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Bayesian approach for evaluating ammonia volatilization nitrogen losses in fertilizers applied to coffee plants

Abordagem Bayesiana para avaliar as perdas de nitrogênio por volatilização de amônia em fertilizantes aplicados no cafeeiro

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ABSTRACT

Ammonia loss through volatilization is an important reason for the lower effectiveness of nitrogen fertilizers in coffee plants. The Bayesian approach uses informative prior distributions, which help improve the precision and accuracy of inferences, leading to more robust parameter estimates. In this study, we compared the performance of different nitrogen sources applied to coffee plants in terms of nitrogen loss due to ammonia volatilization, using the nonlinear von Bertalanffy model with Bayesian inference. The stabilized fertilizers used were prilled urea (45% N), urea treated with copper and boron (44% N, 0.4% B, and 0.15% Cu), and urea treated with NBPT (45% N). The controlled-release fertilizer used was urea combined with anionic polymer (41% N). The controlled-release fertilizer used was urea combined with anionic polymer. Among the sources of nitrogen, urea coated with polymer resulted in the most significant nitrogen loss, whereas urea treated with NBPT resulted in the lowest loss of nitrogen. Compared to the other fertilizers used, urea treated with NBPT resulted in the lowest nitrogen loss through volatilization, with less than 50% of the nitrogen lost relative to urea with anionic polymers. The Bayesian methodology used provided accurate estimates and enabled a direct comparison between the fertilizers based on the marginal distribution of the von Bertalanffy model parameters.

Index terms: von Bertalanffy; urea; stabilized fertilizers.

RESUMO

A perda de amônia por volatilização é uma razão importante para a menor eficácia dos fertilizantes nitrogenados em cafeeiros. A abordagem bayesiana utiliza distribuições a priori informativas, que ajudam a melhorar a precisão e a acurácia das inferências, levando a estimativas de parâmetros mais robustas. Neste estudo, comparamos o desempenho de diferentes fontes de nitrogênio aplicadas em cafeeiros em termos de perda de nitrogênio devido à volatilização de amônia, utilizando o modelo não linear de von Bertalanffy com inferência bayesiana. Os fertilizantes estabilizados utilizados foram ureia granulada (45% N), ureia tratada com cobre e boro (44% N, 0,4% B e 0,15% Cu) e ureia tratada com NBPT (45% N). O fertilizante de liberação controlada foi a ureia combinada com polímero aniônico (41% N). Entre as fontes de nitrogênio, a ureia revestida com polímero resultou na maior perda de nitrogênio, enquanto a ureia tratada com NBPT apresentou a menor perda. Comparado aos outros fertilizantes utilizados, a ureia tratada com NBPT apresentou menos de 50% de perda de nitrogênio em relação à ureia com polímeros aniônicos. A metodologia bayesiana utilizada forneceu estimativas precisas e permitiu uma comparação direta entre os fertilizantes com base na distribuição marginal dos parâmetros do modelo de von Bertalanffy.

Termos para indexação: von Bertalanffy; ureia; fertilizantes estabilizados.

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Introduction

Brazil is the largest coffee producer in the world; the high volume of coffee produced reflects significant advances in agricultural management. According to the Brazilian Coffee Exporters Council, Brazil exported more than 37 million 60-kg bags of coffee to 117 countries in 2022–2023 (Conselho dos Exportadores de Café do Brasil - Cecafe, 2023).

Reetz (2017) showed that the sustainability of agricultural production depends on a viable and efficient global fertilizer industry. This industry plays a crucial role in providing the necessary nutrients in the right amounts, at the right time, and in the right places, thus contributing to high crop productivity. Nitrogen fertilizers play an important role in achieving satisfactory agricultural production (Freitas et al., 2022).

The most commonly used source of nitrogen (N) is urea, which contains more nitrogen per kilogram of product than other nitrogen sources (45%). Because urea is nitrogen-rich, its use has several advantages over the use of different nitrogen sources, such as ammonium nitrate. Urea is more affordable, easier to

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store, and results in lower greenhouse gas emissions related to industrial production. However, it increases the loss of ammonia via volatilization (Fernandes et al., 2015; Guardia et al., 2021).

