Phenological and productive response of white maize to climate change in andean conditions †

[Respuesta fenológica y productiva del maíz blanco al cambio climático en condiciones andinas]

Mirian Capa-Morocho*[1], Fernanda Zapata[1], Rodrigo Abad-Guamán[2] and Diego Chamba-Zaragocín[3]

[1]Research Group in Ecophysiology and Agrarian Production, Carrera de Agronomía, Facultad Agropecuaria y de Recursos Naturales Renovables, National University of Loja, Avenida Pio Jaramillo Alvarado, C.P. 110103, Loja, Ecuador. Email: mirian.capa@unl.edu.ec
[2]Centro de Nutrición Animal, National University of Loja, Avenida Pio Jaramillo Alvarado, C.P. 110103, Loja, Ecuador. Email: rodrigo.abad@unl.edu.ec
[3]Carrera de Agrícola, National University of Loja, Avenida Pio Jaramillo Alvarado, C.P. 110103, Loja, Ecuador. Email: diego.f.chamba@unl.edu.ec
**Corresponding author*

SUMMARY

Background. Climate change has direct impacts on current and future crop productivity, negatively affecting food security, particularly in Latin America. **Objective.** To assess the impact of projected climate change on the phenology and yield of white maize using the DSSAT CERES-Maize model, which was calibrated and validated under Andean conditions. **Methodology.** The crop model was validated using data from field trials carried out in 2018-2019 and 2020-2021 under different planting densities and nutrient management regimes. Climate projections from the sixth Coupled Model Intercomparison Project (CMIP6) and emissions scenarios from Shared Socioeconomic Pathways (SSP) were used. **Results.** Calibration and validation of the CERES maize crop model demonstrated good agreement between simulated and observed values for white maize phenology and yield under Andean conditions. The error rate percentage was less than 10%, which indicates high accuracy of the simulation results. The phenology of white maize was significantly affected under all SSP climate scenarios, particularly in the 2090s, indicating a decrease of up to 83 days (approximately 39%) in the SSP370 and SSP585 scenarios. Regarding maize productivity, a reduction in yield is expected under SSP370 and SSP585 (up to a maximum of 20%), with declines being more significant at the end of the century. Conversely, projections for the SSP126 scenario indicate a slight increase in yields. **Implications.** These results suggest that climate change will have a negative impact on the white maize crop under Andean conditions. Therefore, mitigation and adaptation measures will be necessary to reduce the risk of meeting population demand in the mid-to-late century under the most severe emissions scenario. **Conclusion.** The findings estimate that white maize will considerably shorten the growing season under future climate change, with potential impacts on crop yield.
Key words: CERES-MAIZE; crop model; climate scenarios; white maize; climate change.

RESUMEN

Introducción. El cambio climático tiene impactos directos en la productividad actual y futura de los cultivos, afectando negativamente la seguridad alimentaria, particularmente en América Latina. **Objetivo.** Evaluar el impacto del cambio climático proyectado sobre la fenología y el rendimiento del maíz blanco mediante el modelo DSSAT CERES-Maíz calibrado y validado en condiciones andinas. **Metodología.** El modelo de cultivo se validó utilizando información de ensayos de campo realizados en 2018-2019 y 2020-2021 bajo diferentes densidades de siembra y manejo nutricional. Se utilizaron proyecciones climáticas del sexto Proyecto de Intercomparación de Modelos Acoplados (CMIP6) y escenarios de emisiones de Caminos Socioeconómicos Compartidos (SSP). **Resultados.** La calibración y validación del modelo CERES-Maíz mostró un buen ajuste entre los valores simulados y los datos observados para la fenología y el rendimiento del maíz blanco en condiciones andinas. El porcentaje de tasa de error fue inferior al 10%, lo que indica una precisión de los resultados de la simulación. La fenología del maíz blanco se vio afectada significativamente en todos los escenarios climáticos SSP, particularmente en el periodo 2081-2100, con una disminución del ciclo de hasta 83 días (aproximadamente 39%)

† *Submitted August 7, 2025 – Accepted October 31, 2025.* http://doi.org/10.56369/tsaes.6501

ISSN: 1870-0462.
ORCID = M. Capa-Morocho: http://orcid.org/0000-0003-2003-6986; **F. Zapata**: http://orcid.org/0009-0002-2035-1011; **R. Abad-Guaman**: http://orcid.org/0000-0002-2015-8548; **D. Chamba-Zaragocín**: http://orcid.org/0000-0002-9202-7299

en los escenarios SSP370 y SSP585. Con respecto a la productividad del maíz, se espera una reducción en el rendimiento en SSP370 y SSP585 (hasta un máximo del 20%), con disminuciones más significativas a finales de siglo. Por el contrario, las proyecciones indican un ligero aumento en el rendimiento del maíz bajo el escenario SSP126. **Implicaciones.** Estos resultados indican que el cambio climático tendrá un efecto negativo en el cultivo de maíz blanco en las condiciones andinas. Por lo tanto, serán necesarias medidas de mitigación y adaptación para reducir el riesgo de satisfacer la demanda de la población a mediados o finales del siglo en el escenario de emisiones más severo. **Conclusión.** Bajo cambio climático futuro, se estima que el ciclo del cultivo el maíz blanco se reducirá considerablemente, tanto su fase vegetativa como reproductiva, con impactos potenciales en el rendimiento del cultivo.
Palabras clave: CERES-Maíz; modelo de cultivo; escenarios climáticos; maíz blanco; cambio climático.

INTRODUCTION

Agriculture is among the sectors most vulnerable to climate change globally, as essential crop growth factors, like precipitation and temperature, will be severely impacted. Such changes may reduce crop yields, promote the spread of pests and diseases, and disrupt crop development cycles (Gerald *et al*., 2009; Hultgren *et al*., 2025; Yuan *et al*., 2024). These effects can contribute to food insecurity, particularly affecting rural communities that rely on agriculture for their livelihoods (Arteaga and Burbano, 2018). In many instances, crops have already begun shifting their growing areas altered temperature and humidity conditions in new regions.

By 2055, small-scale farmers in South America are projected to experience a decline in crop production, particularly for maize, with average losses ranging from 10% to 20% (García, 2023). According to Lozano-Povis *et al*. (2021), climate change has the potential to affect yields, cultivated areas, and agricultural production, with variable impacts depending on the crop and country. Notably, the medium-term effects are expected to be negative for yields, cultivated area, and production of crops such as common beans (*Phaseolus vulgaris* L.), soybean (*Glycine max* (L.) Merr.), rice (*Oryza sativa* L.), wheat (*Triticum aestivum* L.), and maize (*Zea mays* L.) (García, 2023; Issifou *et al*., 2022; Na *et al*., 2024; Stewart *et al*., 2018). Furthermore, the impact of climate change on crop yields varies across the different Shared Socioeconomic Pathways (SSPs), which account for diverse social and economic development trajectories and influence factors such as temperatures, precipitation, and CO_2 concentrations that directly affect crops (Riahi *et al*., 2017). These impacts may lead farmers to expand cultivated areas and intensify management practices (García, 2023).

Maize (*Zea mays* L.) is one of the most economically important cereals worldwide, especially in rural and underserved regions where it is a staple food source (Sanodiya *et al*., 2022). In Ecuador's Andean region, 95% of maize production corresponds to white maize, which is harvested either as tender maize (locally known as "choclo") or as dry grain (Zambrano *et al*., 2021). According to ESPAC (2024), production in this region reached 80,903 tons of dry grain and 41,072 tons of tender maize, with respective yields of 3.2 and 3.8 tons per hectare. However, despite the expansion of soft flour maize in southern Ecuador, yields in 2024 remained below both national and regional averages, raising concerns about the capacity of maize production to meet present and future food demand (ESPAC, 2024).

