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Structural and informational absences in irrigation data: a Bayesian zero-inflated approach applied to Minas Gerais, Brazil

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Abstract. Minas Gerais is Brazil's second-largest state in terms of irrigated area, with expansion potential exceeding 1 million hectares. Yet 16% of municipalities reported no irrigation in 2019, revealing a paradox between potential and local absence. This study investigates the determinants of irrigation absence using a Bayesian zero-inflated model with a truncated Student's t-distribution. The results indicate that the baseline probability of a structural zero is approximately 12%, but this probability decreases to 4% in municipalities located in the São Francisco Basin or those with potential irrigable area. In contrast, municipalities with agricultural gross value added below the state average show substantially higher probabilities of structural zeros (around 38%). In the extended specification, the interaction between basin location and potential irrigable area reduces the probability of structural zeros to about 1%, indicating a strong combined mitigating effect. By distinguishing structural from informational constraints, this study provides actionable insights for targeted policy interventions aimed at promoting sustainable and efficient irrigation expansion.

Keywords: irrigation, governance, allocation, institutional barriers.
JEL codes: Q18, C11, R58.

HIGHLIGHTS

- Applies a Bayesian zero-inflated model to distinguish structural from informational irrigation zeros.
- Identifies that nearly half of zero-irrigation municipalities reflect informational gaps rather than structural constraints.
- Finds that irrigable area and the São Francisco river basin location markedly lower the likelihood of structural zeros, with cross-basin hydrological implications.
- Delivers evidence to strengthen basin-level water governance.

1. INTRODUCTION

Despite recognition of irrigation as an essential element of agricultural productivity and resilience to climate shocks, many regions worldwide remain far below their irrigable potential (Altchenko, Villholth, 2015; Smilovic *et al*., 2015; Desta, 2024). Understanding regional structures is important for improving water governance and policy design (Playán *et al*., 2018; Fritsch, Benson, 2024). Such gaps may arise from structural barriers, such as water scarcity, or from informational constraints, where irrigation areas are not integrated into management systems.

While the determinants of irrigation expansion have been extensively studied, highlighting the role of infrastructure investment, productivity gains, technologies, or policy incentives (Cremades *et al*., 2015; Abou Zaki *et al*., 2022; Gautam *et al*., 2024; Asfaw, Mekonen, 2024), few studies have examined why irrigable areas remain underutilised in emerging economies, where institutional and informational barriers may differ substantially (Playán *et al*., 2018; Nhamo *et al*., 2024). Brazil exemplifies this gap: although an estimated 13.7 million hectares are considered suitable for irrigation (Agência Nacional de Águas e Saneamento Básico [ANA], 2021), large portions of potentially irrigable land, such as in the state of Minas Gerais, remain unexplored.

According to the Irrigation Atlas (ANA, 2021), 1,247 of Brazil's 5,570 municipalities report no irrigated area. In 2019[1], irrigated agriculture accounted for an estimated 965 m^3/s of water use, concentrated primarily in flood-irrigated rice (38%). This combination of high national water demand and widespread zero-records underscores the need to explicitly model the 'zero mechanism' when examining irrigation dynamics in regions such as Minas Gerais. This issue is particularly relevant because irrigable potential areas coexist with regional disparities and productivity differentials between irrigated and rainfed areas which in turn translate into distinct labour market dynamics and income levels (Ferrarini *et al*., 2019, 2020).

Brazilian agriculture plays a central role in global food supply, ranking among the world's largest producers and exporters of water-intensive crops (Da Silva *et al*., 2016; Visentin *et al*., 2019). Brazil's rapid structural transformation has positioned it as a pivotal contributor to international markets for soybeans, coffee, sugar, meat, and other commodities (Barros *et al*., 2019; Machado, da Cruz, 2022; Dhoubhadel *et al*., 2023). Within this national context, Minas Gerais combines irrigation potential with spatial heterogeneity in agricultural development and access to technical assistance. According to the Irrigation Atlas (ANA, 2021), the irrigated area in the state was 1,144,428 hectares in 2019 (20.33% of cropped area and 14% of Brazil's total), while 1,180,524 hectares remain available for irrigation expansion, a potential 103% increase. The state also encompasses part of the São Francisco river basin, a critical water source for the semi-arid Northeast, highlighting potential trade-offs in water allocation (Ferrarini *et al*., 2020).

The focus on Minas Gerais is justified not only by its extensive irrigated area but also by its importance in national and global food production systems. The state is an important producer of soybean (34% of cultivated area), sugarcane (17%), and coffee (16%), and it accounts for 56% of the total coffee-planted area in Brazil. In this context, the presence of municipalities with irrigable potential but no irrigated area emerges as a relevant gap. The Irrigation Atlas (ANA, 2021) reports that 139 municipalities in Minas Gerais (16.18%) had no irrigation in 2019, in contrast to the 51 municipalities (6%) recorded in the 2017 Agricultural Census (Instituto Brasileiro de Geografia e Estatística [IBGE], 2019). These differences reflect variations in data collection approaches. The Agricultural Census is based on self-reported information collected from farmers during a specific reference period, whereas the Irrigation Atlas integrates multiple data sources, including remote sensing and administrative records.

Understanding whether the absence of irrigation arises from hydrological constraints, governance failures, or informational gaps is fundamental for basin-level water allocation, compliance monitoring, and long-term planning under increasing climatic variability (Nguyen *et al*., 2020; Multsch *et al*., 2020; Ortiz-Bobea, 2021). Studies using Bayesian zero-inflated (ZIP) models have been applied in different contexts within agricultural economics. Nohamba *et al.* (2022) applied ZIP regression and found that citrus producers lose 4.1% of their production, with sprinkler irrigation increasing exposure to losses by 5.3 times, while regular agricultural extension services reduce such losses. Ng'ombe *et al.* (2022), in turn, employed a Bayesian zero-one inflated beta model to analyse milk sales by smallholder farmers in Zambia, showing that married farmers sell 26% more and payment delays reduce the proportion sold by 16.5%.