Ammonia volatilization is a physicochemical process influenced by soil properties (such as texture, pH, and cation exchange capacity), meteorological factors (including wind speed, temperature, and precipitation), and nitrogen fertilization management practices (such as the source, rate, timing, and placement) (Hurtado et al., 2023). This process is a major contributor to environmental degradation, as it indirectly exacerbates global warming by transforming into N_2O in the atmosphere (Nyameasem et al., 2024; Wu et al., 2024). Furthermore, ammonia volatilization causes soil acidification, water eutrophication, and biodiversity loss (Ferdous et al., 2024).

Several strategies can be implemented to decrease ammonia emissions, such as incorporating fertilizer into the soil, using high-efficiency fertilizers such as coated or slow-release urea, applying urease inhibitors, and applying fertilizer under specific climatic conditions, such as before rain or at low temperatures (Bittman et al., 2014).

Understanding how each of these technologies for nitrogen fertilizer application can contribute to mitigating nitrogen loss and improving the efficiency of fertilizers in coffee plantations is crucial (Souza et al., 2017). The loss of nitrogen in agricultural systems can significantly limit crop production and environmental sustainability (Panday et al., 2020).

Ammonia volatilization follows a sigmoid pattern, with a gradual increase followed by an increase and then a decrease, with volatilization stabilizing at a maximum value (Minato et al., 2020; Trenkel, 2010).

Nonlinear regression models can be used to represent the sigmoidal curve. These models are characterized by considerable fit quality even when a few parameters are used (Fernandes et al., 2024). The estimates of these parameters have practical and/or biological implications.

Generally, studies on nitrogen loss due to volatilization primarily focused on the frequentist approach. An alternative for fitting these models is the Bayesian inference approach. Besides providing greater precision, the Bayesian approach can enable consistent inferences even with a small number of observations (Salles et al., 2020; Fernandes et al., 2022). This approach considers observations and model parameters as random variables (Pereira et al., 2022). Moreover, the Bayesian approach uses informative prior distributions, which make the inferences precise and accurate, leading to more robust parameter estimates. This results in more reliable predictions, especially when there are uncertainties or limited data availability (Carvalho et al., 2017). Another advantage of this approach is its greater efficiency in predicting future values than the frequentist inference approach (Ribeiro et al., 2018). This is the first study to apply the Bayesian approach to assess these losses.

The Bayesian approach entails deriving information from observed samples, represented as likelihood values, combined with prior knowledge regarding the characteristics of interest, referred to as a priori information, to produce a probability density, known as the a posteriori distribution (Salles et al., 2020). This method relies on Bayes' theorem and yields probability distributions for the parameters, enabling a straightforward interpretation of credible intervals (Silva et al., 2020). In this study, we compared the performance of different nitrogen sources applied to coffee plants in terms of nitrogen loss due to ammonia volatilization using the nonlinear von Bertalanffy model with Bayesian inference.

Material and Methods

The data analyzed are from an experiment conducted by Freitas et al. (2022) in coffee plantations under field conditions during the 2016–2017 harvest season in Lavras, Minas Gerais (MG), Brazil. The cultivar used was Catuaí Vermelho IAC 144 of the species *Coffea arabica* L. At the beginning of the experiment, the plantation was six years old. The spacing was 3.7 m between rows and 0.7 m between plants in the same row. The experiment used a randomized block design with three replications. Each experimental plot consisted of 12 plants, with the eight central plants used for evaluation. The plots were arranged along the planting rows within each block, with treatments randomly assigned to these plots. One planting row was always left untreated, serving as a border. The experimental units are independent over the days.

The fertilizers used in this study were selected based on the technologies implemented in coffee production systems in Brazil. All fertilizers were photographed with a Canon DSLR SL3 camera and an Olympus SZ60 microscope from Japan. Controlled-release fertilizers were characterized by scanning electron microscopy (SEM) and energy-dispersive X-ray spectroscopy (EDS).

In this study, we used stabilized fertilizers, which contained additives that could inhibit or delay certain nitrogen transformation processes in soil: 1) prilled urea (45% N), 2) urea treated with copper and boron (44% nitrogen; 0.4% boric acid, and 0.15% copper as copper sulfate), and 3) urea treated with NBPT (45% nitrogen). The controlled-release fertilizer consisted of urea combined with anionic polymer (41% nitrogen).

