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# Applying agroclimatic seasonal forecasts to improve rainfed maize agronomic management in Colombia

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ABSTRACT

Climate variability affects crop production in multiple and often complex ways. The development and use hybrid crops with greater productivity and tolerance to climate shocks is one of the approaches to climate adaptation and agricultural intensification. Since hybrid crops are more expensive for the producer, risk management is of paramount importance. Here, we pose that there is high potential for the Colombian maize sector to use crop-specific climate services for risk reduction. We used the CERES-Maize crop model connected to seasonal climate forecasts developed via Canonical Correlation Analysis (CCA) across key maize growing areas in Colombia to assess the performance of a maize-specific agroclimatic forecast to inform two key decisions, namely, the choice of sowing dates and genotypes. We find that the agroclimatic models perform well at discriminating yield categories (above, below, and normal) with discrimination capacity of up to 70–80 % for the 'below normal' and 'above + below normal' categories. Consistent with this, agroclimatic forecasts typically predict the optimal planting date with an error of 3 pentads or less. They also predict the optimal choice of genotype correctly around 50–70 % of the time depending on the site or season of interest. Notably, we identify specific cases in which the agroclimatic forecast is misleading but argue that the overall value of the forecasts outweighs these cases. Future work should focus on expanding the scope of the agroclimatic prediction to include other relevant farming decisions that are influenced by climate, and on the improvement of climate forecast performance.

**Practical implications**

The current study develops an approach for assessing the performance of agroclimatic forecasts as a climate service for hybrid maize across Colombia –where maize is one of the most important staple crops for food security and farmer incomes. The use of climate forecasts as part of decision support systems for agriculture has been evaluated previously (Capa-Morocho et al., 2016; Han et al., 2019). Here, we go a step further and assess the performance of locally tailored and crop-specific seasonal agroclimatic forecasts toward specific farming decisions, namely, planting date and genotype choice. We used field experiments to calibrate the DSSAT-CERES-Maize crop model and then integrate the calibrated crop model with retrospective seasonal climate forecasts. The combination of historical climate data and a well-calibrated crop model then allowed us to evaluate the overall quality of the forecasts and the responses of the target varieties to the local climate conditions.

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Our paper demonstrates that, while not perfect, these agroclimatic forecasts have adequate skill for identifying, ahead of season, the most likely yield outcome (above normal or top tercile, around normal or middle tercile, and below normal or bottom tercile) with an accuracy of up to 80 % in some cases. Perhaps more importantly, our analyses show that, in many instances, these forecasts also allow selecting the best performing planting dates and varieties. Three main practical implications stem from our work:

*Agroclimatic forecasts can indeed support decision-making.* In Colombia and other parts of the world, where climate risk is high and rainfed agriculture is prevalent, substantial supply of climate information services and products exists (Bouroncle et al., 2019; Chiputwa et al., 2022; Haigh et al., 2018; Vaughan et al., 2019). Many of such products and services remain underused in part because their value and performance are unclear to users or has not been assessed at all. Our study identifies specific situations (sites, seasons) in which the forecasts work best, which may be used by practitioners to guide future implementations and scaling of climate services in the country. Our approach can also contribute to output quality assessment and reporting of existing services such as the *Pronosticos AClimateColombia* forecast system (Sotelo et al., 2020).

*Crop simulation models can act as 'translators' in the climate services value chain.* Climate services encompass the process of generation, translation, transfer, and use. Many climate services and products limit the information generated to probabilistic outlooks of precipitation and temperatures, which can be difficult to interpret for farmers in developing country contexts (Alfaro et al., 2018; McCrea et al., 2005). This effectively means that further translation of the probabilistic information is needed. Our study connects climate forecasts to crop models, which effectively translates the climate forecast probabilities into local- and crop-specific predictions of optimal planting dates and genotypes. These predictions are more actionable and hence more likely to be understood and used by farmers (Guido et al., 2020; Sotelo et al., 2020).

*Lastly, we contribute to advancing the area of climate services evaluation* (Tall et al., 2018; Vogel et al., 2017). Our approach assesses four aspects of agroclimatic forecast performance, namely, (i) climate forecast skill; (ii) crop model skill; (iii) agroclimatic forecast ability to predict yield; and (iv) agroclimatic forecast ability to predict decisions. Especially for the forecast ability to predict decisions, we provide a comprehensive picture of forecast performance across sites, planting seasons, and years. For instance, while Section 3.4 provides a general overview of yield forecast performance, Section 3.5 provides a detailed account of the predictive accuracy of the forecasts for identifying optimal planting dates. Section 3.6 then shows the accuracy for identifying the best-performing genotypes, but also looks at how it varies across planting dates. In a practical situation, this combined information would help the user get a rapid but comprehensive picture of where forecasts have the greatest potential value. Though clearly forecast skill is not the only dimension of importance in evaluating climate services, we believe our method, analyses, and results provide a solid basis for climate services evaluation. Future research and practice may connect our biophysical models with decision models (e.g., agent-based models) or surveys to explore farmer choices and their livelihood benefits.

**Data availability**

Data will be made available on request.

## 1. Introduction

Climate variability affects crop production in multiple ways, ranging from changes in the duration of the growing cycle due to temperature through to variations in soil water availability and total loss of agricultural production (Anderson et al., 2019; Iizumi et al., 2014). This is especially true for small-scale farming areas in the tropics, where adaptive capacity can be low, and farmers lack basic information, extension, and resources and skills to address climate risk (Dayamba et al., 2018; Xue et al., 2008). In many of these areas, and especially so throughout Latin America, Sub-Saharan Africa, and Asia, climatic variation can explain as much as 75 % of the productivity of maize crops (Ray et al., 2015). In Colombia, the focus of the present study, around two-thirds of the rainfed maize yield variation are reportedly explained by climate and management, with rainfall and runoff being key climate-related determinants of crop productivity (Jiménez et al., 2019).

Throughout the tropics, one of the approaches to adaptation is the development and use hybrid crops that have greater productivity and are more resilient to climate shocks (Govaerts et al., 2019; Masuka et al., 2017). Since hybrid crops are more expensive for the producer, risk management is of paramount importance. A season with low productivity and thus poor economic return can result from a variety of factors, including the selection of an inappropriate variety given the expected seasonal conditions, inadequately informed decisions regarding planting dates and agronomic practices (Hammer et al., 1996; Hansen et al., 2009; Klemm and McPherson, 2017). In Colombia, the confluence of these factors leads to low maize yields (1.8 ton ha$^{-1}$ below the Latin American average) and significant interannual variations, resulting in high levels of import dependency (Govaerts et al., 2019).

We pose that there is high potential for the Colombian maize sector to use crop-specific climate services to contribute to closing the maize yield gaps and enhancing climate risk management. Realizing such potential requires a strategy spanning the use of seasonal climate information; understanding of potential agroclimatic influences; availability of high-yielding, resilient and marketable genotypes; and good agronomic practice (Govaerts et al., 2019). Implementing climate services, however, requires a series of interconnected components including reliable seasonal climate forecasts, tools to link climate forecasts with agronomic decisions, and delivery mechanisms (Fraisse et al., 2006; Guido et al., 2020; Roel and Baethgen, 2007). These components facilitate the production and translation of climate information into agricultural terms as well as the construction of the social capital (including institutional and individual capacities) to transfer and use climate information at the farm level (Dayamba et al., 2018; Loboguerrero et al., 2018).

At the core of many climate services in agriculture is the 'agroclimatic forecast'. That is, the integration of three aspects: (i) a reliable seasonal climate forecast, (ii) a well-calibrated crop simulation model, and (iii) the verification of the corresponding combined forecasts. These aspects have not been holistically considered nor systematically assessed for hybrid maize cultivation in the Colombian context. Here, we develop and evaluate seasonal agroclimatic forecasts for hybrid maize production in Colombia. More specifically, we,

(i) Calibrate model parameters of the DSSAT-CERES-Maize model and evaluate maize crop yield simulations using experimental information from three maize-producing areas in Colombia;
(ii) Assess historical (1980–2013) maize yield variability, its causes, and the role of management choices (i.e., planting dates and genotypes);
(iii) Evaluate the integration between the seasonal climate predictions and the crop model with a focus on the correct identification of the highest-yielding planting dates and genotypes.

In the following sections we present the above approach and illustrate how better understanding of the crop-climate interface under conditions of climate variability can be used to better inform variety selection and planting date decisions for hybrid maize.

## 2. Materials and methods

### 2.1. Study areas

In Colombia, maize is a staple crop sown in virtually every department (state), with the Andean and Caribbean regions housing the largest commercial production (FENALCE, 2017; Govaerts et al., 2019). We focused on the departments of Cordoba (Caribbean region), and Tolima and Valle del Cauca (Andean region) (Fig. 1), which together hold a quarter the total commercial maize growing area (Colombia grew 130 thousand hectares of maize in 2021) (MADR, 2021). In collaboration with the National Maize Federation (FENALCE), we selected one locality per department: Cereté (Córdoba), El Espinal (Tolima) and La Union (Valle del Cauca), as representative sites for our analyses.

