potential impacts of climate change on global food systems [22]. Despite the limitations of General Circulation Models (GCMs), integrating their outputs into simulation models can enhance forecast accuracy and support the development of strategies for sustainable agriculture, especially in developing countries. Understanding the relationship between crop growth, yields, and climate change is crucial. Simulation models contribute to efficient agricultural planning and are utilized in research, education, farm management, policy analysis, and yield forecasting [23,24]. They facilitate the integration of knowledge across different crops and disciplines, enabling detailed analyses such as productivity assessment and soil fertility dynamics [25]. These tools also provide valuable insights into genetic traits influencing yields, thereby supporting genetic improvement programs. Currently, crop simulation models such as those from the De Wit school, International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT), and Decision Support System for Agrotechnology Applications (DSSAT), are critical tools in agricultural research and practical applications [26]. Additionally, specific models like AquaCrop are widely used to assess water stress effects, optimize deficit irrigation, and enhance agricultural management [27–30]. The SIMPLE crop model, named "SIMPLE", is a SIMPLE generic crop model , developed based on established principles of crop physiology, and offers relative simplicity with few equations and parameters [31]. Successfully validated against real-world data, this model can assess future climate impacts, particularly for crops not covered by other modeling platforms [31]. While global studies have extensively explored the impacts of climate change on wheat yield [32–34], there is a lack of research specific to Tunisia that integrates climate models with crop growth models to assess these impacts. For instance, Lhomme et al. [35] focused on the cropping calendar and yield response to water deficits. In contrast, Bahri et al. [36] utilized the APSIM model to investigate conservation agriculture and its effects on soil and erosion. Our research advances the field by integrating climate models, GFDL-ESM2M and CNRM-CM5.1, coupled with crop growth models, SIMPLE and AquaCrop. This innovative approach enables a detailed assessment of the combined effects of climate change scenarios RCP 4.5 and RCP 8.5 on critical parameters such as biomass and the growth cycle duration of durum wheat, projected to 2070. The findings will provide valuable insights for Tunisian farmers and policymakers, facilitating the development of targeted adaptation strategies to enhance food security and agricultural resilience. Historical climate data are essential for understanding long-term climate variations and contextualizing future projections. They not only allow for the reconstruction of past climates but also preserve spatial variations due to topographic effects through the anomaly method or delta method. These datasets are crucial for assessing the impacts of climate change and developing adaptation strategies, providing a solid foundation for studies based on advanced climate models. Additionally, the integration of digitally available data with newly digitized records constitutes a valuable resource for future climate analyses [37,38].

The study aims to assess the impact of climate change on durum wheat yield, biomass, and growth cycle duration in northwest Tunisia by comparing historical data from 1970 to 1997 with future projections for the period 2041–2070. This evaluation employs the CNRM-CM5.1 and GFDL-ESM2M climate models, coupled with the SIMPLE and AquaCrop crop growth models, under RCP4.5 and RCP8.5 emission scenarios.

2. Materials and Methods

2.1. Study Area Presentation

Tunisia's climate varies greatly due to its diverse geography. The country can be divided into three primary climatic regions: a northern mountainous area with a Mediterranean climate characterized by mild, rainy winters and hot, dry summers; a semi-arid climate in the south as it transitions towards the Sahara Desert; and an arid steppe climate along the eastern coast. Historical data indicate an average annual precipitation of 158 mm for the entire country, with notable regional variations: less than 100 mm annually in the south and over 700 mm annually in the north. Temperature averages also differ by season and region, with winter temperatures in the northern coastal region ranging from 10 °C to summer temperatures reaching 27 °C, while in the central-western and southern regions, temperatures range from 11 °C in winter to 32 °C in summer [39]. In terms of recent climatic trends, the average temperature has increased by 0.4 °C per decade over the past 30 years, totaling a rise of 1.4 °C during the 20th century. Regarding precipitation, although there was no significant change in annual precipitation from 1901 to 2013, there has been a decrease of approximately 3% in average annual precipitation over the past 30 years. This context is crucial for understanding the effects of climate change on the agricultural production parameters examined in the study [39].

In Tunisia, national wheat production varies between 5 and 30 million tonnes annually, depending on precipitation levels [40]. The national cereal policy, regarded as vital for food security, aims to achieve self-sufficiency in durum wheat by 2025. This includes improving yields to 2.5 t/ha in rainfed areas and 5.5 t/ha in irrigated areas, and expanding irrigated cereal areas to 100,000 ha/year [41]. Our study focuses mainly on the sites of Slougia and Medjez El Beb, situated downstream of the Medjerda Valley. This region is among the most productive and fertile in Tunisia, with rich soils and favorable precipitation levels (Figure 1). The Medjerda Valley plays a crucial role in national cereal production, particularly for wheat, and significantly contributes to the country's food security by providing a substantial share of cereal yields. The strategic productivity of this region makes it an ideal choice for evaluating cereal production in Tunisia.

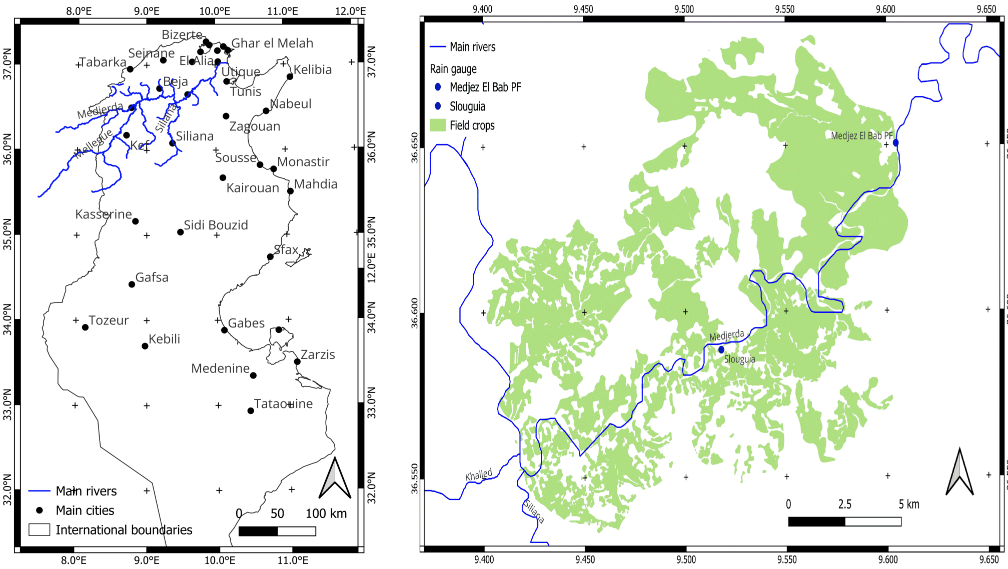

Figure 1. Locations of study area.

In our study, we focused on specific sites, gathering historical meteorological data from 1970 to 1997, as well as future projections for the period 2041–2070. The historical data for the study area were obtained from the National Meteorological Institute (INM). The research utilized two growth models, AquaCrop and SIMPLE, coupled with two climate models: CNRM-CM5.1 and GFDL-ESM2M. We used four grid cells, two per region (Table 1). The daily averages of these climatic parameters were used to predict the growth model outcomes.

Table 1. List of grid cells used to predict wheat growth parameters.

Region	rLat *	rLong **	Raw1	Raw2	Id	Lat	Long
Slougia	−13.695	−6.925	32	140	189	36.66	9.60
	−13.585	−6.815	33	140	174	36.78	9.72
Medjez el Bab	−13.695	−6.815	33	142	190	36.67	9.74
	−13.585	−6.705	34	142	175	36.80	9.85

* Rotated Latitude; ** Rotated Longitude

2.2. Conceptual Flow Diagram

The study aims to analyze the impact of climate change on wheat production parameters in the Northwest sites of Tunisia, focusing on Medjez El Beb and Slougia, over 30 years from 2041 to 2070 (Figure 2). Using the climate models CNRM-CM5.1 and GFDL-ESM2M with RCP 4.5 and RCP 8.5 scenarios (Section 2.3) coupled with two Crop Growth Models (Section 2.4), alongside adjusted historical data (1970–1997) , the study examines the impact on wheat biomass and yield throughout the growing season. Initially, daily climate data, including temperatures and precipitation, are collected. A linear correction method is then applied to align projected data with historical observations. This approach involves applying a linear transformation to the simulated values to match them with the observations, thereby reducing systematic discrepancies between the simulations and the real data [42]. Integrating soil properties and agricultural practices specific to the sites enhances the accuracy of the simulations. Finally, model results, comparing historical trends with future projections, provide insights into the potential impacts of climate change on wheat production in the studied sites.

