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Statistics/ Original Article

Maize productivity based on a distributional regression approach

Abstract – The objective of this work was to propose the use of traditional models based on distributional regression models to analyze maize productivity. The experiment was carried out in an alpha lattice design, with three replicates and 24 blocks. Data used refer to 102 maize plants from the permanent collection of the Centro de Desenvolvimento Científico e Tecnológico para a Agricultura of the Universidade Federal de Lavras. For the maize productivity evaluation, the following explanatory variables were used: weight of 100 seed, plant height, ear height, and days to maturation. The initial analyses involved the fitting of four distributions (gamma, generalized gamma, inverse Gaussian, and generalized inverse Gaussian) to the data, in which the gamma distribution showed the best fit based on the Akaike and Bayesian information criteria (AIC and BIC). Cob height has a considerable influence on the productivity variability because as cob height increases, the productivity variability decreases, whereas the covariates weight of 100 seed and days to maturity explain the increasing average of the productivity. The residual analysis shows that the model based on gamma distribution is suitable for explaining the data and providing useful insights for agricultural research and practice.

Index terms: *Zea mays*, gamma regression, traditional models.

Produtividade do milho com base em uma abordagem de regressão distribucional

Resumo – O objetivo deste trabalho foi propor a utilização de distribuições tradicionais com base em modelos de regressão distribucional, para analisar a produtividade do milho. O experimento foi realizado em um delineamento alfa látice, com três repetições e 24 blocos. Os dados usados referem-se a 102 plantas de milho que são parte da coleção permanente do Centro de Desenvolvimento Científico e Tecnológico para a Agricultura, da Universidade Federal de Lavras. Para a avalição da produtividade do milho utilizaram-se as seguintes variáveis explicativas: peso de 100 sementes, altura da planta, altura da espiga e dias para a maturação. As análises iniciais envolveram o ajuste de quatro distribuições (gama, gama generalizada, inversa Gaussiana e inversa Gaussiana generalizada) aos dados, em que a distribuição gama foi a que melhor se ajustou, com base nos critérios de informação de Akaike e bayesiano (AIC e BIC). Notavelmente, a altura da espiga tem uma influência considerável sobre a variabilidade da produtividade porque conforme a altura aumenta, a produtividade diminui, enquanto as covariáveis peso de 100 sementes e dias para a maturação explicam a média crescente da produtividade. A análise residual mostra que o modelo baseado na distribuição gama é adequado para explicar os dados e fornecer informações úteis para a pesquisa e a prática agrícolas.

Termos para indexação: *Zea mays*, regressão gama, modelos tradicionais.

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Introduction

Maize (*Zea mays*) is an agricultural crop from the Poaceae family that holds significant economic and social importance, being one of the most used and cultivated crops worldwide. According to Erenstein et al. (2022), the high socioeconomic role of this crop is attributable to several aspects, including its high productive potential, its use in both human and animal consumption, and its essential position in agribusiness as a raw material for numerous sectors. However, among the 117 countries producing maize globally, Brazil ranks 33rd in average grain productivity (5,550 kg ha^{-1}), which is considered substantially low in comparison with that of the USA (11,110 kg ha^{-1}) (USDA, 2022).

Several authors have applied traditional statistical regression models to analyses of maize productivity, as following described. Seffrin et al. (2018) used this method to predict maize productivity in Paraná state, Brazil, from 2012 to 2014. Chipenete et al. (2022) employed this model to fit spatial data related to areas cultivated with improved maize seed in Mozambique. Furthermore, Bruning et al. (2023) applied this methodology to evaluate the development and production of maize crops subjected to different magnesium doses by foliar application. Soares et al. (2022) researched the effects of silicon on maize productivity and earworm damage reduction on this crop, in plantations in Teresina, Brazil. Macedo et al. (2023) used this methodology to analyze the physical and physiological quality and on the productivity of 'UFVM 100 Nativo' maize seed, derived from fields fertilized with various levels of poultry litter as top-dressing.

