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OFF-SEASON MAIZE YIELD FORECASTING FOR DIFFERENT SOWING DATES

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ABSTRACT: Brazil is the world's third-largest maize producer. Its yield is influenced by climate, soil conditions, management and their interactions. Identifying the most suitable sowing window and using yield forecasting systems allows for increased yields and better harvest management. Crop simulation models can be used to assess crop responses to various conditions. This study aimed to identify the most favorable planting date for off-season maize by using the DSSAT CSM-CERES-Maize model for Jataí, Goiás state. Using meteorological data from 1986 to 2015, eight productivity forecasting strategies were tested. The results of the model application at different sowing dates indicated that the dates in January tended to present a more favorable attainable yield (Ya), i.e., values closer to the potential yield (Yp) of the crop, whereas in February, Ya were affected by lower precipitation from April to June. The best date for maize sowing was January 25th. The simulations indicated the possibility of predicting the off-season maize productivity in Jataí with high precision and accuracy up to 30 days prior to harvest ($R^2 \geq 0.81$, $d \geq 0.90$, and $c \geq 0.81$).

Keywords: climate risk, DSSAT, *Zea mays***.**

PREVISÃO DE PRODUTIVIDADE DO MILHO SAFRINHA PARA DIFERENTES DATAS DE SEMEADURA

RESUMO: O Brasil é o terceiro maior produtor mundial de milho. Sua produtividade é influenciada pelas condições de clima, solo, manejo e pela interação entre eles. Identificar o posicionamento mais adequado da janela de semeadura do milho e utilizar sistemas de previsão permite maiores produtividades e uma melhor gestão da colheita. Modelos de simulação de cultura podem ser usados para avaliar a resposta das culturas à diferentes condições. Este trabalho visou identificar, usando o modelo DSSAT CSM-CERES-Maize, a data mais favorável à semeadura do milho safrinha, bem como adaptar e avaliar um sistema de previsão de produtividade em Jataí, Goiás. Usando dados meteorológicos de 1986 a 2015, foram testadas oito estratégias de previsão de produtividade. Concluiu-se que a semeadura em janeiro apresenta maior proximidade entre a produtividade atingível (PA) e a potencial (PP) da cultura, enquanto fevereiro é impactado pela menor precipitação de abril a junho. A melhor data para a semeadura do milho safrinha foi 25 de janeiro. As simulações indicaram ser possível prever com alta precisão e acurácia a produtividade do milho safrinha em Jataí, com até 30 dias de antecedência à colheita ($R^2 \geq 0,81$, $d \geq 0,90$ e $c \geq 0,81$).

Palavras-chaves: risco climático, DSSAT, *Zea mays.*

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1 INTRODUCTION

Maize (*Zea mays*) is of great importance worldwide for human and animal consumption, and as a raw material for ethanol production. The United States is the largest producer of maize in the world, with approximately 384 million tons, followed by China (~273 million tons) and Brazil (~88 million tons). The Midwest region of Brazil is the most important maize producer, with the state of Goiás (GO) being the largest producer in the region. The average maize production and productivity in GO are 8.4 million tons and 4.6 thousand kg ha^{-1}, respectively (Oliveira; Miranda; Cooke, 2018; Faostat, 2023).

The cultivation of maize for grain production is influenced by several factors, such as climate, soil, and management practices. Climate is particularly important in agricultural production and is considered a major risk factor in Brazilian agriculture. One of the management practices to increase productivity is the selection of an optimal sowing time, which has a significant impact on the productive potential of the crop, particularly in rainfed agriculture. Adjusting the sowing date to a more favorable time for a specific location is a cost-effective way for farmers to improve their yields (Bannayan; Crout; Hoogenboom, 2013; Andarzian *et al.*, 2015; Duarte, 2018).