Cereté has a unimodal rainfall regime that runs from April to November, with warm temperatures (maximum in the range 31–34 °C and minimum 21–22 °C). Soils in Cereté often have high contents of fine clays and fine sands, with a high-water table, therefore making them susceptible to flooding. In some regions of Cereté, moderate maize yields (ca. 5 ton ha$^{-1}$) can be observed, even in the absence of rain, since the underground water can supply the crop needs. La Unión and El Espinal both have a bimodal rainfall regime, with the March–May and September–November periods representing the peak rainy periods (Fig. 1). With maximum temperatures well above 32 °C and minimum temperatures around 22 °C, El Espinal is warmer than La Unión, which is about 1.5–2 °C degree cooler, and has greater diurnal range. Both localities are characterized by soils of volcanic origin (andisols, vertisols) that are well drained and with high fertility and high clay content. In all three localities, maize is grown in two cropping seasons (herein referred to as A and B). Season A corresponds to planting dates during the first semester of the year (Jan–June), whereas Season B corresponds to planting dates during the second semester of the year (July–December). Table 1 shows the physical soil properties (from on-site soil sampling) and the maize growing seasons in the three localities.

### 2.2. Experimental crop data

We performed field experiments to generate the necessary data for calibration and evaluation of the crop model. These experiments included four hybrid varieties (two yellow-, two white-seeded) prioritized by FENALCE. These hybrids represent a range of abiotic and biotic stress resistance levels and a relatively wide genetic range, which was deemed critical by FENALCE in their efforts to support adaptation of the maize sector to better handle climate variability. All required information (crop and environment) was recorded for these four maize hybrids for the purposes of model calibration and evaluation. For logistical reasons (i.e., availability of sampling, laboratory equipment and personnel), experiments were not feasible at La Union. Hence, we conducted experiments in the nearby locality of Buga, which is 100 km away but has with very similar edapho-climatic conditions. Buga had all the necessary equipment for reliable field sampling. Conversely, La Unión had reliable long-term meteorological station data needed for generating the seasonal climate forecasts.

In each experiment, we recorded the agronomic and physiological performance of the genotypes, as well as the daily temperature, solar radiation, and precipitation throughout the crop cycles. The four hybrids, named P30F35, FNC3056, DK234 and DK7088, were planted in 2013 and 2014 (one experiment per year, per site) at the three sites under a randomized complete block design, with rows of 15 m long, 0.2 m between plants and 0.8 m between rows. Not all hybrids were grown or had data of sufficient quality at all sites. Each experimental plot was composed of 12 rows, evenly distributed for edge, growth, and

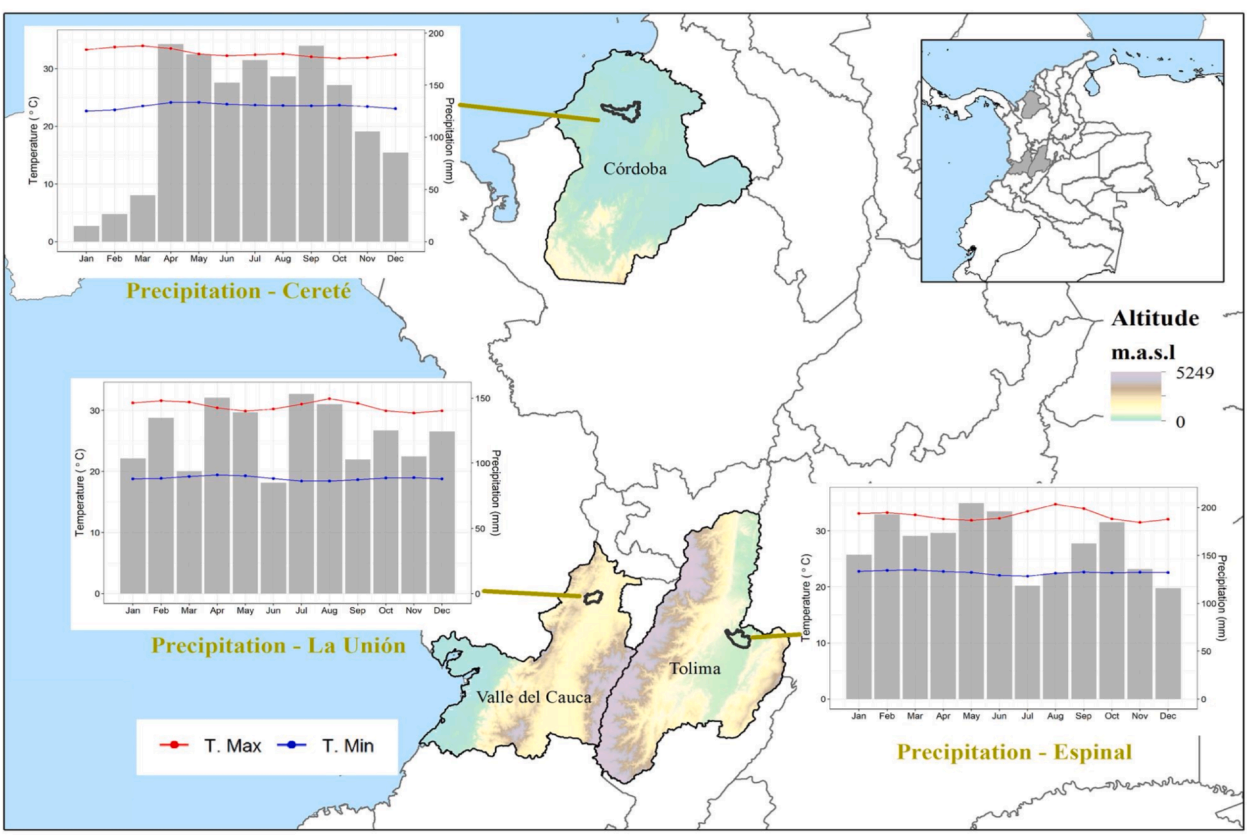


**Fig. 1.** Study areas in Colombia. The bar plots show the climatological means (1980–2013) for monthly total precipitation, whereas the red and blue lines show the monthly climatological means of maximum and minimum temperature. Polygons with thick borders within each department indicate localities where crop modeling was conducted.

**Table 1**
Physical properties of soils, and cropping seasons in the three selected localities in Colombia.

| Site | Sowing window | | Depth (cm) | Bulk density (g cm$^{-3}$) | Clay (%) | Silt (%) | Organic carbon (%) | $\theta_{LL}$* | $\theta_{UL}$* | $\theta_{SAT}$* | USDA texture class |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | A | B | | | | | | | | | |
| La Unión / Buga** | Apr 2 - Jul 16 | Oct 15 - Dec 15 | 0–20 | 1.63 | 28.6 | 35.6 | 0.89 | 0.297 | 0.35 | 0.453 | SC |
| | | | 20–40 | 1.63 | 28.6 | 35.6 | 0.89 | 0.297 | 0.35 | 0.453 | SC |
| | | | 40–60 | 1.57 | 14.5 | 25.3 | 0.59 | 0.226 | 0.337 | 0.454 | L |
| | | | 60–80 | 1.39 | 19.8 | 57 | 0.08 | 0.31 | 0.408 | 0.505 | SL |
| | | | 80–100 | 1.39 | 19.8 | 57 | 0.08 | 0.31 | 0.408 | 0.505 | SL |
| Cereté | Mar 18 - May18 | Oct 2 - Dec 31 | 0–20 | 1.38 | 48.7 | 44.2 | 2.5 | 0.320 | 0.424 | 0.536 | SiC |
| | | | 20–40 | 1.38 | 48.7 | 44.2 | 2.5 | 0.320 | 0.424 | 0.536 | SiC |
| | | | 40–60 | 1.38 | 37.2 | 50.3 | 2.5 | 0.320 | 0.424 | 0.536 | SiC |
| | | | 60–80 | 1.44 | 37.2 | 50.3 | 1.5 | 0.266 | 0.384 | 0.538 | SiC |
| | | | 80–100 | 1.44 | 37.2 | 50.3 | 0.7 | 0.256 | 0.364 | 0.538 | SiC |
| Espinal | May 2 - Aug 1 | Sep 1 - Nov 1 | 0–20 | 1.42 | 13.3 | 32.3 | 0.98 | 0.16 | 0.252 | 0.376 | SL |
| | | | 20–40 | 1.42 | 13.3 | 32.3 | 0.98 | 0.16 | 0.252 | 0.376 | SL |
| | | | 40–60 | 1.42 | 13.3 | 32.3 | 0.98 | 0.16 | 0.252 | 0.376 | SL |
| | | | 60–80 | 1.42 | 13.3 | 32.3 | 0.98 | 0.16 | 0.252 | 0.376 | SL |
| | | | 80–100 | 1.2 | 13.3 | 22.6 | 0.1 | 0.12 | 0.2 | 0.44 | SL |

* Soil hydrological properties: moisture content (by volume) at wilting point ($\theta_{LL}$), field capacity ($\theta_{UL}$) and saturation ($\theta_{SAT}$).
** Note that the soil samples correspond to Buga (crop experiment location), although they are also representative of La Unión. The sowing window for both season A and B is the same at both localities.

phenology sampling. Weekly samples of the biomass gain of the aerial organs (leaves, steam, grains, cobs), as well as the number of grains and leaves, harvest, and leaf area indices, and phenology, were recorded and then used as input into the model calibration and evaluation process (Sect. 2.4). We also input into the model all relevant agronomic management information, namely, sowing date, and quantities and frequencies of fertilization and irrigation applications. Experimental details are shown in Supplementary Table S1.