The problem of using the above-mentioned model lies in the empirical assumption that productivity is completely symmetrical, and that it can be described by the Gaussian distribution, which may not necessarily hold true. Furthermore, covariates are sought solely to influence the mean productivity; however, it may be of interest to examine those that affect variability in this response. In this context, the distributional regression models, firstly introduced as generalized additive models for location, scale, and shape (GAMLSS) (Rigby & Stasinopoulos, 2005) may be an interesting alternative, since, depending on the complexity of the data, they can detect which covariates affect not just the mean of the response, but also all of its properties (for instance, variability). Studies by Agudo-Domínguez et al. (2022) and Righetto et al. (2019) show the growing use of GAMLSS in agricultural applications.

The objective of this work was to propose the use of traditional models based on distributional regression models, to analyze maize productivity.

Materials and Methodss

The experiment was carried out between November 2021 and March 2022, in the experimental area of Muquém Farm (21°12'S, 45°59'W, at 918.84 m altitude), at the Centro de Desenvolvimento Científico e Tecnológico para a Agricultura of the Universidade Federal de Lavras, in the municipality of Lavras, in the state of Minas Gerais, Brazil. The soil is a Latossolo Vermelho-Amarelo, with gently undulating relief, according to the Brazilian soil classification system (Santos et al., 2018), which corresponds to an Oxisol. According to the Köppen-Geiger's classification, the climate is rainy temperate (Cwa), with temperatures of 23.74°C, and precipitation of 232.56 mm during the trial (Lavras Meteorological Station: 21°13'34"S, 44°58'47"W).

Information regarding the 102 full-sib maize progenies resulting from the crossing of two base populations (A and B), which were originally obtained from two commercial single-cross hybrids, was used. The plants were organized in an alpha lattice design, with 3 replicates and 24 blocks. Sowing took place on November 16, 2021, with seeding density at 4 seed per linear meter in plots of 4 m length, and row spaced at 0.6 m apart. Fertilization was applied at planting with 250 kg ha^{-1} of fertilizer comprising 8% N, 28% P_2O_5, and 16% K_2O. A top-dressing fertilization with 200 kg ha^{-1} of granulated urea-N (45% N) was applied 25 days after sowing.

The candidate explanatory variables that were collected in addition to maize productivity, the response variable of interest, as well as their possible values are presented (Table 1). All information on the dataset can be found in Pedro et al. (2023).

For the statistical modelling process, in general, if follows a distribution $D(\theta_k)$, where θ_k represents a parameter vector, then GAMLSS can be defined as

$$g_k(\theta_k) = \eta_k = X_k\beta_k + \sum_{j=1}^{Jk} s_{jk}\left(x_{jk}\right),$$

where: $g_k(\cdot)$, k = 1,2,3,4, denotes a known monotonic function that relates the distribution parameter θ_k to its predictor η_k; X_k is a design matrix; β_k is a vector of parameters; and $s_{jk}(\cdot)$ are smoothing functions, for instance, P-splines (Eilers et al., 2015) used to explain the relationship between the covariate x_{jk} and θ_k (Rigby & Stasinopoulos, 2005). If $\sum_{j=1}^{J_k} s_{jk}(x_{jk}) = 0,$ then we have the full parametric GAMLSS (Righetto et al., 2019).

The first stage in modelling maize productivity is to choose a probability distribution D that would best describe its behavior. Thus, exploratory marginal analyses and residuals are widely used (Nakamura et al., 2017). Among the more than 100 distributions available in the gamlss.data package of the R software (R Core Team, 2023), the four distributions that best suited the response and that were thus considered in this study were the gamma (GA), generalized gamma (GG), inverse Gaussian (IG), and generalized inverse Gaussian (GIG) distributions.

To facilitate the interpretation of GAMLSS, the utilized parameterization of the distributions frequently differs from those generally reported in the literature (Rigby et al., 2019). In the GAMLSS framework, the probability density function (PDF) of the GA distribution is given by

$$f(\mu,\sigma) = \frac{y^{1/\sigma^2-1}}{(\sigma^2\mu)^{1/\sigma^2}\,\Gamma\left(1/\sigma^2\right)}\exp\left[-\frac{y}{\sigma^2\mu}\right],$$

where: $\mu>0$ is the mean of the distribution, and $\sigma>0$ is a dispersion parameter. Furthermore, the PDF of a GG distribution can be expressed as

