Review: corn growth and yield models under climate change scenarios

José Luis Noriega-Navarrete
Raquel Salazar-Moreno§
Irineo Lorenzo López-Cruz

1Postgraduate in Agricultural Engineering and Integral Use of Water-Chapingo Autonomous University. Efraín Hernández Xolocotzi Building, PB. Highway México-Texcoco km 38.5, Chapingo, State of Mexico. ZC. 56230. (luisnoriegan@hotmail.com; loci61@hotmail.com).

§Corresponding author: rsalazarm@chapingo.mx.

Abstract

Climate change (CC) affects the current meteorological conditions and negatively affects the yield of corn, particularly during the rainy season. To estimate the effects of CC on productivity, growth simulation models have been used under different climate change scenarios. This article reviews the models implemented globally, during the period 2006 to 2019, through Scopus and Google Scholar. The reported models are mechanistic, dynamic and stochastic, such as DSSAT-CERES-Maize, APSIM-Maize, CropSyst, AquaCrop, EPIC-Maize, CropWat InfoCrop, and WOFOST. Simulations in various scenarios report decreased corn yields in Sub-Saharan Africa (78%), China (70%), Latin America (61%) and the Middle East (45%), and increases in the European Union (71%), Belt American Corn (57%), Middle East (45%) and India (44.5%). In Mexico, there are estimates of increases in corn yields from 5 to 22% considering the effects of carbonic fertilization, and reductions of up to 49.3% under other conditions. It is necessary to deepen studies on CC effects in the different regions of the country and implement models that can be used to design adaptation and mitigation policies and strategies, given the negative effects of CC in Mexican agriculture.

Keywords: Biosystems, DSSAT-CERES-Maize, mathematical modeling.

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Climate change (CC) refers to the modification in climatic variables, attributed directly or indirectly to human activities, which alter the physical and chemical composition of the Earth's atmosphere, because of the emission of greenhouse gases (GHG), by economic and demographic growth of humanity, from the Industrial Revolution to the present (IPCC, 2014). Due to the foregoing, a series of negative effects are expected in future environmental conditions, in different sectors, in different magnitudes and intensities in the world (Fuhrer and Gregory, 2014; Venkateswarlu and Singh, 2015).

In Mexico, a reduction in the amount and distribution of rainfall, an increase in temperature, an increase in the presence and intensity of extreme events (droughts and tropical cyclones) has been predicted (IDB, 2014; Ruíz *et al*., 2016). These phenomena directly influence the productivity of corn, as a consequence of the modification in the evapotranspiration and water demand of the crop and increase in the degree days of development (GDD) (López *et al*., 2013).

Due to the above, the IPCC (2014) has considered rain-fed agriculture, including corn cultivation, as a highly vulnerable sector to the negative effects derived from CC (Velasco and Celis, 2012). Mexico has signed international commitments such as the Paris Agreement with the aim of limiting the increase in temperature below 1.5 °C and thus minimize the negative impacts of CC.

Corn (*Zea mays* L.) is the main cereal grown worldwide, Mexico ranks eighth in volume produced (FAO, 2019). In 2018, 27.17 million tons were harvested in 50.39% of the national planted area, where 78.4% of the national corn production is under rainfed conditions, with an average yield of 2.46 t ha^{-1} (SIAP, 2019).

In order to analyze the response of crops to changing climatic conditions in a region, there are models whose forecasts can provide information, to implement measures that reduce the negative impacts of CC (Jones *et al*., 2000). The simulation models mathematically reproduce the physiological and biophysical behavior of corn and simulate a response to different environmental conditions (Teh, 2006; Soltani and Sinclair, 2012).

According to Bouman *et al*. (1996) the models reflect three situations in a crop: 1) potential production, limited only by environmental temperature, radiation and CO_2 concentration in interaction with the genotype of the plant; 2) limited production, given by the limited availability of water or nutrients; and 3) real production, which adds the biological effect produced by the interaction with pests, diseases and weeds.