The experimental design involved establishing randomized blocks in the field with three repetitions. The dose of 300 kg ha^{-1} fertilizer was divided into three applications. All fertilizers were applied on the surface and under the canopy of the coffee plants. For the 2016–2017 crop, the fertilizers were applied on November 6, 2016, January 11, 2017, and March 10, 2017.

The volatilization losses of ammonia were quantified using a semi-open collector. Thirty days before the fertilizer was applied, three PVC bases (0.2 m in height and 0.2 m in diameter) were installed in each experimental plot under the coffee plant canopy and at a depth of 0.05 m in the soil. These were placed over fixed bases of the same material on the ground. The collectors were shielded at the top with plastic covering and wire, allowing for a gap between the protection and the collector, thus enabling airflow.

Three bases were established in each plot, and fertilizers were applied within these bases in quantities corresponding to those used in the treated area. Fertilizers were measured using a precision scale one day prior to each application. To ensure uniform exposure to temperature, precipitation, and air humidity, the collectors were rotated among the bases during each assessment. Two sponges (with a density of 0.02 g cm^{-3} and 2 cm thickness) were placed inside the collectors and cut to match the diameter of the chambers. The upper sponge protected the lower sponge from contamination by impurities or insects. The lower sponge was soaked in a solution of phosphoric acid (H_3PO_4; 60 mL L^{-1}) and glycerin (50 mL L^{-1}) to capture the volatilized ammonia and was positioned inside the collector 30 cm above the ground, whereas the upper sponge was placed 40 cm above the ground.

During the 2016–2017 harvest, nitrogen losses were evaluated on the 1st, 2nd, 3rd, 4th, 5th, 6th, 8th, 10th, 13th, 16th, 20th, 24th, 29th, and 34th days of the experiment. After the sponge was changed, the chamber was rotated among the bases to account for spatial variability in ammonia emissions. This rotation was adjusted for significant climatic variations, including changes in temperature and precipitation. The solution from the sponges collected in the field was extracted through filtration using a Büchner funnel attached to a vacuum pump. The process consisted of 10 sequential washes, each utilizing 40 mL of deionized water. The resulting extracts were stored in a cold chamber for up to five days prior to analysis. Subsequently, 20 mL aliquots were taken from the extracts for nitrogen content determination by distillation following the Kjeldahl method (Kjeldahl, 1883). The von Bertalanffy model can represent the losses of ammonia by volatilization from fertilizers applied in coffee cropping systems (Fernandes et al., 2024).

Therefore, the von Bertalanffy regression model (Equation 1) was used to describe the volatilization loss using the following parameterization.

$$Y_i = \alpha\left(1 - \frac{\exp(\kappa(\beta - x_i))}{3}\right)^3 + \varepsilon_i \quad (1)$$

Here, Y_i represents the observed accumulated loss of ammonia for i = 1;...;14, x_i represents the i^{th} observation of the accumulated loss of ammonia; α is the horizontal asymptote, i.e., the highest percentage of nitrogen released by the fertilizer; κ represents the growth rate (the higher the value of κ, the less time it takes to reach α); β represents the abscissa of the inflection point, from which ammonia loss decelerates; and ε_i represents the random error, which is assumed to be independently and identically distributed following a normal distribution with zero mean and constant variance; that is, $\varepsilon \sim N(0,\sigma^2)$ (Pinho et al., 2014).

Thus, the parameter vector for the von Bertalanffy model is represented as θ' = [α, β, κ]. The next step in implementing Bayesian analysis involves specifying prior distributions. Eliciting prior distributions for the parameters is crucial for conducting a Bayesian analysis (Moala & Penha, 2016).

Therefore, in this study, a beta distribution was used because, according to Moala and Penha (2016), it is one of the most commonly used distributions for a priori modeling. $P(\theta) \propto \theta^{a-1}(1-\theta)^{b-1}$, where a and b are hyperparameters (known) of the beta distribution.

As highlighted by Fernandes et al. (2022), the parameters of nonlinear models have practical interpretations. Therefore, defining precise intervals for the parametric space of each parameter is easy; thus, prior distributions were established based on this interpretation and are presented in Table 1.

Table 1: Prior distributions with their hyperparameters for the four fertilizers studied.

