Flowering prediction for flood-irrigated rice in the Midwest and North regions of Brazil[1]

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ABSTRACT

This study aimed to analyze the influence of climatic and geographic variables on the flowering process of flood-irrigated rice in the Midwest and North regions of Brazil. Agronomic data from the breeding program were related to the following variables: air temperature, relative humidity, global solar radiation, rainfall, degree days, latitude, longitude, and altitude. The analysis was performed using Multiple Linear Regression (MLR) and Generalized Additive (GAM) models. Cross-validation determined the most suitable model. The GAM model showed the best performance for both regions. In the Midwest and North of Brazil, flowering was strongly influenced by climate variables related to temperature. The rise in minimum temperatures tends to advance flowering. Higher minimum accumulated temperatures tend to delay flowering.

Keywords: phenology; predictive model; climate; *Oryza sativa* L.

INTRODUCTION

Rice (*Oryza sativa* L.) stands out as the third most produced crop on the planet (0.8 billion tons), being a component of the daily staple diet for 3 billion people (FAO, 2022; Breseghello *et al*., 2016). Flowering stimulated by the environment favors plant survival by ensuring the seed finds a favorable environment for germinating and developing. On the other hand, it makes plants vulnerable to climate change. In addition to providing challenging environmental factors and stress sources, climate change modifies the variables determining the flowering season, such as temperature. Flowering is a key moment for grain production and a determinant of regional and seasonal crop adaptation, allowing plants to adapt to growing conditions in different environments (Srikanth & Schmid, 2011; Tsuji *et al*., 2011; Taiz *et al*., 2017; Ye *et al*., 2019).

Although late flowering provides the greatest accumulation of biomass, grain filling is impaired and plants spend more time in the field subjected to biotic and abiotic stresses. On the other hand, early flowering can result in reduced biomass and, consequently, grain yield (Srikanth & Schmid, 2011; Silva Júnior *et al*., 2023).

Changes in climatic variables lead to modifications in physical characteristics, such as the lipid layer fluidity in biomembranes, and biochemical ones, such as the photosynthetic rate, affecting the crop cycle. Rice is highly sensitive to climate variations, and the flowering stage is critical for rice production (Yang *et al*., 2019). Knowing its phenology and thermal, water, and solar radiation demands is important for rice crop planning (Alves *et al*., 2000; Larcher, 2006).

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The increase in the emission of greenhouse gases may promote, by the end of the century, an increase in the average global temperature of around 3.2 °C (IPCC, 2022). These changes can significantly influence plant growth (Larcher, 2006), dramatically impacting rice crops and potentially causing serious damage to global food security. Although the increase in CO_2 concentration can increase rice yield, through the higher photosynthetic rate, high temperatures can have antagonistic effects, accelerating the cycle, decreasing the number of tillers per plant, grain weight and plant height and increasing spikelet sterility (Hussain *et al*., 2020).

Thus, this study uses statistical models to predict the flowering date of flood-irrigated rice by genotypes and climatic and geographic variables in Brazil's Midwest and North regions. This methodology will allow a better understanding of the climate variables' effect on flowering.

MATERIAL AND METHODS

Description of the experiments

This study used experiments covering municipalities in the Midwest, states of Goiás (Flores de Goiás (Lat: -14.457; Long: -47.038); Goianira (Lat: -16.506; Long: -49.422); Luiz Alves (Lat: -13.213; Long: -50.578)) and Mato Grosso do Sul (Dourados (Lat: -22.227; Long: -54.829); Miranda (Lat: -20.237; Long: -56.385); Rio Brilhante (Lat: -21.804; Long: -54.543)) and in the North, states of Amapá (Mazagão (Lat: -0.115; Long: -51.286)), Roraima (Cantá (Lat: 2.609; Long: -60.602)), and Tocantins (Dueré (Lat: -11.344; Long: -49.265); Formoso do Araguaia (Lat: -11.817; Long: -49.512); Lagoa da Confusão (Lat: -10.800; Long: -49.607) e Pium (Lat: -10.442; Long: -49.179)) regions. Also, it uses a large, accumulated yield data set formed by various trials on commonly grown and well-adapted flood-irrigated rice varieties derivate from the Embrapa Rice Breeding Dataset (Breseghello *et al*., 2021). As standardized by the Embrapa nationwide rice breeding program, each field trial was composed of the best-performing 20 genotypes of the current elite germplasm, and it is conducted in randomized blocks with three repetitions. The trials comprised the years between 1995 and 2017.

The agronomic traits (GY - grain yield (kg ha^{-1}), SD - sowing (date), EMD - emergence (date), FD - flowering (date), and MD - physiological maturation (date) were related to large-scale environmental information, such as daily climate data. The step of collections involves the use of different databases. The climate data set was collected from the weather station from INMET (Brazilian Institute of Meteorology - https://portal.inmet.gov.br/), located at the trial municipality. For trials with no weather stations available in the municipality, we used daily gridded climate data from Xavier *et al*. (2016).