A widely used tool for climate impact studies is crop modeling, which allows for the prediction of crop behavior and helps assess potential positive or negative effects. These models enable the development of probabilistic scenarios regarding crop cycle progression and yield variability (Figarola *et al*., 2020). One of the most extensively used crop simulation models worldwide is CERES-Maize, part of the DSSAT (Decision Support System for Agrotechnology Transfer) framework (Gobezie *et al*., 2025). Previous studies have confirmed the accuracy of DSSAT in simulating maize cultivation under varying environmental conditions (Araya *et al*., 2015, 2017; Lin *et al*., 2014; González *et al*., 2022; Yzarra and Navarro., 2015). The model simulates future phenological development, growth, and yield based on four components: soil, climate, management, and genetics. As such, it supports informed agricultural decisions-making to improve productivity (Castro and Hétier, 2015).

The objectives of this study were to (1) calibrate and evaluate the DSSAT-CERES-Maize crop model for white maize under Andean conditions and (2) assess the impact of climate change on white maize yield using climate simulation outputs from 5 different GCMs under high, moderate and low Shared Socio-economic Pathways (SSPs) scenarios for near-term (2041-2060) and far-term (2081-2100) periods.

MATERIALS AND METHODS

Study site

The study was conducted at the La Argelia Experimental Station in Loja, located in the southern Andean region of Ecuador. The experimental site is situated at a latitude of 4.0° S, a longitude of 79.45° W, and an elevation of 2138 meters above sea level. The region's climate is temperate oceanic (Cfb), characterized by mild temperatures and a complex Andean topography, including both highlands and lowlands (Parra, 2023). The average annual precipitation is 1089.3 mm, with an average temperature of 16.1 °C and relative humidity of 77.5 % (Rubel and Kottek, 2010).

This region is one of the main white maize-producing regions in Ecuador. Sowing typically begins in October/November, and the growing season ends in June or July. Maize cultivation during the wet season is predominantly carried out using conventional tillage practices (Castro *et al*., 2013).

Crop model: calibration and validation

The crop model used in this study was CERES-maize (Jones and Kiniry, 1986), which is included in the Decision Support System for Agrotechnology Transfer (DSSAT v.4.8.0) software package (Hoogenboom *et al*., 2010, 2019 and 2024). CERES-maize is a dynamic, eco-physiological model that integrates the effects of crop genotype, soil profile, weather data, and management options. The crop model simulates crop growth, development, and yield based on genotype, weather, soil characteristics, and management practices.

The model accounts for crop phenology, photoperiod sensitivity, biomass accumulation, and partitioning between roots, stems, and leaves, as defined by cultivar-specific genetic coefficients. These coefficients include the duration in degree days from emergence to the end of the juvenile phase (P1), photoperiod sensitivity (P2), duration in degree days from silking to physiological maturity (P5), maximum potential number of kernels per plant (G2), grain filling rate (G3), and the phyllochron interval (PHINT), which describes the thermal time between successive leaf tip appearances (Hoogenboom *et al*., 1999, 2010).

Model inputs included weather data, soil characteristics, genetic coefficients, and crop management practices. Calibration and validation were performed using independent field experiments conducted during the 2018-2019 and 2020-2021 growing seasons, respectively.

Weather data

Weather data for both growing seasons (2018-2019 and 2020-2021) were obtained from the National Institute of Metrology and Hydrology of Ecuador (INAMHI) and a Davis Vantage Pro 2 meteorological station installed near the experimental plots in La Argelia. The data included daily values for incoming solar radiation (Rad), maximum temperature (Tmax), minimum temperature (Tmin), and precipitation (Prec).

During 2018-2019 season, the minimum and maximum temperatures averaged 12.6 °C and 21.8 °C, respectively. The total precipitation reached 782 mm, and average solar radiation was 14.42 MJ/m^2/day. In 2020-2021 season, minimum and maximum temperatures were 12.5 °C and 20.5 °C, respectively, with total precipitation of 677 mm and radiation of 13.40 MJ/m^2 day (Figure 1).

Soil data

The soil at the experimental site is classified as clay loam, with a pH value 4.26, organic matter content of 1.66%, organic carbon of 0.88% and an average bulk density of 1.46 g/cm^3 in the 0-15 cm layer prior to sowing. Physical, chemical, and hydrological properties of the soil are summarized in Table 1.

Crop material

The CERES-maize model was calibrated and validated for La Argelia site using a locally cultivated white maize variety, INIAP-103 “Mishqui Sara”. This is a floury white maize with high yield potential, high protein quality, and disease tolerance potential. “Mishqui Sara” was developed in Ecuador from the Aychazara 102 variety, originally bred at the Pairumani Phytoecogenetic Center of Bolivia (Moreno and Pintado, 2013). It is widely cultivated in the Ecuadorian Andes at elevations ranging from 1750 to 2650 meters above sea level (Yánez, 2013).

Crop management

Field data for model calibration and validation CERES-maize were obtained from independent plot-scale trials conducted at the experimental site. The calibration trial, conducted in 2018–2019, evaluated two planting densities: 75,000 plants per hectare (three seeds per hole, spaced 0.5 m between plants and 0.8 m between rows) and 62,500 plants per hectare (one seed per hole, spaced 0.2 m between plants and 0.8 m between rows). Sowing was performed on November 9, and fertilization was applied 40 days later, with rates of 102 kg/ha nitrogen, 50 kg/ha phosphorus, and 24 kg/ha potassium.

Table 1. Physical, chemical, and hydrological characteristics of the soil at the experimental site in Loja, southern Ecuadorian Andes.

Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Organic carbon (%)	Organic matter (%)	Saturation (%)	Moisture 1/10 (%)	Moisture 1/3 (%)	Permanent wilting point	Bulk density (g/cm³)
0 - 15	40.36	40.36	19.28	0.88	1.66	30.82	23.92	8.21	4.26	1.46
15 - 40	46.36	34.36	19.28	0.55	1.04	24.46	19.74	11.41	4.10	1.59
40 -75	38.36	46.36	15.28	-	-	31.76	26.91	20.32	3.22	1.44
75 -120	20.36	52.36	27.28	-	-	38.66	34.06	31.48	6.34	1.26
120 - 150	30.36	44.36	25.28	-	-	25.94	22.40	19.71	5.48	1.53