Reductions in maize productivity occur due to the influence of climatic conditions, deficient nutrition, and a lack of pests and disease control. Among these, the influence of climate on crop productivity is the most difficult to manage. Generally, the amount and distribution of rainfall modulate productivity under rainfed conditions, since maize demands high availability of water for its development. Water stress negatively affects plant germination, particularly during seedling establishment. Moreover, water stress during the vegetative stage reduces the expansion of leaf area, thereby limiting the efficient interception of solar radiation by the crop canopy. The consequences extend to the reproductive and grain-filling stages, where water stress disrupts processes such as pollen fertility, resulting in infertility, grain abortion, and a reduction in grain weight (Bergamaschi *et al.*, 2004; Araus; Serret; Edmeades, 2012; Gong *et al.*, 2015; Schauberger *et al.*, 2017; Garcia *et al.*, 2018).

Crop yield can be classified into three categories: potential (Yp), attainable (Ya), and actual (Yr) yields. The factors that determine Yp are genotype, solar radiation, temperature, photoperiod, and the plant population. Ya is related to the yield reduced by the water deficit, whereas Yr considers both the determinant and limiting factors of Ya and is further influenced by reducing factors related to management practices (Bindraban *et al.*, 2000; Fermont *et al.*, 2009; Sentelhas *et al.*, 2015).

Forecasting agricultural production is critical for harvest planning, storage, and marketing (Duarte, 2018), and helps farmers increase their efficiency. By forecasting the productivity of crops before harvest, farmers can plan for their transportation and storage, optimize their sales strategies, and reduce or avoid potential losses related to production. Yield losses can be determined using growth models and their software packages, such as DSSAT (Jones *et al.*, 2003), which are worldwide used under different environmental conditions and management practices (Hoogenboom *et al.*, 2019).

The objective of this study was to identify the most favorable sowing date for off-season maize using the CSM-CERES-Maize model based on productivity forecasting for conditions in Midwest Brazil.

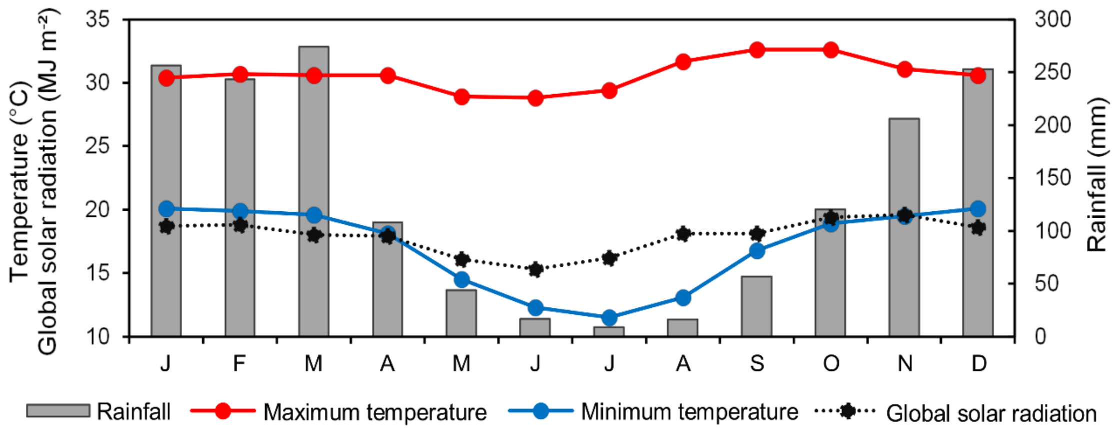
2 MATERIALS AND METHODS

The simulations of growth and yield of maize off-season were carried out for Jataí, in the state of Goiás (17.91° S, 51.71° W), one of the main maize-producing municipalities in the Midwest of Brazil. The model used for the simulations in this study was the CSM-CERES-Maize, in DSSAT version 4.7.5 (Jones *et al.*, 2003; Hoogenboom *et al.*, 2019). A mid-cycle cultivar was used, previously calibrated for Brazilian conditions (Bender, 2017).