$$f(y|\mu,\sigma,\nu) = \frac{|\nu|\theta^{\theta}y^{\nu\theta-1}}{\Gamma(\theta)\mu^{\nu}}\exp\left(-\frac{\sigma y^{\nu}}{\mu^{\nu}}\right),$$

where: $\mu>0$ is a scale parameter, $\sigma>0$ is a dispersion parameter; and $\nu>0$ or $\nu<0$ is a shaper parameter, and $\theta=1/(\sigma^2\nu^2)$. Note that if $\nu=0$, we have the log-normal distribution (Rigby et al., 2019). Moreover, the PDF of an IG distribution is defined as

$$f(\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2y^3}}\exp\left[-\frac{1}{2\mu^2\sigma^2y}(y-\mu)^2\right],$$

where: $\mu>0$ is the mean of the distribution; and $\sigma>0$ is a dispersion parameter. Finally, the PDF of a GIG distribution is given by

$$f(y|\mu,\sigma,\nu) = \left(\frac{b}{\mu}\right)^{\nu}\left[\frac{y^{\nu-1}}{2K_{\nu}\left(\frac{1}{\sigma^2}\right)}\right]\exp\left[-\frac{1}{2\sigma^2}\left(\frac{by}{\mu}+\frac{\mu}{by}\right)\right],$$

where: $\mu>0$ is the mean of the distribution; $\sigma>0$ is a dispersion parameter; $-\infty<\nu<\infty$ is a shape parameter;

$$b = [K_{\nu+1}(1/\sigma^2)][K_{\nu}(1/\sigma^2)]^{-1};\ \text{and}$$

$$K_{\lambda}(t) = \frac{1}{2}\int_0^{\infty} x^{\lambda-1}\exp\left\{-\frac{1}{2}t\left(x+x^{-1}\right)\right\}dx$$

is the Bessel function of the second kind.

Given the possibility of including different explanatory variables in any of the regression structures, distinct variable selection approaches can be used for their selection. The most popular of them is strategy A (Ramires et al., 2021), a stepwise-based procedure. Other research using this method can be found in Righetto et al. (2019).

All fitted models were evaluated using the generalized Akaike information criterion – GAIC, given by

$$GAIC(\kappa) = -2\hat{l}_p + \kappa\cdot df,$$

where: $\hat{l}_p$ is the fitted log-likelihood function; df if the effective degrees of freedom of the fitted model; and κ is a penalty. The smaller is the GAIC(κ), the better will be the model fit. When κ = 2, GAIC is reduced to the Akaike information criterion (AIC) (Akaike, 1974); and when κ = log(n), where n is the sample size, GAIC reduces to the Bayesian information criterion (BIC) (Schwarz, 1978).

After fitting the model, normalized quantile residuals, commonly displayed in worm plots, were used to test the model assumptions; further details can be found in Stasinopoulos et al. (2023).

Table 1. Covariates of maize (*Zea mays*) data set from the experiment carried out between November 2021 and March 2022, in the municipality of Lavras, MG, Brazil.

Variable	Range
Weight of 100 seed (g)	25.40 – 42.20
Plant height (cm)	190.00 – 301.70
Cob height (cm)	86.67 – 200.00
Days to maturity	105.00 – 143.00

Results and Discussion

Some descriptive statistics of the response maize productivity show that the mean and median response were 9,433.00 kg ha^{-1} and 9,321.00 kg ha^{-1}, respectively, with a standard deviation of 2,224.32 kg ha^{-1} (Table 2).

The marginal response distribution (Figure 1) was right-skewed (skewness equals 0.42), with slightly larger and heavier tails than the Gaussian distribution (kurtosis equals 0.46). Based on these characteristics, the GA, GG, GIG, and IG distributions are potential candidates for modelling the dataset under consideration.

After selecting the potential distribution to be considered in the model, pairwise relationships between the response variable and each of the candidate explanatory variables were observed (Figure 2).

The relationship between variables shows the weight of 100 seed and productivity, which has a positive correlation (Figure 2 A). In other words, larger seed may contain more nutrient reserves, which might benefit the plant development, potentially improving initial growth and, consequently, maize productivity. A positive correlation was also observed between both variables in an evaluation for the effect of applying grass inoculant in combination with a plant bioactivator, in the presence and absence of nitrogen top-dressing, on the agronomic development parameters and second-crop maize productivity (Cordeiro Júnior et al., 2019).