In this study, structural zeros refer to municipalities where irrigation is not feasible due to inherent constraints, such as water scarcity. In contrast, informational zeros arise from measurement issues, lack of reporting, or limited access to technical assistance and institutional support. This discrepancy raises the

[1] The latest available information.

research question for this study: which factors explain the absence of irrigation in municipalities with irrigable potential, and to what extent does such absence reflect structural hydrological constraints versus informational or governance limitations relevant to water allocation? The main objective is to identify the determinants of irrigation absence in municipalities with irrigable potential, distinguishing between structural and informational mechanisms. Specifically, the following hypotheses are tested:

> H1 – Structural factors, such as hydrological constraints and geographic location, increase the probability of structural zeros.
> H2 – Institutional and economic factors, such as access to technical assistance and productive capacity, are associated with the presence of irrigation and reduce the likelihood of informational zeros.

To this end, this study employs a Bayesian ZIP model, which decomposes the probability of absence into structural zeros (Lambert, 1992), implemented through a zero-inflated Student's t specification adapted from Agarwal *et al.* (2002). This study is structured into five sections. Section 1 introduces the topic. Section 2 presents the database and methodological framework. Section 3 reports the results, followed by Section 4, which discusses the main findings. Finally, Section 5 concludes the study.

2. DATABASE AND METHODOLOGY

2.1. Case study area

Brazil comprises 26 states and the Federal District, and its hydrological system is organised into major river basins, including the São Francisco river basin, which plays a central role in water availability for agricultural activities. Minas Gerais, located in the Southeast region, is one of the largest states in the country, covering approximately 586,500 km² and comprising 853 municipalities. Figure 1 situates the spatial context of the state within Brazil and displays the distribution of irrigated area in 2019 using a quantile classification.

In 2019, water withdrawal in Brazil was distributed across livestock (8.4%), irrigation (49.8%), mining (1.7%), industry (9.7%), thermoelectric generation (4.5%), rural households (1.6%), and urban consumption (24.3%). Brazil's irrigated area expanded from 4.5 million hectares in 2006 to 6.9 million hectares in 2017 and 8.2 million hectares in 2019. In Minas Gerais, the irrigated area increased from roughly 530,000 hectares in 2006 to about 1.12 million hectares in 2017 and 2019.

The Atlas of Irrigation (ANA, 2021) reports a national potential of 13.69 million hectares for additional irrigated agriculture, of which Minas Gerais accounts for approximately 8%, or nearly 1.14 million hectares. The state's hydrological network comprises 17 federal river basins (Governo de Minas Gerais, 2020).

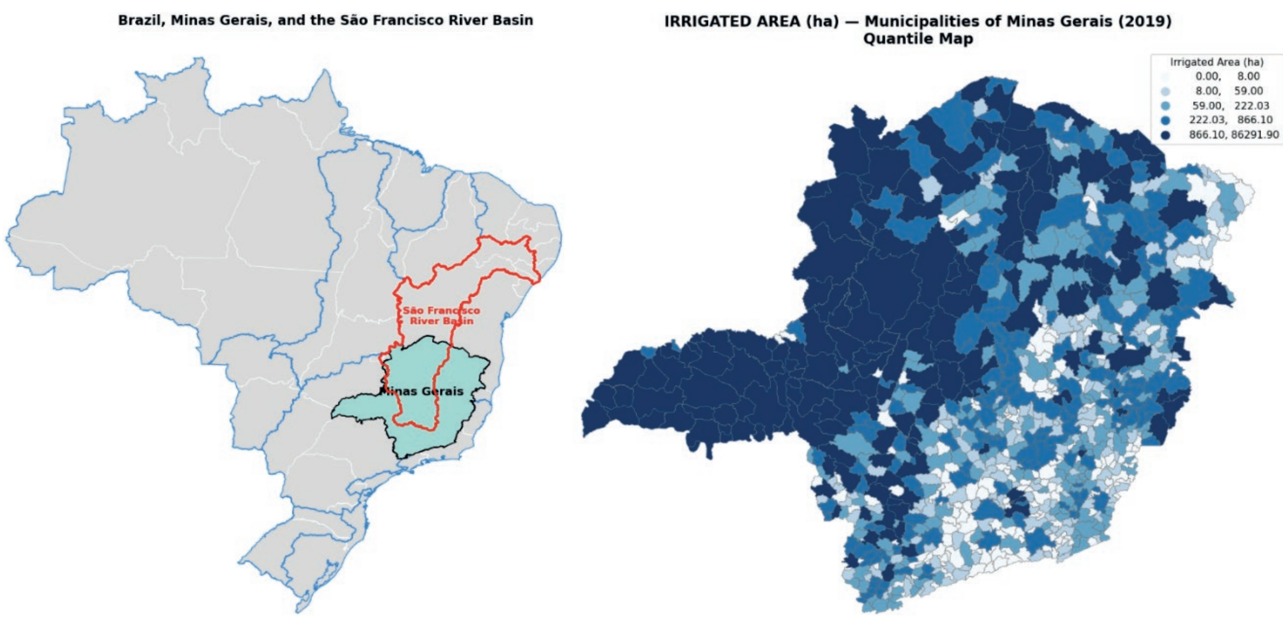

Figure 1. Geographical context of Brazil and the irrigated areas in Minas Gerais (2019). *Source:* Prepared by the author based on the official geographic mesh provided by IBGE (2025) and irrigated area data from the Atlas of Irrigation (ANA, 2021).

Among them, the São Francisco river basin is the third-largest hydrographic basin in Brazil. Within Minas Gerais, it covers approximately 234,557 km^2, encompassing 282 municipalities and serving an estimated 12.37 million inhabitants. Given this spatial heterogeneity and the inconsistencies in available data, a modelling strategy capable of distinguishing structural from informational zeros.

2.2. Database

The database employed in this study brings together information from the National Water and Basic Sanitation Agency (ANA) through the Irrigation Atlas (ANA, 2021), with a focus on irrigated area and potentially irrigable area in municipalities of Minas Gerais for the year 2019. Complementarily, data from the 2017 Agricultural Census, made available by the Brazilian Institute of Geography and Statistics (IBGE), were used to provide the rural numbers associated with cooperatives/associations per municipality.