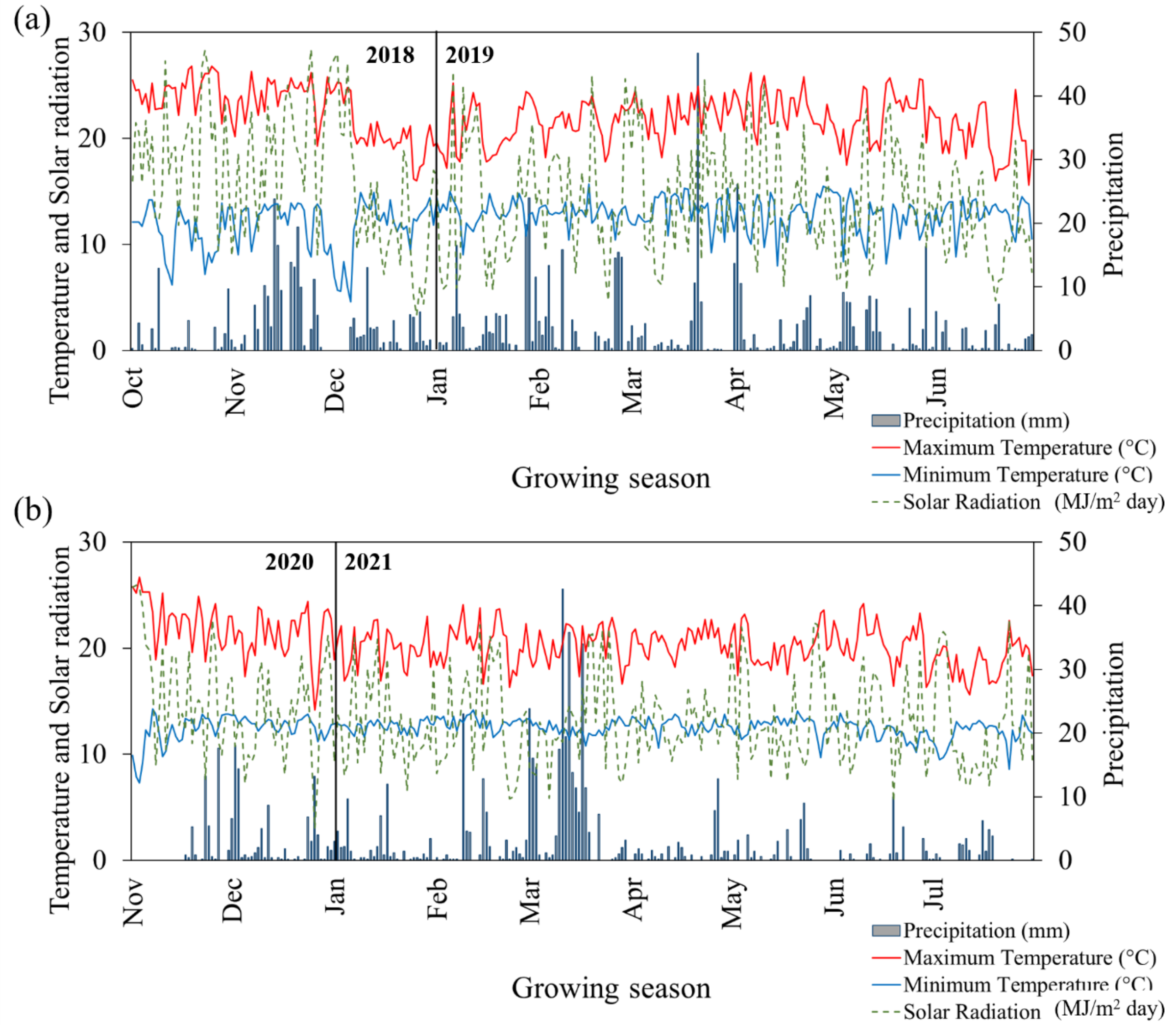

Figure 1. Meteorological conditions recorded during the white maize growing seasons of 2018–2019 (a) and 2020–2021 (b). Climate data were obtained from the National Institute of Meteorology and Hydrology of Ecuador (INAMHI) and a Davis Vantage Pro 2 automatic weather station located in La Argelia, near the experimental plots. Variables include daily maximum and minimum temperatures, solar radiation, and accumulated precipitation.

The validation trial was conducted in 2020–2021 and assessed different nitrogen fertilization levels (0, 40, and 80 kg N/ha), with split applications at 0, 30, and 60 days after sowing. Sowing took place on November 27 using the same plant density of 62,500 plants per hectare (0.2 m between plants and 0.8 m between rows).

Data were collected on crop phenology (planting, flowering, and physiological maturity), grain yield, leaf area index (LAI), and grain nitrogen content.

Each genetic coefficient was fine-tuned to minimize the difference between observed and simulated values for phenology, yield, LAI, and grain nitrogen content. Model performance was evaluated by comparing simulated output with observed data using the following goodness-of-fit statistics:

- Error (%), E=$\frac{(Yobs-Ysim)}{Yobs}$x 100, where *Ysim* is the simulated data, and *Yobs* is the observed value in a given year. The error indicates the deviation between the yields simulated by the model and the observed values. An error close to zero indicates excellent agreement.

- Root mean square error (RMSE= =$\sqrt{\sum_1^n (Yobs - Ysim)^2/n}$, where *Ysim* and *Yobs* are the simulated and observed values in a given year. The RMSE indicates the uncertainty of the model, with values close to zero indicating excellent fit and, therefore, good model performance.

- Root mean square percentage error “RMSPE”, is the root mean square error normalized by the average of observed values (RMSPE=$\sqrt{\sum_1^n \left(\left(\frac{Yobs-Ysim}{Yobs}\right)^2\right)/n\, x100}$).

Percentages close to zero indicate better agreement between simulated and observed values.

After calibration and validation, the model was used to simulate the impacts of climate change on maize yield, aiming to determine attainable maize yields (optimal rainfed yields limited only by weather conditions). It was important to set assumptions that white maize would grow continuously in the future without changes in management practices. This included using representative soil conditions (Table 1) and local sowing management, such as sowing date on November 27th, with a sowing density of 62500 plants per hectare, with a spacing of 0.20 m between plants and 0.80 m between rows, planting one seed per hole following current practices at the study area. Baseline and future simulations reflect only changes in climate variables, assuming well-controlled management (nutrient availability, pest and weed control) and no alterations in cultivar traits.

Climatic data and scenarios

To evaluate the impact of climate change on white maize yield, near-term (1941-1960) and long-term (1981–2100) daily records of precipitation, maximum temperature (Tmax), minimum temperature (Tmin), and solar radiation were retrieved from the Inter Sectoral Impact Model Intercomparison Project (ISIMIP, 2024) accessible at: https://data.isimip.org/search/tree/ISIMIP3b/InputData/climate/atmosphere/.

ISIMIP provides bias-adjusted climate input datasets on a 0.5° x 0.5° global grid, with daily time steps and accompanying socioeconomic projections for future scenarios. This study utilized the ISIMIP3b, which applies bias adjustment and statistical downscaling through version 2.4.1 of ISIMIP3BASD (Lange, 2019, 2020). The observational reference dataset used for downscaling was version 1.0 of WFDE5 over land, merged with ERA5 over oceans (Cucchi *et al*., 2020). ISIMIP3b provides bias-corrected CMIP6 climate forcing for pre-industrial, historical, SSP1-2.6, SSP3-7.0, and SSP5-8.5 scenarios.

For this study, climate projections were obtained from five General Circulation Models (GCMs) (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL). These were evaluated under three Shared Socioeconomic Pathways (SSP126, SSP370, and SSP585). Additionally, Carbon dioxide concentration data corresponding to each scenario and period were also sourced from ISIMIP for use in the crop simulations.

Phenology and yield projection

A total of 15 simulations were conducted using the calibrated and validated CERES-Maize model. These comprised the five GCMs combined with the three SSP scenarios for each projected period. For the 2050s, simulations were averaged for the period 2041–2060; for the 2090s, the period 2081–2100 was used.

Following the simulation of future phenology and yield, a comparative analysis was conducted against current values to quantify the positive or negative impacts of climate change on white maize productivity under Andean conditions. Relative changes were estimated as a fraction of the simulated mean output of the selected parameters based on the climate scenarios for each future period, minus the simulated current data, divided by the simulated current data, multiplied by 100.

Additionally, changes in solar radiation, annual average maximum and minimum temperatures, and precipitation in Loja were analyzed for three scenarios across both future periods, relative to a historical baseline (1984–2013). Baseline monthly climate data were obtained from meteorological yearbooks published by INAMHI (INAMHI, 2024). data analysis and visualization were conducted using R software.

RESULTS

Model calibration and validation

In this study, the genetic coefficients of the INIAP 103 “Mishqui Sara” maize variety were calibrated to achieve the best fit between observed and simulated values for the phenology and yield using the CERES-Maize model. This maize variety requires 255-degree days from emergence to the juvenile stage (P1) and 820-degree days from silking to physiological maturity (P5). It produces an average of 420 grains per plant (G2), with an average grain growth rate of 9 mg/day (G3) and requires 68.3-degree days for leaf tip emergence (PHINT) (Table 2).

Table 2. Genetic coefficients of the INIAP-103 white maize cultivar adjusted during CERES-maize model calibration.

Cultivar	P1	P2	P5	G2	G3	PHINT
INIAP-103	255.0	0.0	820.0	420.0	9.00	68.30

P1: thermal time from emergence to end of the juvenile phase (days); **P2:** photoperiod sensitivity (0-1); **P5:** thermal time from silking to physiological maturity (days); **G2:** potential kernel per plant; **G3:** kernel growth rate under optimum condition (mg/day); **PHINT:** thermal time between successive leaf tip appearance (°C/day).