Fertilizers	Parameter	Prior distributions
Prilled urea	α	64*Beta (2,2)
	β	34*Beta (2,10)
	κ	Beta (10,2)
Urea treated with copper and boron	α	44*Beta (2,2)
	β	34*Beta (2,10)
	κ	Beta (10,2)
Urea + anionic polymer	α	72*Beta (2,2)
	β	34*Beta (2,10)
	κ	Beta (10,2)
Urea treated with NBPT	α	36*Beta (2,2)
	β	34*Beta (2,10)
	κ	Beta (10,2)

The parametric space of the Von Bertalanffy model, in this case, was positive for all parameters; therefore, the priors were defined through an analysis of the scatter plot. A priori for the parameter α was proposed as n * Beta (2,2), where n is the highest observed value for each treatment. Thus, the shape of the density of n * Beta (2,2) will occur at half of this highest observed value for each treatment.

The data were measured over 0–34 days. The inflection point occurred before the midpoint of this range. Therefore, a right-skewed distribution was created for the parameter β; thus, the prior was given by 34 * Beta (2,10).

Regarding the parameter κ, hyperparameters were used for left asymmetry, as a very rapid loss was noted when analyzing the data, suggesting high values for κ.

Considering the independence between the priors, the joint prior distribution for the vector of parameters of interest was determined by the product of the individual priors $P(\theta) \propto P(\alpha)P(\beta)P(\kappa)$. The likelihood was defined assuming normality of the errors, as given in Equation 2.

$$L(\theta \mid Y) = (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left\{\frac{-(Y-\mu)^{'}(Y-\mu)}{2\sigma^2}\right\} \tag{2}$$

As indicated by Bayes' theorem, the posterior distribution is the combination of the a priori distribution with the likelihood given by $P(\theta \mid Y) \propto L(\theta \mid Y)P(\theta)$ (Equations 3 and 4). Therefore, the expression for the joint posterior distribution is as follows:

$$P(\theta \mid Y) \propto (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left\{\frac{-(Y-\mu)^{'}(Y-\mu)}{2\sigma^2}\right\} \times P(\theta) \tag{3}$$

$$P(\theta \mid Y) \propto \exp\left\{\frac{-(Y-\mu)^{'}(Y-\mu)}{2\sigma^2}\right\} \times P(\theta) \tag{4}$$

Where, Y represents the observed data and μ represents a vector composed of the von Bertalanffy model, where σ^2 and θ were previously defined.

The Monte Carlo method using Markov chains (MCMC) was employed to approximate the posterior marginal distributions of each parameter. Due to the unknown expressions of the posterior joint and complete conditional distributions, the Metropolis-Hastings algorithm was applied.

The convergence of the chains was assessed using the criteria proposed by Geweke (1992) and Raftery and Lewis (1992). According to the Geweke criterion, convergence is indicated when the absolute value of the result is less than 1.96. The decision rule for the Raftery and Lewis criterion relies on the dependence factor, which should be approximately equal to 1 (Cowles & Carlin, 1996). The sample mean, standard deviation, and maximum posterior density confidence interval (HPD - 95%) were obtained. In total, 10,000 iterations were considered, with burn-in equal to 6 and thinness equal to 4997.

The R statistical software (R Core Team, 2024) was used for data analysis and all related computations. The coda package was used for diagnostic analysis and chain convergence verification. The figures were generated using the ggplot2 package.

Results and Discussion

The results of evaluating the convergence of the chains generated by the MCMC algorithm, as well as the mean, standard deviation, and HPD interval, were obtained for the parameters of the von Bertalanffy model (Table 2).

For the three fertilizer applications, the dependence factor values from the Raftery and Lewis (1992) were approximately 1.00 for all parameters. According to the Geweke criterion (Geweke, 1992), the absolute values obtained were below 1.96, indicating no evidence of nonconvergence. The Metropolis-Hastings algorithm yielded chain acceptance rates ranging from 0.39 to 0.57, considering the posterior distributions across the three applications.

The satisfactory results of the convergence diagnostics, even with a limited number of longitudinal observations (14), confirmed the reliability of the estimates. These findings further supported the conclusion that the Bayesian methodology produces dependable results to ensure chain convergence (Mezzomo et al., 2022).