The objective of this essay is to carry out a review of the state of the art on the simulation models of corn growth and yield, implemented to estimate the impact under CC scenarios worldwide. Articles published since the formalization of the Nairobi Work Program on the effects, vulnerability and adaptation to climate change, after the entry into force of the Kyoto Protocol (2006) to date (2019) were consulted. A search was carried out through Scopus (https://www.scopus.com) and Google Scholar (https://scholar.google.com), with the words ‘climate change’, ‘modeling’, ‘model’ and ‘maize’ without considering gray literature (Rötter *et al*., 2018).

From the 58 340 results obtained, the APSIM-Maize (Agricultural Production Systems simulator), AquaCrop (crop growth model to improve water productivity, developed by FAO), CropSyst (Cropping Systems simulator), CropWat (Crop Water) were selected. Productivity Model), DSSAT-CERES-Maize (Decision Support System for Agrotechnology Transfer-Crop Environment Resource Synthesis), EPIC-Maize (Erosion Productivity Impact Calculator), InfoCrop (dynamic crop yield model developed by the University of Wageningen in the Netherlands) and WOFOST (WOrld FOod STudies, developed by the University of Wageningen in the Netherlands).

Models of growth and yield of corn under climate change conditions

The present essay consists of four parts: 2.1) mathematical models used to simulate crop growth and yield; 2.2) models used in climate change scenarios; 2.3) regional simulation for estimating corn yield under climate change scenarios; and 2.4) analysis of the application of these models in Mexico.

Mathematical models used for simulation of crop growth and yield

The use of mathematical models in biological systems allows increasing the knowledge of the system and improving its behavior through optimization and control (Haeffner, 2005; Hannon and Ruth, 2014), which has helped to understand practically, quickly and synthetically, the complexity of the biophysical processes that occur in agricultural systems, in different settings and in determined time periods (Long and Stitt, 2013; Van Esse *et al*., 2013).

Teh (2006) and Soltani and Sinclair (2012), classify the models based on four criteria: by the way of representing the processes (mechanistic or empirical), by the response obtained with respect to time (dynamic or static), by the response observed (discrete or continuous) and by randomness (deterministic or stochastic).

Mechanistic models explain and describe general system processes, such as growth and yield, under highly non-linear conditions, while empirical or statistical models relate two variables to each other. Dynamic models predict future conditions of the system, since the estimates are produced over time and the static models do not consider time.

Finally, deterministic models work in the same way for a given set of initial conditions while, in stochastics, randomness is included and they describe the states of variables by probability distributions, where the response of the crop changes due to variations in the input variables to the system.

Models used in climate change scenarios

Simulation models allow a clear conceptualization of the effects of CC on crops, although they are limited by the availability of observed data to compare them with the results obtained from the model (Challinor *et al*., 2009). To locally quantify these effects, Murthy (2004) proposed prediction models of crop growth, which estimate their production, yield and adaptive strategies, based on the analysis of climatological variables (maximum and minimum temperatures, precipitation, radiation, CO_2), edaphic and agronomic, in geographic areas and specific time periods (White *et al*., 2011).

General circulation models (GCM), which numerically simulate the dynamics of the components of the climate system, mainly the atmosphere and the ocean, have been used to carry out future climate projections under CC conditions. To the previous models, techniques of increasing resolution and decreasing scale have been applied, with which regional climate models (RCM) or the weighted coupling model reliability ensemble averaging (REA) have been developed, in order to determine the local effects from global changes (Fernández *et al*., 2015; Martínez, 2016).

To know the impact of CC in different areas, CC scenarios have been proposed, with which it is possible to produce the necessary data related to the future climate, and with them, evaluate the models based on GHG emissions (Mo'allim *et al*., 2016). According to Fernández *et al*. (2015), climate change scenarios are alternative and simplified representations of what could happen in the future, and are an instrument used in the investigation of the potential impact of future anthropogenic GHG emissions through simulation.

