Agrociencia

ESTIMATION OF THE GENETIC COEFFICIENTS OF THE CERES-MAIZE MODEL FOR THE SIMULATION OF YIELD BY NON-DESTRUCTIVE METHODS

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ABSTRACT

The Crop Environment Resource Synthesis-Maize (CERES-Maize) mechanistic model, included in the Decision Support System for Agrotechnology Transfer (DSSAT), is a useful and powerful tool that simulates the growth and grain yield of maize in different environments. The qualitative and quantitative information provided to the CERES-Maize model guarantees reliability in the simulations obtained. However, it requires a lot of information, including soil characteristics, daily climate, crop characteristics and management, and six genetic coefficients. The objective of this research was to assess a non-destructive methodology for estimating the six genetic coefficients P1, P2, P5, G2, G3 (associated with plant maturity stages) and Phyllochron interval (PHINT), based on the maize physiology and measured by the Growing Degree Days (GDD), base 10. Two experiments were established at the International Maize and Wheat Improvement Center (CIMMYT) experimental station in Tlaltizapan, Morelos, Mexico, where 27 white and 14 yellow maize hybrids were manually sown in an irrigation conservation tillage system. Once the maize growth and grain yield simulations were obtained with CERES-Maize model, the genetic coefficients were calibrated using the Generalized Likelihood Uncertainty Estimation (GLUE). After calibration of the six genetic coefficients for all hybrids, average values of P1, G2, and G3 were within the typical range, while P2 and P5 were greater than the typical range and PHINT was below typical range. However, the simulation model showed good performance after calibration, with an average R^2 of 0.9809 and 0.9730 between measured and simulated grain yields for white and yellow hybrids, respectively. The coefficients estimated in this study can be used in the CERES-Maize model to simulate grain yields for the hybrids used in different regions of the country.

Keywords: Dynamic crop models, model parameters, leaf area index–LAI, days to anthesis, days to physiological maturity.

Citation: Noriega-Navarrete JL, Salazar-Moreno R, Burgueño-Ferreira JA, Dhliwayo T, López-Cruz IL, Petroli CD. 2023. Estimation of the genetic coefficients of the CERES-maize model for the simulation of yield by non-destructive methods. **Agrociencia** https://doi.org/ 10.47163/agrociencia.v57i2.2505

Editor in Chief:
Dr. Fernando C. Gómez Merino

Received: August 11, 2021.
Approved: February 02, 2023.
Published in Agrociencia: March 15, 2023.

INTRODUCTION

Maize (*Zea mays* L) is the most important crop in Mexico and in the world. It has undergone numerous growth, development, and yield analyses (Ngoune Tandzi and Mutengwa, 2019). Simulation models help understand the complexities of biophysical processes in agricultural production systems (Long and Stitt, 2013). They have been developed as information technology tools to support strategic decision making in research, crop production and land planning (Balderama *et al.*, 2016). However, the performance of the simulation models is dependent on the quality of input variables and the estimation of parameters for variables calculation (Wallach *et al.*, 2014) such as yield and Leaf Area Index (LAI). Specifically, the crop growth models that encompass DSSAT (Decision Support System for Agrotechnology Transfer) require reliable data to obtain good simulation performance. Daily weather data (minimum and maximum temperature, precipitation, and solar radiation) are inputs for the climate module system; physical and chemical soil data at various depths are inputs for the soil module. DSSAT also includes subroutines to simulate water balance between soil and crop, nitrogen balance and carbohydrate distribution in crop (Hoogenboom *et al.*, 2019). In particular, the Crop Environment Resource Synthesis module (CERES-Maize), originally developed in FORTRAN and BASIC language in the mid-1980s, is considered a mechanistic model. However, it incorporates the estimation of some parameters into its structure (empirical sections). The CERES-Maize model, which is included in DSSAT, simulates vegetative and reproductive development, growth and grain yield in maize as a function of crop and soil characteristics, climatic factors and crop management (Balderama *et al.*, 2016), based on seven phenological stages (germination, emergency, end of juvenile stage, floral induction, 75 % silking, grain fill start, physiological maturity and harvest) related to climate and soil systems, the growth rate and the distribution of biomass in different growth parts of the plant (Liu *et al.*, 2012). The development rate is a function of thermal time in growing degree days (GDD), and potential growth is a linear function that depends on the amount and interception of photosynthetically active radiation (PAR), which is related to the maize leaf area index (LAI) (Hoogenboom *et al.*, 2019).

DSSAT CERES-Maize model has been implemented to simulate maize plant growth under different soil and climatic conditions. Maize yield simulations have been extensively validated by many authors in different places (Balderama *et al.*, 2016; Jha *et al.*, 2021). Basso *et al*. (2016) indicated that the model is adequate if the difference between measured and simulated values is less than 4 %. DSSAT CERES-Maize requires six unique parameters known as genetic coefficients, which describe specific crop cultivar growth and development characteristics (Liu *et al.*, 2012). The parameters are calculated from GDD and based on maize phenology (Table 1). According to Jha *et al.* (2021), P1 and P2 determine anthesis and tassel initiation. Together with P5, these two coefficients determine maturity dates. P5 represents the development of the cultivar after anthesis and maturity. Also, P5, G2, G3 and Phyllochron interval (PHINT) control yield, grain size and canopy weight, while PHINT controls phenology and

Table 1. Genetic coefficients used in the DSSAT CERES-Maize model.