The Bayesian inference approach offers an advantage over the frequentist inference approach by providing posterior high posterior density (HPD) intervals. Conclusions drawn from credibility intervals are more accurate compared to those based on frequentist confidence intervals (Peixoto et al., 2021). Additional advantages of Bayesian inference include greater flexibility in selecting distributions to represent the data and unknown parameters, as well as the incorporation of prior knowledge regarding model parameters. This approach facilitates model convergence and enhances the interpretation of results (Evangelista et al., 2022; Silva et al., 2022; Valadares et al., 2023). All model parameters were significant, as the 95% probability credibility intervals did not include zero (Table 2).

For the urea + anionic polymer fertilizer, the mean α parameter was higher across all three applications (Table 2). This result aligns with the findings illustrated in Figure 1, which depicts the marginal distributions of the α parameter of the von Bertalanffy model for the first, second, and third fertilization.

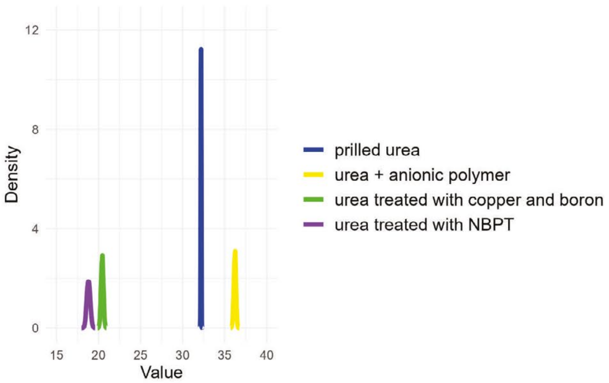
For the three fertilizer application events, the estimates of the maximum asymptotic cumulative loss, represented by the marginal distributions of α, for urea treated with NBPT (purple) and urea treated with copper and boron (green) were lower than those for the other treatments, and the urea + anionic polymer mixture (yellow) presented the greatest loss (Figure 1).

The results obtained for urea treated with copper and boron were similar to those reported by Faria et al. (2013), indicating that ammonia loss through volatilization was comparable to that observed in other treatments in which urea was applied to corn. Dominghetti et al. (2016) reported that urea coated with anionic polymers causes high ammonia loss, which stems from the low efficacy of the additive formulation incorporated into the urea that is responsible for retaining ammonium in the negative charges of the polymer. This outcome reinforced that understanding the characteristics and effectiveness of each technology by coffee farmers is important before it is adopted.

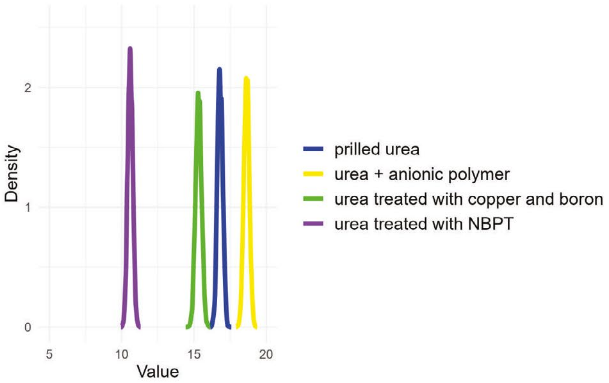
Table 2: Mean, standard deviation (SD), HPD, Geweke, Raftery and Lewis (RL) intervals for the von Bertalanffy model parameters.