For temporal consistency, it is assumed that data from the 2017 Agricultural Census remained constant in 2019[2]. The selection of variables is guided by the literature highlighting the positive role of rural extension in improving productivity and rural development (Birkhaeuser *et al*., 1991; Da Silva, 2001). Municipal economic capacity, measured through agricultural gross value added (GVA), is included to capture the availability of economic resources. In addition, the inclusion of municipalities located within the São Francisco river basin reflects the expansion of irrigated areas in this region (Baiardi, Ribeiro, 2023).

To enhance data transparency and reproducibility, detailed data provenance is provided in Table 1, including the original data sources with specific table references. All variables were harmonised at the municipal level. Continuous covariates were standardised prior to estimation, and the dependent variable was log-transformed for positive observations. No missing values were identified in the original datasets, and the harmonisation process (including numeric conversion and standardisation) did not introduce additional missing observations[3].

Each covariate is included based on its expected role in distinguishing structural from informational mechanisms. In the inflation component, SF$_{_Dummy}$ and Area$_{_Pot}$ capture geographical and hydrological feasibility, as municipalities located in the São Francisco river basin or with irrigable potential are less likely to face structural constraints to irrigation. The variable VAB$_{_AD}$, defined as a dummy equal to 1 if agricultural GVA is below the state average, is used as a proxy for low economic capacity, associated with a higher likelihood of structural constraints to irrigation. In the continuous component, assoc_coop and receb_tec reflect access to information and technical support, respectively, which facilitate irrigation adoption conditional. Finally, VAB$_{_Agro}$ and Part_VAB capture the scale and economic relevance of agricultural activity, respectively, which are expected to be positively associated with irrigated area among municipalities with irrigation. Table 2 presents the descriptive statistics of the continuous variables employed in the model. High skewness and kurtosis indicate a concentration of low values alongside a few extreme observations, supporting the use of Student's t-distribution.

2.3. Theoretical foundations of a zero-inflated model

Following Agarwal *et al.* (2002), the observed outcome is assumed to arise from a structural-zero component and a sampling distribution for positive observations. For a base distribution $n\,(y|\theta)$, the zero-inflated probabilities are:

$$P\,(Y=0|p,\theta)=p+(1-p)n\,(0|\theta) \tag{1}$$

$$P\,(Y=y>0|p,\theta)=(1-p)n\,(y|\theta), y>0 \tag{2}$$

where p is the probability of excess zeros, and $(1-p)$ is the fraction following the base distribution. Covariates may influence both components of the model through separate linear predictors, typically via a log link for the continuous/count part and a logit link for the inflation probability.

$$\log\,(\lambda_{\,i})=\mathscr{B}_i\beta \tag{3}$$

$$logit\,(p_i)=\log\left(\tfrac{p_i}{1-p_i}\right)=G_i\alpha \tag{4}$$

where $\mathscr{B}_i$ and G_i are vectors of covariates for the count and zero-inflation components, respectively, and β and α are the corresponding parameter vectors. In other words, $\lambda_{\,i}$represents the expected outcome (e.g., irrigated area) conditional on being in the count process, while p_i represents the probability of a structural zero. The next subsection presents the adaptation of this framework to irrigated agriculture in Minas Gerais.

[2] Given the relatively short time interval and the structural nature of the variables used (e.g., land suitability and institutional factors), this is not expected to affect the main results significantly.

[3] A diagnostic procedure was conducted to check potential inconsistencies arising from data type conversion. No additional missing values were generated after conversion.

Table 1. Summary of the selected variables.

Abbreviated name	General information	Source	Expected relationship	Variable type	Number of observations
area_irrig	Total irrigated area (hectares) per municipality	Irrigation Atlas – 2nd edition, online dataset (ANA, 2021)	Dependent variable	Continuous	853
assoc_coop	Number establishments with cooperatives/ associations per municipality	Agricultural Census (IBGE, 2019), Table 6846	Proxy for access to technology and markets; a positive relationship with irrigated area is expected	Continuous	853
receb_tec	Number of establishments receiving technical assistance per municipality	Agricultural Census (IBGE, 2019), Table 6779	Proxy for human capital structure A positive relationship with irrigated area is expected	Continuous	853
VAB_Agro	Gross agricultural value added (thousand R$), per municipality	IBGE (2021), Table 5938	Proxy for municipal financial capacity	Continuous	853
Part_VAB	Share of agriculture in gross value added [GVA] (i.e., *valor adicionado bruto* [VAB]) per municipality	IBGE (2021), Table 5938	Proxy for the relative importance of agriculture in the local economy	Continuous	853
VAB_AD	Dummy: 1 if agricultural GVA < state average	IBGE (2021), Table 5938	A positive relationship with structural zeros is expected	Binary	1 = 647; 0 = 206
Area_Pot	Dummy: 1 if the municipality has potential irrigable area	Irrigation Atlas (ANA, 2021), 2nd edition, online dataset	A negative relationship is expected, reducing the likelihood of a structural zero	Binary	1 = 529; 0 = 324
SF_Dummy	Dummy: 1 if located in the São Francisco river basin	Comitê da Bacia Hidrográfica do Rio São Francisco (CBHSF, 2025) (online dataset)	A positive relationship is expected, with a higher likelihood of irrigation	Binary	1 = 239; 0 = 614

Table 2. Descriptive statistics of the continuous variables used in the model.

Statistics	area_irrig	assoc_coop	receb_tec	VAB_Agro	Part_VAB
Count	853	853	853	853	853
Mean	1,341	293	186	30,952	13.42
Standard deviation	5,195	381	225	59,577	10.73
Minimum	0	0	1	44	0
25th percentile	20	58	54	5,812	6.06
50th percentile	114	165	114	12,241	10.76
75th percentile	605	376	221	30,330	18.39
Maximum	86,291	2,910	2,131	782,041	62.24
Skewness	9.92	2.95	3.11	5.95	1.44
Kurtosis	130.18	11.91	13.63	51.14	2.54