After relating trials to climate data, the step of data processing was conducted by adopting different sampling levels of environmental information and then translating them into actual climate covariates capable of better capturing temporal variation across the crop life cycle. The development phases were computed at a field trial level using the mean values of FD and MD as observed in each trial. For the reproductive stage, according to the information supplied by rice breeders from Embrapa Rice & Beans, was assumed that panicle initiation (PI, corresponding to the stage R0 described by Counce *et al*., 2000) began 25 days before FD (Dos Santos *et al*., 2017; Senanayake *et al*., 1994), as PI is not observed at field trials. Then, three phenological phases were established, vegetative (from EMD to PI), reproductive (from PI to FD) and grain filling (from FD to MD) phases. The effective daily heat units (Degree days) were calculated based on daily mean temperature, and three cardinal temperatures: base (8 ºC), optimum (30 ºC), and maximum (42 ºC) thresholds. Details on the equation of degree days is described in Heinemann *et al*. (2017) and Bouman *et al*. (2001).

Thirty-two environmental covariables (28 climatic, three geographic (longitude, latitude and altitude), and genotypes (Table 1)) were evaluated to predict the mean flowering date (FLO_M). The climate variables related to air temperature (°C) in this study were: a) for all crop cycle, maximum value of maximum temperature (Tmax_Max); minimum value of maximum temperature (Tmax_Min); mean value of maximum temperature (Tmax_M); maximum value of minimum temperature (Tmin_Max); minimum value of minimum temperature (Tmin_Min) and mean value of minimum temperature (Tmin_M); b) flowering period (considered five days before and after 50% of plants with flower): maximum value of mean temperature (Tmax_FLO) and minimum value of mean temperature (Tmin_FLO); c) vegetative phase: mean value of maximum temperature (Tmax_V); value of maximum temperature accumulated (Tmax_ACC_V); mean value of minimum temperature (Tmin_V); value of minimum temperature

Table 1: Selected genotypes for Midwest and North regions

Region	Genotypes
Midwest	BRS A704, BRS Alvorada, BRS Biguá, BRS Catiana, BRS Formoso, BRS Guará, BRS Jaburu, BRSMG Rubelita, BRS Pampeira, BRS Tropical, Cica 8, Epagri 108, Epagri 109, IRGA 430, IRGA 97-05, IRGA 97-10, Javaé, Marajó, Metica 1, Ourominas, PR380, Puitá Inta CL, Roraima, SCS 112, SCS 121 CL, SC138, SC173, SCS 114 Andosan, SCSBRS 113 Tio Taka, SCS 116 Satoru, SCSBRS Piracema.
North	BRS A701 CL, BRS A702 CL, BRS A704, BRS Alvorada, BRS Catiana, BRS Formoso, BRS Guará, BRS Jaburu, BRS Pampa, BRS Pampeira, BRS Sinuelo CL, Cica 8, H6, IAPAR 58, IRGA 417, IRGA 422 CL, IRGA 424, IRGA 426, IRGA 427, IRGA 430, Javaé, Marajó, Metica 1, Ourominas, PR380, PR498, Puitá Inta CL, SC138, SCSBRS 113 Tio Taka, SG11551.

accumulated (Tmin_ACC_V); d) reproductive phase: mean value of maximum temperature (Tmax_R); value of maximum temperature accumulated (Tmax_ACC_R); mean value of minimum temperature (Tmin_R); value of minimum temperature accumulated (Tmin_ACC_R). The climate variables related to rainfall (mm) were: a) for all crop cycle, accumulated rainfall (Rain_ACC); b) vegetative phase, accumulated rainfall (Rain_ACC_V) and c) reproductive phase, accumulated rainfall (Rain_ACC_R). The climate variables related to global solar radiation (MJ/m^2) were: a) for all crop cycle, accumulated solar radiation (Rad_ACC); b) vegetative phase, solar radiation (Rad_ACC_V) and c) reproductive phase, solar radiation (Rad_ACC_R). The climate variables related to relative air humidity (%) were: a) for all crop cycle, mean value of relative air humidity (HU_M); b) flowering period, mean value of relative humidity (HU_FLO); c) vegetative phase, mean value of relative humidity (HU_V) and d) reproductive phase, mean value of relative humidity (HU_R). Finally, the variables related to degree days (°C) were: the accumulated value during the panicle initiation to flowering (Degree_days_FLO) and the entire cycle (Degree_days_Cycle). Genotypes present in at least four breeding trials were selected for each region (Table 1).

Statistical Model

This study used two linear structures from statistical models, the Multiple Linear Regression Model (MLR, parametric) and the Generalized Additive Model (GAM, semiparametric). The quantitative variable selection (climatic and geographic) in the MLR and GAM models was performed using the stepwise method, with Akaike's information criterion (AIC) (Akaike, 1973) as the selection criterion. For all models (MLR and GAM), the assumptions of normality and equality of variances (Levene's test) among groups were tested. The quality of the generated models was measured using the adjusted coefficient of determination (R^2) for the MLRs and the explained deviance for the GAMs (Wood, 2006).

The independent variables discriminated by the MLR models were ranked according to their explanatory capacity regarding the variability for predicting flood-irrigated rice flowering for each macro-region. Due to its structural complexity, the GAM model does not allow an equivalent methodology to rank the explanatory capacity of the independent variables.