Fertilizers	Parameter	Mean	SD	$HPD_{95\%}$	Geweke	RL
First fertilization						
Prilled urea	α	32.18	0.03	[32.12;32.25]	-1.93	1.16
	β	1.10	0.00	[1.09;1.11]	-0.68	1.17
	κ	0.89	0.00	[0.88;0.91]	0.68	1.05
Urea treated with copper and boron	α	20.44	0.14	[20.16;20.71]	1.13	1.32
	β	2.74	0.04	[2.66;2.82]	1.27	1.14
	κ	0.72	0.03	[0.66;0.77]	0.44	1.18
Urea + anionic polymer	α	36.21	0.13	[35.96;36.45]	0.03	1.49
	β	1.70	0.02	[1.66;1.74]	-0.86	1.39
	κ	1.85	0.07	[1.70;1.98]	1.24	1.37
Urea treated with NBPT	α	18.81	0.20	[18.42;19.20]	-0.44	1.30
	β	2.06	0.08	[1.89;2.22]	-0.39	1.24
	κ	0.62	0.04	[0.54;0.70]	0.51	1.22
Second fertilization						
Prilled urea	α	16.81	0.18	[16.47;17.16]	-1.44	1.36
	β	1.50	0.08	[1.34;1.64]	-1.14	1.20
	κ	0.61	0.04	[0.52;0.69]	-0.17	1.30
Urea treated with copper and boron	α	15.32	0.20	[14.93;15.71]	1.05	1.28
	β	1.72	0.11	[1.51;1.93]	-1.13	1.16
	κ	0.52	0.04	[0.43;0.59]	-1.42	1.39
Urea + anionic polymer	α	18.63	0.42	[18.28;19.00]	0.66	1.47
	β	1.15	0.07	[1.01;1.28]	-1.02	1.40
	κ	0.84	0.06	[0.72;0.96]	0.59	1.34
Urea treated with NBPT	α	10.59	0.17	[10.26;10.93]	-0.26	1.74
	β	4.03	0.13	[3.79;4.28]	0.49	1.40
	κ	0.44	0.03	[0.37;0.49]	-0,18	1.16
Third fertilization						
Prilled urea	α	22.47	0.12	[22.22;22.70]	-1.16	1.14
	β	1.36	0.03	[1.29;1.43]	-1.02	1.20
	κ	0.91	0.03	[0.85;0.98]	0.38	1.17
Urea treated with copper and boron	α	22.0	0.18	[21.67;22.36]	1.62	1.07
	β	3.12	0.07	[2.99;3.26]	0.99	1.07
	κ	0.31	0.01	[0.29;0.33]	-0.01	1.08
Urea + anionic polymer	α	34.39	0.18	[34.04;34.73]	0.89	1.27
	β	1.33	0.04	[1.26;1.40]	-0.98	1.18
	κ	0.71	0.03	[0.66;0.77]	0.08	1.19
Urea treated with NBPT	α	17.61	0.16	[17.29;17.90]	-0.54	1.16
	β	3.16	0.08	[3.00;3.29]	0.18	1.22
	κ	0.34	0.01	[0.31;0.37]	1.16	1.12

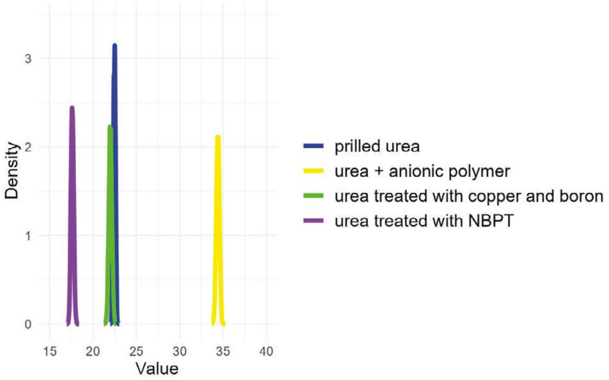
Source: By the author (2024).



(a) First fertilization



(b) Second fertilization



(c) Third fertilization

Figure 1: Marginal distributions of the α parameter of the von Bertalanffy model of the accumulated nitrogen losses in the first (a), second (b), and third fertilizer applications (c) for the four studied fertilizers.

In all three fertilization treatments (Figure 1), the urea in the NBPT treatment resulted in the lowest loss of α. As Mikkelsen et al. (2009) highlighted, the main advantage of urea stabilization by NBPT is a delay in the peak ammonia volatilization. The inhibitor can decrease nitrogen loss via ammonia volatilization by providing an extended period to incorporate fertilizer into the soil after rain. The inhibitory activity of NBPT decreases as the soil temperature increases (Abalos et al., 2014).

By analyzing conventional cropping and no-tillage systems for maize, Santos et al. (2023) reported that, regardless of the culture system, urea supplemented with a urease enzyme inhibitor, i.e., urea treated with NBPT, can effectively prevent considerable ammonia loss via volatilization.

In terms of the α parameter, urea + anionic polymer fertilizer resulted in the greatest loss via volatilization. Fernandes et al. (2024) investigated fertilizers applied to a coffee cropping system and showed that the greatest loss occurred with prilled urea and urea + anionic polymer.