2.4. A zero-inflated model for irrigated agriculture in Minas Gerais

Let y_i denote the irrigated area (in hectares) for municipality i (I = 1, ..., n), and assume that y_i follows a zero-inflated model:

$$y_i = \begin{cases} 0 with probability \psi_i, \\ exp\left(\widetilde{Y}_i\right), where \widetilde{Y}_i \text{~} Student - t\,(\mu_i, \sigma, v) with probability 1 - \psi_i \end{cases} \quad (5)$$

where ψ_i denotes the probability of a structural zero. This specification corresponds to a two-part model, in which the zero outcome and the positive outcomes are modelled separately. The variable $\widetilde{Y}_i = \log(y_i)$ is defined only for municipalities with $y_i > 0$ and is assumed to follow Student's t-distribution with location μ_i, scale $\sigma > 0$, and degrees $v > 0$. The exponential transformation ensures that predictions of irrigated area remain positive. Zero-inflation probability ψ_i is linked to a set of covariates via a logistic regression:

$$\psi_i = logit^{-1}\left(X_i^{infl}\beta^{infl}\right), logit\left(\psi_i\right) = log\left(\frac{\psi_i}{1-\psi_i}\right) = X_i^{infl}\beta^{infl} \quad (6)$$

where X_i^{infl} is a vector of covariates (including an intercept) and β^{infl} is the corresponding coefficients. For municipalities where irrigation is possible ($y_i > 0$), the expected log-irrigated area is modeled as:

$$\mu_i = X_i^{cont}\beta^{cont} \quad (7)$$

where X_i^{cont} representing the standardised continuous covariates, and this component is estimated conditional on $y_i > 0$, implying a truncated likelihood for positive observations.

A Bayesian framework is adopted with weakly informative priors[4]. These priors are calibrated based on two considerations. First, the location parameters reflect the expected direction and approximate magnitude of effects, informed by descriptive statistics and preliminary regressions. In particular, the intercept is centred at a negative value to reflect the relatively low baseline probability of structural zeros. Second, Student's t-distribution provides robustness to misspecification and allows for heavier tails compared with the normal distribution, and avoids sensitivity to extreme municipalities with unusually large, irrigated areas. Therefore, two specifications are simulated. Both models share the same structure defined above but differ in the set of covariates included in the inflation component. The inflation part in Model 1 (equation 8) is formally defined as:

$$logit\left(\psi_i\right) = \beta_0 + \beta_1 SF_{Dummy_i} + \beta_2 VAB_{A_{Di}} + \beta_3 area_{pot} \quad (8)$$

where ψ_i denotes the probability of a structural zero for municipality i, SF_{Dummy_i} indicates whether the municipality belongs to the São Francisco river basin, $VAB_{A_{Di}}$ indicates whether the municipality is below the average of the agricultural GVA (Agricultural), and $area_{pot}$ denotes the presence of potential area for irrigation expansion. In Model 2 (equation 9), the inflation component includes an interaction term ($SF_{interaction}$= $SF_{Dummy_i} \times area_{pot}$ which captures the joint marginal effect of being located in the São Francisco river basin and having potential irrigable area ($SF_{interaction} = 1$) defined as:

$$logit\left(\psi_i\right) = \beta_0 + \beta_1 SF_{Dummy_i} + \beta_2 VAB_{A_{Di}} + \beta_3 area_{pot} + \beta_4 SF_{interaction} \quad (9)$$

Model 2 extends Model 1 by including an interaction term between $SF_{\_Dummy}$ and $Area_{\_pot}$, allowing the analysis to capture whether the effect of irrigable potential depends on geographical location within the São Francisco river basin. This specification is intended to test for heterogeneous effects in the probability of structural zeros, particularly in regions where water availability and irrigation infrastructure may condition the role of potential irrigable area. Predicted probabilities in the inflated component are obtained by transforming the linear predictor through the logistic function $p = \frac{1}{1+\exp(-n)}$. Robustness is evaluated through 95% highest posterior density intervals (HDIs) and posterior probabilities of coefficient signs. Convergence is assessed using the $\widehat{R}$ statistic and visual inspection of trace plots, with Monte Carlo standard errors (mcse_mean and mcse_sd) and effective sample sizes (ess_bulk and ess_tail) reported for all parameters[5].

To evaluate the influence of prior choices on posterior inference, a prior sensitivity analysis is conducted by re-estimating the Model 1 under an alternative set of less informative priors. In this specification, Student's t priors originally assigned to the zero-inflation coefficients are replaced by diffuse normal[6] priors centred at zero *N*(0,2), reducing the influence of prior location assumptions. For the continuous component, the coefficient priors are unchanged, while broader priors are adopted for the scale (σ ~ HalfNormal (1)), and ((ν ~ Gamma (2,0.5)) parameters. The model structure and data remain unchanged. In addition to the zero-inflated specification, a baseline model without zero inflation is estimated for comparison purposes. This model assumes that the logarithm of irrigated area follows a normal distribution for all observations, including those with zero values, which are adjusted by a small constant to enable the logarithmic transformation. It serves as a benchmark to assess whether the additional complexity of the zero-inflated model leads to improvements in predictive performance.

Predictive performance and model comparison

Predictive accuracy is evaluated using approximate leave-one-out cross-validation (LOO) and the widely applicable information criterion (WAIC), both computed from posterior samples (Vehtari *et al*., 2017). These criteria estimate the expected log predictive density (ELPD)

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[4] For the inflation component, the coefficients are assigned Student's t priors with 3 degrees of freedom, a location vector (-2.0, -1.0, 1.5, -1.0), and scale parameters (0.5, 0.3, 0.3, 0.3). These values help stabilise estimation, particularly for the intercept and binary covariates, while still allowing sufficient flexibility.

[5] All programming scripts are available from the author upon request.

[6] The alternative normal prior specification was chosen to represent a more diffuse and less informative benchmark.

and provide a measure of how well each model is expected to predict new observations. For the zero-inflated model, the predicted probability of structural zeros is directly obtained from the posterior distribution of ψ_i. For the baseline model, which does not include a zero-generating mechanism, the predicted proportion of zeros is mechanically equal to zero. Comparing predicted and observed zero shares provides a direct test of whether the model captures the structural features of the data.

Finally, to examine heterogeneity in zero outcomes, the average predicted probability of structural zeros across different municipality types is computed, defined by key covariates such as location in the São Francisco river basin, irrigation potential, and agricultural GVA. This allows the assessment of whether zero outcomes are systematically associated with observable structural characteristics.