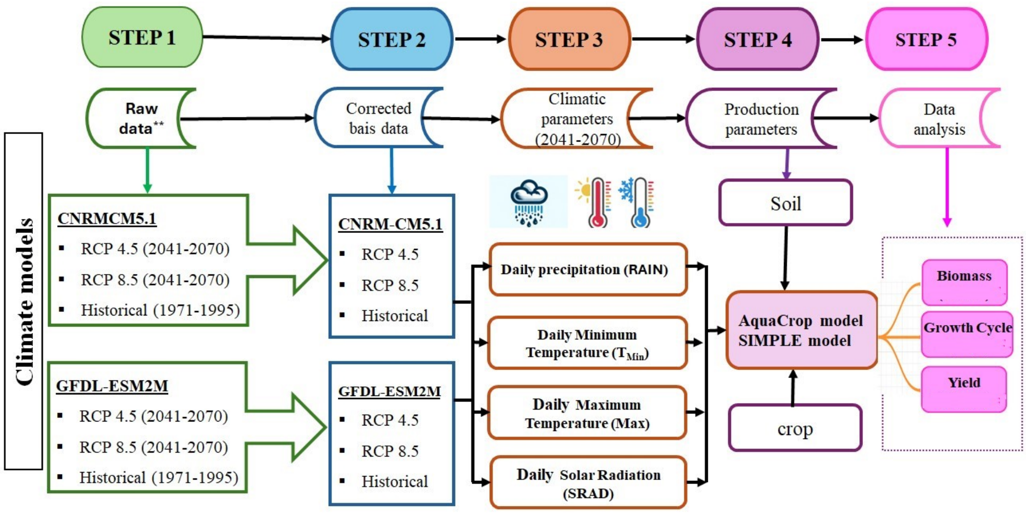

Figure 2. Conceptual flow diagram illustrating the methodology adopted to evaluate the impact of climate change on wheat production parameters in the Northwest sites of Tunisia. ** obtained from the CORDEX portal (www.cordex.org/data-access/esgf/, (accessed on 1 January 2024)).

In this study, the input variables for the SIMPLE and The FAO AquaCrop models (https://www.fao.org/aquacrop/software/aquacropstandardwindowsprogramme/en/, Version 7.1, accessed on 1 January 2024) namely Maximum Temperature (T_{MAX}), Minimum Temperature (T_{MIN}), Rainfall (RAIN), and Solar Radiation (SRAD), were selected for each grid cell in the study area. This selection was made using the GFDL-ESM2M and CNRM-CM5.1 climate models, along with the RCP 4.5 and RCP 8.5 projection scenarios for the period 2040–2070. The determination of the sowing date was based on an analysis of structural surveys on wheat conducted in the northwest sites of Tunisia as part of the KAFACI (Korea-African Food Agriculture Cooperation Initiative) project [43]. Examination of survey data for the period 2009–2020 indicates that the optimal sowing date for the study area is 5 November, with a frequency of 97%.

The performance of the two models was evaluated using datasets from trials conducted by FAO [44]. Data from 2016 to 2020 for the two selected sites and the winter wheat crop were utilized. The experimental data included quantities of seeds sown per Square Meter, observed phenological phases (emergence, tillering, stem elongation, heading, flowering, and maturity), the number of tillers per Square Meter, the weight of 1000 grains, and information on the preceding crop.

To calculate the ARID (Arid Region Irrigation Demand) water stress index [45], soil parameters were obtained from the literature based on general soil information for the study area. The three most common soil textures identified in the study area—Silty Clay Loam [46], Silt-Clay Sandy [47], and Clay Loam [48]—were determined through consultation with local wheat Local Services of Ministry of Agriculture, Hydraulic Resources and Fisheries and a detailed analysis of soil maps. The default soil parameters, including Field Capacity, Wilting Point, Hydraulic Conductivity, and Organic Matter content, were applied to these predominant soil textures within the SIMPLE and AquaCrop models. These parameters were chosen for their ability to represent typical soil behavior accurately, ensuring the reliability of the model outputs while aligning with the well-documented characteristics of the soils in the region [49]. Data on soil texture, bulk density, total porosity, field capacity, wilting point, organic carbon content, total nitrogen, and pH for specific soil profile layers were also available. Initial conditions for available soil water at various depths were also considered. Predicted yields are sensitive to two other parameters: the reference crop index and the initial soil moisture content. The study's initial soil moisture content estimates were derived from hydrological models at the station scale within the study area. The FAO crop calendar ([50]) was used for the input parameters. Simulations were assessed using three statistical metrics: mean biased error (MBE; [51]), root mean square error (RMSE; [52]), and index of agreement (IA; [53]). MBE quantifies average systematic deviations, RMSE measures prediction error dispersion, and IA evaluates agreement between observed and simulated data, with higher values indicating better fit [54]. The Index of Agreement ranges from 0 to 1. An IA value of 1 signifies perfect agreement between observed and simulated data, while an IA value of 0 indicates no agreement. Higher IA values represent a closer alignment between the observed and simulated datasets. The formulas to calculate these criteria are as follows:

$$\text{MBE} = \frac{\sum_{i=1}^{n}(S_i - O_i)}{n} \tag{1}$$

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

$$\text{IA} = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \tag{3}$$

where S_i is the simulated value, O_i is the observed value, $\bar{O}$ is the mean of observed values, and n is the number of observed/simulated pairs.

2.3. Climate Models

Climate change poses a crucial challenge for the agricultural sector, prompting numerous studies. Accurately predicting future climate has thus become a global priority. Various General Circulation Models (GCMs) have been developed to simulate the Earth's climate and forecast its future evolution [55]. However, these models may lack precision for regional and local scale forecasts. To address these uncertainties, "downscaling" techniques such as the Coordinated Regional Downscaling Experiment (CORDEX www.cordex.org/data-access/esgf/) provide more reliable regional climate projections. In this study, climate projections were generated using both GCMs and Regional Climate Models (RCMs), each with different grid resolutions [56]. GCMs generally possess a spatial resolution that exceeds 1°, which limits their ability to effectively capture climate details at the regional or local scale, such as in Tunisia. To address this limitation, GCMs are combined with RCMs that offer a finer spatial resolution, typically less than 0.5°, allowing for more precise downscaling of climate data. This study utilized the MENA domain as outlined in the Coordinated Regional Climate Downscaling Experiment (CORDEX) to ensure that the models accurately reflect Tunisia's specific climatic conditions. The CNRM-CM5.1 and GFDL-ESM2M models each offer specific strengths for climate projections. CNRM-CM5.1 excels in simulating climate processes in Mediterranean regions, which is particularly relevant for our study area in Tunisia. However, its spatial resolution may limit the ability to capture local variations and require substantial computational resources [57]. Similarly, GFDL-ESM2M integrates carbon cycle processes comprehensively, providing high accuracy in temperature and precipitation simulations. Nevertheless, its resolution also presents challenges in detailing local phenomena [58]. Both models, while powerful and widely used, demand significant resources, underscoring their validation and importance within the scientific community [59]. Given that the study area is located in Northern Tunisia, this technique was used to obtain the necessary climate parameters, including maximum and minimum temperatures and precipitation. This study aims to examine the impact of climate change on wheat biomass and yield, utilizing two RCMs, CNRM-CM5.1 and GFDL-ESM2M (Table 2), and two Representative Concentration Pathways (RCP), RCP 4.5 and RCP 8.5 [60].

Table 2. Attributes of the climate models used in the study.

Model	Institution	Full Name	Resolution	References
CNRM-CM5.1	CNRM	CNRM Coupled Model 5.1	0.22° × 0.22°	[57,61]
GFDL-ESM2M	NOAA/GFDL	Geophysical Fluid Dynamics Laboratory Earth System Model 2M	0.22° × 0.22°	[58,62]

Historical climate projections from the GFDL-ESM2M and CNRM-CM5.1 models were downloaded from 1970 to 1997, considering the availability of observed data with less than 10% missing data in the four sites of Northwest Tunisia. The raw data for maximum temperature (TMAX), minimum temperature (TMIN), precipitation (RAIN), and solar radiation (SRAD) were adjusted to eliminate systematic errors, known as biases. We selected the linear scaling technique among the bias correction methods available in the literature [60]. This method applied monthly, involves comparing the observed historical data with the simulated data [63]. Subsequently, this bias correction was applied to the projections for the period 2041–2070, covering the two stations in the study area.