Cross-Validation and Prediction

The k-fold cross-validation algorithm was used to compare the predictive capacity of the MLR and GAM models for each region, targeting the smallest mean absolute error (MAE). When performing cross-validation, the K (number of folders) was set to 100, and based on resample, the data set splitting ratio train/test was 70% for training and the remaining 30% for test (Vrigazova, 2021), following the same methodology described in Dos Santos *et al*. (2021). Thus, the models that showed the lowest MAE were selected for the flowering date prediction.

After the models were selected for the North and Midwest macro-regions, the mean flowering date (FLO_M) was evaluated under several scenarios. Therefore, we varied the values of the climate covariate of interest and kept the other climate covariates in the model at the mean value. This procedure only considered genotypes grouped by similarity. Thus, we could obtain an "optimum" value for the climatic variables for each region. All statistical analyses in this study were performed in the R computing-statistical environment (R Core Team, 2021). Specifically, we use the 'gam()' function from the R 'mgcv' package (Wood, 2021).

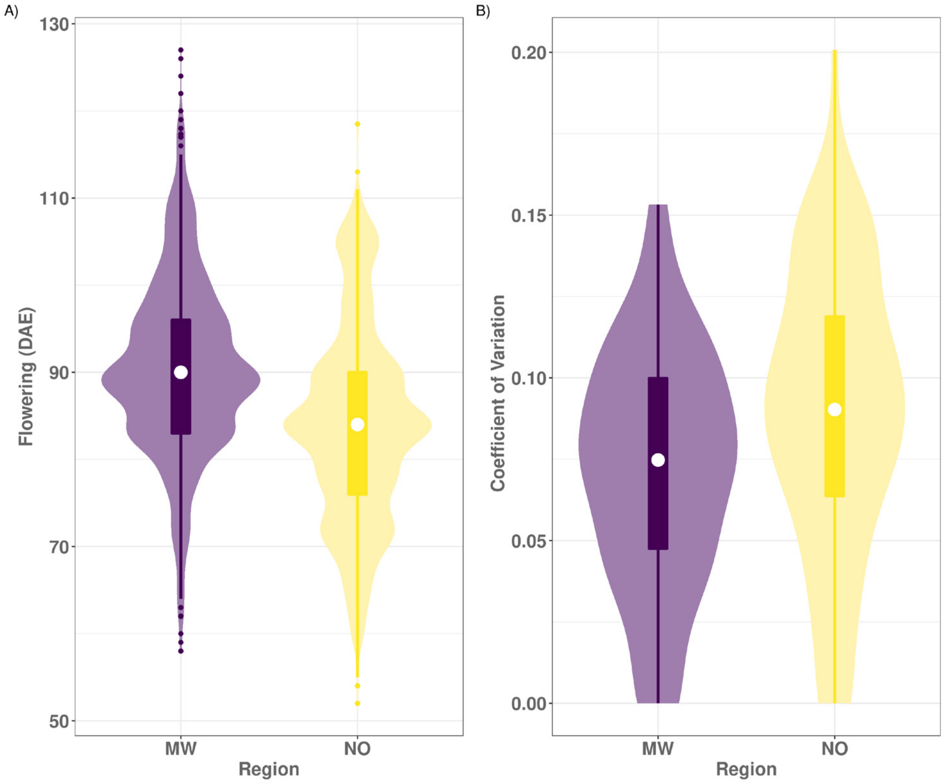

Figure 1: Flowering (A) in days after emergence (DAE) and coefficient of variation (B) for flood-irrigated rice in the Midwest (MW, purple) and North (NO, yellow) regions. The white circle represents the median value.

RESULTS

According to the exploratory analysis, flowering occurred on average (coefficient of variation) at 83.91 (± 11.17) and 90.64 (± 9.85) days after emergence (DAE) for the North and Midwest regions, respectively (Figure 1).

The North region showed the highest thermal averages (28.01 ºC ± 1.19 ºC) compared to the Midwest region (25.37 ºC ± 1.19 ºC) (Figure 2). Despite the variability of optimal temperature recommendations for rice flowering in the literature, values near 27 ºC are commonly accepted. Values below 16 ºC and above 35 ºC are critical for this phase (Sánchez *et al*., 2014). The North and Midwest regions occasionally reach temperatures above 35 ºC, and the Tmax_Max median in both exceeded this value. Thermal heat stress can cause delayed flowering since, above approximately 35 ºC, the plant stops developing, lengthening the vegetative phase (Sánchez *et al*., 2014).

Regarding Tmin_Min, exceeding the lower limit is rare in the North region, but it occurs more frequently in the Midwest region. Therefore, flowering tends to be later due to warmer nighttime temperatures (Figure 2).

The North region showed higher values of mean relative humidity (HU_M) when compared to the Midwest region (Figure 2). Regarding the accumulated rainfall during the crop cycle (Rain_ACC), the North region recorded a median of 831 mm, higher than the Midwest region, whose median was 799 mm. In the Midwest region, there were no accumulated rainfall occurrences during the crop cycle below 375 mm. Figure 2 shows that the North region presents higher values of accumulated rainfall during the crop cycle.