Spatial dependence assessment

Although the models do not include explicit spatial random effects, residual spatial autocorrelation is assessed to determine whether the included covariates adequately capture spatial patterns. To this end, local Moran's I (a local indicator of spatial association) on the residuals of the continuous component (Anselin, 1995) is used. Local Moran's I for a standardised variable *y*, observed in region *i*, z_i, can be expressed as (Almeida, 2012).

$$I_i = z_i \sum_{j=1}^{n} w_{ij} z_j \tag{10}$$

The calculation of I_i considers only the neighbors of observation i, defined according to the spatial weight's matrix w_{ij}, which in this study is specified using the queen contiguity criterion. Model estimation is performed via Markov chain Monte Carlo (MCMC) using PyMC v5.9.0 (2025), with posterior analyses conducted in ArviZ v0.16.1 for convergence diagnostics and exploratory assessment of the Bayesian results (Patil *et al*., 2010; Kumar *et al*., 2019). However, given that the residuals show no evidence of spatial autocorrelation, a parsimonious specification without spatial random effects is adopted.

3. RESULTS

Due to the two-part structure of the zero-inflated model, the likelihood is evaluated using only positive observations in the continuous component. As a result, the number of effective observations differs across model components, preventing direct comparison using standard model ranking procedures. Therefore, LOO and WAIC are interpreted as within-model predictive diagnostics, rather than as strict model selection criteria across specifications (Table 3). The continuous component is estimated using only positive observations ($y_i > 0$), which implies a reduced effective sample size in that component of the likelihood. This feature is intrinsic to hurdle-type models and does not reflect missing data or sample selection.

Table 3 indicates that the zero-inflated model improves predictive performance, particularly in capturing the presence of excess zeros, rather than merely providing a better in-sample fit. The sensitivity analysis indicates that the results depend on prior specification in the zero-inflation component. As discussed by Gelman (2006), priors intended to be noninformative or weakly informative can still exert a substantial influence on posterior inference. Under weakly informative priors, coefficients are well identified and consistent with theoretical expectations, and the model reproduces the observed zero share (≈20% vs 16.2%). In contrast, diffuse priors lead to weak identification, with coefficients shrinking toward zero (posterior mean ≈ 0.02) and wide credible intervals, substantially overestimating the proportion of structural zeros (≈50%). Furthermore, the zero-inflated model reveals substantial heterogeneity in predicted zero probabilities across municipality types. Predicted zero probabilities are higher outside the semi-arid region (26.1% vs 10.3%), in municipalities without irrigation potential (35.1% vs. 13.5%), and among those with lower agricultural value added (26.7% vs. 5.9%).

Table 3. Predictive performance diagnostics and zero-share reproduction across the model specifications.

Model	elpd_loo	p_loo	WAIC	P_waic	Predicted zeros	Observations
Log-normal	-2853.37	4.80	-2853.32	4.75	0.00%	853
Zero-inflated Student's t	-1386.01	8.45	-1385.97	8.41	21.67%	715
Observed	—	—			16.18%	

Note: The ELPD values are not directly comparable across the models due to different likelihood definitions and effective sample sizes.

Convergence diagnostics indicate stable MCMC performance across all specifications, with low Monte Carlo standard errors (≈0.001) and satisfactory mixing in both the central and tail regions of the posterior distributions. The inflation component models the probability of structural zeros via a logit specification, while the continuous component captures the magnitude of irrigated area conditional on positive observations. The parameter estimates for Model 1 and Model 2 are reported in Tables 4 and 5, respectively.

The intercepts provide the baseline reference for each model component. In the inflated part, the intercept of -2.007 corresponds to a baseline probability of 11.9% that a municipality is a structural zero when all predictors are held at their mean values. In the continuous part, the intercept of 5.28 indicates an expected irrigated area of approximately 196.4 hectares, given that irrigation is present.

For the inflated component, the results are presented as predicted probabilities to enhance interpretability. Belonging to the São Francisco river basin ($SF_{\_Dummy}$ = 1) reduces the probability of a structural zero from 11.9% to approximately 4.7%[7], indicating that municipalities in this basin are less likely to lack irrigation. In contrast, municipalities with agricultural GVA below the state average ($VAB_{\_AD}$ = 1) have a higher probability of being structural zeros, increasing from 11.9% to about 37.4%. The presence of irrigable area ($Area_{\_pot}$ = 1) also decreases the structural-zero probability to around 4.7%, reinforcing the importance of land suitability in reducing the likelihood of zero irrigation.

In the continuous component, covariates are standardised (mean = 0, standard deviation = 1), and the results are expressed as percentages to improve comparability across the variables. The variable assoc_coop (0.289) implies that a one-standard-deviation increase in the proportion of farmers associated with cooperatives is associated with an approximate 33%[8] increase in the log-mean irrigated area, highlighting the positive role of corporativism. The coefficient for $VAB_{\_Agro}$ (1.073) corresponds to an increase of about 192% in the expected irrigated area, revealing a strong association between agricultural GVA concentration and irrigation intensity. Finally, receb_tec shows a positive but more uncertain effect: the estimated coefficient (0.121) implies a 12.9% increase, but the posterior interval includes zero, indicating limited statistical certainty about this relationship.

Model 2 (Table 5) introduces an interaction term ($SF_{\_interação}$), identifying 194 municipalities that simultaneously belong to the São Francisco river basin and possess irrigable potential. The interaction coefficient indicates that when both conditions are jointly satisfied (São Francisco river basin and irrigable potential), the interaction term reduces the probability even further, to approximately 1.1% (-0.509), indicating a strong combined protective effect against the absence of irrigation. However, the HDI includes zero, indicating uncertainty in the effect direction in the inflation component.

In the continuous component of Model 2, the results remain consistent with those of Model 1. The presence of more associations and cooperatives is positively associated with larger irrigated areas, and municipalities receiving greater technical support also exhibit a higher irrigated area. The relative participation variable in agricultural GVA shows a positive and statistically significant effect, although smaller than the absolute GVA measure used in Model 1, likely reflecting its lower variability (see Table 1). Additionally, in Model 2, the variable receb_tec becomes statistically significant, indicating improved overall model. The increase in ν = 16 in Model 2 suggests that the interaction term captured part of the extreme variability, resulting in lighter tails compared to Model 1. Table 6 provides a summary of the predicted structural-zero probabilities for both models.