Observed climate data were collected from the National Institute of Meteorology (INM) for the period 1970–1997, which was considered as the reference period and used for climate model corrections in the study area. After bias correction, the projected data for the period 2041–2070 were processed. Corrected daily maximum and minimum temperatures as well as precipitation were used for both stations using the CNRM-CM5.1 and GFDL-ESM2M models. The corrected daily data (maximum and minimum temperatures) and precipitation were coupled to the growth models according to the two projection pathways RCP 4.5 and RCP 8.5. (Figure 3).

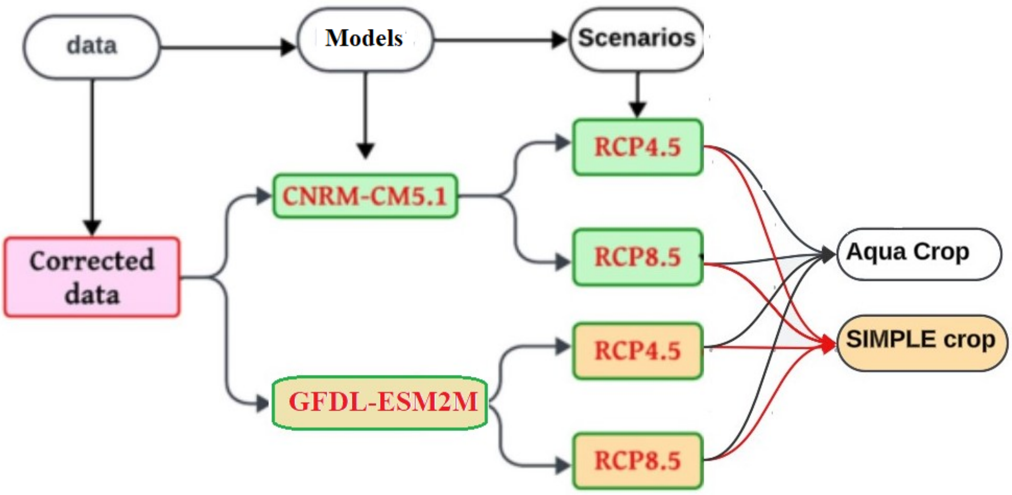

Figure 3. Projection pathways used to evaluate wheat production parameters. This figure shows the simulation pathways combining climate models and RCP scenarios to assess wheat production from 2041 to 2070. Corrected climate data were used in the AquaCrop and SIMPLE models to evaluate the potential impact of different climate scenarios on wheat growth.

2.4. Crop Growth Models

Crop growth models simulate an interconnected soil-plant-atmosphere system, influenced by various agronomic practices and environmental factors [64]. They are commonly used to analyze multiple aspects related to crop growth, development, yield, and related soil processes. The increased use of these models is particularly evident in assessing the potential impacts of climate change on agriculture and developing adaptation strategies [65,66]. However, due to the inherent complexity of modeling, some uncertainty persists in the results, primarily due to the need for simplifications compared to real systems [67]. To mitigate this risk of error, it is recommended to use multiple models simultaneously. Studies have shown that model ensembles provide more robust assessments than individual models, offering a more reliable approach for predicting future impacts on wheat [68,69]. In this study, the SIMPLE Crop and AquaCrop models were used to assess the potential impact of climate change on wheat production in Northwest Tunisia.

SIMPLE Model, AquaCrop Model

The SIMPLE crop model is designed to characterize different types of crops using 13 parameters, four of which are tailored to the specific traits of cultivars [31]. The 13 parameters are listed in Table 3. The four parameters particular to cultivars are base temperature (T_{base}), optimal temperature for growth (T_{opt}), radiation use efficiency (RUE), and relative increase in RUE per ppm of CO_2 (SCO2). These specific parameters allow the model to be adjusted according to the distinct characteristics of each cultivar.

Table 3. Crop and cultivar parameter values used in the SIMPLE model [31].

Parameter	Description	Value
T_{sum}	Cumulative temperature requirement from sowing to maturity (°C·d)	2200
HI	Potential harvest index	0.36
I_{50A}	Cumulative temperature requirement for leaf area development to intercept 50% of radiation (°C·d)	480
I_{50B}	Cumulative temperature till maturity to reach 50% radiation interception due to leaf senescence (°C·d)	200
T_{base}	Base temperature for phenology development and growth (°C)	0
T_{opt}	Optimal temperature for biomass growth (°C)	15
RUE	Radiation use efficiency (above ground only and without respiration) ($g \cdot MJ^{-1} \cdot m^{-2}$)	1.24
I_{50maxH}	The maximum daily reduction in I_{50B} due to heat stress (°C·d)	100
I_{50maxW}	The maximum daily reduction in I_{50B} due to drought stress (°C·d)	25
T_{max}	Threshold temperature to start accelerating senescence from heat stress (°C)	34
Text	The extreme temperature threshold when RUE becomes 0 due to heat stress (°C)	45
SCO2	Relative increase in RUE per ppm elevated CO_2 above 350 ppm	0.08
S_{water}	Sensitivity of RUE (or harvest index) to drought stress (ARID index)	0.4

This model relies on daily weather data, crop management information, and soil water retention parameters for optimal operation. To validate its accuracy, the SIMPLE model was calibrated using data from 25 field experiments covering four different crops, with a relative root mean square error (RRMSE) of 25.4% for final yield prediction [31]. This highlights its ability to accurately predict wheat yields. The SIMPLE model uses the cumulative temperature concept to evaluate phenological development, as indicated by CERES-Wheat [70].

AquaCrop is a versatile and essential tool for simulating wheat yields, developed by the Food and Agriculture Organization (FAO) of the United Nations [71]. Specifically designed for a diverse range of users, such as engineers, economists, extension specialists, and water managers, AquaCrop can be used for strategic, tactical, and operational planning. It facilitates management decisions based on reliable data and is useful for comparing potential yields to actual yields, identifying constraints, and enabling corrective actions. Additionally, AquaCrop is suitable for simulating future scenarios and conducting climate change research. According to [71], this model stands out for its simplicity regarding parameters and input data, making it easier to model plant responses to water for various crops. AquaCrop's growth simulations are based on water consumption, considering evaporation and transpiration, crucial factors in greenhouse environments. Therefore, calibrating AquaCrop's parameters is essential to ensure an accurate representation of water consumption and yield improvements [71–73]. For the SIMPLE model, the fraction of plant available water-holding capacity, the runoff curve number, the deep drainage coefficient, and the root zone depth (mm) were either obtained from the literature or estimated from general soil information for each location.

3. Results

3.1. Performance Assessment of SIMPLE Crop and AquaCrop Model

Performance metrics for growth cycle duration (days), biomass (q/ha), and yield (q/ha) of the SIMPLE Crop and AquaCrop models at Slougia and Medjez El Beb are summarized in Table 4.

At Slougia, SIMPLE Crop exhibits a mean bias error (MBE) of −3.6 days and a root mean square error (RMSE) of 5.8 days for growth cycle duration, accompanied by an index of agreement (IA) of 0.78, indicating relatively accurate predictions. Conversely, AquaCrop shows a higher RMSE of 8.9 days but a slightly better IA of 0.83, suggesting more prediction variability. At Medjez El Beb, SIMPLE Crop performs better with a growth cycle duration MBE of −3.8 days and an RMSE of 8.1 days, while AquaCrop shows an MBE of −5.0 days and an RMSE of 7.3 days, with both models achieving high IA values of 0.85 and 0.87, respectively.

For biomass prediction at Slougia, SIMPLE Crop has an MBE of 2.50 q/ha and an RMSE of 1.12 q/ha, while AquaCrop shows slightly lower errors with an MBE of 2.15 q/ha and an RMSE of 1.21 q/ha. At Medjez El Beb, SIMPLE Crop predicts biomass with an MBE of 2.30 q/ha and an RMSE of 1.20 q/ha, while AquaCrop performs well with an MBE of 1.95 q/ha and an RMSE of 1.02 q/ha. Both models achieve high IA values (0.89 and 0.88 for SIMPLE Crop, 0.89 and 0.97 for AquaCrop). Regarding yield, SIMPLE Crop performs better at Slougia with an MBE of 2.26 q/ha and an RMSE of 1.32 q/ha, whereas AquaCrop shows higher errors with an MBE of 2.10 q/ha and an RMSE of 1.32 q/ha. At Medjez El Beb, SIMPLE Crop predicts yield with an MBE of 1.36 q/ha and an RMSE of 1.23 q/ha, compared to AquaCrop with an MBE of 2.79 q/ha and an RMSE of 1.35 q/ha. Both models maintain good IA values (0.77 and 0.79 for Slougia, 0.88 and 0.83 for Medjez El Beb).