Scenarios are defined as the difference between a future context and the current weather. It is important to note that they are not climate forecasts, but rather, they represent alternatives for future climate behavior. The IPCC initially proposed the special report on emissions scenarios (SRES), based on demographic changes, socioeconomic development and technological changes, in which four evolutionary lines and families of scenarios were grouped (A1, A2, B1, B2).

The evolutionary line and family of scenarios A1, considered unfavorable, assumed rapid economic growth and maximum population growth towards the middle of the century; it had some variants, such as the intensive use of fossil fuels (A1F1), the balanced use of fossil fuels with clean energy (A1B) and the exclusive use of renewable energies (A1T). The evolutionary line and family of scenarios A2 refers to a heterogeneous world with continuous population growth.

The evolutionary line and family of scenarios B1, considered as favorable, describes a population that grows in the middle of the century and then decreases, with less intensive technological dependence combined with the use of clean technologies and efficient use of resources. Finally, the evolutionary line and family of scenarios B2 describes a sustainable world, although with an increase in population at a slower rate than in A2.

As of the 5$^{th.}$ IPCC report, at the end of 2013, these socio-economic scenarios were replaced by the representative concentration trajectories (RCP), referring to the global increase in the imbalance between the incoming and outgoing radiative energy of the terrestrial system (radiative forcing), measured in W m^{-2} (Moss *et al*., 2010; Fernández *et al*., 2015).

These new projections of the RCP's are based on anthropogenic GHG emissions derived from socio-economic and demographic development, which describe the calculation of the increase in total radiative forcing through four trajectories until the end of the 21$^{st.}$ century compared to the year 1750 (IPCC (2014). Thus, the current CC scenarios consider future projections under different cases of terrestrial radiative forcing (W m^{-2}) and are known as RCP's.

In this way, there is currently a mitigation scenario that considers an increase of 2.6 W m^{-2} (RCP 2.6), which has been exceeded by current conditions, one of stabilization of GHG emissions that considers the increase in 4.5 W m^{-2} (RCP 4.5), another realistic one, with an increase of 6 W m^{-2} (RCP 6) and a last extreme, which considers the highest GHG emissions, whose increase is 8.5 W m^{-2} (RCP 8.5) (Fernández *et al*., 2015).

Models used to simulate corn growth in climate change scenarios

The use of information from the different mathematical models allows local decision makers to have adequate tools to reduce the negative effects of CC in the face of risk and uncertainty in CC scenarios (IPCC, 2014). Each of these models has particular characteristics in its structure and internal functioning, some being more complex than others, in terms of the input information requirement to feed the system, as well as the end user interface.

Table 1 describes the different variants that may exist in a model such as: type of model (TM) according to simulated production: potential (P), limited (L), real (R). Limiting factor (FL): water stress (H); thermal (T); by nitrogen (N); by oxygen (Ox); saline (S); light (L). Yield calculation (CR): harvest index (IC); total (aerial) biomass (B); number of grains and grain growth rate (Gn); partition during reproductive stages (Rt) and post-anthesis partition (Rta).

Table 1. Characteristics of corn growth and yield simulation models used in climate change scenarios.

Model	TM	FL	CR	FC	ETP	N	VEM	NVE
APSIM	PL	HOxT	Prt	TFP	PT	5	PTMtmRS	7
AquaCrop	PL	HNTS	BIC	T	PM	13	PTMtmRS	4
CropSyst	PL	HTNL	ICBRta	TFP	PM	13	PTMtmPrRSV	4
CropWat	PL	H	ICBRt	TO	PM	3	PTMtmSV	-
DSSAT-CERES-Maize	PL	HNOx	Gn	TFP	PM	6	RTMtmRS	4
EPIC	PLR	HTN	ICB	TFP	PM	59	RSTMtmHRV	27
InfoCrop	PLR	HNT	BGnRt	TFP	PM	10	PTMtmRSeV	22
WOFOST	PL	HOxN	RtB	TFP	P	6	TMtmRSeV	7

Culture phenology (FC): function of temperature (T), photoperiod (FP); other effects -hydric or nutritional stress- (O). Potential Evapotranspiration (ETP): calculated by Penman’s equations (P); Penman-Monteith (PM); Priestley-Taylor (PT). Number of parameters considered in the model (N). Input variables -climatic- considered in the model (VEM): precipitation (P); maximum temperature (TM); minimum temperature (tm); dew point temperature (Pr); solar radiation (RS); vapor pressure (e), relative humidity (RH); wind speed (V); fraction of hours of sunshine (S); and potential evapotranspiration (ET).