Daily weather data were obtained from the gridded database of Xavier, King and

Scanlon (2016) for the period of 1986 to 2015 (30 years), which has been shown to be suitable for process-based modeling purposes (Battisti; Bender; Sentelhas, 2019; Bender; Sentelhas, 2018). Climate variables considered in this study were maximum and minimum air temperatures, global solar radiation, rainfall, wind speed, and relative humidity (Figure 1). The carbon dioxide concentration level for the historical series was set at 380 parts per million (ppm).

Figure 1. Monthly averages of maximum temperature, minimum temperature, global solar radiation and total rainfall, from 1986-2015, for Jataí, GO, Brazil.



In this region, the rainy season is between September and April, with the heaviest amounts from November to March (over 200 mm per month). Consequently, the periods of greater water deficit and less water storage in the soil coincide with the off-season maize growing period, which can extend until July, depending on the sowing season. In maize, water deficits during the flowering and grain-filling stages cause production losses ranging from 20% to 50% (Pegorare *et al.*, 2009).

A sandy loam texture was considered for the simulations, since the soils at the study site were mainly latosols, cambisols, and neosols (Battisti; Sentelhas, 2017). The physical-hydraulic soil characteristics included in the model were soil water saturation, field capacity, permanent wilting point, soil density, and saturation conductivity (Table 1).

Table 1. Texture and physical-hydric characteristics of the sandy loam soil used for maize simulations in Jataí, GO, Brazil.

Depth	Cl	Si	S	Soil water saturation	CC	PMP	Soil density	Ksat
m		%			$cm^3\ cm^{-3}$		$Mg\ m^{-3}$	$cm\ h^{-1}$
0 - 0.15	19	2	79	0.387	0.13	0.07	1.55	15
0.15 - 0.30	19	2	79	0.387	0.13	0.07	1.55	9.4
0.30 - 2.0	19	2	79	0.343	0.13	0.07	1.70	15

Cl: clay; Si: silt; S: sand; CC: field capacity; PMP: permanent wilting point; Ksat: saturated hydraulic conductivity.

A planting density of 70,000 plants ha^{-1} and emergence of 55,000 plants ha^{-1} were established, with row spacing of 80 cm and planting depth of 5 cm. Twelve sowing dates were selected at five-day intervals within the recommended sowing window. Harvest was specified to occur at plant maturity, which varied from year to year due to climatic variability. For the off-season maize simulations, management was defined to obtain

Ya of the cultivar for the region (Yp penalized by water deficit). That is, the model was adjusted to maintain optimal conditions for plant development, except for water limitation, which was simulated with local rainfall.

To assess the effect of using daily climatic average data to predict the yield of the maize off-season, eight prediction strategies (S1, S2, S3, S4, S5, S6, S7 and S8) were considered and simulated using historical data only from the last 15, 30, 45, 60, 75, 90, 105 and 120 days, compared to the control condition. In the control condition (S0), the productivity simulation was considered only with the daily meteorological data observed for each year.

The performance of each prediction strategy was based on statistical analysis. The following statistical indicators were used: determination coefficient (R^2), Willmott's concordance index (d) (Willmott, 1982), confidence or performance index (c) proposed by Camargo and Sentelhas (1997), mean error (ME), mean absolute error (MAE) and root mean square error (RMSE) proposed by Wallach *et al.* (2013), according to Equations 1 to 6.