### 2.3. Meteorological information.

Two types of meteorological data were needed in this study. Firstly, fitting and evaluating the seasonal climate forecast models (see Section 2.6) required monthly precipitation data for all available meteorological stations in the three departments (Cordoba, Tolima, and Valle del Cauca). Secondly, understanding historical yield variability (see Section 2.5) and generating site-specific agroclimatic forecasts in the three select localities (Cereté, Espinal, La Unión) required daily data for crop model variables (i.e., precipitation, maximum temperature, minimum temperature, and solar radiation) at each locality.

We gathered observed daily meteorological data from the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM) –the Colombian Meteorological Service. For each of the three departments of study, we gathered 34 years (1980–2013) of daily precipitation data for a total of 34 (Cordoba), 34 (Tolima), and 27 (Valle del Cauca) meteorological stations. For three of these meteorological stations (one at each of Cereté, Espinal, and La Unión), we also gathered daily minimum, maximum temperature, and solar radiation data.

We then performed quality control for these data. For precipitation, quality control followed Esquivel et al. (2018) by using the RClimTool software (Llanos-Herrera, 2014). Three filters were applied to eliminate any incorrect values: (i) precipitation below zero or above 350 mm day$^{-1}$; (ii) outlying values (beyond five times the inter-quartile range); and (iii) >3 non-zero equal consecutive values. The amount of missing data was very low: 7 % (Cordoba), 6 % (Tolima), and 5 % (Valle del Cauca). We then aggregated daily data for all weather stations to monthly, and then gap filled any months with missing data following Esquivel et al. (2018) by using a linear regression model that combines the Climate Hazards Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015) and the observed weather data from IDEAM.

Quality control for temperatures used the same filters as for precipitation, with the only difference that for filter (i) we removed values above 45 °C (28 °C) and below 20 °C (15 °C) for maximum (minimum) temperatures. The three weather stations reported sunshine hours, rather than solar radiation directly; hence, a conversion using the Angstrom-Prescott equation was necessary (parameters A = 0.29, B = 0.50 for the Angstrom-Prescott equation). Gap filling at the daily scale was performed using a multi-site auto-regressive weather generator as implemented in the R package RMAWGEN (Cordano and Eccel, 2012) for temperatures and through a Random Forest model (using temperature as predictor) for solar radiation (Breiman, 2001). Daily data of the four meteorological variables for the three select localities (Cereté, Espinal, La Unión) were transformed into model-ready files for crop simulation (Sections 2.5 and 2.6).

### 2.4. Crop model description, calibration, and evaluation

We used the CERES-Maize to simulate crop growth and development. CERES-Maize is a daily timestep deterministic model that simulates the accumulation of biomass based on the interception of light and the partitioning of that biomass to plant organs through source-sink dynamics. Individual genotype behavior is simulated through the specification of six cultivar coefficients. Four of these coefficients relate to the accumulation of thermal time: from emergence to the end of the juvenile stage 'P1′ (vegetative growth), from flowering to physiological maturity 'P5′ (grain filling window), the successive appearance interval of leaf tips 'PHINT' (the phyllochron interval), and the delay in vegetative stage development cause by increase in photoperiod 'P2′. Two parameters control crop yield potential, namely, the maximum number of grains per plant ('G2′), and the grain filling rate under optimal conditions 'G3′ (mg day$^{-1}$ during the linear grain filling stage). In addition to cultivar coefficients, the model uses ecotype and species coefficients, which are typically not calibrated individually. Ecotype coefficients prescribe cardinal temperatures for crop development, photoperiod sensitivity, the duration of the anthesis silking interval, and photosynthesis parameters (radiation use efficiency and canopy extinction coefficient). Species parameters, on the other hand, are all the same for all cultivars of the species, and include seed growth parameters, temperature effects on photosynthesis, initial seed conditions, amongst others. For a complete description of the model the reader is referred to Jones et al. (1986) and Basso et al. (2016).

Model calibration consisted of determining values for each of the six cultivar coefficients (i.e., P1, P5, PHINT, P2, G2, G3) that allow the model to simulate in a successful way the behavior of each of the hybrids evaluated under experimental field conditions. Given the relatively low number of parameters to calibrate (six), in this study, we calibrated the crop model by exploring all possible combinations of the parameters. We developed and implemented an algorithm to determine and simulate all cultivar coefficient permutations. Using the R statistical software, for each hybrid, we then selected the set of cultivar coefficients that best described the data recorded in the field. We first calibrated all phenological coefficients (P1, P5, PHINT, and P2) based on the flowering and maturity dates, cycle length and total number of leaves, and then calibrated growth parameters (G2 and G3) based on the total and organ-specific biomass accumulation. We used the means for observations and simulations, root-mean-squared error (RMSE) and the Willmott agreement index (d-statistic) (Willmott et al., 1985) to evaluate the performance of the model. For all hybrids, calibration was performed with experiments from year 2013, whereas experiments from 2014 were used for model evaluation. We note that experiments from Buga could not be used for calibration or evaluation due to the low quality of the weather station data.

### *2.5. Assessment of the crop response to climate variability*

The historical evaluation of crop yield behavior over time facilitates improved understanding the levels of climate risk to which farmers are exposed. In this study, we assessed the historical yield response of the four calibrated hybrids using the historical (1980–2013) daily meteorological information provided by IDEAM at each of the three sites (Cereté, Espinal, and La Unión). Simulations were performed for each cultivar and site, a total of twelve planting dates, separated every-five days in two growing cycles (as reported in Table 1), for a total of 9,792 simulations (i.e., 12 planting dates × 2 cycles × 34 years × 4 hybrids × 3 sites). We used descriptive and inferential statistical analyses to understand yield variation in recent history as a response to climate, across the three study sites.

### *2.6. Seasonal climate forecast*

For the seasonal forecast, we used Canonical Correlation Analysis (CCA) (Glahn, 1968; Goddard et al., 2001; Hotelling, 1936), implemented via the Climate Predictability Tool (CPT) software package (Mason and Tippett, 2017). CCA determines patterns between the predictand and predictor to develop probabilistic forecasts, expressed in three categories (terciles): below normal, near normal, and above normal. Here, we develop all climate predictions using the National Centers for Environmental Prediction (NCEP) Climate Forecast System version 2 (CFSv2) Sea Surface Temperature (SST) forecast (Saha et al., 2014) as the predictor variable, and seasonal precipitation from the set of weather stations as the predictand. The predictor domain used was the wide global tropics (30°S–30°N) as this ensures covering all major modes of variability and regions of the ocean that have influence in Colombia. The main performance metric used to assess forecast skill was the Kendall's tau correlation coefficient. All forecasts are produced for an aggregated period of 3 months, as is standard in seasonal climate prediction using CCA (Alfaro et al., 2018; Esquivel et al., 2018). All forecasts were generated considering the scenario where the forecast is made in the month before the season of interest. For instance, if the beginning of the sowing window is April then the season of interest will be March-April-May (so that April is the middle month of the 3-month period) and the forecast will be released in February (the month before the start of the 3-month period); hence, the CCA run must be made with the outputs of the CFSv2 model with a 2-month lead time.

Our objective is to be able to input the climate forecast in the crop model (see Sect. 2.7). The length of crop cycle for the four hybrids analyzed ranges between 90 and 120 days, and we simulate a total of 12 planting dates (spaced at a 5-day time interval, see Sect. 2.7) per growing cycle (cycles A, B as shown in Table 1). This necessitated forecasted data for a total of 180 days (6 months) after the start of the planting date. We ran six seasonal climate forecasts for the 6-month cropping season. Each run included a forecast for a 3-month period centered at each of the six months of the cropping season. These forecasts were generated retrospectively for the period 2005–2013 and for each growing cycle (A, B as in Table 1), which produces forecast information for a total of 9 years.

Next, we converted the 9 years of 6-months probabilistic forecasts for cycles A and B, for the three localities into daily data for use into the crop model (see Sect. 2.7) via a forecast resampler (Capa-Morocho et al., 2016). The first step consists in resampling the observed record for the middle month of the 3-month period of interest (e.g., January for December-January-February), with replacement, following the probabilities specified by the precipitation forecast for each tercile category. For example, if January has a tercile forecast of 40 % above normal (top tercile), 35 % around normal (middle tercile), and 25 % below normal (bottom tercile), this means that 40 % of the samples drawn will be from the lowest tercile (below normal) of the January observations, 35 % from the middle tercile (normal), and 25 % from the highest tercile (above normal). We then repeat this procedure for all other middle months, after which we concatenate the daily data of all relevant months into a 6-month weather time series. The resampling is repeated 99 times to explicitly capture uncertainty in the resampling process and the probabilistic nature of the seasonal climate forecasts. As a result of the resampling process, a total of 99 weather realizations with 180 days of weather are produced for each site and forecast year, for use in the crop models. We generated crop model simulations for each of these (see below).