Both models demonstrate strong performance, particularly in biomass predictions, as indicated by their high IA values. SIMPLE Crop generally shows better accuracy in predicting yield and growth cycle duration at Slougia, while AquaCrop demonstrates stronger agreement in biomass predictions. These findings underscore the critical role of model calibration and highlight opportunities for further enhancement in prediction accuracy.

Table 4. Evaluation of Growth Cycle Duration (days), Biomass (q/ha), and Yield (q/ha) Using MBE, RMSE, and IA for SIMPLE Crop and AquaCrop Models at Slougia and Medjez El Beb.

Crop Model	Site	Growth Cycle Duration (days)			Biomass			Yield		
		MBE (q/ha)	RMSE (q/ha)	IA	MBE (q/ha)	RMSE (q/ha)	IA	MBE (q/ha)	RMSE (q/ha)	IA
SIMPLE Crop	Slougia	−3.6	5.8	0.78	2.50	1.12	0.88	2.26	1.32	0.77
	Medjez El Beb	−3.8	8.1	0.85	2.30	1.20	0.89	1.36	1.23	0.88
AquaCrop	Slougia	−4.3	8.9	0.83	2.15	1.21	0.97	2.10	1.32	0.79
	Medjez El Beb	−5.0	7.3	0.87	1.95	1.02	0.89	2.79	1.35	0.83

The discrepancies observed in the results at Slougia between the SIMPLE Crop and AquaCrop models, particularly concerning the Index of Agreement (IA), can be attributed to several factors, as noted by Kostková et al. [74]. Firstly, the differences in performance between the models may arise from the inherent characteristics of each model. SIMPLE Crop and AquaCrop utilize distinct methodologies for simulating crop growth, which can impact the accuracy of their predictions. For instance, while SIMPLE Crop shows more favorable MBE and RMSE values, indicating better average accuracy, its lower IA suggests that it may not capture the observed data variations as effectively. This observation is consistent with Kostková et al. [74], which found that the median of model ensembles can provide better yield modeling accuracy than the average ensemble or individual models.

3.2. Yield

Figures 4 and 5 show wheat yields for the sites of Medjez El Beb and Slougia under similar conditions. Table 5 summarizes the results of the same combinations of climate models, RCP scenarios, and growth models for both sites.

The average wheat yields under identical climatic conditions and growth models show minimal differences between the two areas (Figures 4 and 5). For example, with the CNRM-CM5.1 climate model and the RCP 8.5 scenario, Medjez El Beb has an average yield of 6.89 q/ha with the AquaCrop model and 7.53 q/ha with the SIMPLE Crop model. In comparison, Slougia, under the same scenario, has averages of 6.97 q/ha and 7.89 q/ha, respectively, for the same growth models. These yield differences, although present, are relatively small, indicating that the specific local conditions of each region do not significantly impact yields within the framework of the climate and growth models used. This suggests that regional differences have a limited effect compared to the influence of climate models and crop growth models.

The results show notable variations in wheat yields according to different climate models (CNRM-CM5.1 vs. GFDL-ESM2M), emission scenarios (RCP 4.5 vs. RCP 8.5), and growth models (AquaCrop vs. SIMPLE Crop) (Tables 5 and 6). Statistical analysis, notably ANOVA, reveals that the observed differences are significant with an F-value of 3.58 and a p-value of 0.0014, indicating that the variations between groups are significant.

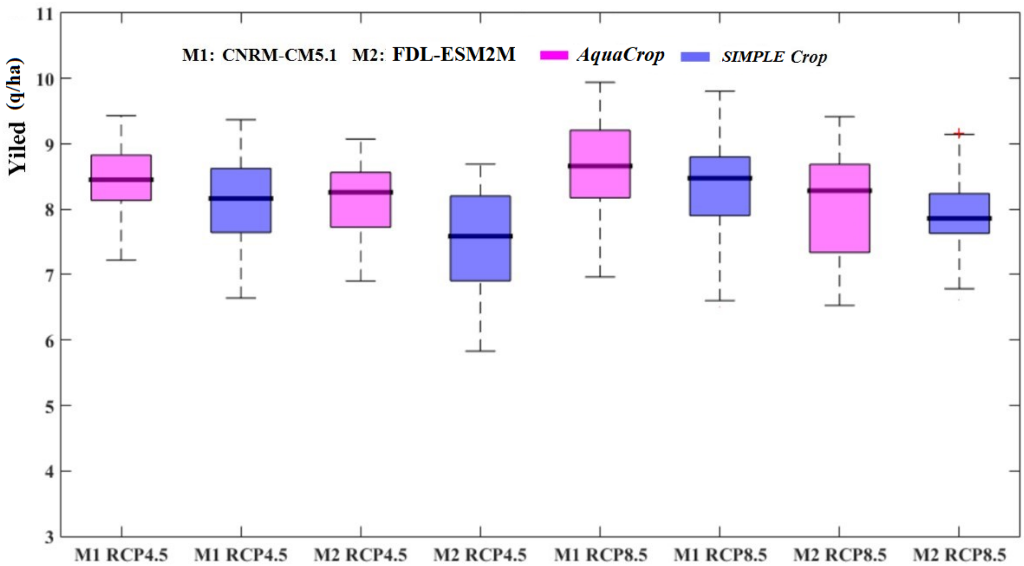

Figure 4. Simulation of wheat yields in Slougia under different climate scenarios and growth models, using the AquaCrop and SIMPLE crop models for the period 2041–2070.

The differences between climate models are particularly marked. For example, GFDL-ESM2M under RCP 4.5 shows a higher average yield of 7.73 q/ha compared to CNRM-CM5.1 under RCP 8.5 with 6.89 q/ha, suggesting that GFDL-ESM2M's climate projections predict more favorable conditions for wheat. In general, yields under RCP 4.5 are higher than those under RCP 8.5, indicating that reduced emissions (RCP 4.5) are associated with better-growing conditions for wheat.

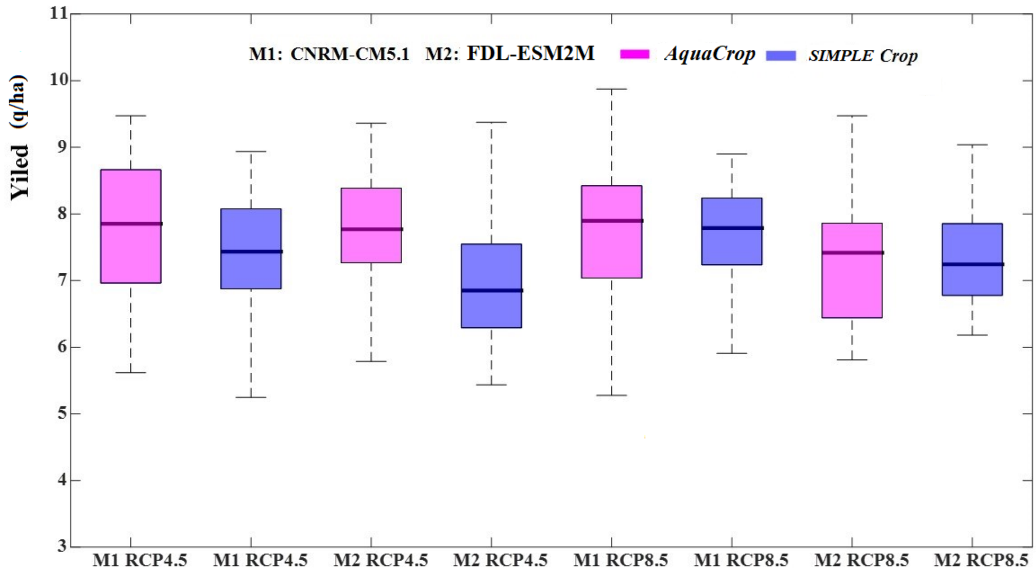

Figure 5. Simulation of Wheat yields in Medjez el Beb under different climate scenarios and growth models, using the AquaCrop and SIMPLE crop models for the period 2041–2070.

The differences between the AquaCrop and SIMPLE Crop growth models are also significant, although the impact is less pronounced compared to the differences due to climate models and emission scenarios. For example, for CNRM-CM5.1 under RCP 4.5, the yield with AquaCrop is 7.55 q/ha, while with SIMPLE Crop it is 7.36 q/ha. These variations, although smaller, highlight the importance of the choice of growth model in yield projections.

Table 5. Wheat yields for different combinations of the climate model, RCPs, and crop model for the period 2041–2070 (q/ha).