Number of model state variables (NVE), (Williams *et al*., 1989; Van Evert and Campbell, 1994; Jones *et al*., 2003; Keating *et al*., 2003; Aggarwal *et al*., 2006a; Aggarwal *et al*., 2006b; Boogaard *et al*., 2011; FAO, 2012; Hoogenboom *et al*., 2019).

From the search carried out, 94 published articles were found related to corn production in climate change scenarios, in different regions of the world. Due to the number of articles published, the DSSAT-CERES (43), APSIM (15), CropSyst (10), Aquacrop (10) and EPIC (8) models stood out, which together represent 92% of the total publications analyzed (Figure 1).

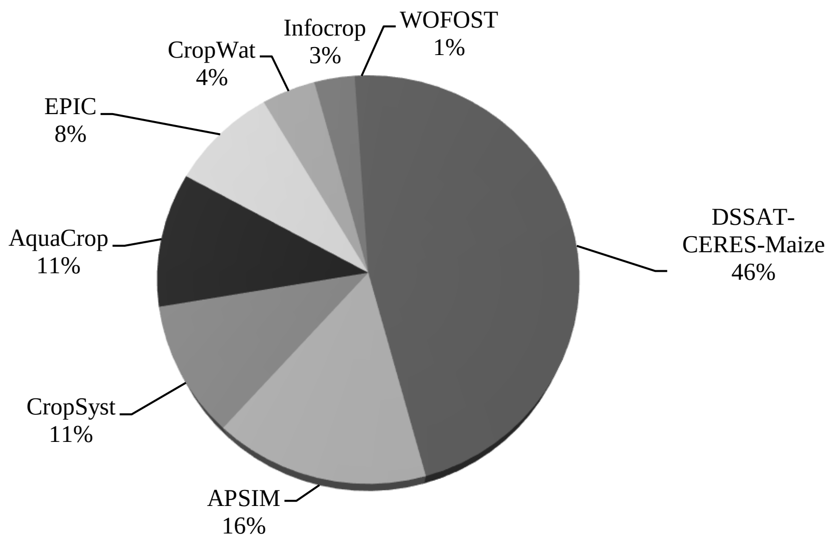

Figure 1. Percentage of articles reported by model used to simulate the growth and yield of corn in climate change scenarios during the 2006-2019 period.

The DSSAT-CERES-Maize (Universities of Georgia and Florida), APSIM (University of Queensland), CropSyst (University of Washington) and EPIC (Texas AM Agrilfe Research Center) models classified as closed-structure, dynamic mechanistic models offer the advantage of not requiring the payment of licenses for their use, they have a friendly interface and simulate the growth and yield of corn with a wide range of interactions between the plant with the climate, soil and agronomic management, as well as the ease of simulate the effects of CC on the crop.

The AquaCrop (FAO) model has been used lately because it is free access software, it requires less detail and specifications of the input variables, which is why it is useful in regions where there is no availability of input data, be it climate, soil or crop and that these are of good quality and in sufficient quantity to perform the simulations, as occurs in Mexico.

The CropWat (FAO) model, although little used for simulation purposes in CC scenarios (4%), was designed for irrigation purposes and simulates the water consumption of the crop and its consequent irrigation sheet. The WOFOST (Wageningen University) model, reported 1% of the analyzed articles, has the advantage of being an open program, freely accessible, which allows its structure to be modified at the code level, adjustments can be made for particular conditions, although it loses its general applicability.