The model calibration for the INIAP-103 "Mishqui Sara" variety under Andean conditions demonstrated a strong agreement between simulated and observed data (Table 3). For anthesis, the RMSEP was 0.90% during calibration and 0.85% during validation, indicating that the model adequately simulates this growth stage. For the physiological maturity phase (harvest), the RMSEP values were 6.22% (calibration) and 5.97% (validation).

Grain yield simulation showed excellent agreement, with RMSEP values of 5.56% for calibration and 8.96% for validation, both below the 10% performance threshold. The mean absolute error was 250 kg/ha during calibration and 493 kg/ha during validation. Meanwhile, the model did not perform satisfactorily for Leaf Area Index (LAI) and grain nitrogen content, where RMSEP values exceeded 10%, indicating limited accuracy in simulating these parameters (Table 3).

Climate Change Effects on the Phenology

Projected changes in maize phenology for the 2050s and 2090s under three SSP scenarios are shown in Figure 2 and Table 4. Results indicate that the crop cycle is expected to shorten under all scenarios, with reductions more pronounced in the 2090s than in the 2050s. For the vegetative phase, an average reduction of 26-30 days (22.4%- 26%) is projected for 2041 to 2060. A similar, pattern is observed for 2081–2100, with greater reductions under SSP370 and SSP585, reaching 39 and 42 days (22% and 36%), respectively.

In addition, the results obtained from the projection of the reproductive phase (anthesis-harvest) predict a reduction in the two periods evaluated (Table 4). There were small differences in simulated days from anthesis to harvest among the two future periods for most of the GCMS. In the SSP126 scenario, the decrease in this phase was between 24 and 26 days (less than 27%). However, for SSP370 and SSP585, the decrease in the reproductive phase will be more significant, with a reduction of 37 and 42 days (less than 42%), respectively, for the 2081-2100 period. In contrast, the reductions in this phase were 34 days for the SSP370 and 30 days for the SSP585 scenarios during the 2050s (less than 35%).

Therefore, the reduction in both the vegetative and reproductive phases has a significant impact on the crop cycle (Table 4). The maize growing season is expected to decline by a considerable reduction of 2 to 3 months, depending on the scenario and period. In the SSP126 scenario, a maximum average decrease of 52 days (25%) was predicted. Meanwhile, under the SSP370 and SSP585, this decrease is observed to be much more pronounced in the 2090s, with decreases of 76 and 83 days (35.7% and 39%), respectively, compared to the projected averages for the 2050s, which show averages of maximum reduction of 64 days (30%) to harvest.

The model that showed the maximum reductions in phenology was UKESM1-0-LL in both study periods for all the scenarios studied; meanwhile, the MPI-ESM1-2-HR model projected the least change in crop phases for all scenarios and periods (Figure 2).

Climate Change Effects over Maize Yield

The projected effects of climate change on white maize yield, INIAP-103 "Misqui Sara maize vary according to the Shared Socioeconomic Pathways (SSP126, SSP370, and SSP585) (Table 4). The results indicate that, for both periods analyzed, the average yield of maize is projected to increase under SSP126 by 2.14% in the 2050s and 4.01% in the 2090s.

In contrast, a reduction in yield is expected under SSP370 and SSP585, with declines being more significant in the 2090s than in the 2050s. Notably, under the SSP370, the average white maize yield could decline by 14.86% in the 2050s and 17.65% in the 2090s. Under the SSP585 scenario, the expected decreases are 2.84% and 20.18%, respectively (Table 4).

Table 3. Comparison of observed and simulated phenological, growth, and yield variables for the INIAP-103 white maize cultivar during calibration (2018–2019) and validation (2020–2021) of the CERES-Maize model.

Parameters	Calibration (2018-2019)					Validation (2020-2021)				
	Obs.	Sim.	Error (%)	RMSEP (%)	RMSE	Obs.	Sim.	Error (%)	RMSEP (%)	RMSE
Sowing	0	0	0	0	0	0	0	0	0	0
Anthesis day	111	110	1	0.90	1	117	116	1	0.85	1
Physiological maturity day	209	196	13	6.22	13	201	213	-12	5.97	12
Leaf area index (m^2/m^2)	2.15	1.55	0.6	27.55	0.63	1.90	1.43	0.205	17.94	0.38
Nitrogen (%)	1.06	1.70	-0.64	61.21	0.65	1.41	1.37	0.035	16.45	0.24
Grain yield (kg/ha)	5073	5324	-250	5.56	291.6	5123	4290	493	8.96	511.7

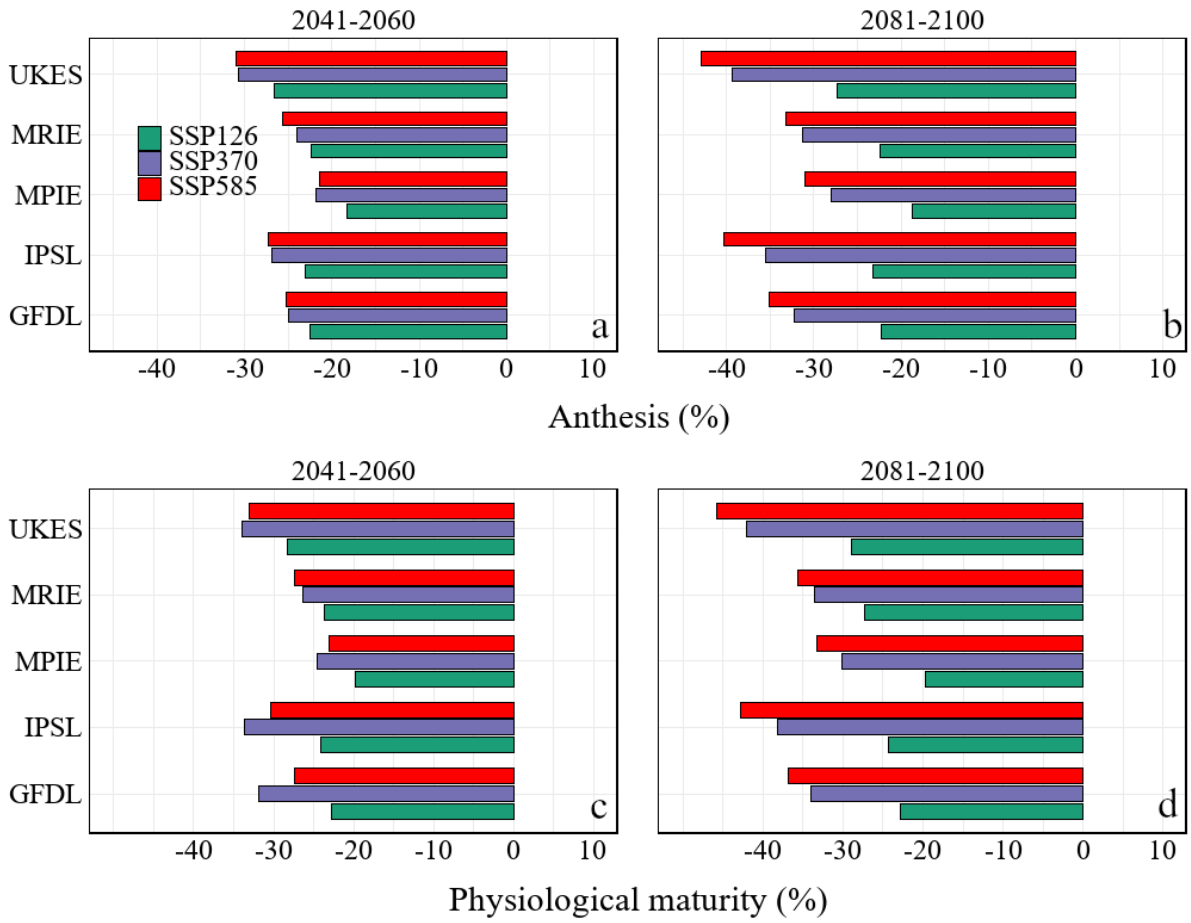

Figure 2. Projected changes in the duration to anthesis (a, b) and to physiological maturity (c, d) of white maize under climate scenarios for the 2050s (2041–2060) and 2090s (2081–2100). Values indicate percentage differences relative to the baseline period. Estimates are based on the ensemble of five CMIP6 climate models for the SSP126, SSP370, and SSP585 emission scenarios in Loja, located in the southern Ecuadorian Andes.