### *2.7. Agroclimatic forecast generation and evaluation*

We used the 9 years of 6-month seasonal climate forecasts for each of the seasons generated in Sect. 2.6 into the CERES-maize crop model. Planting windows were defined as specified in Table 1. We performed simulations for a total of 12 planting dates for each of the two cycles (A, B, as in Table 1), distributed in pentads, for all the 9 forecast years (2005 to 2013), sites, and for all 99 resampled weather realizations. As a benchmark against which to evaluate forecasts, we conducted simulations for the same planting dates using historical meteorological observations for the same years, planting dates, and sites. All simulations were rainfed and assumed no nutrient limitations.

We then used observation- and forecast-based simulations to produce an evaluation of forecast skill focused on three aspects: (i) simulated yield; (ii) highest-yielding planting date; and (iii) highest- and lowest-yielding hybrid. For (i), we used the area under the ROC (Receiving Operating Characteristic) curve averaged across yield tercile categories, which we refer here as the GROC. For (ii) and (iii) we used the frequency of correctly identified planting dates and hybrids across sites, seasons, and years.

## 3. Results

### *3.1. Performance of the DSSAT-CERES-Maize model*

Model calibration and evaluation indicates that the CERES-maize model adequately captured the development (phenology) and growth (biomass, LAI, harvest index and yield) dynamics during the growing season in both calibration and evaluation experiments (see Table 2 for performance, and Table 3 for cultivar coefficients). Performance metrics indicated high model accuracy in relation to biomass, harvest index and yield for all hybrids in both calibration and evaluation experiments, except for FNC3056 season B 2013 and DK7088 season A 2014 were the model over and under-estimated grain weight respectively. Leaf area index (LAI) was generally underestimated. We observed a low RMSE for all the variables (biomass, harvest index, LAI, and yield) except for LAI in the calibration experiments for DK234 and DK7088. Likewise, the Wilmott d-statistic was generally high (>0.88 in most cases). The growth dynamics for each experiment can be visualized more clearly in Supplementary Figs. S1–S8. We conclude that the model is useful to perform crop growth predictions in these sites, and, due to its deterministic nature, likely in other areas of Colombia.

**Table 2**
Summary of model performance for four hybrids across all localities where the model was calibrated and evaluated.

| | Biomass | | | | Leaf area index | | | |
|---|---|---|---|---|---|---|---|---|
| Hybrid* | Mean obs | Mean sim | RMSE | d-Stat | Mean obs | Mean sim | RMSE | d-Stat |
| P30F35 (C) | 9,235 | 8,649 | 2,037 | 0.976 | 3.79 | 3.33 | 1.02 | 0.614 |
| P30F35 (E) | 8,703 | 8,712 | 1,005 | 0.992 | 3.18 | 3.14 | 0.47 | 0.949 |
| DK234 (C) | 11,027 | 9,178 | 2,572 | 0.970 | 4.41 | 3.40 | 1.36 | 0.652 |
| DK234 (E) | 10,499 | 9,234 | 2,266 | 0.972 | 3.17 | 3.44 | 0.44 | 0.962 |
| DK7088 (C) | 7,816 | 7,576 | 1,594 | 0.979 | 3.61 | 2.34 | 1.41 | 0.652 |
| DK7088 (E) | 6,519 | 7,245 | 1,464 | 0.978 | 2.85 | 2.22 | 0.96 | 0.839 |
| DK7088 (E) | 7,666 | 6,838 | 1,266 | 0.984 | 2.94 | 2.15 | 1.01 | 0.812 |
| FNC3056 (C) | 8,508 | 7,697 | 1,997 | 0.973 | 3.51 | 2.54 | 1.09 | 0.807 |
| FNC3056 (E) | 6,592 | 8,155 | 2,032 | 0.960 | 2.72 | 2.49 | 0.66 | 0.914 |
| FNC3056 (E) | 6,477 | 7,015 | 1,051 | 0.987 | 2.85 | 2.49 | 0.76 | 0.885 |
| | **Harvest index** | | | | **Yield** | | | |
| **Hybrid*** | **Mean obs** | **Mean sim** | **RMSE** | **d-Stat** | **Mean obs** | **Mean sim** | **RMSE** | **d-Stat** |
| P30F35 (C) | 0.29 | 0.32 | 0.05 | 0.980 | 4,795 | 4,550 | 1,049 | 0.976 |
| P30F35 (E) | 0.33 | 0.37 | 0.05 | 0.976 | 4,631 | 4,948 | 682 | 0.984 |
| DK234 (C) | 0.25 | 0.27 | 0.05 | 0.975 | 4,972 | 4,580 | 605 | 0.992 |
| DK234 (E) | 0.26 | 0.27 | 0.04 | 0.980 | 4,876 | 4,426 | 749 | 0.984 |
| DK7088 (C) | 0.18 | 0.24 | 0.09 | 0.893 | 2,646 | 3,229 | 988 | 0.953 |
| DK7088 (E) | 0.22 | 0.26 | 0.05 | 0.972 | 2,710 | 3,588 | 1,046 | 0.957 |
| DK7088 (E) | 0.30 | 0.23 | 0.08 | 0.937 | 4,107 | 2,764 | 1,698 | 0.883 |
| FNC3056 (C) | 0.22 | 0.25 | 0.08 | 0.914 | 3,675 | 3,557 | 823 | 0.972 |
| FNC3056 (E) | 0.24 | 0.32 | 0.09 | 0.883 | 3,035 | 4,552 | 1,581 | 0.882 |
| FNC3056 (E) | 0.21 | 0.22 | 0.07 | 0.925 | 2,661 | 2,601 | 1,180 | 0.904 |

* Results for calibration (C) and evaluation (E) are shown separately.

**Table 3**
Calibrated crop model parameters for the four hybrids used in this study.

| Genotype | P1 (°C day) | P2 (days) | P5 (°C day) | G2 (#) | G3 (mg day$^{-1}$) | PHINT (°C day) |
|---|---|---|---|---|---|---|
| P30F35 | 210 | 0.5 | 1000 | 1000 | 8.6 | 30.0 |
| DK234 | 220 | 0.5 | 920 | 900 | 8.3 | 37.0 |
| DK7088 | 249 | 0.5 | 911 | 957 | 7.8 | 55.0 |
| FNC3056 | 233 | 0.5 | 1000 | 900 | 7.0 | 50.6 |

Genotype performance in the field was consistent across hybrids. For example, in Córdoba, P30F35 and DK234 presented the same flowering and physiological maturity dates. Little variation was also observed in the phenology response of the hybrids in Tolima and Valle del Cauca. Consistent with that, the model parameters did not vary significantly among the calibrated hybrids with respect to phenology, with P1 between 210 and 249 and P5 between 911 and 1000 (see Table 3). The maximum number of grains possible (G2) varied between 900 and 1000. The coefficients that generated most differentiation between hybrids were the grain filling rate (G3) and the thermal time required for leaf emission (PHINT). The higher yielding hybrids (P30F35 and DK234) showed greater values of G3 and lower values of PHINT.

### 3.2. Interannual yield variability and its causes

Based on crop yield simulations, we analyzed the historical yield response to climate variation of rainfed hybrid maize cultivation in the three study sites (Fig. 2). The analysis shows greater yield variation in La

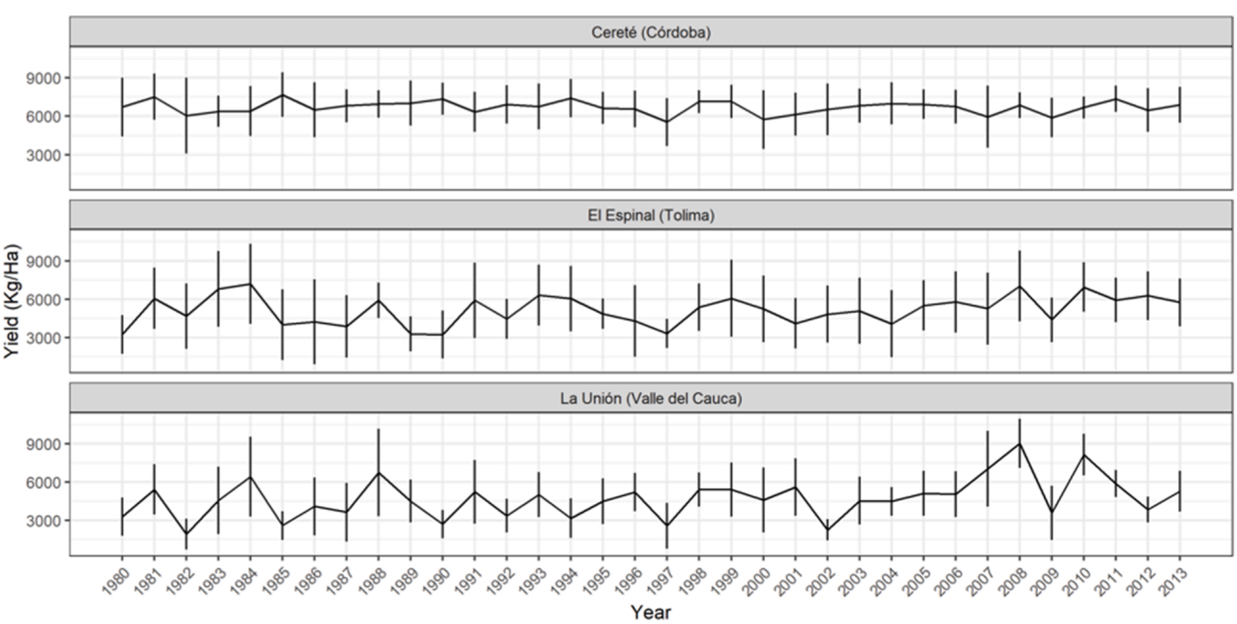


**Fig. 2.** Simulated yield for four hybrids across the three localities for the period 1980–2013.

Union (Valle del Cauca) and Espinal (Tolima), whereas Cereté (Córdoba) presents greater yield stability due to better environmental supply. In Cereté, interannual variability is larger in season B (end of rainy season) as compared to season A (first rainy season) (Fig. 3). The other two localities show more consistent results across both growing seasons.