Combination	Average	STD	Minimum	Maximum
CNRM-CM5.1, RCP 4.5, AquaCrop	7.55	1.12	5.62	9.20
CNRM-CM5.1, RCP 4.5, SIMPLE Crop	7.36	1.06	5.25	8.98
CNRM-CM5.1, RCP 8.5, AquaCrop	6.89	1.14	5.74	9.47
CNRM-CM5.1, RCP 8.5, SIMPLE Crop	7.53	1.17	5.61	9.33
GFDL-ESM2M, RCP 4.5, AquaCrop	8.06	1.16	6.10	9.88
GFDL-ESM2M, RCP 4.5, SIMPLE Crop	7.73	1.12	5.79	9.21
GFDL-ESM2M, RCP 8.5, AquaCrop	6.97	1.16	5.81	9.36
GFDL-ESM2M, RCP 8.5, SIMPLE Crop	7.89	1.21	5.86	9.37

Statistical analysis shows that variations in future wheat yields are mainly influenced by climate models and emission scenarios, with growth models playing a secondary role. GFDL-ESM2M's climate projections seem to offer more favorable conditions for wheat, particularly under the RCP 4.5 scenario (Table 5). These results underline the importance of adopting specific adaptation strategies based on precise climate projections to ensure food security in the context of climate change.

The yield differences between AquaCrop at 7.55 q/ha and SIMPLE Crop at 7.36 q/ha are attributed to the limitations of the SIMPLE Crop model, which is less sophisticated and does not capture the complex interactions between climate and plant growth as effectively as AquaCrop. AquaCrop is a more detailed model that integrates variables such as evapotranspiration, water management, and crop responses to stress conditions [73]. These aspects allow AquaCrop to provide more accurate and realistic yield projections under various climate scenarios. Thus, the results show that the choice of growth model can significantly influence yield estimates, highlighting the importance of using appropriate models to assess the impact of climate change on agriculture.

Table 6. Analysis of variance of the combinations of climate models, emission scenarios, and crop growth tools.

Source of Variation	Sum of Squares	df	Mean Squares	F-Value	p-Value
Climate Model (M)	7.92	1	7.92	4.57	0.045
RCP Scenario (R)	4.15	1	4.15	2.40	0.135
Growth Model (C)	11.87	1	11.87	6.86	0.017
Interaction M × R	0.84	1	0.84	0.49	0.490
Interaction M × C	1.29	1	1.29	0.75	0.395
Interaction R × C	0.47	1	0.47	0.27	0.610
Error	34.55	20	1.73		
Total	61.08	26			

3.3. Biomass

Figures 6 and 7 depict wheat biomass production for the sites of Medjez El Beb and Sloughia under different climate scenarios and growth models. Table 7 summarizes the average biomass for both sites under various combinations of climate models, RCPs, and growth models.

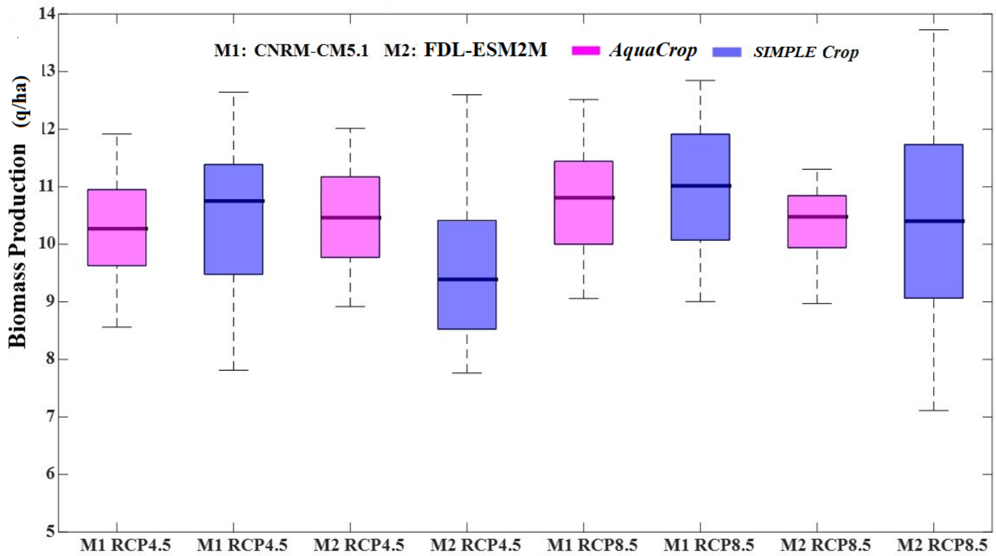

Figure 6. Wheat biomass production in Sloughia under climate scenarios RCP 4.5 and RCP 8.5, projected by the CNRM-CM5.1 and GFDL-ESM2M models, and simulated using AquaCrop and SIMPLE Crop models for the period 2041–2070.

Biomass projections for Medjez El Beb and Sloughia for the period 2041–2070 reveal similar averages when the same climate model (RCP 8.5) and growth model conditions are applied.

For Medjez El Beb, under the CNRM-CM5.1 climate model with the AquaCrop growth model, the average biomass is 17.99 q/ha. Using the SIMPLE Crop growth model, the average slightly increases to 18.73 q/ha. For Sloughia, under the GFDL-ESM2M climate model with AquaCrop, the average biomass is 18.90 q/ha, while with SIMPLE Crop, it is 19.04 q/ha (Figures 6 and 7).

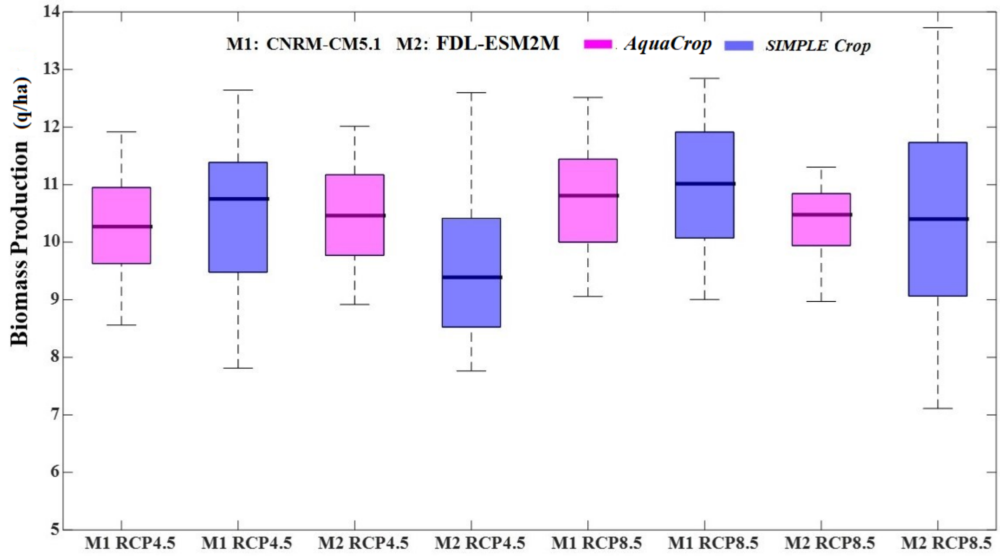

Figure 7. Wheat biomass production at Medjez El Beb under climate scenarios RCPs 4.5 and RCP 8.5, projected by the CNRM-CM5.1 and GFDL-ESM2M models and simulated using AquaCrop and SIMPLE Crop models for the period 2041–2070.

Table 7. Average wheat biomass (q/ha) in Medjez El Beb and Sloughia under different climate models and growth Models (2041–2070).

Region	Climate Model	Growth Model	Average Biomass (q/ha)
Medjez El Beb	CNRM-CM5.1	AquaCrop	17.99
	CNRM-CM5.1	SIMPLE Crop	18.73
Sloughia	GFDL-ESM2M	AquaCrop	18.90
	GFDL-ESM2M	SIMPLE Crop	19.04

These slight differences in biomass between the two sites are relatively negligible, suggesting that the specific local conditions of both sites similarly influence the projections of climate and growth models. This indicates that biomass variations are primarily due to differences between the climate and growth models used, rather than intrinsic regional characteristics. The results thus emphasize the importance of selecting appropriate models to achieve accurate projections of future biomass in the context of climate change. The results of the wheat biomass analysis for the sites of Medjez El Beb and Sloughia for the period 2041–2070 show moderate differences between the projections obtained with AquaCrop and SIMPLE Crop growth models under the RCP 8.5 climate scenario. For Medjez El Beb, the average biomass projected by AquaCrop is 17.99 q/ha, while SIMPLE Crop projects a slightly higher biomass of 18.73 q/ha. This difference of 0.74 q/ha, although modest, suggests that the SIMPLE Crop model, despite its simplifications, effectively captures the growth dynamics under future climatic conditions.