Table 4. Simulated grain yield and phenological stages of white maize in current planting dates (November) for baseline and changes in potential yields using five climate models under SSP126, SSP370 and SSP585 scenarios in two time periods for Loja.

Decade	Scenario	Mean yield (kg/ha)	Anthesis day	Physiological maturity day	Reproductive phase (day)
Baseline		5314.0	116	213	97
2050	SSP126	5427.6	90	163	73
	SSP370	4524.5	86	149	63
	SSP585	5162.9	86	153	67
2090	SSP126	5527.2	90	161	71
	SSP370	4376.3	77	137	60
	SSP585	4241.6	74	130	56

Among the five GCMs used in this study, the IPSL-CM6A-LR model indicates the highest impact on maize yield in both study periods under the SSP370 and SSP585 scenarios. The MRI-ESM2-0 model predicted a slight decrease in yield under SSP126 during both study periods (Figure 3).

When comparing projected climate data for the 2050s and 2090s with the baseline period (1984–2013), increases were observed in solar radiation and precipitation across all three SSP scenarios. Solar radiation increased by >12.6%, and precipitation by >26%. Maximum temperature rose by over 5.8 °C in both periods, while minimum temperature exhibited a slight decrease (<1.5 °C) in the 2050s under all scenarios, followed by an increase (>1.2 °C) in the 2090s under SSP370 and SSP585 (Table 5).

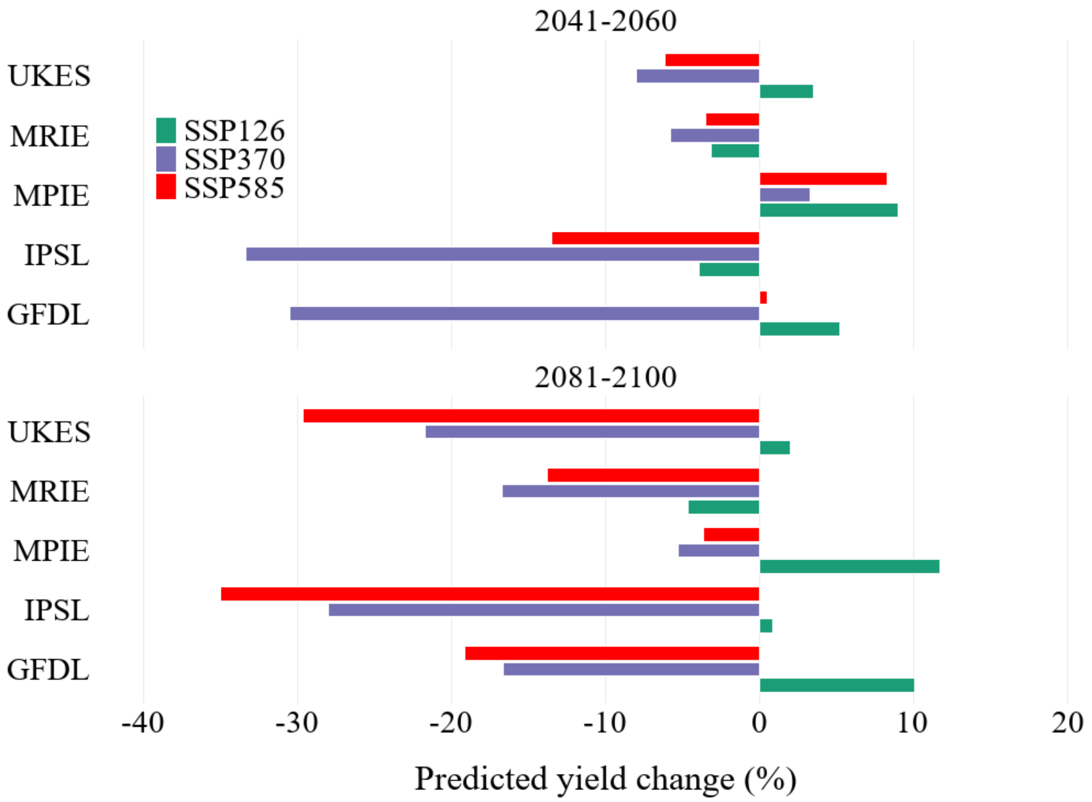

Figure 3. Estimated yield variation of white maize under future climate change scenarios for the 2050s (2041–2060) and 2090s (2081–2100). Projections were derived from five downscaled climate models under SSP126, SSP370, and SSP585, using the CERES-Maize model calibrated for local conditions in Loja, Ecuador. Values are expressed as relative changes compared to the historical baseline.

Table 5. Projected changes in solar radiation, annual average maximum and minimum temperature, and precipitation at Loja relative to the baseline under SSP126, SSP370 and SSP585 scenarios for 2050s (2041-2060) and 2090s (2081-2100).

Scenarios	Solar radiation (%)		Maximum temperature (ºC)		Minimum temperature (ºC)		Precipitation (%)	
	2050s	2090s	2050s	2090s	2050s	2090s	2050s	2090s
SSP126	13.30	13.59	5.91	5.87	-1.47	-1.34	27.60	30.90
SSP370	12.60	13.10	6.48	8.40	-0.83	1.21	26.40	29.00
SSP585	13.11	13.84	6.68	9.38	-0.68	1.95	29.10	36.70

DISCUSSION

This study utilized a site-specific, calibrated, and validated crop model alongside future climate data to evaluate the impact of climate change on white maize phenology and yield under Andean conditions. Our findings demonstrate that white maize is highly sensitive to projected climate change scenarios. The significant reduction in the crop cycle—up to 83 days under SSP370 and SSP585 scenarios—aligns with global observations that warming accelerates maize development and shortens its growth period (Wang *et al.*, 2016). However, Wang *et al.* also emphasize that late-maturing cultivars may mitigate these effects, suggesting that genetic adaptation strategies could be decisive for Andean maize systems.

Our calibrated DSSAT CERES-Maize model for the INIAP 103 "Mishqui Sara" variety achieved high simulation accuracy. RMSEP values were 0.90% for anthesis, 6.22% for physiological maturity, and 5.56% for yield during calibration. These values fall well below the 10% threshold considered "excellent" (Rodríguez *et al.*, 2021; Clarke *et al.*, 2021; Lin *et al.*, 2014), confirming the model's reliability for scenario-based forecasting. However, early developmental stages like sowing-emergence and leaf area index showed lower agreement (RMSEP >16%), a pattern consistent with other DSSAT evaluations in Latin America and Asia (Amiri *et al.*, 2022). This acceptable agreement between observed and simulated yields and phenology using the calibrated and validated CERES crop model indicates its utility as a tool to obtain a long-term series of attainable yields using future climate projections (Rugira *et al*., 2021). This capability is critical for exploring future impacts on white maize production. The calibration and validation results could allow this variety (genetic coefficients) to be used in other regions of the Andes, considering variations in soil, climate, and crop management. This may be relevant for predictability studies in agricultural planning and management, such as changes in planting dates. Reducing the risks associated with increased variability and climate change has great potential to increase productivity and quality while protecting the environment (Ogallo *et al*., 2020).

In Ecuador, recent studies using the LINTUL5 model have shown that semi-arid regions like Loja are already experiencing yield losses due to rising temperatures and declining precipitation (Lopez *et al*., 2021). These findings reinforce the urgency of localized modeling efforts such as the one presented here, which offer site-specific insights essential for adaptive planning in mountainous regions.