In general, there are larger yield variations across localities and planting dates as compared to genotypes (Supplementary Fig. S9). Our analysis suggests that early planting dates produce greater yields in virtually all locations and seasons. Favoring earlier planting dates also has the benefit of lower variability across years (Fig. 3).

Low seasonal rainfall can affect maize at any moment during the crop cycle, but the greatest yield reductions are often associated to water deficiencies in seedling, pollination, and grain filling stages. Exceptionally dry years (e.g., 1982, 1997, 2002 and 2009) could have caused substantial crop yield losses for all localities and seasons. Because maize genotypes perform differently across planting dates, some degree of yield loss can always be avoided by adjusting these two management factors. The average yield advantage between the best and the worst choices of planting date and genotype can be up to 100 % in dry years, and up to 300 % in other (wetter) years (Supplementary Fig. S9).

### *3.3. Seasonal precipitation forecast performance*

The skill of seasonal climate forecasts and the sources of predictability are well documented for Colombia (Córdoba-Machado et al., 2015; Esquivel et al., 2018; Fernandes et al., 2020). Hence, here we provide a general overview of forecast skill to the extent that is useful to contextualize the agroclimatic forecast results shown in Sect. 3.4 and 3.5. In general, consistent with previous work (Esquivel et al., 2018), seasonal climate forecast skill (measured by Kendall's tau) varies in the range –0.05 and 0.5 (Fig. 4). Results are presented as averages across each department as is customary for CCA models. The greatest seasonal climate forecast skill occurs in Valle del Cauca (where La Unión is located) during the middle months of both seasons, when the rains are fully established. Forecast skill is moderate to high in Tolima (where Espinal is located) toward the end of season A, and in Cordoba (where Cereté is located) in the middle of season B. Season A in Cordoba and season B in Tolima show the lowest forecast skill.

### *3.4. Ability of the agroclimatic forecast to discriminate yield categories*

For agroclimatic forecasts to be useful they need to at the very least be able to discriminate low yield situations (especially from high yielding outcomes), since managing these will be most critical for farmers. We find that the agro-climatic forecast performs better than a random prediction (GROC $>$ 0.5 in virtually all sites and seasons) at discriminating yield categories (above, below, and near normal), with especially high (ROC $>$ 0.8) for the 'below normal' and combined 'above-below normal' categories for Cereté season B (Fig. 5). In fact, except for Cereté season A, the ability to discriminate yield categories below normal (crosses in Fig. 5) and jointly above-below normal (triangles in Fig. 5) was consistently high (ROC $>$ 0.7). Furthermore, the below normal category also shows consistently greater ROC as compared to above normal.

In Cereté season A, high yield stability causes the above and below normal categories to be close together and hence the discrimination power is reduced. In Espinal season B, yield forecast skill is low due to limited seasonal climate forecast skill (see Fig. 4).

### *3.5. Ability of the agroclimatic forecast to produce planting date recommendations*

An optimal planting date makes the best use of the available seasonal rainfall and soil moisture, thus optimizing the use of environmental resources to maximize yield (Comas et al., 2019; DeJonge et al., 2012). Consistent with the capacity of the crop and climate model to predict yield categories, we find that generally, agro-climatic forecasts can predict the optimal planting date, with an error of 3 pentads or less (Fig. 6), except in Cereté for season A. Consequently, we observe consistent trends in forecast and observations for average predicted yield across planting dates (Fig. 7).

In Espinal (season A and B), Cereté (season B), and La Unión (season B), the agroclimatic forecast predicted the 'optimal planting date' less than 2 pentads (10 days) of error for multiple years. In roughly 20 % of year-by-site combinations, 'optimal planting dates' were predicted with less than 2 pentads of error in >90 % (50 %) of the weather scenarios and cultivars. In 2009, for instance, 95 % or more of the simulations show the same error range (less than 2 pentads) for various sites or

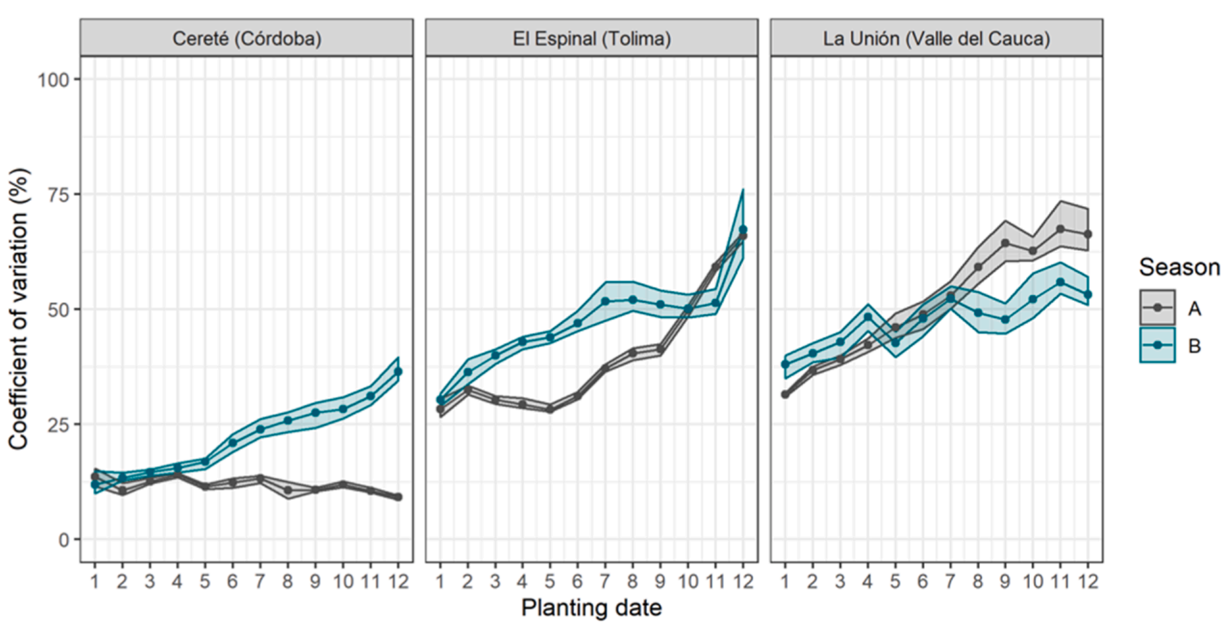


**Fig. 3.** Variation of 33-year coefficient of variation across planting dates for both seasons. Shaded area encompasses the maximum and minimum values across the four hybrids being simulated. Planting dates are ordered from 1 to 12 by date for each season and correspond to evenly spaced dates within the planting windows specified in Table 1.