In comparison, for Sloughia, the average biomasses are slightly higher, with AquaCrop projecting 18.90 q/ha and SIMPLE Crop 19.04 q/ha, indicating an even smaller difference of 0.14 q/ha. These results show that both growth models provide relatively consistent projections between the two sites. However, it is important to note that AquaCrop can offer more detailed and precise projections by integrating more complex interactions between climatic variables and crop responses. Nevertheless, SIMPLE Crop remains a viable alternative when resources or detailed data are limited while ensuring globally comparable projections. The regional characteristics have a minor impact on biomass projections compared to the choice of climate and growth models, it is essential to carefully select and use models that fit available data and specific study needs.

3.4. Growth Period

The box plots illustrate variations of the growth period in days for Medjez El Beb and Sloughia, analyzed across various climate models, RCP scenarios, and growth models. In Medjez El Beb, the growth period primarily ranges from 150 to 230 days, with notable nuances depending on the growth models used, particularly AquaCrop and SIMPLE Crop (Figure 8). Similarly, in Sloughia, the growth periods show comparable variation, also between 150 and 230 days, but with significant differences influenced by the climate models and RCP scenarios (Figure 9). Although the growth period appears slightly longer in Sloughia than in Medjez El Beb, these results highlight a similar sensitivity of both sites to climate projections and growth model choices, underscoring the importance of a robust approach in evaluating the climate impacts on local agriculture.

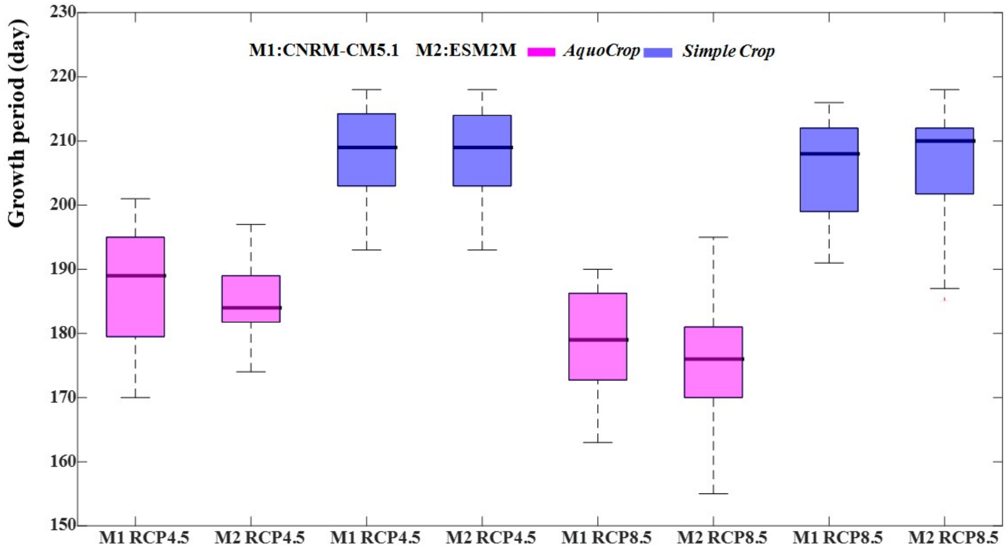

Figure 8. Growth period in Medjez El Beb under different RCPs scenarios according to the CNRM-CM5.1 and GFDL-ESM2M climate models, simulated by the AquaCrop and SIMPLE Crop models for the period 2041–2070.

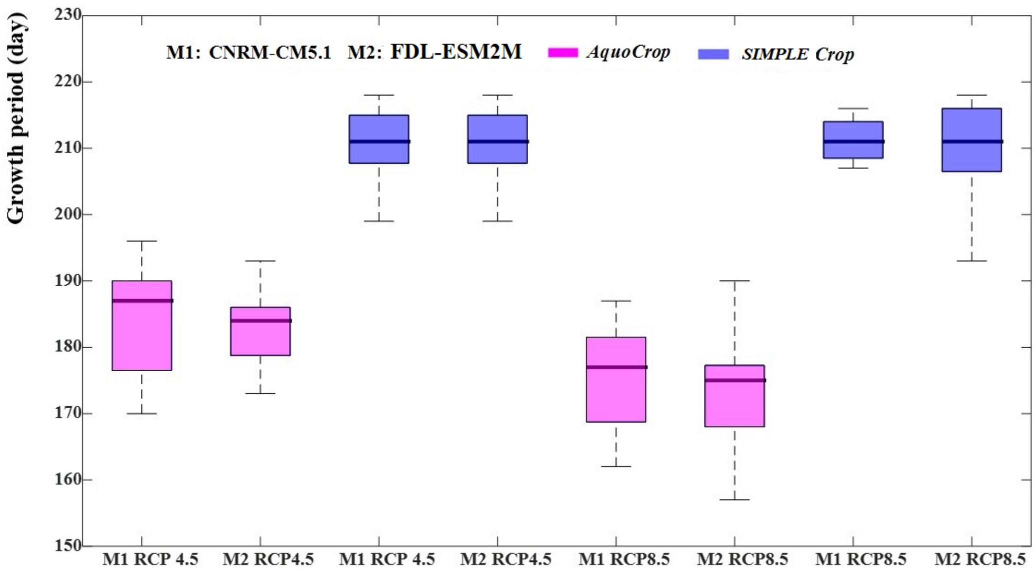

Figure 9. Growth period in Sloughia under different RCP scenarios according to the CNRM-CM5.1 and GFDL-ESM2M climate models, simulated by the AquaCrop and SIMPLE Crop growth models for the period 2041–2070.

The analysis of crop growth period projections, based on a fixed sowing date of November 15, underscores the crucial influence of climate models, RCP scenarios, and growth models, corroborated by several studies. Previous research by Sanchez [75] has demonstrated that variations between the CNRM-CM5.1 and GFDL-ESM2M climate models can lead to significant differences in the length of the growth season, with average growth periods of 180 days for CNRM-CM5.1 and 170 days for GFDL-ESM2M (Figure 10), as well as notable variability represented by standard deviations of ±10 days for each model [75]. These results indicate that CNRM-CM5.1, projecting more moderate temperature increases and stable precipitation, tends to favor slightly longer and less variable growth periods compared to GFDL-ESM2M, which predicts warmer and drier conditions under certain RCP scenarios [76].

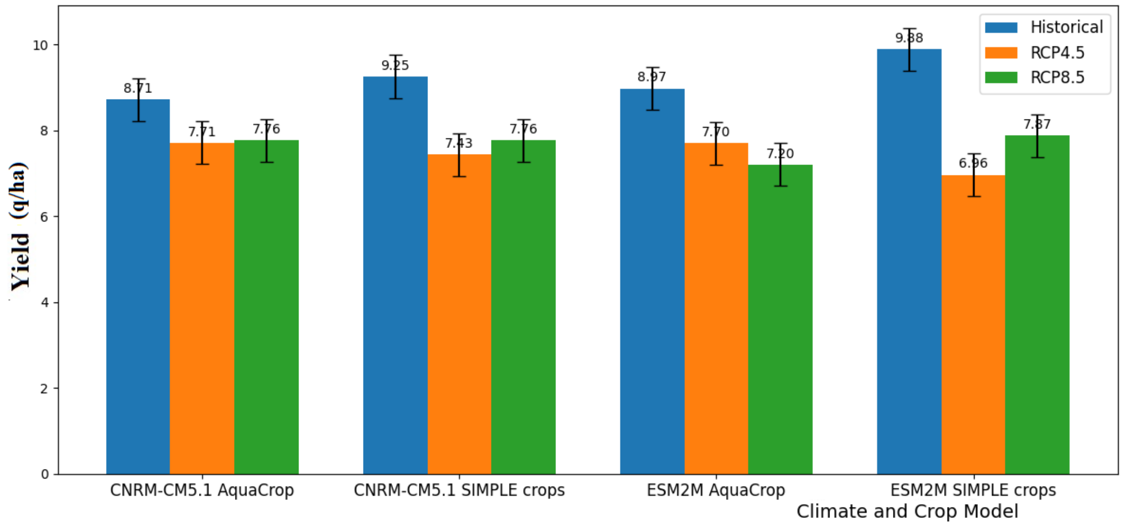

Figure 10. Comparison of Means and Standard Deviations of Crop Growth Periods Across sites, Crop Models, and Climate Scenarios (RCP4.5 and RCP8.5) for the Period 2041–2070.