This property is favorable in regions with very particular or specific conditions, such as the micro-regions of Mexico, where there is a great agrobiodiversity of creole and native maize, which are adapted to local conditions and the use of these genetic materials is limited in time and geographic space. This implies that, for a great heterogeneity of environments, it is not possible to use data that are valid in large regions and where the crop is under homogeneous conditions.

The Infocrop model of the Indian Agricultural Research Institute (IARI), reported 3% of the investigations referring to CC, is characterized by considering the effect of pests and diseases on crops, elements that will be modified with climate change in the future under the effect of GHG.

Regional simulation for estimating corn yield under climate change scenarios

The articles were grouped by geographic regions: Sub-Saharan Africa, China, India, the European Union, the Middle East, Latin America, the American Corn Belt, and Canada. The scenarios reported in the publications were A1, A2, A1B, B2 and B1, RCP 2.6, RCP 4.5 and RCP 8.5. The largest number of articles reported are concentrated in Africa, where almost all the models have been used, except WOFOST and Infocrop.

In China, the most used models are DSSAT-CERES and APSIM and to a lesser extent EPIC and CropWat. For the European Union, most of the models have been used, with the exception of CropWat and Infocrop. In India, the use of the local Infocrop model stands out. In Latin America, the studies carried out in Chile, Argentina, Brazil, Bolivia, Panama and Mexico have been reported in DSSAT-CERES, although the region contributes 13% of the reviewed publications (Figure 2).

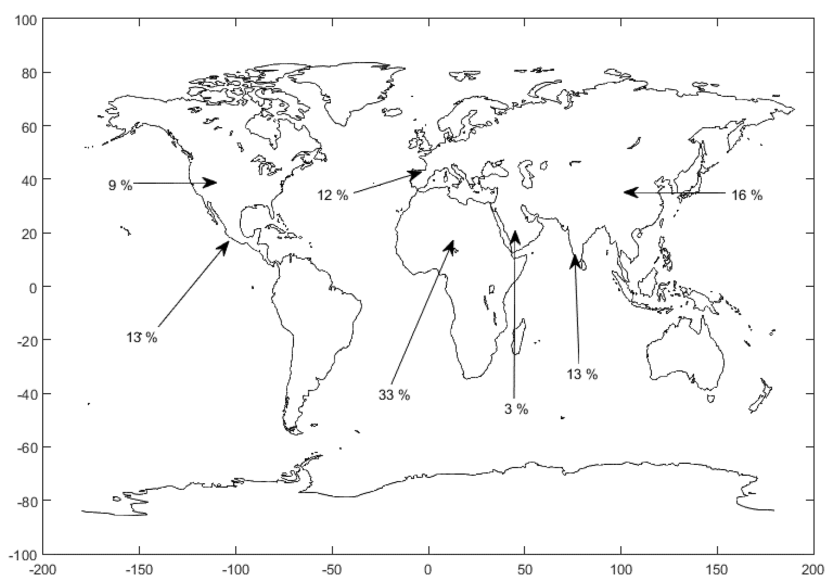

Figure 2. Percentage of articles on simulation models used regionally to estimate corn yield under climate change scenarios.

The projections of CC scenarios in most of the studies estimate the decrease in corn yield, in different regions of the world, mainly attributed to the increase in temperature (Table 2). This condition reduces the vegetative period, affects pollination and interrupts the grain filling phase, which translates into less dry matter production and reduced yield.

Table 2. Changes in average corn yields (%) simulated under climate change scenarios.