Coefficient	Definition	Units
P1	Thermal time from crop seedling emergence to the end of the juvenile stage.	Degree days above base 10 °C
P2	Delay in development with photoperiod above 12.5 h.	d h^{-1}
P5	Thermal time from silking to physiological maturity.	Degree days above base 10 °C
PHINT	Phyllochron interval. The interval in thermal time between two successive leaf tip emergences.	Degree days per tip
G2	Maximum possible number of kernels per plant.	kernels per plant
G3	Potential kernel growth rate.	mg per kernel per day

Source: Liu *et al.* (2012); Malik *et al.* (2019).

growth; more information about the coefficients is given in the materials and methods section.

The incorporation of specific hybrid genetic coefficients improves the model performance. Thus, experimental data are required to perform specific measurements on each maize hybrid to obtain simulations of the variables: days to anthesis (DAA), days to physiological maturity (DPM), leaf area index (LAI, m^2 m^{-2}), and yield (kg ha^{-1}), as closely as feasible to actual conditions. A disadvantage of the DSSAT CERES-Maize model is the lack of a detailed methodology for measuring the genetic coefficients required, which has limited its implementation. Also, the maize genetic coefficients are not available for Mexican maize hybrids. For this reason, the objectives of this research were 1) to describe a non-destructive procedure for measuring the genetic coefficients required by the CERES-Maize model applied to hybrids in Tlaltizapan, Morelos, Mexico; 2) to calibrate six genetic coefficients for white and yellow maize hybrids to be used as a starting point in future maize yield simulations by the scientific community; and 3) to evaluate the performance of the model DSSAT-CERES for maize yield prediction. The hypothesis was that after calibration of the genetic coefficients, the performance of the DSSAT CERES-Maize model would improve substantially, with better predictions of the maize grain yield.

MATERIALS AND METHODS

Field experiment

Two field experiments were established in the year 2018 at the International Maize and Wheat Improvement Center (CIMMYT) experimental station in Tlaltizapan, Morelos (18° 41′ 12″ N, 99° 07′ 33″ W, 956 m altitude), which represents a warm sub-humid climate with pelvic vertisol soils. The average monthly temperature is 24.3 °C, with January being the coldest month (21.2 °C) and May being the warmest (26.7 °C), and a total average annual precipitation of 930 mm (INEGI, 2017). Twenty-seven white hybrids (Experiment 1) and 14 yellow hybrids (Experiment 2) (adapted to the mid-altitude tropical environments of Mexico) were machine-planted on June 13th, 2018 in a no-till system; a list of the hybrids is provided (Table 2). The experimental unit for each hybrid consisted of four rows of 4 m length, 0.75 m between rows, and an average of 0.15 m between plants, with a density of 9.3 plants per m^2. The first experimental design was an alpha-lattice (3 × 9) and second (3 × 5) with two replicates. The experiments were gravity-irrigated three times on July 13th, July 21st, and August 15th, with an average of 50 mm applied in each irrigation. When necessary, herbicides and pesticides were applied to control weeds and insects, respectively. Both experiments were harvested by hand and mechanically shelled on November 8th, 2018.

Table 2. Measured and calibrated genetic coefficients and yields of 27 white and 14 yellow maize hybrids used for yield simulation in the DSSAT CERES-Maize.

Hybrids		P1	P2	P5	G2	G3	PHINT	Yield
STHW1	Calculated	159	0.18	934	503	6.1	38	10671
	Calibrated	203	1.83	967	509	6.4	31	10750
STHW2	Calculated	144	0.18	981	574	5.7	36	12085
	Calibrated	198	0.22	994	572	6.4	40	12564
STHW3	Calculated	159	0.16	997	575	5.9	39	12954
	Calibrated	170	1.58	980	577	6.8	41	12948
STHW4	Calculated	144	0.15	817	487	7.7	35	10298
	Calibrated	244	0.89	851	483	7.5	28	10042
STHW5	Calculated	144	0.18	981	603	5.4	34	9323
	Calibrated	153	1.97	985	440	6.3	35	9331
STHW6	Calculated	159	0.18	921	537	5.9	37	10091
	Calibrated	173	1.53	982	536	5.7	40	10284
STHW7	Calculated	159	0.16	996	619	5.3	34	9939
	Calibrated	208	0.27	994	616	4.7	43	9745
STHW8	Calculated	174	0.17	1028	538	5.1	39	7891
	Calibrated	236	1.12	998	469	5.1	28	8051
STHW9	Calculated	144	0.15	965	555	6.0	33	12270
	Calibrated	171	0.85	975	558	6.8	51	12522
STHW10	Calculated	159	0.14	1012	640	5.5	41	10627
	Calibrated	174	1.96	993	644	4.9	33	10622
STHW11	Calculated	159	0.14	1058	499	5.6	36	8848
	Calibrated	224	0.57	998	496	5.3	35	9022
STHW12	Calculated	144	0.10	906	542	6.7	37	12050
	Calibrated	208	1.79	890	544	7.7	35	12441
STHW13	Calculated	144	0.23	1012	623	5.5	36	11640
	Calibrated	141	1.94	994	618	5.6	44	11649
STHW14	Calculated	129	0.18	966	526	6.4	36	13034
	Calibrated	186	0.34	976	523	7.4	38	13027
STHW15	Calculated	144	0.15	1043	578	5.5	35	12569
	Calibrated	176	1.43	974	574	6.5	44	12312
STHW16	Calculated	159	0.15	997	526	6.1	33	12391
	Calibrated	176	1.08	994	523	6.9	52	12147

Continued...

Table 2. Continue...