IPCC results [3] confirm that the RCP 8.5 scenario with high greenhouse gas emissions, could significantly reduce the available growth period for crops, compared to RCP 4.5 (Figure 10), which offers more favorable prospects with average growth periods of 185 days and standard deviations of ±8 days [3].

Agronomic growth models like AquaCrop and SIMPLE Crop, analyzed by vanuytrecht [77], demonstrate their ability to simulate crop responses to projected climate conditions, with average growth periods of 175 days for AquaCrop and 180 days for SIMPLE Crop, and standard deviations of ±12 days for both models [77]. This level of detail is crucial for assessing and anticipating the impacts on the growth period of wheat crops in various contexts of climate change. Thus, the fixed sowing date of November 15 serves as an essential reference point to evaluate how these factors interact to modulate the effective duration of the crop growth season.

3.5. Projected Impact of Climate Change on Wheat Growth Parameters

The analysis of climate projections using the CNRM-CM5.1 and GFDL-ESM2M models, coupled with AquaCrop and SIMPLE Crop growth models for wheat cultivation, highlights significant concerns regarding the future impact of climate change on wheat yields (Table 8). Historical data, representing stable conditions over past decades, contrast starkly with projected yields under RCP scenarios. Under the CNRM-CM5.1 model, historical average wheat yields were 8.63 q/ha, reflecting stable production patterns. However, under the RCP 4.5 and RCP 8.5 scenarios, projected yields for AquaCrop show noticeable declines to 6.94 and 6.74 q/ha, respectively. Similar trends are observed with the GFDL-ESM2M model, where historical yields of 9.02 q/ha decrease to 7.65 and 7.39 q/ha under RCP 4.5 and RCP 8.5, respectively (Figure 10, Table 8).

For the SIMPLE Crop model under CNRM-CM5.1, historical yields averaged 8.77 q/ha. Projections under RCP 4.5 and RCP 8.5 scenarios suggest yields of 6.44 and 6.52 q/ha, respectively. Meanwhile, under GFDL-ESM2M, historical yields of 9.62 q/ha shift to projections of 7.68 and 7.22 q/ha under RCP 4.5 and RCP 8.5 (Figure 10, Table 8).

These findings underscore the vulnerability of wheat cultivation to climate change, with both climate models projecting reduced average yields across all scenarios. The increase in standard deviations indicates heightened variability in projected yields, reflecting uncertain future agricultural productivity under changing climatic conditions. Such insights are crucial for informing adaptive strategies and policy interventions aimed at mitigating the adverse impacts of climate change on global food security.

Table 8. Comparison of Historical Yields (1970–1997) and Future Projections (2041–2070) for Each RCP Scenario and Climate Model in Medjez el Bab and Slouguia.

Climate Model	RCP/Historical	Crop Model	Mean	Std
CNRM-CM5.1	Historical	AquaCrop	8.63	1.07
	RCP 4.5	AquaCrop	6.94	0.98
	RCP 8.5	AquaCrop	6.74	1.07
GFDL-ESM2M	Historical	AquaCrop	9.02	1.09
	RCP 4.5	AquaCrop	7.65	1.03
	RCP 8.5	AquaCrop	7.39	1.07
CNRM-CM5.1	Historical	SIMPLE Crop	8.77	0.92
	RCP 4.5	SIMPLE Crop	6.44	0.88
	RCP 8.5	SIMPLE Crop	6.52	0.95
GFDL-ESM2M	Historical	SIMPLE Crop	6.62	1.08
	RCP 4.5	SIMPLE Crop	7.68	0.92
	RCP 8.5	SIMPLE Crop	7.22	0.95

The results obtained with the AquaCrop and SIMPLE Crop models for wheat cultivation under different climate scenarios align with several previous scientific studies examining the impact of climate change on agricultural yields. For instance, research conducted by Rezaei et al. [32] indicated that each degree Celsius increase could reduce wheat yields by several percentages due to wheat's sensitivity to temperature and precipitation variations. Similarly, the work of Hu et al. [18] highlighted that climate changes could significantly decrease wheat yields globally, affecting food security. Additionally, the study by Asseng et al. [78] corroborated these findings by highlighting the increased variability in wheat yields and the heightened risks of production losses due to climate changes.

The analysis of climate projections using the CNRM-CM5.1 and GFDL-ESM2M models, coupled with AquaCrop and SIMPLE Crop growth models for wheat cultivation, highlights significant concerns regarding the impact of climate change on wheat biomass. Historical data reveal that the average biomass for the CNRM-CM5.1 model with AquaCrop is 10.82 q/ha, while with SIMPLE Crop, it is 9.37 q/ha. For the GFDL-ESM2M model, the historical average biomass is 10.69 q/ha with AquaCrop and 10.51 q/ha with SIMPLE Crop.

However, projections under the RCP 4.5 scenario show a marked decrease in biomass. For CNRM-CM5.1 with AquaCrop, the projected biomass is 6.94 q/ha, indicating a significant decline of 36% compared to historical yields. For SIMPLE Crop, the projected biomass drops to 6.44 q/ha, a reduction of 31%. With the GFDL-ESM2M model, projected biomass is 7.65 q/ha for AquaCrop and 7.68 q/ha for SIMPLE Crop, representing reductions of 28% and 27%, respectively (Figure 11).

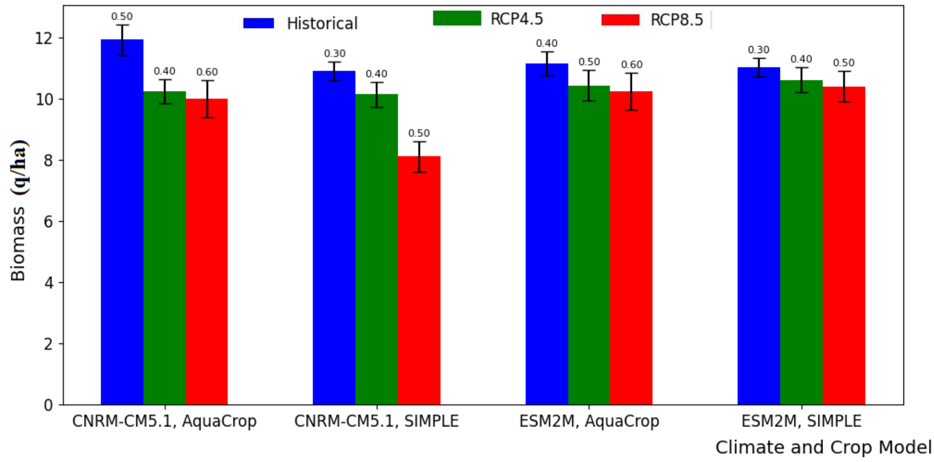

Figure 11. comparison of historical (1970–1997) and projected (2041–2070) biomass using climate models coupled with AquaCrop and SIMPLE Crop models.

Projections under the RCP 8.5 scenario are even more alarming. For CNRM-CM5.1, the projected biomass for AquaCrop is 6.74 q/ha, a decrease of 38%; for SIMPLE Crop, 6.52 q/ha, a reduction of 30%. For the GFDL-ESM2M model, projected biomass is 7.39 q/ha with AquaCrop, a decrease of 31%, and 7.22 q/ha with SIMPLE Crop, a reduction of 31%. Projections of growth cycle duration for AquaCrop and SIMPLE Crop models under climates simulated by CNRM-CM5.1 and GFDL-ESM2M reveal significant anticipated changes by 2070 compared to the historical period from 1970 to 1997. Under the CNRM-CM5.1 model, AquaCrop shows a trend towards a reduction in cycle duration under RCP 4.5 (172.62 days) compared to historical values (196.33 days), with a slight increase projected under RCP 8.5 (172.75 days). In contrast, SIMPLE Crop exhibits a more pronounced reduction under RCP 4.5 (182.31 days) compared to historical values (208.52 days), followed by a slight improvement under RCP 8.5 (174.45 days) (Figure 12).