MODEL	CH	IN	MO	AS	UE	AL	EU	O
Infocrop	ND	Δ12-45	ND	ND	ND	ND	ND	ND
CropWat [*]	Δ9	Δ1.8-26 ▼54	ND	Δ30-110	ND	▼31-38	ND	ND
AquaCrop	ND	ND	ND	Δ 1-20 ▼0.5-30	Δ 17	Δ 10-50 ▼9-11	ND	ND
WOFOST	ND	ND	ND	ND	Δ10-34	ND	ND	ND
CropSyst	ND	Δ1.5-22	ND	Δ3.4-56	Δ 7.3-14 ▼3-53	Δ 48-61 ▼3-8	ND	ND
APSIM	Δ2.5-70 ▼12-86	ND ▼27-45	Δ14-23	Δ0.3-78 ▼201	Δ 20-29	ND	Δ 10-40	Δ 18-80[δ]
EPIC	Δ20-40 ▼18.6	ND	ND	Δ 4-22 ▼5-20	Δ 5.7-25	ND	ND	Δ4-47[ϒ] ▼0.4-43[ϒ]
DSSAT-CERES	Δ 4-30 ▼1.4-42	Δ 5-40 ▼7.2-42	Δ 1-45	Δ 0.4-58 ▼1.7-23	Δ 3.5-52 ▼71	Δ 0.1-36 ▼15-22	Δ 5.8-57 ▼1.8-11	ND

CH= Includes the North Plain of China and Korea; IN= India including Bangladesh and Nepal; MO= Middle East; AS= Sub-Saharan Africa; EU= European Union; AL= Latin America; EU= United States, including Corn Belt and Canada, O= Other; ΔIncrease, ▼= decrease, [δ]= New Zealand; ϒ= global. [*]= changes expressed as a percentage of water requirement; ND= not available.

But there are also regions where conditions will be favorable and will have positive effects on increasing yield, especially in temperate regions (Table 2). The forecast of the increase in production would be achieved by considering the effect of fertilizer, CO_2 and without water restrictions, a situation that will not necessarily be fulfilled.

According to Conde *et al*. (2004) a reduction in precipitation is foreseen, on which rainfed crops depend; however, short-cycle varieties can develop better since increasing the minimum temperature reduces the risk of frost.

The simulated corn yield with the different models, under CC conditions, had both negative and positive impacts for the same region (Table 2). The variation of the obtained simulations can be attributed to the modification of the environmental conditions and not necessarily to the model used, as demonstrated by Eitzinger *et al*. (2013), when comparing maize yield using DSSAT-CERES-Maize, EPIC, WOFOST, AquaCrop and CropSyst and verifying that these models predict yields with a low level of uncertainty.

The positive effects of CC for the same region can be attributed to mitigation practices, such as cultural work, soil moisture conservation practices and conservation agriculture, the use of improved varieties, the implementation of irrigation systems, associations between crops, or the fertilizing effect of atmospheric CO_2, which reduce the effects derived from the increase in temperature and decrease in precipitation (Table 2).

The necessary condition to implement and evaluate the various growth and development models conventionally used in CC studies is that they must be subjected to the same phases of the generation process of a mathematical model applied to biosystems: uncertainty analysis, sensitivity analysis (local and global), parameter estimation/data assimilation and evaluation, in order to increase its reliability.

In DSSAT-CERES, these adjustments are made particularly for each variety or hybrid of maize, when estimating the genetic coefficients through the analysis of the generalized maximum likelihood estimator Generalized Likelihood Uncertainty Estimator (GLUE) and sensitivity analysis, while in others, such as WOFOST, the calibration is carried out in the different phenological stages. In any case, the use of experimental data is necessary to evaluate, calibrate and evaluate the model, in CC scenarios.

For this reason, the development of models is considered an art, the assembly of which combines mathematical skills for data processing, in a highly non-linear complex agronomic context, characteristic of the models implemented in a biosystem. Most of the models studied require a large number of input variables and parameters for the simulation of the state variables, which translates into structurally complex models, with laborious processes, difficult to execute with a minimum of data, and with it, simulate properly.

On the contrary, simple models, with few input variables, can be useful when a good amount of data is not available, although the uncertainty associated with the result is high and they are no longer a reliable tool. For the use of simulation models in CC scenarios, the uncertainty generated in the cultivation model must be reduced, since more uncertainty is added in the estimation of future scenarios, the accumulation of which can produce results that overestimate or underestimate the yield.