The accumulated global solar radiation (Rad_ACC) showed distinct values among the regions (Figure 2). The lowest values of accumulated solar radiation occur in the North region (with a median of 2137 MJ/m^2) due to the high rainfall, where the cloudiness hinders the sun's rays from passing through. In the Midwest region, accumulated solar radiation of 2488 MJ/m^2 (median) was verified during the crop cycle. The Midwest region showed a lower accumulated degree days demand than the North region (Figure 2). According to Funari & Tarifa (2017), the Northern region of Brazil has relatively high cloudiness due high rainfall, especially in Amapá State and the Amazonas River mouth. In the Midwest region, the lowest values occur in the southeast of the Mato Grosso do Sul State.

Regarding the inferential part, both statistical models (MLR and GAM) showed better performance in the North region (R^2 = 92% and deviance = 92%) compared to the Midwest region (R^2 = 80% and deviance = 83%). It should be noted that values above 80% provide favorable indications for the proposed adjustment's quality.

Figure 3 shows the genotype impact on flowering for the MLR (A, B) and GAM (C, D) models for the Midwest (A, C) and North (B, D) macro-regions. It is worth noting that in this figure, the center value 0 represents the intercept, interpreted as the mean flowering.

The MLR model for the North region had the lowest variability among genotypes for advancing or delaying flowering (± 1 day) (Figure 3B) compared to GAM (Figure 3D). The greatest effect of advancing flowering promoted by the genotypes among all MLR occurred in the Midwest region, in which the IRGA 430 genotype advanced flowering by an average of 13.02 days. For this same region, the SCS116 Satoru genotype was the most delayed, delaying flowering by an average of 10.79 days (Figure 3A). In GAM, IRGA 430 had the greatest tendency to advance flowering by an average of 14.67 days. The Epagri 109 genotype delayed flowering the most, by an average of 10.03 days (Figure 3C).

Explanatory capacity of independent variables

Compared to MLR models, the GAM models required fewer discriminating climate variables. The latitude, altitude, Rain_ACC, Rad_ACC_R, Rad_ACC_V, Tmax_FLO, Tmax_Max, Tmin_FLO, Tmin_M, Tmin_Min, HU_FLO, HU_M, and HU_V variables were not discriminant in the GAM models for any region. For the MLR models, the Rad_ACC_R and latitude variables were also not discriminant for any region. The lack of significance of Rad_ACC_R can be attributed to the reduction of light