There was an apparent positive relationship between plant height and productivity and a noticeable dispersion (Figure 2 B). Our findings are consistent with those by Aman et al. (2020), who studied the phenotypic and genotypic relationships between grain yield and other morphological characteristics; these authors observed positive correlations between both variables and also between the weight of 100 seed and the response indicated in Figure 2 A. Furthermore, it is worth noting that plant height in most observations exceeds 220 cm, a finding also verified by Liu et al. (2017), who evaluated high-yielding maize plants with a potential yield of 22.5 Mg ha^{-1}, and also found a plant height value above 220 cm. Similarly, Doggalli et al. (2024), in their assessment of genetic diversity among 50 maize inbred lines found heights similar to those observed here.

The relationship between cob height and productivity showed a slight positive correlation with notable variability (Figure 2 C). Similar results were also found by Souza et al. (2020), in a study comparing the performance of different maize cultivars in organic systems; these authors found slight positive correlations between cob height and productivity

Table 2. Descriptive statistics for maize (*Zea mays*) productivity (kg ha^{-1}) from the experiment carried out between November 2021 and March 2022, in the municipality of Lavras, MG, Brazil.

Mean	Median	Standard deviation	Skewness	Kurtosis
9,433.00	9,321.00	2,224.32	0.42	0.46

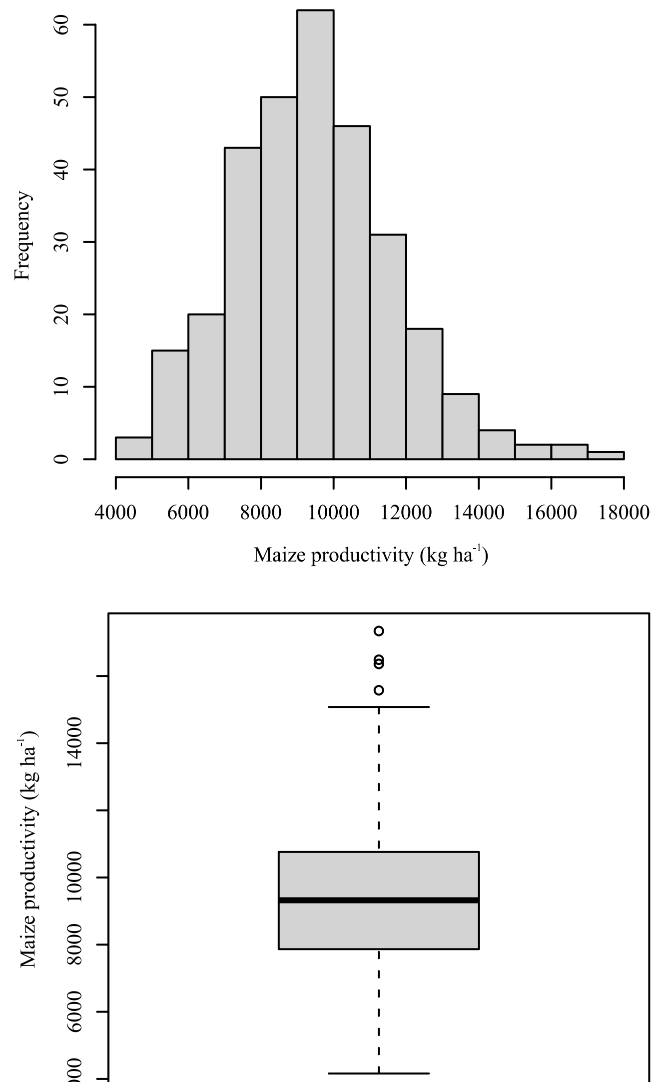

Figure 1. Maize (*Zea mays*) productivity from the experiment carried out between November 2021 and March 2022, in the municipality of Lavras, MG, Brazil: A, histogram; B, box plot.

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(0.39), as well as between plant height and response (0.47), suggesting that an increase in both covariates boosts productivity. Additionally, most observations show that the cob height reaches 120 cm, which is consistent with the findings by Melo et al. (2018), who assessed the performance of maize genotypes under water stress, in the southern part of Tocantins state, Brazil, and observed cob heights similar to those observed in the present work.