Hybrids		P1	P2	P5	G2	G3	PHINT	Yield
STHW17	Calculated	129	0.20	965	528	5.7	36	12940
	Calibrated	196	1.85	979	526	7.4	32	13102
STHW18	Calculated	144	0.15	965	578	5.6	36	10467
	Calibrated	178	1.34	975	577	5.5	41	10473
STHW19	Calculated	144	0.22	965	599	5.6	35	9424
	Calibrated	202	1.25	972	595	4.8	35	9425
STHW20	Calculated	159	0.11	981	573	5.3	36	9745
	Calibrated	247	0.20	997	568	5.0	34	9747
STHW21	Calculated	144	0.20	1027	632	5.3	35	13261
	Calibrated	143	1.80	998	628	6.4	42	13794
STHW22	Calculated	159	0.18	950	593	5.7	35	10722
	Calibrated	158	1.92	992	590	5.4	51	10724
STHW23	Calculated	159	0.09	967	542	5.7	35	12203
	Calibrated	262	0.51	971	541	6.7	31	11962
STHW24	Calculated	144	0.11	1027	565	5.5	34	12856
	Calibrated	175	1.18	998	562	6.8	41	13116
STHW25	Calculated	159	0.23	1027	541	5.9	35	12113
	Calibrated	237	0.47	998	537	6.7	29	12348
STHW26	Calculated	159	0.17	1027	552	5.2	36	10916
	Calibrated	180	1.88	995	550	5.9	38	11137
STHW27	Calculated	144	0.11	997	609	5.7	34	10368
	Calibrated	185	0.25	989	604	5.0	46	10365
STHY1	Calculated	144	0.17	920	444	6.4	37	10724
	Calibrated	198	0.83	946	442	7.7	29	10782
STHY2	Calculated	144	0.16	965	871	6.5	39	12279
	Calibrated	221	1.34	972	865	4.2	30	11989
STHY3	Calculated	129	0.17	950	547	6.5	38	12053
	Calibrated	183	1.00	978	545	6.7	35	12050
STHY4	Calculated	144	0.18	874	459	6.5	38	9631
	Calibrated	165	1.56	914	457	6.8	40	9640
STHY5	Calculated	144	0.14	861	515	6.5	34	11434
	Calibrated	216	0.60	885	513	7.5	32	11427
STHY6	Calculated	144	0.13	965	517	5.8	42	8248
	Calibrated	193	1.29	976	521	4.8	40	8418
STHY7	Calculated	144	0.16	920	503	6.0	38	9424
	Calibrated	175	0.81	952	504	5.9	39	9420
STHY8	Calculated	159	0.17	965	528	5.7	37	11219
	Calibrated	168	1.40	988	529	6.3	41	10998
STHY9	Calculated	159	0.15	936	467	6.2	40	9266
	Calibrated	179	0.51	959	470	6.1	45	9272
STHY10	Calculated	174	0.16	965	438	6.0	40	10500
	Calibrated	175	1.90	983	437	7.0	38	10297
STHY11	Calculated	144	0.16	934	529	6.4	37	10759
	Calibrated	229	0.96	982	526	6.2	29	10977
STHY12	Calculated	159	0.19	877	559	7.1	40	12535
	Calibrated	225	0.37	925	559	7.5	31	13005
STHY13	Calculated	144	0.15	966	473	7.0	36	11614
	Calibrated	166	1.38	982	470	7.2	37	11391
STHY14	Calculated	159	0.18	936	524	6.6	35	11784
	Calibrated	235	0.16	948	521	7.0	32	11554

† STHW: white hybrids; ¶ STHY: yellow hybrids; yield (kg ha^{-1}).

Soil and climate variables

Daily climatological data such as maximum and minimum temperature (°C), precipitation (mm), relative humidity (%), and solar radiation (W m^{-2}) were collected from experimental weather station in Tlaltizapan from the 1973–2018 period. Missing data values were imputed using information available from nearby weather station (Temilpa, Morelos) of the National Water Commission (CONAGUA). According to Herrera-Oliva *et al.* (2017), if the Pearson's correlation coefficient between variables measured in two stations is greater than or equal to 0.8, the estimator from a linear regression model between the two stations can be used to fill in the missing precipitation values. Aieb *et al.* (2019) stated that similarity is considered if the correlation coefficient between the station with missing data and the nearest stations is greater than 0.89, so this latter criterion was applied. In the case of isolated missing data (temperature or precipitation), the moving average was calculated using the previous three days, according to the persistence principle that characterizes these meteorological variables. For missing solar radiation (*SR*), average relative humidity (*RH*) and evapotranspiration (*ETo*) data, the methodology established by FAO Manual 56 was applied (Allen *et al.*, 2006). The Solar Radiation (*SR*) was calculated using Equation 1.

$$SR = k_{Rs} \, (T_{\max} - T_{\min})^{1/2} \, R_a \tag{1}$$

where k_{Rs} is an adjustment coefficient for terrestrial areas (0.16); $T_{\max}$ is the maximum temperature (°C), $T_{\min}$ is the minimum temperature (°C), and R_a is the extra-terrestrial radiation (MJ m^{-2} d^{-1}).

The average RH (%) was obtained using maximum (RH_{max}) and minimum (RH_{min}) relative humidity described in Equation 2:

$$RH_{\max} = \frac{e_a}{e^0 \, T_{\min}} 100, \quad RH_{\min} = \frac{e_a}{e^0 \, T_{\max}} 100 \tag{2}$$

where e_a is the actual vapor pressure (kPa); e^o is the vapor saturation pressure (kPa).

The potential evapotranspiration (*ETo*, mm d^{-1}) was calculated from the Penman Monteith equation (Equation 3) given in FAO Manual 56 (Allen *et al.*, 2006).

$$ETo = \frac{0.408\Delta \, (R_n) + \gamma \dfrac{900}{T + 273} u_2 \, (e_a - e_a)}{\Delta + \gamma \, (1 + 0.34 \, u_2)} \tag{3}$$

where Δ is a slope of the vapor pressure curve (kPa °C^{-1}); R_n is the net radiation data on the crop surface (MJ m^{-2} d^{-1}); γ is a psychrometric constant (kPa °C^{-1}); T is the average air temperature at 2 m from the floor (°C); u_2 is the wind speed (m s^{-1}) and e_s is the saturated vapor pressure (kPa).