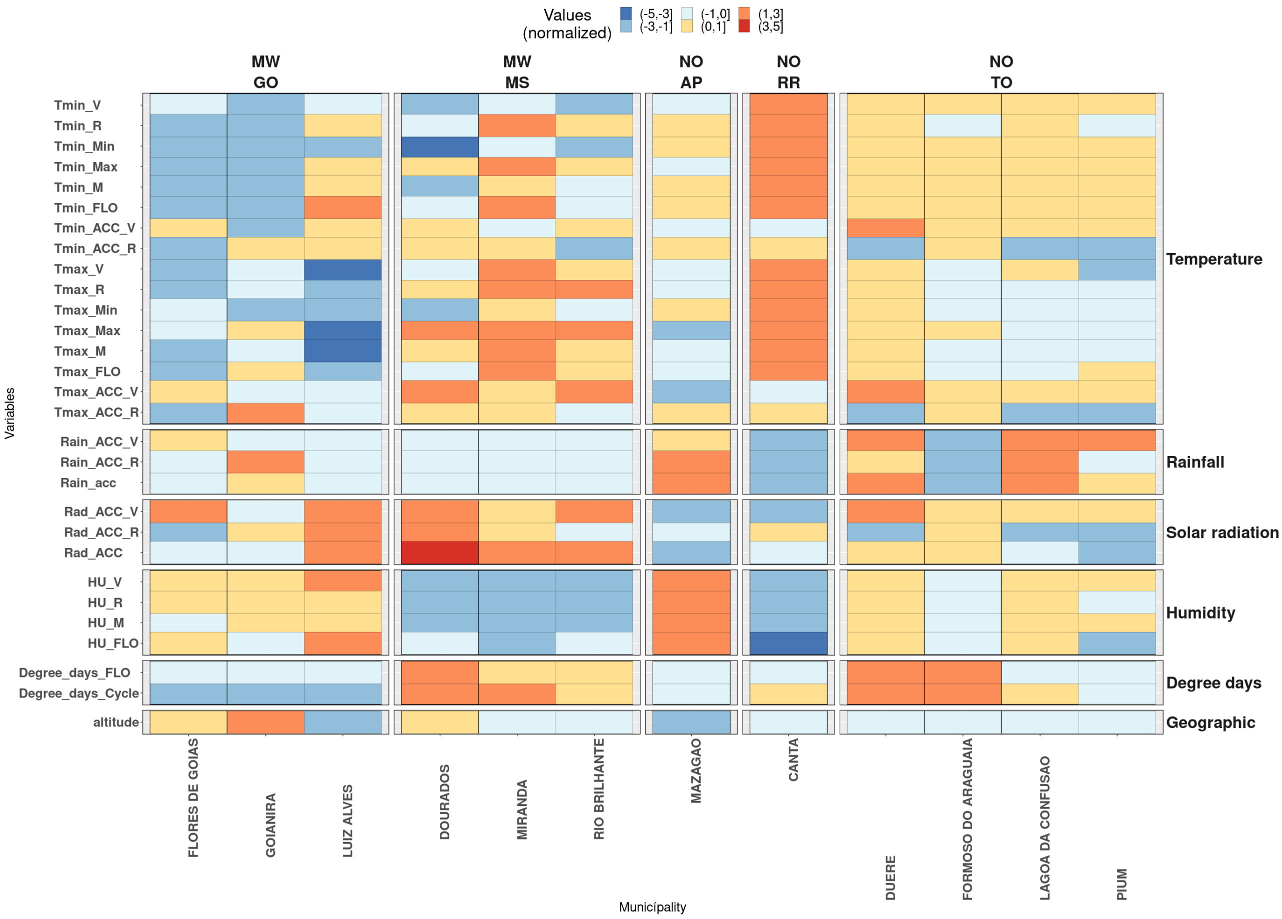

Figure 2: Distribution of climatic (air temperature, rainfall, solar radiation, relative humidity, and degree days) and geographical (altitude) variables normalized by z-score across regions and municipalities.

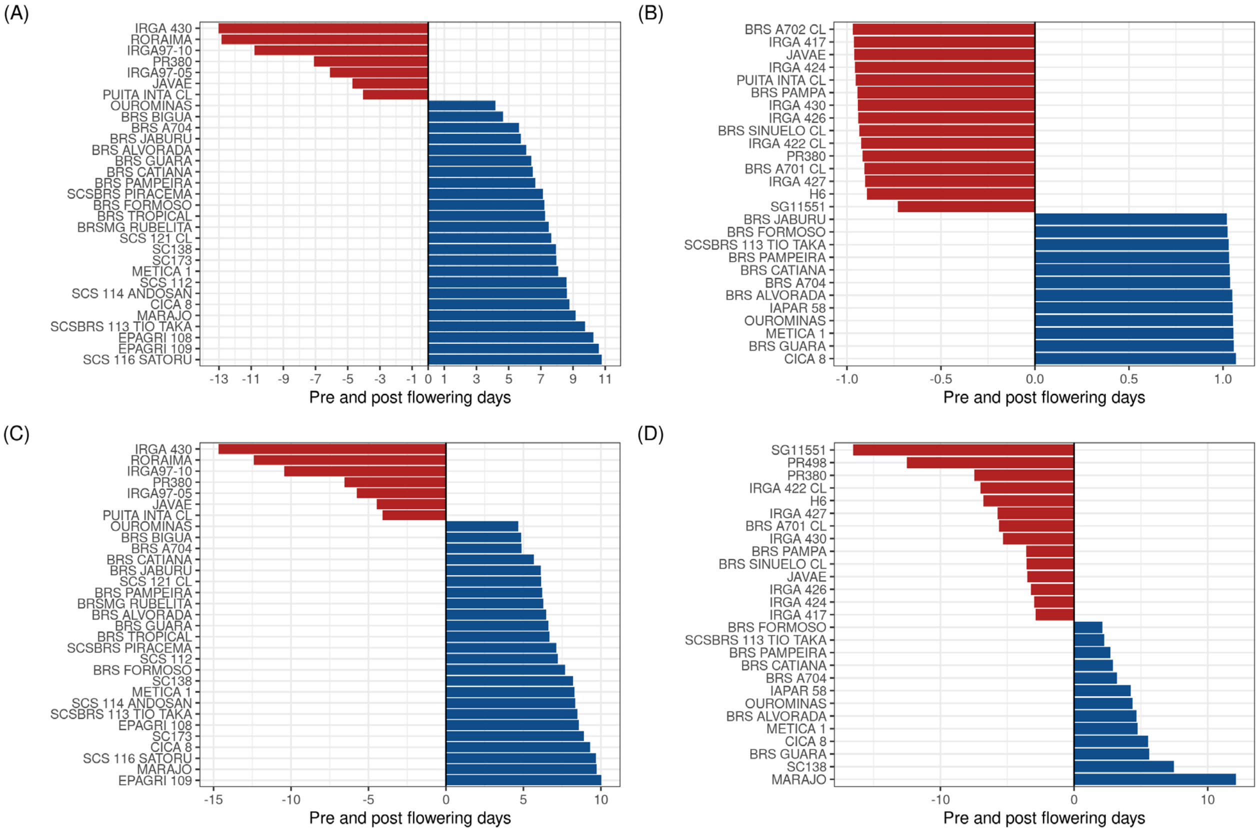

Figure 3: Mean pre and post-flowering days per genotype listed in linear models (A and B) and generalized additive models (C and D), regarding genotypes grouped in the mean, on flowering of flood-irrigated rice grown in the Midwest (A and C) and North (B and D) regions. The value 0 represents the mean flowering in the region.

energy absorption after anthesis (Campbell *et al*., 2001). For both regions, the variables related to air temperature were discriminant in both models (MLR and GAM). It evidences the impact of temperature, especially the minimum temperature, on flowering. Fukai (1999) points out that in irrigated crops grown in the dry season, low temperature commonly delays flowering and, consequently, plant development even in the tropics.