The relationship between days to maturity and productivity with some variation was observed as exceeding 120 days (Figure 2 D). Similar results were also observed in the estimation of water demand and crop coefficients in maize intercropped with brachiaria, with values greater than 120 days to maturity (Fietz et al., 2020).

Regarding the statistical modelling based on the GAMLSS framework, we proceeded with our analysis by selecting the covariates for each regression structure, in the four fitted distributions using strategy A. The values of AIC and BIC for the best-fitted model for each of these distributions are presented (Table 3).

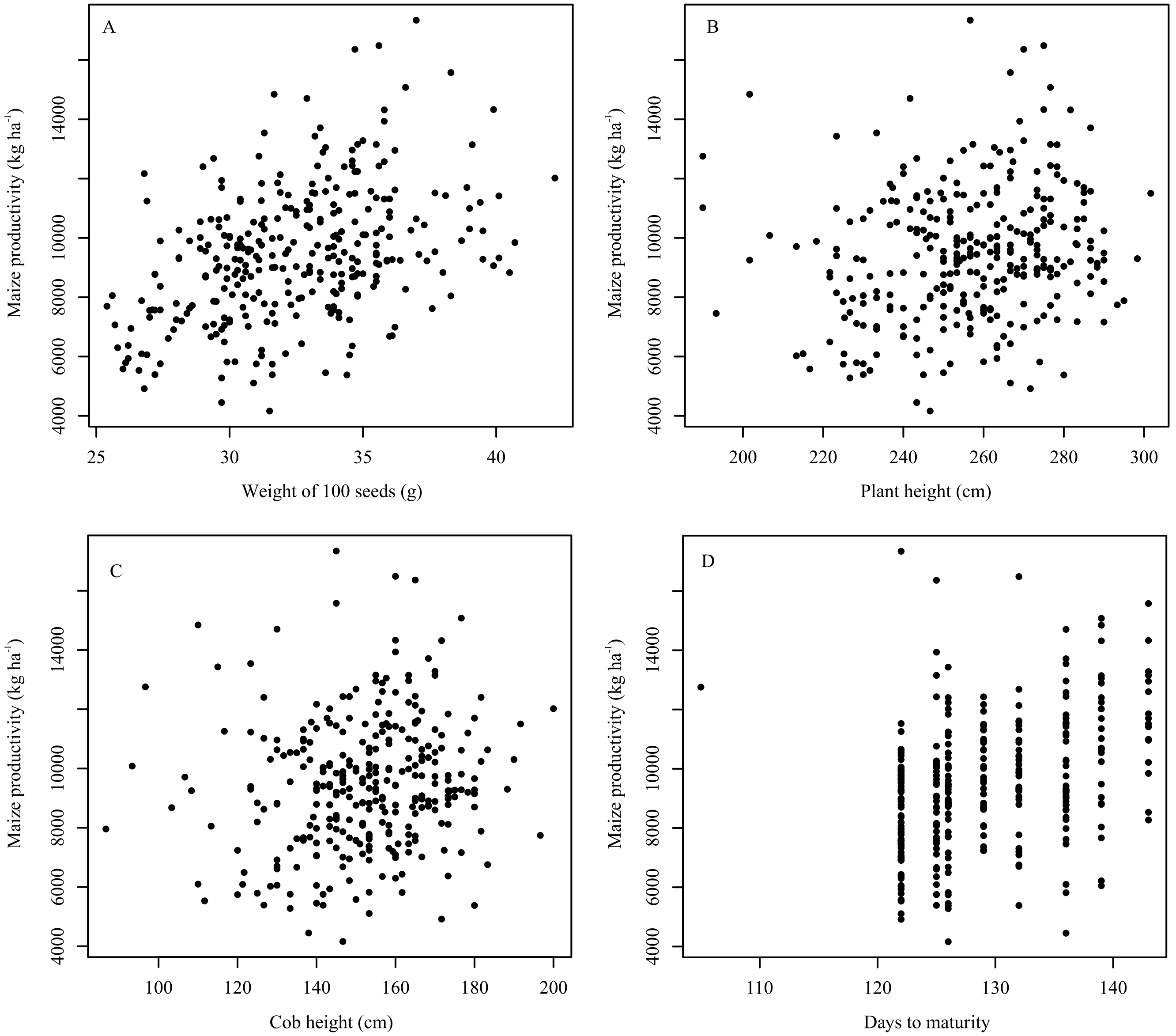

Figure 2. Relationship between maize (*Zea mays*) productivity and explanatory variables: A, weight of 100 seed; B, plant height; C, cob height; and D, days to maturity.