Soil physical properties required by the model such as bulk density (g cm^{-3}); sand, silt and clay content (%); texture, chemical properties like organic matter (%); $N^{-}NH_4^+$, $N-NO_3^-$, P, and interchangeable bases (K^+, Ca^{2+}, Mg^{2+}, Na^+) concentration (mg kg^{-1}); and CIC (cmol kg^{-1}), EC (dS m^{-1}), and pH were obtained by analysing a composite stratified random sampling of the soil consisting of 10 subsamples at three depth levels (0.30, 0.60 and 0.90 m) at the National Laboratory of Research Agri-food and Forest Service (LANISAF) on June 1st, 2018.

Morpho-physiological variables

Comprised by the following: the number of days after emergency (DAE); number of days after anthesis (DAA) or VT stage; days to physiological maturity (DPM) or R_6 stage; the leaf area index (LAI, m^2 m^{-2}), and grain yield (kg ha^{-1}).

The vegetative (V_n) stages last from emergence to anthesis, and the reproductive (R_n) stages from silking to physiological maturity (Ritchie and Alagarswamy, 2003). The number of days to 50 % emergence (DAE) and the number of days to emergence of the first leaf (V_1) up to the n^{th} leaf (V_n) were obtained from daily leaf counts starting at the time the first leaf appeared. The number of days to anthesis (DAA), equivalent to the V_T stage, and the number of days to female flowering (R_1) were recorded when 50 % of the plants in a plot were shedding. Days to physiological maturity (DPM) in R_6 stage were estimated using the time to the appearance of the black layer at the base of the corn grain when grain moisture was close to 35 % on at least three ears. Plant height (m) was measured as the distance from the ground to the flag leaf using a 3 m wooden ruler.

The leaf area index (*LAI*) was calculated using Equation 4 (Nguy *et al*., 2012).

$$LAI = \log_{0.6}\left[\frac{-(NDVI - 0.943)}{0.731}\right] \tag{4}$$

where *NDVI* is the Normalized Difference Vegetation Index determined 30 days after sowing (das), between stages V_7 and V_{12}, using a portable Earth sensor (Greenseeker). At the end of the anthesis (V_T), the maximum LAI was determined using Equation 5 suggested by Mananze *et al*. (2017) and Sánchez-Mendoza *et al*. (2017).

$$LAI_{\max} = \frac{FAP}{NP} DP \tag{5}$$

where *DP* is the plant density per m^2, *NP* is the number of sampled plants, *FAP* is the foliar area per plant.

FAP was estimated using the average of the sum of the leaf area of the green leaves from four plants at physiological maturity. Leaf area was obtained using a factor of

0.75 to multiply the length (L) and maximum width (A) of each leaf (m) as proposed by Mananze *et al*. (2017). The yield was assumed to be at 14 % grain moisture content.

Parameter estimation (genetic coefficients for maize)

The thermal time of maize hybrids were expressed in growing degree days (GDD), according to Equation 6 (McMaster and Wilhelm, 1997).

$$GDD = \frac{T_{\max} - T_{\min}}{2} - T_{base} \tag{6}$$

where T_{base} is the base temperature (°C).

For this study T_{base} = 10, which is appropriate for maize with tropical and subtropical adaptation according to local experimental conditions (Ruíz-Corral *et al*., 2011; Arista-Cortes *et al*., 2018).

Seed companies, based on heat accumulation, give information about relative maturity to understand the crop maturity period with specified GDD from planting to silking and to maturity, respectively (Jha *et al*., 2021). The six genetic coefficients used in DSSAT CERES-Maize model were described according to Liu *et al*. (2012) (Table 1).

Calculation of the six genetic coefficients

The P1 coefficient (Equation 7) represents the meristematic differentiation of the male inflorescence in 50 % of the studied plants using destructive sampling (Esteves *et al*., 2012). In contrast, a non-destructive method was used in this study, where P1 was counted by the sum of GDD base 10 (Equation 6) between V_4 and V_6 (Martínez-Álvarez, 2015) because the differentiation of the reproductive organs starts in the early stages of cultivation.

$$P1 = \sum_{i=4}^{i=6} GDD_i \tag{7}$$

where GDD corresponds to GDD_i at V stages i = 4, 5, and 6.

P2 (Equation 8) was estimated as the average of the proportional degree of delay in the anthesis date when comparing data hybrids from two experiments located at different times or places (Hoogenboom, 2019) to evaluate the duration of the day effect. In this study, DAA were collected from two different experiments with the same hybrids, the first of them located at Chinameca, Morelos (DAA_2) (18° 38′ N, 98° 55′ W, 1050 m altitude) and the second one located at Coatlán del Río, Morelos (18° 44′ N, 99° 26′ W, 1020 m altitude) (DAA_3). Both were compared with local DAA to obtain proportion; finally, the mean was obtained.

$$P2 = \frac{\frac{DAA_2}{DAA-1} + \frac{DAA_3}{DAA-1}}{2} \tag{8}$$

$P5$ (Equation 9) was calculated counting the *GDD* base 10 (Equation 6) from the stage of appearance of stigmas (R_1) to the physiological maturity stage (R_6).

$$P5 = \sum_{i=1}^{i=6} GDD_i \tag{9}$$

where *GDD* corresponds to GDD_i at R stages i = 1 to 6.