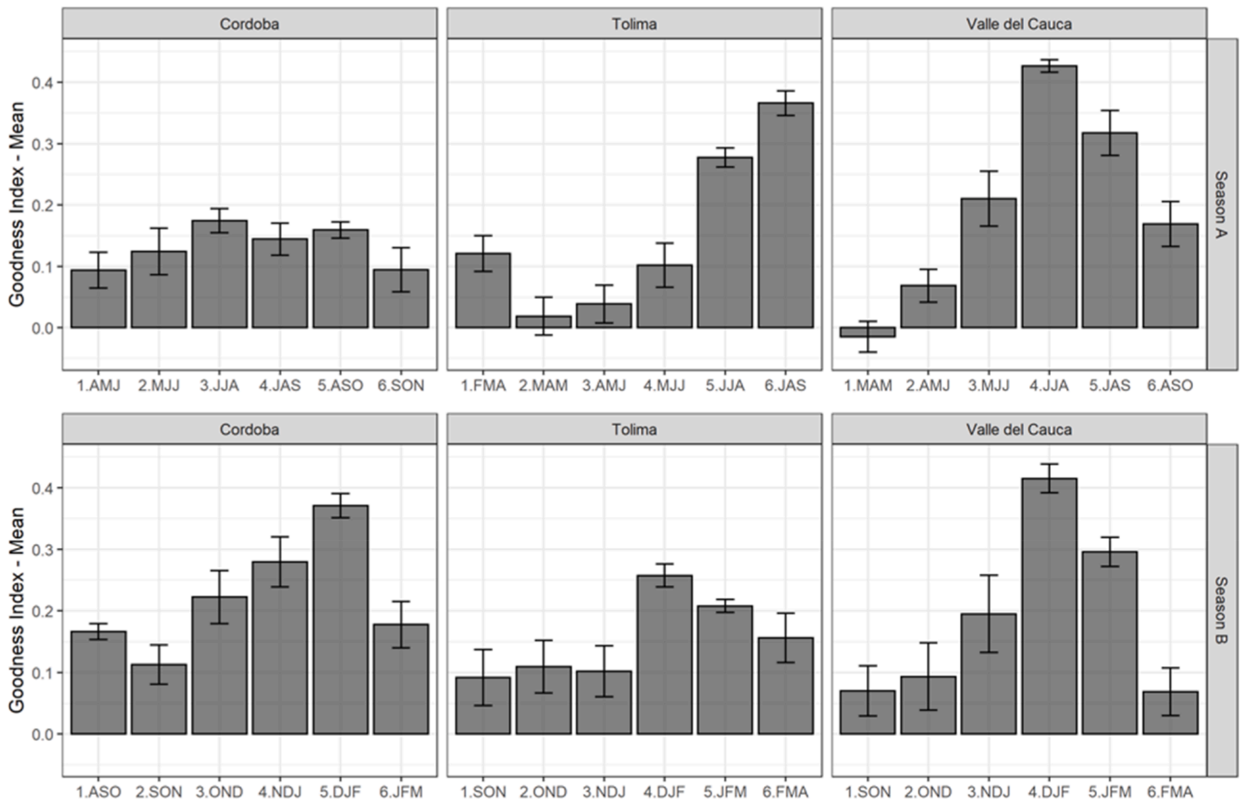


**Fig. 4.** Variation in goodness index (Kendall's tau) across months for cropping seasons A and season B across the three departments of interest. For reference, season A is May–October (Cordoba), Oct–Mar (Tolima), and Apr–Sept (Valle del Cauca); and season B is Sept–Feb (Cordoba), Mar–Aug (Tolima), Oct–Mar (Valle del Cauca).

seasons (La Unión season A and B, and Cereté season B). A small error in the prediction of planting date means that the risk of yield loss is reduced substantially, especially in years of low rainfall when abiotic stress is high.

We note that in Cereté (season A) the value of the planting date forecast is limited, with forecast error uniformly distributed. This is because interannual yield variation across planting dates is very low in simulation with weather observations (Fig. 3). This means that farmers can use any planting date and they will achieve more or less the same yield (Fig. 7). In Cereté, genotype selection may be a more important decision to maximize yield (see Sect. 3.6). Beyond season A in Cereté, there are other situations in which most of the forecasted planting dates are far from those simulated with weather observations. In some of these the prediction is opposite to the observed optimal sowing date such as in El Espinal (2008, season B). The latter highlights a potential danger, as it could constitute a form of maladaptation; however, we highlight that it does not occur in many years and locations.

### 3.6. Ability of the agroclimatic forecast to produce hybrid selection recommendations

Fig. 8 shows the frequency of correct prediction of the highest yielding genotype across planting dates, sites, and seasons. Colors are used to show the distribution of correct predictions across genotypes. We find that seasonal agro-climatic forecasts correctly identified the best performing genotype in at least 50 % of the cases in most sites. This was especially true for early planting dates in Cereté season B, Espinal season A, and La Unión season A. Cereté season A shows the highest accuracy in forecasting the highest yielding genotype. This is consistent across planting dates and years, primarily due to low interannual variation.

Several additional findings become apparent. Firstly, in some sites regardless of genotype if farmers choose a sub-optimal planting date yield will be low (e.g., La Unión season B). Secondly, the consistency in hybrid performance is greater when average cross-hybrid yield is lower and decreases as average cross-hybrid yield increases. This means that in years with favorable weather conditions the choice of hybrid is key to maximizing yield, whereas in less favorable years the choice of hybrid carries less weight and yield is most dependent on the correct choice of planting date. Third, despite the dominance of P30F35 as the highest yielding genotype, there are several instances in which other genotypes are correctly forecasted to perform better (e.g., early planting dates in season B for La Unión). This means that the high forecast performance found here is not biased by genotype choice. Lastly, it is important to note that forecasts also accurately predicted the genotype with lowest yield (Supplementary Fig. S10). In many circumstances, identifying and avoiding worst-performing choices may be enough to orient farmer decisions.

## 4. Discussion.

### 4.1. Performance of the agroclimatic forecast

The DSSAT-CERES-Maize crop model is one of the most frequently used in agricultural research because of its consistent performance across a number of contexts (Basso et al., 2016), but also because of its versatility and the ease use of the DSSAT interface (Jones et al., 2003; White et al., 2011). Here, we assessed the predictive capacity of CERES-Maize to reproduce field-scale growth and development dynamics for various hybrid maize genotypes. We also measured combined climate-crop model performance for yield and decision support. While the crop model performed very well at predicting maize growth and development, the combination of climate forecast and crop model (agroclimatic forecast) performed less well, partly due to the skill of the seasonal climate forecast. Despite that, the agroclimatic forecasts proved to be of value for predicting yield outcomes, as well as to identify the best planting dates and genotypes in at least 50–60 % of the situations

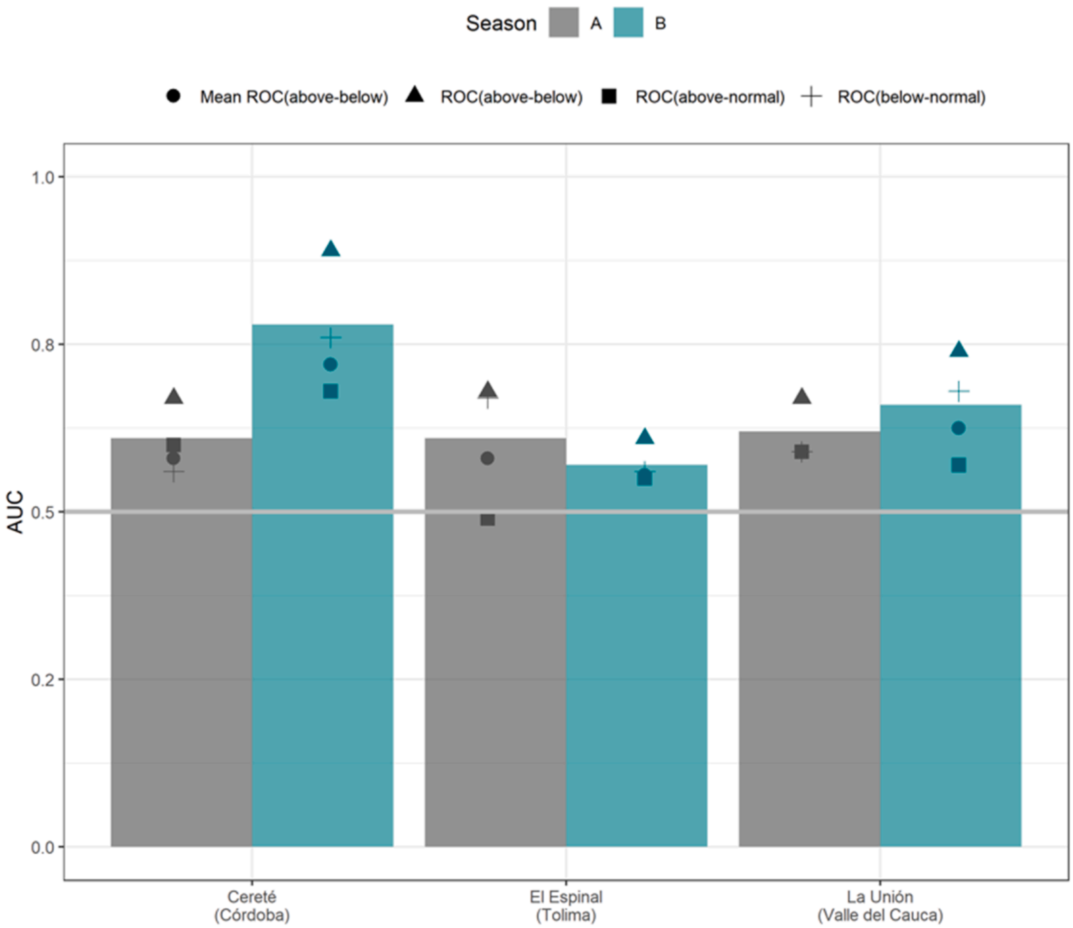


**Fig. 5.** Generalized area under the Receiver Operating Characteristic curve (GROC) for predicted yield categories the three sites and both growing seasons. The size of the bar is the GROC, and the symbols indicate ROC values for different tercile combinations. The square is the ROC of the above normal category; the cross indicates the ROC of the below normal category; the circle is the average of the square and the cross; and the triangle is a ROC calculated after excluding the 'normal' category from the prediction.