$$R^2 = \frac{\sum (E_i - \overline{O})^2}{\sum (O_i - \overline{O})^2} \quad (1)$$

$$d = 1 - \left[\frac{\sum (E_i - O_i)^2}{\sum (|E_i - \overline{O}| + |O_i - \overline{O}|)^2}\right] \quad (2)$$

$$c = d\sqrt{R^2} \quad (3)$$

$$ME = \frac{1}{n}\sum (E_i - O_i) \quad (4)$$

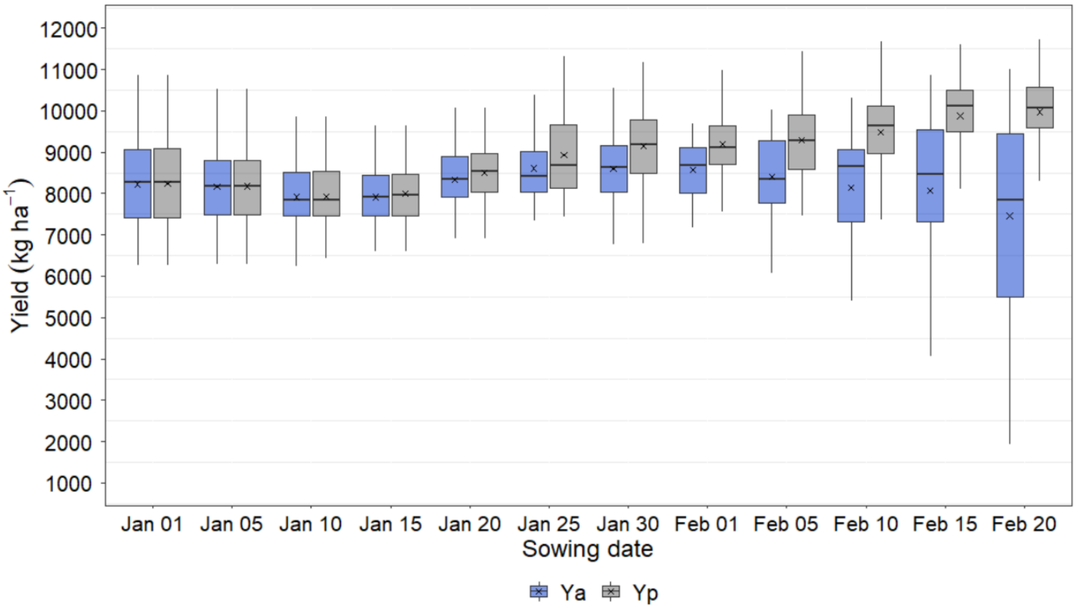
$$MAE = \frac{1}{n}\sum |E_i - O_i| \quad (5)$$

$$RMSE = \frac{1}{n}\sqrt{\sum (E_i - O_i)^2} \quad (6)$$

3 RESULTS AND DISCUSSION

The best sowing date was January 25th (Figure 2), which had the highest Ya (8611 kg ha^{-1}) and low variability. The mean Ya did not differ significantly when considering different sowing dates, ranging from 7460 to 8611 kg ha^{-1}. However, the amplitudes of the "boxplots" in the second half of February were higher, indicating a higher climatic risk for sowing dates during this period. In addition, there was an increasing downward shift in these values until their maximum values were lower than the minimum values of Yp. These results reflect the local climatology, with a decrease in the minimum temperature, in addition to a reduction in rainfall amount as the cycle progresses by increasing the water deficit, thus reducing the productivity achieved with the delay of sowing within the recommended sowing window.