The *PHINT* coefficient (Equation 10) was determined as the *GDD* base 10 accumulated in the period of appearance between two ligulate or true leaves, over n-1 leaves. The *GDD* base 10 was counted between the consecutive appearance of two leaves, from the appearance of the first ligulate leaf (V_1) and the subsequent leaf (V_2), to the nth ligulate leaf (V_n).

$$PHINT = \sum_{i=1}^{i=1} \frac{GDD_i}{n-1} \tag{10}$$

$G2$ (Equation 11) was calculated as the average of the multiplication between the number of rows per ear (r_e) by the number of grains per row (g_r), based on seven ears randomly selected per hybrid.

$$G2 = r_e \times g_r \tag{11}$$

$G3$ (Equation 12) was obtained as the ratio of 100 weight grain per ear (wg) expressed in mg over the number of days (n) between the perlite grain stage (R_2) and physiological maturity (R_6). This coefficient is directly related to yield because the number of grains and number of cobs are associated with the interception of PAR by the plant during the non-linear stage of grain filling (Marek *et al*., 2017).

$$G3 = \frac{wg}{\sum_{i=2}^{i=6} n} \tag{12}$$

where wg corresponds to weight grain per ear at stages i = 2 to 6, and n to number of days from R_2 to R_6.

Overview of the simulation model

The dynamic model DSSAT-CERES-Maize v. 4.7.5 (Hoogenboom *et al*., 2019) was used for the simulation of hybrid growth and grain yield. Meteorological information was incorporated into the Weather Data sub-module; soil analysis data were introduced into the Soil Data sub-module; information on the agronomic management of the hybrids was incorporated into the Crop Management Data sub-module; and experimental data was included in the Experimental Data sub-module. The calculated genetic coefficients for each hybrid were incorporated into the model database, and the standard ecotype was modified with a base temperature of 10 °C. Subsequently, the corresponding simulations were performed.

Based on a methodology proposed by Jones *et al.* (2011), the genetic coefficients were calibrated through 1000 simulations using the GLUE (Generalized Likelihood Uncertainty Estimation) method, which was incorporated in DSSAT to find the maximum probability of finding the best coefficient values leading to a better fit between simulated and measured yields. Following the procedure implemented by Batchelor *et al.* (2020) a linear regression was performed between measured and simulated values for the variables, days to anthesis (DAA), days to physiological maturity (DPM), leaf area index (LAI) and grain yield. Model performance was measure through the determination coefficient (R^2) (Equation 13), the root of the mean square error (RMSE) (Equation 14) and the mean absolute error (MAE) (Equation 15).

$$R^2 = 1 - \frac{\sum_{i=1}^{12}\left(y_i - \hat{y}_t\right)^2}{\sum_{i=1}^{12}\left(y_i - \bar{y}\right)^2} \tag{13}$$

$$RMSE = \left[\frac{\sum_{t=1}^{n}\left(y_t\ \hat{y}_t\right)^2}{n}\right]^{1/2} \tag{14}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|y_t - \hat{y}_t\right|}{n} \tag{15}$$

where n is the number of samples, $\bar{y}_i$ is the sample mean, y_i and $\hat{y}_i$ are the measured and predicted values, respectively.

RESULTS AND DISCUSSION

Estimation of genetic coefficients for maize

The genetic coefficients measurement for each maize hybrid involves a high investment of technical, human and economic resources. In Mexico, due to the diversity of maize genetic resources, it is recommended that values be adjusted with some precision. However, it is preferable to use coefficients obtained from experimentation to obtain the most reliable model simulations. The genetic coefficients for 27 white maize hybrids and 14 yellow maize hybrids were calculated and then calibrated to find the best parameters values (Table 2). P1, P2 and P5 coefficients are associated with crop development, and they have influence over DAA, DPM and LAI. Since maize grows for a limited photoperiod, P1 and P2 were calibrated simultaneously using GLUE. These coefficients showed greater changes after calibration, which may imply a higher hybrid sensitivity to photoperiod.

The average values of the six coefficients for the white and yellow hybrids and their coefficients found by other authors are shown (Table 3). The calculated and calibrated average thermal time from crop seedling emergence to the end of the juvenile stage (P1) was within the typical range; values obtained after calibration were 193 and 195 degree days for white and yellow hybrids, respectively, indicating that more degree days are required to complete the juvenile stage, and thus anthesis is delayed. Only the P1 values found by Jaha *et al.* (2021) in an experiment conducted in Michigan are close to our results (Table 3).

Average P2 values after calibration were above the typical range, implying that development was delayed by 1.18 and 1.01 days for each hour increase photoperiod, for white and yellow hybrids, respectively. Marek *et al.* (2017) reported a P2 range of 0.53 to 1.55 for two drought-tolerant corn hybrids grown in Texas, USA. Also, the average value found for the yellow hybrids was equal to the one found by Jaha *et al.* (2021) for commercial maize hybrids in Michigan.

The days (d) from silking to physiological maturity (P5) after calibration were 978 and 956, for white and yellow hybrids, respectively, which were higher than typical range, indicating that the calibrated hybrids require more thermal time from silking to physiological maturity. Similar results were found by Yang *et al.* (2009) (Table 3) for four hybrids in North Carolina, USA, who associated the coefficient P5 with the total

Table 3. Calculated and calibrated average maize genetic coefficients of 27 white and 14 yellow hybrids and their comparison with other authors.