The baseline probability of a structural zero remains around 12%, but this probability drops to approximately 5% in municipalities located in the São Francisco river basin or those with potential irrigable area. In contrast, municipalities with agricultural GVA below the state average exhibit higher probabilities of structural zeros (around 38). In Model 2, the interaction term indicates that municipalities simultaneously located in the São Francisco river basin and endowed with potential irrigable area have the lowest probability of structural zeros (about 1%), suggesting a strong combined mitigating effect.

Figure 2 presents the posterior distributions of the mean probability of structural zeros (ψ_i)across municipalities in Minas Gerais to assess the predicted effects on structural zeros from Models 1 and 2. The distributions show that both models estimate a higher proportion of structural zeros than observed. Some considerations follow: (i) according to the 2017 Agricultural Census, which collected data directly from farmers, only 6% of municipalities reported no irrigation; (ii) Irrigation Atlas estimates are indirect, based on remote sensing, hydro-

[7] With an intercept of -2.007, the baseline probability of a structural zero is (11.9%). Setting $SF_{\_Dummy}$ = 1 shifts the linear predictor from to -2.007 to -0.996, yielding (4.7%).

[8] Because the explanatory variables were standardised (mean = 0, standard deviation = 1), the interpretation is given in terms of standard deviations. For example, , meaning that an increase of one standard deviation in assoc_coop is associated with a 33.5% higher irrigated area on average. The same calculation applies to the other standardised count variables.

Table 4. Model 1 results.

Component	Variable	Mean	3% hdi	97%hdi	MCSE mean	MCSE sd	ESS bulk	ESS tail	$\widehat{R}$
Inflated part	Intercept	-2.00	-3.47	-0.56	0.013	0.012	6365	3304	1
	$SF_{\_Dummy}$	-0.99	-1.88	-0.17	0.006	0.007	8246	3521	1
	$VAB_{\_AD}$	1.48	0.61	2.37	0.007	0.005	7792	3233	1
	$Area_{\_pot}$	-1.00	-1.82	-0.20	0.005	0.005	9275	3802	1
Count part	Intercept	5.28	5.15	5.39	0.001	0	8897	6202	1
	assoc_coop	0.28	0.16	0.39	0.001	0	7605	6361	1
	$VAB_{\_Agro}$	1.07	0.89	1.25	0.001	0.001	6063	6088	1
	receb_tec	0.12	-0.01	0.25	0.001	0.001	6384	6079	1
	Sigma (σ)	1.46	1.33	1.58	0.001	0.001	5065	5359	1
	Nu (ν)	10.38	4.56	18.73	0.079	0.056	4609	4069	1

Table 5. Model 2 results.

Component	Variable	Mean	3% hdi	97%hdi	MCSE Mean	MCSE sd	ESS bulk	ESS tail	$\widehat{R}$
Inflated Part	Intercept	-1.97	-3.39	-0.468	0.009	0.008	8469	3454	1
	$SF_{\_Dummy}$	-1.00	-1.82	-0.119	0.006	0.006	8805	3681	1
	$VAB_{\_AD}$	1.48	0.63	2.374	0.007	0.005	7538	3547	1
	$Area_{\_pot}$	-0.98	-1.84	-0.063	0.007	0.008	7846	2751	1
	$SF_{\_interação}$	-0.50	-1.93	0.865	0.012	0.018	7146	3234	1
Count Part	Intercept	5.26	5.14	5.385	0.001	0.001	8503	5829	1
	assoc_coop	0.39	0.26	0.516	0.001	0.001	7562	6038	1
	$Part_{\_VAB}$	0.51	0.39	0.639	0.001	0	9162	6305	1
	receb_tec	0.51	0.38	0.657	0.001	0.001	7510	5997	1
	Sigma (σ)	1.64	1.52	1.759	0.001	0.001	6458	6583	1
	Nu (ν)	16.00	5.76	30.918	0.112	0.081	6200	5530	1

Table 6. Marginal effects on the probability scale for dummy variables in both models.

	Model 1			Model 2	
Variables	Logit (n)	Predicted probability	Variables	Logit (n)	Predicted probability
Baseline	-2.007	*11.9%*	Baseline	-1.972	*12.2%*
$SF_{\_Dummy}$	-0.996	*4.7%*	$SF_{\_Dummy}$	-2.978	*4.8%*
$VAB_{\_AD}$	1.489	*37.4%*	$VAB_{\_AD}$	1.486	*38.1%*
$Area_{\_pot}$	-1.005	*4.7%*	$Area_{\_pot}$	-2.959	*4.9%*
			$SF_{\_interação}$	-4.474	*1.1%*

logical models, imputations, and other data sources, resulting in 16.8% zeros.

The discrepancy observed in Figure 2 reflects the uncertainty inherent in the 2019 dataset, which may explain why the tested models exhibit a wider posterior distribution centred around a ψ value slightly above 20%. When comparing the two models, the inclusion of the interaction variable in Model 2 results in distributions more concentrated near zero, suggesting evidence that the absence of irrigation in these municipalities is not due to structural barriers, but rather to informational constraints (institutional, policy-related, etc.).

Municipalities classified as informational zeros (low ψ) exhibit a substantially higher irrigated area, agricultural GVA, and access to technical assistance compared to those classified as structural zeros. Spe-