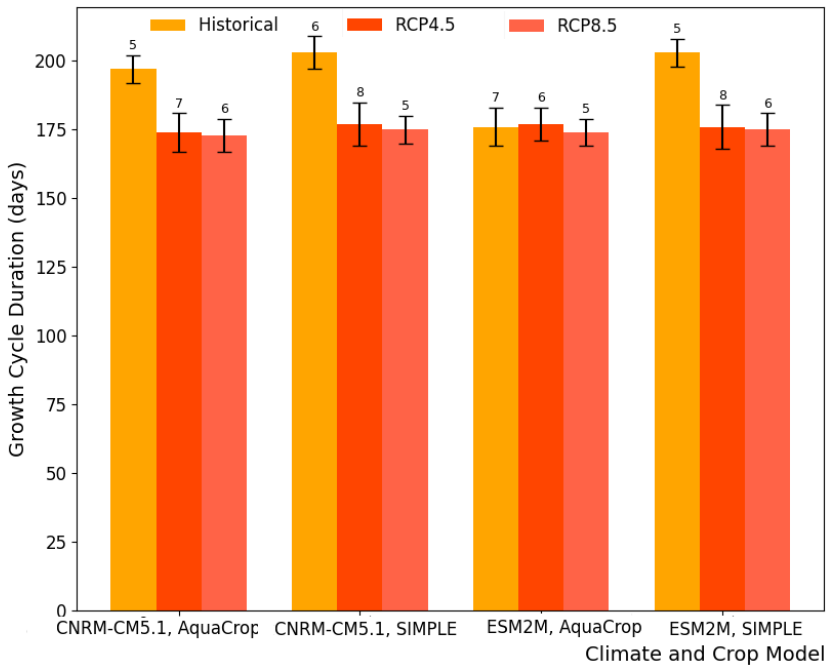

Figure 12. Comparison of historical (1970–1997) and projected (2041–2070) growth cycle duration using climate models coupled with AquaCrop and SIMPLE crop models.

For the GFDL-ESM2M model, AquaCrop maintains a relatively stable cycle duration between historical values (179.73 days) and RCP 4.5 (180.45 days) and RCP 8.5 (172.75 days) scenarios, while SIMPLE Crop shows a slight decrease under RCP 4.5 (180.31 days) and a slight increase under RCP 8.5 (176.45 days). These results suggest that projected climate changes could lead to significant adjustments in crop growth cycle duration by 2070, necessitating ongoing adaptation of planting dates and agricultural practices to maintain productivity and resilience of agricultural systems

4. Discussion

The study results provide valuable insights into the performance and projections of the SIMPLE Crop and AquaCrop models for wheat cultivation under changing climatic conditions in Slougia and Medjez El Beb.

In Slougia, SIMPLE Crop generally provided more accurate predictions for the growth cycle duration and yield compared to AquaCrop, as indicated by lower mean bias errors (MBE) and root mean square errors (RMSE). Specifically, SIMPLE Crop's predictions for the growth cycle were closer to observed values with a lower RMSE, and it also outperformed AquaCrop in yield predictions. For biomass, AquaCrop showed slightly better accuracy in terms of MBE, though both models had comparable RMSE values. In Medjez El Beb, the SIMPLE Crop model again exhibited lower errors for the growth cycle duration compared to AquaCrop. However, AquaCrop demonstrated superior performance for biomass predictions, achieving lower MBE and RMSE values. For yield, SIMPLE Crop showed higher MBE and RMSE than AquaCrop, indicating that AquaCrop provided more accurate yield forecasts in this region.

These results highlight the challenges related to quantifying the uncertainties of climate change impacts on agricultural yields. Variations in greenhouse gas emissions and climate responses significantly influence model predictions. The different structures and parameter values between SIMPLE Crop and AquaCrop led to variations in wheat yield projections. For example, projections under GFDL-ESM2M and RCP 4.5 generally showed higher yields than under CNRM-CM5.1 and RCP 8.5.

The RCP 4.5 scenario represents a trajectory where substantial efforts are made to reduce greenhouse gas emissions, thereby limiting the global temperature increase to a moderate level compared to higher emission scenarios like RCP 8.5. In this context, while the climate conditions under RCP 4.5 are still affected by climate change, they are less extreme. This can result in more favorable temperatures, a more balanced distribution of precipitation, and a lower frequency of extreme weather events, such as prolonged droughts or intense heatwaves [79,80].

These more moderate conditions are likely to promote crop growth by reducing thermal and water stress on plants, which could explain why the RCP 4.5 scenario is associated with better growing conditions. This contrasts with the RCP 8.5 scenario, where climate conditions could become more extreme and less conducive to optimal crop growth [79,80].

It is important to note that the beneficial effects of increasing GHG concentrations on crop yields depend on soil nutrient availability. As indicated in the literature, high GHG concentration reduces protein concentration in grains, which is an important quality trait [81–84]. To fully benefit from the positive impact of increasing GHG concentrations and minimize negative impacts on grain quality, nitrogen fertilization needs to be adjusted in high GHG environments [82,83,85,86].

Crop models have also been used to manage trade-offs between agricultural production and externalities under climate change. For example, in northeastern Germany, research has explored the trade-off between grain yield and groundwater recharge management through variable nitrogen inputs for future climate change scenarios [87]. These simulations showed that the trade-off between deep drainage and grain yield can potentially be controlled by nitrogen management. However, this control is more effective under current climatic conditions than future ones. The results of this study are consistent with those of Lhomme et al. [35]. Indeed, climate projections for 2040–2070 forecast a reduction in the length of the wheat growing cycle and an earlier sowing period due to the systematic increase in temperatures and changes in precipitation patterns. These climatic changes lead to yield deficits, highlighting the need to adapt agricultural practices to new climatic conditions. We recommend advancing sowing dates and adopting shorter-cycle wheat varieties to mitigate negative impacts and optimize wheat production in Tunisia. Early-maturing and drought-tolerant varieties, such as those identified in our study, are particularly suited to the projected conditions and could significantly improve yields. These recommendations are based on our current observations and align with previous research, emphasizing the need for innovative agricultural management to address future climatic challenges. We also observed that impacts vary depending on specific sites in Tunisia, notably Medjez El Beb and Slougia. These results are confirmed by Lhomme et al. [35] for other sites in Tunisia. For instance, in Kairouan, while yield deficits slightly improve with better water management, conditions deteriorate in Jendouba. Projected climatic conditions for these two sites indicate variations in water availability and temperature needs for optimal wheat growth, underscoring the importance of local-level selection and screening. Furthermore, according to Kone et al. [20], there is a significant lack of research on climate change impacts in certain African sites, including North Africa, Central Africa, and South Africa, including Tunisia. This research gap concerns the impacts on crop production parameters, water resources, and management techniques. These gaps highlight the importance of expanding research to better understand and address the specific challenges faced by these sites in the face of climate impacts. Therefore, it is crucial to continue refining and improving adaptation strategies to cope with the progressive aggravation of climate change. Finally, rising average temperatures due to future climate change will create new opportunities to increase cropping frequency in some agricultural systems. For example, simulation studies have shown that recent temperature increases favor double cropping of wheat and soybean in the southern pampas of Argentina [88] and that delaying wheat planting and maize harvesting in China can increase the total grain yield of wheat–maize double cropping systems [89]. These various adaptations underscore crop management's importance in taking advantage of opportunities offered by climate change while minimizing its negative impacts. These adaptation strategies are essential to maintain and improve wheat production in northern Tunisia in the face of future climatic challenges.

5. Conclusions

Future projections for the period 2041–2070 indicate a significant decrease in average wheat yields in the study region under the RCP 4.5 scenario. Models CNRM-CM5.1 and GFDL-ESM2M coupled with AquaCrop and Simple Crop models project average yields of 7.709 q/ha, and 7.703 q/ha, respectively, marking a notable decline compared to historical averages. These results highlight the major challenges posed by climate change on wheat production in northern Tunisia.

These findings also underscore the crucial importance of selecting appropriate models to project future agricultural biomass in a changing climate. The slight differences between AquaCrop and SIMPLE Crop projections suggest that AquaCrop, with its comprehensive modeling of climate-crop interactions, offers more detailed projections, while SIMPLE Crop remains valuable, especially when detailed data are limited.

Furthermore, understanding the variability and uncertainties associated with these projections is essential for developing effective adaptation strategies. Policymakers and stakeholders in the agricultural sector can use this information to plan for future scenarios, ensure food security, and optimize resource use in response to climate change. The next steps in this research will involve expanding the projections to encompass a broader range of climate scenarios and agricultural models. Future efforts will also focus on integrating socio-economic factors to better assess the wider impact of climate change on agricultural sustainability. It is estimated that these measures can significantly contribute to maintaining food security and the sustainability of agricultural production in northern Tunisia despite the growing challenges of climate change. In conclusion, the data presented in this study emphasize the urgent need for concerted action to enhance the resilience of the agricultural sector. The alarming projections of agricultural yields underscore the urgent need for strategic policies and initiatives aimed at ensuring sustainable yields and food security in the northern region of Tunisia.

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