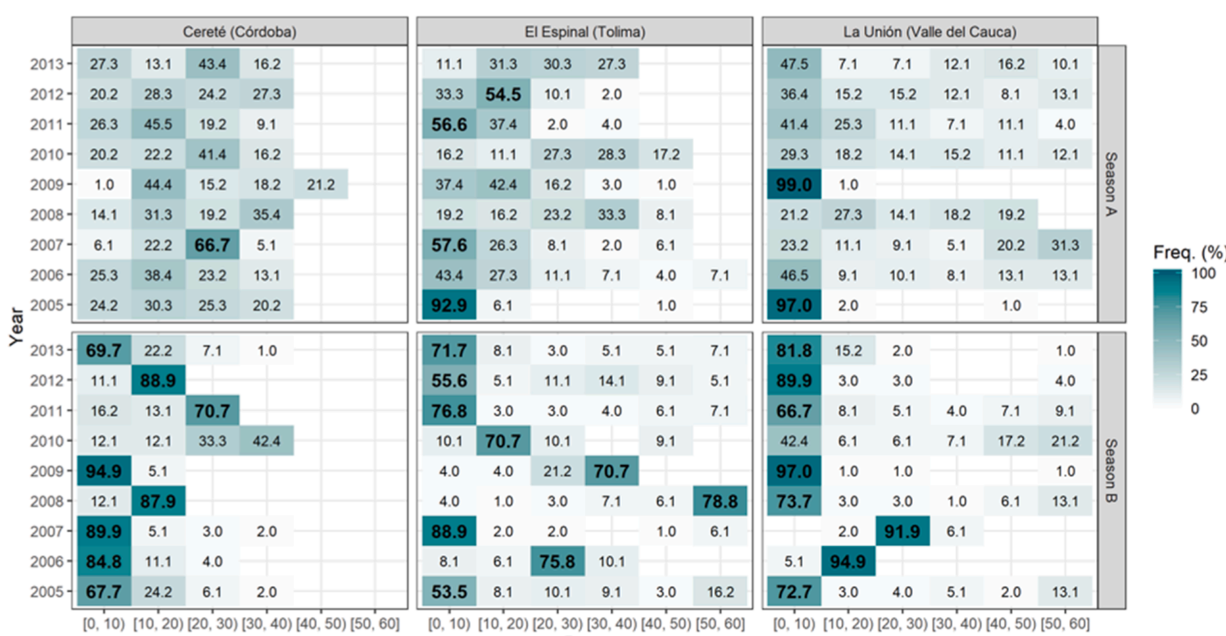


**Fig. 6.** Frequency of correct prediction of planting date. The *x*-axis shows error ranges (in days), plotted against all retrospective forecast years (*y*-axis). The values in each cell correspond to the percentage of simulations (considering all four cultivars and weather realizations) for each site, season and year that are in each error range.

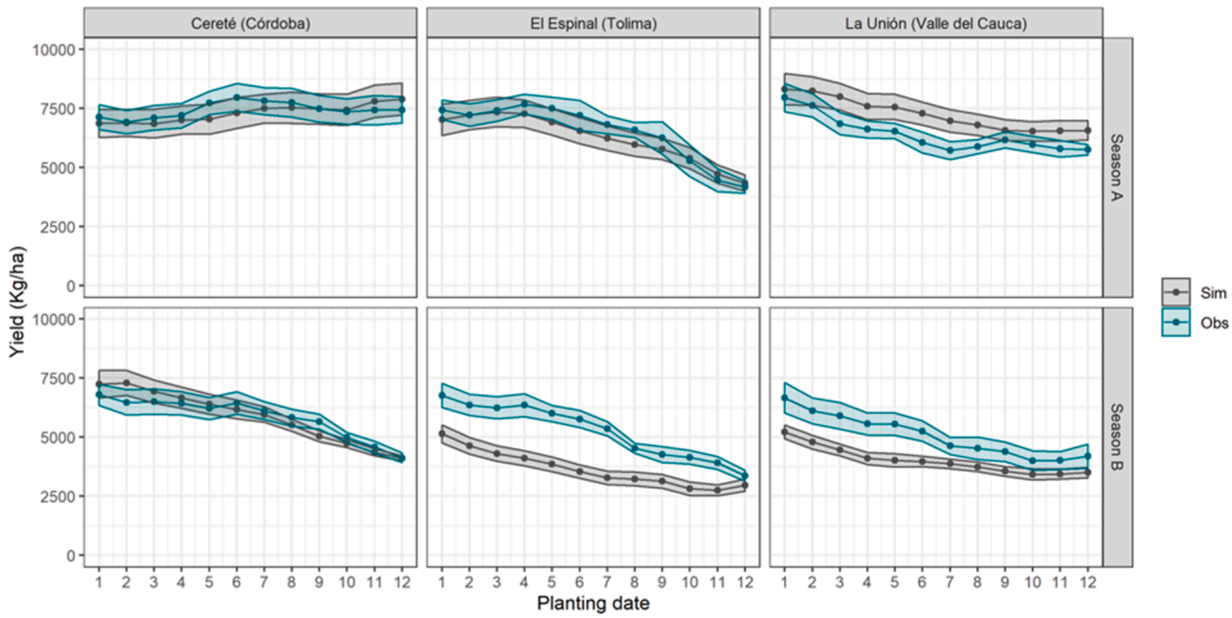


**Fig. 7.** Average simulated yield across planting dates for forecast (grey line and shading) and observations (green line and shading). Shading shows variation across cultivars and, in the case of forecast, also of weather realizations.

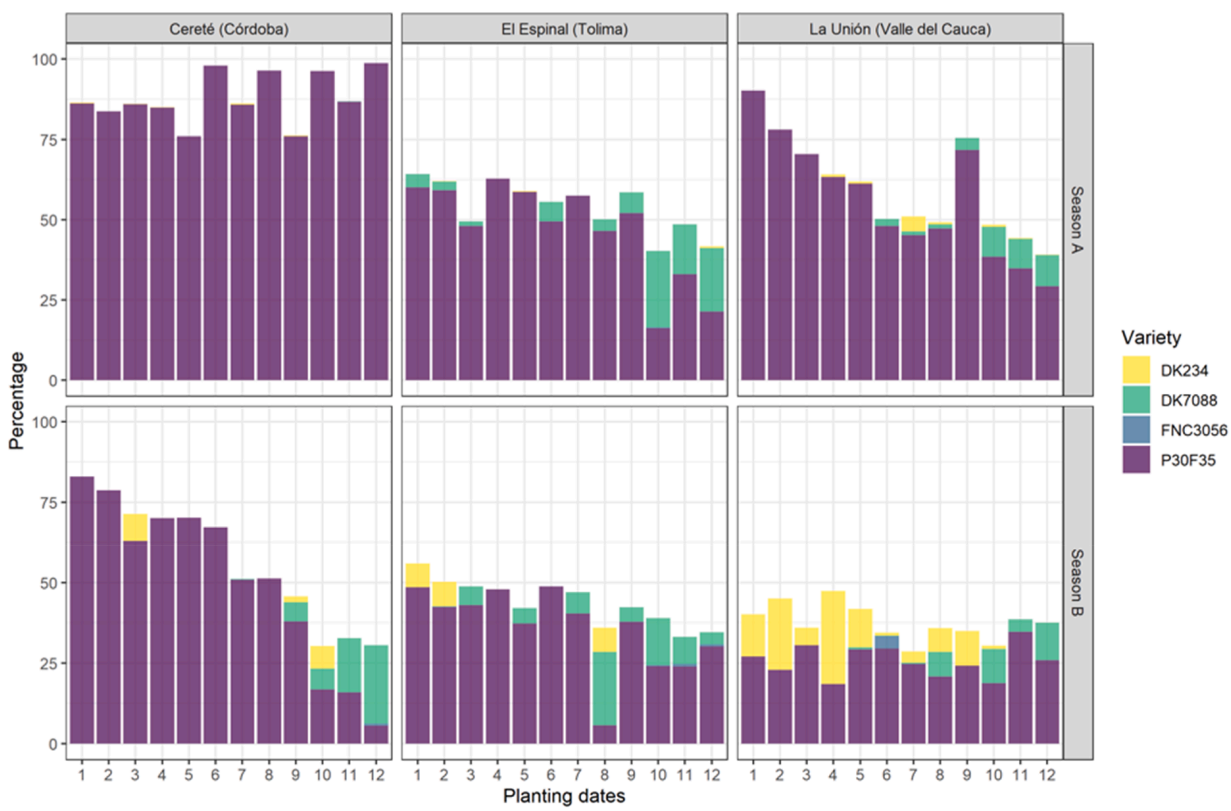


**Fig. 8.** Frequency of correct prediction of the highest yielding genotype across planting dates. Colors show the distribution of correct predictions across genotypes.

analyzed (sites × years × seasons).