The best-fitted distribution was GA (with AIC and BIC values of 5,503.397, and 5,530.317, respectively), indicating that it provided the best fit for predicting maize productivity (Table 3). The final fitted GAMLSS based on the GA distribution can be expressed as

$\hat{\mu}$ =exp{7.2863+s[weight of 100 seeds]+s[days to maturity]} and $\hat{\sigma}$ =exp{-0.4143-0.0077[cob height]}.

It can be seen that smoothing functions were only necessary to model the average of maize productivity ($\hat{\mu}$). According to Ramires et al. (2019), we usually do not perform tests for such functions. In these circumstances, only the effect of the function on the parameter of the response distribution is graphically examined (Figure 3).

To explain the average productivity based on the covariate weight of 100 seed, a smoothing function has been fitted (Figure 3 A). It is clear that the function accurately captured the behavior observed (Figure 2 A); namely, an increasing average up to approximately 38 g, followed by a much slower growth is evident. This finding is consistent with prior studies by Cordeiro Júnior et al. (2019), Devasree et al. (2020), and Verma et al. (2020).

The average productivity remained constant until approximately 120 days, after which it begun to increase (Figure 3 B). This behavior is similar to the one indicating that productivity positively varies after 120 days of maturity (Figure 2 D). Such results are similar to those obtained by Fietz et al. (2020), but differ from those reported by Pranay et al. (2022), who found a nonsignificant negative correlation. Linear relationships as imposed by traditional regression models (or simply computing the Pearson's correlation coefficient) would not adequately explain the relationships (particularly in Figure 3 B). Regarding the fitted model to explain the dispersion parameter ($\hat{\sigma}$), we can see that the cob height was significant at 5% probability, showing its influence on maize productivity variability. For each additional centimeter of the cob height, there is an expected decrease of units, that is, units in the variability of maize productivity, whose pattern can be observed (Figure 2 C).

The worm plot obtained from the normalized quantile residuals of the final fitted model (Figure 4)

Table 3. Akaike (AIC) and Bayesian (BIC) information criteria for the best-fitted generalized additive models for location, scale, and shape (GAMLSS), based on each of the four distributions under study from the experiment carried out between November 2021 and March 2022 in the municipality of Lavras, MG, Brazil.

Distribution	AIC	BIC
GA	5,503.397	5,530.317
GG	5,504.024	5,534.989
GIG	5,506.865	5,539.168
IG	5,519.702	5,539.466

GA: gamma distribution. GG: generalized gamma distribution. GIG: generalized inverse Gaussian distribution. IG: inverse Gaussian distribution.