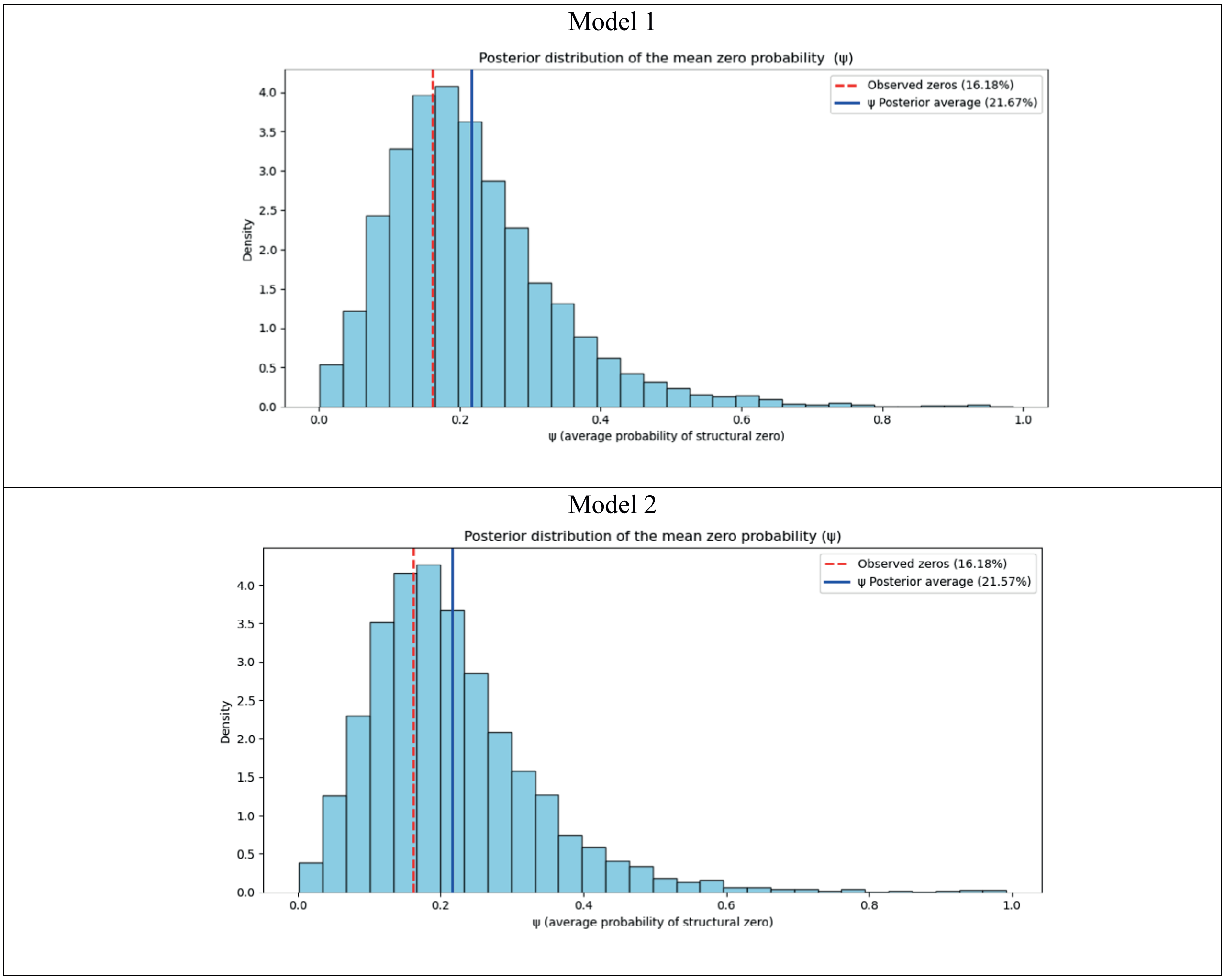


Figure 2. Posterior distribution of the mean zero probability ψ_i.

cifically, average irrigated area in informational municipalities exceeds 3,200 hectares, compared with less than 150 hectares in structurally constrained municipalities (Table 7). Similarly, agricultural value added in informational municipalities is nearly eight times higher than in structural ones.

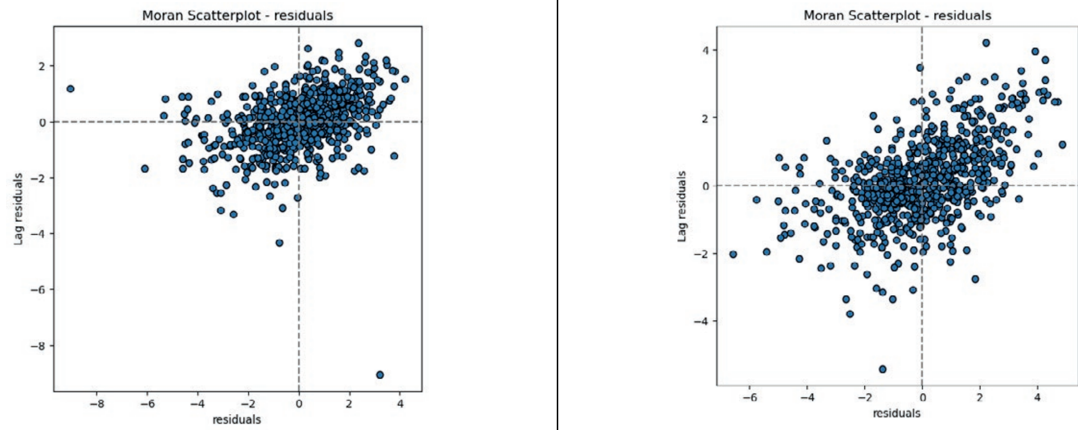
The differences shown in Table 7 have important distributional implications. Policies targeting municipalities classified as informational zeros may disproportionately benefit regions that are already more economically dynamic and better connected to agricultural services, reinforcing existing inequalities. The results are also evaluated in terms of residual spatial dependence. Moran's I is applied to the continuous part of the model ($y > 0$) to assess whether, within this subset, the inclusion of a spatial structure could directly influence the response variable (irrigated area).

Table 7. Characteristics of municipalities by zero classification.

Zero classification	Irrigated area (hectares)	Agricultural GVA (R$)	Technical assistance (index)
Informational	3,291.68	63,136.78	284.86
Intermediate	293.59	16,184.89	148.00
Structural	146.43	8,501.61	110.38

Note: The values represent group means. Municipalities are classified according to the terciles of the predicted probability of structural zeros (ψ). Informational municipalities correspond to the lowest tercile, while structural municipalities correspond to the highest tercile.