		P1 ($^oC\ d^{-1}$)	P2 ($d\ h^{-1}$)	P5 ($°C\ d^{-1}$)	PHINT†	G2¶	G3§
Balderama *et al.* (2016)		287	1.32	986.7	45	528.9	16.43
Hammad *et al*. (2017)		311	0.84	752	42.5	725.2	10.3
Liben *et al*. (2018)		180-280	0.30-0.80	675-978	38.9–50	436-675	5.5-12.35
Liu *et al*. (2012)		260	0.30	870	53	820	9
Malik *et al*. (2019)		243	0.20	800	59.9	800	8.75
Marek *et al*. (2017)		285-320	0.53-1.55	800	43–50	534-760	10.5-12.5
Yang *et al*. (2009)		275-290	-	880-985	-	600-1000	6-9.5
Hoogenboom *et al*. (2019) Typical range		100-400	0-0.4	600-900	40-55	500-1000	5-12
Results in this study							
White	Calculated	151	0.16	982	36	564	5.76
	Calibrated	193	1.18	978	38	554	6.13
Yellow	Calculated	149	0.16	931	38	498	6.40
	Calibrated	195	1.01	956	36	526	6.49

† $°C\ d^{-1}$per tip; ¶kernels per plant; § mg per kernel per day.

yield, due to its effect on the final weight of the grain. Also, Balderama *et al.* (2016) reported higher P5 values for maize in the province of Isabela in Philippines.

The PHINT coefficient (the interval between successive tip appearances) did not change much before and after calibration (38 and 36 for white and yellow hybrids, respectively), and it was below the values found by other authors (Table 3), but very close to the lower bound of the typical values. Besides, according to Hoogenboom *et al.* (2019), this coefficient never can be above 55; in our case the PHINT values met this requirement. Some authors like Hammad *et al.* (2017) and Yang *et al.* (2009) use the same value for PHINT for any hybrid; however, we noticed that its variation modifies the simulations slightly, with no great difference between measured and calibrated values.

The reproductive crop growth and development are associated with G2 and G3. The G2 coefficient, together with grain weight, can simulate potential yield (Ritchie and Alagarswamy, 2003). G2 represents the maximum number of kernels per plant (554 and 526 for white and yellow hybrids, respectively), which is related to photosynthesis during the critical grain filling stage and plant stress, so it is highly sensitive to environmental stress conditions. The G3 coefficient is directly related to yield, because the number of grains and number of ears are associated with the interception of PAR by the plant during the non-linear stage of grain filling (Otegui and Andrade, 2000). In other words, G3 is the kernel filling rate during the linear grain filling stage (6.13 and 6.49 mg d^{-1} for white and yellow hybrids, respectively). The calibrated G2 and G3 values were within the typical range but below the values reported by Balderama *et al.* (2016), Malik *et al.* (2019), and Jha *et al.* (2021) (Table 3).

Morpho-physiological variables

The number of days to emergence (DAE) remains very close before and after calibration (Table 4). On the other hand, days to anthesis (DAA), days to physiological

Table 4. Comparison of the average measured and simulated variables before and after calibration for white and yellow maize hybrids.

Variable	DAE[†]	DAA[¶]	DPM[§]	LAI[♭] (m^2 m^{-2})	Yield (kg ha^{-1})
			White maize hybrids		
M[¤]	5	57 ± 1	124 ± 3	5.4 ± 0.5	11174 ± 1461
BC[††]	6	48 ± 2	113 ± 4	4.5 ± 0.2	10730 ± 742
AC[¶¶]	6	57 ± 1	122 ± 2	5.1 ± 0.9	11246 ± 1512
			Yellow maize hybrids		
M[¤]	5	57 ±2	120 ± 3	5.5 ± 0.5	10819 ± 1277
BC[††]	6	49 ±1	111 ± 3	4.3 ± 0.2	9861 ± 957
AC[¶¶]	6	57 ±1	120 ± 3	5.4 ± 0.7	10801 ± 1263

[†]DAE: days to emergency; [¶]DAA: days to anthesis; [§]DPM: days to physiological maturity; [♭]LAI: leaf area index; [††]BC: simulation before calibration; [¶¶]AC: simulation after calibration; [¤]M: measurement.

maturity (DPM), leaf area index (LAI), and grain yield, change after calibration of genetic coefficients for both white and yellow hybrids, generating values close to the measured values (Table 4 and Figure 1). Before calibration, DAA, DPM, LAI and grain yield values were far from the measured values, so it was necessary to calibrate the coefficients to improve them (Table 4). After calibration, the differences in DAE, DAA and DPM were ranged from 1 to 4 d (Table 4), which are like those obtained by Yakoub *et al.* (2017). In addition, the model performance improved for all variables, according