Seasonal climate forecasts in Colombia have been assessed by Esquivel et al. (2018), who conclude that forecasts have largely suitable skill, but could benefit from improvement especially targeted at wet periods in the inter-Andean valleys. Fernandes et al. (2020) explore ways to improve seasonal predictions. The latter study shows that alternative predictands (e.g., the number of wet days) to the total seasonal precipitation can offer greater predictive skill and be more meaningful for agricultural productivity. Forecast results reported here are largely consistent with those and other earlier results in Colombia and elsewhere (Alfaro et al., 2018; Córdoba-Machado et al., 2015; Recalde-Coronel et al., 2014). These studies highlight the opportunities that lie in skillful seasonal climate forecasts, but also the limited predictability often associated with peak rainy periods.

One important aspect of our study is that it translates seasonal climate forecasts not only into yield forecasts, but also into key specific agricultural decisions. Both the choice of planting date and the choice of genotype are crucial in Colombia (Sotelo et al., 2020) and elsewhere as strategies to respond to climate variability and climate change (Heinemann et al., 2020; Waha et al., 2013). Generally, in the absence of suitable and trustable information, farmers often use misleading and inaccurate heuristics based on past cropping seasons (Blundo Canto et al., 2016; Guido et al., 2020). Our results suggest that, while not perfect, agroclimatic predictions do offer significant potential value to support farmers in identifying positive and negative yield outcomes, as well as in selecting adequate planting dates and best-performing genotypes ahead of the cropping season. Using a similar approach to ours, Hammer et al. (1996) estimate that Australian wheat farmers could reduce risk by 35 % and increase profit by 20 % if they made management (fertilizer and genotype choice) decisions using seasonal forecasts. Likewise, Soler et al. (2007) conclude that accurate yield forecasts can be made with up to 45 days lead time for maize in Brazil. We find low predictive skill in instances where yield was stable either across planting dates or genotypes, but also when climate forecast skill was low. While the latter situations create potential risks if these agroclimatic forecasts were to be used by farmers, we argue that the value of the forecasts outweighs these risks. This is due to the insight that forecasts offer compared to the benchmark of little to no information access or use by farmers (Guido et al., 2020; Hansen et al., 2011).

Several avenues exist for the improvement of the agroclimatic forecasts presented here, which are applicable for Colombia and other tropical regions. Foremost, our results indicate that the performance of the agroclimatic forecast model is most limited by the climate component. Thus, any improvements in climate forecast capabilities will directly translate into better agroclimatic forecasts. Since we use CCA-based forecasts with a single climate model (CFSv2) as the source of SST predictions, improvements could be made for instance by using alternative predictands to total rainfall (Fernandes et al., 2020) or by using a multi-model ensemble approach (Muñoz et al., 2020). Fundamental changes in the modeling approach toward high-resolution dynamical models can also potentially result in gains in climate forecast skill (Coelho et al., 2006; Semenov and Doblas-Reyes, 2007; Weisheimer and Palmer, 2014). Artificial intelligence and machine learning also show promise toward the improvement of climate forecasts (Ham et al., 2019; Lubkov et al., 2019). While crop model skill was high in our study, improvements in crop models for example to enable better consideration of drought and high temperature interactions would allow use of agroclimatic forecasts in a wider range of environments.

Additionally, model parameters (and especially G2 and G3) prescribe the individual genetic advantages of each genetic material. These parameters are calibrated using field data (see Sect. 2.4), and consequently both the quality and quantity of the field data are likely to affect model performance in predicting optimal planting dates, best-performing cultivars, and yield. It is therefore possible that greater data availability and/or quality can improve model parameterization and hence reduce prediction error for planting date, genotype, and yield. We note, however, that this is only one of various potential sources of error in the seasonal agroclimatic predictions presented here, and that our model evaluation results suggests that crop model performance is high (see Sect. 3.1). Furthermore, many factors not currently considered by the model can affect hybrid performance for a given site and season (e.g., soil fertility, pest and diseases, waterlogging). This may lead to systematically placing hybrids P30F35 and DK234 (the highest yielding under controlled experimental conditions) as superior in most of the available environmental conditions, whereas in reality they may be outperformed by other hybrids in some situations. Model improvement is warranted to fully account for the set of conditions that constrain genotype performance to adequately inform farmer decision making. Similarly, more comprehensive models that allow accurately simulating practices such as intercropping, tillage, and soil macro- and micronutrient inputs would allow expanding the set of decisions considered here. Finally, improvements are also possible to the input data used (meteorological, soil, and crop management) as well as in the forecast resampling process through for instance the use of weather generators specifically designed for the tropics (Capa-Morocho et al., 2016; Jones and Thornton, 2000).

### *4.2. Provision of climate services for agricultural decision making*

The development and evaluation of decision support tools has been one of the most important drivers of scientific model development for both climate and crops. The CERES-Maize model, and DSSAT more generally have been used as decision support tools for agronomic management (MacCarthy et al., 2017), precision agriculture (Thorp et al., 2008), and agroclimatic prediction (Fraisse et al., 2006; Han et al., 2019). In Colombia, a recent study integrated CERES-Maize and the ORYZAv3 rice crop models into a decision support system (*Pronosticos AClimateColombia*) employing the same methods and data we use here (i.e., weather station data, and CCA-based climate forecast models and a forecast resampler) (Sotelo et al., 2020). The system is currently in operation and use by various organizations and users across the country. Our study provides clear, compelling evidence of the value of the agroclimatic forecasts provided in *AClimateColombia*, as well as a framework and methodology to evaluate agroclimatic predictions for other crops and regions.

But demonstrating the value of agroclimatic forecasts and supplying them through an online system may not be sufficient to achieve success in climate services for agriculture (Vaughan et al., 2019). The climate services value chain encompasses the generation, translation, transfer and use of climate information (Trenberth et al., 2016; Vaughan et al., 2018). Agroclimatic forecasts constitute one important technical ingredient for climate services for agriculture, as they contribute to the generation and the translation parts of the climate services value chain. But success in climate services is also contingent on (i) the identification, characterization and monitoring of prioritized areas due their importance and interest, (ii) the translation and integration of model-based climate and crop information into understandable and useful language, and (iii) the design and dissemination of content and recommendations tailored to local needs, along with effective agro-technology extension and transfer programs (Bernardi, 2013; Dayamba et al., 2018; Vaughan et al., 2016). Several endeavors have been or are being carried out in Colombia that connect model-based forecasts with farmers ensuring use and benefit from climate information.

Foremost, a sector-level plan has been drawn that will facilitate the transformation of the maize sector toward sustainable intensification and risk reduction, with the overarching goal of achieving national maize self-sufficiency, and contribute toward food security and nutritional outcomes (Govaerts et al., 2019). Several other initiatives have been or are being carried out led by the Ministry of Agriculture (CIAT-MADR, 2015) as well as international and national research organizations (CIAT, 2020; CORPOICA, 2017; Ramirez-Villegas et al., 2018), and have resulted in substantial institutional capital in support of climate risk management for food security (Pazos et al., 2018). As a result of these initiatives, participatory approaches including the Local Technical Agroclimatic Committees (LTACs) (Loboguerrero et al., 2018) and the Participatory Integrated Climate Services for Agriculture (PICSA) (Ortega Fernández et al., 2018) have been implemented throughout the country, with significant development outcomes and impact (Giraldo et al., 2020). These initiatives play a central role in building institutional networks around the climate services value chain, but also in building institutional and stakeholder (extension agent, farmer) capacities to use agroclimatic information. Furthermore, participatory approaches also create two-way user feedback loops to improve information provision, or to expand the scope of the service (Vaughan and Dessai, 2014; Vogel et al., 2017).

Finally, we highlight the complexity in the decision-making processes at the farm scale and the challenges that exist regarding the use of agroclimatic forecasts, especially where investment in farming is substantial and agroecological landscapes are so diverse (as is the case of hybrid maize production). Farming involves many decisions including the choice of crop(s) and crop rotations; method and time for land preparation; planting density; sowing dates; genotype(s); irrigation and fertilization methods, amounts and timing; harvesting time and method; and financial resources. Each of these decisions carries a risk and may be influenced by climate as well as other factors such as the availability of labor and machinery, market price, amongst others. Thus, to fully exploit the potential of climate services for agriculture, we pose that integrated information services that support the variety of decisions farmers make but also take account of farmer adaptive capacity do have the potential to contribute to enhancing food security and resilience (Dayamba et al., 2018; Tall et al., 2018).

## 5. Conclusions

The development and evaluation of decision support tools has been one of the most important drivers of scientific model development for both climate and crops. We assessed the predictive capacity of CERES-Maize to reproduce field-scale growth and development dynamics, but also its performance in combination with a seasonal climate forecast for yield prediction and decision support for planting date and genotype choice. Three conclusions become clear from our work. First, the model performed well at predicting crop development and yield at a series of representative sites in Colombia. Secondly, the combination of climate forecast and crop model (termed here agroclimatic forecast) performs well with regards to predicting yield outcomes. Of special importance is the fact that the identification of negative outcomes (lowest yield tercile) is the most skillful, reaching a predictive accuracy upwards of 80 % in some cases. Finally, we conclude that despite limitations agroclimatic forecasts offer value for informing the selection of sowing dates and genotype for farmers in Colombia. Future work should focus on expanding the scope of the agroclimatic prediction to include other relevant farming decisions that are influenced by climate, and on the improvement of the climate forecast via different methods including dynamical modeling and artificial intelligence.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2022.100333.

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