The marginal distributions of the β parameter of the von Bertalanffy model for the first, second, and third fertilizer applications are shown in Figure 2. The parameter β represents the abscissa of the inflection point, at which the concavity of the curve changes its upward growth trajectory to a less accentuated growth trajectory. At this point, the curve also has its highest growth rate.

Urea treated with NBPT (purple) resulted in the most significant delay in the ammonia peak (Figure 2 (b)). In the third fertilization treatment (Figure 2 (c)), an overlap of urea treated with NBPT (purple) and urea treated with copper and boron (green) was found.

Similar trends were observed in the 2016–2017 coffee crop, where urea treated with copper and boron and urea treated with NBPT presented inflection points of 3.7 and 4.3, respectively, as reported by Freitas et al. (2022).

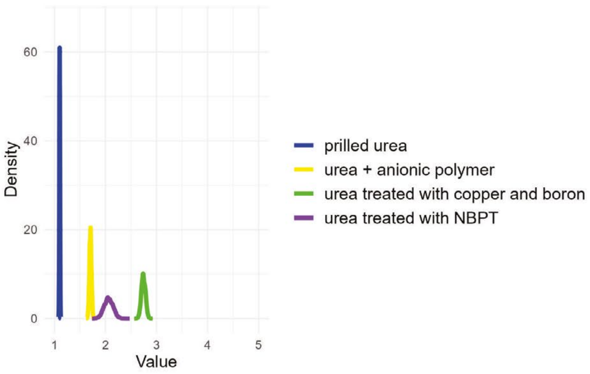
The marginal distributions of the κ parameter of the von Bertalanffy model for the first, second, and third fertilization are shown in Figure 3. For the parameter κ, in the first fertilization event (Figure 3(a)), the urea treatments with copper and boron (green) and the urea treatment with NBPT (purple) overlapped. In the second and third fertilization events, the urea treated with NBPT (purple) overlapped with the urea treated with copper and boron (green).

In the first and second fertilization treatments (Figures 3(a) and (b)), urea + anionic polymer (yellow) had higher values than the other treatments, which indicated that in this treatment, the time to reach maximum nitrogen loss was shorter.

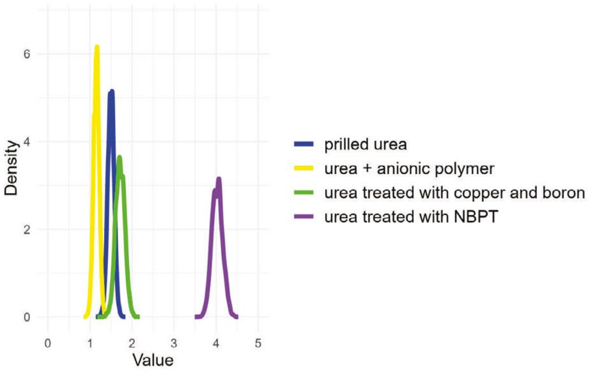
Our findings revealed that urea treatment with NBPT and urea + copper + boron resulted in significantly lower ammonia loss, which is a key finding with potential implications for agricultural practices. This finding was similar to that reported by Santos et al. (2023), who reported that regardless of the type of fertilizer and cropping system studied, a greater loss of ammonia occurred in the first few days after fertilizer application.

Among the treatments, the urea treated with NBPT fertilizer exhibited lower values for the parameter κ across the three fertilization events. This result indicates that this treatment effectively reduced volatilization by mitigating the rapid hydrolysis of urea on the soil surface (Dominghetti et al., 2016).

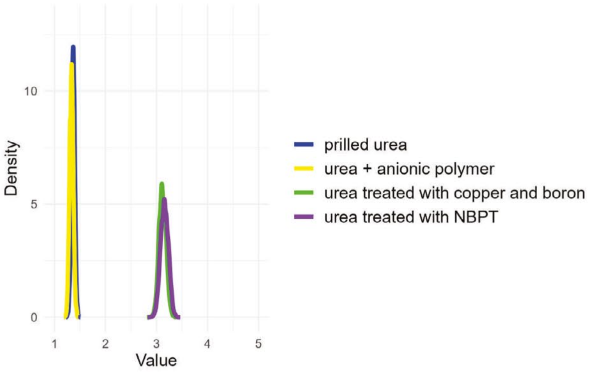
Santos et al. (2023) investigated alternatives to minimize the loss of nitrogen to the atmosphere. Among the evaluated compounds, NBPT showed significant results, followed by NPPT, metal cations, boron, and organic nitrogen compounds.