Considering only the MLR models, in the Midwest region, 42% of the variation in flowering is explained by the maximum accumulated temperature in the vegetative phase (Tmax_ACC_V) (Figure 4A). In the North region, longitude was considered the most explanatory variable in flowering (Figure 4B). Genotype is the second most explanatory variable in both regions. When comparing the MLR and GAM models by cross-validation, targeting the mean absolute error (MAE), GAM was more assertive in predicting the days required for flowering in both regions.

For the Midwest region, the GAM model discriminated three unsmoothed climate variables (linear form) - minimum temperature at the vegetative phase (Tmin_V); minimum temperature at the reproductive phase (Tmin_R); and minimum accumulated temperature at the vegetative phase (Tmin_ACC_V) - and two smoothed climate variables (functional form) - degree days to flowering (Degree_days_FLO) and minimum accumulated temperature at the reproductive phase (Tmin_ACC_R). The Rad_ACC and minimum-maximum temperature (Tmax_Min) climate variables for the entire crop cycle significantly comprised the GAM model for the Midwest region but were not analyzed. In practical terms, they represent the entire crop cycle and not the period until flowering, which is this study's focus.

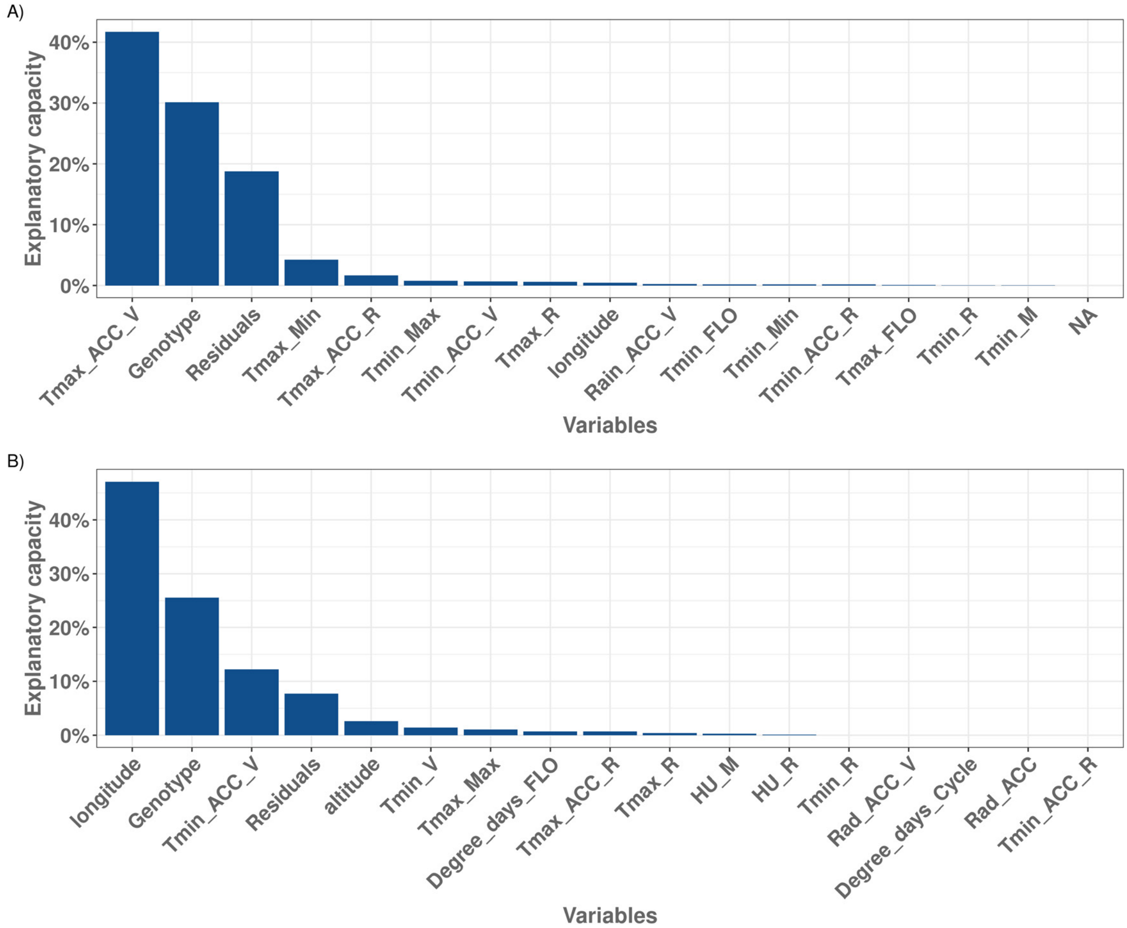

Figure 4: Explanatory capacity of independent variables making up the linear model (MLR) to predict flowering of flood-irrigated rice grown in the region: A) Midwest and B) North.

Seven of the 31 genotypes evaluated in the Midwest region (Table 1) showed a tendency to advance flowering and 24 to delay it (Figure 3A and C). This region had the largest number of discriminant variables in the GAM model, demonstrating its complexity compared to the North region. Figure 5 shows the impact of the discriminating variables (Degree_days_FLO, Tmin_V, Tmin_R, Tmin_ACC_R, and Tmin_ACC_V) on flowering in the Midwest region.