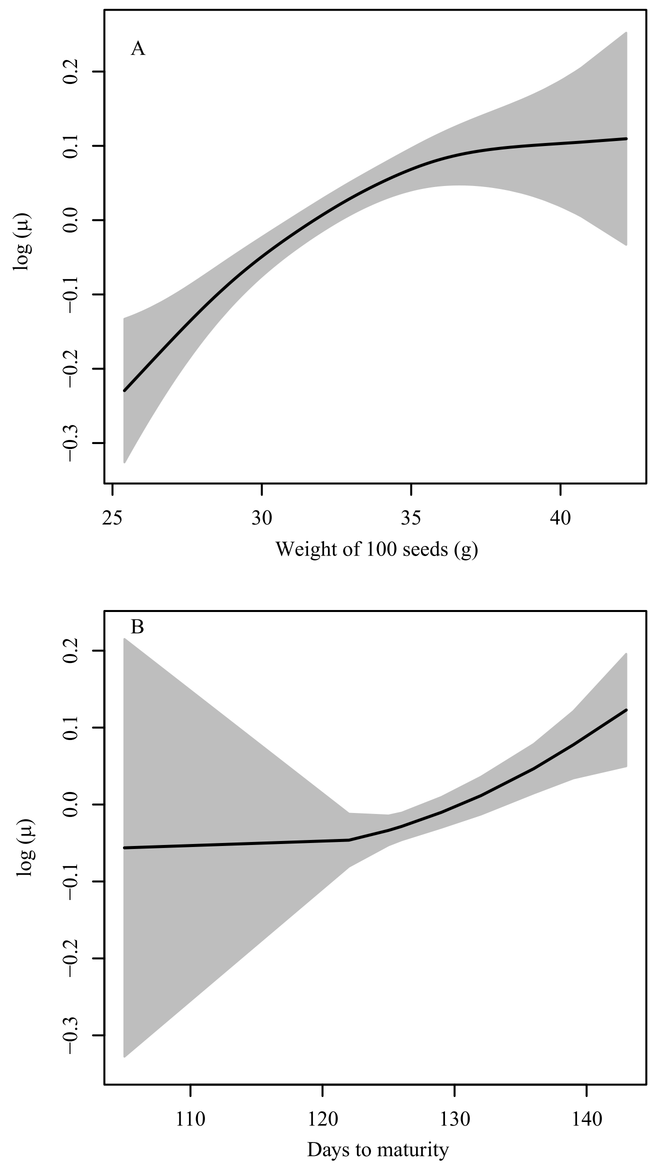

Figure 3. Smoothing function fitted to explain maize (*Zea mays*) mean productivity by the following covariates: A, weight of 100 seed; and B, days to maturity.

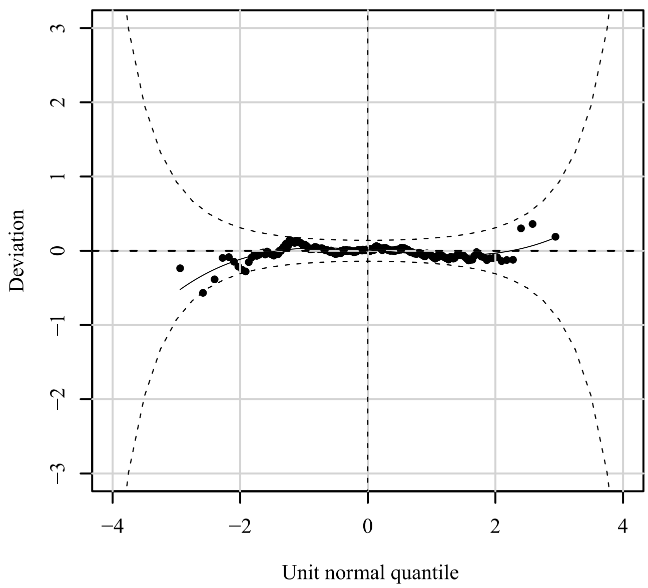

Figure 4. Normalized quantile residuals obtained from the fitted generalized additive models for location, scale, and shape (GAMLSS) based on the gamma distribution (GA).

shows that all observations fall within the 95% confidence interval, and no clear pattern is evident. Therefore, we may conclude that the GAMLSS based on the GA distribution is appropriate for explaining maize productivity and produces reliable inferences. For future research, additional features, such as ear length, cob diameter, number of ears per plant, and anthesis-silking interval should be considered. Furthermore, this methodology is easily adaptable to other cultivars, varieties, and crops.

Conclusions

1. The generalized additive models for location, scale, and shape (GAMLSS), also known as distributional regression models, are appropriate for evaluating maize (*Zea mays*) productivity data.

2. After evaluating four distributions with the stepwise-based procedure strategy A, the gamma distribution is the most suitable for representing the response, providing a precise description of the dataset under review.

3. This model gives useful insights for modelling both the average and dispersion of the productivity, allowing of a clear and objective interpretation of the nature of the response variable.

4. The importance of cob height in the modelling of the dispersion parameter emphasizes its major effects on productivity variability, with each additional centimeter of this covariate related to 0.77% decrease in the productivity variability, whereas both the weight of 100 seed and days to maturity are important to explain the productivity mean.

5. The study of the worm plot – created from normalized quantile residuals – validates the ability of the fitted GAMLSS based on the gamma distribution to effectively describe, interpret and predict the data.

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