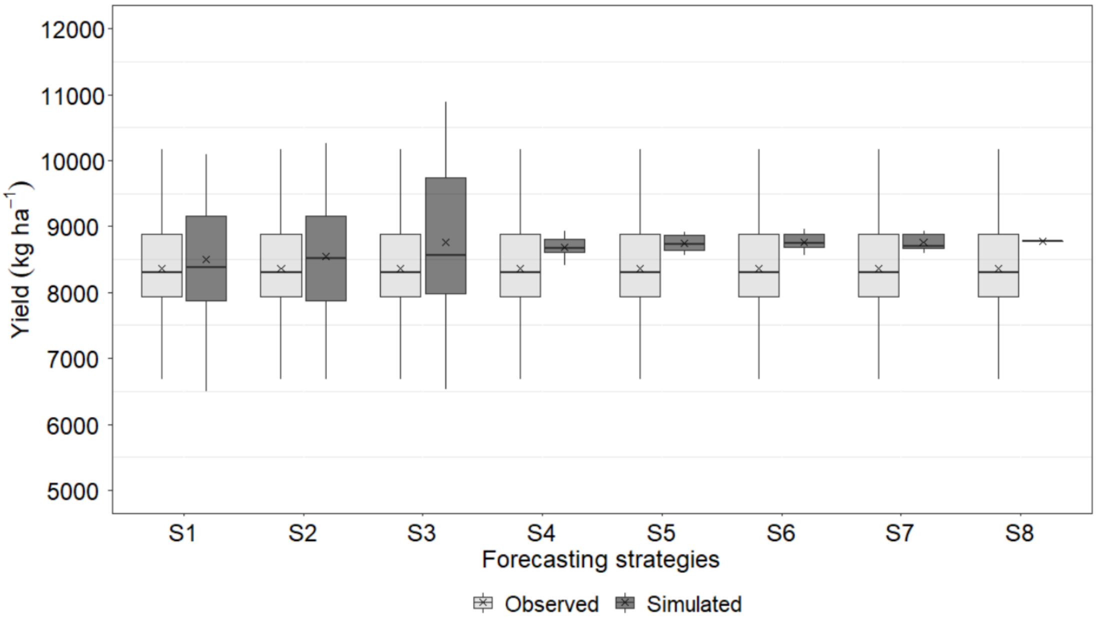
Figure 2. Boxplots of Potential (Yp) and Attainable (Ya) Yield of maize off-season in Jataí (GO), for sowing dates every five days.



Maize cultivation follows a growing cycle of approximately 120 days, where sowing in January results in a harvest in May, whereas sowing in February leads to a harvest in June. Consequently, February sowings are subject to weather conditions that are less favorable to optimal productivity than those experienced in January. This observation highlights that sowing undertaken throughout January tends to exhibit Ya values that closely align with those of Yp.

In general, better performance was observed in forecasting strategies that used fewer average historical data (Figure 3). Strategies S1 and S2, for forecasts 15 and 30 days before harvest, respectively, presented the best performance in relation to S0. These findings support the observations of Soler (2004), who concluded that maize yield estimation remains highly accurate up to 45 days before the scheduled harvest date.

Figure 3. Variability and comparison of means of the eight strategies in relation to simulated yields with observed climatic data (S0) for Jataí, GO, Brazil.



Strategy S3 showed the highest productivity values among all the strategies. Furthermore, the amplitude of variation of S3 was almost twice as high as that of S0 (control). The worst productivity performance was observed for strategies S1 and S2. Strategies S4, S5, S6, and S7 showed a strong flattening of variability and amplitude due to the use of a high amount of average meteorological data, as also observed by Duarte (2018). These results differ from those of Martins (2007), who used the ETA climate forecast model combined with climate data from the years of their simulations and suggested that the maize yield forecast can be satisfactorily made between 45 and 60 days before harvest.

The application of strategies based on average meteorological data spanning 60–105 days of the maize crop cycle (representing 50–87.5% of the available meteorological data) resulted in increased errors when predicting maize productivity in Jataí, GO. This can be attributed to the significant inter-annual variability characteristic of tropical regions. The utilization of the average values leads to the loss of a portion of this inherent variability. Consequently, the predicted annual productivity tended to converge across different years. The predicted average Ya increases in relation to the control productivity, as a greater number of days with average meteorological data are considered (lower water deficit in the growing cycle).

The MAE ranged from 204.3 to 816.7 kg ha^{-1} for the different forecasting strategies with sowing on January 25th, resulting in values of the "c" index ranging from 0 to 0.92 (Table 2). The S8 strategy resulted in higher accuracy and precision levels than those of S4, S5, S6, and S7. There was superiority in the performance of strategies that used fewer average climate variables in the simulations, and strategy S1 (c = 0.92, MAE = 204 kg ha^{-1}, RMSE = 58 kg ha^{-1}) was the best, followed by strategy S2 (c = 0.86, MAE = 267 kg ha^{-1}, RMSE = 76 kg ha^{-1}). These results are similar to those found by Duarte (2018), who used a historical series of meteorological data from 1980 to 2010 and average data for 30 years for each day and tested harvest forecast strategies for first and second maize harvests with average data at 5, 25, 45, 65, and 85 days from harvest. The best performing strategy was 5 days, and the worst was 85 days.