(a) First fertilization

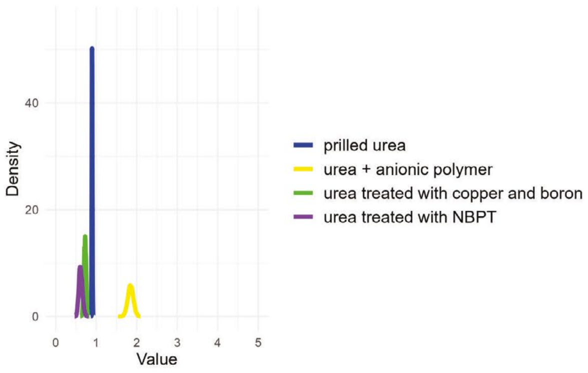


(b) Second fertilization

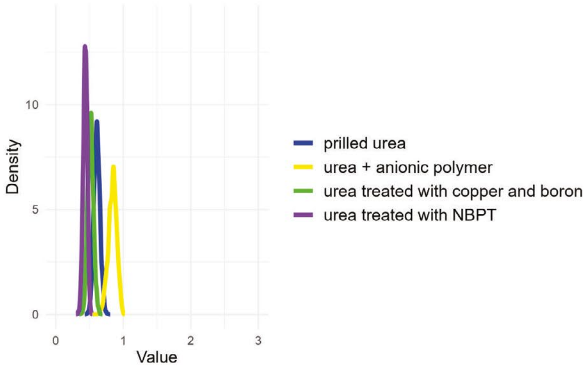


(c) Third fertilization

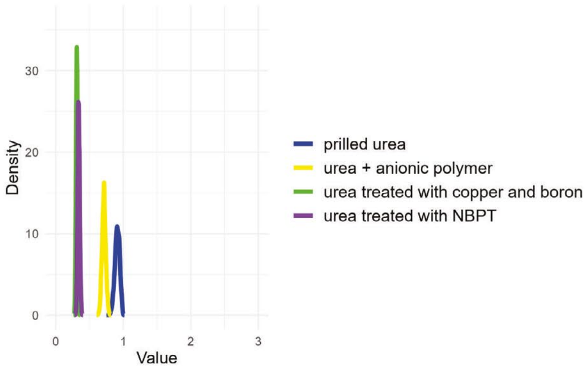
Figure 2: Marginal distributions of the β parameter of the von Bertalanffy model of the accumulated nitrogen loss in the first (a), second (b), and third (c) fertilizer application events for the four studied fertilizers.



(a) First fertilization



(b) Second fertilization



(c) Third fertilization

Figure 3: Marginal distributions of the κ parameter of the von Bertalanffy model of the accumulated nitrogen loss in the first (a), second (b), and third (c) fertilizer application events for the four studied fertilizers.

Dominguetti et al. (2016) reported that the costs of fertilizer technologies decrease in the following order: controlled-release > slow-release > stabilized nitrogen fertilizers. Among the fertilizers evaluated in this study, urea combined with an anionic polymer was identified as the most expensive option. As highlighted in this discussion, urea treated with NBPT reduces nitrogen losses but remains more expensive for farmers compared to pure urea. Alexandre et al. (2024) noted that in Minas Gerais, Brazil, the price of a 50 kg sack of NBPT-treated urea is R$ 335.00, while the same quantity of common urea costs R$ 280.00.

Conclusions

The Bayesian methodology used provided accurate estimates and enabled a direct comparison between the fertilizers based on the marginal distribution of the von Bertalanffy model parameters. It is concluded that urea + anionic polymer fertilizer caused the highest nitrogen loss, while urea with NBPT resulted in the lowest nitrogen loss. Additionally, urea with NBPT reduced nitrogen volatilization by more than 50% compared to urea with anionic polymers, making it the most efficient option.

Author Contribution

Conceptual idea: Rosa, M, Fernandes, T. J.; Methodology design: Rosa, M., Fernandes, T. J., Pereira, A. A.; Data collection: Fernandes, T. J.; Data analysis and interpretation: Rosa, M.; and Writing and editing: Rosa, M., Fernandes, T. J., Pereira, A. A.

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