Our projections, showing yield reductions of up to 20% under SSP370 and SSP585 scenarios, are consistent with Zhang *et al*. (2022), who developed a climate suitability model in Henan, China, confirming that temperature and precipitation are the dominant factors affecting maize yield (Ojeda *et al*, 2011). The observed reduction in yield can be attributed to an ecophysiological mechanism; a shorter grain filling implies lower crop yield, as the crop has less time to accumulate biomass in the harvestable fraction (Andrade *et al*., 1993; Echarte *et al*., 2013; Muchow *et al*., 1990). Therefore, higher maximum and minimum temperatures during grain filling result in lower yields, as they imply a shortened grain filling period (Badu-Apraku *et al*., 1983; Wheeler *et al*., 2000). Additionally, the observed increase in solar radiation and maximum temperature in Loja may intensify evapotranspiration and water stress. This increases the risk of physiological stress during flowering (Fahad *et al*., 2017; Young *et al*., 2021). Contrastingly, Liu *et al*. (2017) reported that in some East Asian regions, the vegetative phase shortened while the reproductive phase lengthened. In our study, both phenological phases are significantly reduced, suggesting that altitude-induced photothermal stress, limited water retention capacity, and soil variability play critical roles in shortening the overall crop cycle in Andean zones.

Crop models are sensitive tools for detecting climate variability and change and can reflect their effects at critical stages of crop development, whenever a reliable site-specific crop model calibration and validation with field data is accomplished (Capa-Morocho *et al*., 2016). Simulation models, such as CS-Maize and Aquacrop, have demonstrated strong performance in projecting phenological shifts and yield changes under climate stress (Feleke *et al*., 2021; Medina *et al*., 2019; Plomitallo and Selicati, 2023). Their application, when paired with precise climate inputs and validated local parameters, enables strategic evaluations of adaptive techniques like adjusted planting schedules, fertilization timing, and optimized cultivar choice. The need for further research is also highlighted to integrate more cropping models with the edaphoclimatic conditions, as well as management practices, of the Andean regions. This integration will enable a more accurate assessment of the impacts of climate change in these environments, allowing for more informed decision-making.

Furthermore, studies in the Andean-Amazon foothills suggest that maize may lose over half of its suitable cultivation area by the 2080s under RCP8.5 scenarios (Beltrán-Tolosa *et al*., 2020). This underscores the need for land-use zoning and crop diversification. Indigenous farming systems in Ecuador, such as the *chakra* model, provide valuable lessons in agrobiodiversity-driven resilience and climate adaptation (Groundswell International, 2024).

Nevertheless, it is important to acknowledge the limitations observed in simulating certain variables. Specifically, the CERES-Maize model showed reduced accuracy in predicting leaf area index (LAI) and grain nitrogen content under the studied conditions. These discrepancies have also been reported in other applications of DSSAT in tropical and subtropical contexts (Amiri et al., 2022; Hultgren *et al*., 2025). For this reason, we do not recommend the current calibration for purposes requiring high precision in biomass estimation or forage potential. However, given that the main objective of this study was to assess phenology and grain yield under future climate scenarios, the model's performance is adequate and aligned with similar works (Feleke *et al*., 2021; Capa-Morocho *et al*., 2016). Model calibration levels should be adjusted depending on the specific application (e.g., grain production vs. total biomass), as suggested by Rugira *et al*. (2021) and Clarke *et al*. (2021), highlighting the flexibility and limitations of crop simulation models.

Finally, the systematic review by Lozano-Povis *et al*. (2021) and Noriega-Navarrete *et al*. (2021) affirms the increasing vulnerability of Andean agriculture to climatic shifts, including elevated evapotranspiration and reduced water availability. To address these challenges, integrated mitigation and adaptation frameworks, such as encompassing breeding programs, improved soil management, traditional agroecological knowledge, and responsive policy mechanisms, are imperative for sustaining white maize productivity and regional food security.

CONCLUSIONS

This study highlights the potential application of the CERES-maize model in projecting maize yield and phenology in the Andes. A site-specific calibrated and validated crop model meets the requirements for accurately simulating maize growth and yield, making it a suitable tool for studying the impacts of variability and climate change.

The results of the climate change projections showed a significant reduction in the phenology of white maize under all SSPs climate scenarios used, particularly by the 2090s. A simulated decrease of up to 83 days (approximately 39%) is estimated in the most critical scenarios (SSP370 and SSP585), affecting both the vegetative and reproductive phases. Regarding the crop yield, white maize yield under the future climate may increase slightly under the SSP126 scenario. Meanwhile, a reduction in yield is expected under SSP370 and SSP585, with declines being more significant in the 2090s than in the 2050s. However, the effect of adaptive management strategies to mitigate its adverse effects must be analyzed. In this regard, future research should focus on evaluating adaptive strategies of the maize crop to reduce the negative effects of climate change on white maize and ensure food security for the Andean population in southern Ecuador.

Funding. The authors did not receive support from any organization for the submitted work.

Conflict of interests. Nothing to declare.

Compliance with ethical standards. The nature of the present work does not require approval by an ethical committee.

Data availability. Data are available with Mirian Capa-Morocho, mirian.capa@unl.edu.ec, upon reasonable request.

Author contribution statement (CRediT). M. Capa-Morocho – Formal analysis and Writing – review & editing; **F. Zapata** – Investigation; **D. Chamba-Zaragocin** – Investigation and Resources; **R. Abad-Guamán** – Formal analysis and Visualization.

REFERENCES

Amiri, E., Irmak, S. and Araji, H., 2022. Assessment of CERES-Maize model in simulating maize growth, yield and soil water content under rainfed, limited and full irrigation. *Agricultural Water Management*, 259, p. 107271. https://doi.org/10.1016/j.agwat.2021.107271

Andrade, F.H., Uhart, S.A. and Cirilo, A., 1993. Temperature affects radiation use efficiency in maize. *Field Crops Research*, 32(1–2), pp. 17-25. https://doi.org/10.1016/0378-4290(93)90018-I

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, KM, Kisekka, I. and Martorano, LG., 2015. Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. *Agricultural and Forest Meteorology*, 214, pp. 252-265. https://doi.org/10.1016/j.agrformet.2015.08.259

Araya, A., Kisekka, I., Lin, X., Prasad, PV, Gowda, PH, Rice, C. and Andales, A., 2017. Evaluating the impact of future climate change on irrigated maize production in Kansas. *Climate Risk Management*, 17, pp. 139-154. https://doi.org/10.1016/j.crm.2017.08.001

Arteaga, L., and Burbano, J., 2018. Efectos del cambio climático: Una mirada al Campo. *Revista de Ciencias Agrícolas*, 35(2), pp. 79-91. https://doi.org/10.22267/rcia.183502.93

Badu-Apraku, B., Hunter, R.B. and Tollenaar, M., 1983. Effect of temperature during grain filling on whole plant and grain yield in maize (Zea mays L.). *Canadian Journal of Plant Science*, 63(2), pp. 357-363. https://doi.org/10.4141/cjps83-040

Beltrán-Tolosa, L.M., Navarro-Racines, C., Pradhan, P., Cruz-Garcia, G.S., Solis, R. and Quintero, M., 2020. Action needed for staple crops in the Andean-Amazon foothills because of climate change. *Mitigation and Adaptation Strategies for Global Change,* 25, pp. 1103–1127. https://doi.org/10.1007/s11027-020-09923-4

Capa-Morocho, M., Rodríguez-Fonseca, B. and Ruiz-Ramos, M. (2016), El Niño influence on potential maize yield in Iberian Peninsula. *International Journal of Climatology*, 36, pp. 1313-1330. https://doi.org/10.1002/joc.4426

Castro, I. and Hétier, J. M., 2015. Modelización y experimentación agronómica. *Tierras Llaneras de Venezuela… tierras de buena esperanza. 1ra ed. Venezuela: Consejo de Publicaciones de la Universidad de Los Andes*. https://horizon.documentation.ird.fr/exl-doc/pleins_textes/divers15-12/010065645.pdf