The Degree_days_FLO variable (Figure 5A) showed the least impact on flowering. This climate variable's predicted "optimal" value is between 1440 and 1680 °C days. In this range, there is no tendency to advance or delay flowering.

The climate variables related to temperature strongly influence flowering in the Midwest region. The increase in Tmin_V and Tmin_R linearly advanced flowering (Figures 5B and C). On the other hand, the accumulation of these temperatures (Tmin_ACC_V and Tmin_ACC_R) delayed flowering (Figures 5D and E).

In the North region, the GAM model discriminated three variables with a linear trend (longitude, Tmin_ACC_R, and Tmin_max) and three smoothed independent variables (Rain_ACC_R, Rad_ACC, and Tmin_ACC_V). Among these predictor variables comprising the GAM model, only Tmin_ACC_R, Rain_ACC_R, and Tmin_ACC_V were discussed. Fourteen of the 27 genotypes showed a tendency to advance and 13 to delay flowering (Figure 3B and D). Figure 6 shows the impact of the discriminating climate variables (Tmin_ACC_R, Rain_ACC_R, and Tmin_ACC_V) on flowering in the North region. Temperature-related climate variables also have the greatest impact on flowering, similarly to the Midwest region.

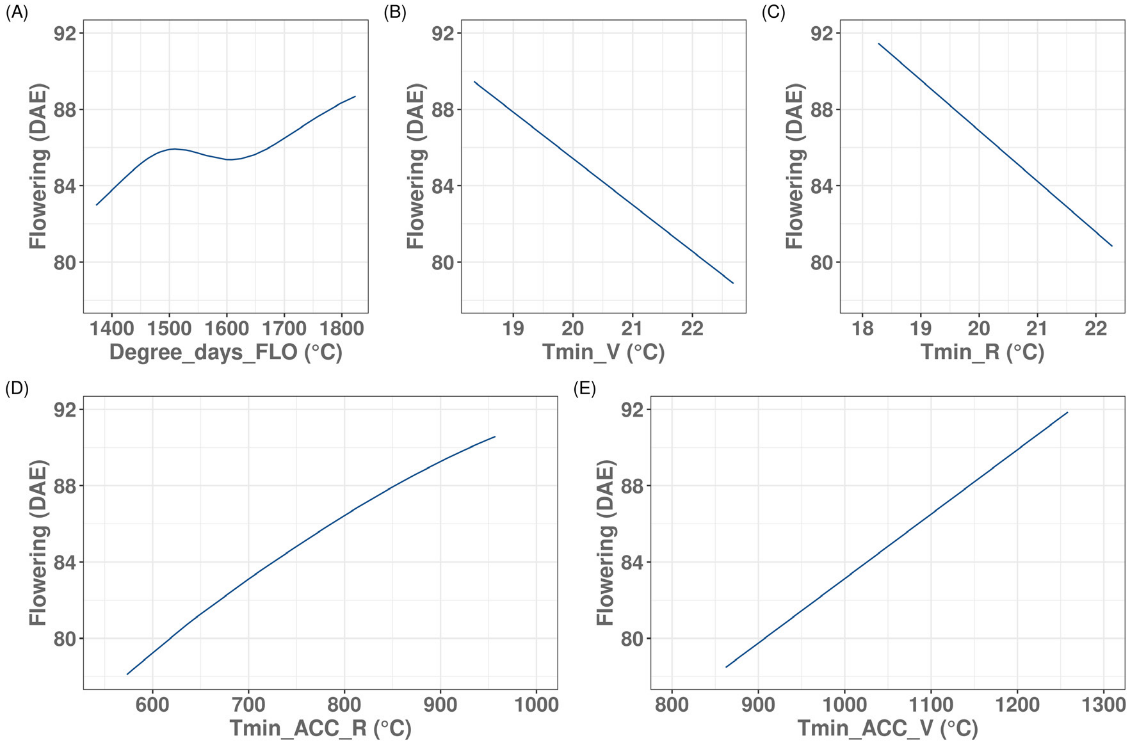

Figure 5: Flood-irrigated rice flowering prediction in the Midwest region by varying the predictors and keeping the other covariates fixed at the mean.