The most used measures to evaluate the yield of the model were: efficiency (E) and the mean square of the prediction error (MSEP) and to estimate the precision, the variance or the coefficient of variation were used (Wallach *et al*., 2014).

Simulation of corn yield under climate change scenarios in Mexico

In Mexico, despite the importance of cultivation, there are only three studies published in the period studied, with the 64 native races of Mexico, at least one study corresponds to each of the climate change scenarios, and at least one study for each commercial variety or hybrid planted in the national territory (Ruíz *et al*., 2011a).

To achieve the above, the development of preferably mechanistic models is required, according to local conditions and data availability, to generate reliable information on projected corn production in real scenarios (RCP 4.5) and extreme conditions (RCP 8.5) of CC. Once the model has been developed, calibrated and evaluated, adaptation and mitigation policies and strategies can be designed in the face of the negative effects of CC on Mexican agriculture, especially in rainy conditions, while promoting food sovereignty.

Conde *et al*. (2004) using DSSAT-CERES, estimated an increase of 5 to 12% and up to 22% in corn yields for a temperate region of Mexico, under an ideal scenario (B2). The foregoing agrees with Ruiz *et al*. (2011b), who indicate that these regions will be favored by the effects of CC. In contrast, Arce *et al*. (2017), in an extreme scenario (RCP 8.5), estimated a 49.3% decrease in corn yield (between 1 and 1.7 t ha^{-1}) using AquaCrop, which places the population dependent on this crop in a situation high degree of vulnerability.

The negative impact influences arid and tropical zones, due to the thermal increase and the reduction in rainfall (imbalance between the demand for water and the evapotranspiration of corn), which reduces the accumulation of GDD and the stay of the crop in the field (Ruiz *et al*., 2011a; Ruiz *et al*., 2016). Research focused on the simulation of local effects of CC on the yield and growth of the corn crop is essential given that the microclimatic diversity of Mexico associated with the presence of native and creole maize are an important genetic reservoir for obtaining improved materials adapted to climate change.

Likewise, field evaluation of CC adaptation strategies is necessary, such as: 1) changes in the sowing date according to the growing season of the crop; 2) efficient use of irrigation water; and 3) implementation of mitigation actions such as conservation agriculture and zero tillage, change of cultural practices and protection measures against extreme weather events.

Mexico is a pioneer in Latin America in the legislative advance of CC issues; however, studies related to the modeling of the negative effects of CC on corn production have yet to be developed, in order for decision-makers to establish scientifically-based measures, according to the context of Mexican agricultural production.

Advances in the investigation of the yields of corn and other crops under CC scenarios are essential for the members of the IPCC and national experts, to obtain the adaptation and mitigation measures necessary to reduce the negative effects of CC in various regions.

Conclusions

There are various mathematical models implemented to simulate the growth and yield of corn that, due to their characteristics, can be used as computational tools to estimate the yields of corn in future scenarios of climate change. The main models evaluated for this purpose were: DSSAT-CERES, APSIM, CropSyst, Aquacrop and EPIC. Each one estimates both increases and decreases in yield, this variation depends on the set of factors considered in the mathematical simulation.

It is considered that the regions most affected in the future maize yield could be Africa, China, the European Union and India, with maximum decreases of 201%, 86%, 71% and 45% respectively; for Latin America, a reduction of 38% is estimated.

Particularly Mexico, is a region with a high degree of vulnerability due to megabiodiversity, geographical position and socioeconomic and cultural conditions and despite the importance of corn for the Mexican population, there are few recent case studies and simulations that estimate the effect of climate change in the production of this cereal in the different climate change scenarios.

For the simulated corn yields to be validated, the models must be calibrated and evaluated, for each of the local conditions, so that it is feasible to obtain regional results on the effects of global climate change. It is recommended that the models used are mechanistic, dynamic, and open source.

The results obtained from the modeling of the biosystem can be used by decision makers to establish adaptation measures and mitigation strategies in the face of the negative effects of climate change at the local level in corn production and even take advantage of the benefits that could exist.

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