Castro, L. M., Calvas, B., Hildebrandt, P. and Knoke, T., 2013. Avoiding the loss of shade coffee plantations: how to derive conservation payments for risk-averse land-users. *Agroforestry Systems*, 87(2), pp. 331-347. https://doi.org/10.1007/s10457-012-9554-0

Clarke D., T. Hess, D Haro-Monteagudo, M.A. Semenov, J W Knox, 2021. Assessing future drought risks and wheat yield losses in England, *Agricultural and Forest Meteorology*, 297, p. 108248. https://doi.org/10.1016/j.agrformet.2020.108248

Cucchi, M., Weedon, G. P., Amici, A., Bellouin, N., Lange, S., Müller Schmied, H., Hersbach, H., and Buontempo, C., 2020. WFDE5: bias adjusted ERA5 reanalysis data for impact studies, Earth System Science Data Discussions, 2020, pp. 1–32. https://doi.org/10.5194/essd-2020-28

Echarte, L. et al., 2013. Grain Yield Determination and Resource Use Efficiency in Maize Hybrids Released in Different Decades. Agricultural Chemistry, InTech. https://doi.org/10.5772/55287

ESPAC., 2024. Tabulados de la Encuesta de Superficie y producción Agropecuaria Continua. Instituto Nacional de Estadística y Censos. https://www.ecuadorencifras.gob.ec/estadisticas-agropecuarias-2/

Fahad S., Bajwa AA, Nazir U., Anjum SA, Farooq A., Zohaib A., Sadia S., Nasim W., Adkins S., Saud S. and Huang, J., 2017. Crop production under drought and heat stress: plant responses and management options. *Frontiers in Plant Science,* 8, p. 1147. https://doi.org/10.3389/fpls.2017.01147

Feleke, H. G., Savage, M. J. and Tesfaye, K. 2021. Calibration and validation of APSIM–Maize, DSSAT CERES–Maize and AquaCrop models for Ethiopian tropical environments. *South African Journal of Plant and Soil*, 38(1), pp. 36–51. https://doi.org/10.1080/02571862.2020.1837271

Figarola, L. A., Ghersa, F., Castro, R. and Ferraro, D. O., 2020. Automatización del Modelo de Simulación de Cultivos DSSAT para Evaluar el Desempeño Productivo Bajo Distintas Estrategias de Manejo y Escenarios Ambientales. In: *XII Congreso de AgroInformática (CAI 2020)-JAIIO 49 (Modalidad virtual)*. http://sedici.unlp.edu.ar/handle/10915/115512

García Montero, P. 2023. El cambio climático: posibles impactos en la agricultura en el contexto de América Latina y Venezuela. *Agroalimentaria Journal-Revista Agroalimentaria*, 28(55), pp. 167-189. https://doi.org/10.22004/ag.econ.338827

Gerald, N., Rosegrant, M. W., Koo, J., Robertson, R., Sulser, T., Zhu, T. and Lee, D., 2009. Cambio Climático El impacto en la agricultura y los costos de adaptación. *International Food Policy Research Institute.* https://doi.org/10.2499/0896295370

Gobezie, A., Ademe, D., and Sharma, L. K., 2025. CERES-Maize (DSSAT) Model Applications for Maize Nutrient Management Across Agroecological Zones: A Systematic Review. *Plants*, 14(5), p. 661. https://doi.org/10.3390/plants14050661

González, D., Rodríguez, O., Florido, R., Vázquez, R. and Socorro, M., 2022. Determinación de parámetros para la calibración del modelo DSSAT en el cultivo del maíz. *Ingeniería Agrícola*, 12(4). https://www.redalyc.org/journal/5862/586272874006/html/

Groundswell International, 2024. Indigenous Farming Systems in Ecuador: Lessons for Adapting to Climate Change. https://www.groundswellinternational.org/blog/indigenous-farming-techniques-ecuador-lessons-adapt-climate-change/

Hoogenboom, G., CH Porter, KJ Boote, V. Shelia, P.W. Wilkens, U. Singh, J.W. White, S. Asseng, J.I. Lizaso, L.P. Moreno, W. Pavan, R. Ogoshi, L.A. Hunt, G.Y. Tsuji and J.W. Jones., 2019. El ecosistema de modelado de cultivos DSSAT. En: p.173-216 [KJ Boote, editor] Avances en el modelado de cultivos para una agricultura sostenible. *Burleigh Dodds Science Publishing, Cambridge, Reino Unido*. https://dx.doi.org/10.19103/AS.2019.0061.10

Hoogenboom, G., CH Porter, V. Shelia, KJ Boote, U. Singh, W. Pavan, FAA Oliveira, LP Moreno-Cadena, TB Ferreira, JW White, JI Lizaso, DNL Pequeno, BA Kimball, PD Alderman, KR Thorp, SV Cuadra, MS Vianna, FJ Villalobos, WD Batchelor, S. Asseng, MR Jones, A. Hopf, HB Dias, A. Jintrawet, R. Jaikla, E. Memic, LA Hunt and JW Jones. 2024. Sistema de Apoyo a la Decisión para la Transferencia de Agrotecnología (DSSAT) Versión 4.8.5. *Fundación DSSAT, Gainesville, Florida, Estados Unidos*. https://www.dssat.net

Hoogenboom, G., et al., 2010. The Decision Support System for Agrotechnology Transfer (DSSAT), Version 4. 5 [CD-ROM]. *University of Hawaii, Honolulu, Hawaii*.

Hoogenboom, G., Wilkens, P.W., Thornton, P.K., Jones, J.W., Hunt, L.A. and Imamura, D.T., 1999. Decision support system for agrotechnology transfer v3.5. In: Hoogenboom, G., Wilkens, P.W., Tsuji, G.Y. (Eds.), DSSAT version 3, vol. 4 (ISBN 1-886684-04-9). *University of Hawaii, Honolulu*, HI, pp. 1-36.

Hultgren, A., Carleton, T., Delgado, M., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., Jina, A., Kopp, R., Malevich, S., McCusker, K., Mayer, T., Nath, I., Rising, J., Rode, A. and Yuan, J., 2025. Impacts of climate change on global agriculture accounting for adaptation. *Nature*, 642, pp. 644-652. https://doi.org/10.1038/s41586-025-09085-w

INAMHI, Instituto Nacional de Meteorología e Hidrología del Ecuador. 2024. Biblioteca: anuarios meteorológicos. https://www.inamhi.gob.ec/biblioteca/

ISIMIP, Inter-Sectoral Impact Model Intercomparison Project., 2024. ISIMIP Repository. https://data.isimip.org/search/tree/ISIMIP3b/InputData/climate/atmosphere/

Issifou Moumouni, Y., Kindjinou, T., Adougan, B., Hounkanrin, B., Koumassi, H., Ezin, A. V., Yabi, I., and Ogouwale, E., 2022. Impact of climate change on the dynamics of soybean (Glycine max) (L.) Merr. production areas in the second agricultural development pole of the Sudanian region of Benin (West Africa). *Legume Science*, 4(3). https://doi.org/10.1002/leg3.135

Jones, C. A., and Kiniry, J. R., 1986. CERES-Maize: A Simulation Model of Maize Growth and Development. Texas A&M University Press, Texas, First edition, p. 194.