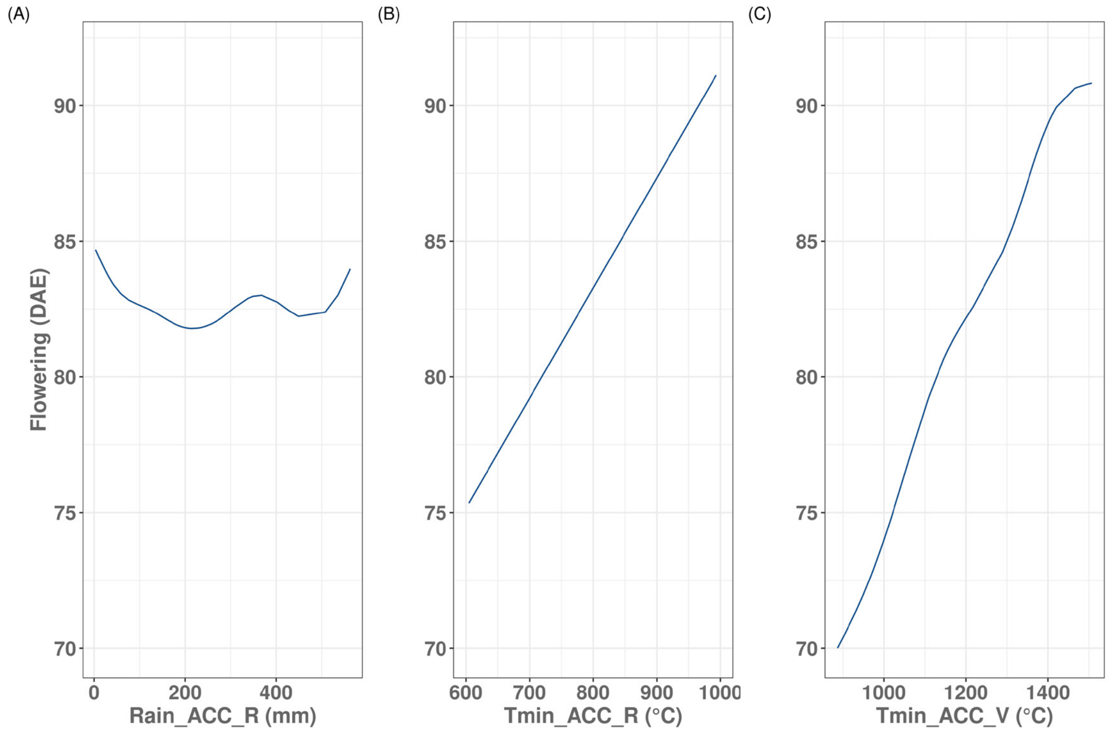

Figure 6: Flood-irrigated rice flowering prediction in the North region by varying the predictors and keeping the other covariates fixed at the mean.

Among the climate variables, Rain_ACC_R had the least impact on flowering (Figure 6A). On the other hand, increasing Tmin_Max accelerates flowering linearly. Furthermore, as observed in the Midwest region, the increase in Tmin_ACC_V and Tmin_ACC_R delays flowering (Figures 6C and B).

DISCUSSION

There are similarities in the trends of climate variables between the regions. That is particularly noticeable for the temperature-related variables. The increase in minimum temperature tends to advance flowering, as it stimulates photoinduction in rice (Yin *et al*., 1996). However, suppose the maximum temperature exceeds the photosynthetic thermal optimum, approximately 27 °C (Sánchez *et al*., 2014), at which maximum development occurs. In that case, the vegetative phase may be extended, given the decreased photosynthetic rate and increased respiration rate.

Studies report that temperature is the main determinant of the time and length of key developmental phases, including flowering, and an important determinant of plant growth (Craufurd & Wheeler, 2009; Bahuguna & Jagadish, 2015). Flowering late may not be interesting because it may lead to less grain filling despite promoting greater biomass accumulation. Moreover, longer periods in the field make plants subject to biotic and abiotic stresses (Srikanth & Schmid, 2011).

According to this study's results, the main environmental factor in both regions advancing flowering is the increase in minimum temperature. We observed through prediction that the increment of days over flowering is greater when related to air temperature. Rushing & Primack (2008) found that the temperature rise by 2.4 °C from 1852 to 2006 modified the flowering time of North American species, leading to a seven-day advance in the flowering date. Furthermore, historical flowering date data for over 400 plant species collected over a few centuries evidenced that flowering periods advanced, on average, by 4-6 days per degree centigrade increase (Jagadish *et al*., 2016).

On the other hand, early flowering can result in reduced biomass and, consequently, reduced grain yield (Srikanth & Schmid, 2011). Plants also have mechanisms to prevent early flowering. The thermal sum requirement is an important mechanism (Steinmetz *et al*., 2009; Taiz *et al*., 2017).

Plants can accurately answer the change in temperature, which is simultaneously perceived in all cellular components. In contrast, plant responsiveness to thermal variation can change depending on phenological and developmental phases (Bahuguna & Jagadish, 2015). In the juvenile phase, the plant does not respond to the flowering stimuli. However, as the plant moves into the adult vegetative phase, it becomes fit for flowering. Therefore, in the GAM model, only Tmin_ACC_R, Rain_ACC_R, and Tmin_ACC_V were discussed, as they represent the correct stimuli (Taiz *et al*., 2017). This response is also strongly influenced by other environmental factors, such as relative humidity and global solar radiation (photoperiod) (Bahuguna & Jagadish, 2015).

CONCLUSIONS

The genotypes' choices and tendencies, the climate variables set, and their importance and effect depend on the cultivation region.

Overall, temperature-related variables were present in greater numbers in the statistical models used in this study.

The GAM model performed better than the linear model for predicting flood-irrigated rice flowering in the Midwest and North regions.

The permanence of longitude as a discriminated variable for the North region may be a warning that this macro-region should be segmented in new analyses.

Increased minimum temperatures, regardless of phenological phase, tend to advance flowering, while increased minimum and maximum accumulated temperatures tend to delay flowering.

For the studied regions, it is recommended to avoid periods of low temperatures regardless of the phenological stage.

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