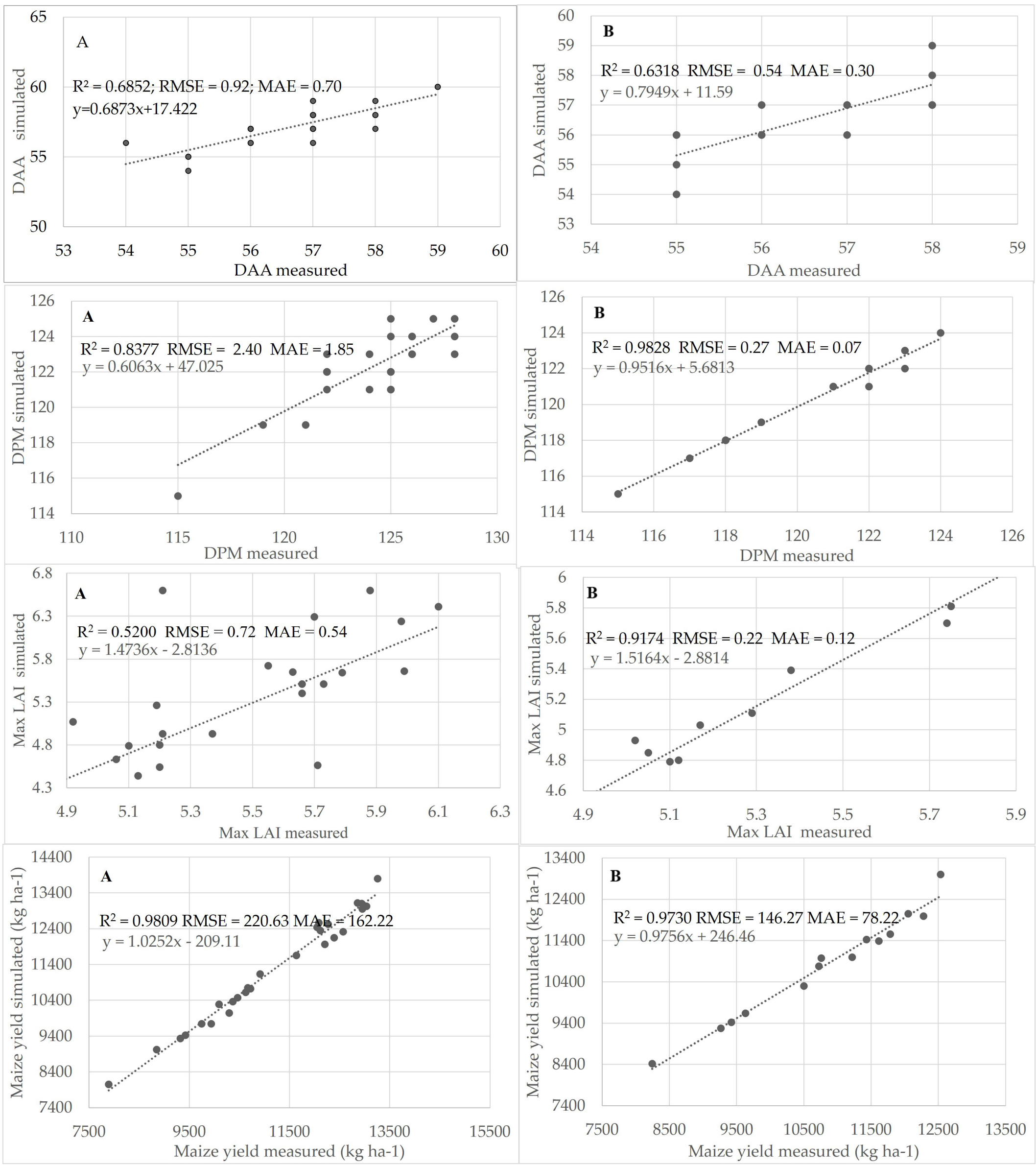

Figure 1. Linear regression between simulated and measured values of the variables for A: white and B: yellow maize hybrids, after calibration of the genetic coefficients.

to the indicators R^2 (determination coefficient), RMSE (root of the mean square error), and MAE (mean absolute error) (Figure 1).

Grain yield

According to Figure 2 grain yields were overestimated for 7 white hybrids while for the rest of the hybrid yields were underestimated using the measured genetic coefficients. For the case of the yellow hybrids, the yields were underestimated using the measured genetic coefficients, except for one of the hybrids (Figure 3). However, after calibration the performance of the model was improved (Table 5). The RMSE and MAE between measured and simulated grain yields presented a better approximation, compared to those reported by Yakoub *et al.* (2017).

The DSSAT CERES-Maize model overestimated and underestimated yields for white and yellow hybrids. After coefficients calibration, overestimations for white and yellow hybrids were 3–257 kg ha^{-1} and 3–290 kg ha$^{-1,}$ respectively (Table 2). Malik *et al.* (2019) also found an overestimation (330 kg ha^{-1}) for a Pioneer PR34N43 maize crop, a value higher than our results. On the other hand, the yields underestimation was 1–533 kg ha^{-1} and 6–470 kg ha^{-1} for white and yellow hybrids, respectively (Table 2). However, the bias grain yield simulated in this study was smaller than that obtained by Liben *et al.* (2018), who found a bias between 850–1090 kg ha^{-1}.

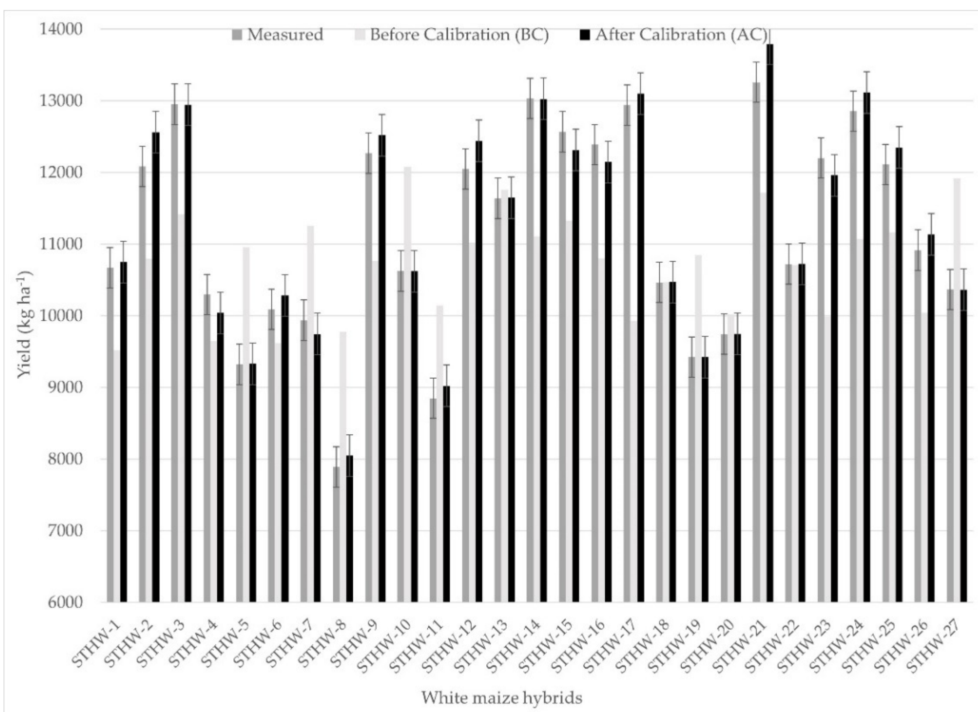

Figure 2. Average yield measured and simulated (kg ha^{-1}) before and after calibration of genetic coefficients for the 27 white maize hybrids.