Lange, S., 2019. Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1. 0). *Geoscientific Model Development*, 12(7), pp. 3055-3070. https://doi.org/10.5194/gmd-12-3055-2019

Lange, S., 2020. ISIMIP3BASD v2.4.1, https://doi.org/10.5281/zenodo.3898426

Lin, Y., Wu, W., and Ge, Q., 2014. CERES-Maize model-based simulation of climate change impacts on maize yields and potential adaptive measures in Heilongjiang Province, China. *Journal of the Science of Food and Agriculture*, 95 (14), pp. 2838-2849. https://doi.org/10.1002/jsfa.7024

Liu, Y., Qin, Y., Ge, Q., Dai, J. and Chen, Q. 2017. Responses and sensitivities of maize phenology to climate change from 1981 to 2009 in Henan Province, China. *Journal of Geographical Sciences*, 27(9), pp. 1072–1084. https://doi.org/10.1007/s11442-017-1422-4

Lopez, G., Gaiser, T., Ewert, F. and Srivastava, A. 2021. Effects of recent climate change on maize yield in Southwest Ecuador. *Atmosphere,* 12(3), p. 299. https://doi.org/10.3390/atmos12030299

Lozano-Povis, A., Alvarez-Montalván, C.E. and Moggiano, N. 2021. El cambio climático en los Andes y su impacto en la agricultura: una revisión sistemática. *Scientia Agropecuaria,* 12(1), pp. 101–108. https://doi.org/10.17268/sci.agropecu.2021.012

Medina, S., Cruz, W. and Cuellar, J. 2019. First maize AquaCrop modeling for adaptation to climate change for Andean and arid zones production. *INIA Perú*. https://app.ingemmet.gob.pe/biblioteca/pdf/TGS-23.pdf

Moreno, J. and Pintado, P., 2013**.** *INIAP-103 "Mishqui Sara": Nueva variedad de maíz blanco harinoso para consumo humano* [Ficha técnica]. *Instituto Nacional de Investigaciones Agropecuarias (INIAP), Estación Experimental del Austro, Programa de Maíz.* https://repositorio.iniap.gob.ec/bitstream/41000/2342/1/FT3.pdf

Muchow, R.C., Sinclair, T.R. and Bennett, J.M., 1990. Temperature and Solar Radiation Effects on Potential Maize Yield across Locations. *Agronomy. Journal*, 82(2), pp. 338-343. https://doi.org/10.2134/agronj1990.00021962008200020033x

Na Li, Yating Zhao, Jinsheng Han, Qiliang Yang, Jiaping Liang, Xiaogang Liu, Yazhou Wang, Zhengzhong Huang. 2024. Impacts of future climate change on rice yield based on crop model simulation—A meta-analysis. *Science of The Total*

Environment, 949, p. 175038. https://doi.org/10.1016/j.scitotenv.2024.175038

Noriega-Navarrete, P., Rubel, J. L., Salazar, R. and López-Cruz; I., 2021. Revisión: Modelos de crecimiento y rendimiento de maíz en escenarios de cambio climático. *Revista Mexicana de Ciencias Agrícolas*, 12(1), pp. 127-140. https://doi.org/10.29312/remexca.v12i1.2552

Ogallo, L.A., Boulahya, M.S. and Keane, T., 2000. Applications of seasonal to interannual climate prediction in agricultural planning and operations. *Agricultural and Forest Meteorology*, 103(1–2), pp. 159-166. https://doi.org/10.1016/S0168-1923(00)00109-X

Ojeda, W., Sifuentes, E., Íñiguez, M., and Montero, M. 2011. Impacto del cambio climático en el desarrollo y requerimientos hídricos de los cultivos. *Agrociencia,* 45(1), pp. 1-11. https://www.scielo.org.mx/pdf/agro/v45n1/v45n1a1.pdf

Parra, R. 2023. Assessment of Land Surface Schemes from the WRF-Chem for Atmospheric Modeling in the Andean Region of Ecuador. *Atmosphere*, 14(3), pp. 508. https://doi.org/10.3390/atmos14030508

Plomitallo, V. and Selicati, R.E., 2023. Thermal index-based phenology models for maize: A review. *International Journal of Agricultural Science and Food Technology*. 5(2), pp. 138–141. https://doi.org/10.33545/2664844X.2023.v5.i2b.184

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., and Tavoni, M., 2017. Las trayectorias socioeconómicas compartidas y sus implicaciones en la energía, el uso del suelo y las emisiones de gases de efecto invernadero: Una visión general. *Cambio Ambiental Global*, 42, pp. 153-168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rodríguez, O., Florido, R., Hernández, N., Soto, F., Jeréz Mompié, E., González, D., and Vázquez, R., 2021. Simulación de estrategias de manejo a partir del modelo DSSAT para incrementar los rendimientos de un cultivar de maíz. *Cuban Journal of Agricultural Science*, 55(2), http://scielo.sld.cu/scielo.php?script=sci_arttext&pid=S2079-34802021000200008&lng=es&tlng=es

Rubel, F. and Kottek, M., 2010. Observed and projected climate shifts 1901-2100 depicted by world maps of the Köppen-Geiger climate classification. *Meteorologische Zeitschrift*, 19(2), pp. 135-141. https://doi.org/10.1127/0941-2948/2010/0430

Rugira, P., Ma, J., Zheng, L., Wu, C., and Liu, E., 2021. Application of DSSAT CERES-Maize to Identify the Optimum Irrigation Management and Sowing Dates on Improving Maize Yield in Northern China. *Agronomy*, 11(4), p. 674. https://doi.org/10.3390/agronomy11040674

Sanodiya, P., Tiwari, P., Gupta, Ch., 2023. Maize (Zea mays L.) -The future potential cereal crop of an indispensable significance in agro-forestry system. *Maize Journal*, 12(2), pp. 61-71.

Stewart, B. A., Thapa, S., Xue, Q., and Shrestha, R., 2018. Climate change effect on winter wheat (Triticum aestivum L.) yields in the US Great Plains. *Journal of Soil and Water Conservation*, 73(6), pp. 601-609. https://doi.org/10.2489/jswc.73.6.601

Wang, Z., Chen, J., Li, Y., Li, C., Zhang, L., and Chen, F., 2016. Effects of climate change and cultivar on summer maize phenology. *International Journal of Plant Production*, 10(4), pp. 509-526.

Wheeler, T.R., Craufurd, P.Q., Ellis, R.H., Porter, J.R. and Vara Prasad, P.V., 2000. Temperature variability and the yield of annual crops. *Agriculture, Ecosystems & Environment*, 82(1–3), pp. 159-167. https://doi.org/10.1016/S0167-8809(00)00224-3

Yánez, G., 2013. INIAP-103: "Mishqui Sara". Quito, Ecuador: INIAP, Estación Experimental Santa Catalina, Programa de Maíz. https://repositorio.iniap.gob.ec/bitstream/41000/2413/1/iniapsc337.pdf

Young, M. D., Ros, G. H., and de Vries, W., 2021. Impacts of agronomic measures on crop, soil, and environmental indicators: A review and synthesis of meta-analysis. *Agriculture, Ecosystems & Environment*, 319, p. 107551. https://doi.org/10.1016/j.agee.2021.107551

Yuan, X., Li, S., Chen, J., Yu, H., Yang, T,; Wang, C., Huang, S., Chen, H. and Ao, X., 2024. Impacts of Global Climate Change on Agricultural Production: A Comprehensive Review. *Agronomy*, 14, p. 1360. https://doi.org/10.3390/agronomy14071360

Yzarra, W. J., and Navarro, M. L., 2015. Ministerio del ambiente. Obtenido de Calibración y validación del modelo CERES MAIZE-DSSAT en la costa central: https://hdl.handle.net/20.500.12542/434

Zambrano, J.L., Velásquez, J., Peñaherrera, D., Sangoquiza, C., Cartagena, Y., Villacrés, E., Garcés, S., Ortíz, R., León, J., Campaña, D., López, V., Asaquibay, C., Nieto, M., Sanmartín G., Pintado, P., Yánez, C. and Racines, M., 2021. Guía para la producción sustentable de maíz en la Sierra ecuatoriana. INIAP, Manual No. 122. Quito, Ecuador. https://repositorio.iniap.gob.ec/bitstream/41000/5796/1/GUIA%20CULTIVO%20DE%20MAIZ%202021-1.pdf

Zhang N, Qu Y, Song Z, Chen Y, and Jiang J., 2022. Responses and sensitivities of maize phenology to climate change from 1971 to 2020 in Henan Province, China. *Plos One,* 17(1), p. e0262289. https://doi.org/10.1371/journal.pone.0262289