In Model 1, there is no strong evidence of spatial clusters in the residuals, and residual autocorrelation is weak (8.39%). In Model 2, using the relative share of



Model 1	Model 2
High-high: 60 municipalities (8.39%)	High-high: 91 municipalities (12.73%)
Low-high: 12 municipalities (1.68%)	Low-high: 11 municipalities (1.54%)
Low-low: 43 municipalities (6.01%)	Low-low: 41 municipalities (5.73%)
High-low: 12 municipalities (1.68%)	High-low: 11 municipalities (1.54%)
Not significant: 588 municipalities (82.24%)	Not significant: 561 municipalities (78.46%)

Figure 3. Scatterplots of Moran's I for Model 1 and Model 2.

agricultural GVA instead of the absolute value variable, the results indicate an increase in residual autocorrelation (12.73%), suggesting that the adoption of an alternative regional variable could better capture the observable characteristics in the region and/or the addition of a spatial variable via a conditional autoregressive model could capture some spatial effect.

4. IMPLICATIONS FOR WATER GOVERNANCE

The distinction between structural and informational zeros has direct implications for water governance in Minas Gerais. In Brazil, water governance operates across multiple levels. At the federal level, water resources are regulated through national policies and legal frameworks. The current National Water Resources Plan (PNRH) adopts basin-level water balance assessments as an important premise for constructing management scenarios. Although the second PNRH cycle identifies the expansion of water-use permitting, significant information gaps persist.

At the basin level, watershed committees coordinate allocation and mediate conflicts among users, while at the municipal level, local governments and rural extension services facilitate access to irrigation technologies and technical support. Underestimating irrigated areas leads to systematic biases in the estimation of consumptive water demand, which in turn affects basin-level water allocation and the planning of water-use charges (Wisser *et al.*, 2008). Accurate identification of irrigated areas is also essential for understanding regional water budgets and improving allocation efficiency (Kumar *et al.*, 2015; Li *et al.*, 2018). In basins such as that of the São Francisco River, where agricultural expansion is spatially uneven, inaccurate identification of irrigated areas can lead to systematic over-allocation or under-allocation of water (Maneta *et al.*, 2009; Ferrarini *et al.*, 2020; Andrade *et al.*, 2024), undermining both equity and efficiency in basin governance.

The predictive results indicate that the zero-inflated model improves the representation of observed zero shares and reveals substantial heterogeneity across municipalities. Of the 139 municipalities without recorded irrigation, approximately 80 are associated with structural constraints, while 59 exhibit characteristics consistent with informational or institutional limitations. These results suggest that a non-negligible share of observed zeros reflects informational gaps rather than physical infeasibility.

These findings underscore the importance of policies that map and promote the efficient use of these areas, including financing programmes for converting rainfed agriculture into irrigable productive land, such as the National Sustainable Irrigation Program, launched under the 2025/26 family farming crop plan or with irrigation policies with cooperative support measures, such as targeted credit lines (e.g., Pronaf Cooperativo). The effectiveness of irrigation policies is often constrained by institutional barriers. The complexity of water rights allocation may limit access to water, particularly for smaller producers. This situation can be mitigated through basin-level coordination and simplified allocation procedures.

Regarding the identification of whether zeros reported in the Irrigation Atlas are structural, it is important to consider that irrigation decisions, particularly among smallholders (e.g., timing and crop choice), reflect farmers' flexibility in managing uncertainties to maximise profit and productivity. High-value perennial crops are generally water-limited, whereas decisions on annual crops involve yearly planning depending on water availability (Marques, Howitt, 2005). In Brazil, crops such as soybean, corn, wheat, and beans are often part of rotation systems to reduce costs and enhance productivity (Canalli *et al*., 2020), complicating the accurate measurement of irrigated areas.

Another relevant point is that the agricultural GVA used in this study includes both crop and livestock production, without distinguishing irrigated from rainfed agriculture. Although it is a relevant indicator of rural economic activity, it serves only as a general proxy of local agricultural dynamism and cannot isolate irrigation-specific effects. Consequently, municipalities with high GVA may have productivity concentrated in extensive livestock, which does not necessarily reflect structural irrigation conditions. These findings are consistent with this study's hypotheses. Structural factors are positively associated with the probability of structural zeros, supporting H1. In contrast, institutional and economic variables such as technical assistance and productive capacity are linked to lower probabilities of zero outcomes and characterise municipalities with informational zeros, supporting H2. Therefore, zeros reported in the Irrigation Atlas and related datasets should be interpreted cautiously, as they may indicate temporary or strategic non-use rather than permanent impossibility. Finally, while this analysis focuses on Minas Gerais, the approach and findings may inform irrigation policy design in other emerging economies with heterogeneous agricultural landscapes.

5. CONCLUSION

The results show that structural and informational zeros are associated with differences in agricultural capacity, access to technical assistance, and regional characteristics. In particular, municipalities with lower agricultural GVA and limited technical support are more likely to be classified as structural zeros, as hypothesised. Considering the discrepancy between the empirical zero share (16.8%) and the estimated posterior distribution (20%), the results suggest that the dataset may contain a substantial proportion of informational zeros, with the model compensating for data uncertainty through its statistical structure. This underscores the importance of statistical approaches capable of differentiating between structural and contextual absence of irrigation.

Despite the contributions of this study, some limitations should be acknowledged. First, irrigated area data from the Irrigation Atlas rely on remote sensing and integrated data sources, which may introduce classification uncertainties, particularly in heterogeneous and smallholder-dominated regions. Second, the agricultural GVA used in this study does not distinguish between irrigated and rainfed production, limiting its interpretation as a proxy for irrigation-specific economic performance. Third, the analysis is based on a single cross-section (2019), preventing a dynamic assessment of irrigation expansion. Fourth, the model does not incorporate infrastructure-related variables, such as water withdrawal systems or irrigation technologies, which could further refine the identification of structural constraints. Fifth, the analysis is conducted at the municipal level and does not capture within-municipality heterogeneity. Potentially relevant covariates, such as producer-level characteristics (e.g., education), are not considered in this study, although they may provide additional insights in future research. Finally, the results may be sensitive to prior specification, although robustness checks indicate that the main inferences remain stable under alternative prior choices.

Future research should incorporate additional variables to capture this informational dimension, such as the presence of irrigation projects (public or private), climatic indicators (average temperature, cumulative precipitation), intra-annual water availability, and measures of local governance. This study highlights the relevance of the Irrigation Atlas for improving public datasets and integrating technical information on irrigated agriculture in Brazil. Recognising that many zeros are not definitive allows targeting interventions where they can have the greatest impact, such as in designated irrigation clusters.

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