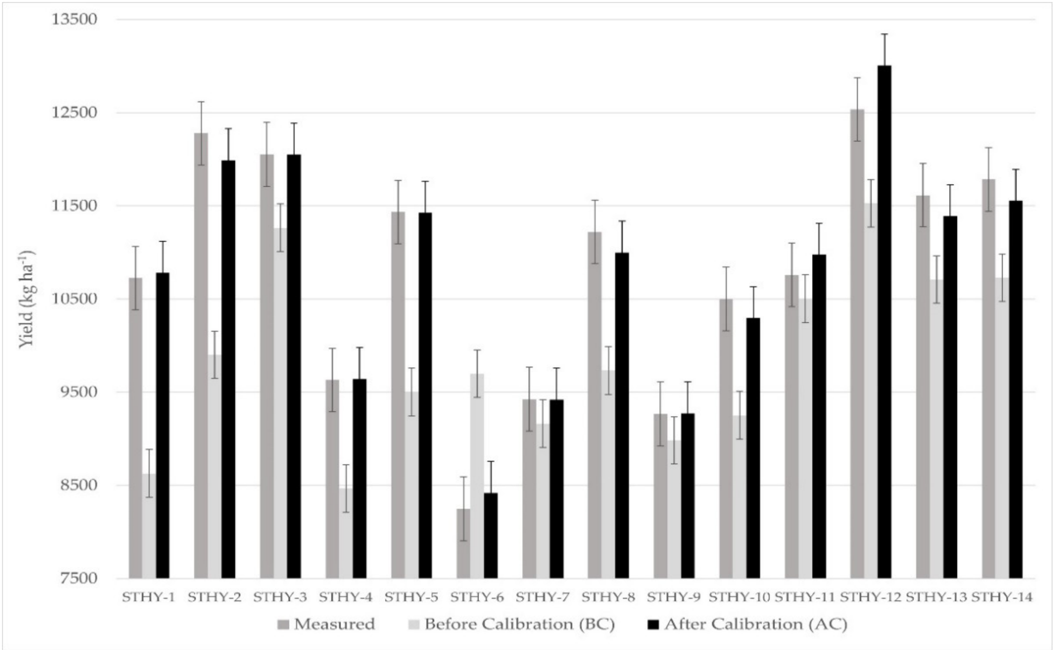

Figure 3. Average yield measured and simulated (kg ha^{-1}) before and after calibration of genetic coefficients for the 14 yellow maize hybrids.

Table 5. Model performance of the variables before (BC) and after (AC) calibration for white and yellow hybrids.

Variable	DAA†		DPM¶		LAI§ (m^2 m^{-2})		Yield (kg ha^{-1})	
	BCᵇ	AC¤	BC	AC¤	BC	AC¤	BC	AC¤
				White maize hybrids				
R^2	0.0931	0.6852	0.6942	0.8377	0.1146	0.5200	0.1315	0.9809
RMSE	8.41	0.92	10.59	2.40	1.01	0.72	1420.85	220.63
MAE	8.30	0.70	10.48	1.85	0.89	0.54	1248.85	162.22
				Yellow maize hybrids				
R^2	0.0007	0.6318	0.5738	0.9828	0.1890	0.9174	0.4435	0.9730
RMSE	5.37	0.54	6.98	0.27	0.89	0.22	958.52	146.27
MAE	3.78	0.30	4.93	0.07	0.60	0.12	604.41	78.22

†DAA: days to anthesis; ¶DPM: days to physiological maturity; §LAI: leaf area index; ᵇBC: simulation before calibration; ¤AC: simulation after calibration.

CONCLUSIONS

Five morpho-physiological variables were simulated in the Crop Environment Resource Synthesis-Maize (CERES-Maize) mechanistic model, included in the Decision Support System for Agrotechnology Transfer (DSSAT). Variables were the number of days after emergency (DAE); number of days after anthesis (DAA) or VT stage; days to physiological maturity (DPM) or R_6 stage; leaf area index (LAI (m^2

m^{-2}); and yield (kg ha^{-1}) for 27 white and 14 yellow maize hybrids. The six genetic coefficients fundamental in the model were estimated by an extensive non-destructive phenological monitoring of the crop in Tlaltizapan, Morelos, Mexico.
After model calibration using the Generalized Likelihood Uncertainty Estimation methodology (GLUE), the best genetic coefficient estimators were found by improving the model performance. The model developed after calibration simulated average days to physiological maturity, leaf area index, and yields with high precision (R^2 > 0.91) for the white and yellow maize hybrids. The coefficients estimated for the hybrids analysed in this study can be used in maize simulations for different regions in Mexico.

ACKNOWLEDGEMENTS

This work was the research of a PhD student, supported by Consejo Nacional de Ciencia y Tecnología (CONACYT) and implemented by the Universidad Autónoma Chapingo in collaboration with CIMMYT as part of the Seeds of Discovery (SeeD) Initiative, made possible by the generous support of Sustainable Modernization of Traditional Agriculture (MasAgro) Project funded by the Ministry of Agriculture, and Rural Development (SADER) of the Government of Mexico. Any opinions, findings, conclusion, or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the view of SADER.

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