Table 2. Performance of different strategies for predicting the productivity of off-season maize for planting on January 25th in Jataí, GO, Brazil.

Strategy	R^2	d	c	ME	MAE	RMSE
				kg ha^{-1}		
S1	0.90	0.97	0.92	128	204	58
S2	0.83	0.94	0.86	183	267	76
S3	0.49	0.79	0.55	396	513	158
S4	0.03	0.34	0.06	313	745	168
S5	0.01	0.32	0.03	384	816	178
S6	0.02	0.35	0.05	397	791	180
S7	0.00	0.38	0.00	397	774	176
S8	0.50	0.37	0.26	412	781	177

In contrast, strategies S4, S5, S6, S7, and S8 performed the worst, with the "c" index ranging from zero to 0.6 and the RMSE from 168 kg ha^{-1} to 180 kg ha^{-1}. Bannayan, Crout and Hoogenboom (2003) employed a combination of daily meteorological data generated by the SIMMETEO meteorological data generator integrated with the DSSAT platform to forecast wheat yield during the milky grain stage. Their study revealed that, as the simulations were conducted at later stages, the errors decreased. Specifically, RMSE values exceeded 950 kg ha^{-1} for simulations performed 132 days after sowing, but were below 700 kg ha^{-1} for simulations carried out 244 days after sowing.

In a study conducted by Monteiro *et al.* (2017) in southern Brazil, maize productivity was estimated using relatively simple agrometeorological models based on the technological level of the production systems. The authors observed a strong correlation between the estimated and observed productivity, with coefficient of determination (R^2) values ranging from 0.76 to 0.92 ($p<0.01$). The mean absolute error (MAE) was less than 70 kg ha^{-1}, further indicating the accuracy of the predictions. In general, maize production can be predicted using crop models and climate forecasts; however, region-specific approaches may be required, as suggested by Ogutu *et al.* (2018).

Strategies S1, S2, and S3, although with a smaller number of average climatic data, showed a trend towards greater variability and overestimation of simulated values, with mean errors ranging from 128 kg ha^{-1} to 396 kg ha^{-1}. This is in partial agreement with the findings of Duarte (2018), who reported an overestimation of productivity in sowing between January and February, with mean errors ranging from 153 kg ha^{-1} to 5038 kg ha^{-1}. On the other hand, S1 and S2 presented R^2, d and c higher than the other strategies, reaching values of 0.92 and 0.86 for the c index, respectively.

Our results suggest that the closer the harvest date, the better the performance in determining the yield, which was also observed by Chipanshi, Ripley and Lawford (1997) and Duarte (2018). Although the use of average data does not guarantee a long and safe period for forecasting maize productivity, it appears to be a practical and economical alternative (Duarte, 2018) and can help in planning from storage to transportation of the crop. This allows for satisfactory forecasts of maize productivity up to 45 days before harvest, as demonstrated by Soler (2004) and Martins (2007). This strategy can predict, on the determined sowing date, maize productivity 30 days in advance, enabling decision-making support at a critical moment in maize harvesting and marketing.

4 CONCLUSIONS

The off-season maize sowing date with the highest attainable yield and lowest climate risk observed for the planting window period was January 25th. The strategies for predicting maize off-season yield indicated that the lower the number of remaining days between the prediction and harvest date, the better the performance. Strategy S2 showed the best performance, as it allowed the prediction of maize off-season yield 30 days ahead satisfactorily in the edaphoclimatic conditions of central Brazil.

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